

Informing Public Sector Decision Making with Operations Research

Three Applications Examining Health Care, Defense, and Energy

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Who am I? Professional Experience

● University of Missouri

- Department of Industrial and Manufacturing Systems Engineering
- Harry S Truman School of Public Affairs
 - Associate Professor, with tenure, September 2019 - present
 - Assistant Professor, August 2013 - August 2019
 - Associate Site Director, Center for Excellence in Logistics and Distribution (CELDi)
 - Coordinator, Ph.D. program in Public Affairs
 - Core Faculty Member, Institute for Data Science and Informatics

● RAND Corporation

- Adjunct Operations Researcher, August 2013 - present
- Senior Operations Researcher, September 2002 - July 2013
 - Supporting Federally Funded Research & Development Center (FFRDC) Project AIR FORCE
 - Core faculty member, Pardee RAND Graduate School

Who am I? Educational Background

- **Pennsylvania State University**

- Ph.D., Industrial Engineering and Operations Research, December 2002
 - Thesis: *On determining the location and capacity of competitive facilities*
- M.S., Industrial Engineering and Operations Research, May 1999

- **Indiana University of Pennsylvania**

- B.S., Applied Mathematics, May 1997

Presentation Overview

- Since its origins in the 1940s, operations research has had a multi-disciplinary focus, making its greatest impacts when partnering with experts from other fields to improve decision-making
- This presentation will discuss three projects in which I collaborated with researchers in other disciplines to address problems arising in the public sector
 - ① Evaluating diabetes management at community health centers (CHCs); collaborating with a sociology professor
 - ② Determining cost-effectiveness of government vs. commercial provision of intra-theater airlift (ITA) to deployed military forces; collaborating with an economics professor
 - ③ Identifying optimal multi-state partnerships to reduce carbon pollution via biopower generation; collaborating with a forestry professor

Diabetes Poses Significant Challenge to US Healthcare System Generally, to Underserved Populations Particularly

- Diabetes affects 30 million American adults (9.4% of US population)
 - Seventh leading cause of death in US
 - Of all dollars spent on healthcare in US, 25% spent caring for people with diagnosed diabetes
- Many authors have shown management of diabetes in population to reflect social determinants of health and access to quality health care
 - Persistent inequalities in diabetes prevalence, with higher rates among non-Hispanic Blacks, Hispanics, American Indians and Alaskan Natives, low SES
 - Poorer glycemic control, indicating worse diabetes management, found for Hispanics, Blacks, American Indians, individuals without medical insurance
 - Neighborhood characteristics, such as economic disadvantage, low social cohesion, food insecurity, also linked with poorer glycemic control

This research was supported by the National Institute of General Medical Sciences of the National Institutes of Health under Award Number P20GM104417.

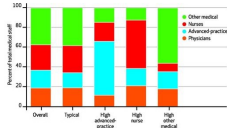
Community Health Centers (CHCs) Play a Key Role in US Healthcare Delivery to Underserved Populations

- CHCs provide comprehensive health services to medically under-served and uninsured populations
- CHCs provide community-based, patient directed healthcare with the support of federal grant funding, and charge patients on a sliding fee scale in accordance with their ability to pay
- There are nearly 1,400 CHCs in the US, providing service to 24.3 million Americans in 2015 (HRSA, 2015)
- CHCs play important role providing diabetes care
 - In 2015, CHCs served 2.1 million patients with diabetes, for a total of 7.1 million visits

Staffing Patterns Influence CHC Performance on Diabetes Patient Outcomes

- Recognized link between multidisciplinary healthcare teams and improved patient outcomes, reduced disparities (Proser et al., 2015)
 - ADA recommends best practice of integrating psychosocial care into patient-centered delivery
 - Integration of behavioral health into primary care important for diabetes outcomes (Katon et al., 2010; Reiss-Brennan et al., 2016)
 - Patient-centered collaborative care teams may be effective, since changes in HbA1C influenced by patient behavior (Litaker et al., 2003)
- Prior research identified four different CHC staffing patterns: typical, high advanced-practice staff, high nursing staff, and high other medical staff (Fu et al., 2015)
 - Authors utilized “cluster analysis” across four categories of medical staff (physicians, advance-practice, nurses, other)
 - Excluded mental health, dental, vision, enabling services (e.g., interpretation services)

Exhibit 1 Composition Of Medical Staff in Community Health Centers Overall And For Four Staffing Clusters, 2012



Research Questions

- What typologies of community health center staffing patterns exist?
- How are operational characteristics of health centers (staffing patterns and efficiency), along with composition of patient populations and sociodemographic settings of communities served by CHCs, associated with diabetes management among patients?

