THREE ESSAYS ON SOCIAL COST ELEMENTS OF ELECTRICITY GENERATION AND STORAGE IN THE MID-ATLANTIC REGION

by

Yosef A. Shirazi

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Marine Studies

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The journey through my doctoral studies did not follow a straight path. It was, however, a tremendously worthwhile experience. Upon entering the Marine Studies program, I had only a vague concept of how to describe and systematically assess complex trade-offs. Upon graduation, I will leave with a well-developed research language, a robust set of quantitative tools, and sufficient expertise to contribute meaningful new insights to the fields of environmental decision-making and cost-benefit analysis.

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ABSTRACT

Electricity generation and storage systems are experiencing dramatic shifts in the United States. Each decision underpinning these shifts involves a variety of complex trade-offs. From an economic welfare perspective, these trade-offs are described in terms of social costs and social benefits. Three essays presented in this dissertation explore aspects of social costs—and to a lesser extent social benefits—of electricity generation and storage technologies in the Mid-Atlantic region. While the social costs of mature technologies are generally well known, the social costs of emerging technologies or mature technologies in emerging environments have not been studied extensively.

The first essay investigated the economics of vehicle-to-grid enabled electric school buses. This emerging storage technology was found to impose a variety of novel costs that have been frequently overlooked in the literature. Contrary to previous findings, a vehicle-to-grid enabled electric school bus was found to increase net present cost per seat relative to a conventional diesel bus. Vehicle-to-grid technology may become economically justifiable in future years contingent upon favorable technological, market and regulatory developments.

A second essay investigated cost increases at a nuclear generating station from expected future salinity increases in the Delaware River and Estuary. This mature technology is projected to encounter an emerging operational environment as ambient water used for cooling increases in salinity from sea level rise and a deepened navigational

channel. To estimate cost increases, a linked physical-economic model was developed to generate daily forecasts of ambient salinity under different future conditions and the resulting changes in the facility's cooling water treatment and pumping requirements. On an equivalent annual basis (discounted at 5%), average cost increases were estimated as $0.4M per year. Methods developed here can be adapted to other estuarine facilities to estimate future cost increases under different salinity and operating regimes.

The final essay investigated recreational impacts from offshore wind power projects by analyzing data from four in-person survey events. Respondents ($n \approx 1500$) were provided with simulated images of a large offshore wind project at different distances from shore and indicated if their beach enjoyment would have been made better or worse. In addition, respondents indicated whether they would have canceled their last beach trip due to the presence of the project at each distance. At policy relevant distances of 12.5 - 15 miles, mostly neutral and positive impacts to beach recreation were found. In addition, cancelation rates at these distances were generally under 10%. Trip cancelation rates varied significantly across surveys, suggesting responses may be sensitive to seemingly minor changes in survey format, wording and/or timing.

These essays provide estimates and insights that can assist in identifying socially optimal electricity generation and storage systems. In addition, they illuminate ongoing uncertainties in the fields of vehicle-to-grid, salinity-induced cost increases to evaporatively cooled generating stations and visual impacts from offshore wind power.

NOMENCLATURE

BEV:	Battery Electric Vehicle
CBA:	Cost Benefit Analysis
COC:	Cycles of Concentration
CNG:	Compressed Natural Gas
FR:	Frequency Regulation
HCGS:	Hope Creek Generating Station
Kgal:	Thousand Gallons
kWh:	Kilowatt Hour
MGD:	Million Gallons per Day
MW:	Megawatt
NPC:	Net Present Cost
PJM:	Pennsylvania – New Jersey – Maryland Grid
PLI:	Possible Logical Inconsistencies
ROMS:	Regional Ocean Modeling System
PSU:	Practical Salinity Units
SLR:	Sea Level Rise
USACE:	U.S. Army Corps of Engineers
V2G:	Vehicle-To-Grid

Chapter 1

INTRODUCTION

This dissertation aims to estimate social cost elements of three electricity generation and storage technologies. Modern society depends on widely accessible, reliable and affordable electricity. The system of electricity generation and transmission, however, is undergoing dramatic transformation in the US and other parts of the world. For environmental, health and financial reasons, the way society generates electricity is changing from one based primarily on fossil fuels to a non-fossil system. In addition, the process of electrification is converting an increasing number of services and processes to electrical power. These changes are accelerated by forces in the political and technological landscape.

The bulk of this transformation, however, is likely to take many years and neither the path nor the destination of this transformation is determined. Optimal solutions depend in part on local factors, like supply chains, climatological factors, technological progress, patterns of land use, and culture, among many others. Complicating these efforts are long lead times for large projects and interactive effects between different electricity system technologies.

A robust framework is required to find optimal solutions to this transition. Perhaps chief among the various elements of this framework, are estimates of the costs and benefits to society of various alternatives. This dissertation informs small elements of this vast intellectual space by illuminating certain elements of social costs from three select technologies. However, the contributions of the present work are not as narrow as nominal results suggest. For example, a chapter on battery electric buses in a Philadelphia suburb has implications for calibrating owner/operator expectations on all electric vehicles costs and benefits, as well as implications for benefits and limitations of battery-based storage systems generally. Likewise, a chapter on a nuclear generating facility facing increasing cooling water salinity in coming decades establishes a methodology that can be adapted to any evaporatively cooled generating station expecting elevated salinity regimes. Lastly, a chapter on recreational impacts from offshore wind power projects highlights areas of concern for survey-based assessments for wind power siting more generally.

While the market and non-market cost of development in the electricity sector are well understood for existing technologies in existing conditions, understanding of other elements remains incomplete. For example, the costs associated with emerging electricity generating technologies, or mature technologies in emerging environmental conditions are not fully understood.

Three essays are reported here to further quantify elements of social cost and to a lesser extent, benefits, of electricity generation and storage in the Mid-Atlantic region. Each explores multi-disciplinary areas that leverage distinct methodologies. One essay conducts a cost-effective analysis of alternatively fueled buses and ancillary market electricity grid services including health and environmental externalities. Another integrates hydrodynamic, engineering, and economic models to estimate changes to operating costs for an evaporatively cooled nuclear generating station facing future salinity rise. The last essay estimates impacts of offshore wind power projects to recreation through survey instruments and statistical interpretations. Overviews of each essay are provided below.

These essays are accompanied by related co-authored publications published during my doctoral studies (Carr et al., 2018; Kecinski et al., 2017; Shirazi et al., 2018; Veron et al., 2018;).

Essay 1 (Ch. 2): A cost-benefit analysis of alternatively fueled buses with special considerations for V2G technology[1]

This first essay in this dissertation explores the cost and benefits of replacing a diesel-powered school bus with one powered by either compressed natural gas or electricity. Both marginal and fleetwide models are explored. The electric bus has the additional opportunity to be outfitted with special hardware allowing it to participate in electricity grid services through a concept called Vehicle-to-Grid (V2G). This study models the total cost of ownership and external costs for each technology over a 14-year horizon. The electric bus is modeled to benefit from additional revenues and costs from V2G operation. V2G buses were found to be uneconomic from a social perspective in the present and near future given current projections for the relevant inputs. This is true despite not quantifying

[1] This essay was published in 2015 in *Energy Policy* 87 (591-603).

several additional unique cost elements for the V2G bus. One main contribution of this study is the identification of V2G cost elements that are both large in magnitude and frequently overlooked in existing V2G analyses. For example, aggregator fees, electrical losses, low temperature limitations, demand charges, and appropriate normalization for capacity reductions are all highlighted as necessary cost elements that are frequently overlooked. However, electric buses may make financial sense to fleet operators given available subsidies.

Essay 2 (Ch. 3): Increased operational costs of electricity generation in the Delaware River and Estuary from salinity increases due to sea-level rise and a deepened channel[2]

Like many estuaries in the world, salinity levels in the Delaware River and Estuary are expected to increase due to a deepened navigational channel and sea-level rise. This study estimated operational cost increases resulting from increased ambient salinity likely to be incurred at PSEG-Hope Creek, an evaporatively cooled electricity generating station. To estimate cost increases, a linked physical-economic model was developed to generate daily forecasts of salinity and the resulting changes in facility's cooling water treatment and pumping requirements. Salinity increases under potential future bathymetric configurations were simulated using a hydrodynamic model. On an equivalent annual basis (discounted at 5%), average cost increases were \$0.4M per year, or approximately 0.1% of estimated total annual operating costs for the facility. Methods developed here could be employed at other facilities anticipating future salinity increases. Results inform cost-

[2] This essay was published in 2019 in *Journal of Environmental Management* 244 (228-234)

benefit analyses for dredging projects and contribute to estimates of the indirect costs to society from carbon emissions through sea-level rise. Future research refinements can focus on modeling changes in suspended sediment concentrations and estimating their impacts on operational costs.

Essay 3 (Ch. 4): Visual impacts of offshore wind projects on beach recreation: Results from four in-person person surveys

This final essay analyzes data from four in-person survey events regarding recreation impacts from offshore wind power projects. Offshore wind power features prominently in some visions of future electricity generation on the East Coast of the US. One concern with offshore wind development is potential impacts to recreational activity and enjoyment along adjacent coastlines. This study presents results from four in-person surveys on the impacts to beach-based recreation. Surveys were implemented over a sample of nearly 1,500 respondents in Delaware between 2013 and 2017. Respondents were provided with simulated images of a large offshore wind project at distances of 2.5 to 20 miles from shore and asked if their last beach trip would have been made better or worse at each distance if the project was present. In addition, respondents were asked if they would have canceled their last beach trip due to the presence of the project at each distance. This study is a companion study and validity check to a similar survey conducted. Regressions models identify variables explaining differences in cancellation rates across the sample observations. Cancelation rates show significant differences across the surveys, suggesting responses may be sensitive to seemingly minor changes in survey format, wording and/or timing.

These essays aim to inform market participants, academics, and policymakers at the local and national levels on additional cost elements of technologies explored here. They should be understood as steps along an intellectual journey subject to much further refinement. However, I am confident that each essay as it currently stands offers meaningful contributions that can help inform the transformation to a future and more socially desirable electricity system.

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Chapter 2

A COST-BENEFIT ANALYSIS OF ALTERNATIVELY FUELED BUSES WITH SPECIAL CONSIDERATIONS FOR V2G TECHNOLOGY

2.1 Introduction

For decades, school buses have been powered almost exclusively by diesel and gasoline. The long history of mass production and adoption of these vehicles provides for significant economies of scale, as well as predictable performance characteristics and maintenance schedules.

While diesel touts numerous desirable properties as a fuel for heavy-duty vehicles, concerns over volatile petroleum prices, as well as health and environmental externalities have spurred interest in alternative fuels for heavy-duty vehicles (US DOE, 2014a).

A combination of factors--both technological and social--have recently expanded the available fuel technologies for transportation. Compressed natural gas (CNG) is a popular fuel for municipal and commercial fleets in the US due to its low cost, reduced emissions, and domestic extraction (National Research Council, 2010). Major school bus manufacturers, including Thomas, Blue Bird and International, offer CNG and/or propane options (Florida Department of Education, 2014).

Battery-electric buses, or eBuses, have also been developed, albeit by more specialty manufacturers. Proterra, BYD, and New Flyer manufacture transit eBuses, while eTrans and TransPower manufacture eBuses specifically for school applications. Battery-electric vehicles (BEVs) derive energy from an on-board electrochemical battery, typically of a lithium-ion variety. These vehicles offer zero tailpipe emissions, decreased fuel costs, lower maintenance costs, but higher initial purchase costs relative to diesel counterparts (Electrification Coalition, 2010).

Successful pilot runs have been demonstrated for school eBuses in California (Clements and Nagrani, 2014; Ramsey, 2011; TransPower, 2014). Pilot projects for electric transit buses are also underway in various European cities under the Zero Emission Urban Bus System (ZeEUS, 2015).

BEVs with Vehicle-to-grid (V2G)

If properly equipped, BEVs can also perform vehicle-to-grid (V2G) services while not operating routes, receiving payment in return and thereby offsetting a portion of total ownership costs. During V2G, a vehicle's battery provides services to the electrical grid, helping to maintain high quality and reliability of electricity for grid customers.

The specific grid service most lucrative for V2G is frequency regulation (Kempton and Tomić, 2005). Frequency regulation (FR) is the contracted availability to provide short bursts of power into and/or out of the electrical grid as directed by the grid operator. Vehicles that provide FR are compensated primarily as a function of total hours of service, amount of service offered (measured as power), and market rates during each hour service is offered.

Kempton and Tomić (2005) conducted the first cost-benefit analysis (CBA) for a V2G-enabled vehicle. The battery-electric version of a Toyota RAV4, a compact sport-utility vehicle, was found to generate $411 in monthly revenue and $213 in monthly profit providing FR services to the California-area grid.

More recently, Noel and McCormack (2014) present the economics of operating a school eBus with V2G capabilities in PJM, the electrical grid across thirteen states in the eastern US. Their analysis advances the limited literature regarding V2G economics by considering new FR pricing regimes in the aftermath of the 2012 implementation of US FERC Order 755, and by explicitly accounting for environmental externalities. The authors report that a 24-seat V2G-capable eBus yields a $6,070 lower net present cost (NPC) per seat than a 32-seat diesel counterpart over an expected 14-year life. The higher purchase price for the eBus is more than offset by V2G revenues, as well as lower fuel, maintenance and externality costs.

However, Noel and McCormack (2014) overlook several substantive issues that are addressed in the current study. Such omissions, including driver salary, electrical losses from V2G, non-taxable diesel-fuel for school districts and reduced V2G availability during cold weather, skew the findings of that paper in favor of the V2G-enabled eBus.

The present analysis fills considerable literature gaps by identifying nuanced technical, regulatory, and economic challenges imposed by V2G-enabled vehicles. In addition to incorporating oft-overlooked inputs in the cost-benefit calculations, this analysis provides more robust assumptions and includes an additional alternative fuel

(CNG) for a three-way analysis. The present analysis is also the first of its kind to highlight the importance of operating temperature impacts on expected V2G revenue generation.

Temperature and V2G

Previous attempts to estimate V2G revenue rely on applying an average price for FR derived from a simple average of all hours over some previous period. (Kempton and Tomić, 2005; Noel and McCormack, 2014). Such approaches do not represent actual price conditions fleet operators are likely to expect for their fleets. Because V2G participation for fleet vehicles exhibits recurring and predictable availability with respect to time of day (business hours) and ambient temperature (due to constraints in battery performance at extreme temperatures), average prices are best computed from prices that prevail only during these conditions.

Of particular concern are low ambient temperatures. During extremely low temperatures, FR prices can spike to one-hundred times higher than average, greatly increasing average FR prices. However, V2G during these hours is likely not possible due to thermal limitations of the lithium-ion cells.

Like many fleet vehicles, school buses are parked outside, exposed to ambient conditions. Outside of narrow optimal temperatures (roughly 10º - 30º C), lithium-ion cells suffer degraded performance, longevity and/or efficiency (Concha, 2007; Pesaran et al., 2013). Thermal management systems can alleviate some shortcomings outside of this range, but only with increasing efficiency penalties. Much below freezing (below -5º to -10º C), typical lithium-ion batteries are only able to operate under limited power, if at all, due to reductions in power capacity as well as programmatic cut-offs designed to preserve long-term battery longevity (Pesaran et al., 2013; Zhang et al., 2011; personal experience with University of Delaware V2G fleet). However, the exact ambient temperature cutoff for these batteries varies by a myriad of factors including cell chemistry, form factor, arrangement of cells within the vehicle, and others (Samadani et al., 2013).

Outline

We investigate the costs and benefits of V2G-enabled school buses compared to CNG and diesel counterparts using a Monte Carlo-based NPC framework in two distinct scenarios. The first scenario adopts the framework and vehicles of Noel and McCormack (2014), consisting of a marginal addition of a single small school bus to an existing fleet. Both Noel and McCormack (2014) and this analysis compare a Type C diesel bus with a smaller TransTech eBus, using current prices for bus purchase costs. However, the present work differs in that it re-specifies inputs with more realistic values, enhances the model with previously omitted factors, and includes a CNG bus for a three-way comparison.

The second scenario analyzes the NPC implications of establishing and operating an entire fleet of large school buses of a specified technology (either eBus, diesel or CNG). Importantly, it assumes a projected eBus purchase price benefitting from the significant future price decreases anticipated in coming years. The diesel and CNG in this scenario, however, do not benefit from any advancements in cost or performance. As a result, this scenario structurally favors the V2G-enabled eBus.

For both analyses, findings represent optimistic accounting of eBus costs due to the several additional challenges identified but not accounted for explicitly in the analysis. The additional challenges to eBus implementation are discussed qualitatively in Section 4.5 and should be carefully considered when interpreting results presented here and in related studies. These additional factors, often unacknowledged in V2G literature, further deteriorate V2G-enabled eBus economics in real world implementation.

2.2 Methods

2.2.1 Frequency Regulation Pricing with Temperature Considerations

We estimate eBus revenue while performing V2G services in the PJM frequency regulation market, incorporating limitations in bus timing and temperature availability. To address these limitations, we model revenue using frequency regulation prices for those hours outside of normal school bus operating hours (5AM - 8AM and 2PM - 5PM) on school days using a local academic calendar.

We also use a range of cutoff temperatures of 0ºF (-18ºC) to 50ºF (10ºC) using U.S. NOAA National Climatic Data Center temperatures for Philadelphia International Airport, PA (USA). Hourly time-series data for the regulation price is based on dynamic frequency regulation market for the PJM grid in 2014 (PJM, 2015b). The resulting effective regulation price is used to inform subsequent sections of this analysis.

2.2.2 Net Present Cost Framework Calculation

Costs and benefits of purchasing diesel, CNG, and eBus technologies are modeled using a Monte Carlo net present cost (NPC) framework. The Monte Carlo approach iteratively runs model simulations for which it randomly assigns a value to each model input according to user-defined probability density function for each model variable. All results are interpreted from Monte Carlo analyses of 100,000 iterations.

The analysis horizon is 14-years for a newly purchased bus, in accordance with National Association of State Directors of Pupil Transportation Services (NASDPTS, 2010). Variables used in the NPC framework calculations are provided in Table 2.1. The discount rate is set to 3%, as recommended in governmental CBAs (Boardman et al., 2010), and results are tested for sensitivity to different rates

NPC for diesel and CNG vehicles are estimated using the following equation:

$$NPC_{Diesel\ and\ CNG} = Capital\ Cost + \sum_{y=0}^{y=14} \frac{fuel\ cost + externality_{health} + externalities_{carbon} + maintenance + salary}{(1 + discount\ rate)^y} \tag{1}$$

Because V2G profit offsets total ownership costs for the eBus, V2G profit is subtracted from costs to determine total eBus NPC (see section 2.3.6):

$$NPC_{Diesel\ and\ CNG} = Capital\ Cost + \sum_{y=0}^{y=14} \frac{fuel\ cost + externality_{health} + externalities_{carbon} + maintenance + salary - V2G\ profit}{(1 + discount\ rate)^y} \tag{2}$$

Table 2.1: Model variables and ranges of assigned values.

Description and units	Value (Lower Bound, Baseline, Upper Bound)	Source(s)
General		

Hours/day driving students*	5, 6, 7	Rineer, J. (2014)
Driver salary + benefits (46% of salary)	$19,341; $30,622; $43,418	BLS (2015)
Miles driven per year*	8000, 8500, 9000	Rineer, J. (2014)
Monetary discount rate (%)*	2.0, 3.0, 6.0	Boardman et al., 4th ed. (2011)
Number of school days per year	180	
Life of bus (years)	14	
Diesel		
Diesel health externalities ($/mile)*	0.0124, 0.0917, 0.5444	NRC, 2010
Price of diesel less taxes* ($/gal) (year 1 costs)	2.17, 2.76, 3.65	American Petroleum Institute (2015); EIA (2014)
Diesel fuel carbon emitted (lbs. C/gal)	22.2	EPA (2005)
Small Diesel MPG*	7, 8, 9	Rineer, J. (2014)
Large Diesel MPG*	6, 7, 8	Rineer, J. (2014)
Social cost of carbon ($/MgCO2e)	$41.05	EPA (2013)
Diesel maintenance rate ($/mile)*	$0.15, $0.44, $0.60	Rineer, J. (2014)
Compressed Natural Gas (CNG)		
CNG health externalities ($/DGE)*	0.039, 0.052, 0.065	NRC (2010)
Price of CNG ($/DGE) (year 1 costs)*	2.34, 2.42, 2.45	EIA (2015)

Small CNG MPGe*	6, 7, 8	Rineer, J. (2014)
Large CNG MPGe*	5, 6, 7	Rineer, J. (2014)
CNG Maintenance Rate ($/mile)*	$0.15, $0.44, $0.60	Rineer, J. (2014)
CNG CO_2 emissions (kg CO2/DGE)	7.57792	
CNG Station costs (2 hose, time-fill)	$48,545	Smith and Gonzales (2014)
Electric Bus (eBus)		
Price of electricity (¢/kWh) (year 1 costs)*	10.00, 10.14, 10.37	EIA (2014)
% Coal used for generation in the Reliability First Corporation/East (year 1)	29.6	EIA (2014)
Carbon dioxide produced per unit electrical energy (kg CO_2/kWh)	0.50	PJM (2014)
Regulation Price from 2012-2014 ($/MW-h) before adjustments	30.28 (with Stand. Dev. of 13.3, negative values set to zero)	PJM (2015b)
Round-trip electrical efficiency (AC-DC-AC) (%)	73	Kempton and Tomić (2005)
*Denotes triangular distribution bounded with low, modal, and high values.		

Marginal Analysis: NPC for an additional small bus

This marginal approach investigates the financial impacts of replacing a single bus with a new bus of the specified technology. Similar to Noel and McCormack (2014), we compare a Type C bus with a slightly smaller eBus.[3] Because the eBus is two to three times the cost of the other buses, school districts are likely to consider the smallest eBus varieties in order stay within yearly expenditure limits.

Fleet-wide Analysis: NPC for a fleet of large buses

An analysis was also conducted for a large bus fleet. This latter approach captures a schedule of costs for 100 new buses for each bus type. Similar to the small bus, a marginal analysis was also conducted for large buses. However, these results are not reported as they are similar in all important respects to the fleet-wide analysis.

2.2.3 Materials: Diesel, CNG, and eBus

The diesel and CNG buses are current Thomas Built[4] buses. The small eBus is the TransTech eTrans, while the large eBus is the TransPower EESB (TransPower, 2014).

Bus operational characteristics are based on data from the Lower Merion School District (LMSD) in Pennsylvania, USA (Personal Communication, Gerald Rineer, November 2014). All buses are assumed to operate 180 school days per year. On school days, buses average six hours driving routes, divided into 5AM to 8AM block, and a 2PM to 5PM block (Personal Communication, Gerald Rineer, November 2014). Furthermore, buses are assumed to average 8,500 miles per year and operate within 14-year lifetimes. During all non-route hours (including the entirety of non-school days), the eBus is assumed to perform V2G. In reality, eBuses would experience additional non-V2G hours

[3] While the same bus sizes are used, this study accounts for seating capacity slightly differently than in Noel and McCormack (2014). This analysis includes wheelchair wells in capacity determination.
[4] Thomas Built is one of the three main companies in the US mass producing large school buses.

due to maintenance, charging[5], and other downtime. However, this is optimistically assumed in our model and serves as an upper-bound on V2G revenues.

