Computational Models for Renewable Energy Target Achievement & Policy Analysis

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Abstract

To date, over 84% of countries worldwide have renewable energy targets (RET), requiring that a certain amount of electricity be produced from renewable sources by a target date. Despite the worldwide prevalence of these policies, little research has been conducted on *ex-ante* RET policy analysis. In an effort to move toward evidence-based policymaking, this thesis develops computational models to assess the tradeoffs associated with alternatives for both RET achievement and RET policy formulation, including the option of creating renewable energy credit (REC) markets to facilitate meeting an RET goal. A mixed integer linear program (MILP), a probabilistic cost prediction model and a mixed complementarity problem (MCP) serve as the theoretical bases for the RET alternative and policy formulation analyses. From these models it was found, *inter alia*, that RET goals set too low run the risk of creating technological lock-in and could inhibit achievement of higher goals; probabilistic cost predictions give decision-makers essential risk information, when cost estimation is an integral part of alternatives assessment; and though REC markets may facilitate RET achievement, including REC markets in an RET policy formulation may not result in the lowest possible greenhouse gas emissions (GHG).

Resumo

Atualmente mais de 84% dos países do mundo têm metas definidas para quotas de produção de energia de fontes renováveis (renewable energy target ou RET). Apesar da prevalência global destas políticas, pouca investigação tem sido conduzida na área da análise ex ante de políticas de RET. Com o objetivo de contribuir para uma formulação fundamentada destas políticas, esta tese propõe modelos computacionais para avaliar os compromissos associados a diferentes alternativas de cumprimento de metas e de formulação de políticas de RET, incluindo a opção de criar mercados de créditos de energias renováveis (renewable energy credit ou glsrec) para facilitar o cumprimento de metas de RET. Um modelo de programação linear inteira mista (mixed integer linear program ou MILP), um modelo probabilístico de previsão de custos, e um problema de complementaridade misto (mixed complementarity problem ou MCP), constituem as bases teóricas para as análises de alternativas de cumprimento de metas e de formulação de políticas de RET. Com recurso a esses modelos, mostra-se, inter alia, que metas de RET demasiado baixas podem criar dependências tecnológicas (technological lock-in) e podem também impedir o cumprimento de metas mais ambiciosas; que previsões probabilísticas de custos disponibilizam aos decisores informação de risco essencial, quando a estimação de custos é parte integrante da avaliação de alternativas; e que embora os mercados de REC facilitem o cumprimento de metas de RET, a sua inclusão numa política de RET poderá não conduzir ao nível mais baixo de emissões de gases com efeito de estufa (greenhouse gas emissions ou GHG).

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Contents

List of Figures

List of Tables

List of Acronyms

AC Alternating Current. 36, 37

AE Absolute Error. 38, 42

AF Activity Factor. 25

APE Absolute Percent Error. 38

CAN Canadian Dollar. 45, 46

CCGT Combined Cycle Gas Turbine. 55

CDF Cumulative Distribution Function. 43

CRPS Continuous Ranked Probability Score. 43

Cu Copper. 36

CVaR Conditional Value-at-Risk. 2, 48, 49

DC Direct Current. 36

EENS Expected Energy Not Served. xviii, 45, 46

EF Emissions Factor. 25

ERSE Entidade Reguladora dos Serviços Energéticos. xvii, xviii, 7, 15, 16, 62

ETS Emissions Trading Scheme. 7, 26, 55

EU European Union. 5–7, 26, 30, 34, 55

GAM Generalized Additive Model. 38

GEP Generation Expansion Planning. 7, 9, 13, 17, 19, 58

GHG Greenhouse Gas. xviii, 2, 3, 55, 63, 65–67, 72

GLM Generalized Linear Model. 38

GW Gigawatts. 34

IEA International Energy Agency. xvii, xviii, 16, 62

IPCC Intergovernmental Panel on Climate Change. 5–7

IRENA International Renewable Energy Agency. xvii, xviii, 16, 62

KKT Karush-Kuhn-Tucker. 57

km kilometers. 33, 34, 39, 46

kV kilovolts. 36

kW kilowatt. 10, 14–16

kWh kilowatt-hour. 10, 15, 16, 18, 21, 24, 25

LOOCV Leave-One-Out-Cross-Validation. 38, 42

LR Learning Rate. 40

m meters. 37

MAC Marginal Abatement Cost curve. 7

MAE Mean Absolute Error. 42, 43

MAPE Mean Absolute Percent Error. 42, 43

MARS Multivariate Adaptive Regression Splines. x, 38, 40–43, 45, 46, 48, 49

MCP Mixed Complementarity Problem. iii, 57

MILP Mixed Integer Linear Program. iii

MW Megawatt. xviii, 34, 36, 64, 65

MWh Megawatt-hour. xviii, 46

NREL U.S. Department of Energy's National Renewable Energy Laboratory. 7, 25

PTDF Power Transfer Distribution Factor matrix. 59

REC Renewable Energy Credit. xi, 1–3, 53, 54, 56–62, 64–66, 68, 72

ReEDS Renewable Energy Deployment System. 7

RET Renewable Energy Target. iii, ix, xi, xviii, 1–3, 5–10, 12–14, 16–27, 30, 53–56, 58–68, 70–72

RPS Renewable Portfolio Standard. 1, 53

TSO Transmission System Operator. xi, 59–61

U.S. United States of America. 5–7, 25, 53, 54

UCE Unit Cost Estimation. 34, 35

USD United States Dollar. 24, 37, 45, 46

VaR Value-at-Risk. 2, 48, 49

Chapter 1

Introduction

This thesis develops computational models to aid decision making in renewable energy policy formation. The models developed in this work specifically focus on informing a policy aimed toward initiating the transition to a low-carbon electricity grid, known as a Renewable Energy Target (RET), or Renewable Portfolio Standard (RPS). An RET mandates that a certain percentage of electricity be produced from renewable generation sources. Generally, the models in this thesis address the three main alternatives to RET achievement: 1) direct investment in renewable energy power generation, 2) investment in grid interconnection to areas with greater renewable energy supply, and 3) Renewable Energy Credit (REC) markets, aimed to facilitate RET achievement when an electricity firm/region cannot directly invest in its own renewable energy.

It is recognized that the policy, legislation and formulation process is fundamentally political, with special interest groups often able to influence policy language. This thesis represents an attempt to ground the political discussion in technical facts, using structured, methodological paradigms. The models developed aim to gain insights on the effects of different RET policy formulations on society. Our analysis seeks to identify who is rendered better-off under a certain policy, and who, if anyone, is left worse-off.

1.1 Research questions

We put forth three research questions to address the issue of RET policy analysis:

1. ***Geographic Attribution of an RET.*** What are the economic, social and environmental tradeoffs associated with different geographic attributions of an RET? Does direct investment in renewable energy shift significantly from one location to another? Are carbon emissions more efficiently reduced in a certain geographic attribution? Does the cost of a policy fall onto one region more than another? (Chapter 2)

2. ***Probabilistic Cost Prediction of Submarine Power Cable Projects.*** It is hypothesized that offshore wind power could significantly aide countries in achieving renewable energy targets. Given the global projected growth in the submarine power cable industry, what statistical learning model best predicts the probability distribution of the cost of a subsea power cable project? (Chapter 3)

3. ***RET Achievement through REC Trading or Renewable Energy Investment.*** Under what renewable energy target policy formulation does an REC market facilitate RET achievement? Does the timing of target compliance significantly affect social welfare? (Chapter 4)

1.2 Thesis overview

In Chapter 2, the geographic attribution of an RET is analyzed. The economic, environmental and social impacts are assessed to generate insights on the associated tradeoffs. The Azores Islands off the coast of Portugal are used as a case study for the model. We find that a regional geographic attribution of the RET achieves the lowest cost, and yields the greatest reduction in greenhouse gas (GHG) emissions, though renewable energy investment is less distributed across islands.

In Chapter 3, we develop a probabilistic cost prediction model for submarine power cables to aid decision-makers in government, academia and industry to more accurately assess alternatives for RET achievement. The model we developed is globally applicable, from offshore wind power to grid interconnection applications. The best performing statistical learning model has slightly more predictive power than a simpler, linear econometric model. The specific decision context will determine whether the additional precision of the statistical learning model is worth the extra data-gathering effort. A case study illustrates that incorporating the uncertainty associated with the cost prediction to calculate risk metrics - value-at-risk (VaR) and conditional-value-at-risk (CVaR) - provides useful information to the decision-maker about cost variability and extremes.

In Chapter 4, we adapt a complementarity model of the electricity market and power system, and include an REC market. Eight different RET policy scenarios are defined, and analyzed based on greatest renewable energy investment, lowest GHG emissions reductions and largest increase in social surplus. It was found that, in a market where players have the option to invest in renewable energy expansion and unlimited transmission capacity, an RET policy design of multi-stage targets at the firm-level, without an REC market, is optimal. This design not only achieves the highest social surplus, but also the highest renewable investment and the greatest reduction in greenhouse gas emissions.

Our three investigations provide considerable insights into RET policy analysis. Not only do we analyze RET policy formulation *ex ante*, but we also conduct robust assessments of alternative methods of achieving these targets. In the process, we both enhance existing models (*Research Question 1* and *Research Question 3*) and develop new ones (*Research Question 2*).

Chapter 2

Geographic Attribution of an Electricity System Renewable Energy Target: Local Economic, Social and Environmental Tradeoffs

The 2014 Intergovernmental Panel on Climate Change (IPCC) report asserts that investment in low-carbon electricity production will need to rise by several hundred billion dollars annually, before 2030, in order to stabilize greenhouse gas concentrations in the atmosphere by 2100. In recognition of this urgent need to mitigate climate change, many governments have already established policies to spur renewable energy investment in the electricity sector. One such policy measure is a *renewable energy target* (RET), which sets a target percentage of electricity production to be generated from renewable sources by a specified

This chapter is based on Schell et al., 2015 [15].

date. Variations on this policy have been implemented around the world, from the EU 20-20-20 to diverse renewable portfolio standards in U.S. states and municipalities. This work analyzes economic, environmental and social aspects of a geographic attribution (*i.e.* Isolated, Regional or Country) of an RET to gain insights on the associated tradeoffs. In the case study of the Azores Islands, Portugal, the regional geographic attribution of an RET captures the best of all three tradeoffs.

2.1 Introduction

In its most recent report (2014), the IPCC has, for the first time, specifically stated that investment in low-carbon electricity production is a "key measure" in climate change mitigation [16]. The IPCC stresses that investment in low-carbon electricity supply will need to support an increase from the current share of 30% production globally, to at least 80% by 2050. In order to achieve this goal, hundreds of billions of dollars annually, by 2030, will need to be invested in low-carbon electricity [16].

2.1.1 Renewable Energy Targets (RETs)

Climate change is an urgent problem, and political pressure to address it has already led to the development of numerous policy instruments to encourage investment in renewable energy. Many governments have issued renewable energy targets (RETs), which mandate that a certain percent of electricity production is generated from renewable sources by a specified date. The European Union (EU) famously enacted its EU 20-20-20 policy in 2007, which, among other targets, requires 20% of its total energy supply to come from renewable resources by the year 2020 [17]. In 2001, the Australian government implemented the world's first nationally mandated RET of 20% by 2020 [18].

In addition to the 27 EU member states and Australia, many major global players - including China and South Africa - have instituted RETs as policy tools to encourage investment in renewable energy. Though the United States (U.S.) does not have a federal energy policy, over half the states have implemented RET regulation, encouraging renewable energy development in the electricity sector. Two of the highest targets are in the states of Hawaii and California, with a 40% RET by 2030 [19], and a 33% RET by 2020 [20], respectively. State-level renewable targets are so common [21] that the U.S. Department of Energy has established a database to track legislative targets and developments [22].

Table 2.1: **List of abbreviations** used throughout this article.

Abbreviation	Description
ERSE	Entidade Reguladora dos Serviços Energéticos *(*Portuguese Energy Regulator)
EU	European Union
ETS	Emissions Trading Scheme
GEP	Generation Expansion Planning *model*
IPCC	Intergovernmental Panel on Climate Change
MAC	Marginal Abatement Cost *curve*
ReEDS	Renewable Energy Deployment System *model*
RET	Renewable Energy Target
U.S.	United States of America

2.1.2 RET Policy Analysis

Due to the worldwide prevalence of RET policies, work in several fields, including public policy [18][23][24], economics [25][26], and operations research [27], has been conducted to address the varying impacts of RET policies. To the best of the authors' knowledge, little analysis exists on how best to set an RET. Whether RETs are better set at the local, regional, or country level remains an unexamined question.

In practice, setting a renewable energy target is fundamentally political. Once an RET is agreed upon by the government, an analysis of the policy is usually undertaken, such as through a *Regulatory Impact Assessment* in the U.S., to ensure the policy will not recklessly effect existing market players [28]. This type of evaluation typically involves

Marginal Abatement Cost (MAC) curves, which are usually developed for a specific region and timeframe, to assess available technology options and associated costs. A recent study from the World Bank [29], however, asserts that MAC curves have a tendency to be misinterpreted, specifically when designing an RET policy. For an RET, it is usually most effective to implement the highest cost technologies first. The study also finds that RET targets set too low (below 25%) may be adversely effecting future investment in renewable energy, and hindering achievement of higher goals [29].

2.1.3 RET Technical Analysis

Despite the prevalence of RET policy and policy analysis, little has been done on the technical side to incorporate RETs into electricity system modeling for long term planning. Bird, et al. [30] have used the U.S. National Renewable Energy Laboratory's (NREL) model, ReEDS [31], to examine the least-cost generation and transmission expansion plans under a renewable energy target policy, a carbon cap-and-trade policy, and a combination of the two. The highest RET considered, however, is 25%. Wave generation capacity is not considered as a technology option in their model.

Furthermore, to the best of the author's knowledge, no studies have looked at the effects of the geographic attribution of an RET. The term *geographic attribution* defines the area (isolated, regional, or country) that must meet the target. Many RET policies are defined as a country goal, such as in China. Liu, et al. [32] take the country RET for China and develop a model to decompose the national RET to the regional level. However, they do not determine whether the RET is best set at the isolated, regional, or country level.

Hiremath, et al. [33] stress that socio-economic and environmental impacts should be evaluated by the model at the local level. Foley, et al. [34] review numerous electricity system models and emphasize the need for electricity system models that can incorporate key policy changes, including targets to increase the share of renewable energy production.

Zhou et al. [35] have developed a complex, bilevel optimization model of the generation side of the electricity system that considers incentive policies for electricity producers - such as production tax credits, an investment tax credit, or a carbon tax - and compares these policies to a mandatory RET. They conclude that incentive policies can be as efficient as an RET, though their analysis only considers a low RET range, from 10% - 25%. They concede that incentive policies may be much less effective at higher RETs. The question of the optimal geographic attribution of an RET is not addressed.