Our Analytic Strategy Utilizes a Variety of Operations Research and Data Analytics Tools

- We conduct a **latent class analysis (LCA)** to identify CHC typologies
- We utilize **data envelopment analysis (DEA)** to obtain an efficiency score for each CHC, using a gated approach to address quality metrics, comparing each CHC only to members of its latent class
- We use **generalized linear models (GLM)** specified with a logit-link function for a binomially-distributed dependent variable to examine how these typologies and other contextual measures are related to the proportion of CHC patients with uncontrolled diabetes (i.e., *patients with hemoglobin A1c > 9% or not tested during the year*)

Data Collected at Level of Individual CHCs, Capturing Staffing, Patients and Regional Characteristics

- After some exclusions, obtain sample size of 1,229 CHCs
- **CHC-level data** [HRSA Health Program Grantee Data (2015)]
 - Full-time equivalents (FTE) in six staffing categories
 - Total number of patients
 - Number of adult patients with diabetes, and their number of visits
 - Number of patients with uncontrolled diabetes (HbA1C level > 9%)
 - Race, poverty, and insurance status of patients
- **Regional data** [ACS (2010-14), Behavioral Risk Factor Surveillance System (2009-12)]
 - Obtained by averaging zip-code tabulation area (ZCTA)-level data across all ZCTAs served by CHC
 - Variables capture *percent urban, in poverty, non-white, obese, with no access to usual source of care*

We Conducted an LCA to Identify CHC Typologies

Table 2. Means of CHC Staffing Percentage (%) Full-Time Equivalents (FTEs) Indicators by Latent Class Membership

	Full Sample	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
<i>% of Total FTE</i>								
Physicians	10.37	11.77 <i>bcdfg</i>	6.66	7.63 <i>f</i>	9.92 <i>bfg</i>	30.85 <i>abcdfg</i>	4.81	2.76
Vision/Dental	13.61	2.32	39.69 <i>acdefg</i>	7.68 <i>a</i>	16.83 <i>acefg</i>	4.18 <i>a</i>	7.40 <i>a</i>	0.95
Nursing/Medical Tech.	40.25	51.94 <i>bcddefg</i>	26.96 <i>g</i>	25.86 <i>g</i>	40.32 <i>bcfg</i>	41.50 <i>bcfg</i>	23.47	15.81
Advanced Practice (NP/PA/CNM)	12.03	16.14 <i>bdef</i>	8.65 <i>e</i>	10.81 <i>e</i>	10.82 <i>bef</i>	5.10	7.71	63.80 <i>abcdef</i>
Behavioral	6.72	3.81	5.12	9.64 <i>abdeg</i>	6.00 <i>a</i>	4.74	41.78 <i>abcdeg</i>	3.12
Enabling	17.02	14.03	12.85	38.38 <i>abdefg</i>	16.11 <i>ab</i>	13.66	14.84	13.56
N	1,234	309	106	102	632	39	38	8
Proportion	100%	25.0%	8.6%	8.3%	51.2%	3.2%	3.1%	0.6%

Notes: ^{a-g} represents that the mean is significantly larger than the mean for another class at $p < 0.05$ based on Bonferroni post hoc paired comparisons of Analysis of Variance (ANOVA) tests (classes 1-7 coded as *a-g*). **Class 1** “High Nursing/Med Tech and Adv. Practice”, **Class 2** “High Vision/Dental”, **Class 3** “High Enabling”, **Class 4** “Typical”, **Class 5** “High Physician”, **Class 6** “High Behavioral”, **Class 7** “High Advanced Practice”

Consider Two Approaches to Estimating CHC Efficiency

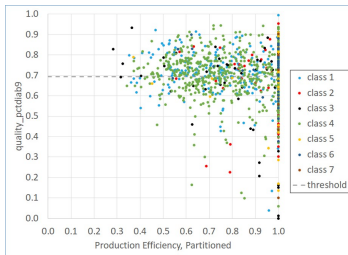
- CHC cost per patient varied significantly across latent classes

Table 3. Comparisons of Efficiency and Cost Per Patient by Staffing Latent Class (Analysis of Variance)

		Full Sample	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Cost per Patient	Mean	\$890	\$740	\$805	\$1,654 _{abde}	\$816	\$903	\$1,428 _{abde}	\$1,599 _{abd}
	St. Dev.	\$661	\$320	\$305	\$1,671	\$331	\$404	\$1,092	\$1,491

Notes: ^{a*} represents that the mean is significantly larger than the mean for another class at $p < 0.05$ based on Bonferroni post hoc paired comparisons of Analysis of Variance (ANOVA) tests (classes 1-7 coded as a-g). Class 1 "High Nursing/Med Tech and Adv. Practice", Class 2 "High Vision/Dental", Class 3 "High Enabling", Class 4 "Typical", Class 5 "High Physician", Class 6 "High Behavioral", Class 7 "High Advanced Practice"

- DEA calculates a more nuanced measure of CHC efficiency



GLM Examined Relationships Between Diabetes Control and Patient/Regional Characteristics

Table 4: Patient and Regional Characteristics and the Odds of Having a Patient with Uncontrolled Diabetes at a Community Health Center (GLMs; Odds Ratio)