Bus driver compensation averages $30,622 in salary per year plus an additional 46% to account for benefit compensation also borne by the school district (Bureau of Labor Statistics, 2015).

2.2.3.1 Bus Costs

Marginal Analysis (Small bus)

For the marginal analysis of a small bus, the CNG and diesel buses are modeled as the Thomas Built 310TS Type C with 32 seats in addition to wheelchair lift and 3 wheelchair wells (Thomas, 2004). The price of this vehicle in diesel configuration is $88,691, while the estimated[6] CNG configuration is $108,687 (Florida Department of Education, 2014). The small V2G-enabled eBus is a Smith-Newton eTrans with 24 seats, wheelchair lift and two wheelchair wells. As specified by Noel and McCormack (2014), this vehicle costs $230,000 with an 80-kWh A123 lithium iron-phosphate battery. Additional specifications for all buses are outlined in Table 2.2.

Fleet-wide Analysis (Large bus)

The large CNG and diesel buses are modeled as the lift-equipped Thomas HDX 141YS Type D with 54 seats, wheelchair lift and 3 wheelchair wells (Thomas, 2003). The

[5] The optimal battery state for V2G is 50% charge. Upon returning from school routes, eBuses would charge to 50% before beginning V2G. At some point before their next driving event, (ranging from minutes to an hour) eBuses would cease V2G in order to charge from 50% to 100%.

[6] CNG conversion costs are listed as $24,995 incrementally more than the diesel for large-sized Thomas Built Type D buses. We assume conversion costs are proportional to fuel tank size, and price the small CNG at $19,996 incrementally more than the diesel variety, reflecting relative tank size.

price for diesel is $115,118, and $140,113 for CNG (Florida Department of Education, 2014).

The large eBus is a similarly sized TransPower Thomas HDX Type D. Due to anticipated cost reductions in electric vehicle production, we apply a projected purchase cost estimate for large eBuses in mass production. TransPower currently produces only prototype vehicles and does not provide pricing information on these pilot vehicles. Projected purchase price in mass production was estimated at $200,000, not including the on-board bi-directional charger (Personal Communication, Joshua Goldman, February 2015). Because this value is highly uncertain, we vary this value between $180,000 and $250,000, representing relatively greater risk for slower-than anticipated cost reductions.[7]

Table 2.2: Bus types, sizes and specifications used in the analyses

Fuel	**Vehicle Chassis**	**Capacity**	**Length (m)**	**Price**	**Driving Efficiency**
Small bus					
CNG	Thomas 310TS Type C	35	11.0	$108,687	7 MPGe
Diesel	Thomas 310TS Type C	35	11.0	$88,691	8 MPG
eBus	TransTech EN200DSFP900	26	9.1	$230,000	1.54 kWh/mi (AC)
Large bus					
CNG	Thomas 141YS Type D	57	12.2	$140,113	6 MPGe

[7] This anticipated future purchase price averages less than the current purchase price for the small eBus. The larger eBus offers over twice the seating capacity, 28kwh additional battery capacity and a more powerful motor.

Diesel	Thomas 141YS Type D	57	12.2	$115,118	7 MPG
eBus	Thomas '84 seat' Type D	57	12.2	$200,000	2.35 kWh/mi (AC)

2.2.3.2 Fueling Infrastructure Costs

Fueling infrastructure is necessary for all buses. The marginal analysis assumes that infrastructure already exists for an additional diesel bus, but CNG infrastructure would need to be installed at a cost of $50,000 to service a single bus (Smith and Gonzales, 2014). Infrastructure costs for all eBuses consist of a 70 kW on-board bi-directional charger priced at $30,000 per vehicle (Noel and McCormack, 2014).

Fueling Infrastructure to service a fleet of 100 buses are modeled as $500,000 for diesel and $1.8 million for CNG (Smith and Gonzales, 2014). While fueling also has operation and maintenance costs, EIA already embeds these in diesel and CNG fuel estimates.

2.2.3.3 Fuel Costs

Fuel costs for all buses are obtained from EIA's 2014 Annual Energy Outlook (EIA, 2014) for the transport sector and the geographic region corresponding to Philadelphia, PA. Prices in future years are modeled from the 2014 EIA Reference, High Growth, and Low Growth scenarios using a triangular distribution for all fuels. EIA Reference is our mean estimate, while EIA High Growth and Low Growth represent our upper and lower bounds, respectively. Diesel fuel prices are adjusted to account for federal and Pennsylvania taxes, from which school districts are exempt, by subtracting

$.0886/diesel gallon (American Petroleum Institute, 2015; IRS, 2014; Transportation Research Board, 2009).

Driving efficiencies are informed by the experience of Lower Merion School District (LMSD) outside of Philadelphia, PA (Personal Communication, Gerald Rineer, November 2014) for their fleet of variously sized buses. Small diesel buses are assumed to average 8 MPG while small CNG buses average 7 MPGe. Large bus efficiencies are slightly lower at 7 MPG and 6 MPGe, respectively. These values are similar to those found in other reports (see for example Wyoming DAI, 2012).

Because empirical data on driving efficiency for the eTrans small eBus are not available, we estimate efficiency from similar vehicles. An eBus pilot project in Kings Canyon, CA tested an eBus with two-thirds the seating capacity and a Gross Vehicle Weight Rating (GVWR) roughly half that of the eTrans. Reported driving efficiency for that eBus was about 1.18 kWh/mi AC (Clements and Nagrani, 2014).

NREL reports operational statistics for a geographically dispersed fleet of commercial vehicles.[8] They report average efficiency of 1.54 kWh/mi AC for this fleet of vehicles (US DOE, 2014b). Though these vehicles are also smaller than the eTrans specified here, we adopt the 1.54 kWh/mi AC driving efficiency for the eTrans eBus in our model.

Driving efficiency for the large eBus is reported from empirical field trials as 2.2 to 2.5 kWh/mi AC (TransPower, 2014) based in southern California. We use the

[8] Similar to the eTrans, vehicles in NREL's test fleet are electrified with Smith-Newton componentry.

midpoint of these values for driving efficiencies of 2.35kWh/mi AC, but again note this may be optimistic due to the relatively mild climate of the trial location.

2.2.3.4 Maintenance Costs

Diesel maintenance rates are reported in a variety of outlets (Chandler and Walkowicz, 2006; Clark et al., 2007; Laughlin and Burnham, 2014; Stasko and Gao, 2010; Transportation Research Board, 2009), ranging from \$0.15-\$0.60 per mile. Various sources report CNG maintenance rates equivalent to those of diesel (Wyoming DAI, 2012). The similarity in maintenance costs between diesel and CNG was also found by LMSD for their current fleet of CNG buses. This analysis assumes a modal value maintenance cost of \$0.44/mi for diesel and CNG buses, as observed by LMSD (Personal Communication, Gerald Rineer, November 2014), and lower and upper bounds of \$0.15 and \$0.60 per mile reported in the literature.

In a cost-benefit analysis of city buses, Lajunen (2014) sets maintenance costs equal across variously fueled buses including diesel and eBus. Chandler and Walkowicz (2006) distinguish between propulsion-related maintenance costs (\$0.12/mi) and non-propulsion costs (\$0.36/mi) for diesel city buses. Variation in maintenance costs between the present fuel technologies arises almost exclusively from variation in propulsion-costs. According to this assessment, eBus maintenance costs are at least three-quarters those of diesel.

The Electrification Coalition (2010), an advocacy group promoting electric transportation, estimates that heavy-duty electric vehicles incur half the maintenance costs of heavy-duty diesel vehicles. We adopt the Electrification Coalition's (2010) more aggressive savings in maintenance costs for BEV's to assume that eBus maintenance rates are half those of diesels, with a modal value of $0.22/mile and a range of $0.075 to $0.30/mile.

Finally, due to battery degradation over time, we model both large and small eBuses needing to replace the entire battery once during the operating life, occurring in year 9, similar to Noel and McCormack (2014). Battery replacement costs are estimated at $300/kWh[9] of installed battery capacity per US Department of Energy goals (Howell, 2009).

2.2.3.5 External Costs

All three fuel types generate externalities through health and environmental impacts, and thereby impose societal costs. This study attempts to quantify these costs and attribute them to the offending bus.

Greenhouse gas emissions impose social costs related to climate change, and are valued at $41.05/MgCO2e (EPA, 2013). Only per-mile direct emissions from the bus (or electrical grid for the eBus) are included in the emission total and are listed in Table 2.1. Externalities from other aspects of the bus lifecycle are omitted.

Per-mile health damages from all three vehicles are also quantified using estimates from the National Research Council (2010). For the health impacts from the eBus, only damages from that fraction of electricity generated from coal are considered as this source of electricity drives the majority of health damages. Current and projected

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[9] This cost projection is for standard vehicle grade li-ion batteries, not the high performance A123 li-ion batteries specified in the eBus. A123 batteries command price premiums over standard vehicle grade batteries.

coal generation for First Reliability Corporation East is provided by the EIA Annual Energy Outlook. As a result, all non-coal generation is assumed to impose no health cost on society[10].

2.2.3.6 V2G Profit

V2G profit in both marginal and fleet-wide scenarios equals V2G revenues minus V2G costs. Annual V2G revenue is approximated with the following equation:

$$V2G\ Revenue\ =\ Effective\ Regulation\ Price * \ Annual\ V2G\ hours * \ Power\ Offered \tag{3}$$

where *Effective Regulation Price* is the average price of FR in the 2014 PJM during which a school bus would be able to perform V2G assuming a thermal cutoff of 20ºF (-7º C); where *Annual V2G hours* is the total hours the eBus is not operating school routes; and where *Power Offered* is 70 kW (0.07 MW) for both the large and small eBus, limited by the onboard bi-directional charger.

As mentioned previously, the eBus is optimistically assumed to provide V2G services all hours outside of the school operations determined annually by the following equation:

$$Annual\ V2G\ Hours\ =\ school\_day\_V2G\ *\ 180\ +\ (24\ *\ (365-180)) \tag{4}$$

[10] Health damages from electricity generation in this analysis is premised on the *average* mix of generation on the local electricity grid in future years. A superior approach would be premised on expected *marginal* generation in future years.

where schools meet 180 days per year; and where *school_day_V2G* is the number of hours each school day the bus is not running school routes.

2.2.3.7 V2G Costs

V2G operational costs have been previously accounted for in a number of ways or ignored. Kempton and Tomić (2005) calculate increased battery degradation rates and electrical energy losses resulting from V2G, while and Noel and McCormack (2014) do not account for V2G operational costs in their calculations. The present model accounts for V2G costs arising from electrical energy losses while performing V2G. Accelerated battery degradation is not accounted for but is discussed in section 4.5.

Lithium-ion cells are nominally estimated to achieve in excess of 90% electrical efficiency in converting charging energy to stored energy. However, the efficiency of in-use lithium-ion battery systems is substantially lower than the efficiency of new individual cells (Heymans et al., 2014). The literature often uses the latter while the former is more appropriate. Thermal management, on-board power/communication electronics, inverter losses and increased cell resistance with age, all impart additional inefficiencies (Heymans et al., 2014).

Round-trip electrical efficiency is a term used to describe the percentage of AC electricity that returns to the electrical outlet after passing through an inverter, the vehicle's battery, and various power/communication/thermal management systems. While round-trip electrical efficiency for V2G is not reported widely, this value is estimated as 64% (Heymans et al., 2014) and 73% (Kempton and Tomić, 2005).

Furthermore, data from the EESB show a one-way charging efficiency of 85% at the midpoint (TransPower, 2014). The square of this one-way charging efficiency yields a round trip-efficiency for the system of 72%. This analysis adopts the highest of these values for a roundtrip efficiency of 73%.

In this analysis the cost of V2G equals the quantity of electrical energy lost during V2G multiplied by the price of electricity.

$$V2G\ Costs\ = (\,Power\_Offered * av2g * Ut\_factor)(1 - rt\_ef) * E\_price \qquad (5)$$

where *Power Offered* is the kW of capacity offered into the FR market; *av2g* is the annual V2G hours from equation (4); *Ut_factor*, or the utilization factor, identifies the proportion of averaged one-way regulation power requested relative to power offered; *rt_ef* is round-trip electrical efficiency; and *E_price* is the electricity price in $/kWh.

2.3 Results

2.3.1 V2G Revenue and Temperature

Frequency regulation prices in PJM exhibited a detectable correlation with extreme low temperature events. In particular, extremely high prices tended to coincide with the lowest hourly temperatures.

Figure 2.1 shows the simultaneity of low temperatures at the Philadelphia International Airport in January 2014 with spikes in FR price. This month exhibits a Pearson Correlation coefficient of -0.397, denoting a negative correlation between temperature and regulation price. The Pearson correlation coefficient for the months of Jan., Feb. and Mar. 2014 is -0.394.

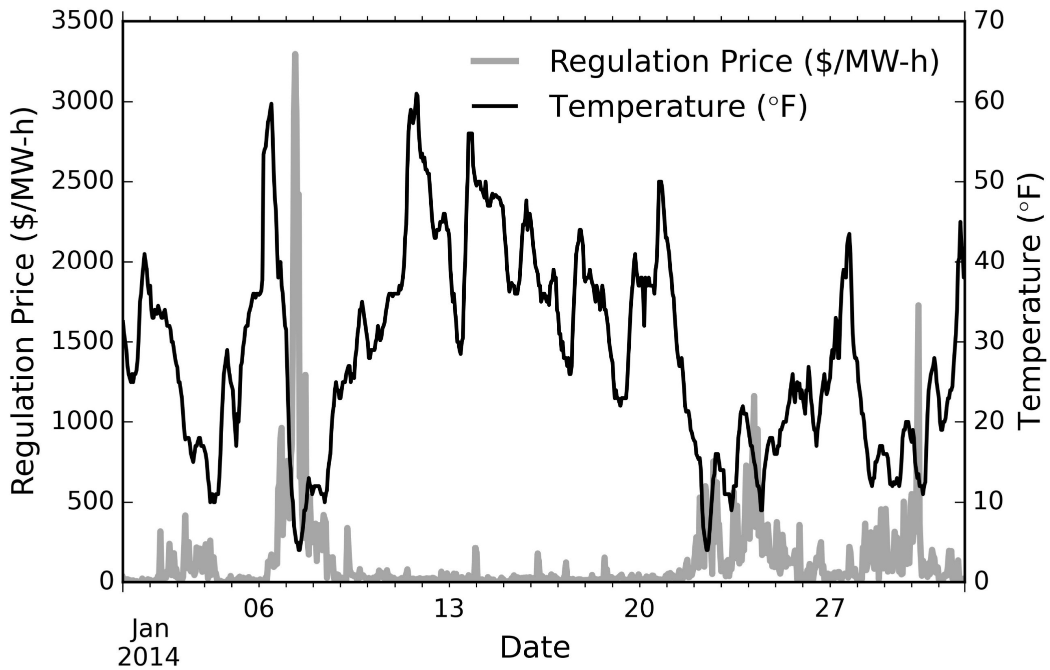

Figure 2.1: Temperature at Philadelphia International Airport and PJM regulation price for January 2014.

While the annual mean and median FR price in 2014 was $39.63/MW-h and $17.69/MW-h, respectively, the mean and median prices for Jan., Feb., and Mar., roughly double to $87.99 and $31.21, respectively. Prices peaked at $3,296 on January 7, 2014 when temperatures fell to 4ºF (-16ºC).

Furthermore, extremely high hourly prices (> 3 standard deviations above the mean) are isolated and plotted in Figure 2.2. These extreme prices are clustered at the lowest temperatures experienced over the year, further supporting the relationship between extremes in low temperature and high FR prices. Of the 115 data points indicating extreme prices observed, 88% occurred at temperatures below 32ºF (0ºC), shown by the dark dots in Figure 2.2 below. For comparison, only 13% of hours in 2014 experienced ambient temperatures below 32ºF (0ºC).

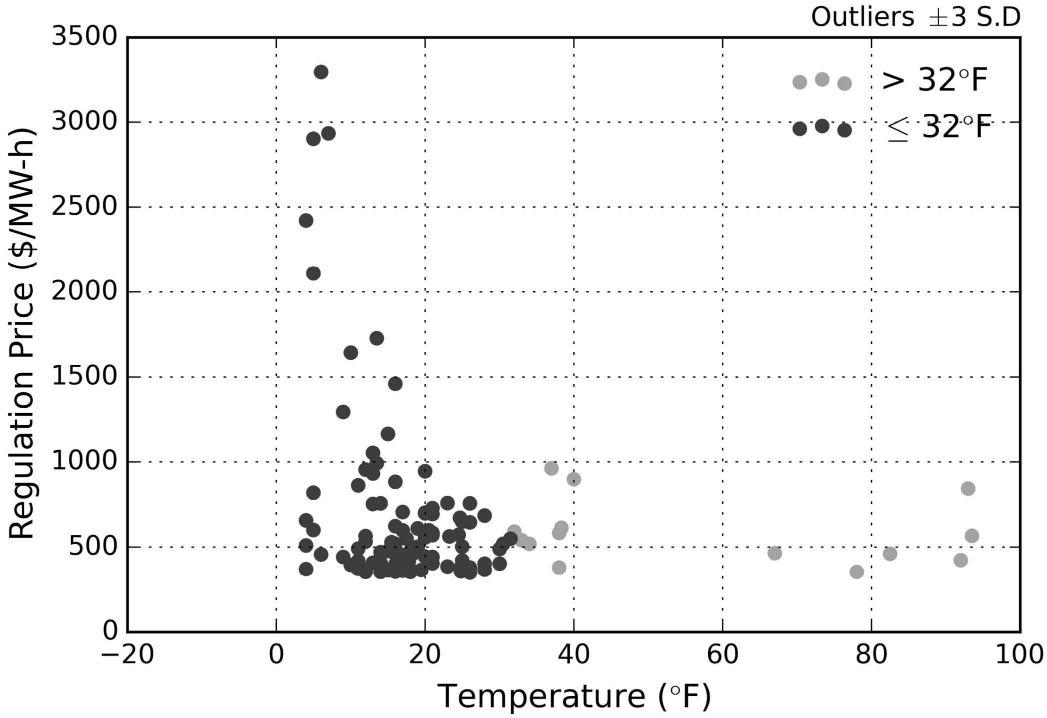

Figure 2.2: Extreme regulation prices in 2014 PJM grid. Prices shown are those above three standard deviations from the mean 2014 price of $39.63/MW-h.

Projected 2014 V2G revenue for an eBus providing 70 kW of FR services in PJM are displayed in Figure 2.3 at various ambient temperature cutoffs. Ambient temperatures did not drop below 0ºF in 2014, thus the maximum V2G revenue possible is $18,300. After accounting for thermal limitations, V2G revenue decreases disproportionately to the hours at these temperatures. Assuming a thermal operating limit for V2G services of the eBus at 20ºF (-7ºC), the expected annual revenue for the eBus decreases from $18,300 to $14,400.

For analysis in subsequent sections, we adopt the three-year PJM mean value for FR (2012-2014) of $30.28 and adjust it downward by the ratio between $14,400 and $18,300, or 0.78. This adjustment estimates the proportion of FR value that would be unavailable to an electric vehicle exposed to the elements.

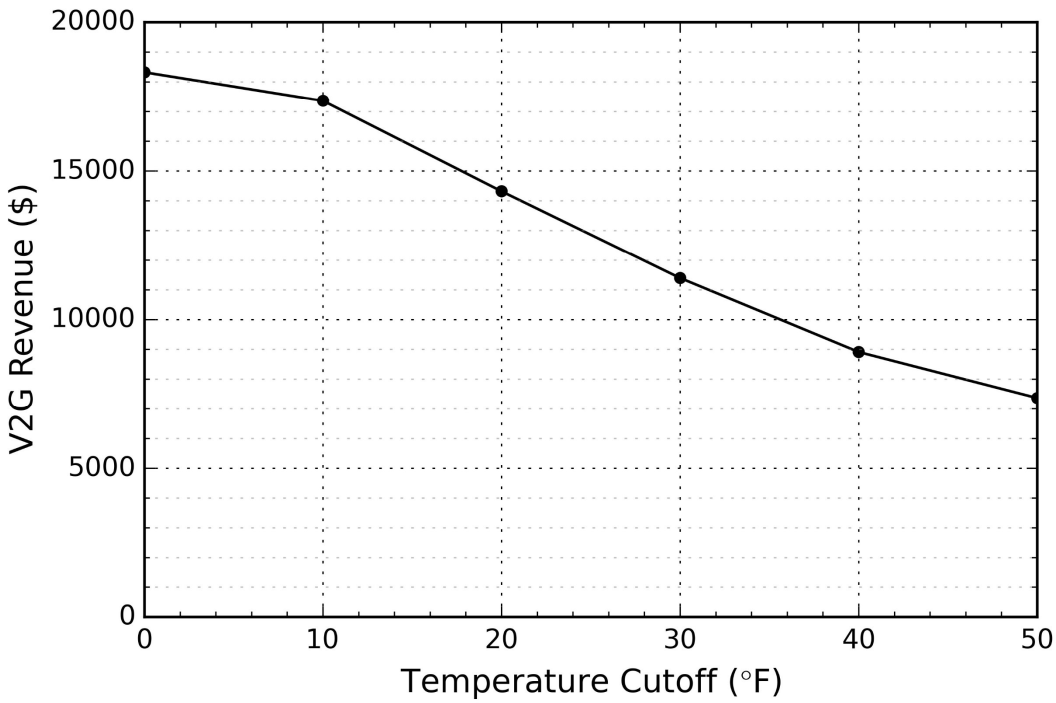

Figure 2.3: Annual V2G revenue for the specified eBus over a range of temperature cutoffs from 0ºF (-18ºC) to 50ºF (10ºC) using 2014 hourly weather and frequency regulation price data.

The economic analyses presented below assume a V2G cutoff temperature of 20ºF (-7ºC), in-line with the authors' experience of V2G-enabled vehicles at the University of Delaware. Adopting this threshold results in an effective FR price for the eBus of $23.62/MW-h.

Lastly, utilization of dynamic FR resources (like batteries) in the PJM grid averaged 0.135 in each direction (regulation up and regulation down) for 12 months of publicly available PJM data during May 2013 to April 2014 (2015a). This value represents the average power requested by PJM as a proportion of power offered for FR. For the e-Buses specified above offering 70 kW, this utilization rate results in average energy flows of roughly 9.5 kWh charged and 9.5 kWh discharged from the 80 kWh battery (or roughly 1/8th of a full cycle) for each hour performing V2G.

2.3.2 Net Present Cost Analysis

2.3.2.1 Marginal Analysis

Total Net Present Cost

The total NPC for each bus in the marginal analysis is detailed below in Figure 2.4. The small diesel bus exhibits the lowest NPC at $594,200, followed by the small eBus and small CNG at $630,000 and $639,000 respectively. The eBus and CNG represent total NPC increases of 6% and 8%, respectively.