2.1.4 RET Social Benefits

Politically, renewable energy targets are designed to increase investment in renewable energy generation and thereby decrease greenhouse gas emissions. RET policies can also have added societal benefits, including air emissions reductions and the resulting health benefits [36], energy security, fuel diversity, and job creation [37]. This work examines the social and environmental benefits of an RET in terms of emissions reductions, as well as the economic cost of implementation.

2.1.5 Aim and Objectives

The aim of this research is to analyze the local economic, social and environmental impacts of the geographic attribution of a renewable energy target. The authors seek to uncover the tradeoffs associated with a local, regional and country RET policy. Through analyzing these tradeoffs, we hope to inform both policymakers and stakeholders about the potential effects that the geographic attribution of an RET can have on optimal generation investment, equitable renewable investment distribution across localities and local emissions reductions. Our ultimate objective is for the conclusions of this work to help inform RET policy formation.

2.1.6 Article Structure

In Section 2.2 we describe the modeling framework with which the geographic attribution of an RET is analyzed. Section 2.3 presents the results of this analysis, the local effects of an RET attribution and the model limitations. Section 2.4 reports the main findings of this study.

2.2 Methodological Framework

In this section, we describe the methodological approaches we employ in analyzing the effects of different geographic attributions of an RET. We also present the parameters of the case study analyzed - the Azores Islands, Portugal.

2.2.1 Generation Expansion Planning

We adapt an electricity system planning technique commonly used in the literature [30] [38] [39] [40] [41] [42], known as Generation Expansion Planning (GEP)[1]. GEP refers to electricity system power generation capacity [43]. Mixed integer optimization methods are used to find the optimal way to expand the generating capacity in an electricity system in order to meet predicted demand growth, given a set of expansion alternatives. We include the restriction that the capacity expansions must also enable sufficient renewable energy production to meet a given RET.

Decision Variables and Parameterization

The generation expansion planning model solves for three major decision variables: 1) how many capacity additions should be made to what technology, on what island, CE_{gi}; 2) the

[1]For a more in-depth discussion on the applicability of GEP to Island/Isolated electricity systems, see 2.5

total capacity (existing plus expansions) of each technology, on each island, C_{gi}; 3) and the operating level of each technology, on each island, W_{gil}.

To describe the electricity generation system on the islands, we include the existing capacity of electricity generation as of the start of 2008 [4]. Using demand growth predictions and natural resource limitations from the Green Islands Azores Project [44] [2][2], the GEP model solves for the least-cost expansions that will meet the renewable energy target in 2018. Table 4.1 completely details the model parameters, with data presented in Section 4.3.

Table 2.2: Model parameters

Symbol	Description	Units
α_g	investment cost of technology *r*	[$/kW]
δ_g	operating cost of technology *r*	[$/kWh]
D_i	annual demand on island *i*	[kWh]
L_l	approximation of load duration curve by load type *l* (base, middle, peak)	[%]
$C0_{gi}$	existing generation capacity, *g*, on island *i*	[kW]
CM_{gi}	natural resource limitation to generation capacity expansion, on island *i*	[kW]
CEI_{gi}	size of expansion for generation capacity, *g*, on island *i*	[kW]
CF_{gi}	capacity factor of generation capacity, *g*, on island *i*	[%]
Pl_i	annual peak load on island *i*	[kW]
RM	reserve margin	[%]
Ar_g	availability of generation capacity *g* for reserve capacity	0/1
RE_g	classification of generation capacity *g* as renewable	0/1
B_{gl}	availability of generation capacity *g*, by load type *l*	0/1
RET	renewable energy target	[%]
h	number of hours per year	
M	sufficiently large number	

[2]The Green Islands Azores Project Report assessed the future electricity demand on the islands based on detailed studies predicting sector-level economy expansion (i.e. agriculture, industry, residential, *etc.*) on each island. The results of the analysis conducted for renewable energy expansion potential on the islands is informed by a detailed resource analysis, including land availability for both the siting of new generation and the potential expansion of the electricity grid. Thus, infeasible siting locations are not considered in our analysis.

Objective Function

The objective of the model is to minimize *system cost*, which we define as the annualized investment cost of new capacity, plus the operating cost of both new and existing capacity. This is mathematically defined as Equation (2.1).

$$minimize \sum_g \sum_i (\alpha_g CE_{gi} CEI_{gi} + \sum_l \delta_g W_{gil}) \tag{2.1}$$

Capacity Constraints

Any expansion that occurs must take into consideration the existing capacity on the island, $C0_{gi}$, (2.2), and the natural resource limitations, CM_{gi}, on the island (2.3).

$$C_{gi} = C0_{gi} + CE_{gi} CEI_{gi} \qquad \forall g \in G, i \in I \tag{2.2}$$

$$CE_{gi} CEI_{gi} \leq CM_{gi} \qquad \forall g \in G, i \in I \tag{2.3}$$

Additionally, there must be enough generation capacity in the system that can act as reserve capacity (2.4). As is common practice, we require a reserve margin of 20% [38][45][46].

$$\sum_g Ar_g C_{gi} CF_{gi} \geq Pl_g(1 + RM) \qquad \forall i \in I \tag{2.4}$$

This reserve margin is a conservative estimate of what might be needed in a system with a high penetration of intermittent renewable energy, such as wind and solar power [47].

Operating Constraints

The following contraints ensure that the system meets operational standards, such as requiring that supply must always meet demand (2.5).

$$\sum_g B_{gl} W_{gil} = D_i L_l \qquad \forall l \in L, i \in I \tag{2.5}$$

Equation (2.6) ensures that a generation technology is assigned only to a load type to which it can reasonably respond. Illustratively, this constraint protects against solar power being assigned to meet night-time base load. In our analysis we consider that geothermal, diesel, fuel oil and biogas can meet all load types, while the other generation capacities are only available to meet middle load.

$$W_{gil} \leq B_{gl} M \qquad \forall g \in G, l \in L, i \in I \tag{2.6}$$

Further, the operating level of each technology cannot exceed its expected availability, given by its annual average capacity factor (2.7). The capacity factors used in this study were taken from the results of the Green Islands study [2]. The annual average capacity factor ranges are presented in Table 2.3.

$$\sum_l W_{gil} \leq C_{gi} CF_{gi} h \qquad \forall g \in G, i \in I \tag{2.7}$$

The final operational constraint provides that the renewable energy generation capacity in the system is sufficient to meet the renewable energy production target. Renewable generation capacity investments considered for the islands are wind, offshore wind, hydropower, geothermal, solar photovoltaic, wave and biogas. The only renewable technology considered

[3] Where islands have differing average annual capacity factors for a certain generation capacity, a range among the island values is presented. Where the capacity factor is the same among islands, that single annual average value is presented.

Table 2.3: Average annual capacity factors [2]

	Capacity factor, CF_g[3] [%]
Wind	25.0 - 32.9
Offshore Wind	27.0 - 34.9
Hydropower	40.0
Geothermal	72.1
Solar	11.6
Wave	30.0
Diesel	79.1
Fuel Oil	79.1
Biogas	79.1

that has not yet been implemented somewhere on the Azores is offshore wind [4].

$$\sum_g \sum_l RE_g W_{gil} \geq (RET) D_i \qquad \forall i \in I \tag{2.8}$$

Total capacity and operating level decision variables are subject to non-negativity constraints, as presented in (2.9) and (2.10).

$$C_{gi} \geq 0 \qquad \forall g \in G, i \in I \tag{2.9}$$

$$W_{gil} \geq 0 \qquad \forall g \in G, i \in I, l \in L \tag{2.10}$$

The number of capacity expansions permitted are restricted to integer values.

$$CE_{gi} \; in \; \textit{integer} \tag{2.11}$$

This constraint precludes investment in half a wind turbine, for example.

2.2.2 Maximum Renewable Energy Production Per Island

The generation expansion planning model presented in the previous section (2.2.1), solves for the least-cost expansion plans to meet an RET. We utilize an optimization methodology known as the *e-constraint method* [48], to also solve for the maximum renewable energy production possible on each island. To do so, we simply change the objective function of the original GEP model to maximize the production of renewable energy, z^*, on the island, as in (2.12).

$$z^* = maximize \sum_g \sum_l RE_g W_{gl} \tag{2.12}$$

This value, z^*, is used again in the original GEP model, and replaces the right hand side of Equation 2.8, as shown below in (2.13).

$$\sum_g \sum_l RE_g W_{gil} \geq z^* \qquad \forall i \in I \tag{2.13}$$

The solution of this revised problem gives the least-cost expansion plan, at the maximum renewable energy production. The results of this analysis are presented in Table 2.10, Section 2.3.1.

2.2.3 Case Study and Data

We apply our analysis to a geographically diverse case study: the Azores Islands, Portugal. An archipelago of nine islands off the western coast of the Iberian peninsula (see Figure 2.1), their dependence on fossil fuels has driven the Azorean government to establish an ambitious RET of 75% by 2018 [2]. How best to meet this target will depend on its geographic attribution.

Each island in the Azores archipelago has a unique electricity system, isolated from the

Figure 2.1: **The Azores Islands** [1]. An autonomous region of Portugal, the Azores Islands lie 1,400 km off the western coast of the Iberian peninsula. The archipelago's geographical isolation has led to a reliance on fossil fuel imports (diesel and fuel oil) for electricity production. The electric utility is expanding investment in renewable energy, to meet the government's 75% RET for 2018.[2]

Table 2.4: **Existing Generation Capacity in 2008.** Electricity generation on the islands is dominated by diesel and fuel oil, which together account for over 81% of total generation capacity [4].

	2008 Generation Capacity, $C0_{gi}$ [kW]								
	Corvo	Flores	Graciosa	Santa Maria	São Jorge	Pico	Faial	Terceira	São Miguel
Wind	-	600	800	900	1,150	1,800	1,800	4,500	-
Offshore Wind	-	-	-	-	-	-	-	-	-
Hydropower	-	1,484	-	-	-	-	320	1,432	5,030
Geothermal	-	-	-	-	-	-	-	-	27,800
Solar	-	-	-	-	-	-	-	-	-
Wave	-	-	-	-	-	-	-	-	-
Diesel	536	2,327	4,230	5,680	7,090	-	-	-	-
Fuel Oil	-	-	-	-	-	13,388	17,010	61,116	98,064
Biogas	-	-	-	-	-	-	-	-	-

others. Table 2.4 shows that all islands currently rely heavily on fossil fuels in the form of diesel and fuel oil. Some have limited renewable resource production from sources such as wind, hydropower and geothermal energy.

Existing natural resource limits preclude unlimited renewable resource exploitation on the islands. Table 2.5 shows the best data available concerning the Azores Islands [2]. A major limiting factor on the islands is the dearth of exploitable geothermal resources on seven out of the nine islands. Available hydropower expansion is almost as scarce. Fuel for biogas production, using cow manure as a feedstock, is estimated based on the number of cows on each island [49]. Agriculture and dairy production is a large part of the Azorean economy, with cows outnumbering the human population on some of the smallest

Table 2.5: **Natural resource limitations on generation capacity expansion.** Based on the Green Islands study of the natural resource reserves of renewable energy on the islands, the table shows that possibly binding limits exist for wind, hydropower, geothermal and biogas expansion [2].

	Maximum Capacity Expansion, CM_{gi} [kW]								
	Corvo	Flores	Graciosa	Santa Maria	São Jorge	Pico	Faial	Terceira	São Miguel
Wind	140	160	280	600	1,700	800	800	9,100	18,300
Offshore Wind	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
Hydropower	-	527	-	-	1,670	1,230	25	293	6,754
Geothermal	-	-	-	-	-	-	-	12,000	47,650
Solar	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
Wave	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
Diesel	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
Fuel Oil	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
Biogas	48	396	471	528	894	1,419	1,501	5,312	12,805

Table 2.6: **Capacity Expansion Integral.** Expansions in generation capacity are limited by the size of the turbine [4].

	Turbine size of generation capacity, CEI_{gi} [kW]								
	Corvo	Flores	Graciosa	Santa Maria	São Jorge	Pico	Faial	Terceira	São Miguel
Wind	300	300	200	300	164	300	300	900	300[4]
Offshore Wind	300	300	300	300	300	300	300	300	300
Hydropower	500	370	500	-	500	500	320	475	700
Geothermal	-	-	-	-	-	-	-	3,000	5,000
Solar	290	290	290	290	290	290	290	290	290
Wave	400	400	400	400	400	400	400	400	400
Diesel	135	500	700	945	1,000	2,200	2,000	6,000	12,000
Fuel Oil	135	500	700	500	1,000	2,200	2,000	6,000	12,000
Biogas	48	390	470	500	890	700	1,500	5,300	12,000

islands [50]. In technologies where there is almost unlimited potential for expansion, an unattainable expansion value of 50,000 kilowatts [kW] is given.

Capacity expansions are additionally limited by the size of the generator. As shown in Table 2.6, the typical size of a wind turbine on the Azores is 300 kW, while the size of a diesel generator ranges from 135 - 12,000 kW [4]. The difference in sizing can make different technologies attractive at different RETs. A small generator is more advantageous to meet an incremental increase in an RET, whereas larger investments will be attractive for higher RETs. The diversity of the alternatives available, however, makes this decision nontrivial.

[4] The data presented here are from the Green Islands Report [2], published in 2010. Since then, larger wind turbines (900 kW) have been used on São Miguel.

Capacity expansions will be necessary in order to meet future growth in demand on the islands. Demand projections for the Azores target year of 2018 are derived from economic growth projections completed by the Green Islands study [2]. The forecasted percentage increase in demand for each island are applied to the realized demand on the islands in 2008 [4].

Table 2.7: **Demand and peak load in 2018.** The annual demand per island, as well as annual peak load, using forecasted growth values from the Green Islands study [2].

Annual Demand and Peak Load	2018 Demand, D_i [kWh]	2018 Peak Load, Pl_i [kW]
Corvo	1,463,212	299
Flores	15,687,379	2,721
Graciosa	18,195,214	3,108
Santa Maria	27,188,099	4,641
São Jorge	37,968,238	6,330
Pico	63,031,316	10,847
Faial	69,715,622	11,719
Terceira	295,291,599	51,476
São Miguel	606,926,090	102,092

Total demand is apportioned into an approximated annual load duration curve using percentages from the energy regulatory utility of Portugal, Entidade Reguladora dos Serviços Energéticos (ERSE), in Table A.3 [5].

Table 2.8: **Annual load duration curve approximation.** The percentages in the table below divide the annual load duration curve into the amount of base, middle and peak load that must be met in 2018 [5].

Load Duration Curve Approximation L_l	[%]
Base	41.67
Middle	41.67
Peak	16.66

ERSE has also published operating costs for renewable energy production on the Azores Islands (Table 2.9). Many renewables, including wind, hydropower, geothermal, solar and wave energy, are cheaper to operate on the islands than on mainland Portugal. Data for mainland Portugal is presented in A.1.