	Model 1	Model 2	Model 3	Model 4	Model 5*
<i>Patient Characteristics</i>					
% Black	1.035* (0.02)		1.081*** (0.03)	1.095*** (0.03)	1.084** (0.03)
Black X R. non-White				0.964^ (0.02)	0.948** (0.02)
% Asian/Pacific Isl.	0.941*** (0.01)		0.970^ (0.02)	0.884*** (0.02)	0.903*** (0.02)
Asian X R. non-White				1.053*** (0.02)	1.038** (0.02)
% Hispanic	1.006 (0.02)		1.009 (0.02)	1.009 (0.02)	0.989 (0.02)
Hispanic X R. non-White				0.941*** (0.02)	0.947** (0.02)
% American Indian	1.044^ (0.02)		1.057* (0.03)	1.063* (0.03)	1.048^ (0.03)
Amer. Ind. X R. non-White				0.966 (0.02)	0.965^ (0.02)
% in Poverty	1.020 (0.02)		1.011 (0.02)	0.999 (0.02)	0.977 (0.02)
% Uninsured	1.025 (0.03)		0.999 (0.03)	0.991 (0.03)	0.997 (0.03)
% Medicaid	0.982 (0.03)		0.980 (0.03)	0.990 (0.03)	0.989 (0.03)
% Medicare	0.938* (0.03)		0.932** (0.03)	0.929** (0.03)	0.912*** (0.02)
<i>Regional Characteristics</i>					
Urban		1.094** (0.03)	1.049 (0.03)	1.046 (0.03)	1.046 (0.03)
% in poverty		0.986 (0.02)	0.996 (0.02)	1.006 (0.03)	1.012 (0.02)
% non-White		0.989 (0.02)	0.932** (0.02)	0.947* (0.03)	0.965 (0.02)
% obese		1.070*** (0.02)	1.038^ (0.02)	1.027 (0.02)	1.019 (0.02)
% no access to care		1.070*** (0.02)	1.068*** (0.02)	1.071*** (0.02)	1.049*** (0.02)

Notes: a Model 5 includes staffing latent classes and efficiency. ^ p < .1, * p < .05, ** p < .01, *** p < .001; standard errors are in parentheses, standard errors scaled using square root of deviance-based dispersion.

- CHC patients' diabetes control influenced by interactions between patient-racial and regional-racial compositions

CHC Efficiency Significantly Impacts Odds of Patients Exhibiting Uncontrolled Diabetes

Table 5: Staffing Patterns, Cost per Patient, Efficiency and the Odds of Having a Patient with Uncontrolled Diabetes at a Community Health Center (GLMs; Odds Ratio)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6 ^b
<i>FTE Latent Classes^a</i>						
Class 1	1.192 [^] (0.13)		1.134 (0.12)		1.174 [^] (0.11)	1.198 [^] (0.11)
Class 2	1.325* (0.16)		1.272* (0.16)		1.276* (0.14)	1.245* (0.14)
Class 3	1.154 (0.14)		1.168 (0.14)		1.158 (0.12)	1.149 (0.12)
Class 4	1.124 (0.12)		1.085 (0.11)		1.135 (0.11)	1.120 (0.11)
Class 5	1.063 (0.14)		1.116 (0.14)		1.096 (0.13)	1.147 (0.14)
Class 7	2.043 (0.92)		1.919 (0.86)		1.538 (0.64)	1.369 (0.55)
Cost per patient (per \$100)		0.984*** (0.00)	0.985*** (0.00)			
Efficiency				0.763*** (0.06)	0.757*** (0.06)	0.696*** (0.06)

Notes: ^a Class 6 is reference; ^b Model 6 controls for patient characteristics (race, poverty, insurance status), regional characteristics (urban, poverty, non-White, obese, no access to care) and patient-regional race interactions. Class 1 "High Nursing/Med Tech and Adv. Practice", Class 2 "High Vision/Dental", Class 3 "High Enabling", Class 4 "Typical", Class 5 "High Physician", Class 6 "High Behavioral", Class 7 "High Advanced Practice". Models with efficiency also controls for the exclusion criteria flag; [^] $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$; standard errors are in parentheses, standard errors scaled using square root of deviance-based dispersion.

Conclusions

- Intersection of racial compositions (patients' with area where patients live) associated with level of diabetes management at CHCs
 - Diabetes control worse at CHCs serving racial minorities (Blacks, Hispanics, and American Indians) living in predominantly White areas
 - Consistent with large body of work finding that living in areas where one is a racial minority associated with reduced access and poorer care
 - Processes appear to reversed for Asians, warranting future research
- Staffing profile matters: CHCs which focus a larger percentage of FTE towards behavioral health care have lower rates of uncontrolled diabetes among patients
- Relationship between diabetes control and efficiency differs, by metric
 - With simple metric (cost per patient), found support for inverse relationship: increases in amount spent per patient (reduced efficiency) associated with lower odds of a patient having uncontrolled diabetes
 - With more nuanced metric (DEA), found evidence for direct relationship: increases in DEA efficiency score associated with lower odds of a patient having uncontrolled diabetes

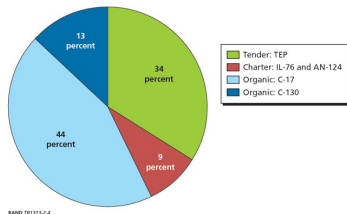
Issue and Research Questions

- Intratheater airlift (ITA) delivers critical and time-sensitive supplies (e.g., blood products for transfusions, repair parts for vehicles) to deployed forces
 - ITA within combat theater of operations has traditionally been provided by military (organic) aircraft
- However, within US Central Command (USCENTCOM), a significant amount of ITA has been performed by commercial providers
 - In 2009, DoD spent \$600M on commercial ITA (CITA) movements in USCENTCOM
- Were these expenditures cost-effective? That is, did DoD get a “good value” on these purchases?
 - How would this be measured?
 - Should use of CITA be expanded (or reduced)?