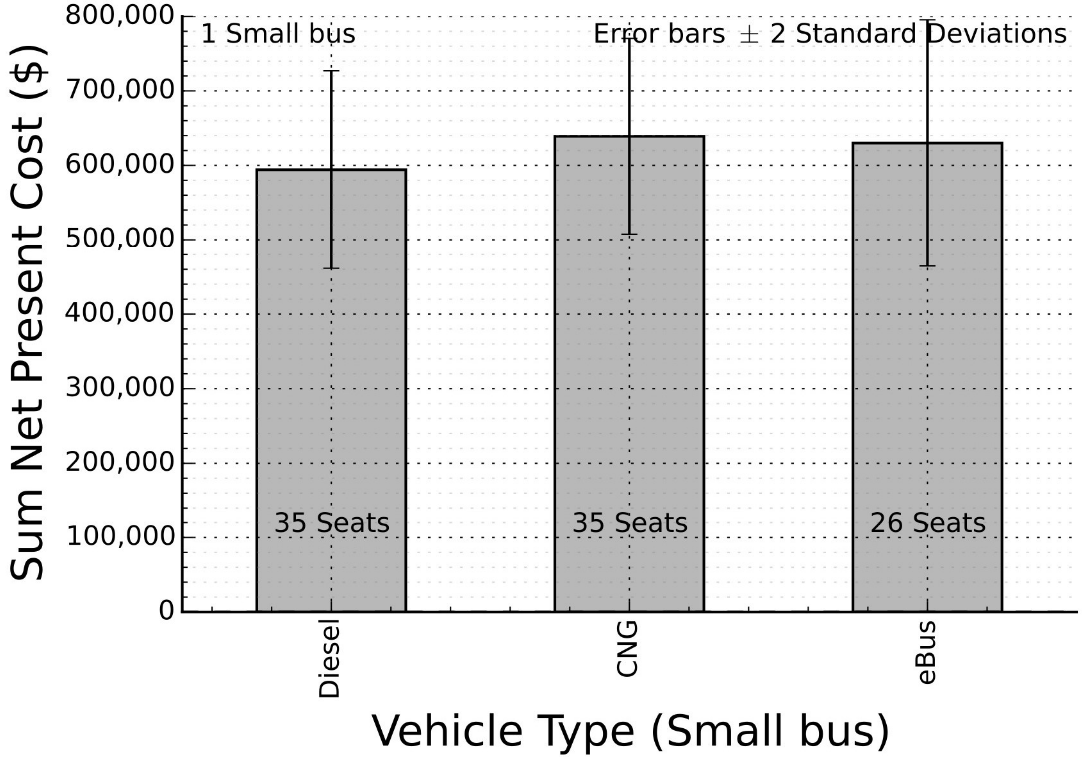

Figure 2.4: Net present costs for marginal addition of a small diesel, CNG, and electric school bus over a 14-year life using a 3% discount rate.

Despite overlapping standard deviations, the high number of simulations (100,000) in the Monte-Carlo analysis determines that the NPC per bus is significantly different ($p<0.01$) for all vehicles in both the small and large bus analysis.

Net Present Cost per Seat

NPC normalized on a per seat basis is a more meaningful measure for fleet operators than total bus costs as it allows for comparison across differently sized buses. Figure 2.5 shows NPCs per seat for the small school buses. The small diesel bus (35 seats) represents an NPC per seat of $17,000 per seat over a 14-year life. The NPC per seat of the small CNG bus (35 seats) is $18,200, while the NPC per seat of the small eBus

(26 seats) is $24,200. Relative to diesel, the CNG and eBus exhibit capacity-normalized NPC increases of 7% and 42%, respectively.

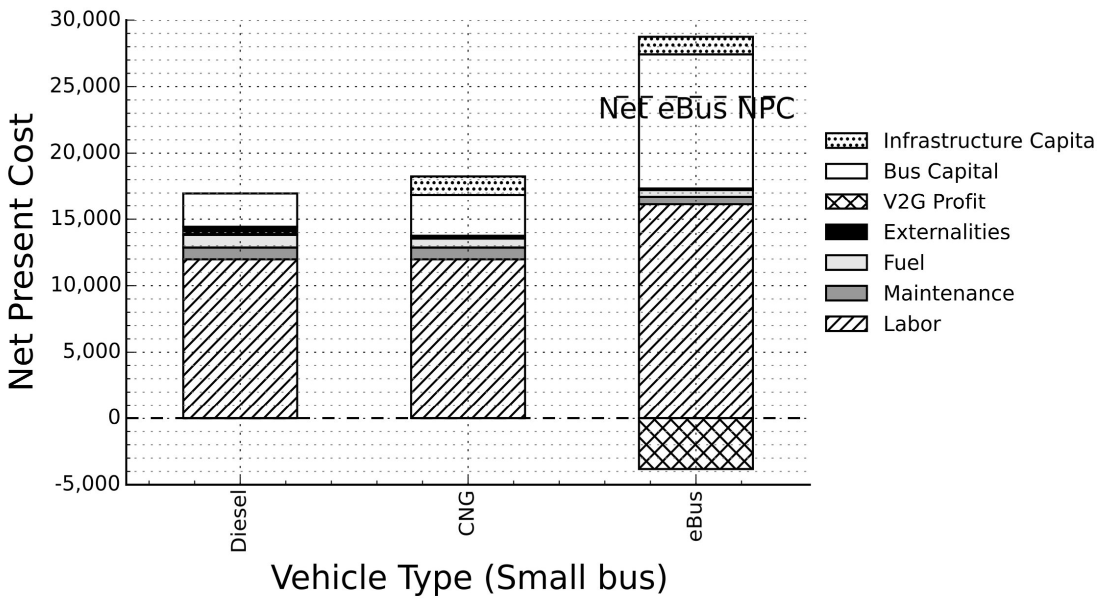

Figure 2.5: Mean NPC per seat for marginal addition of a small school bus from Monte Carlo simulation using a 3% discount rate. Dotted line for eBus includes benefit of V2G profit.

On a per seat basis, driver salary constituted the largest fraction of costs for all technologies, and was proportionally highest for the eBus, which has the fewest seats. Bus capital was the second largest fraction of cost, followed by fuel and maintenance. Health and environmental externalities were found to contribute minimally to NPC for all buses, accounting for $600, $210, and $130 per seat for diesel, CNG, and eBus, respectively.

The small eBus earns yields \$4,500 in net present value in revenues from V2G and \$700 in net present costs per seat from electricity losses. This results in a net V2G profit of \$3,800 in net present value per seat. V2G revenue is subtracted from eBus costs to determine sum NPC, as shown by the dotted line in Figure 2.5. Despite the benefits of V2G revenue generation and lower fuel and externality costs, high per seat bus capital and labor costs result in the highest net present cost per seat of the three fuels technologies analyzed.

Importantly, if a CNG bus is able to utilize an existing commercial filling station, the purchase of on-site fueling infrastructure would be unnecessary. The NPC for the CNG bus would decrease by \$50,000 per bus or \$1,563 per seat, making it the lowest cost of the three fuel alternatives.

2.3.2.2 Fleet-wide Analysis

The mean NPC for a fleet of 100 large buses is estimated at \$63,063,000, \$64,416,000, and \$62,426,000 for diesel, CNG, and eBus respectively, as shown in Table 2.3. All large buses in the fleet-wide analysis have 54 seats plus three wheelchair berths. As previously described, the fleet-wide analysis represents a structurally favorable scenario for eBus because it assumes aggressive decreases in production costs of the eBus without allowing for advances in cost or performance of CNG and diesel buses.

Relative to the eBus, the diesel and CNG fleets result in NPC increases of 1% and 3%, respectively. Per bus estimates can be obtained by dividing results in Table 2.3 by 100.

Despite higher bus capital and infrastructure costs, the NPC of CNG are competitive with those of diesel due to lower fuel and externality costs. The eBus capital costs are roughly 40% and 70% higher than those of CNG and diesel, respectively. However, lower externalities, maintenance rates, fuel costs, and especially the generation of V2G profit reduce the eBus NPC to nominally be the least cost option.

Table 2.3: Fleetwide NPC in dollars for 100 large diesel, CNG, and electric buses using a 3% discount rate.

	Diesel	**CNG**	**eBus**
Labor	41,917,000	41,917,000	41,917,000
Maintenance	3,122,000	3,122,000	1,561,000
Fuel	3,858,000	2,778,000	1,968,000
Externalities	2,167,000	856,000	513,000
V2G Profit	N/A	N/A	-9,293,000
Bus Capital	11,511,000	14,007,000	25,343,000
Infrastructure Capital	500,000	1,748,000	3,000,000
Total Net Present Cost (NPC)	**63,075,000**	**64,428,000**	**65,029,000**

2.4. Discussion

2.4.1 Temperature and Regulation Prices

Temperature plays a key role in determining FR prices in the PJM grid. In turn, FR prices determine the economics of V2G-enabled vehicles (Noel and McCormack, 2014). However, temperature limitations of electric vehicle batteries have been ignored in

V2G analyses. The temperature sensitive V2G profit analysis presented here illustrates that accounting for low temperature limitations meaningfully reduces effective FR prices and V2G profit for vehicles exposed to ambient conditions. V2G revenue is decreased by 22% and V2G profit is decreased by 25%. Simple hourly average prices for FR should not be relied on to inform actual prices a fleet operator could expect. We propose the use of an effective FR price in future V2G analyses, to account for time-of-use and thermal considerations.

2.4.2 Net Present Cost Analyses

Our cost analyses differ considerably from previous studies in both inputs and results. The present findings suggest that V2G-enabled eBuses are not economical at current prices but may be economical at future prices in the PJM area. Unsurprisingly, results suggest that eBus costs must be reduced and regulation prices must remain at or above current levels for future viability of V2G-enabled eBuses.

This analysis differs from previous work by assuming lower diesel fuel costs, removing diesel taxes, accounting for driver cost, calculating V2G revenue based on temperature-dependent regulation prices, and by accounting for electrical losses during V2G. For all buses across both small bus (marginal) and large bus (fleet-wide) scenarios, the combined purchase price and driver costs account for the vast majority of total operating costs. While externalities contribute very little to total costs regardless of the technology, they vary between technologies in relative magnitude.

Marginal Analysis

The small bus marginal findings presented here directly contradict those by Noel and McCormack (2014). Whereas Noel and McCormack find a net present decrease in cost of $6,070 per seat for the small eBus relative to the diesel, this analysis finds a per seat net present increase in cost of $7,200, or 43%, for the eBus relative to diesel. The CNG is also not cost-effective, imposing a $1,200 or 8% increase in net present cost per seat relative to the diesel. However, the small CNG is the least cost option if there already exists an existing filling station with suitable properties.

Results indicate that the relatively high purchase cost and infrastructure costs reduce the economic viability of the CNG and eBus options. Per seat eBus costs are further elevated as a result of lower seating capacity. Because findings are normalized on a per seat costs, fixed driver costs distributed over fewer seats severely penalize the smaller eBus, an important detail overlooked by Noel and McCormack (2014).

Fleet-wide Analysis

The fleet-wide analysis of large buses represents a structurally favorable scenario for the eBus. This bus is of the same capacity as the diesel and CNG versions and benefits from anticipated future cost reductions but does not allow for projected improvements in diesel or CNG technologies.

Unlike the marginal analysis of small buses, the fleet-wide result for large buses is roughly even in cost across all technologies. Nominally, the large eBus is more cost-effective than the large diesel and CNG buses. Anticipated cost reductions are a necessary requirement for eBuses to be the low-cost option. The additional challenges to eBus adoption, found in section 2.4.5, are not explicitly incorporated into the economic model but must also be addressed.

2.4.3 Sensitivity Analysis

We performed sensitivity analyses on results from the large bus analysis to investigate the contribution of each variable to the overall findings. Using the Fourier Amplitude Sensitivity Test (FAST) method in the SALib python library[11], CNG and diesel were most sensitive within our specified ranges of salary and discount rate. The eBus results were most sensitive to variations in regulation price, followed by salary and discount rate. For diesel (Figure 2.6a) and CNG (Figure 2.6b), variation in externalities, maintenance rate, MPG, fuel price and miles driven contributed minimally to cost results, while salary and discount rate dominated. Note that results do not sum exactly to 1.0 due to rounding errors.

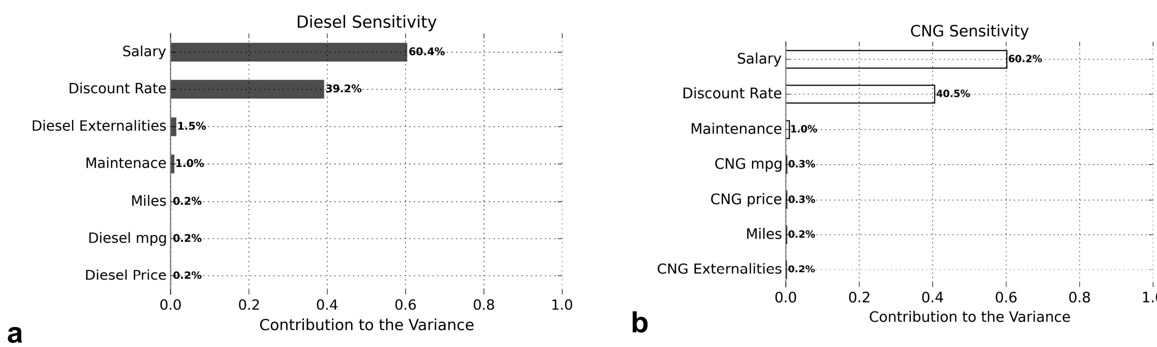

Figure 2.6: Sensitivity of fleet-wide Diesel (a) and CNG (b) results were driven by variation in the salary and discount rate variables.

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11 <https://github.com/SALib/SALib>

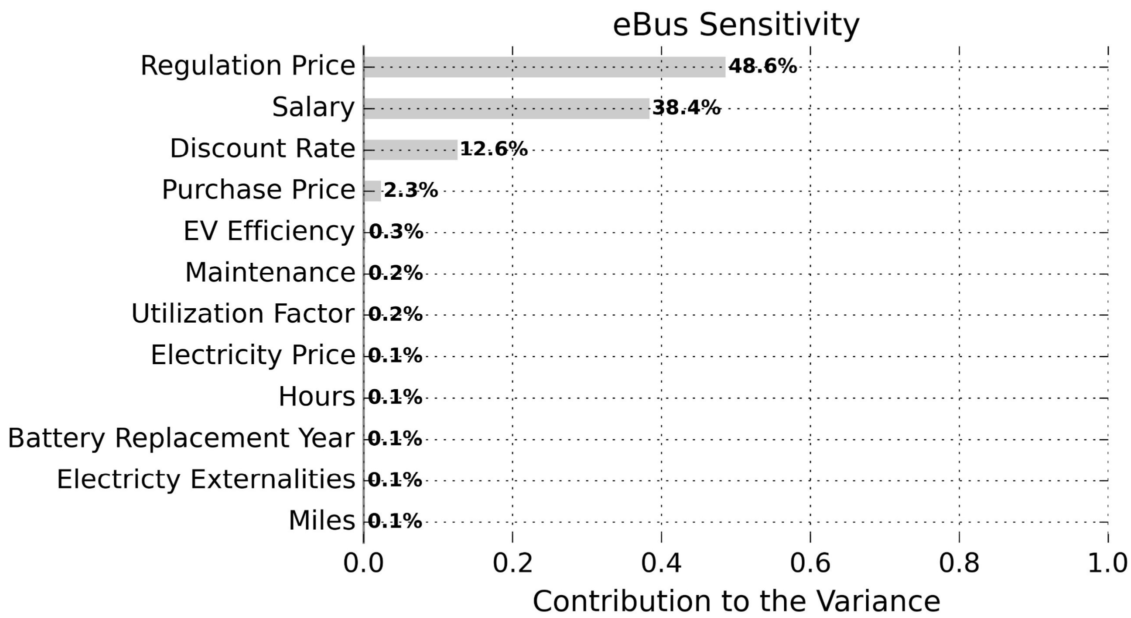

Figure 2.7: Sensitivity of fleet-wide eBus mean NPC to input variables.

To investigate the that impact specific variables have on the relative cost efficiency of the three fuel technologies, we ran Monte Carlo simulations holding a specific variable constant at different values.

Variation in salary does affect the NPC for each of our technologies, but as all vehicles have the same number of seats, each technology is affected equally and results co-vary perfectly. In the baseline scenario, diesel (D) has the lowest NPC (wins) in 43% of model runs (Figure 2.8) followed by the eBus (E) at 39%. The CNG (C) bus wins in 18% of model runs.

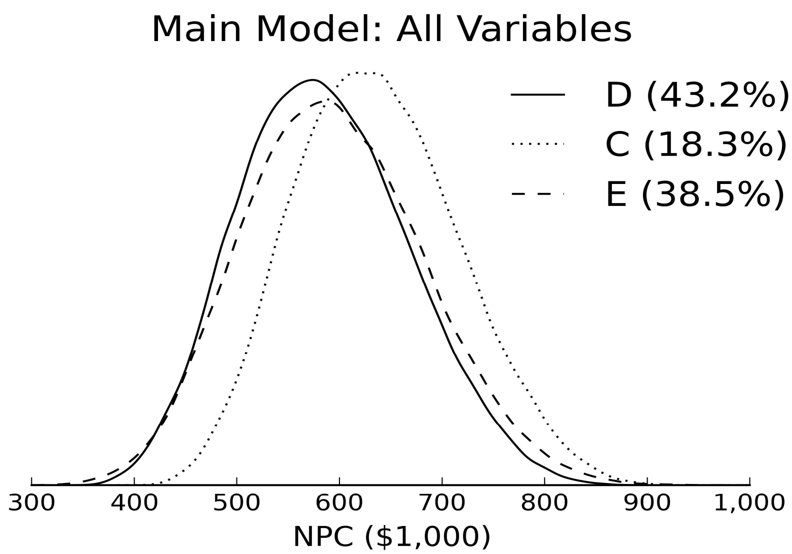

Figure 2.8: Distribution of NPC results from a Monte Carlo analysis allowing all variables to vary. Diesel (D) wins in 44.7% of model runs. CNG (C) and eBus (E) win in 36.3% and 19% of model runs, respectively.

The relative economic efficiency of the large buses in a fleet setting are most sensitive to discount rate and regulation price. We investigated the response to varying these attributes and estimated the winning percentage while holding other variables constant. Given uncertainties in eBus final production prices, we also investigate the effect of varying the eBus price.

Discount rate has an important effect on overall results (Figure 2.9). At low discount rates of 2%, the eBus wins in 49% of model runs, with the diesel winning 35% and the CNG winning 16%. At a high discount rate of 6%, results favor the diesel bus, winning 63% of model runs.

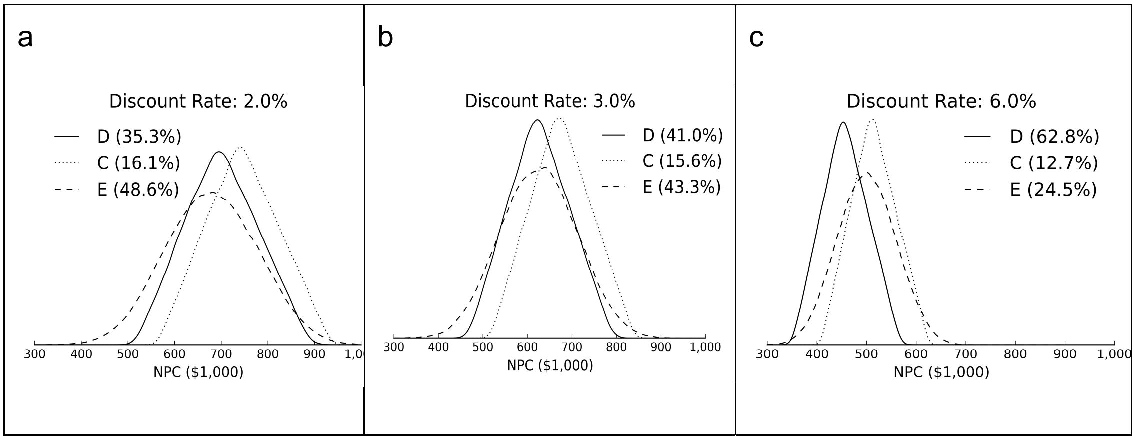

Figure 2.9: Impact of discount rates on winning percentage.

Figure 2.10 presents a sensitivity analysis concerning the impact of regulation price on the economic favorability of eBus relative to the other technologies. At two standard deviations above and below a 3-year (2012-2014) unadjusted mean FR price, the eBus is the least cost option on 74% and 11% of model runs, respectively.

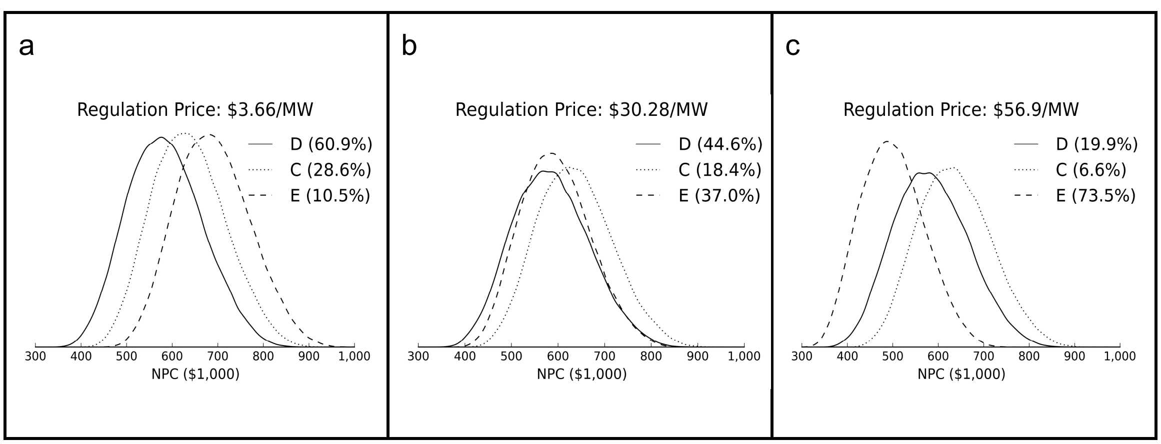

Figure 2.10: Impact of regulation price on winning percentage.

If eBus purchase price in mass production are $250,000, or 25% higher than forecasted cost, the winning percentage of the eBus drops to 25%, similar to the percentage for CNG buses (Figure 2.11). However, greater cost reductions than forecasted increase the economic favorability of eBus relative to other fuel technologies, resulting in a 49% winning percentage.

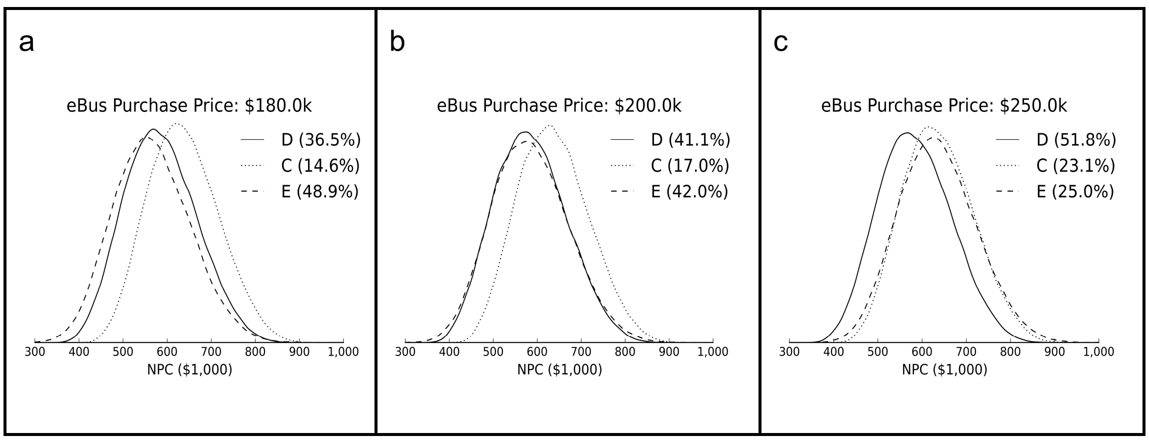

Figure 2.11: Impact of large eBus purchase price on winning percentage.