Table 2.9: **Cost data.** The cost data for the Azores Islands is from ERSE [5], the International Renewable Energy Agency (IRENA) [6], and the International Energy Agency (IEA) [7]. Costs are annualized based on an 8% discount rate and a 20 year lifetime of generation investments.

	Annualized Costs	
	Operating Cost, δ_g [\$/kWh]	Investment Cost, α_g [\$/kW]
Wind	0.0900	261
Offshore Wind	0.0490	562
Hydropower	0.0900	615
Geothermal	0.0220	397
Solar	0.3250	569
Wave	0.0560	629
Diesel	0.0420	130
Fuel Oil	0.0430	137
Biogas	0.0800	574

2.2.4 Scenarios

The Azores Islands case study is analyzed using a set of three scenarios, based on the geographic attribution of the RET. In *Scenario 1 - Isolated*, each island is individually required to meet the RET, as a proportion of its own demand. This is represented mathematically in Equation 4.5.

Scenario 2 - Regional sets the geographic bound of the RET as the entire archipelago, allowing renewable energy production from any island to count toward meeting the target. In this case, the RET is applied to the combined demand of all islands in the archipelago. This modifies the right hand side of constraint 2.8, as in Equation 2.14 below.

$$\sum_g \sum_l \sum_i RE_g W_{gil} \geq (RET) \sum_i D_i \tag{2.14}$$

The largest geographic attribution of the RET is at the country level, *Scenario 3 - Country*, where renewable electricity production in Portugal qualifies as meeting the Azores RET. In this situation, Equation 2.8 becomes:

$$\sum_l (\sum_g \sum_i RE_g W_{gil} \ + \sum_{gport} RE_{port} W_{gportl}) \quad \geq \quad (RET)(\sum_i D_i \ + \ D_{port}) \tag{2.15}$$

The generation capacity technologies available on mainland Portugal are different from the generation technologies used on the islands (see A.1). Therefore, a new parameter, RE_{port} must be defined, to specify which of these technologies are renewable. The GEP model is also expanded with duplicates of Equations 2.2 - 2.7 and Equations 2.9 - 2.11, specified for the electricity system of mainland Portugal. Similarly, the objective function is updated to include investment and operating costs specific to the continent. Data for mainland Portugal can be found in Appendix A.1.

2.2.5 Limitations

The model proposed above does not consider electricity storage or energy efficiency as technology options available to meet an RET because reliable data are not available for these technologies for the Azores Islands.

2.3 Results

2.3.1 Scenario 1 - Isolated

Using the *e-constraint method* described in Section 2.2.2, we obtain the maximum renewable energy production achievable on each island. Table 2.10 displays these results, with the islands ordered from lowest annual electricity demand (Corvo) to highest (São Miguel). Due to varied natural resource limitations, only two islands can reach the 75% RET on their own. These two islands, São Miguel and Terceira, are endowed with sufficient geothermal resources to produce renewable electricity beyond the 75% RET. No other islands have geothermal capacity suitable for electricity generation. A combination of wind, offshore wind, biogas and wave are the preferred investments on such islands. A.2 details the optimal generation capacity investments for each island, at each RET, up to its maximum achievable RET. We note that investment decisions are discretized by RET percentage point. Thus, reaching an RET of 50% does not depend on the investment decisions made to reach an RET of 49%. The decisions are separate and, as such, the graphs in A.2, as well as in the rest of the article, do not represent an evolution of investments from zero to X% RET, rather they represent discrete investment plan solutions.

In the lower RET range, generally from zero up to 25%, wind is the preferred renewable investment across the islands. After this point, a preference for biogas appears to replace fossil fuels used in baseload capacity. Offshore wind is utilized at higher RETs, as a complement to wind and biogas. If an island has some existing renewable capacity, such as Flores, biogas is the only renewable energy generation capacity investment made. This is due to its dispatchability for any load type.

Table 2.10: **Maximum renewable energy production by island**, with associated annualized cost.

	Maximum Achievable Renewable Energy Production	Annualized Cost [$2012]	Annualized Cost [$2012/kWh]
Corvo	64%	274,291	0.1875
Flores	58%	1,487,443	0.0948
Graciosa	59%	2,464,624	0.1355
Santa Maria	54%	3,426,387	0.1260
São Jorge	57%	5,530,256	0.1457
Pico	57%	8,751,799	0.1388
Faial	56%	9,408,336	0.1350
Terceira	79%	40,969,367	0.1387
São Miguel	100%	52,054,621	0.0858
Azores archipelago	85%	124,367,124	0.1095

The least cost investments necessary to achieve the maximum renewable energy production vary by island. The size of the islands' electricity demand and the indivisibility of turbine/generator investments are the main drivers of this difference. This indivisibility is known as "lumpiness" in the operations management literature [51]. In the context of generation capacity investment, it is not possible to invest in half of a wind turbine. The investment must be made for a whole turbine, even if it means this will result in a slight overcapacity. The effect of lumpiness is seen clearly in the generation capacity expansion graphs in A.2, as well as in Figure 2.8, in Section 2.3.5. Up to 22% RET on Corvo island, in *Scenario 1* - Isolated (Figure 2.8), can be met with a single expansion in biogas that provides from 1% to 22% renewable energy production.

We note that it is the islands with a high proportion of existing renewable energy capacity that incur the lowest overall cost. The annualized cost per unit of production [$2012/kWh], in Table 2.10, shows São Miguel with the lowest cost, followed by Flores, which is the second smallest island in terms of demand. Flores incurs the second lowest cost, however, because it already has significant investment in hydropower and wind on the island. Likewise, São Miguel has significant existing investment in geothermal electricity production. Thus, the higher the share of renewable sources, the lower the cost of system operation. While initial achievement of an RET will have high associated capital costs, the long-term operational costs of a high renewables system will be lower than a carbon-intensive system.

2.3.2 Scenario 2 - Regional

Even with the seemingly abundant natural, renewable resources available among all islands in the archipelago, the highest RET that can be reached with a regional attribution is 85%. This is due to operating constraints on each island, and their lack of interconnection. While São Miguel has abundant geothermal capacity, it cannot overproduce to meet demand on another island because the extra power cannot be transmitted off the island. Subsea power cable transmission lines do not currently connect any of the islands in the archipelago. Our GEP does not take into account possible expansions in transmission capacity, though this could be a direction for future work, as increasing transmission capacity could improve the maximum regional RET attainable.

In setting a regional RET, we see investment in renewable energy on smaller islands only with an RET of 50% or higher. This is illustrated in the cost curves shown in Figure 2.2, which are flat until the 50% RET. Least-cost capacity expansion plans by island and by RET are detailed in Appendix A.3.

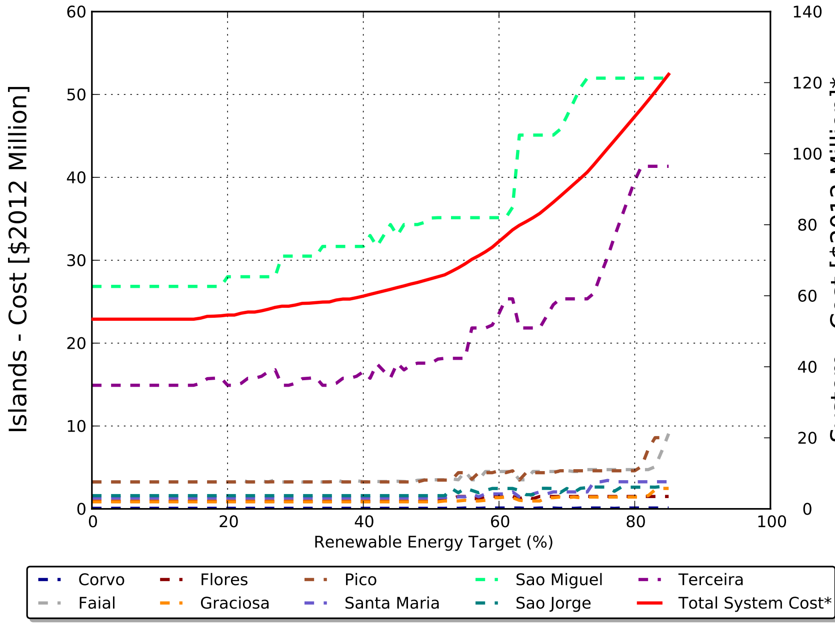


Figure 2.2: ***Scenario 2*** - ***Regional***: **Annualized system cost** by island and for the entire archipelago ("System" axis), under a regional attribution of the RET.

The regional RET is met first by existing renewable energy capacity on the islands, then by investments in flexible renewable generation capacity that can meet multiple load types, such as geothermal and biogas. As seen in Table 2.11, existing renewable energy on the islands and investment in only geothermal capacity suffices up to a 50% RET. For higher RETs, a combination of wind, geothermal and biogas is necessary. It is not until the highest RET range, [76 - 85%], that investment occurs in offshore wind and additional hydropower. The higher cost of these generation technologies make them less desirable investments at lower RETs. Similarly, least desirable are solar and wave, which are never invested in, in a regional RET attribution. A combination of high investment cost and low capacity factor make solar generation unattractive on the Azores Islands. This is particularly true with the resources available regionally, including geothermal, which can contribute more efficiently to the RET. The investment cost of solar would need to fall to less than one-

Table 2.11: **Average percent [%] of total capacity expansions in an RET range, by generation technology**. The capacity expansions included here are the expansions that occur on the islands and do not include capacity expansions in mainland Portugal. In Scenario 1, only the first two ranges can be reported, as not all islands can meet the higher RETs. Similarly, the final RET range for Scenarios 2 and 3 go up to the maximum RET that is achieved in that scenario, 85% and 95%, respectively.

	Scenario 1 Isolated				**Scenario 2** Regional				**Scenario 3** Country			
RET range:	[0-25%]	[26-50%]	[51-75%]	[76-100%]	[0-25%]	[26-50%]	[51-75%]	[76-85%]	[0-25%]	[26-50%]	[51-75%]	[76-95%]
Wind	0.96	6.19	-	-	0	0	7.83	20.33	0	0.39	16.55	24.60
Offshore Wind	0.20	9.33	-	-	0	0	0.15	17.81	0	0	0	20.19
Hydropower	0	0.72	-	-	0	0	0	0.04	0	0	0	0
Geothermal	7.85	25.41	-	-	4.58	54.94	60.20	37.96	19.75	64.99	53.77	46.17
Solar	0	0	-	-	0	0	0	0	0	0	0	0
Wave	0	0.43	-	-	0	0	0	0	0	0	0	0
Diesel	87.47	49.32	-	-	94.68	44.36	17.04	8.81	75.86	28.95	14.80	10.04
Fuel Oil	0.45	0	-	-	0.74	0.70	0.20	0.07	4.23	2.17	1.06	0.77
Biogas	3.07	8.62	-	-	0	0	14.58	14.98	0.16	3.50	13.80	18.23

tenth of its current value, before it became an attractive investment. Even at such a low cost, investment would not be advantageous at lower RETs ($\leq$ 50%). With a 30% higher capacity factor than solar, the investment cost for wave generation would need to fall by only 13% before it becomes an attractive investment.

2.3.3 Scenario 3 - Country

As described in Equation 2.15, the country scenario refers to an RET that includes production in both the Azores Islands and mainland Portugal. Thus, renewable energy capacity in both places counts toward achieving this common goal. Table 2.11 shows that investment in biogas on the islands occurs at lower RETs than it does under the Regional scenario. The same is true for investment in wind power, though investment in wind does not occur until at least 25% RET. Because additional renewable energy production from mainland Portugal is available to meet the RET, investment in offshore wind on the islands is not needed until RETs are set to the highest levels ([75-95%]). In this scenario, we see no investment in additional hydropower, as well as no investment in solar or wave energy. This is largely due to the higher costs associated with these technology options.

Compared to the Regional scenario shown in Figure 2.3, a country RET (Figure 2.4) results in higher levels of renewable energy production on the islands, at lower RETs.

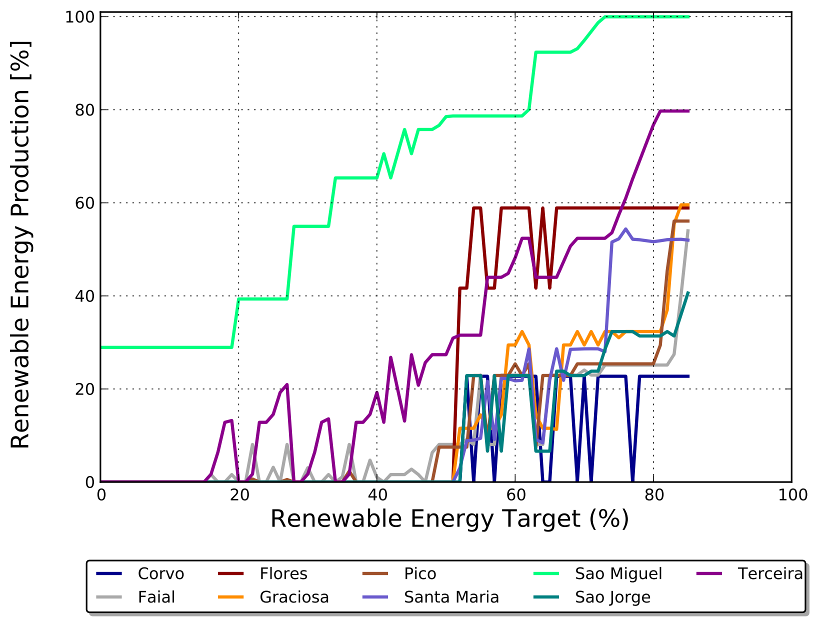


Figure 2.3: ***Scenario 2 - Regional*****: renewable energy production on each island, per RET.** In a regional attribution of the RET, the smallest island, Corvo, never achieves higher than 22% renewable energy production. This is compared to 64% renewable production achieved in *Scenario 1 - Isolated*.

A country attribution of an RET must meet a higher overall demand. This requires more renewable energy investments at lower RETs, compared to Scenario 2. Even though mainland Portugal can make larger lump investments in renewable energy than the islands can, the smaller additional renewable energy capacities offered on the islands are still useful in reaching a country RET. The lower cost of some renewables on the islands, compared to mainland Portugal, is also a contributing factor to investment in renewables on the islands in a country RET attribution. These two contributing factors interact, resulting in a local investment mix that can change dramatically from one RET percentage point to the next.

Even up to the highest RETs, investments and production on relatively small islands still occur. On São Jorge and Santa Maria, two middle-sized islands, investments are made at even high RETs (greater than 60%). As with *Scenario 1* and *Scenario 2*, A.4 details the optimal capacity expansion investments by island and by RET.