This research was sponsored by the United States Air Force under Contract FA7014-06-C-0001.

Commercial Sources Provided Significant Amount of ITA in USCENTCOM in 2009, Via Two Primary Means

Figure 2.4
Intra-USCENTCOM Airlift Tons, by Mode, 2009



- Tendering of movements by Theater Express Program (TEP)
 - Each day, DoD identifies set of movements and offers them to carriers
 - Relatively flexible terms, but highly variable costs
- Chartering of whole aircraft such as IL-76 and AN-124
 - DoD leases the use of an entire aircraft for a specified duration
 - Relatively inflexible terms, but very predictable costs

* In addition to carrying cargo, C-17 and C-130 also perform intratheater passenger movements on many of these sorties (CITA do not transport passengers); these passenger movements are not included in the cargo tonnage or ton-miles

Examined Over 16,000 Tender Offers to Identify Extent of Price Elasticities of Demand

Table B.2
Regression Results for Tender Cost Regressions

Model	1a	1b	2
Dependent variable	$\log(p_{odt})$		
β (coef. on $\log(t_{odt})$)	0.415**	0.297**	NA
Standard error	0.006	0.008	NA
δ (coef. on $\log(q_{odt})$)	-0.266**	-0.282**	-0.296**
Standard error	0.004	0.004	0.004
ϕ (coef. on $\log(N_{odt})$)	-0.554**	-0.475**	-0.383**
Standard error	0.008	0.009	0.009
Month dummies (γ_m)	No	Yes	Yes
Origin and destination dummies ($\eta_o, \mu_o, \text{ or } \lambda_{od}$)	No	Yes	Yes
Observations	17,618	17,618	17,725
Parameters	4	73	325
R ²	0.522	0.622	0.681

NOTE: Within this table, * indicates the coefficient is different from 0 with at least 95 percent confidence, and ** indicates the coefficient is different from 0 with at least 99 percent confidence.

- **Competition is important for reducing tender cost:** 10% increase in number of bidders on tender causes tender costs to decline between 3.8-5.5% (ϕ)
- **Cargo bundling can reduce costs:** as weight of given tender increases 10%, costs per pound transported decline by between 2.7-3.0% (δ)
- **Differences in flight time explain some of the cost variation between routes:** as flight times increase 10%, tender costs increase by between 3.0-4.2% (β)
- **Specific location of cargo origin and destination are also important predictors of tender cost:** influence extends beyond just flight time between origin and destination pair

Further Analyses Examined How Demand for Tender Services Affects Number of Carriers Who Bid on a Tender

Table B.3
Regression to Predict Number of Bidders

Model	1a	1b	2a	2b
	(OLS)	(OLS)	(Poisson)	(Poisson)
Dependent variable	$\log(N_{odt})$		N_{odt}	
ν (Coef. on $\log(Q_{odt})$)	0.192**	0.149**	0.158**	0.1347**
Standard error	0.004	0.005	0.004	0.0049
Origin and destination dummies	No	Yes	No	Yes
Observations	17,725	17,725	17,725	17,725
Parameters	2	22	2	22
R ²	0.123	0.232	NA	NA
Log-likelihood	NA	NA	-35,771.1	-34,957.4

NOTE: Within this table, * indicates the coefficient is different from 0 with at least 95 percent confidence, and ** indicates the coefficient is different from 0 with at least 99 percent confidence.

- **Carriers prefer to bid on more active routes:** routes with 10% more tenders had, on average, between 1.3-1.9% more carriers bidding on cargo movements (ν)

We Assumed That Price Elasticities Did Not Exist for Commercial Charter Movements

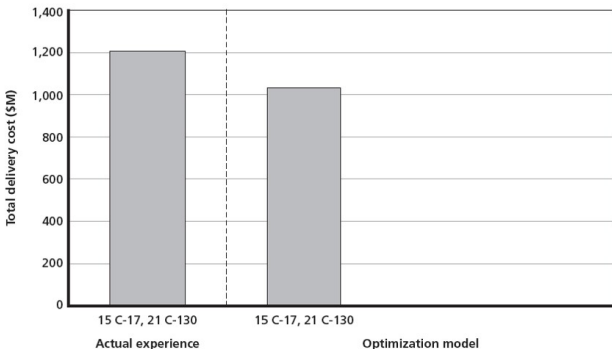
- We instead applied contract language from a 2010 contract within USCENTCOM to all potential ITA charters, stating
 - Specific prices for movements between certain origin-destination pairs (e.g., \$134,000 for a sortie between Kuwait and Bagram)
 - \$89/mile rate for movements between other locations in USCENTCOM
 - \$17,000 cancellation charge per mission not utilized below the contract's guaranteed level
- When an aircraft is placed on charter, we assume that it will then be on contract, and must be utilized on all subsequent days (or face a cancellation charge)