2.4.4 Analytical Limitations

This analysis comes with a suite of limitations. While attempting to identify the least cost bus technology, our analysis only selects a subset of those technologies commercially available. Diesel-electric hybrid buses, though not analyzed here, may be particularly cost-effective.[12]

[12] See for example Hallmark, 2012; Hallmark et al., 2011; Transportation Research Board, 2009.

The models presented here do not account for various costs that might be associated with adoption of a CNG bus, and especially, an eBus. One consideration relates to the 'soft', or administrative, costs associated with introducing additional complexity to an already-established fleet's composition. Electric vehicle pilot programs, for example, require additional resources dedicated to alternative training protocols, maintenance procedures and additional certifications that apply to mechanics and drivers alike.

Furthermore, increased off-site infrastructure costs for CNG and electric fuels were not explicitly addressed. While we do include on-site infrastructure costs, off-site costs such as extending gas mains (for CNG buses) or upgrading transmission lines' power capacity (for eBuses) may be substantial. For the latter, a 100 vehicle eBus fleet draws 7MW in peak electricity demand. Whether bus depots are serviced by electric infrastructure having 7MW of spare capacity, especially during peak demand when buses return from afternoon routes,[13] is beyond the scope of this analysis but could determine whether fleet electrification as presented here is even technically viable.

2.4.5 V2G and eBus Limitations

The vast majority of V2G economic studies identify and quantify the novel benefits of V2G-enabled vehicles. However, we infer disproportionately less effort in the relevant literature examining the novel technical, economic and legal challenges that also emerge from V2G implementation.

[13] eBuses return from afternoon routes with little available charge. Because the optimal charge point for performing V2G is 50%, charging will likely occur in the early evening.

The findings in this analysis highlight several novel caveats to V2G technology, including the coincidence of extremely low temperatures with highest pricing for FR. However, many other novel challenges to successfully implementing V2G are difficult to quantify accurately at this time and are only discussed qualitatively here. Therefore, the present eBus results should be understood as optimistic in proportional magnitude to the costs imposed by unaddressed factors described below. We hope this discussion guides future inquiry of these issues and stimulates acknowledgement of their existence in the BEV and V2G-related literature.

The first issue is demand charge, or a charge by the electric utility based on peak power consumption (kW) to non-residential customers. This charge allows utilities to recoup investment in costly infrastructure sized for peak load and incentivizes customers away from exhibiting 'spiky' electricity usage. While the cost of electricity is typically only modeled as energy charges, or the cost of kWh consumed, the inclusion of increased demand charges resulting from electric vehicle charging can dramatically increase electricity costs. In the Philadelphia area, for example, PECO charges general service business and industrial clients $4.96 per peak kW each month (PECO Energy Company, 2015), in addition to the energy charge for electricity. If a bus depot is unable to discontinue large electrical loads while charging an eBus, as we expect to be the case, the depot would incur $386 in demand charges alone each month per eBus in addition to the electrical energy charge. In this case, the demand charge alone is nearly double the modeled electrical energy costs for the small eBus. Thus, for the small eBus, inclusion of demand charge transforms electric fuel from providing a substantial cost savings (-49%) to a substantial cost penalty (+44%) per seat relative to diesel fuel costs.

The low range and high variability in range of electric vehicles between recharges is another complication. We estimate average driving efficiency for the small eBus to be 1.3 kWh/mi DC, resulting in expected range of 50 miles in typical conditions with the specified battery when new. However, this same vehicle's range in highly unfavorable conditions (i.e. extremely cold), towards the end of the battery replacement cycle is likely under 30 miles.[14] In extreme cold weather conditions, BEVs undergo demanding auxiliary loads such as heating the large interior cabin, experience reduced battery efficiency and battery effective capacity, and are unable to recapture braking energy through the regenerative braking process (Concha, 2007; Pesaran et al., 2013). Thus, the specified eBus would be at high risk of failing to complete school routes on the coldest days of the year, and while stranded, would not have remaining charge to heat the cabin area.

Battery longevity is also inadequately acknowledged. For example, this paper as well as Noel and McCormack (2014) model the 80 kWh eTrans battery needing replacement in year nine. However, given the eBus operating characteristics assumed in both analyses, along with data of PJM utilization rates presented above, the battery may require replacement far sooner. Hill et al. (2012) and Marongiu et al. (2014) show that

[14] A nominal 80 kWh battery has roughly 70 kWh of usable capacity. In temperatures of 0ºF, effective battery capacity is reduced by roughly 40%, yielding just 42 kWh capacity (Pesaran et al., 2013). Driving efficiency for the small eBus may be reduced to 2.0 kWh/mi DC because of dramatically increased heating and the loss of regenerative braking.

lower depths of discharge, like those performed under FR, may actually increase battery degradation rates, holding energy throughput constant. In fact, results reported by Marongiu et al. (2014) for batteries with similar chemistry to those specified here, show that the eTrans batteries could experience greater than 20% capacity loss in the third year of operation.[15] Degradation coefficients found for A123 batteries in ambient lab conditions as provided by Peterson et al. (2010) also suggest that battery life as modeled here and in Noel and McCormack (2014) are optimistic. On the other hand, this analysis does not address potential future trade-in value for the eBus' battery upon replacement that could offset a portion of battery replacement costs.

Legal issues may also arise with batteries performing V2G. For example, there is no indication that vehicle manufacturers will honor original battery warranties for vehicles that perform non-transport related functions, like V2G. The cost of securing third-party warranty coverage for a battery performing V2G is unknown and may be relatively expensive as the risk level imposed by V2G is highly uncertain.

Though overlooked here as well as in Noel and McCormack (2014), PJM does not recognize–and therefore provides no payments to–any entity under 100 kW. Thus, the ability of an eBus to earn V2G revenue as specified here and in Noel and McCormack (2014) is nil.[16] A competitive market of third-party aggregators is presumed to appear to act as an intermediary between PJM and V2G providers falling under the 100 kW

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[15] For the small eBus, FR offered at 0.88C for 7,680 hrs/yr at 13.5% utilization results in over 900 full discharge equivalents per year from V2G alone.

[16] See for example, <http://www.pjm.com/~/media/committees-groups/committees/mic/20110510/20110510-item-03-dr-as-problem-statement.ashx>.

threshold. Any fee such third-party aggregators would charge further deteriorates the economics of a V2G-enabled vehicle, but is not modeled in this, nor other V2G economic analyses.[17]

Lastly, national school bus standards direct all buses to meet a minimum vehicle driving range. A range of 200 miles is prescribed for all buses, except electric buses which are directed to achieve 80 miles (NASDPSTS, 2010). We find it highly unlikely the 80-mile range can be met in anything but favorable conditions for the eTrans, and only when relatively new with most of the battery capacity intact.

2.5 Conclusions and Policy Implications

Largely driven by health, climate and economic considerations, interest in alternative technologies for heavy-duty vehicles has expanded in recent years. We present a CBA in net present value per seat of variously fueled school buses. Results demonstrate that the marginal addition of a small eBus is not economical at current prices, but large eBuses may be economical if aggressive target price reductions are achieved, technical and legal issues surrounding V2G are meaningfully addressed, and other bus fuel technologies fail to improve their own cost structure. Such results are likely to hold true in European geographies as well, because diesel fuel is a highly fungible commodity and non-taxed motor fuel costs are similar throughout the developed world. Motor fuel taxes represent a wealth transfer rather than a true social cost.

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[17] A cost analysis for a V2G vehicle is provided on the University of Delaware V2G website defaults to an aggregator fee of 33% of V2G revenue. See <http://www.udel.edu/V2G/resources/Gasoline-Electric-Comparison.xlsx>.

Furthermore, we find that CNG vehicles are generally slightly less cost-effective than diesel. CNG is more cost-effective than the eBus in the marginal analysis, but less cost-effective than the eBus in fleet-wide analysis, although at a fleet-wide level all three technologies are roughly on par with each other. It is important to note that if a CNG bus is able to utilize an existing CNG filling station, it becomes the most cost-effective technology.

Results highlight the impact of accounting for cold temperatures on electric vehicles operations and V2G-capability. During the coldest periods of the year, frequency regulation prices spike, but vehicles left outside may be unable to provide regulation service. Furthermore, cold weather can dramatically reduce vehicle range, preventing electric buses from completing their routes. School districts and electric bus manufacturers should be cognizant of these issues.

Findings also suggest that V2G-enabled EVs are comparatively more favorable in geographies with mild year-round temperatures. V2G and driving performance will be less impeded by low temperatures, while battery degradation is not accelerated by high temperatures.

Previous studies have overlooked several key limitations of V2G-enabled vehicles. Our analysis underpins the importance in acknowledging the novel economic and technical costs of electric vehicles, and V2G specifically, rather than just the novel benefits. While difficult to quantify, nuanced legal, technical and economic issues should be further acknowledged and explored. In particular, we believe that warranty coverage, third-party aggregator fees, demand charges, round-trip efficiencies, extensive range testing, and accelerated battery degradation rates under V2G deserve further study to inform more thorough cost-benefit analyses.

Emerging and promising 'green' alternatives are becoming available for applications from power generation to environmentally friendly materials and processes. Yet, few of these technologies actually reach widespread commercial adoption. Transportation sector alternatives are no exception and lay at a critical crossroad for new fuel choice paradigms. In this paper, we consider the cost and benefits of three transportation alternatives for school districts considering alternative bus technologies, but these findings offer insight for other vehicle fleets compositions.

Previous authors have argued that market failures are largely to blame for low rates of electric vehicle adoption, subsequently offering various solutions to the relevant political and economic barriers (Kempton et al., 2014). However, such conclusions may be overstated and should be interpreted with caution. The underlying rationale for policies more favorable to electric vehicles and V2G is a determination that electrified transport and V2G is socially optimal. The findings presented here suggest that this view may be based on an incomplete accounting of all benefits and costs. First, this study provides an in-depth example of one case in which a V2G-enabled electric bus does not make economic sense despite a published finding to the contrary. More importantly, this study illuminates seldom-acknowledged aspects of V2G economics, representative of real-world conditions, which deteriorate the relative cost efficacy of V2G compared to alternatives.

As the present results suggest, nuanced cost details affect the ultimate economic viability for V2G-capable EVs. Policymakers and analysts should be aware of these nuanced costs and recognize these interrelated tradeoffs when considering this technology. While EVs offer some health and climate-related benefits, they are not necessarily the most cost-effective way to achieve societal aims, relating to health or environment.

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Chapter 3

INCREASED OPERATIONAL COSTS OF ELECTRCITY GENERATION IN THE DELAWARE RIVER AND ESTUARY FROM SALINITY INCREASES DUE TO SEA LEVEL RISE AND A DEEPEEND CHANNEL[18]

3.1 Introduction

For facilities that withdraw and utilize water from naturally brackish estuarine waters, total operational costs partially depend upon the characteristics of the water, which in turn depend upon environmental conditions. This study investigates how ambient salinity and the operational costs for one facility along the Delaware Estuary are altered by the anthropogenic factors of sea-level rise and a deepened navigational channel from dredging.

3.1.1 The Delaware Estuary

The Delaware Estuary is a funnel-shaped waterbody located in the US Mid-Atlantic, bordering Pennsylvania, New Jersey, and Delaware (Fig. 1). The watershed spans approximately 35,000 square kilometers, including the cities of Philadelphia, PA

[18] This work was partially funded by an NSF grant under the Coastal SEES program Award #1325102.

and Wilmington, DE (Bryant and Pennock, 1988; Partnership for the Delaware Estuary, 2012). Combined, the Delaware River and Estuary have the fifth highest water withdrawal volumes of any river system in the United States (USEPA, 2014a). Facilities withdrawing water along the Delaware River and Estuary include petrochemical and manufacturing, oil refineries, municipal water systems, and electricity generating stations.

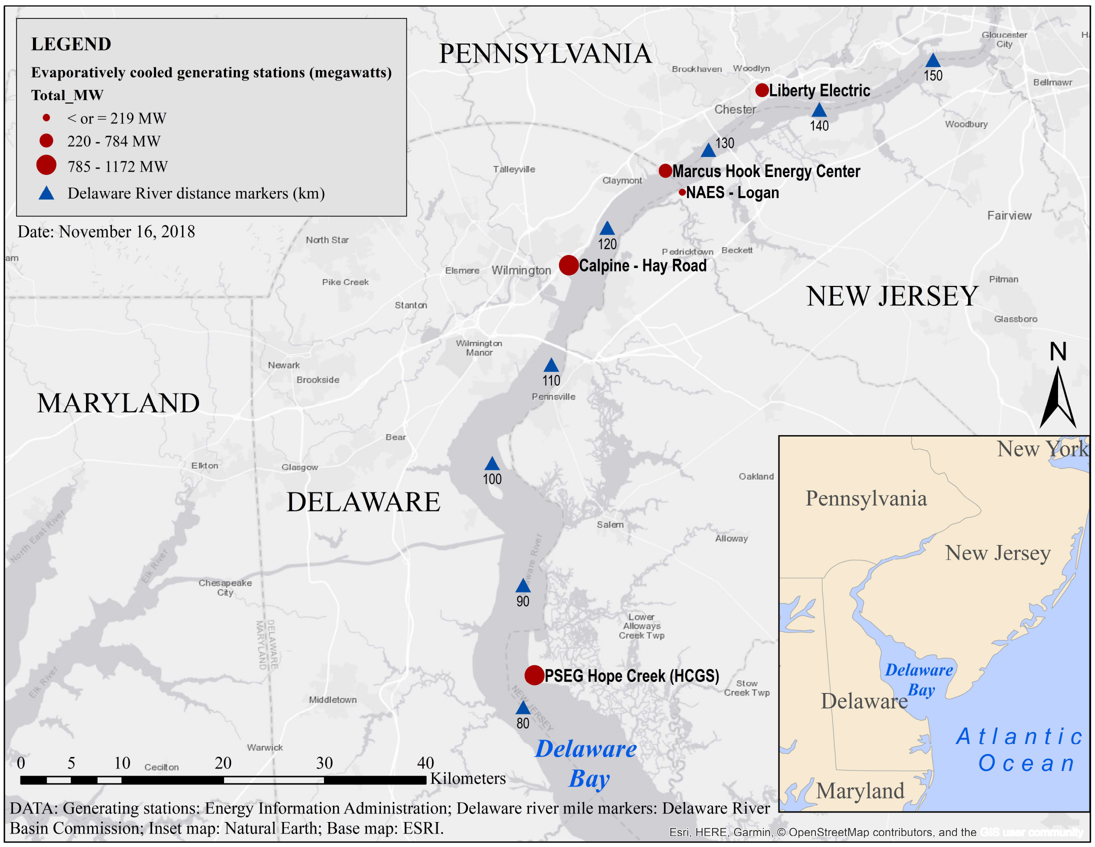

Figure 3.1: The study area showing middle and upper sections of the Delaware River and Estuary with evaporatively cooled generating stations.

Salinity in the estuary decreases travelling upstream from the mouth of Delaware Bay (i.e., River KM 0). The salinity distribution in the estuary varies spatially and temporally, depending upon river flow, tides, sea level, and bottom topography, among other factors. Prior research has reported salinity variations and trends in the Delaware River and Estuary (Wong, 1995).

Salinity in the estuary is typically highest in the summer/fall, and lowest in winter/spring, while river discharge exhibits the opposite pattern (Ross et al., 2015). Compared to many estuaries, the Delaware exhibits a weak response to changes in discharge, as both tidal salt flux due to lateral processes and steady salt flux in the channel increase with discharge (Aristizábal and Chant, 2015; Garvine et al., 1992). The median and historic maximum locations of the salt front are located at River KM 115 and 164, respectively (Delaware River Basin Commission, n.d.).

Sea levels at a nearby monitoring station have risen an average 3.54mm/yr between 1956 and 2016 (NOAA, 2016). Higher sea levels result in greater seawater forcing in the upstream direction and increased average salinities in the estuary.

In 2010, the US Army Corps of Engineers began deepening the Delaware main channel from 12.2m to 13.7m, partially in response to a recently expanded Panama Canal (USACE, 2011). As of November 2018, the Delaware deepening project was nearly complete (USACE, 2018). Because estuarine circulation and associated landward salt flux increase nonlinearly with water depth, the extent of salinity intrusion is also anticipated to increase with a deepened channel (Hansen, D.V., Rattray, 1965; MacCready and Geyer, 2010).

3.1.2 Electricity Generating Stations on the Delaware

Twelve large electricity generating stations withdraw water from the lower Delaware River and Delaware Estuary, representing a combined generating capacity of over 8,000 megawatts (MW), equivalent to the average electricity draw of six million US homes (US EIA, 2017). These facilities include two large nuclear stations and numerous smaller fossil fuel-fired stations. In 2017, these 12 stations withdrew over 3,200 million gallons per day (MGD) or approximately 140m^3/s, mostly for cooling purposes (US EIA, 2018). Evaporatively cooled stations (Figure 3.2) were responsible for less than 2% of the total volume of water withdraws, yet they generated approximately half of the total electricity (US EIA, 2018). Continual evaporation and circulation of cooling water within an evaporatively cooled system decreases the volume of water withdrawals but increases the sensitivity of the cooling system to changes in water composition (Ting, B., Suptic, n.d.; Zhang and Dzombak, 2010).

Of the evaporatively cooled stations in the estuary, PSEG's 1,161MW nuclear powered Hope Creek Generating Station (HCGS) has the greatest power capacity, capacity factor, and water volume requirements (DRBC, 2013). HCGS withdraws approximately 50 MGD (US EIA, 2018) and has an average capacity factor exceeding 90% (Nuclear Energy Institute, 2017). HCGS is also the most seaward of the evaporatively cooled stations (River KM 83), located in the stretch of the estuary where salinity increases from SLR are expected to be the most pronounced (Hull and Titus, 1986; Ross et al., 2015) and where a significant signal of SLR on salinity increase has been detected in the historical record (Ross et al., 2015).

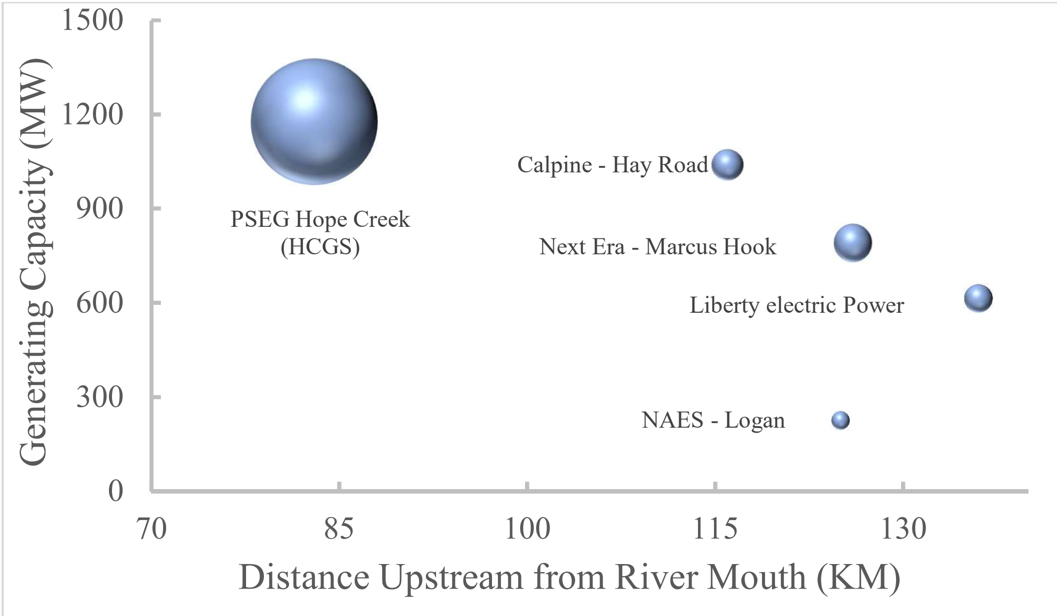

Figure 3.2: Evaporatively cooled generating facilities in the Delaware River and Estuary. Bubble size represents the relative rate of water withdrawals.

3.1.3 Cooling Water Systems

Cooling water is essential to most thermo-electric generating station designs. Cooling water condenses the working fluid to help maintain a large pressure difference across the turbine. This pressure difference drives the turbine's operation. Without sufficiently cool water or sufficient flow of cooling water at the low-pressure side of the turbine, 'backpressure' would build, resulting in lower power cycle efficiency and/or reduced electricity generation.

Water-cooled systems use either once-through or evaporative cooling. Briefly, once-through systems extract cooling water from a waterbody and pass it across a heat-exchanger before releasing it directly back. For these systems, the waterbody is the primary recipient of waste heat. Once-through systems in brackish environments typically require limited chemical treatment, often consisting of only occasional chlorine pulses (Nickel Development Institute, 1994; Zhang and Dzombak, 2010). Due to ecological concerns, a shift away from once-through cooling began in the 1970s (US EIA, 2014), although many such stations still operate with decades of remaining operational life.

Evaporative cooling systems, on the other hand, consist of a heat exchanger, one or more evaporative towers, and pumps to circulate water within the system. The atmosphere is the primary recipient of waste heat through the latent heat of evaporation. As pure water evaporates, dissolved solids (i.e., salts) concentrate in the recirculating water. The level to which dissolved solids concentrate in this manner is controlled by facility operators through a flushing process called “blowdown.” Due to the greater surface areas and water residence time—relative to once through systems—evaporatively cooled systems are typically coupled with more intensive chemical treatments to limit corrosion, scaling, and fouling in the cooling towers and the condenser. (Maulbetsch and Difilippo, 2008; Zhang and Dzombak, 2010). While costly, these chemical treatments increase can increase the effectiveness of the cooling system thereby increasing power cycle efficiency and reducing overall station costs when implemented properly. Walker et al. (2012), for example, explores a methodology for assessing cost-impacts of fouling in cooling systems.

Prior studies have investigated the marginal costs for constructing a new evaporatively cooled systems using brackish or saline water (Maulbetsch and Difilippo,

2008) and for operating with treated municipal wastewater relative to freshwater for cooling purposes (Barker and Stillwell, 2016; Walker et al., 2013). Another study investigated the impact of sea-level rise on the increased flooding probabilities of electricity generating station, finding that sea-level rise will place the majority of current electricity generating capacity in Delaware and New Jersey at risk of major flooding events by the end of the century (Bierkandt et al., 2015). We are aware of no study that estimates cost increases for an existing facility facing future salinity increases, however.