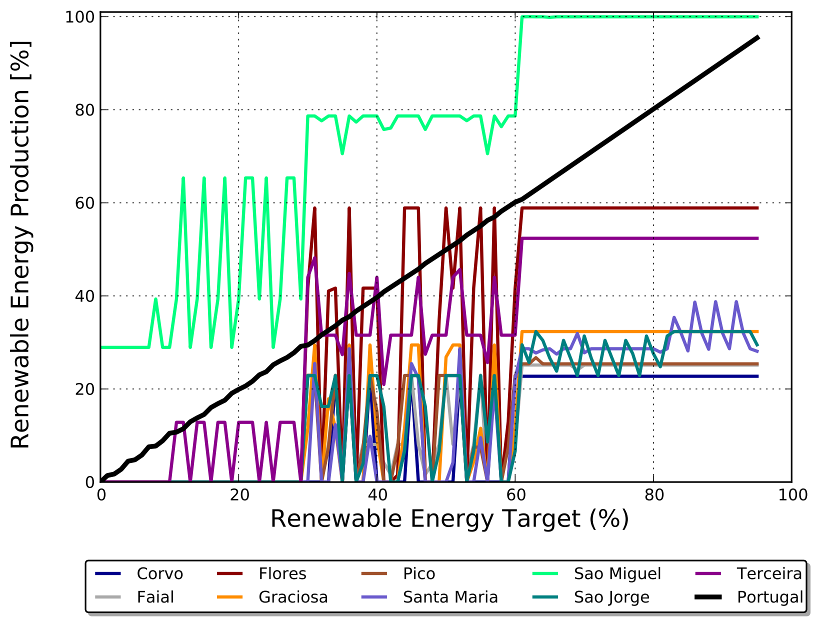


Figure 2.4: ***Scenario 3*** **-** ***Country*****: renewable energy production on each island, per RET.** In a country RET, smaller islands have higher renewable energy production, at lower RETs, when compared to a regional RET. Because the demand pool is larger, relatively cheap renewable energy on the islands is attractive at lower RETs.

2.3.4 Economic Implications

Figure 2.5 shows the archipelago-wide cost of the three different scenarios. Expectedly, *Scenario 1 - Isolated* has the highest combined cost across RETs, as islands are required to meet the RET with the limited insular capacity available to them. Scarcity of supply means the islands must rely on generation options with higher costs.

Scenario 2 - Regional has lower archipelago-wide costs across RETs, as the pool of renewable generation capacity expands. As the pool expands even further, in *Scenario 3 - Country*, the resulting cost on the archipelago is generally more expensive than the regional RET attribution, but less than the isolated. Intuitively, as the generation pool widens, the cost should decrease because more and cheaper options become available. In the case of mainland Portugal and the Azores, the cheaper renewables on the islands are attractive to helping mainland Portugal meet its large demand. Thus, the country RET attribution results in more investment in geothermal, wind and biogas on the islands at lower RETs, than in the regional scenario. This means that a country RET results in a more costly exploitation of renewable energy from the Azores Islands standpoint.

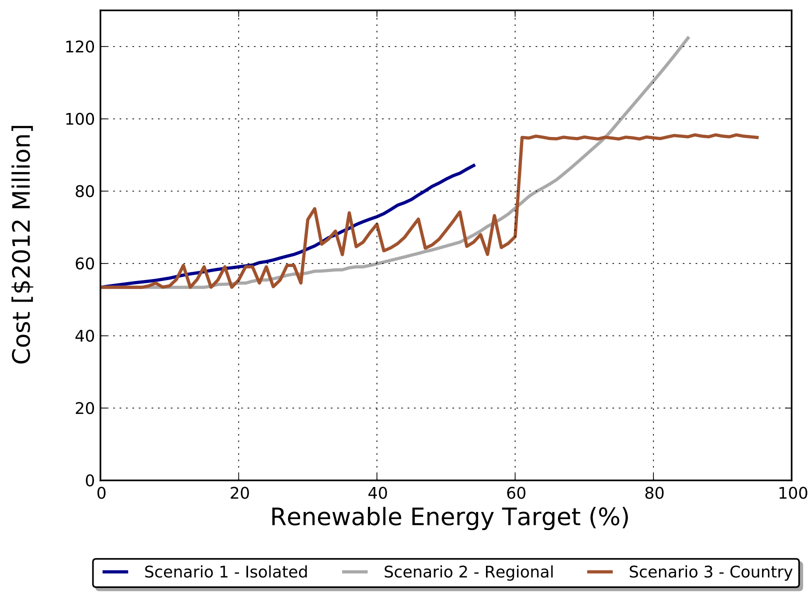


Figure 2.5: **Costs per scenario** *Scenario 1 - Isolated* has the highest archipelago-wide system cost, while the broader geographic RET attribution in *Scenario 2 - Regional* takes advantage of lowest cost renewables across the archipelago, resulting in a lower system cost across RETs. *Scenario 3 - Country* generally results in costs between *Scenarios 1 and 2*, though it is the least cost option for the RET range 54% - 60%, and above 72%.

The cost of reaching an 85% RET in *Scenario 2 - Regional* is just over \$122 million, or \$0.1077/kWh on the archipelago, whereas the cost of reaching a country-wide 85% RET is \$95.8 million, or \$0.0844/kWh on the archipelago. The distribution of investments, and thus the corresponding costs per island, vary widely. As is shown in A.5, the lowest cost scenario for each island oscillates between a regional and a country RET attribution, with the regional RET generally becoming the least cost solution in the higher RET range.

This is true for every island except São Miguel, whose lowest cost solution is always *Scenario 1 - Isolated*, shown in Figure 2.6. In *Scenarios 2 and 3*, investment in and production from geothermal energy is called upon earlier than is required for in the isolated scenario.

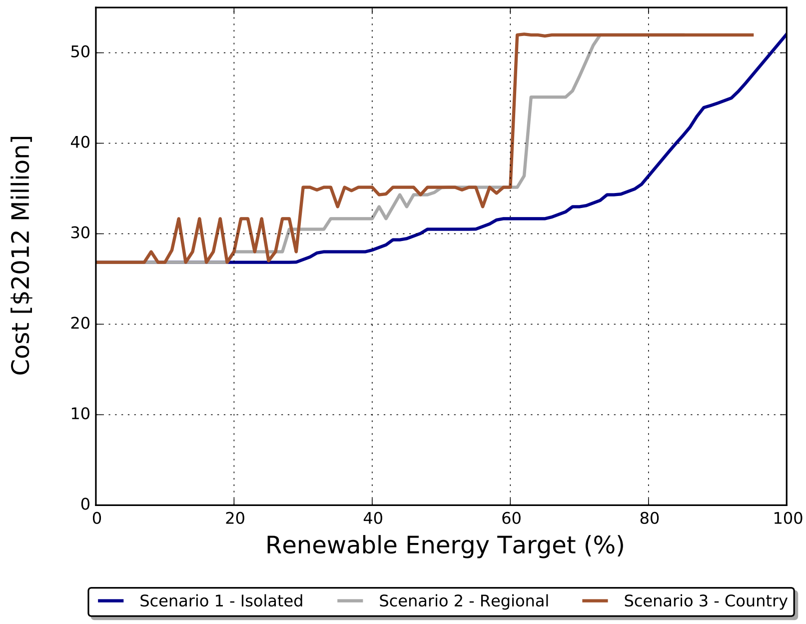


Figure 2.6: **Costs per scenario** on *São Miguel* island. The least cost solution for the island of São Miguel is always *Scenario 1 - Isolated*. This is because, under any wider geographic attribution of an RET, the geothermal resources on São Miguel are heavily exploited. This makes the other two scenarios more costly for São Miguel locally.

Additionally, geothermal on São Miguel is preferred to geothermal on Terceira because the turbine size on São Miguel is larger. The interactions of an increased level of demand, availability of low cost geothermal, and large size of the geothermal generation capacity prioritize investment in geothermal on São Miguel to meet regional and country RETs. Thus, both a country and regional RET result in a more expensive use of the renewable capacity on São Miguel than in the isolated case.

For the archipelago as a whole, however, a broader geographic RET attribution generally results in a net savings to the archipelago population. Figure 2.7 shows the cost savings of a regional RET, as compared to isolated and country RETs.

Compared to *Scenario 1 - Isolated*, a regional RET is always cheaper, with a net annual savings as high as $78 per capita, across the archipelago. The same is generally true of the comparison with *Scenario 3 - Country*, except after a 72% RET. This crossover point represents when investments in the regional RET maximize geothermal and biogas resources

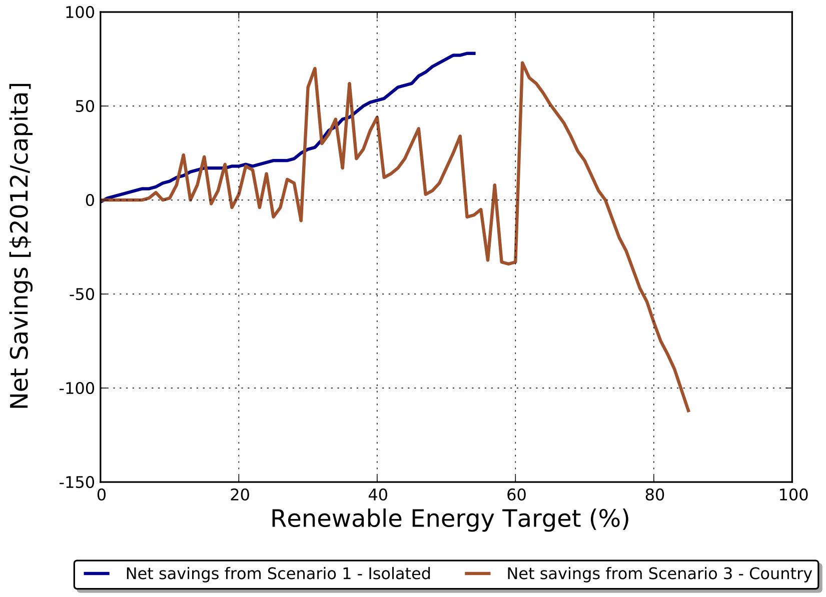


Figure 2.7: **Net savings per capita of** *Scenario 2 - Regional* RET attribution. Compared to *Scenario 1 - Isolated*, a regional RET is always cheaper. The same is generally true of the comparion to *Scenario 2 - Country*, except after a 72% RET. This crossover point represents when investments in the regional RET maximize geothermal and biogas resources on the islands.

on the islands. The same investment decisions occur in the country RET, but at 61%. After this point, investments in renewable energy in mainland Portugal are used to achieve higher RETs. While the country RET attribution represents a cost savings to the islands, it comes at a social and environmental cost, discussed in Sections 2.3.5 and 2.3.6.

2.3.5 Social Considerations

As Figures 2.3 and 2.4 illustrate, investment and production of renewable energy at high levels does not occur equally on the islands. Figure 2.8 shows the investment changes that occur on two selected islands, between the three scenarios. Diverse investments occur on the smallest island of Corvo when the RET is attributed at the geographically isolated level (*Scenario 1*). As the geographic attribution of the RET becomes wider, other renewable energy resources become available at lower cost. Consequently, investment on Corvo occurs

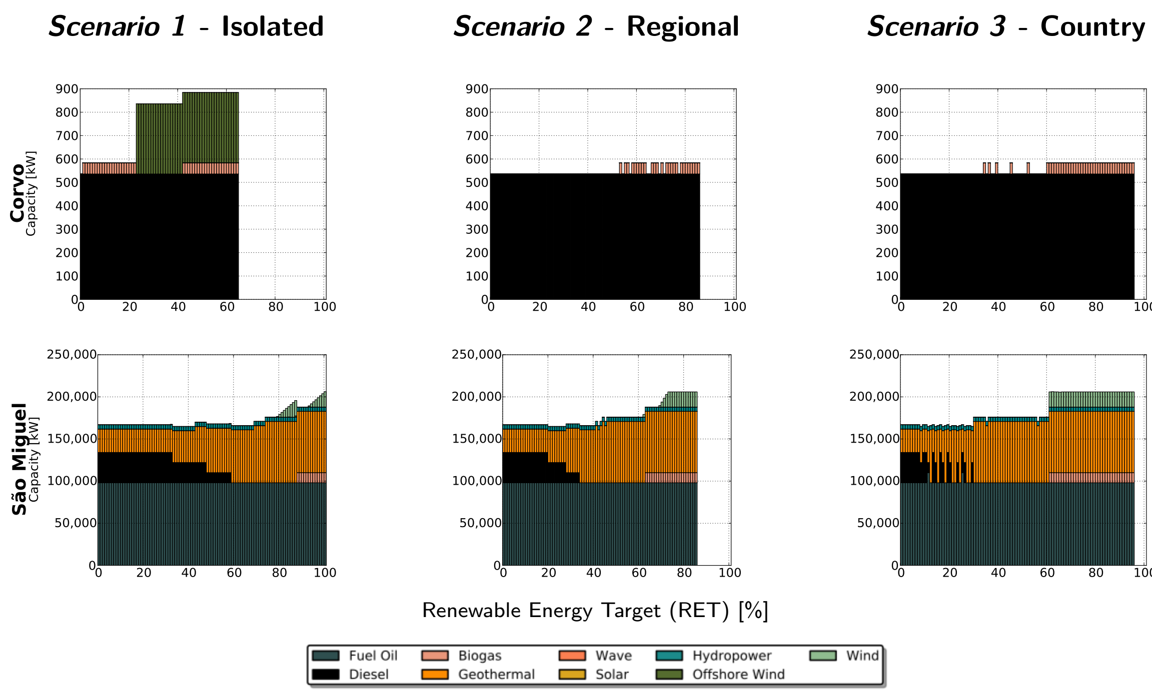


Figure 2.8: **Generation Capacity Investments According to RET Attribution**: This figure shows how the generation capacity investments change on the smallest island (Corvo) and largest island (São Miguel), when the Renewable Energy Target geographic attainment boundary is enlarged. The broader the geographic RET region is, the less investment is made on smaller islands.

only at higher RETs, when investment in its flexibly dispatchable biogas resource becomes advantageous.

Investment in geothermal energy on São Miguel, the island with the highest demand, consistently occurs in all three scenarios. This investment becomes more advantageous at lower and lower RETs, as the geographic attainment boundary widens. At its broadest, in Scenario 3, investments in biogas and wind energy on São Miguel also occur at lower RETs than in the first two scenarios. These resources on the islands are valuable to mainland Portugal because of their higher capacity factors than their counterparts on the mainland (see Table 2.3 and Table A.1). Located in the middle of the Atlantic Ocean, the islands have better wind potential than the mainland. Biogas also has a higher capacity factor in the smaller electricity system of the Azores, as it is needed to meet all three load types. Biomass on mainland Portugal is typically used for middle load only, though our results suggest major expansion may be necessary in biomass, particularly for RETs higher than 30% (see A.4).

Because of this disparity between investment locations, we analyze a policy mandating a certain renewable energy production quota on each island, while also meeting the larger RET. Figures 2.9 and 2.11 show the effect of an island renewable energy production quota on annualized system cost. The quotas vary from zero to 54%, which is the minimum-maximum isolated renewable energy production (see Table 2.10). Figure 2.9 shows that a quota of 54% renewable energy production on each island is achievable for a small increase in cost (4.4%, or 4.4 million [\$2012]), at an overall RET of around 75%.