Utilized Optimization Model to Assess Cost-effectiveness

- To make accurate comparisons, one must solve an assignment problem: which movements to assign to which missions?
- Model's objective function is to minimize total expenditures on ITA
- Constraints limit the use of individual C-130, C-17 and charters
 - Maximum payload, pallet positions, daily operating hours
 - C-130 and C-17 begin and end all missions at an "overnight" location
 - Assume all passenger movements must occur via C-130 or C-17
- "Binning" models nonlinear relationship between tender cost and:
 - Tender weight: [0,5], (5,15] or (15, 25) tons
 - Total movements along $o - d$ pair thus far: [0,20), [20,40] or >40 bids
 - Binary assignment variable for weight bin-activity bin pair. **Bins are necessary because we're trying to minimize a concave function.**
- Allowed model one day of "look ahead" at future demands
 - Each day, the model is aware of that day's demands plus the demands that will generate on the following day
 - Assume all deliveries must occur no later than date delivery was actually accomplished in historical data (but could occur earlier)

Optimization Identified \$175M Potential Savings, For Similar Level of Employed C-17s and C-130s

Figure 4.1
Total Delivery Cost for a Level of USAF Resources Equal to Actual USCENTCOM Usage in 2009



RAND TR1313-4.1

How Did Optimization Model Differ From Experience, For Similar Number of C-17 and C-130?

Table 4.3
Optimization Model Solution Versus Historical Experience, Each Utilizing an Equal Number of C-17s and C-130s

Airlift Type	2009 Experience*					Optimization Solution				
	Cargo (000 tons)	Passengers (000s)	Cargo Ton-Miles (M)	Passenger-Miles (M)	Cost (\$M)	Cargo (000 tons)	Passengers (000s)	Cargo Ton-Miles (M)	Passenger-Miles (M)	Cost (\$M)
C-17	173	542	167	346	378	183	621	207	411	303
C-130	54	592	18	219	234	43	512	19	209	157
TEP	133	—	103	—	382	41	—	43	—	182
IL-76**	38	—	52	—	214	137	—	85	—	392

* 6,300 tons flown via C-5 intra-USCENTCOM, these demands included in all optimization results

** Value includes 2009 AN-124 movements, optimization model utilized only IL-76 for charter ITA

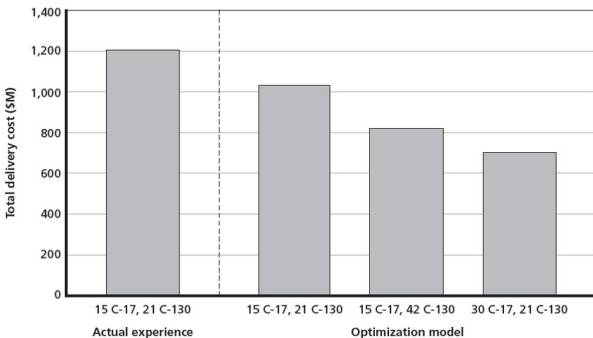
- A few origin-destination country pairs accounted for most of the changes in cargo movements:
 - C-17 displaced TEP across long movements
 - IL-76 displaced TEP across short movements
 - **Primary factor:** cargo aggregation across multi-sortie missions

Table 4.4
Optimization Model Solution Versus Historical Experience, by Airlift Type and Origin-Destination Country Pairs

Airlift Type	Optimization Model Minus 2009 Experience, by Origin-Destination Country Pairs (000 tons of cargo)		
	Iraq-Iraq	Kuwait-Iraq	Kuwait-Afghanistan
C-17	-12	+6	+20
C-130	+6	0	0
TEP	-20	-25	-15
IL-76	+26	+18	-5

Increasing Number of DoD Aircraft Generated Even Greater Reductions in Total Annual Costs

Figure 4.3
Total Delivery Cost with Double the Number C-17s and the Same Number of C-130s, Versus 2009 Levels



RAND TR1313-4.3

Finding That C-17 and C-130 More Cost-Effective than CITA Holds Across Large Changes to Cost Structure

Table 4.9
Sensitivity Analysis

Airlift Type	Cargo Moved (000 tons)			
	2009 Experience (daily average 21 C-130s)	Optimization Model Results, with 48 C-130s		
		Best Estimates of Costs	TEP Costs Scaled by 9/10, Other Costs Scaled by 10/9	TEP Costs Scaled by 4/5, Other Costs Scaled by 5/4
C-17	173	239	235	232
C-130	54	87	88	83
TEP	133	21	34	50
IL-76	38	57	47	38