For an existing evaporatively cooled system, given various technical and regulatory constraints, costs are minimized by optimizing recirculating water chemistry. Allowing salinity to concentrate to high levels within the cooling system reduces the need for makeup water and associated pumping and treatment costs. On the other hand, higher salinities accelerate the processes of corrosion, fouling, and/or scaling along the surfaces of the cooling tower and the condenser, thereby decreasing thermal performance (Ibrahim and Attia, 2015; Keister, 2008; Maulbetsch and Difilippo, 2008).

Higher salinity in the cooling system also increases particulate emissions associated with "drift," the small quantity of liquid-state emissions entrained in the evaporation plume. Drift contains solutes at the same concentration as the circulating water and is frequently regulated under air quality permits for particulate matter.

From an economic perspective, nuclear stations comprise baseload generation, meaning that they tend to generate electricity nearly continuously with low marginal operating costs. Consequently, cost increases at HCGS due to increases in treatment and pumping requirements approximate a reduction in social welfare. In comparison to a scenario without SLR and channel deepening, more societal resources are required to provide each additional unit of electricity. All else equal, this implies fewer resources available for other desired goods and services in the economy.

3.2 Materials and Methods

Future salinity forecasts were created by combining historic salinity variability, a modest historic trend of decreasing salinity, and estimates of future salinity increases from SLR and deepened channel. The resulting salinity regimes were used to inform changes in daily water throughput in a salinity-constrained cooling tower at HCGS. Increased water throughput was monetized by applying a volumetric cost for pumping and treatment to all incremental makeup water. The summation of discounted costs over baseline conditions—absent SLR and a deepened channel—represent present value of social costs. A Monte Carlo analysis was performed over each forecast to assess results over a range of input values. The presumption in this analysis is that operators respond to increased salinity by increasing blowdown and incurring greater pumping and treatment costs that result.

3.2.1 Baseline Forecast

Daily salinity data were derived from specific conductivity measurements at the USGS station at Reedy Island, DE (USGS, 2017) during the period from June 4, 1976 to February 28, 2010, just prior to channel deepening operations began. Conductivity data were converted into salinity following industry standards (Schemel, 2001).

From 34 years of historic daily salinities, a salinity distribution was created for each calendar month. These 12 distributions were sampled probabilistically within each month to build a forecast of daily salinities into the future.

Because the Reedy Island station is 5km upstream from HCGS and samples higher in the water column, an adjustment was necessary to account for the higher salinity that would be present at HCGS' intake. A 3-D hydrodynamic model of the estuary using the Regional Ocean Modeling System (ROMS) was used to evaluate concurrent salinity at Reedy Island and Hope Creek locations over a range of discharge conditions. Development and validation of this circulation model have been described in prior work (Chen et al., 2018, 2016). Based on the model results, a linear relationship ($1.1830\,x + 1.5853$) was derived to estimate salinity at Hope Creek from observed salinities at Reedy Island. The salinity estimates resulting from the linear transformation ranged from 0.1psu to 19psu with a mean of 7.0psu, similar to previous reports for HCGS (Nickel Development Institute, 1994; PSEG Nuclear, 2010). Salinity exhibited a modest but statistically significant decrease over time, averaging 0.087psu/yr, explained in other studies by increases in regional precipitation and greater river discharge (Najjar et al., 2012; Ross et al., 2015). This trend is captured for the duration of the analysis by incorporating iterative decreases in baseline salinity forecasts at the beginning of each model year. Because the future magnitude of this trend is uncertain, dependent on both future precipitation and river basin management trajectories, this factor was modeled in the Monte Carlo simulation between zero and twice the recently observed rate of decrease (-0.0174psu/yr) across model iterations.

3.2.2 Anthropogenic-1 Forecast

An alternative salinity forecast (Anthropogenic-1) was created by adjusting the Baseline forecast upwards to account for the marginal salinity impacts from SLR and a deepened channel. Salinity increases from SLR required estimation of both the magnitude of SLR in each future year, as well as the sensitivity of salinity at this location to each increment of rise. Five SLR projections, (Low, Medium-Low, Medium, Medium-High and High) corresponding to between approximately 0.24m and 0.63m of rise by 2067 relative to 2018 levels, were created based on the 2017 Delaware Sea Level Rise Technical Committee Report (Callahan et al., 2017) (Fig. 3). Callahan et al., (2017) provide three SLR scenarios and their respective probabilities for the state of Delaware based upon the work of Kopp et al., (2014) within the RCP 8.5 “business as usual” framework. We created two additional intermediate SLR cases through interpolation of the original three for more granular results.

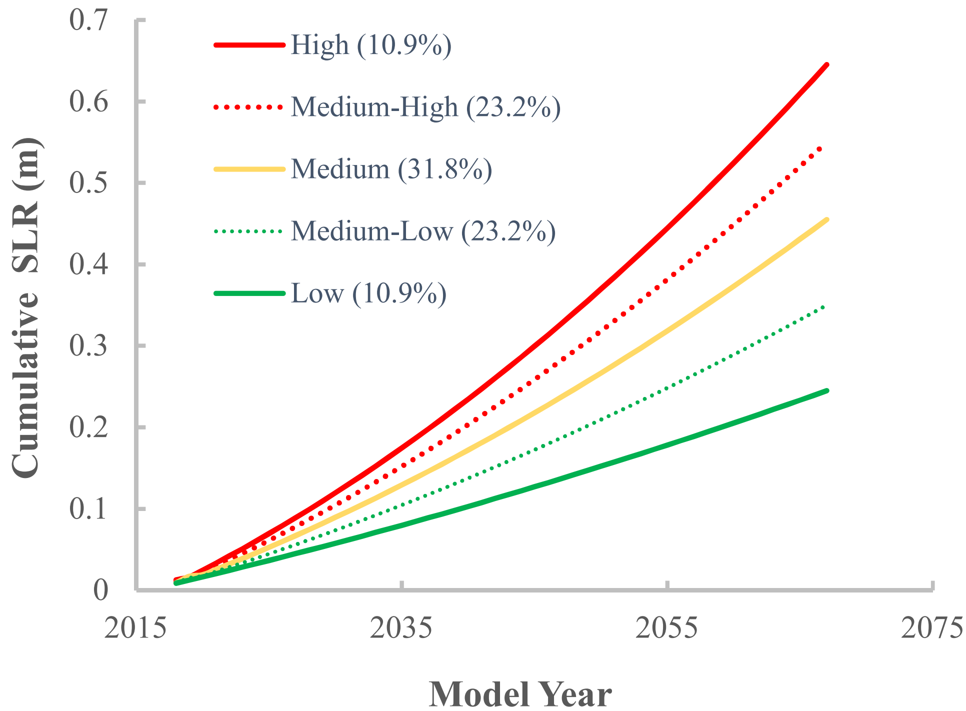

Figure 3.3: The five sea-level rise paths and their assigned probabilities in model simulations based on Callahan et al. (2017).

The 3-D hydrodynamic model of the estuary was used to characterize the response of the salinity field to changes in water depth due to dredging or SLR. To incorporate the dependence of the salinity response to discharge, the model was run to equilibrium for constant river discharge cases of 100, 300, 600, and 1000 m^3/s. Three versions of model bathymetry were compared: a baseline case with a 12.2m (40ft) navigation channel, a dredged case with a 13.7m (45ft) navigation channel, and SLR case with the 12.2m navigational channel plus a uniform increase in depth of 0.18m, equal to the SLR over a 50yr period given a constant current trend of 3.54mm/yr. The salinity increase from SLR relative to the baseline is expressed as a sensitivity (i.e., salinity increase per meter of SLR), and the salinity increases from the 0.18m SLR model case were used to scale the other levels of future SLR. This approach simplifies potential nonlinearities in the response of the salinity intrusion to the full range of SLR scenarios and the combination of dredging with SLR, but within the constraints of running a feasible number of hydrodynamic model cases, this approach provides scaling for the sensitivity of the estuary to the different deepening factors.

This hydrodynamic modeling also did not incorporate potential morphological feedbacks between the deepening and sediment transport processes that might mitigate the increase in estuary depth with SLR, nor did it evaluate inundation of land with SLR.

For each bathymetry case, modeled salinity at the HCGS intake was evaluated to develop relationships between salinity and river discharge. In all cases, salinity decreased as discharge increased, consistent with previous observations and modeling of the Delaware (Aristizábal and Chant, 2015; Garvine et al., 1992).

In the model case with 0.18 m SLR, salinity at the HCGS intake increased by 2.6psu/m of SLR in normal and low flow conditions and increased by a smaller magnitude in high flow conditions (Fig. 4). For a channel deepened from 12.2m to 13.7m, the hydrodynamic model indicated a salinity increase of 1.7psu (or 1.1psu/m of deepening) in normal and low flow conditions, and less of an increase in high flow conditions (Fig. 3.4). Refer to Table 3.1 for additional detail. Salinity increase due to SLR was implemented in annual increments according to the simulated SLR schedules, whereas salinity increase from channel deepening was implemented in full upon the first model year.

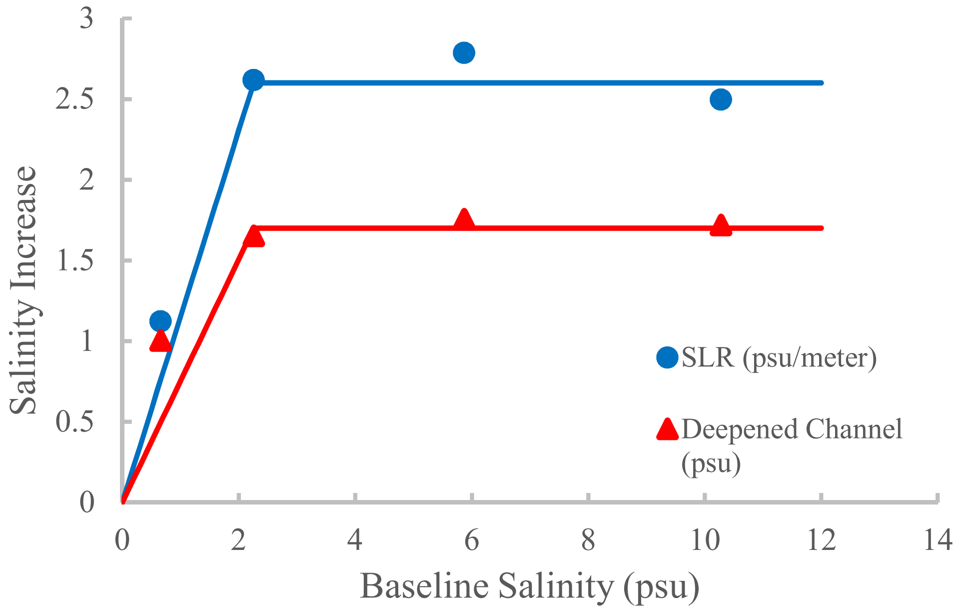

Figure 3.4: Salinity increase over baseline due to SLR and a deepened channel for HCGS.

Table 3.1: Salinity increase from SLR and Deepened Channel from Anthropogenic-1 and Anthropogenic-2, where S_b is salinity under Baseline.

	Anthropogenic-1		**Anthropogenic-2**
	Salinity increase if S_b >2.3 psu	Salinity increase if S_b <2.3 psu	Salinity increase for all S_b
SLR (psu/m)	2.6	$S_b \times (1.13)$	4.9
Deepened Channel (psu)	1.7	$S_b \times (0.74)$	0.2

3.2.3 Anthropogenic-2 Forecast

A second forecast (Anthropogenic-2) was created in which salinity increases over the Baseline forecast were informed by a previous study of salinity increases in the DE Estuary (Johnson, 2010). This study, prepared for the US Army Corps of Engineers, estimated salinity increases at HCGS from SLR of 4.9psu/m, and increases from a deepened channel of 0.2psu (or 0.13psu/m of deepening). These estimates were inferred from the graphical outputs 40(b) and 100(b) that were specific to the HCGS location in Johnson (2010). In these figures, salinity increases from SLR and a deepened channel were weakly related to baseline salinity. Therefore, for Anthropogenic-2, one salinity sensitivity is applied for all flow conditions. Values for salinity increases for both Anthropogenic-1 and Anthropogenic-2 are displayed in Table 3.1.

3.2.4 Operating Costs

To determine cost increases at HCGS, the cooling system was modeled as continually adjusting cycles of concentration (COC) through differential rates of blowdown to maintain the maximum designed salinity for recirculating water. HCGS was reported to have a maximum recirculating water salinity of 33.6psu based on air quality regulations limiting particulate emissions from drift at this facility to approximately 42lbs/hr (Sargent and Lundy LLC., 2006). In this mode of operation, fouling and corrosion rates are not likely to be altered from baseline conditions because the salinity of recirculating water is independent of ambient salinity. Operating cost increases at HCGS from elevated salinity were determined by differencing the Baseline pumping and treatment costs from those costs under scenarios Anthropogenic 1 and 2.

The present value of cost increases from salinity increase at HCGS was determined by[19]:

$$C = \sum_{i=1}^{n}\{Tc_i^{Anthro} + Pc_i^{Anthro}\} \cdot \beta^i - \sum_{i=1}^{n}\{Tc_i^{Baseline} + Pc_i^{Baseline}\} \cdot \beta^i \qquad (1)$$

where n was the study horizon in days, Tc_i and Pc_i were the per day treatment costs and pumping costs in day i for their respective scenarios. Additionally, $\beta^i = 1/(1+r)^i$ was the discounting factor where the equivalent annual discount rate was specified as 2% or 5%. Tc_i and Pc_i were determined by:

$$Tc_i = M_i * Tr \qquad (2)$$

$$Pc_i = M_i * Pr \qquad (3)$$

where M_i was the quantity of makeup water in day i, Tr was the volumetric treatment rate ($/ thousand gallons or kgal) and Pr was the volumetric pumping rate ($/kgal).

Makeup water is water withdrawn from the local water body and injected into the recirculating water system to maintain constant water levels. The volume of makeup water, M, required in day i can be approximated by (US DOE, 2011),

$$M_i = E_{ij} + BD_i \qquad (4)$$

where E_{ij} was the mass of water lost to evaporation day i and season j.

Typical evaporation rates for HCGS were reported as 13.6 kgal per minute in the summer months and 11.3 kgal per minute in the winter months (PSEG Nuclear, 2010). An intermediate value of 12.5 kgal per minute was assumed for the spring and fall months. BD_i was the volume of blowdown discharged from the recirculating system in

[19] While the Delaware River Basin Commission charges for surface water withdraws these fees are not representative of social costs.

day i to maintain cooling water salinity at the desired level. Higher ambient salinities necessitate lower COC, requiring higher rates of blowdown and makeup. BD_i, and COC_i were defined as

$$BD_i = \left(\frac{E_{ij}}{(COC_i - 1)}\right) \tag{5}$$

$$COC_i = \frac{s^m}{s_i^a} \tag{6}$$

where s^a_i was ambient salinity in day i, s^m was the maximum salinity of recirculating water for the cooling system, 33.6psu. Combining equations **(2-6)** yields,

$$Tc_i = \left(E_{ij} + \frac{E_{ij}}{\left({s^m}/{s_i^a}\right) - 1}\right) * Tr \tag{7}$$

$$Pc_i = \left(E_{ij} + \frac{E_{ij}}{\left({s^m}/{s_i^a}\right) - 1}\right) * Pr \tag{8}$$

Average treatment rate, Tr, of makeup water varies in the literature between \$0.12 and \$4.60/kgal (Wolfe et al., 2009), with a median value of \$1.16/kgal (Freedman and Wolfe, 2007) all adjusted for inflation. Values at the upper end of this range represent impaired water sources like treated wastewater and are not applicable here. A value for Tr over the range of \$0.12-\$1.00/kgal of makeup water was assumed, with each increment having equal draw probabilities in the Monte Carlo analysis.

Treatment at HCGS covers three major tasks; physical filtration, chemical treatment and disposal of accumulated sludge. Chemical treatments typically consist of chlorination (as sodium hypochlorite), scale-inhibition (as sodium hydroxide), and dechlorination (as ammonium bisulfite) (PSEG Nuclear, 2010; Sargent and Lundy LLC., 2006).

This analysis assumes that Tr remains constant at HCGS. In reality, one component of Tr, chemical treatment, is not fully independent of ambient salinity. Because losses of treatment chemicals increase with higher rates of blowdown (i.e. higher ambient salinity), chemical costs per unit of makeup water may increase with higher rates of blowdown. For the purposes of comparing Baseline to Anthropogenic 1 and 2 scenarios, this simplification is likely to slightly bias results by understating the true cost increase from sea-level rise and a deepened channel.

The incremental energy required for pumping additional makeup water into the cooling system increase was calculated from a simple pump-lift equation where 2.7 million lb-ft of water is equivalent to one kWh[20]. The social cost of this parasitic energy was valued as foregone emission-free electricity. This foregone electricity was monetized as \$0.12/kWh, composed of marginal electricity generation costs (~\$0.05/kWh) and pollution externalities from marginal generation (~\$0.07/kWh) in the PJM grid. Externality costs were driven primarily by air pollutants from natural gas and coal combustion. Therefore, Pr, the volumetric pumping cost, was assigned to equal \$0.02/kgal of makeup water.

3.2.5 Study Horizon

According to industry statements, HCGS is currently licensed to operate until 2047, 30 years from the present, with the possibility of additional 20-year renewal (US

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[20] Estuarine water weighs approximately 8,400 lbs/kgal. An effective pumping height of 30 ft and pumping system efficiency of 80% were assumed. An additional 30% energetic requirement per kgal is required to drive screen wash pumps and screen drive motors (Sargent and Lundy LLC., 2006). Therefore, total pumping energetic requirements are 0.17 kWh/kgal of makeup water.

EIA, 2014c). A 20-year extension would allow for a 50-year reactor life from the present, totaling 80 years, considered to be an upper limit on the age of an existing reactor (Schwitters et al., 2013; Voosen, 2009). It was assumed that a new nuclear facility would not be constructed at this location after the existing facility was decommissioned. Therefore, the remaining facility lifetime was specified with equal probabilities as either 30 years or 50 years.

3.2.6 Monte Carlo Analysis

To account for uncertainty over input values, the model described above was run within a Monte Carlo framework consisting of 100,000 simulations. Within each Monte Carlo iteration, with the exception of daily salinity, one value was chosen for each variable and retained within each run. These variables were daily historic salinity, background salinity decrease, the treatment rate of the makeup water, the remaining station lifetime, and predicted SLR scenario. Model inputs are presented in Table 3.2.

Table 3.2: Overview of model inputs

Variable	Values	Distribution in Monte Carlo	Notes
Background salinity trend (psu/yr)	0 - 0.0174	Uniform	Historic 34-yr mean served as the midpoint (USGS, 2017)
SLR Path	Low, Medium-Low, Medium, Medium-High, High	Low:10.9% Medium-Low: 23.2% Medium: 31.8% Medium-High: 23.2% High: 10.9%	See Figure 4-4, (Callahan et al., 2017)

Remaining Life of HCGS (years)	30, 50	Uniform	(American Physical Society - Panel on Public Affairs, 2013; Voosen, 2009)
Tr: Treatment Rate ($/kgal)	0.12 – 1.00	Triangular	(Freedman and Wolfe, 2007; Wolfe et al., 2009)
Pr: Pumping Rate ($/kgal)	0.02	Constant	See methodological discussion
E: Evaporation rate (gallons per minute)	11,300 - 13,600	Constant within season	(PSEG Nuclear, 2010)
S^a: Ambient Salinity (psu)	0.1 - 18	Probabilistic draws from within month observations	(USGS, 2017)
S^m: Salinty maximum in cooling system (psu)	33.6	Constant	(Sargent and Lundy LLC., 2006)
Discount Rate (%)	2, 5	-	Calculated separately

3.3 Results

3.3.1 Baseline Costs

The present value of Baseline costs averaged $121M and $78M at discount rates of 2% and 5%, respectively. The highest and lowest estimates at each discount rate spanned nearly and order of magnitude. For example, at the 2% rate, the present value of costs ranged between $25 and $254M, and $17M to $152M at the at 5% rate (Figure 3.5). This wide variation was attributable primarily to the eight-fold range in the specified treatment rate of the makeup water, *Tr*. The largest values in each distribution plateaued at lower levels of probability density than the remainder of the distribution. These lower plateaus corresponded with the draws of a high *Tr* and a long (50yr) station life. The plateau for the 5% discount rate scenario was less pronounced than that for the 2% scenario because years 31-50 were more heavily discounted. The wide range and substantial impact of the treatment rate for makeup water tended to flatten the remainder of the distributions.

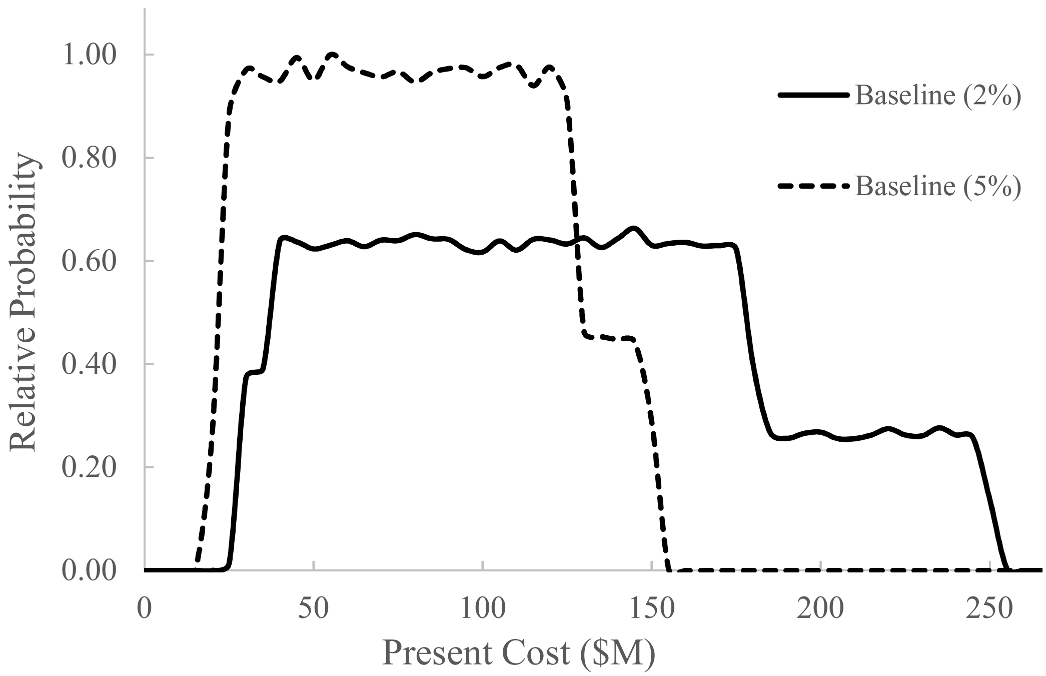

Figure 3.5: Distribution of present costs estimated for the Baseline forecast at 2% and 5% discount rates.

3.3.2 Anthropogenic-1 Costs

In the Anthropogenic-1 scenario, the estimated present value of cost increases over the Baseline scenario averaged $12.1M and $7.2M at discount rates of 2% and 5%, respectively. The range of these cost increases were $2.0M to $32.7M at the 2% rate, and $1.4M to $17.1M at the 5% rate. Probability densities for these cost increases are displayed in Figure 3.6.