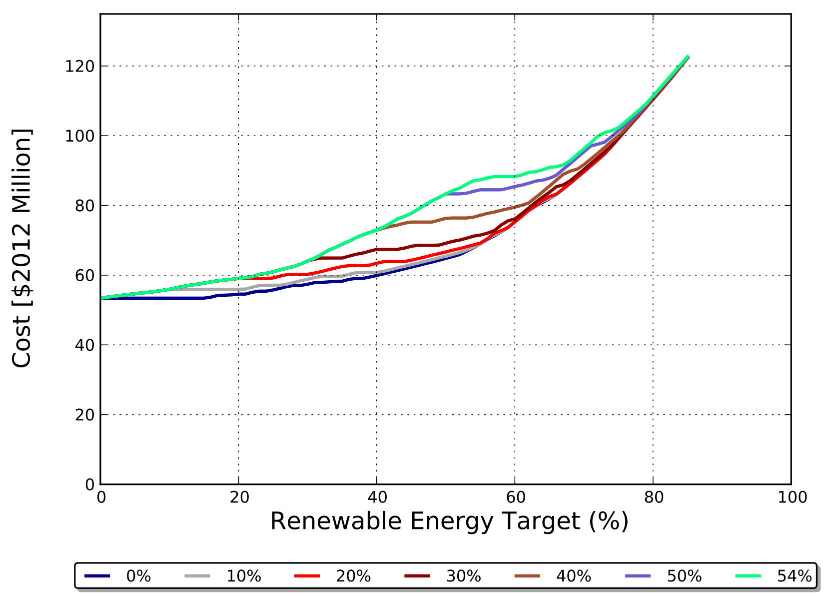


Figure 2.9: ***Scenario 2*** - ***Regional*****: Effect of renewable energy production quota [%] per island on system cost.** Establishing a quota for renewable energy production per island, while also meeting a regional RET, forces distribution of renewable energy investments across the islands. At high RETs, such as the 75% target of the Azores government, the effect of a quota on overall cost is small.

These results indicate that investment in renewable energy can be distributed among the islands at a small increase from the absolute least-cost solution. Residents of the Azores Islands may view distributed investments as fairer, or more socially equitable, and may favor such a solution. Besides mandating renewable energy production, Figure 2.10 shows that an increase in fossil fuel prices can also instigate investment in renewable energy.

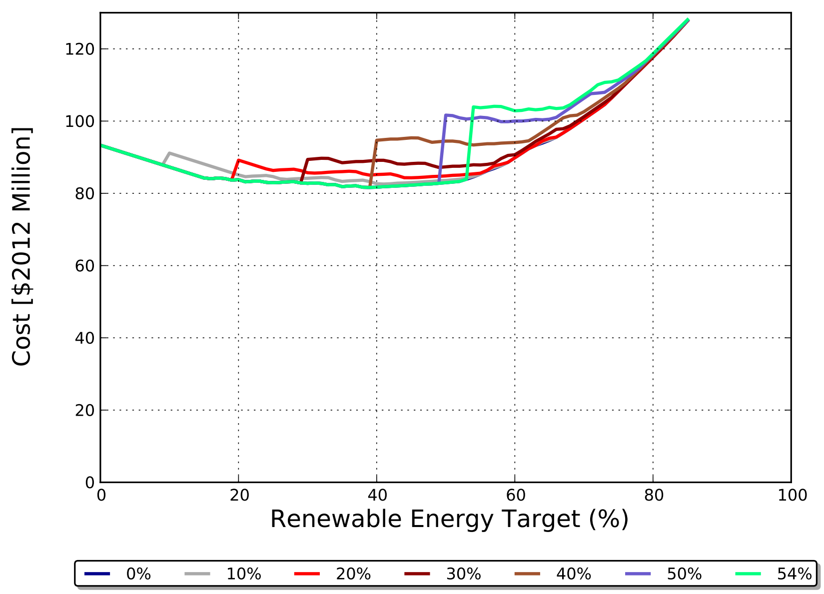


Figure 2.10: ***Scenario 2 - Regional*: Effect of 75% diesel and fuel oil price increase on system cost.** If the cost of diesel and fuel oil were to rise by 75% each, the resulting increase in system cost would make a 50% archipelago-wide RET cost-effective.

Figure 2.10 shows how system costs change when diesel and fuel oil prices each increase by 75%. The cost of continuing to use fossil fuel is 11% higher than running a system with 50% renewable energy production. Thus, a significant increase in fossil fuel prices can also induce investment in renewable energy. With the current slump in oil prices, however, this may not be likely to happen soon.

The effect of a per island quota on total cost (the Azores archipelago plus mainland Portugal) in Scenario 3 becomes insignificant, when comparing the associated cost increase with the total cost of the system. The annualized cost to meet any RET in Scenario 3 ranges from 6.8 to 11.7 billion [$2012 USD]. The cost of investment needed to meet demand levels in mainland Portugal dominates the cost of renewable energy investment distribution among the islands. At the highest RET, 95%, the difference between the least cost solution (0% renewable energy quota per island) and the highest cost solution (54% renewable energy quota per island) is a mere 0.017%, around 2 million [$2012 USD].

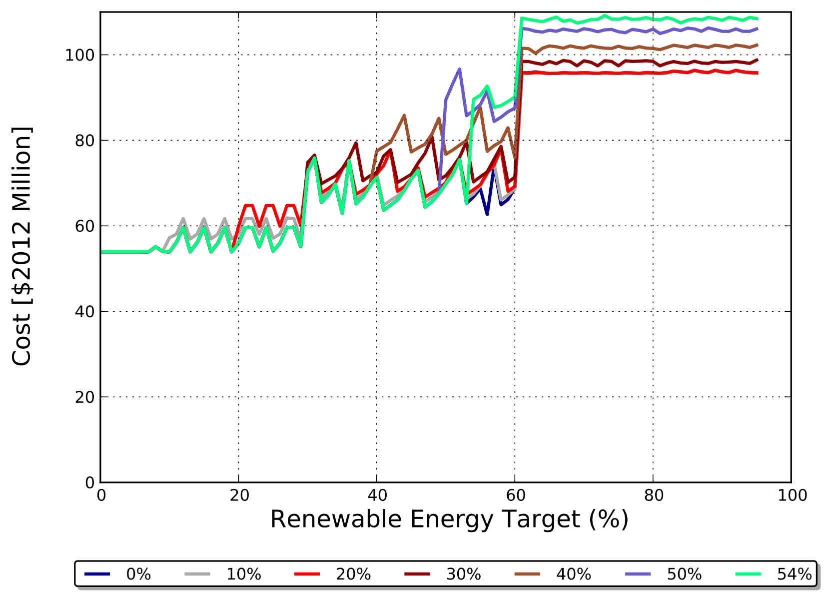


Figure 2.11: ***Scenario 3 - Country*: Effect of renewable energy production quota [%] per island on system cost.** Requiring a per island production quota of renewable energy has a negligible effect on cost, when meeting a country RET. The investment costs needed in mainland Portugal dominate the costs incurred on the Azores Islands.

Figure 2.11 shows the archipelago-wide cost of a country RET attribution, with island renewable energy quotas. Above a 54% RET, the cost curves show that a higher renewables requirement (*i.e.* higher per island renewable production quota) means higher cost. Below 54% RET, the 54% per island renewable production quota coincides with the 0% quota because they are the same; the per island production quota is not required below its equivalent RET value. Above a 60% RET, the costs of achieving a 10% or 20% per island renewable production quota are equivalent.

At the highest RET of 95%, the difference between the least cost quota and the highest cost quota is a 13.2% increase, or 12.7 million [$2012]. This cost is equivalently represented as $0.0111/kWh. If a 150% increase in diesel and fuel oil prices were to occur, the 54% renewable energy quota per island becomes economically cheaper. This is because a country

RET attribution results in less renewable expansion on the islands when a quota is not present, so increasing diesel prices will increase cost in such a system. This result shows that a system with higher renewable energy generation capacity is more robust to fossil fuel price shocks.

2.3.6 Environmental Effects

To approximate the environmental effects of the different scenarios, we estimate the carbon dioxide equivalent (CO_2eq) emissions associated with the production of electricity [52]. The calculation of CO_2eq emissions follows from Equation 2.16, where AF is the *activity factor* and EF is the *emissions factor*. Here, the *activity factor* is the production of electricity, W_{gil}.

$$Emissions = AF * EF \tag{2.16}$$

The emissions factors used are harmonized life-cycle emissions factors, derived from a meta-analysis study conducted at the U.S. Department of Energy's National Renewable Energy Laboratory (NREL) [8]. The values per generation technology are presented in Table 2.12 below. We analyze emissions from generation on the Azores Islands only. Because the emissions factors are life-cycle, and include emissions incurred during construction, as well as ancillary operational emissions, we note that a 50% RET does not generally result in a 50% reduction in emissions. Similarly, a 100% RET does not mean zero greenhouse gas emissions. This finding supports the climate mitigation argument for emissions-based targets, in conjunction with renewable energy targets [17].

Figure 2.12 shows the annual emissions of operating the electricity system on the Azores Islands, under the three scenarios of RET geographic attribution. We also analyze a high (54%) and low (10%) case of renewable energy production quota per island, under a

Table 2.12: **Life-cycle emissions factors** by generation technology [8].

	Emissions Factor [g CO_2eq/kWh]	Source
Wind	11	[53]
Offshore Wind	12	[53]
Hydropower	7	[54]
Geothermal	40	[54]
Solar	20	[55]
Wave	8	[54]
Diesel	979	[54]
Fuel Oil	979	[54]
Biogas	40	[54]

simultaneous Regional and Country RET attribution.

All three Regional scenarios generally have the highest emissions at any RET. *Scenario 1 - Isolated* coincides with the *Regional 54%*. Though the regional attribution with a 54% renewable energy production quota produces the absolute lowest emissions at an 85% RET, after 60% RET, emissions from all three regional scenarios approximately converge.

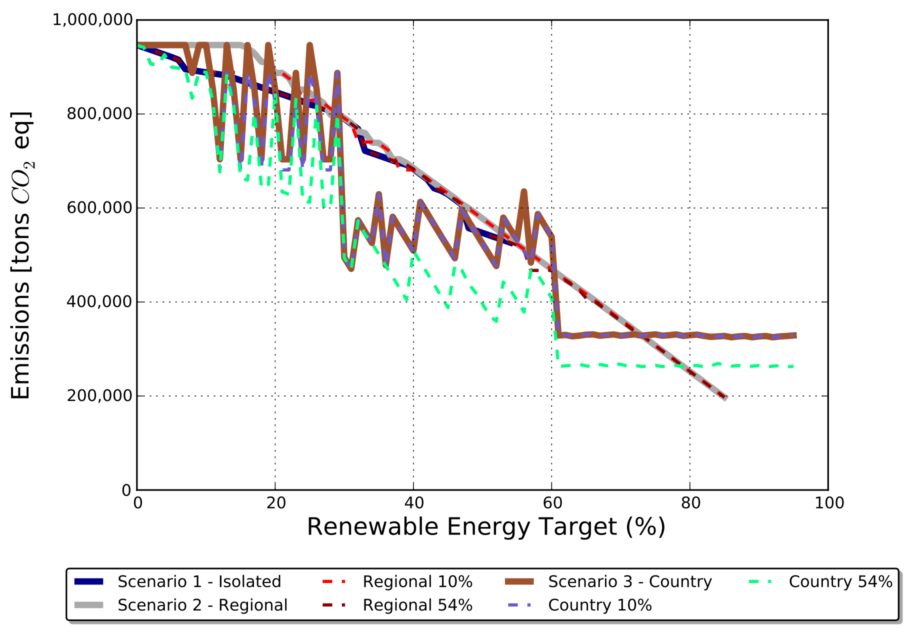


Figure 2.12: **System operating emissions per scenario.** This graph shows the carbon dioxide-equivalent (CO_2eq) emissions associated with the annual operation of the electricity system on the Azores archipelago, under each scenario. As renewable energy investment increases with higher RETs, emissions decrease. The greatest emissions reductions are achieved at the the highest RET under the regional attribution.

Scenario 3 - Country shows a step-wise decrease in emissions with increasing RET. *Scenario 3* with a renewable energy production quota of 54% consistently has the lowest emissions out of all scenarios, until an 80% RET, after which all three regional scenarios outpace it. A country RET attribution is the best for emissions reduction at RETs less than 30%. For RETs greater than 60%, however, emissions reductions stagnate to around 263,000 tons CO_2eq, while a regional RET can achieve further reductions of up to 65,000 tons CO_2eq at its highest RET.

The tradeoffs between environmental, economic and social concerns are threefold: 1) lower emissions occur under a country RET attribution, but 2) the cheaper RET attribution is the regional, which, 3) also results in more diverse renewable generation investments across the islands. The cost-effectiveness of each scenario, in terms of emissions reductions, is assessed in Figure 2.13. This graph shows the increase in cost from the base case (0% RET), per reduction in emissions from the base case. Lower RETs have less absolute emissions reductions than higher RETs (see Figure 2.12).

At some low RETs in the country attribution, absolute zero cost per emissions reduction represents the case where zero emissions reductions occur because there is no investment in renewable energy on the islands. Sharp dips in the graph show where the rate of emissions reductions is small, compared to the cost increase; both cost and emissions reductions are always increasing from one RET to the next.

The isolated scenario is always the most costly way to reduce emissions, whereas the regional scenario is generally the cheapest. Under a country RET, however, the islands could achieve a 52% RET for $32 per ton CO_2eq reduced. This is towards the top range of the highest carbon trading price ever seen in the European Union Emissions Trading Scheme (EU ETS) [56]. If in Phase III of the EU ETS carbon market returns its heyday, investing in renewable energy on the Azores Islands could be quite attractive to high-carbon emitters, such as jet planes and cement factories.