- Performed additional optimization model runs to examine sensitivity of cargo allocations to variations in cost structure:
 - Large increases in cargo moved by C-17 and C-130 (versus 2009 experience) relatively insensitive to increases in C-17 and C-130 cost
 - Large decreases in total cargo moved by TEP (versus 2009 experience) somewhat sensitive to decreases in TEP cost, although TEP displaces IL-76 and not USAF-organic movements as TEP costs decrease and all other aircrafts' costs increase

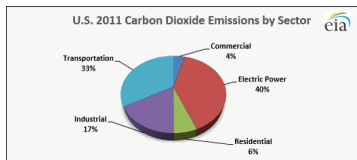
Conclusions

- Based on 2009 USCENTCOM intra-theater airlift (ITA) demands:
 - C-17 and C-130 are both generally more cost-effective than CITA, but CITA options should be retained to supplement USAF aircraft
 - IL-76 charters somewhat more cost-effective than movement tenders
 - Findings are insensitive to fairly large changes to cost structure
- Decision-support tools are needed to assist the CAOC Air Mobility Division and CDDOC with daily airlift cargo allocation decisions
- In contrast to 2009 USCENTCOM historical performance of \$1.2B in total ITA cost, an optimization-based approach could:
 - Reduce total ITA cost by \$175M, without increasing number of employed C-17 and C-130
 - Reduce total ITA cost by \$390M or \$500M by doubling number of employed C-130 or C-17, respectively
- **Impact of analysis-** a DoD analyst wrote:

The report enlightened senior leadership which gave the analysts at JDPAC/AMC/TRANSCOM the “horsepower” to influence changes in the tender program... resulted in the reduction from \$450 million annually to \$250 million annually. Although the changes in the report were not implemented exactly as written, w/o the report highlighting areas for improvement, my opinion is that the tender program would still be in the \$400+ annual range.

Co-firing Woody Biomass Can Help Reduce Carbon Emissions from Electricity Generation

- Power plants are the largest source of carbon dioxide emissions in the United States, making up roughly 40% of all domestic greenhouse gas emissions



- The U.S. Environmental Protection Agency (EPA) proposed a rule that aims to reduce carbon emissions from U.S. coal-fired power plants, providing state-specific rate-based goals to achieve a total U.S. carbon emission reduction of 32% below 2005 levels by 2030
 - Co-firing woody biomass (considered a carbon neutral energy source) with coal can allow electricity providers to achieve emissions reductions without significantly modifying their existing infrastructure
- Despite proposed changes to EPA regulations, over half of US states have adopted a Renewable Portfolio Standard aiming to increase the share of electricity generated from renewable resources (DSIRE 2016).

This research was supported by the United States Department of Agriculture under grant number 2017-67019-26286.

Research Questions

- To what extent can the use of woody biomass in electricity generation support CO₂ emissions reduction targets?
 - Are existing power plants well suited to co-fire woody biomass? If not, what facility upgrades would be required (at what cost)?
 - Is there sufficient wood energy feedstock located sufficiently close to existing power plants?
 - How would increased demand for wood energy feedstocks impact procurement costs?
- What are the most cost-effective approaches for states to achieve reductions in CO₂ emissions via co-firing?
 - Individually? Or in collaborative multi-state plans?
- How would uncertainty in facility upgrading cost, coal electricity generation cost, and plants emission rate impact the decision making?
- *Illustrate our approach with application to 18 states in Northeast US*

Estimating Biomass Procurement Costs

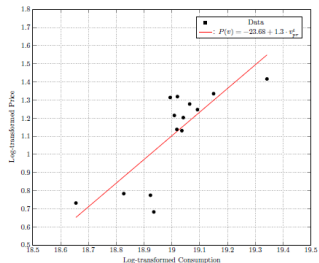
- Define biomass procurement variable
 - v_{pr}^t : amount of woody biomass utilized at power plant p from sources within radius r during time period t
- Using USDA Forest Inventory and Analysis data, we estimate
 - $\bar{\zeta}_{pr}^t$: average per-ton price of woody biomass for plant p within radius r during time period t
 - φ_{rp} : potential biomass available within radius r for power plant p ;
thus $v_{pr}^t \leq \varphi_{rp} \quad \forall t, p, r$
- Use constant elasticity demand response model to estimate how quantity of woody biomass consumed impacts woody biomass price

$$P(v_{pr}^t) = \alpha_{pr}^t (v_{pr}^t)^\beta$$

- Use a log-transformation to estimate elasticity parameter β

$$\ln(P(v_{pr}^t)) = \ln(\alpha_{pr}^t) + \beta \ln(v_{pr}^t)$$

Estimating Biomass Procurement Costs



- Use Energy Information Administration data to estimate $\beta = 1.3075$
 - That is, 1% increase in demand is associated with a 1.3075% increase in woody biomass price per ton

- Obtain α_p value for plant p as follows:

- Estimate initial intercept as

$$K_{p1}^t = \bar{\zeta}_{p1}^t - \left(\frac{\bar{\zeta}_{p2}^t - \bar{\zeta}_{p1}^t}{2} \right)$$