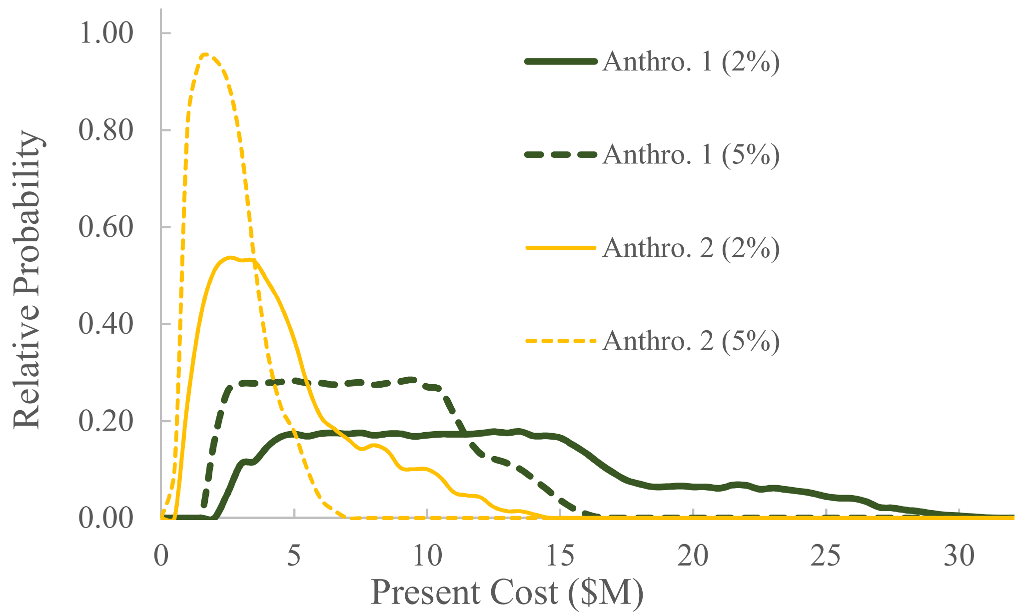

Figure 3.6: Distribution of cost increases over Baseline for the Anthropogenic-1 and Anthropogenic-2 scenarios at 2% and 5% discount rates.

3.3.3 Anthropogenic-2 Costs

In the Anthropogenic-2 scenario, the estimated present value of cost increases over the Baseline Scenario averaged $4.3M and $2.2M at discount rates of 2% and 5%, respectively. The ranges of these cost increases were $0.5M to $14.9M at 2%, and $0.3M to $6.7M at 5% (Figure 3.6). Average cost increases from Anthropogenic-2 are approximately one-third as large as those estimated under Anthropogenic-1. The smaller cost increases relative to Anthropogenic-1 can be explained by the substantially lower estimates of salinity increases from channel deepening, partially offset by higher estimates of salinity sensitivity to SLR.

3.3.4 Relative Contribution of Factors

In Anthropogenic-1, a deepened channel accounted for approximately 85% of the cost increase, while SLR accounted for the remainder. A deepened channel resulted in the majority of the cost increases because of its large, immediate impact on salinity compared with an initially small increase from SLR, followed by progressive salinity increases that were increasingly discounted.

3.4 Discussion

This research pursued three objectives: (i) to identify electricity generating stations in the Delaware River and Estuary most at risk from future salinity increase from SLR and a deepened channel; (ii) to model the magnitude of salinity increases from these factors; and (iii) to estimate the adaptations and associated social costs at the most vulnerable station. A method was developed to estimate the costs at evaporatively cooled facilities that face elevated salinities. While this paper focused on a single facility on the estuary, the method could be applied to other evaporatively cooled facilities subject to future salinity increases. Dozens of such stations exist worldwide (Eftekharzadeh et al., 2003; Maulbetsch and Difilippo, 2008), including the nearby Chalk Point and Possum Point generating stations in Maryland and Virginia. Results could also inform more complete cost-benefit analyses on channel deepening and help to refine estimates of the social cost of carbon through the impacts of SLR.

Cost increases were estimated through a novel method and are subject to several limitations. First, this analysis assumed that the cooling system would operate at maximum salinity as determined by air pollution permit compliance. In certain cases, however, the economic salinity maximum may be lower than the regulatory salinity maximum. In such cases, estimates of cost increases using the method described here may be overstated. This study did not investigate other factors related to climate change, such as shifts in ambient water temperature or turbidity patterns that could also impact cooling station operation and deserve further attention.

Further, this study omitted the social costs associated with the increased impingement and entrainment of aquatic organisms due to greater water throughput necessitated by higher volumes of makeup water. For a detailed discussion of social costs from impingement and entrainment of aquatic organisms, see US EPA (2014).

At the outset of this research, cost increases were expected to be large due to the scale of channel deepening in the Delaware River and Estuary. The estimates presented in the current study, however, suggested only modest impacts relative to operational costs. HCGS generates approximately 10.6 million MWh per year (US EIA, 2018). Assuming average production costs of $27 per MWh (Lazard, 2018), yearly production costs total $286M. Converted to equivalent annual costs, Baseline conditions represented just $4.0M or 1.4% of annual facility operating costs. The additional costs imposed by elevated salinity under Anthropogenic-1 conditions represent an incremental $0.4M, or 0.1% of annual operating costs.

3.5. Conclusions

The results of this work lead to several general conclusions. First, the salinity increases calculated from ROMS diverged meaningfully from previous work. These divergent results may be explained by differences in model resolution and the ranges of river discharge investigated, among other factors. A third study estimated salinity sensitivity to SLR at this location of 3.3psu/m, intermediate in magnitude to the two values modeled here (Ross et al., 2015). To the extent regulatory bodies like Delaware River Basin Commission rely on existing models for planning, they may be substantially underestimating the future salinity intrusion resulting from a deepened channel.

Second, a recently updated cost-benefit analysis conducted for the Delaware channel deepening project estimated annual net benefits of the project of \$13.7M (USACE, 2018). However, only a limited set of costs and benefits were included in that analysis, with no quantification of impacts from salinity changes. Using the 5% discount rate for comparability, the 85% share of costs from a deepened channel estimated in the Anthropogenic 1 forecast would offset approximately \$0.3M, or 2% of expected annual benefits from dredging. At the upper end of findings for the Anthropogenic 1 forecast, \$0.9M or 7% of net benefits would be offset. Including other indirect social costs from a deepened channel, for example changes in wetland carbon sequestration (Carr et al., 2018) or increased risk of salt intrusion at Philadelphia area water intakes, could further reduce the estimated net benefits of the Delaware channel deepening project.

Finally, estimates of salinity changes and associated cost increases could improve the capabilities of HCGS or the regional electric grid to forecast future market conditions. Small changes to operating conditions at HCGS could cascade into much larger social costs if they accelerate retirement schedules due to diminished profitability. Of course, factors affecting larger wholesale energy market are likely to be more influential on the profitability of baseload generating stations. Nevertheless, the premature loss of HCGS's annual production of 10.6M MWh of predictable, low-carbon electricity could impose substantial social costs through higher levels of pollution and the increased generating costs of any fossil fuel powered electricity generation that increases production to compensate (Berkman and Murphy, 2017).

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Chapter 4

VISUAL IMPACTS OF OFFSHORE WIND PROJECTS ON BEACH RECREATION: RESULTS FROM FOUR IN-PERSON SURVEYS

4.1 Introduction

Offshore wind power is one source of renewable electricity being considered for wide scale deployment on the US East Coast (McClellan, 2019). For example, the US Department of Energy set a goal for 54 gigawatts (GW) of offshore wind power by 2030 (US DOE, 2008). While areas of northern Europe have decades of experience with offshore wind installations and roughly two-dozen operational projects, the US offshore wind industry is relatively nascent, consisting of just a single small-scale commercial project (30 MW capacity) as of this writing in early 2019.

Offshore wind power offers several advantages over many existing sources of electricity generation including lower environmental and human health impacts (McCubbin and Sovacool, 2013) primarily through reduced emissions of air pollutants. Further, winds offshore of the US East Coast tend to be stronger and more consistent than over suitable land locations nearby (Kempton et al., 2010), potentially leading to lower grid integration costs (Veron et al., 2018). Offshore wind on the US East Coast is also proximal to electricity demand (i.e., load) centers, potentially reducing capital costs and electrical losses from long-distance electricity transmission (Kempton et al., 2010).

Offshore wind power also presents several disadvantages. The levelized cost of energy (LCOE) of offshore wind power in this region is far higher than for natural gas combined-cycle, utility scale solar and onshore wind projects (Lazard, 2018). Costs are, however, expected to decrease in future years for all renewable technologies.

Another potential disadvantage of offshore wind projects, like their onshore counterparts, is the potential for creating a viewshed disamenity (for example, Krueger, 2011; Ladenburg and Dubgard, 2009). In the case of offshore wind projects, this change in amenity can manifest as changes in local housing markets as quantified through hedonic valuation (Carr, 2017; Gibbons, 2015; Heintzelman and Tuttle, 2012; Hoen et al., 2015; Lang et al., 2014) tourism patterns and recreational enjoyment as quantified through various survey methods (Alvarez-Farizo, and Hanley, 2002; Krueger et al., 2011; Ladenburg and Dubgaard, 2009), and influence willingness participate in green-energy programs (Knapp, 2018). One notable potential outcome of these impacts is reduced support for projects by local communities (Musial and Ram, 2010). High levels of local support and involvement are essential to a successful project implementation (Haggett, 2011).

Some beach recreators find that the presence of nearby offshore wind power projects decreases their enjoyment of beach recreation. In a recent survey, Parsons et al. (2019) found that negative changes to beach experiences from offshore wind power projects were motivated by perceived diminishment of the natural seascape and concerns for marine life. However, changes to an individual's beach enjoyment need not be in the negative direction. Parsons et al. (2019) found that positive changes to beach experience were motivated most frequently by perceived benefits to the environment and to energy security.

Potential changes in beach visitation patterns are also important for nearby coastal communities. Robust studies that quantify impacts to tourism patterns and other socio-economic impacts can inform the decision-making process and can help identify optimal locations and offshore distances of future projects.

One strategy to mitigate visual impacts of offshore wind projects is to locate these projects beyond view. For offshore wind turbines of 3MW to 3.6MW, or approximately half the capacity of the current generation, maximum visually perceptible distance was found to be approximately 25 miles from shore in clear conditions. At 10 miles and closer, these turbines were found to be a major focus of visual attention (Sullivan et al, 2013). Offshore wind power projects also benefit from stronger and more consistent winds that tend to exist with increasing distance from shore.

Counteracting these motivations for greater project distance from shore are project capital costs that tend to rise with greater distance from shore. There is likely an optimal project distance that solves for cost minimization in the absence of visual externalities (Jacobsen et al., 2016). A cost optimization solution for distance that includes visual externalities will likely be further from shore compared to one that does not.

Areas designated for offshore wind power development, also called lease blocks, along the Delaware and Maryland coasts range from approximately 10-20 miles offshore (BOEM, 2018). These distances are, therefore, deemed the most policy relevant for the present study.

The US Bureau of Ocean Energy Management (BOEM) commissioned a large study to systematically quantify recreational impacts and how they vary with distance for the East Coast of the US. Findings from that effort are reported in Parsons and Firestone (2018), Tousssaint (2016), and Parsons et al. (2019).

Most similar to the present study (hereafter, 'in-person surveys'), Parsons et al. (2019) (hereafter 'internet survey') is a large internet-based study in collaboration with the US Bureau of Ocean Energy Management (BOEM). It represents an extensive multi-year undertaking to estimate the potential impact of offshore wind power projects on beach recreation enjoyment and the rate of beach trip cancellation or trip displacement, among other measures. The internet survey captured a large and detailed dataset from a random draw of households from 20 states on the East Coast. Respondents were shown visual simulations like those employed here, but the simulations differed by being viewed on a digital screen at the participants' homes and in different simulated image lighting conditions (clear, hazy, and at night).

The internet survey also conducted a brief review of existing studies that assessed trip cancellation rates to beaches near offshore wind projects through visual simulations. The literature on the rate of such beach avoidance ranges from approximately 1% to approximately 70% depending on project distance, question formulation, sample population characteristics, method of data analysis, etc. Highest cancellation rates were associated with offshore wind projects closest to shore and cancellation rates decrease monotonically as project distance increases. A more quantitative assessment of these studies is provided in the discussion.

The in-person survey is designed to test the validity of the visual simulations in a different format, i.e., in-person and non-computerized. This study was partially motivated by concerns raised by Parsons et al. during discussions with BOEM that an online format could possibly impart a systematic bias on results, particularly relating to the question of cancellation rates. If cancellation rates remain stable across studies despite changes in survey wording and social environmental factors, rates reported in the internet survey would enjoy greater conviction.

In-person surveys presented here are abbreviated and conveniently sampled forms of the internet survey. In-person surveys were conducted over a span of four years, as we considered different formats of presentation, wording and populations across iterations. Post hoc, these iterations provided an opportunity to investigate the impacts of slight modifications in the in-person survey on cancellation rates. However, definitive results from this line of investigation are confounded by the multiple changes that occurred from one iteration to the next.

4.2 Methods

This study reports data from four survey events conducted between 2013 and 2017. Each survey event corresponds to a slightly improved survey instrument. All survey events captured in-person, convenient samples in the state of Delaware. The only qualifications for participation were verbal acknowledgment that the would-be participant was at least 18 years old and had visited an East Coast beach at least once in the previous two years. In total we collected 1,494 surveys questionnaires. The functional form and key questions were very similar across all four in-person surveys, but sample demographics, sampling location, and select aspects of survey wording and presentation differed.

4.2.1 Survey Overview

Each of the in-person survey instruments can be divided conceptually into four sections. Common aspects are described in the following paragraphs, while minor differences across surveys are described in the next section. We estimate that a typical respondent took 5 to 10 minutes to complete a survey.

The surveys began by asking respondents to recall their most recent recreational trip to any US East Coast beach and to indicate basic aspects of that trip including date, location, and duration. The second section asked two questions about wind power generally; an attitudinal question assessing the respondent's favorability toward wind power in the United States, and whether the respondent was aware of plans to install wind projects offshore of the US East Coast.

The third section posed the central questions of this study. The respondent viewed simulated images of offshore wind projects at various distances from shore according to instructions and was asked to imagine the simulation depicted the beach they had most recently visited. At each distance, respondents indicated how their beach experience/enjoyment would have changed along a 5-point Likert scale (ranging from *Much Better* to *Much Worse*). In addition, respondents indicated if they would have canceled their most recent trip if the simulated project was located at each distance offshore. In this context, 'cancel' indicates either of two actions: recreating at another beach or forgoing a beach trip altogether. Some surveys also included a question about a novelty trip specifically to see the project.

The questions in this third section of the study had the following wording and the following potential responses (with small changes between surveys):

- ‘For each image, how would the presence of offshore turbines impact your beach experience?’ (*Much Better, Somewhat Better, Neither, Somewhat Worse, Much Worse*)
- ‘Would the presence of offshore turbines as shown in each image have caused you to cancel your last trip or caused you to modify the trip destination?’ (*Yes, No*)
- ‘Would the presence of offshore wind turbines as depicted in these images have caused you to take a trip specifically to see these turbines?’ (*Yes, No*)

The offshore wind project distances shown to each participant were 2.5, 5, 7.5, 10, 12.5, 15, and 20 miles (and in one survey, a subset thereof). The foreground of each image is an unpopulated sandy beach on a clear day. The simulated image used an actual photo taken on Assateague Island, Maryland (US). Appropriately scaled wind turbines determined through mathematical equations were inserted into images at an attempt to simulate the true visual impact of the project at each distance. Of note, previous research has found that mathematically correct simulations of offshore wind turbines may understate the visual impact of those wind-turbines compared to their real-world implementation (Takacs and Goulden, 2019).

The order in which images are viewed can influence responses of enjoyment and cancellation, especially for the last images seen (Day et al., 2012). This ordering effect is described as anchoring[21] on the first images seen. All surveys incorporated two strategies to mitigate possible ordering effects. Respondents were instructed to view images of all project distances before responding to any image related questions. The second strategy was haphazardly dividing respondents into two approximately equally sized groups. One group responded to images ordered from closest to furthest, while the other group responded to images ordered from furthest to closest.

The simulated wind project represented in all images was composed of 60 wind turbines, arranged 10 units across and 6 units deep. The distance between each turbine was 1.2 km. Each turbine had a 100m hub height and 150m rotor diameter, equivalent in dimensions to the 6 MW turbines[22] used in the Deepwater Block Island offshore wind project near Rhode Island, US. The total generating capacity of the simulated project is therefore 360MW. Assuming an average capacity factor of 40%, this project would serve the electricity demand for 115,000 homes drawing 1.25 kW each (US EIA, nd).

The final section of each survey asks general demographic data including age, home zip code, gender, educational attainment, and income. An overview of important similarities and differences between the survey events is presented in Table 4.1.

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[21] Anchoring is a cognitive bias whereby an individual relies on an initial piece of information to a degree that seems irrational to an outside observer.

[22] Of note, these turbines are substantially smaller than next generation of offshore wind turbines that are anticipated to be important for reducing levelized costs of offshore wind from present levels.

Surveys were pre-tested before the first survey was conducted and at several additional points along the survey evolution. Pre-tests were completed by University of Delaware faculty, staff, and graduate students. In total, we conducted in excess of 50 pre-tests.

Table 4.1: Survey descriptions

Survey name	**Coast Day 2013**	**UD Campus 2015**	**Ag Day 2017**	**Coast Day 2017**
Abbreviation	CD13	UD15	AD17	CD17
Date Conducted	October 2013	Spring 2015	April 2017	October 2017
Survey Format	2-sided, single sheet of paper (8.5"w x 11"h)	4-sided, two sheets of paper (8.5"w x 11"h)	4-sided booklet (5.5"w x 8.5"h)	4-sided booklet (5.5"w x 8.5"h)
Images Dimensions	48" x 18"[a] Poster Board	22" x 7" Flip Charts	22" x 7" Flip Charts	22" x 7" Flip Charts
Self-Administered	Yes	No	No	No
Incentive to Participate in Study	None	None	Voucher for free ice cream[b]	Voucher for free ice cream[b]
Response options to 'Cancellation' question	*Yes/No*	*Yes/No*	*Yes/Probably Yes/ No/Probably No*	*Yes/No* with 3 levels of self-reported certainty[c]
Distances seen	5[d]	7[e]	7[e]	7[e]
Extended Preamble[f]	No	No	Yes	Yes
Sample Size	177	151	588	559
Population	General Population	Students	General Population	General Population
Location	Lewes, DE	Newark, DE	Newark, DE	Lewes, DE

[a] This is an approximate dimension.
[b] The voucher was redeemable for one free scoop at the University of Delaware's Creamery (UDairy). A UDairy food truck was operating within short walking distance at both events where this voucher was offered.
[c] The three levels of self-reported certainty were described as *Confident/In Between/ Not Confident*
[d] Participants saw one of the two following distance (miles) combinations, in order: (20, 12.5, 10, 5, 2.5) or (2.5, 7.5, 10, 15, 20)

4.2.2 Survey Differences

With each successive iteration of the survey, an opportunity existed to improve the instrument with respect to clarity, level of self-administration, and granularity of responses. Changes across surveys include the physical survey format, level of background detail provided, and wording of questions and possible responses.

CD13 was implemented at University of Delaware's annual open exhibition of marine studies in Lewes, DE, called Coast Day. Delaware's only commercial sized wind turbine (2MW) is located less than one-half mile away from this location. This is a popular one-day event each October attracting thousands of attendees from the region, showcasing the university's research in marine and environmental fields. In addition to university research, for-profit and not-for-profit organizations host informational booths in large outdoor tents and food trucks are parked in a nearby lot. The survey was implemented in an outdoor tent that also contained posters on renewable energy and related research. This survey was administered by researchers, with high levels of interaction between respondent and researcher throughout the survey process. Researchers actively recruited participants from communal areas outside the tent, provided verbal instructions throughout the survey, and answered participant questions that arose during the survey. Unlike all subsequent surveys, researchers presented the simulated images on large poster boards to 1-5 respondents at a time by shuffling among the seven large images. Seating distance of the respondents was calibrated to ensure accurate scaling of turbines in each image.

UD15 was implemented over the spring and summer of 2015 on the University of Delaware campus in Newark, DE as part of a senior thesis project for an undergraduate student in economics from the University of Delaware. Participants were recruited through convenience sampling at popular communal areas on campus. Due to the location of intercepts and the age of participants, it was inferred that most participants were primarily students at the university, although a question on educational status was not included. This survey and all subsequent surveys charged respondents with viewing all images in image booklets viewed individually and at the respondent's own pace. As a result, these surveys were primarily self-administered. Booklets were spiral bound collections of seven simulated offshore wind projects, with one borderless simulated image per sheet. Each sheet was made of durable stock that survived survey events without observable degradation.

AD17 was implemented at University of Delaware's annual open exhibition of agricultural studies in Newark, DE called Ag Day. Thousands of attendees participate in the event each year, which showcases agriculture research and provides attendees with several opportunities to participate in research in exchange for cash and non-cash rewards. Participants were incentivized to participate in this survey with vouchers for free scoop of ice-cream from UDairy, the University of Delaware's on campus creamery. Researchers and poster board advertisements were stationed at communal areas to recruit participants and provided directions to the survey location. The research team was composed of one faculty member and approximately ten graduate students. The survey took place in a classroom near the geographic center of the day's activities. Participants were seated by researchers at one of four tables with seating for eight participants each. To each participant, a set of brief instructions was provided verbally by a researcher along with a self-guided survey booklet and an image booklet. The AD17 survey also added an expanded project preamble before eliciting responses to the project visuals. This expanded preamble informed participants that, in a real-world implementation of a wind power project, the turbine blades would often be spinning, red lights would periodically blink atop the towers at night, and no noise from the turbines would be audible from shore. These factors may be particularly important from an aesthetic perspective (Hevia-Koch and Ladenberg, 2016; Jensen et al., 2014). AD17 also changed the possible response options to the cancellation from two (*Yes/No*) to four (*Yes/Probably Yes/Probably No/No*) to allow for uncertain responses.

CD17 was hosted at the same venue as CD13. Again, the survey was conducted in a large outdoor tent that included other research regarding renewable energy. Poster advertisements and researchers were placed outside the tent to recruit participants. Likewise, a voucher for ice cream was provided for successful survey completion. CD17 used a survey instrument similar to the AD17 instrument. Similar to AD17, participants sat individually along several long tables, and they were provided brief verbal instructions along with a self-guided survey booklet and an image booklet. The only noteworthy change relative to the AD17 survey instrument was that the question on trip cancellation took the form of a two-choice response (*Yes/No*) with a follow-up question on the respondent's level of certainty of their choice at each distance. The certainty question had three possible responses (*Confident/In Between/Not Confident*).

4.2.3 Data Cleaning

All data related to enjoyment and trip cancellation were checked for indications of possible logical inconsistencies (PLIs). PLIs could imply lack of comprehension or that an individual was insufficiently motivated to respond thoughtfully.