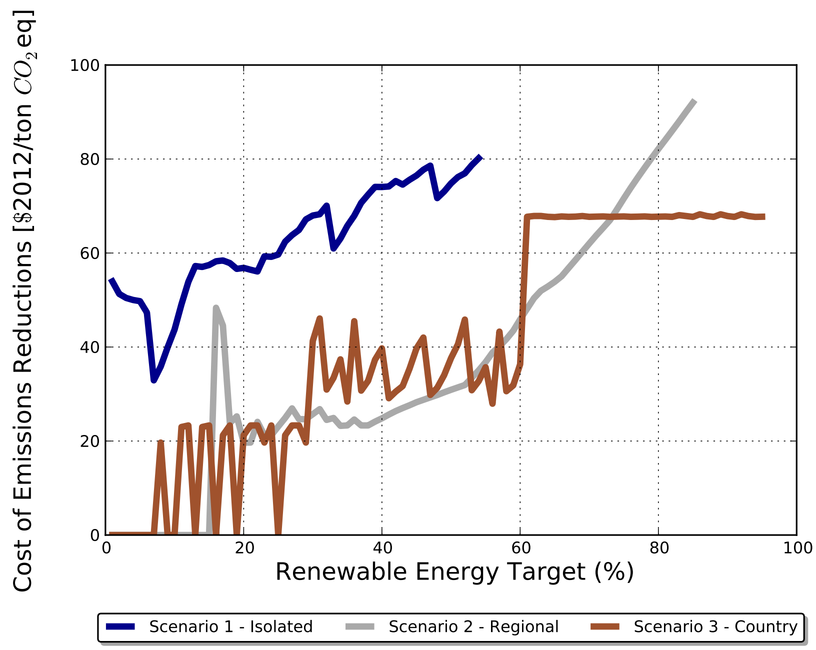


Figure 2.13: **Cost-effectiveness of emissions reductions, in dollars per ton CO_2eq reduced.** The cost-effectiveness metric displayed here is a typical metric displayed to policy makers. It illustrates the cost of carbon abatement per scenario, per RET.

2.3.7 Discussion

Geographic attribution of an RET significantly affects economic, social and environmental consequences of an RET policy. While an isolated, local attribution of an RET may be the most expensive way to increase renewable energy production, it results in the most diverse portfolio of renewable investments. In this locally attributed RET, investment is also spread more widely across localities than when the RET geographic attribution is broader.

A regional attribution of an RET may be necessary in order to meet a high target. As is the case for the Azores Islands, local natural resource limitations prohibit seven out of nine islands from meeting the government's 75% RET on their own. The regional RET allows up to 85% renewable energy production, while taking advantage of lower-cost resources available on different islands. Investments are not distributed equally across localities, however. This disparity may result in social equity complaints from constituents. The emissions associated with a regional attribution closely follow the emissions seen in an isolated attribution, but allow for higher emissions reductions at high RETs when compared to a country RET attribution. The cost of emissions reductions ranges from $20 - 92 per ton CO_2eq abated, depending on scenario and RET. It is possible that carbon markets will rebound such that these numbers are attractive for trading, though the recent price of two euros per ton make this look unlikely.

Due to cost differences between regions, a country attribution of the RET still results in local investment, though local investment and local renewable energy production is highly dependent on the percentage point of the target. Similarly, local emissions reductions can vary drastically by RET percentage point, with emissions reduction efforts stagnating at high RETs.

To maximize the benefits of renewable energy production, a regional attribution of an RET, along with a local renewable energy production quota, could be the best geographical attribution, given local social considerations and emissions reductions standards. More costly than a similar country RET, the regional RET plus local quota represents a middle ground between economic considerations of least-cost investment and benefits of local investment diversity and local emissions reductions.

2.4 Conclusions

We analyzed three different geographic attributions of an RET - *Isolated, Regional and Country* - using a generation capacity expansion planning model to discern the optimal investment strategies in renewable energy. Evaluating the economic, social and environmental tradeoffs of each scenario, the findings inform renewable energy target policy formation.

The results obtained from the Azores Island, Portugal case study indicate that target setting is a delicate task, which should be subject to careful scrutiny prior to enacting official mandates. Indivisibility of generation capacity means that the optimal investment strategy can change dramatically from one RET percentage point to the next. This is particularly important for lower energy targets, which are currently the aim of many regional policies, including the EU 20-20-20. Due to lumpiness, the portfolio of investments can change completely; from biogas only at 22% RET, to offshore wind only at 23%, for example. If the long-term goal is to maximize the amount of renewable energy production in the system, the investment mix at the highest considerable RET should be investigated, as incremental investments to meet lower RET targets may be contrary to the investments for higher targets, possibly resulting in overcapacity and future unuse.

The modeling conducted in this study provides insights into how localities, regions and countries can meet RETs in the short term (10 years out). With the possibility of future investments in high voltage transmission lines, however, regions may be able to see RET achievement at even lower cost. Transmission network expansion would allow greater exploitation of flexible renewable resources, such as geothermal, since overproduction can be transmitted to areas with subpar renewable resources. In the case of islands, adding submarine power cable transmission may allow RET achievement even if an island has few natural resources.

2.5 Addendum

This Addendum addresses comments from the dissertation committee members, regarding the preceding chapter. The same is true for subsequent addenda.

2.5.1 Modeling Island/Isolated Power Systems

Islands are among the most carbon intensive nations in the world, with the US Virgin Islands ranking second highest in carbon usage per capita [57]. Further, it is estimated that Small Island Developing States (SIDS) spend between 5% to 20% of their GDP on fossil fuel imports [6].

The ease of transport and high energy density of fossil fuels, along with various political incentives, have resulted in island states' and territories' dependence on expensive fuel sources for their electricity generation needs. Hawaii and the US Virgin Islands both face electricity prices three and a half to over four times that of the average electricity price on the continental US ($0.42/kWh [58] - $0.51/kWh [59] vs. $0.12/kWh [57], respectively). Confronting dramatic increases in fossil fuel prices, many island states have adopted ambitious renewable energy targets, to take advantage of their oftentimes-ample existing renewable resources [60]. Hawaii has imposed a renewable energy target of 100% production by 2040 [22], while the Azores Islands, Portugal have set a 75% RET for 2018 [2]. In both cases, investment in new renewable electricity generation facilities will most likely be required. Finding the optimal plan for how, when and where these investments should take place is the goal of the field of *generation expansion planning* [61].

Generation Expansion Planning (GEP)

Both the irreversibility of the investment, and the large capital expenditure incurred Lead to the desire to make optimal decisions when investing in electricity generation systems.

Models for optimal generation capacity expansion have been studied widely in both the electric power research literature [40]. Originally a part of general, long-term resource planning, GEP models were developed to meet predicted future growth in demand by expanding generation capacity at the least cost [62]. Few publicly available models exist, however, for governments, utilities and interested stakeholders to examine how to optimally achieve least-cost generation expansion plans [63]. Furthermore, to the best of the authors' knowledge, there is no publicly available model built to achieve a GEP specifically to meet specific renewable energy targets.

Publicly Available Energy Planning Tools

Governments, utilities and public stakeholders have at their disposal a select few free electricity planning tools to help them analyze the cost of expanding generation to meet growing demand. The only publicly available GEP optimization model was built by the International Atomic Energy Agency (IAEA) in the 1980s, to help countries analyze and incorporate nuclear generation into their long-term national electricity expansion plans [64]. The resulting model, the *Wien Automatic System Planning Package* (WASP), was made freely available to IAEA member states. Indeed, WASP was used for this purpose in 2007, to analyze the competitiveness of nuclear generation on Sumatra island, Indonesia [65]. While WASP will give the user the the optimal long-term, least-cost expansion plan, it comes at a price of 4 to 6 weeks of training [63]. Additionally, existing renewable energy generation can be accounted for in the model, but the modular design of WASP renders it unable to develop a GEP to meet a specific renewable energy target [64].

HOMER (Hybrid Optimization of Multiple Energy Resources)[5] is a microgrid simulation and optimization tool, that will determine the least-cost annual system operation, given a user-selected portfolio of generators from which to invest. HOMER builds a system from

[5]Free 30-day trial, with reduced academic license fees.

scratch, and thus is not an expansion planning tool that considers already available generation. Furthermore, as a microgrid tool, it cannot handle modeling more than 20 generators, which is only 16% of the total number of generators currently installed across the entire Azores archipelago. Thus, while potentially useful as for a single, small island, HOMER cannot handle the Regional or Country scenarios performed in 2.2. Finally, HOMER does not have a feature to optimize the system configuration to a certain RET, further necessitating the need for the GEP model that was developed in 2.2.

A popular entire *energy system* planning tool used by governments and stakeholders is *LEAP* (Long-range Energy Alternatives Planning). It is a very broad tool, typically used to "track energy consumption, production, and resource extraction [across] all sectors of the economy " [63]. As such, it can be used to model only the electricity system, with its own methodology for determining generation capacity expansion. The underlying methodology, however, is simply a scenario analysis, not an optimization [66].

While other long-term energy planning models exist, with the capability of being adapted to generate a GEP, these models are either not truly free (*MARKAL/TIMES, H2RES, NEMS, SimREN, WILMAR Planning Tool, TRNSYS16*), and/or not give optimal solutions (*EnergyPLAN, EMCAS, RETScreen, SimREN, TRNSYS16*) [63]. For a full review of "computer tools for analyzing the integration of renewable energy into various energy systems," we direct the reader to Connolly [63].

2.5.2 Recent literature

Generation expansion planning

The recent literature in generation expansion planning has moved away from the centralized decision maker and towards strategic investment in competitive, restructured markets [39] [43] [61] [40]. For most islands, however, the electricity market is non-competitive, and the

GEP problem can be simplified into one of a centralized decision maker. Antunes, et al. [38] adopt the view of the single decision maker, and develop a multi-objective mixed-integer linear program for optimizing GEP. Their model does not include renewable generation, however, and is not validated on a real electricity system. Bakirtzis, et al. [43] formulate a centralized GEP problem and include renewables as expansion options. They model grid reliability requirements by allowing a maximum renewable energy penetration, and, while they test their model on the Greek electric system, it is not validated on it [43]. Similarly, Bird, et al. allow for certain renewable generation expansion in their joint GEP and TEP (transmission expansion planning) optimization model, but the highest RET tested is 25%.

Renewable energy penetration on Islands

Various models have been used to analyze the feasible penetration of renewable energy into island grids, but the following have been formulated as least-cost, optimal GEPs. Karapidakis, et al. [67] utilized LEAP to analyze a 20% RET for the island of Crete. The candidate renewable energy generation expansions are set exogenously and compared to a base scenario, thus giving no indication of the optimality of the RET solution. Duic and Carvalho apply the H_2RES model to the water, electricity and heat energy sectors of Porto Santo, in Madeira archipelago. The model uses as much renewable energy as is technically feasible, which is defined by the user. The model does not consider costs, and thus is not an optimal least-cost solution. This model seeks to fill the gap between optimal generation expansion planning models and the feasible achievement of renewable energy targets, specifically for the island context.

2.5.3 Methodology

In its extended form, GEP is a "large-scale, highly constrained mixed-integer non-linear programming problem, the global optimum of which can be reached only by complete enumeration" [43]. The combination of decision variables considered in real systems, including the amount of capacity in the system and the output of this capacity, can quickly make the GEP problem intractable. Full enumeration of a GEP at the hourly-time scale could take months to solve. In order to reduce run time and make the model useful for decision makers, we develop a GEP that reasonably accurately models the actual island system, yet is as simple as possible. Following a common approach in the literature, we consider a static investment plan for 20 years in the future [39] [40] [41]. We build the model using open-source Python 2.6.7 [68], with the PYCpx wrapper [69] for CPLEX, an optimization solver that is freely available for academic use [70].

2.5.4 GEP Limitations

A GEP answers the aforementioned question of *what type, when, where and how much* generation capacity should be invested in, in order to meet predicted future demand and RETs. The model results give a first-order idea of what new renewable capacity should be considered for further investigation. In the context of the Azores Islands case study, for example, the least-cost GEP results suggest significant investment in offshore wind and biogas generation, two generation types which are not yet being fully studied by the electric utility. Consequently, a GEP analysis can bring to the forefront plausible generation alternatives that may ordinarily not be under consideration.

The GEP results, however, cannot be directly used for investment decisions. They must first be verified in a shorter time-frame, production simulation model, such as a unit-commitment/dispatch model [71]. This requires more detailed data and predictions of the actual renewable energy output, including hourly predictions for wind, offshore wind and solar power output. This is necessary for two main reasons: 1) island and isolated electric power systems are particularly fragile, and are markedly vulnerable to frequency fluctuations; 2) high penetrations of renewable generation, in general, require *detailed*, hourly-level operational planning, particularly if there is no storage in the electricity system. It is widely recognized that high levels of renewable penetration (above 50%) in small, non-interconnected island/isolated electricity systems require some type of storage (flywheels, pumped hydropower or grid batteries) in order to maintain system reliability.

An area of future work would be to assess the impact of storage on the optimal GEP output. This would require model enhancements to account for at least hourly level unit-commitment plans. The results of such an analysis would likely show a slight decrease in the number of new renewable generation investments required. If pumped-hydro storage is a cost-effective option on the islands, the necessary generation investments may be even further reduced.

2.5.5 Assumption Limitations and Future Work

In the case study in 2.3, it was assumed that geothermal generation on the Azores Islands was flexible and dispatchable, and therefore could be used to meet peak load. While there are many different types of geothermal power plants [72] with many different efficiencies, it is generally not possible to ramp up geothermal power generation fast enough to be considered dispatchable. In the Azores Islands case, it is not possible at all to control the output of their geothermal power plant [73]. Altering this assumption would change the optimal investment plans presented in 2.3. Investment in biogas would substitute for the current investment in geothermal expansion. Given the tradeoffs in economics and resource availability on São Miguel, investments in wind, offshore wind and wave energy would likely follow.

This mix of highly stochastic, non-dispatchable renewable energy illustrates the importance of carefully considering the generation needed for operational reserves, in an electric system with a high amount of renewable energy generation [74][75]. 2.2 assumed a reserve margin of 20%, but the adequacy of this assumption should be subjected to further reliability tests [74]. Combining operational reserve studies with GEP is a promising area of future work.

Chapter 3

Probabilistic Cost Prediction for Submarine Power Cable Projects

It is estimated that Europe alone will need to add over 250,000 km of transmission capacity by 2050, if it is to meet renewable energy production goals while maintaining security of supply. Estimating the cost of new transmission infrastructure is difficult, but it is crucial to predict these costs as accurately as possible, given their importance to the energy transition. Transmission capacity expansion plans are often founded on optimistic projections of expansion costs. We present probabilistic predictive models of the cost of submarine power cables, which can be used by policymakers, industry, and academia to better approximate the true cost of transmission expansion plans. The models are both generalizable and well-specified for a variety of submarine applications, across a variety of regions. The best performing statistical learning model has slightly more predictive power than a simpler, linear econometric model. The specific decision context will determine whether the extra data gathering effort for the statistical learning model is worth the additional precision. A case study illustrates that incorporating the uncertainty associated with the cost predic-

This chapter is based on Schell et al. 2016 [76].

tion to calculate risk metrics - value-at-risk and conditional-value-at-risk - provides useful information to the decision-maker about cost variability and extremes.

3.1 Introduction

The first submarine power cable used for electricity transmission was commissioned in 1954, connecting the electric grid of Gotland Island to Sweden's mainland grid. The cable was rated at 20 megawatts (MW), traversing a submarine route length of 98 kilometers (km) [77]. On the opposite end of the spectrum, the proposed EuroAsia Interconnector would connect the electricity grid of Israel to Greece via Cyprus, with a total rated transmission capacity of 2,000 MW, traversing a submarine route length of over 1,500 km, at a maximum depth of over 2,700 meters. The most ambitious to date, this submarine cable project has an estimated cost of 1.5 billion euros [78].