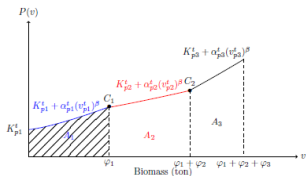
- Integrate area under curve (A_1 in figure) to obtain α_{pr}^t for radius $r = 1$:

$$\int_0^{\varphi_1} K_{p1}^t + \alpha_{p1}^t (v_{p1}^t)^\beta dv = \bar{\zeta}_{p1}^t \varphi_1$$

- At point C_1 , $K_{p2}^t + \alpha_{p2}^t (\varphi_1)^\beta = K_{p1}^t + \alpha_{p1}^t (\varphi_1)^\beta$

- Can then compute K_{p2}^t and α_{p2}^t using

$$\int_{\varphi_1}^{\varphi_1 + \varphi_2} K_{p2}^t + \alpha_{p2}^t (v_{p2}^t)^\beta dv = \bar{\zeta}_{p2}^t (\varphi_2)$$



Single-state Robust MINLP

- We utilize a robust MINLP, based on Bertsimas & Sim (2003), to identify the minimum-cost set of decisions that allow the power plants in state s to satisfy electricity generation level i , at emission level j , satisfying robustness level j , as follows:
- Upgrading decision variables
 - $x_p^t = \begin{cases} 1 & \text{if power plant } p \text{ upgrades its MHS at time } t, \\ 0 & \text{otherwise} \end{cases}$
 - $w_p^t = \begin{cases} 1 & \text{if power plant } p \text{ upgrades its boiler at time } t, \\ 0 & \text{otherwise} \end{cases}$
- Electricity generation variables
 - y_p^t : MWh generated from woody biomass at power plant p during time period t
 - z_p^t : MWh generated from coal at power plant p during time period t
- Assume boiler upgrade cost (associated with w_p^t) and coal electricity generation cost (associated with z_p^t) are **uncertain** data parameters

Single-state Robust MINLP

Our robust nonlinear **objective function** is thus:

$$\begin{aligned} \min \quad & \sum_{t \in T} \sum_{p \in P} \sigma_p^t x_p^t + \sum_{t \in T} \sum_{p \in P} \gamma_p^t w_p^t + \int_0^{\varphi_1} (K_{p1}^t + \alpha_{p1}^t (v_{p1}^t)^\beta) dv + \int_{\varphi_1}^{\varphi_1 + \varphi_2} (K_{p2}^t + \alpha_{p2}^t (v_{p2}^t)^\beta) dv \\ & + \int_{\varphi_1 + \varphi_2}^{\varphi_1 + \varphi_2 + \varphi_3} (K_{p3}^t + \alpha_{p3}^t (v_{p3}^t)^\beta) dv + \sum_{t \in T} \sum_{p \in P} \lambda_p^t y_p^t + \sum_{t \in T} \sum_{p \in P} \rho_p^t z_p^t + \bar{\omega}_0 \Gamma_0 + \sum_{(t,p) \in P_0} \bar{\omega}_{tp}^0 + \sum_{(t,p) \in P_1} \bar{\omega}_{tp}^0 \end{aligned}$$

Integrate these terms to obtain following closed form objective function:

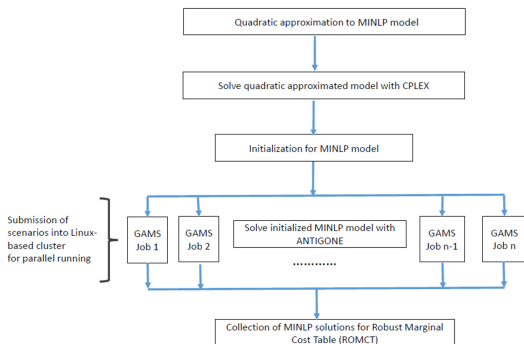
$$\begin{aligned} \min \quad & \sum_{t \in T} \sum_{p \in P} \sigma_p^t x_p^t + \sum_{t \in T} \sum_{p \in P} \gamma_p^t w_p^t + \sum_{t \in T} \sum_{p \in P} \sum_{r \in R} K_{pr}^t v_{pr}^t + \alpha_{p1}^t \frac{(v_{p1}^t)^{\beta+1}}{\beta+1} + \\ & \alpha_{p2}^t \left(\frac{(\varphi_{p1}^t + v_{p2}^t)^{\beta+1}}{\beta+1} - \frac{(\varphi_{p1}^t)^{\beta+1}}{\beta+1} \right) + \alpha_{p3}^t \left(\frac{(\varphi_{p1}^t + \varphi_{p2}^t + v_{p3}^t)^{\beta+1}}{\beta+1} - \frac{(\varphi_{p1}^t + \varphi_{p2}^t)^{\beta+1}}{\beta+1} \right) + \\ & \sum_{t \in T} \sum_{p \in P} \lambda_p^t y_p^t + \sum_{t \in T} \sum_{p \in P} \rho_p^t z_p^t + \bar{\omega}_0 \Gamma_0 + \sum_{(t,p) \in P_0} \bar{\omega}_{tp}^0 + \sum_{(t,p) \in P_1} \bar{\omega}_{tp}^0 \end{aligned}$$