A small minority of respondents indicated beach enjoyment impacts that were not monotonic with distance. For example, enjoyment increased and decreased in complex patterns along the distance axis for certain individuals. However, we see no compelling reason why this type of pattern, or any other pattern of enjoyment by distance, is incompatible with a true preference pattern. Therefore, no data were removed by investigating enjoyment data alone.

A different type of unusual response was identified through the comparison of beach enjoyment and trip cancellation for a given individual at a given distance. In particular, we flagged observations for which an individual indicated a trip cancellation without also indicating a worsened beach experience at the same distance. Of the total 2108 indicated cancellations, 130 (6%) were paired with a change to beach enjoyment of much better or somewhat better, while another 251 (12%) cancellations were paired with a change to beach enjoyment of neither.

We propose two possible explanations for the existence of these PLIs that do not rely on insufficient respondent motivation. First, it is possible that some individuals interpreted the enjoyment and cancellation questions with different assumptions about agency. An individual may have answered the enjoyment question from their personal perspective. For example, ‘how will this influence *my* beach enjoyment?’. Alternatively, we recognize that beach trips are often multi-person outings with de-centralized or external (from the respondent) decision making. Therefore, some respondents may have answered the cancellation question from a group perspective. For example, 'Would *my group/family* decide to change *our* beach plans?' There was some evidence of this in the pretests.

A second possible explanation results from a misunderstanding of the beach enjoyment question. Instead of indicating how the presence of an offshore wind project would impact enjoyment relative to exiting conditions (i.e., no wind power project), some respondents may have compared the images at different distances against each other or entered into a bargaining exercise. As an example of the latter, an individual harboring a strong objection to wind projects at close distances, may have indicated *Better* at further distances in an implicit bargain in order to 'ensure' the project would not be located close to shore where the respondent's welfare losses would be far higher. While language was included in each survey to compare images to baseline and not to each other, some respondents may not have read, understood or followed these instructions. Again, there was some evidence of this in the pretests.

Table 4.2 displays PLIs by distance. While the absolute number of PLIs are relatively stable across distances, the proportion of cancellations that are PLIs increase monotonically with distance. This supports the second possible explanation for the existence of PLIs. Respondents may indicate projects are Better at furthest distances, believing this metric was relative to closer distances. If this thought pattern occurs for an individual that would cancel at far distances, we could expect to see an increasing proportion of cancellations at greater distances as exhibited in Table 4.2.

Table 4.2: Possible logical inconsistencies (PLIs) by distance

Distance	Total cancellations	PLI cancellations	Proportion of cancellations that are PLI
2.5	694	51	7%
5	547	62	11%
7.5	363	60	17%
10	228	66	29%
12.5	132	54	41%
15	85	45	53%
20	59	43	73%
Total	2108	381	N/A

In the main analysis going forward, we do not omit observations flagged as PLIs because it appears there are rational explanations for their occurrences. Further, if the motivations behind these answers are indeed logically inconsistent, we believe they are more indicative of unreliable responses to the enjoyment question rather than to the cancellation question, due to the former's higher susceptibility to misinterpretation. However, results do display the impact of omitting PLIs where noted for comparison.

4.3 Results

4.3.1 Demographic data

A total of 1,494 surveys were collected. Completed questionnaires with greater than 50% non-response in either trip enjoyment or trip cancellation questions were removed. Additionally, questionnaires completed by individuals providing a year of birth corresponding to an age less than 18 were removed. After this cleaning process, 1,475 in-person surveys were accepted for final data analysis.

Demographic data for the in-person surveys are shown in Table 4.3 alongside a comparison to the internet survey. Participants at CD13 and CD17 were older, more likely to hold bachelor's degrees or higher, and more likely to indicate Delaware as a primary address relative to respondents in UD15 and AD17.

In-person respondents indicated high favorability towards wind power development and high awareness of plans to develop offshore wind power projects in the Mid-Atlantic region. These characteristics were particularly high at CD13 and CD17, two events which included many sustainability themed exhibits. In-person respondents tended to favor wind development generally, with rates at or near 90% for all surveys but UD Campus.

Total support (*support* and *somewhat support*) for wind power among in-person participants (85%) was significantly higher ($p < 0.01$) than in the representative internet survey (66%), as was awareness to develop offshore wind power projects ($p < 0.01$).

Table 4.3: Descriptive statistics of respondents for in-person and internet surveys.

	CD13 (*n* = 177)	**UD15 (*n* = 151)**	**AD 2017 (*n* = 588)**	**CD17 (*n* = 559)**	**All In-person Surveys (*n* = 1475)**	**Internet Survey (*n* = 1725)**
Mean age	49	22	33	51	**40**	**-**
Delaware Resident	68%	26%	57%	77%	**63%**	**1%**
Bachelor's degree or higher	64%	43%[a]	50%	65%	**58%**	**40%**
Aware of plans for offshore wind in Mid-Atlantic	95%	42%	61%	88%	**73%**	**46%**
"Support" wind power	70%	31%	65%	71%	**64%**	**42%**

"Somewhat Support" wind power	18%	25%	23%	19%	**21%**	**24%**

[a] This question was not asked in the UD Campus 2015 survey. However, intercepts were made on a college campus during the academic school year. Therefore, we assumed that respondents aged 22 years and greater held a bachelor's degree and those over 25 years held a graduate degree.

4.3.2 Impacts to beach experience

Negative impacts to beach enjoyment were highest at the closest distances and lowest at the furthest distances. Positive impacts to beach enjoyment displayed the opposite trend (Figure 4.1). Here, 'Better' captures the sum of *Much Better* and *Somewhat Better*[23]. Likewise, 'Worse' captures the sum of *Much Worse* and *Somewhat Worse*.

At distances beyond 10 miles, more than half of respondents chose *Neither*, indicating that most respondents' beach enjoyment is largely unaffected by the presence of offshore wind power projects at these distances.

[23] In two surveys (CD13 and UD15), the gradations for 'Better' response options were *Much Better*/*Somewhat Better*, while in other surveys (AD17 and CD17) the gradations were *Better*/*Somewhat Better*. The is also true for 'Worse' response options.

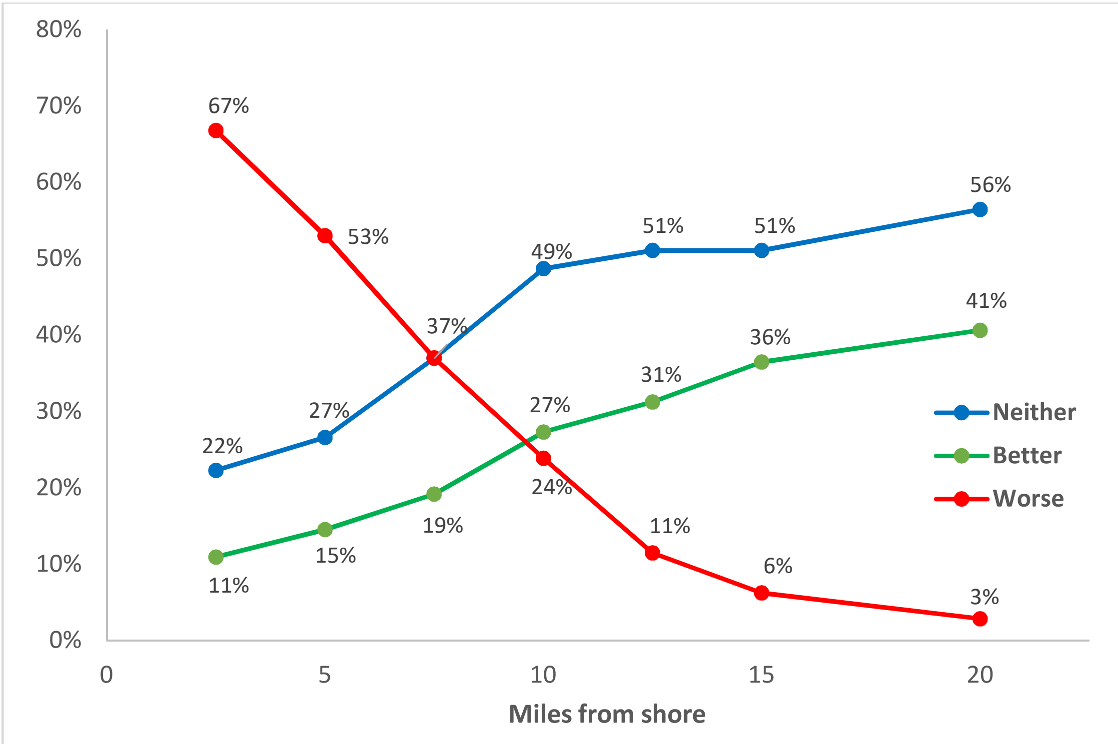

Figure 4.1: Impacts to beach experience averaged across in-person responses

By subtracting the proportions of ‘Better’ from ‘Worse’ at each distance, we derive an estimate of ‘Net Worse’ that is composed of possible values ranging from negative 100% to positive 100%. However, for the purpose of statistical testing, we remapped ‘Net Worse’ to a scale of 0 to 100, hereafter called an Enjoyment Index. We performed the same remapping for internet data. Along this re-mapped scale responses of ‘Worse’ in the absence of offsetting ‘Better’ responses would score 0%, equal responses of ‘Worse’ and ‘Better’ (and also the baseline beach without an offshore wind project) would score 50%, and responses of ‘Better’ without any offsetting ‘Worse’ responses would score 100%.

This metric must be caveated in that we make no assumption that the magnitude of Better and Worse are symmetrical nor that they necessarily offset from an economic perspective.

Enjoyment Index scores are generally higher for in-person data compared to internet data, as displayed in Figure 4.2. This is particularly true at distances of 10 miles and beyond. Results of a proportion Z-test are provided in Table 4.4. At 2.5 miles, internet data yield a significantly higher index score, while the opposite is true at 7.5 miles and beyond.

Enjoyment Index scores for each of the four in-person surveys are shown in Figure 4.3. Overall, there is modest variation across the different surveys. At distances beyond 10 miles, there is no statistical difference between the highest and lowest values at each distance.

The Enjoyment Index rises monotonically for all distances in all surveys, except for the 15-mile distance in the CD13 event. The UD15 survey exhibits the greatest sensitivity to distance as indicated by having the steepest average slope. UD15 has the highest Enjoyment Index score for the closest distances and the lowest Enjoyment Index score for the furthest turbines of any in-person survey. Data also show a bowtie effect where the lines converge near distances of 10 and 12.5 miles and have overall less convergence at closer and further distances.

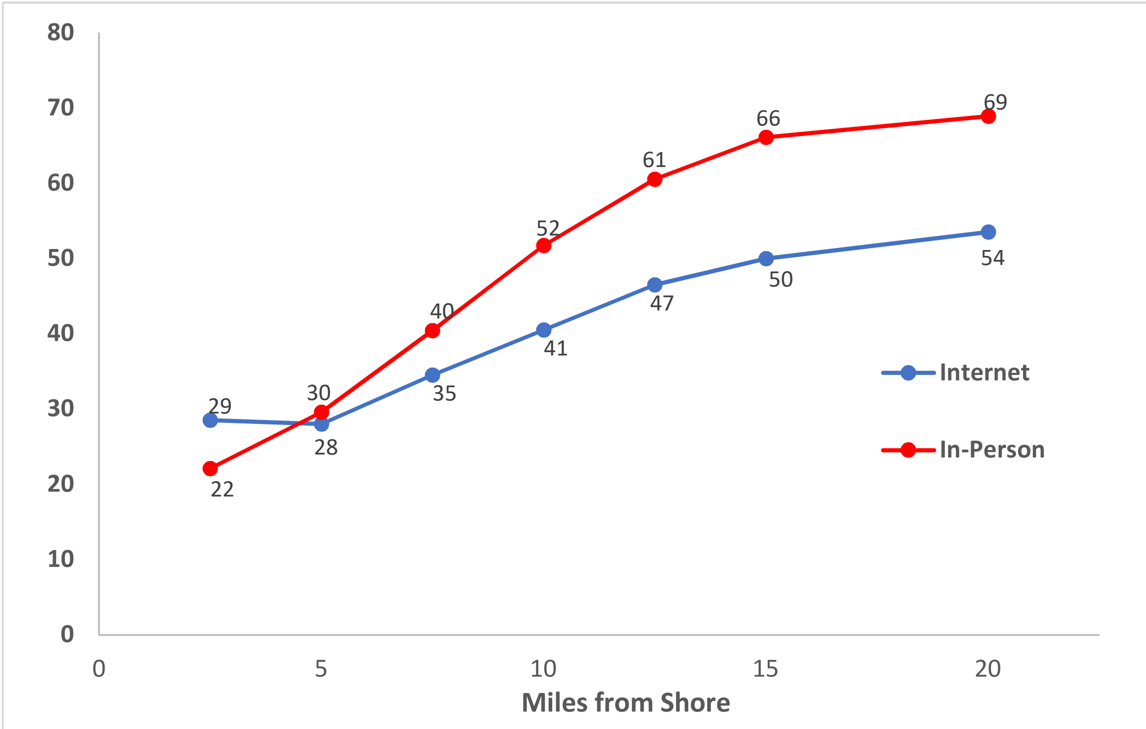

Figure 4.2: Enjoyment Index scores for the internet and in-person surveys

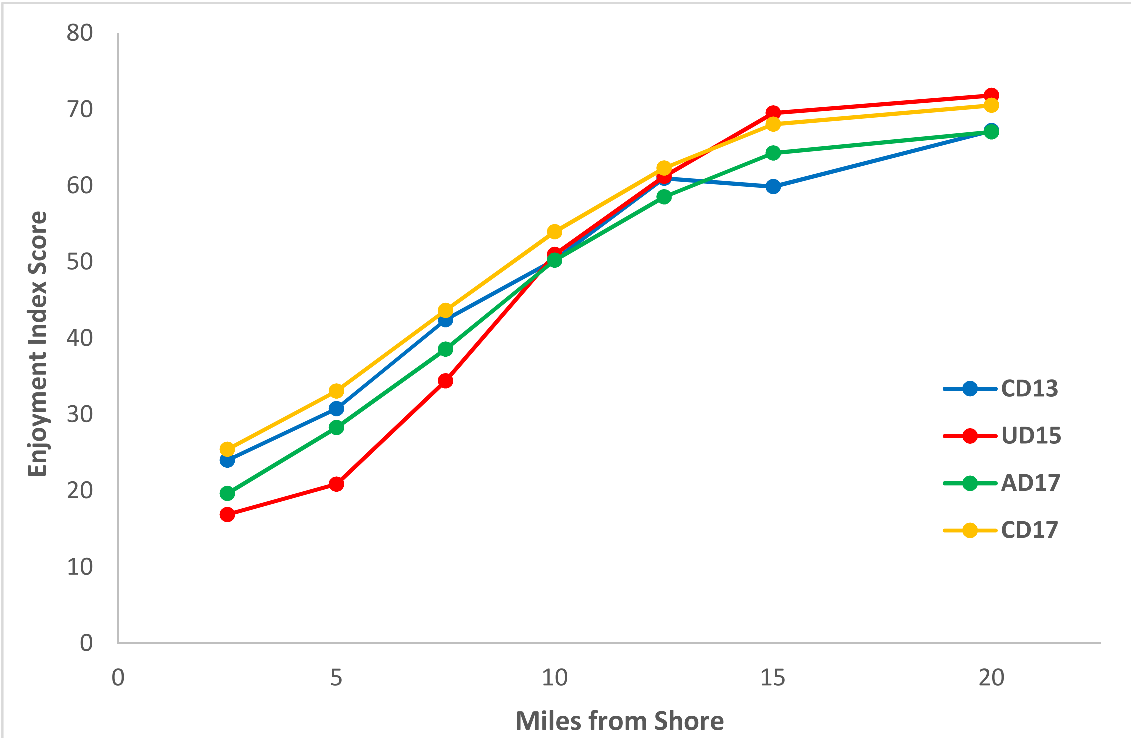

Figure 4.3: Enjoyment Index scores across the four in-person surveys

Table 4.4: Differences in Enjoyment Index across surveys (Proportion Z-test)

Survey Comparison	**Distance (Miles)**						
	2.5	5	7.5	10	12.5	15	20
Internet vs in-person	**		**	***	***	***	***
Highest in-person vs. lowest in-person	**	***	**				

** Significant at p<0.10; ** Significant at p<0.05; *** Significant at p<0.01.*

4.3.3 Trip cancellation

Recall that we define trip cancellation as a trip to a specific beach that no longer occurs due to the project. This may include either a trip to a different beach or no beach trip at all. First, we explore average cancellation rates from all in-person survey participants without confidence adjustments. In other words, we treat all in-person responses with equal weight, all responses of *Cancel* as fully certain and all responses to *Not Cancel* as fully certain. We term this approach Respondent Average.

Analyzed in this manner, cancellation rates were highest at 2.5 miles (47% cancellation) and decrease monotonically with greater distance from shore until 20 miles (4% cancellation) (Figure 4.4). A comparison to internet survey results is also provided. Note that internet results are reported in Parsons et al. (2019) only as cancellation adjusted. Survey cancellation rates are significantly lower ($p < 0.05$) than in-person cancellation rates at the distances of 2.5, 5, and 7.5 miles but are not statistically significant at the more policy relevant distances of 10 miles and beyond (Table 4.5).

Another way to analyze cancellation is by adopting the certainty adjustment technique embedded in the cancellation data of the internet survey. CD13 and UD15 offered only *Yes/No* as possible responses for the cancellation question, and therefore they are unable to be adjusted for certainty. AD17 and CD17 (together representing approximately 80% of all observations) elicited a confidence factor for cancellation questions at each distance, however. To adjust for certainty, we followed the approach[24] used by Parsons et al. (2019) whereby responses to the cancellation question that are self-reported as less than certain are treated probabilistically. Cancellation data from CD13 and UD15 are unchanged. AD17 had four possible responses (*Yes/Probably*

[24] The internet survey offered respondents higher numbers of intervals to assess certainty. Whereas AD17 and CD17 only offered 4 and 6 total ‘bins’ for certainty of response, respectively, the internet survey offered 20 bins.

Yes/Probably No/No), these were assigned cancellation probabilities of 100%/67%/33%/0%, respectively. CD17 had two possible cancellation responses and three possible certainty responses, for a total of six possible certainty combinations at each distance. These combinations (*Yes-Certain/Yes-In Between/Yes-Uncertain/No-Uncertain/No-In Between/No-Certain*) were assigned cancellation probabilities of 100%/80%/60%/40%/20%/0%, respectively. We term this analysis approach Certainty Adjusted.

When cancellation rates are analyzed in this manner, rates at close distances are unchanged, while those at farther distances increase moderately (Figure 4.4). Certainty Adjusted data from in-person surveys are significantly higher than internet survey data at all distances as reported in Table 4.5.

Comparing across the in-person surveys (Figure 4.5), cancellation rates from the most recent studies exceeded those in the earlier surveys at all distances. CD13 yielded the lowest cancellation rates at all distances. Statistical tests on the impact of the survey instrument were also evaluated.

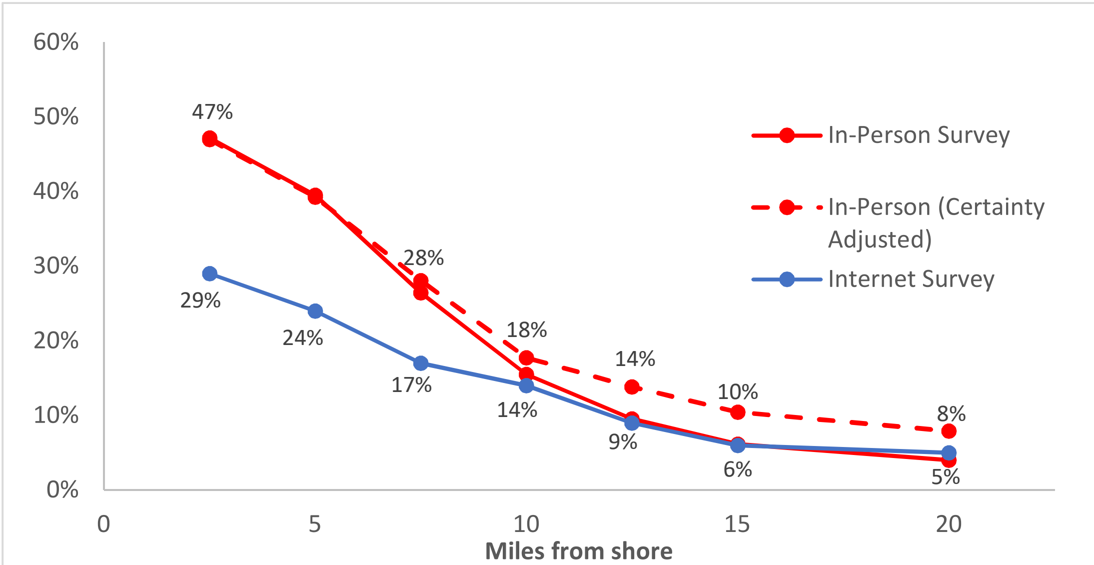

Figure 4.4: Cancellation rates for in-person and internet surveys

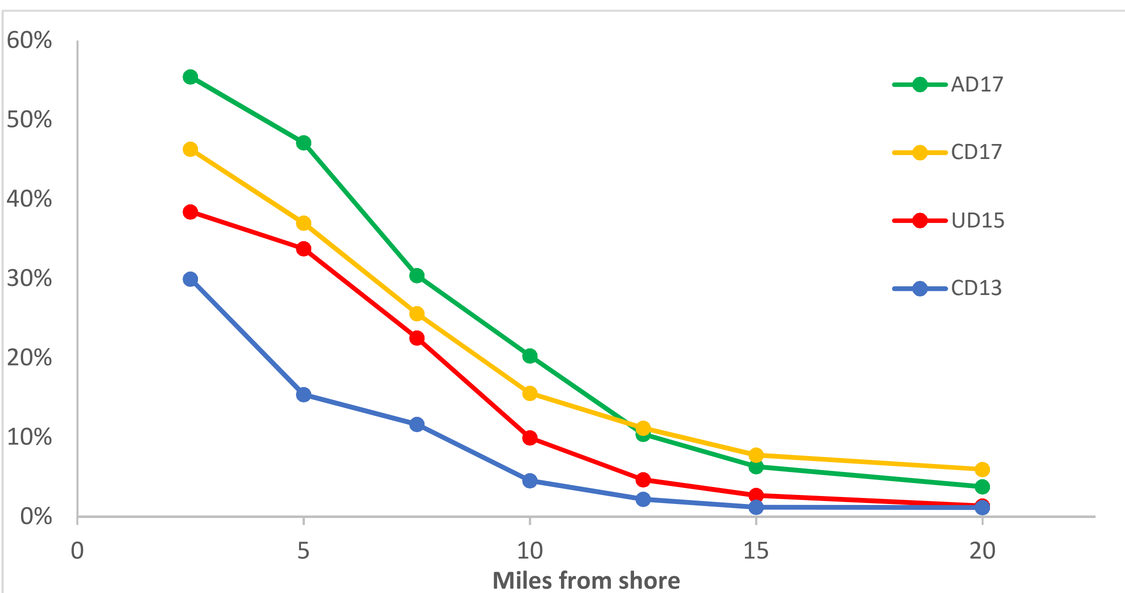

Figure 4.5: Cancellation rates (unadjusted) for all in-person surveys

Table 4.5: Differences in cancellation rates across surveys (Proportion Z-test)

	2.5	5	7.5	10	12.5	15	20
In-person (unadjusted) vs. Internet	***	***	**				
In-person (certainty adjusted) vs. Internet	***	***	***	**	***	***	***

** Significant at p<0.10; ** Significant at p<0.05; *** Significant at p<0.01.*

There are other possible methods to analyze cancellation rates. Taken together, these can serve as a robustness check on the chosen analytical approach. Three alternative approaches are described as a variation from the Respondent Average approach (Figure 4.6). Rather than treating each response with equal weight, we could treat average results from each survey with equal weight, termed Survey Average. In other words, in the absence of a compelling rationale, it may not be justified to provide more weight to data from survey events that happened to attract more participants.