Over the past fifty years, submarine power cables have been employed in diverse applications, including: crossing bays, lakes or rivers; providing supply to islands from mainland grids; sharing supply between islands; interconnecting national grids; providing supply to offshore oil and gas rigs; and, most recently, for offshore wind power connection [77].

Both offshore wind power and national-level grid interconnections - in the seas of Northern Europe and the Mediterranean - figure heavily in the European Union's (EU) plans for achieving ambitious renewable energy goals. In Germany, the North and Baltic seas alone are seeing the construction and operation of 33 offshore wind farms, totaling 13.5 Gigawatts (GW) of capacity [79][80]. The push for renewable production is not limited to Europe: and so, worldwide, the submarine power cable industry is expected to grow by 45% in the next decade [81].

3.1.1 Cost Estimation Techniques

When project cost estimation is conducted in the planning phase of large infrastructure projects, it is usually done through *Unit Cost Estimation* (UCE) [82]. This method requires a cost estimate for each unit or process being built, as well as knowledge of the unit's depreciation rate, salvage value, expected lifetime, and expected repair and maintenance costs. An informative example of this method of cost estimation is illustrated in [83]. As in most engineering economic models, these cost estimates are based on the expected values of the costs of many individual components. This is problematic because it does not account for the uncertainty surrounding each individual input cost, or how the costs relate to each other; positively correlated costs compound uncertainty, but negatively correlated costs can reduce uncertainty. Thus, using expected value inputs does not guarantee an expected value output of a UCE model.

Because the required data for UCE is too often proprietary, researchers have recently studied how to apply statistical methods to infrastructure project cost estimation. With more sophisticated mathematical models, a reasonably accurate cost estimate could be made with less detailed input data.

3.1.2 Early Cost Prediction for Infrastructure Planning

Infrastructure planning is a major undertaking, with just the planning phase typically spanning years. To determine the potential feasibility of an infrastructure project, an estimate of the project cost is needed fairly early in the planning stage, when specific project details are not fully known. However, it is in the early planning stages that management decides whether or not to proceed with a project. Thus, it is imperative to have the cost estimated as early and as accurately as possible.

To this end, several types of infrastructure projects have utilized methods in statistical learning for early cost prediction. These methods include linear regressions, classification trees and artificial neural networks, applied to various infrastructure projects such as metro network planning [84], bridge construction [85], highway projects [86], and road reconstruction [87].

The statistical methods used in these studies have been applied to either small data sets of projects (n = 12 to 18) [84][86], or to data sets within a specific region [85][87][88]. The results of model-fit from such data sets can seem excellent (with R^2 values of greater than 0.9), but are usually too optimistic, as such a model is not generalizable to many other cases.

In this paper, we develop probabilistic models to support early cost prediction for submarine power cable projects. The final models presented in Section 3.3 are based on a global database of 61 submarine cable projects. This makes the models both generalizable and well-specified for a variety of applications (i.e. submarine power cable projects for island supply, offshore wind farm connection, and grid interconnection, *inter alia*), across a variety of regions.

3.1.3 Paper Structure

The structure of the paper is as follows. Section 3.2 describes the global submarine power cable project database. Section 3.3 elaborates on the statistical learning methods applied to the data set. Section 3.4 details the predictive accuracy of the final models. Section 3.5 applies the final models to a case study on submarine power cable replacement for Vancouver Island, Canada.

3.2 Data

The data is based on a privately maintained submarine power cable project database [89]. At the time of this study, the database contained a record of 296 projects, with each record comprised of various project features. Data collected included project attributes like the power (MW) and voltage (kV) of the submarine cable, manufacturer, armoring material, and insulation type. Of the 36 project attributes sought, 22 were reported with sufficient frequency to enable collection for a large number of projects. The contract cost of the submarine power cable project was also collected for 106 projects.

The data was verified through a significant effort of cross-referencing sources of project details: from company press releases to industry technical reports and presentations. When not reported in the company press release, the maximum depth of the cable route was obtained from bathymetry maps. After the verification of the 296 project records, it was determined that the data for only 61 projects could be reliably substantiated. To reduce the variability in the cost data, only costs reported in press releases from manufacturers were used (e.g. [90]).

3.2.1 Project Attributes

There are many features of a project that can affect its cost. For submarine power cable projects, materials costs, such as the cost of copper or aluminum used in the conductor, is thought to be a large contributor to project cost. Thus, project attributes that represent material cost were collected such as, the number of conductor cores in each cable (one core for direct current (DC) and three cores for alternating current (AC)); the cross-sectional area of the conductor in square-millimeters; the type of current (AC or DC); the number of cables; the length of the submarine route of the cable(s); the type of conductor (copper, *Cu*, or aluminum, *Al*); the voltage (kV) and power (MW) of the cable; and the market price of copper.

Project attributes aimed at approximating the equipment cost of a submarine power cable project included: the cable laying vessel used; the maximum depth along the submarine route; and the application for which the cable will be used (island supply; grid interconnection; offshore wind power; bay/ lake/river crossing; or oil and gas offshore platform power supply).

Market conditions for labor costs were approximated by the following project attributes: country of project; manufacturer of the submarine cable; cable customer; contract year; and estimated project length in years.

3.2.2 Data Transformation and Variable Selection

Finally, the contract cost for each submarine power cable project was converted to real values in 2012 USD [91]. The natural logarithm of the cost is used as the dependent variable in all models presented in Section 3.3, due to its normality. Modeling the cost data as a Gamma distribution did not improve predictive performance.

As described in Section 3.3, many different statistical models were tested with different combinations of the 21 aforementioned project attributes. Table 3.1 details the project attributes, the inclusion of which resulted in the best prediction of project cost. The most useful attributes from this perspective were eight continuous variables and three categorical variables.

Table 3.1: **Submarine Power Cable Project Database**

Independent Variables Continuous, X_i	**Mean** μ_i	**Minimum**	**Maximum**
Submarine cable route [km]	94.1	2.20	425
Maximum depth [m]	176	10.0	1,620
Number of cables	2.4	1.0	9.0
Cumulative length, worldwide [km]	5,672	61.0	11,144
Market price, copper [$2012 USD/ton]	10,576	2,471	13,983
Voltage [kV]	253	52.0	600
Project length [years]	3.43	1.00	6.00
Contract year [year]	2009	1998	2015
Independent Variables Categorical, X_i	**Number of Levels**	**Least Frequent**	**Most Frequent**
Country	27	Bahrain +15 (1)[1]	Norway +1 (8)
Application	5	Oil & Gas Power Supply (6)	Island Supply (27)
AC/DC	3	AC/DC (1)	AC (39)

Dependent variable Y_i	**Mean** μ_i	**Minimum**	**Maximum**
Cost [M$2012 USD]	216.8	15.00	1,240
Ln(Y_i)	18.75	16.52	20.94

[1] The number in parentheses represents the number of times the categorical level (or levels, where indicated by "+" *some number*) appear(s) in the data.

3.3 Model Development and Selection

The primary research question of this work is to determine the best statistical model for submarine power cable cost prediction. Industry insight on predictors was obtained through conversations with industry representatives to determine which variables they believe affect the cost of submarine cable projects. Using this insight, along with insights gained from exploratory data analysis, various statistical models with different variable combinations, were fit to the database. The statistical models initially explored included linear models, generalized linear models (GLM) with a *gamma* cost distribution, principal component regression, generalized additive models (GAM), GAMs with model-based boosting (`mboost` [92]) for optimized variable selection, bagged regression trees, random forests, and multivariate adaptive regression splines (MARS). All models were trained and tested in the `R` statistical programming environment, using the packages `stats`, `mgcv`, `mboost`, `randomForest`, `rpart`, `gbm` and `earth` [93].

Models that performed well based on standard goodness-of-fit statistics and limited predictive tests were selected for further study. The best performing models were then subjected to predictive accuracy tests via Leave-One-Out-Cross-Validation (LOOCV) [94]. The final models are assessed via their predictive errors: absolute error (AE); and absolute percent error (APE).

3.3.1 Linear Models

Three linear models were studied for use as baseline comparison models (Eqs. 3.1, 3.2 and 3.4). While model interpretability is not the focus of this study, it is essential to compare less complex models with more complex models. If the less complex model can perform almost as well as the more complex, the less complex may suffice in certain decision contexts. This could be especially true in the planning/feasibility phase of a project, when not all the technical project details are known, such as insulation choice, current type, or conductor size. Thus, a model that can make accurate predictions based on the least number of inputs is desirable. Such a model would also be advantageous for academics and policy analysts, as these two groups do not typically have access to detailed input data.

Null Model

The *null* model is a linear model (Eq. 3.1) with an intercept and a normally distributed error term, ϵ, with zero mean and finite variance, σ^2, as described by $\mathcal{N}(0, \sigma^2)$. With no predictors, the intercept is the unconditional expected mean of the response; as such, it is often used as a baseline comparison to test whether input variables truly improve the predictive accuracy of higher order models.

$$Y = \beta_0 + \epsilon \tag{3.1}$$

If higher order models do not perform better than the null model, then a simple mean cost estimate could be used as the predicted cost of all future submarine power cable projects. However, Table 3.4 shows that the best predictive models outperform the null.

Linear Model

Due to the lack of public data on submarine power cable projects, several consulting and industry agencies have attempted to use limited project data to predict cost solely by submarine route length [95][96]. As these models are based on only a limited number of projects (16 [95]), the idea is tested here with a larger sample size (n=61). Eq. 3.2 represents the linear regression of submarine power cable cost based on X_1, the length of the submarine route (km), and the error term, ϵ ($\mathcal{N}(0, \sigma^2)$).

$$Y = \beta_0 + \beta_1 X_1 + \epsilon \tag{3.2}$$

Table 3.4 shows that this model does not predict submarine power cable costs well.

Econometric Learning Curve Model

A model of submarine power cable cost based on the theory of technological learning curves was also explored. The basic idea behind learning curves is that implementing the project brings valuable lessons-learned, which reduce the cost of subsequent projects. A secondary effect is that, as learning helps a firm improve performance and reduce cost, the firm becomes more competitive in the market, in turn increasing overall competition, which itself decreases cost [97][98].

The learning curve model developed for submarine power cables is specified in Eq. 3.3, and is adapted from the most commonly used specification of the learning curve in energy modeling [99]. The project cost, C_t, is based on the historical data for the cumulative length, CL_t, of submarine power cable that had been laid up to year, t. Using the database described in Section 3.1, cumulative length was calculated based on the years 1998 to 2015. In Eq. 3.3, δ_L is the shape of the curve representing the learning rate, δ_0 is the cost of the cable at a specific cumulative length, N_t is the number of cables laid in the project, and L_t is the submarine route length. Economies of scale effects can be included using the exponents δ_1 and δ_2, however, it was found that for this data set, the best cost prediction occurs with δ_1 and δ_2 set equal to one. By taking the natural logarithm of Eq. 3.3, an estimate of the learning rate can be calculated (Eq. 3.4), with the error term, ϵ_t ($\mathcal{N}(0, \sigma_t^2)$).

$$C_t = \delta_0 N_t^{\delta_1} L_t^{\delta_2} CL_t^{\delta_L} \tag{3.3}$$

$$\ln C_t = \ln \delta_0 + \delta_1 \ln N_t + \delta_2 \ln L_t + \delta_L \ln CL_t + \epsilon_t \tag{3.4}$$

The standard representation of a learning rate (LR) is defined as $LR = 1 - 2^{\delta_L}$, which gives the change in cost after a doubling of cumulative cable length [100]. Under the theoretical assumption that learning-by-doing leads to cost reductions, the learning rate, LR, should be positive [99]. Modeling using Eq. 3.4 and the submarine power cable database results in $\delta_L = -0.073$, which represents an LR equal to 4.96%. That is, the cost of a submarine power cable project will decrease by 4.96%, per doubling of cumulative length laid.

3.3.2 Multivariate Adaptive Regression Splines (MARS) Model

The desire for an accurate predictive model based on readily accessible data drives the model development search to statistical learning models. The sophisticated algorithms behind statistical learning models allow for less demanding data gathering efforts, as such models can exploit potential non-linear relationships between the predictors and the dependent variable. Though a well-performing predictive model still depends on highly relevant data, these models typically require less ancillary data than econometric models, such as market price data. Higher-order statistical learning models are oftentimes advantageous in this respect, when such market data is commonly proprietary, and unavailable to energy system modelers.

While many different statistical learning models were tested (see Section 3.3), the best performing model was a MARS model [101]. The generic MARS model is formulated as in Eq. 3.5, where $\boldsymbol{X}$ is a vector of predictor inputs, $X_j \, \mathrm{for} \, j = 1, 2, \ldots, p$, $h_m(\boldsymbol{X})$ are basis functions dependent on the predictors' discovered relationship with Y, and the error term, ϵ ($\mathcal{N}(0, \sigma^2)$).

$$Y = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(\boldsymbol{X}) + \epsilon \tag{3.5}$$

Basis functions allow for non-linear relationships between predictors and the dependent variable. They take the general form $h_m(X) = (X - c)_+$, where $+$ represents the positive part of the linear basis function and zero otherwise, and c is the hinge point of the basis function, or the product of two functions, when variable interactions are allowed.

The collection of possible basis functions is shown in Eq. 3.6, for each input X_j, with knots, c, possible at each observed value of that input, x_{ij} [94].

$$C = \Big\{(X_j - c)_+, (c - X_j)_+\Big\}_{c \in \{x_{1j}, x_{2j}, \ldots, x_{Nj}\}} \tag{3.6}$$

The best performing MARS model in terms of prediction contained the variables displayed in Eq. 3.7.

$$\begin{aligned} Y = 19.41 &- 0.0983(40 - SubRoute)_+ \\ &+ 0.0137(SubRoute - 40)_+ \\ &- 0.0004(CumulLen - 3135)_+ \\ &- 0.0035(300 - Voltage)_+ \\ &+ 0.4967(ConYear - 2007)_+ \\ &- 0.0001(3 - NumCables)_+ * CuPrice \\ &+ 0.0206(40 - SubRoute)_+ * ProjLen \\ &- 0.0094(SubRoute - 40)_+ * DC \end{aligned} \tag{3.7}$$

The model allowing three degrees of variable interaction performed best in LOOCV testing, with 8 out of 9 predictors utilized. The final model is specified in Eq. 3.7. The last three basis functions are multiplied by the linear predictors, $CuPrice$, $ProjLen$, and DC cable type, respectively.