Model's **constraints** address:

- Total electricity demanded
- RPS target for renewable energy generation
- Power plant capacity
- Power plant CO₂ emissions (rate for each plant obtained from EPA data, and assumed to be **uncertain** data parameter)
- Minimum and maximum biomass generation at each power plant, depending upon the facility upgrades that have been performed
- Additional constraints account for robustness in uncertain data

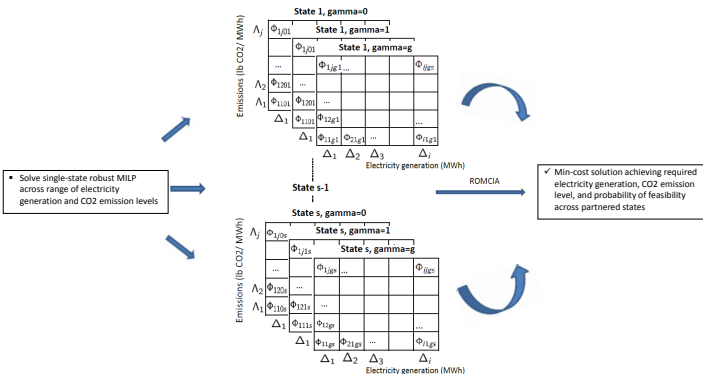
Solving Single-state MINLP

- We solve MINLP using two-stage approach (recall that nonlinear terms in objective function are raised to power $\beta + 1 = 2.3075$)
 - However, we need to solve this MINLP for each state, across a variety of electricity generation level i , emission level j , and robustness level j
 - In total, over 215,000 instances were solved



Robust Marginal Cost Integrated Approach (ROMCIA)

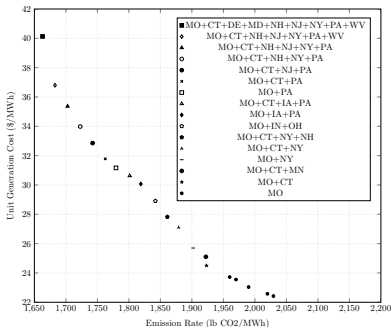
- To solve the multi-state model, we developed a robust marginal cost integrated approach (ROMCIA) MILP
- Define binary variable $u_{ijgs} = 1$ if state s joins partnership at electricity generation level i , emission level j , robustness level g



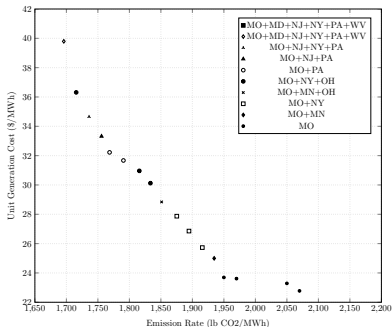
Efficient Frontier of Emission Rate and Generation Cost

- Can identify efficient frontier of multi-state collaborations for any desired subset of states (one state, MO, presented here)
- Every multi-state model solution has at least Ψ likelihood of feasibly satisfying emission constraint
- Observe that increasing Ψ increases cost at any desired emission rate

$\Psi = 0\%$

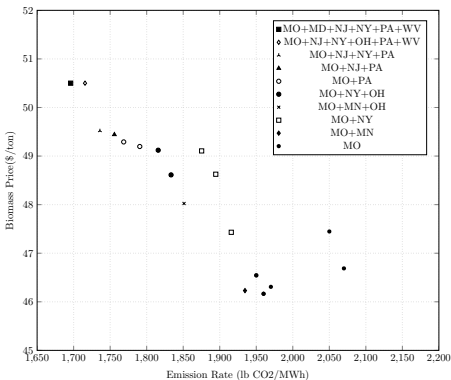


$\Psi = 90\%$



Woody Biomass Procurement Price: $\Psi = 90\%$

- Aggregate price of woody biomass impacted by target emission rate
 - High price at lower emission rates partly due to MO collaborations with states where biomass price higher than it is in MO
 - However, price increases also due to increased demand for woody biomass to achieve lower emission rates



Conclusions

- Woody biomass procurement price significantly affected by demand
 - Aggregated price higher at lower emission rates, due to increased demand and necessity to partner with states that have large amounts of woody biomass availability but relatively high prices
- Considering uncertainty and demand-price relationships, often preferable for a state (e.g., MO) to enter into multi-state partnerships
 - Operating independently, MO can efficiently achieve emission rates of 1950 lb/MWh and higher
 - To achieve emission rate below this level, advantageous from aggregate cost perspective for MO to enter into multi-state partnerships
 - Ignoring emission rate uncertainty, MO can achieve 15% emission reduction below 1950 lb/MWh level by partnering with other states
 - If uncertainty in emission rate included in model, MO can achieve 13% emission reductions below this 1950 lb/MWh level by partnering with other states, at feasibility probability of 90%