A second alternative is to include results from only the two most recent surveys (AD17 and CD17). These surveys enjoyed the greatest level of survey refinement, including additional project background, improved instructional clarity and offered the ability to adjust for certainty. In addition, these survey results are also the most recent and capture any temporal trends that may be influencing results. We term this analysis Recent Surveys.

Lastly, it is possible to analyze cancellation data by removing all data flagged as PLI. Recall that responses indicating no trip cancellation are not subject to PLI detection. We term this analysis PLIs Omitted.

Relative to the initially reported Respondent Average results, alternative approaches yield somewhat higher and lower results. Omitted PLI and Survey Average tend to suppress cancellation rates, whereas Certainty Adjusted and Recent Studies tend to increase cancellation rates. The average difference between the highest and lowest approach across all distances is approximately seven percentage points. Importantly, these analytical approaches are not mutually exclusive and can be stacked in various combinations.

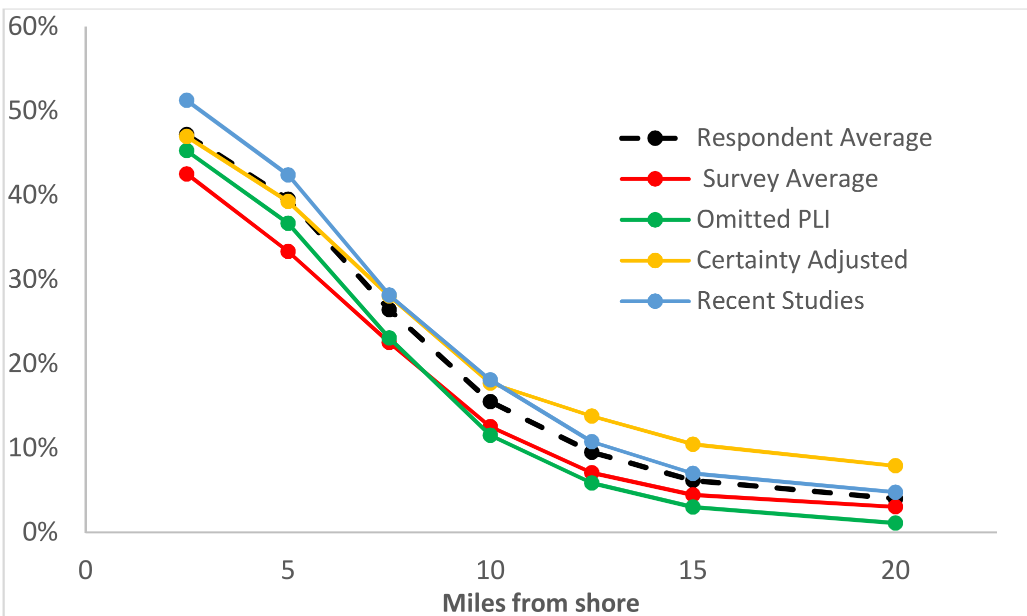

Figure 4.6: Cancellation rates for in-person surveys analyzed with different approaches

We have already discussed why we believe PLIs are not likely to be reliable indicators of irrational behavior with respect to the cancellation question. Certainty Adjusted is the approach taken by Parsons et al. (2019) for reporting the internet data, so we adopt this methodology for maximum comparability. Lastly, we have highest confidence in our recent surveys (AD17 and CD17), they comprise nearly 80% of our total observations, and they are the only surveys able to be certainty adjusted. The probabilistic cancellation data this adjustment provides also allow for a readily interpretable linear regression.

To elucidate the marginal effects of various survey and respondent factors on trip cancellation, we estimated three regression models with cancellation as the dependent variable:

- Model 1: A binary logistic regression Respondent Average (unadjusted) data
- Model 2: A linear regression of the Recent Studies, Certainty Adjusted data
- Model 3: Same as Model 2, except PLIs Omitted.[25]

The explanatory variables take three categories: distance, survey, and respondent. The distance variables are composed of dummies for each distance (20 miles omitted) and a dummy denoting whether the respondent viewed images of increasing or decreasing distance. Survey variables include a dummy for each of the surveys (CD13 omitted in Model 1; AD17 omitted in Models 2 &3). The respondent variables are age, level of educational attainment, a dummy for respondent being aware of existing plans for offshore

[25] This could have alternatively been assessed through a PLI dummy variable.

wind project off the US east coast, and a dummy for each level of support for wind power generally ('Unfavorable' omitted).

Results of the regressions are shown in Table 4.6. In general, coefficients variables in Model 1 are highly significant and have a sign as to be intuitively expected. Exceptions to this are the coefficients for the educational dummy variables, neither of which are significant, and the coefficient for somewhat_unfavorable attitude toward wind which was significant but not in the expected direction. Relative to the omitted unfavorable attitude, somewhat_unfavorable attitude significantly increases the expected probability of cancellation.

Model 1 also allows for the comparison of survey coefficients. Chi-squared tests reveal no difference on cancellation rates between UD15 and CD13 coefficients ($p > 0.10$). However, the coefficients for AD17 and CD17 are each significantly higher than either those for UD15 or CD13 ($p<0.05$). Lastly, the coefficient for AD17 is significantly higher than that for CD17 ($p<0.05$).

Model 2 also estimates coefficients that are mostly significant and of the expected sign. Again, the exception is again the somewhat_unfavorable attitude, which has an unexpected sign. However, here the coefficient is not significant ($p = 0.138$). At distances of 10 miles and closer, distance coefficients suggest that each 2.5 mile closer to shore increases the expected probability of cancellation by approximately 10%. Beyond 10 miles, the marginal effect of 2.5 miles greater distances on cancellation is far lower. Responding to images ordered in ascending distance (near_far) decreases expected cancellation by 7%.

Relative to the omitted AD17 survey, the coefficient for CD17 reduces the expected probability of cancellation by 4%. The coefficient for aware is associated with a 5% expected decrease in probability of cancellation, while each unit increase in log_age is associated with an 8% increase in probability of cancellation. For example, an increase in respondent age from 20 to 55 increases ln(age) by one, whereas an increase in respondent age from 55 to 90 increases ln(age) by one-half. Respondents with favorable attitudes are associated with 38.2% increase in expected probability of cancellation, relative to unfavorable attitudes.

Table 4.6: Results of regression models explaining cancellation rates (standard errors in parentheses)

Variable Name	**Model 1**	**Model 2**	**Model 3**
Intercept	-3.303*** (0.387)	0.392*** (0.044)	0.382*** (0.042)
Dist_2.5	3.378*** (0.149)	0.404*** (0.013)	0.417*** (0.012)
Dist_5	2.964*** (0.149)	0.316*** (0.013)	0.323*** (0.012)
Dist_7.5	2.286*** (0.151)	0.198*** (0.013)	0.202*** (0.012)
Dist_10	1.591*** (0.156)	0.108*** (0.013)	0.105*** (0.012)
Dist_12.5	0.937*** (0.166)	0.061*** (0.013)	0.059*** (0.012)
Dist_15	0.430** (0.178)	0.023* (0.013)	0.023* (0.012)
Near-Far	-0.562*** (0.059)	-0.074*** (0.007)	-0.075*** (.007)
UD15	0.081 (0.172)	-	-
AD17	1.162*** (0.140)	-	-
CD17	0.888*** (0.136)	-0.038*** (0.008)	-0.050*** (0.008)
Aware	-0.280*** (0.068)	-0.048*** (0.009)	-0.038*** (0.008)

Favorable	-1.916*** (0.186)	-0.383*** (0.031)	-0.386*** (0.030)
Somewhat_ Favorable	-0.936*** (0.189)	-0.249*** (0.031)	-0.251*** (0.030)
Neutral	-0.910*** (0.198)	-0.225*** (0.033)	-0.209*** (0.031)
Somewhat_ Unfavorable	0.674*** (0.243)	0.060 (0.040)	0.073* (0.039)
Log_age	0.664*** (0.176)	0.080*** (0.019)	0.069*** (0.018)
Bach_degree (only)	-0.082 (0.070)	-	-
Grad_degree	0.076 (0.073)	-	-
Psuedo R^2 or R^2	0.226	0.247	0.287
Prob > Chi-squared	0.000	-	-
Prob > F	-	0.000	0.000

4.3.4 Special Trip

Surveys AD17 and CD17 asked participants if they would make a special trip specifically to see a hypothetical wind project 12.5 miles offshore of Fenwick Island, DE. Approximately two-thirds of respondents chose one of the options for Yes (Table 4.7). Approximately 12% of respondents in AD17 would take a trip from their primary residence. This proportion rises to 41% in the CD17 survey. This is intuitive because the CD17 venue is located just approximately 30 minutes from Fenwick Island, DE, while the AD17 venue is located approximately 2 hours away. Alternatively, respondents in AD17 were more likely to take a trip while already in the area.

Table 4.7: Special trips to see an offshore wind power project

	Yes, from primary residence	Yes, while in the area	No
AD17	12%	50%	39%
CD17	41%	27%	32%

It is possible to compare trip cancellation rates and special trip rates at 12.5 miles. Approximately 64% of respondents across AD17 and CD 17 indicated they would engage in a special trip to see an offshore wind project compared to 10% that indicated a trip cancellation at this distance. For a beach with low background visitation, special trips may greatly outnumber canceled trips to the beach, especially in the short term when the project is relatively novel. However, canceled trips and novelty trips may not be symmetrical from an economic impact or economic welfare perspective.

4.4 Discussion

4.4.1 Impacts to enjoyment and cancellation

The enjoyment and cancellation results obtained are unexpected for several reasons. First, depending on the analytical approach, there are significant differences for both beach enjoyment and cancellation rates between the in-person and internet surveys. Further, the directions of these differences appear contradictory. In-person surveys elicit lower reductions to beach enjoyment (and even net increase to Enjoyment Index beyond 7.5 miles) but higher cancellation rates. There are no clear explanations for this dichotomy but could be related to different willingness to substitute to alternative beaches between the primarily Delaware respondents in the in-person survey and the respondents in the internet survey drawn from the eastern US.

In addition, we observe significant differences in cancellation rates between the earlier and later in-person surveys. This is also surprising because all in-person surveys were very similar to each other.

We propose three potential explanations that may simultaneously explain higher cancellation rates in the recent in-person surveys on one hand, and the internet survey and earlier in-person surveys on the other. First, attitudes toward the necessity of wind projects in the viewshed may have shifted between 2013 and 2017 alongside dramatic decreases in the percentage of oil imports and energy prices that prevailed over this period (EIA, 2018a; EIA, 2018b). This is supported by internet data that showed 23% of respondents listed energy independence as the primary reason for their increases in beach enjoyment (Parsons et al., 2019). In periods of high prices and energy insecurity, some may view offshore wind projects as akin to a 'necessary blight'. As prices and concerns of energy security ease, as they did in the latter half of the decade, the motivation for this compromise may shift accordingly.

Second, the recent in-person surveys include additional project information that are not present in the internet surveys nor the earlier in-person surveys. That opinions toward offshore wind projects can be shaped to a large degree by contextual project information is discussed in Bush and Hoagland (2016). Most importantly, a note was added in AD17 and CD17 that the wind turbines would often be spinning while the project was in operation. This reality may not have otherwise been obvious to many respondents. The imagined spinning blades superimposed on the photo simulation may have increased apparent visual disamenity, leading to higher cancellation rates. In a review of wind turbine visualizations, Hevia-Koch and Ladenberg (2016) discuss this concept:

> *"[o]ne of the main characteristics of wind turbines is the movement of their blades. It has been shown that human vision responds more to moving objects (Franconeri and Simons, 2003), and therefore when looking at a wind farm this movement might make the wind turbines much more noticeable than if they were fully static. For this reason, visualizations that only include still images are unable to fully capture the visual impact arising from the movement of the wind turbines' blades."*

While the images here did not capture such movement, the explicit reminder in AD17 and CD17 may have had a similar impact. On the other hand, Lilley et al. (2010) hypothesize that disamenity rates are higher for turbines when blades are static rather than when spinning.

Lastly, the cancellation response options for AD17 were unique in that they attempted to embed a certainty measure into the *Yes/No* response options, rather than as a follow-up to the *Yes/No* question. The follow-up certainty measure is the more commonly accepted method. It is possible that providing people a soft *Yes* to cancel directly in the primary *Yes/No* question may attract many respondents who would otherwise choose *No* in the context of a hard *Yes/No* choice.

We also note two important factors that would be expected to decrease cancellation rates in the in-person surveys. The demographics of in-person surveys show high levels of support for wind power generally relative to the population at large, a factor that has been shown to be associated with reduced cancellation rates. When coefficients from models reported here are enumerated with representative samples, cancellation rates would rise materially increase.

Secondly, the survey instruments did not include a mechanism to minimize cognitive dissonance (for example, Morrison and Brown, 2009). This approach typically consists of an additional response option to a behavior-based question that allows people to show support for the pro-social cause while opting out of the pro-social behavior. In this case, many may deem the pro-social behavior as not canceling a beach trip to affirm their support of 'green' energy. Cognitive dissonance may be particularly acute for the in-person sample because 85% of in-person respondents indicated support for US wind development as one of the first questions to the survey. Omitting a dissonance minimizing mechanism also likely decreased cancellation rates.

The cancellation results reported in this study are net of all listed potential factors effects, indicating that those factors driving cancellation rates higher relative to the internet study have greater influence than the demographic factor driving cancellation rates lower. We acknowledge that other factors we have not identified may also be materially impacting results.

4.4.2 Comparison to other studies

Figure 4.7, adapted from Parsons et al. (2019), plots cancellation curves from across the literature and includes curves from both in-person and internet surveys (Figure 4.7). Lilley et al. (2010) samples out-of-state tourists on Delaware beaches. Landry et al. (2012)

samples beachgoers in North Carolina. Voltaire et al. (2017) investigates the effects on beach use in Spain. Fooks et al., (2017) investigates impacts to hotel demand in Delaware.

Except for Voltaire et al. (2017), in-person data reported here exhibit the highest cancellation rates over tested range of distances. At close distances, in-person cancellation rates are meaningfully higher than the others, again excluding Voltaire et al. (2017). However, at the further and more policy relevant distances, in-person cancellation rates are only modest higher than other studies, in absolute terms. The same rationales suggested in the previous section to explain differences in cancellation rates between the in-person surveys and internet survey can be applied to the other surveys listed below.

However, wind turbine size is not held constant across studies. In general, the prior surveys base photo simulations around individual wind turbines of roughly half the generating capacity, and concomitant reduction is physical size per turbine. On one hand a larger turbine may have a greater impact on the visual amenity, all else equal. On the other hand, larger turbines are associated with higher generating capacities, meaning fewer are needed. This latter factor may reduce the impact on visual amenity. How these two counteracting factors impact net visual amenity is not clear but is an important research question. However, it seems likely that for a given offshore project capacity, fewer larger turbines interrupt the seascape to a greater degree than more numerous smaller turbines. Future wind power projects turbines are anticipated to be composed of turbines far larger than current iterations (Wiser et al., 2016).

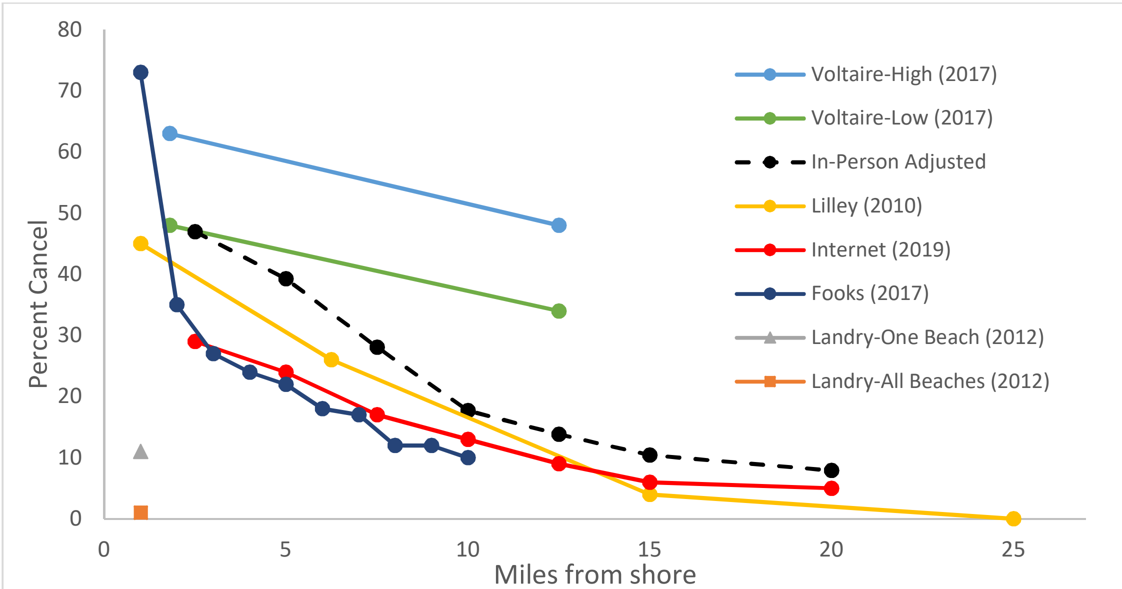

Figure 4.7: Cancellation rates compared to other studies

4.5 Conclusion

The present study reports estimated changes in beach enjoyment and trip cancellation rates for wind power projects at different distances offshore. In addition, we have reported rates of special trips for a specific hypothetical project.

The cancellation rates estimated here are generally higher than a similar internet-based study and are also generally higher than rates reported in the existing literature. The wide range of estimated cancellation rates among these suggest that survey methodology can benefit from future refinement. In addition, the divergent cancellation rates among the in-person surveys rates suggest respondents may be highly sensitive to seemingly minor changes in survey wording, presentation, or timing. It is not possible to know with the available data which factors contribute most to this difference, but future studies can include additional A/B tests within the context of larger studies to identify drivers impacting stated cancellation.

Limitations of this study revolve generally around survey methodology and sample demographics. Future efforts should enumerate data reported here with demographics from a representative population. In addition to hypothetical biases inherent to survey research, respondents might change attitudes and behaviors in unexpected ways as projects are commissioned and after recreators become accustomed to this feature along the seascape.

Decision-makers can benefit from insight into the magnitude of changes in amenity and disamenity values caused by offshore wind projects, and how these changes manifest in socioeconomic environment. It is also desirable to optimize decisions regarding project characteristics. For example, offshore wind projects are typically costlier to install and operate at greater distances from shore, while disamenity typically exhibits the opposite pattern (Parsons et al., 2019). An informed balance between these trade-offs (among others) can be achievable with robust data that captures each factor’s sensitivity to distance at each point along the coast.

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Chapter 5

CONCLUSION

A variety of electricity generating and storage technologies exist and can be incorporated into a future electricity grid in near limitless possible combinations. Identifying the combination that imposes the lowest net social costs is a worthwhile but difficult endeavor. Research like that presented here can help inform a more complete ledger of social costs and social benefits, while also highlighting interactive effects between certain combinations of technologies, reducing uncertainty about technology implementation and subsequent impacts.

In the Mid-Atlantic region, some evaporatively cooled stations are poised to continue generating for several more decades and will have to adapt to emerging conditions both in the physical operating environment and in the electricity marketplace. Offshore wind generation and V2G storage, on the other hand, seem poised for growth from very low current rates of penetration. All three technologies will likely have a place in a future electricity grid. Each technology offers a unique set of social costs and benefits that should be well understood for informed decision making.

The main findings presented above include V2G is not currently economically efficient from a social welfare perspective at present but may be in future years if a variety of improvements are realized. Some existing electricity generation on the Delaware Estuary will be impacted by future salinity increases which will modestly increase operational costs. Offshore wind power has complex impacts on recreational measures and can either enhance or deter recreational activity depending on the project distance and certain other factors.

Emerging generation technologies are primarily low carbon and exhibit intermittent generation. While these technologies can be more expensive than existing conventional generation based on market costs alone, their total social cost including external effects can sometimes yield comparable or lower costs per unit of energy generated. Future price declines in these low carbon technologies, to the extent realized, are likely to promote their increased adoption and an increased need for energy storage technologies to ensure consistent and reliable electricity supply.

Regardless of the rate of adoption of these low carbon technologies, real economic costs will be borne by society. In the case of rapid transition to a low carbon energy system, social costs will be incurred through elevated incremental cost to install and operate the new technologies (Nordhaus et al., 2018). Alternatively, continuing with business as usual will yield large social costs through the myriad impacts of climate disruption, ocean acidification and other natural process sensitive to global warming and carbon emissions (Nordhaus et al., 2018).

As illustrated in the previous chapters, the costs and benefits of electricity generation and storage technologies are often difficult to identify, let alone quantify and monetize. The robust efforts presented here, undertaken by interdisciplinary teams with diverse backgrounds have material shortcomings and uncertainties. Improving these analyses by reducing uncertainty, validating input values, and expanding the geographic scope will all be crucial in delivering higher quality findings for future decision-making efforts.

In addition to findings about the topics, this research also uncovered insights into the individual research fields themselves. In the case of V2G, it was found that existing economic literature greatly overstates the net benefits of V2G primarily through failing to acknowledge many of its unique costs. Because the costs of V2G are numerous, novel and dispersed across widely disparate fields, a comprehensive outline of V2G social costs and benefits should be created to guide future research.

Regarding the field of offshore wind impacts on recreation, data suggest survey responses are sensitive to seemingly minor aspects of survey design, timing, and/or wording in ways not previously recognized in the literature. As a result, substantive questions remain regarding the robustness of findings in survey implementations. Regarding evaporative cooling in estuarine systems, channel deepening and SLR increased costs in previously unexplored ways, highlighting the existence of indirect impacts of these two processes that remain unidentified and/or unquantified in existing cost-benefit analyses.

As the methods and findings here show, many elements of social costs and benefits are inconspicuous or dispersed across several disciplines. The research methods employed here were necessarily varied and multi-disciplinary. Principles from survey research, engineering, hydrodynamics, and welfare economics among others were all necessary in pursuit of the research questions. In society's quest to identify low cost electricity generation scenarios, society should be open to diverse research approaches and a full accounting of all material impacts.

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Appendix A

HUMAN SUBJECTS

Chapter 4 involved the use of human subjects through intercept surveys. My role consisted of data analysis only. Dr. George Parsons sought and received IRB approval for this study and the required survey intercepts.

Appendix B

PERMISSION RIGHTS

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