Table 3.2: **Prediction Error by Model**

	AE [Ln($2012 USD)]				APE [%]					AE [Million$2012 USD]				APE [%]			
	μ	σ	min	max	μ	σ	min	max		μ	σ	min	max	μ	σ	min	max
Null	0.81	0.61	0.022	2.3	4.34	3.36	0.12	13.7	Null	142	193	2.45	1,106	117	166	2.16	864
Linear	0.67	0.45	0.037	1.8	3.63	2.54	0.19	10.9	Linear	121	131	4.78	529	85.9	103	3.63	509
Econometric	0.55	0.43	0.025	2.2	3.00	2.33	0.13	11.4	Econometric	106	134	2.83	623	62.5	61.9	2.57	254
MARS	0.54	0.40	0.008	1.4	2.89	2.13	0.043	7.42	MARS	111	170	0.982	933	59.0	58.6	0.80	249

3.4 Results - Model Predictive Accuracy

3.4.1 Mean Prediction

The models in Section 3.3 were tested for predictive accuracy using LOOCV. This allows the distribution of model errors to be evaluated, the results of which are presented in Table 3.4.

Table 3.4 shows that the MARS model has better predictive accuracy on the log scale than the Econometric learning curve model, out-performing the latter in both mean absolute error (MAE) and mean absolute percent error (MAPE). When the results are transformed back to the original dollar scale, however, the Econometric Learning Curve model performs slightly better than the MARS in the AE metrics, though the standard deviation of the MARS AE is much better than the Econometric. Which model would better serve a particular practitioner will depend on which error metric is more important to him or her.

3.4.2 Probabilistic Prediction

While the distribution of absolute and absolute percent errors from testing gives a sense of the predictive power of the model, it does not give any information about the uncertainty associated with a specific point prediction. The models presented in Section 3.3 output mean-value predictions. These predictions represent an expected value considering a probability density function for the error, which has been assumed to be Gaussian, of the form $Y \sim \mathcal{N}(0, \sigma^2)$.

Using the vector of residuals obtained from testing the models on the data set, a normal distribution is fit, with the standard deviation determined from the fitted curve. The standard deviation from the residual curve is then applied to the mean-value estimates from the prediction model, giving the full uncertainty distribution around the prediction. This method can be applied to any statistical learning model from which residuals can be calculated.

To compare the errors between models that output probability density predictions, the normal methods of MAE and MAPE do not apply. One applicable method is the *continuous ranked probability score* (CRPS) [102]. The CRPS compares the probability distribution of the prediction to the probability distribution of the observed data value, as in Eq. 3.8, via the cumulative distribution functions (CDFs) of each (Eq. 3.9).

$$CRPS = CRPS(F, x_a) = \int_{-\infty}^{\infty} [F(x) - F_a(x)]^2 dx \tag{3.8}$$

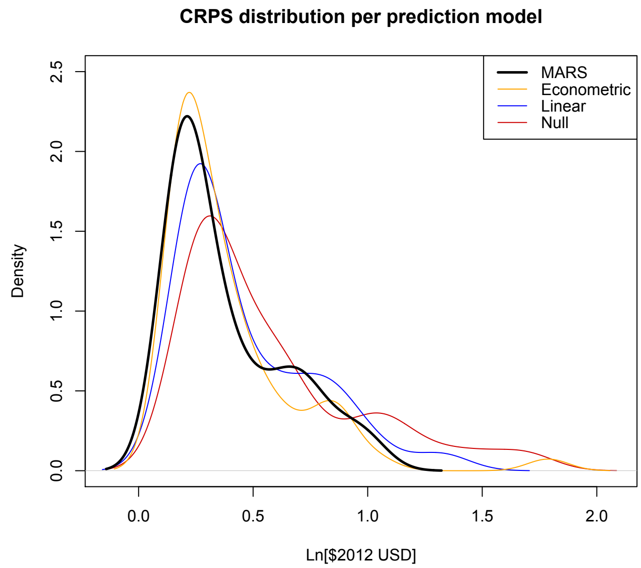
and where, F and F_a are cumulative distribution functions:

$$\begin{aligned} F(x) &= \int_{-\infty}^{x} \rho(y) dy \\ F_a(x) &= H(x - x_a), \end{aligned} \tag{3.9}$$

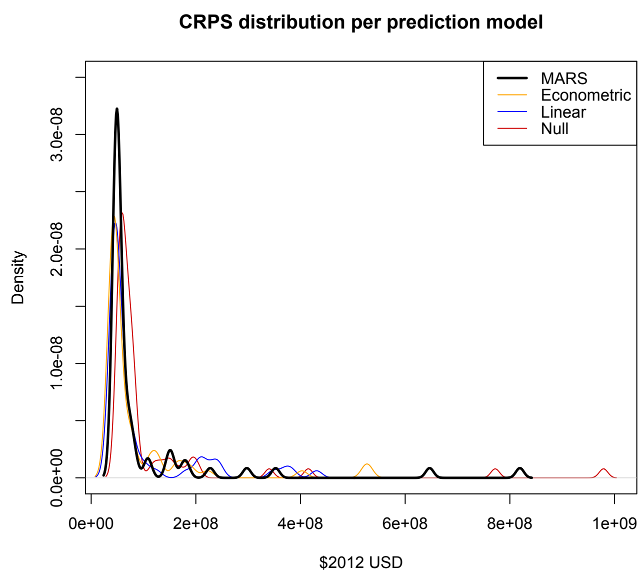
where Eq. 3.10 is the Heaviside function,

$$H(x) = \begin{cases} 0 & \text{for} \quad x < 0 \\ 1 & \text{for} \quad x \geq 0 \end{cases} \tag{3.10}$$

Thus, the CRPS measures the difference between the predicted and actual CDFs. This is true even for the case when the actual observation is a single value, where the CDF is represented as a single step function from zero to one at the observed value.



(a) CRPS of Model Output



(b) CRPS of Exponentially Transformed Model Output

Figure 3.1: Comparison of probabilistic error results by CRPS, in terms of direct comparison of model output (Ln(ConCost)), and the exponentially transformed model output, which gives cost in familiar units of $2012 USD.

Fig. 3.1 shows a clear shift left of the CRPS for the MARS model, illustrating a better distribution of probabilistic errors, compared to the Linear and Null models. Compared to the Econometric model, the CRPS for the MARS has a much shorter right tail. Fig. 3.1 shows the same for the dollar values of the errors, with the maximum MARS CRPS an order of magnitude *smaller* than the other models. This order of magnitude decrease in error is extremely valuable for decision-makers.

3.4.3 Model Limitations

While the best performing model, MARS, clearly outperforms the baseline Linear and Null models, the error distributions could be closer to zero. Hundreds of statistical learning models were tested with the data set on-hand, which leads the authors to recognize that other, more predictively powerful explanatory variables for submarine power cable cost may exist, beyond the scope of this data set. One variable that could not be collected for a sufficient number of projects was the *cross-sectional area* (mm^2) of the conductor core per cable. In conversations with industry representatives, it emerged that this might be a valuable piece of information to approximate material cost. The best data that could be acquired from the public domain was the global market price of copper. However, this variable might be neither the only, nor the best, to aid in predicting cost. As with all large infrastructure projects, there are many factors that contribute to the uncertainty of the final cost. It is hypothesized that any single new variable will bring only a modest decrease in model errors.

3.5 Case Study

The two best-performing predictive models - MARS and Econometric Learning Curve - are applied to a case study described below. The analysis shows that the probabilistic prediction

Table 3.3: **Reduction of EENS (MWh) and Risk Cost [M$]** Due to Replacing the Cable [9]

Failure Year of Cable	Reduction of EENS (MWh)	Cost of risk reduction [M$2006 CAN]	Cost of risk reduction, b_y [M$2012 USD]
2006	1,957	6.008	6.986
2007	718	2.204	2.563
2008	450	1.382	1.607
2009	214	0.657	0.763

gives more valuable information to the decision-maker than the single, mean-value point estimate does.

3.5.1 Problem Description

The submarine power cable system that connects Vancouver Island, British Columbia, Canada to the mainland was chosen for the case study. In 2007, Li *et al.* developed a risk-based approach to assess different cable replacement strategies. It probabilistically assessed the risks of cable failure to the power system, by calculating the expected energy not supplied (EENS) [9], which is one of the most important reliability indices in transmission expansion planning [61]. However, uncertainty in the cost estimate of the replacement cable is not considered. The cost of replacing the submarine power cable is estimated as $8 million CAN 2006, which is $9,298,653 USD 2012. Table 3.3 replicates the results reported in Li *et al.*'s Tables IX [9], and updates the cost data to 2012 real values in USD [91].

The final two columns in Table 3.3 represent the value of the benefit to the system; column three with the original 2006 cost data, while column four is updated to 2012 USD real values. Li *et al.* divide this benefit value by the estimated cost of the cable replacement, $8 million CAN 2006, to get a benefit/cost ratio. If the benefits outweigh the costs, i.e., the benefit/cost ratio is greater than one, then the advised strategy is cable replacement.

The dynamics of system upgrades makes this case study particularly relevant. While the overall risk to the system is predicted to decrease over time due to other system upgrades,

Table 3.4: **Vancouver Island Cable Cost Prediction Data**

	Predictors							
	NumCables	*SubRoute* [km]	*CumulativeLength* [km]	*Voltage* [kV]	*ProjLen* [Years]	*CuPrice* [$2012 USD/ton]	*ConYear*	*AC/DC*
2006	1	5	2,088	300	1	10,653	2006	DC
2007	1	5	2,588	300	1	11,281	2007	DC
2008	1	5	3,135	300	1	11,024	2008	DC
2009	1	5	3,625	300	1	8,127	2009	DC

it is never predicted to be nil. Even this relatively short (5 km) system component could play a big role in reducing system risk. The ultimate decision of whether or not to reduce system risk even further, by replacing the cable, is equally dependent on the cost estimate of the cable replacement, as it is on the estimate of risk reduction. Therefore, emphasis on careful study into cost estimation is just as important as the analysis of system risk.

3.5.2 Probabilistic Model Application

The cost of the Vancouver Island cable replacement is probabilistically estimated using both the MARS model and the Econometric Learning Curve model described in Section 3.3. The data used for prediction is from the British Columbia Transmission Company (BCTC) [103], with all predictor values falling within the range of the training data used to develop the model (see Table 3.1).

Assuming a normal distribution, the cost estimate (μ_y) and the standard deviation (σ_y) (see Table 3.5) have been derived from the testing residuals of the respective model, as discussed in Section 3.4.2.

3.5.3 Uncertainty Analysis and Risk Measures

The decision-making framework for cable replacement, as presented by [9], is a benefit/cost analysis. The cable cost estimate can inform decision-makers in either a deterministic or probabilistic way. The decision analysis with deterministic information, i.e. when only the

Table 3.5: **Probabilistic Cost Prediction** of Vancouver Island Cable

	MARS		**Econometric**	
Year	Mean, μ_y Ln([M$2012 USD])	σ_y	Mean, μ_y Ln([M$2012 USD])	σ_y
2006	15.56	0.6657	15.75	0.6975
2007	15.49	0.6657	15.73	0.6975
2008	16.01	0.6657	15.72	0.6975
2009	16.62	0.6657	15.71	0.6975

Table 3.6: **Deterministic and Probabilistic Analyses**

MARS	Deterministic	Uncertainty Analysis & Probabilistic Risk Measures		
Failure Year of Cable, y	Benefit/Cost ratio, BC_y	$P(BC_y \geq 1)$	BC_y VaR	BC_y CVaR
2006	1.22	61.7%	0.52	0.36
2007	0.48	13.4%	0.20	0.14
2008	0.18	0.47%	0.07	0.05
2009	0.05	0.0002%	0.02	0.01
Econometric	Deterministic	Uncertainty Analysis & Probabilistic Risk Measures		
Failure Year of Cable, y	Benefit/Cost ratio, BC_y	$P(BC_y \geq 1)$	BC_y VaR	BC_y CVaR
2006	1.01	50.6%	0.41	0.28
2007	0.38	8.08%	0.15	0.11
2008	0.24	2.02%	0.10	0.07
2009	0.11	0.096%	0.05	0.03

mean cost estimate is presented to the decision-maker, is shown in Table 3.6. Using Li *et al.*'s calculations of the benefit per year (see Table 3.3), the benefit/cost ratio is calculated. Given only a point estimate of cost, a decision-maker would choose to replace the cable if the benefit/cost ratio is greater than one. As seen in Table 3.6, this occurs only in the first year, 2006.

Because the cost of the cable investment is large and irreversible, in such a setting it is natural to consider the variability in cost, in addition to the deterministic, average cost; namely, through mean-risk formulations. These formulations have two important benefits: they require only two moments, which can be estimated, and they provide useful recommendations [104].

We illustrate these analysis possibilities with three different types of risk measures: a probability - the probability that the cost is higher than the benefit, i.e., that the benefit/cost ratio is lower than one; a quantile - the 90% *value-at-risk* (VaR), i.e., the minimum benefit/cost ratio likely to happen with a 90% probability; and a tail expectation - the 90% *conditional-value-at-risk* (CVaR), i.e., the expected value of the 10% worst benefit/cost ratios.

Using the full distribution of the cable cost estimate, the probability that the benefit/cost ratio, BC_y, will be greater than one is given in Eq. 3.11. This is determined by calculating the probability that the cost is less than or equal to the benefit value in that year b_y, where y is the year of cable failure. This is according to the probability density function (Eq. 3.11) of the log-normal random variable cost estimate, X_y, where μ_y is the mean cost estimate, σ_y is the standard deviation of the cost estimate, and b_y is the value of the benefit. This calculation gives the probability that the cost estimate would equal the benefit, making the benefit/cost ratio at least one. The results are shown in column three ($P(BC_y \geq 1)$) of Table 3.6.

$$P(X_y \leq b_y) = \int_{-\infty}^{b_y} \frac{1}{\sqrt{2\pi}\sigma_y b_y} e^{-(ln(b_y)-\mu_y)^2/2\sigma_y^2} \qquad \forall y \qquad (3.11)$$

A quantile risk measure often used by decision-makers, termed *Value-at-Risk* (VaR) and given by Eq. 3.12, calculates the value of the random variable (i.e. the submarine cable cost estimate) at the desired q-quantile.

$$VaR(q) = exp(\mu_y + \sigma_y \Phi^{-1}(q)) \qquad \forall y \qquad (3.12)$$

The results shown in column four of Table 3.6 were calculated at the 90th percentile of the cost. These results tell the decision-maker that, for example, according to the MARS model in the year 2006, with 90% probability the benefit/cost ratio will be higher than 0.52. Thus, the risk of a benefit/cost ratio below 0.52 is very low. Using the VaR risk metric gives the decision-maker not only the value of a worse-than-expected benefit/cost ratio, but the variability of the cost distribution. A very risk averse decision-maker may decide that, even though the expected benefit/cost ratio is significantly greater than one, the VaR of 0.52 is too far from the expected, and too low, to go ahead with the investment. It is left to the decision-maker to assess what value of risk s/he is willing to take on.

A third risk metric, a tail-expectation termed the *Conditional-Value-at-Risk* (CVaR), is also calculated. CVaR measures the expected value of the cost random variable at the specified tail of the distribution. The BC_y CVaR results given in column five of Table 3.6 are again at the $q =$ 90th percentile of cost.

$$CVaR(q) = \frac{e^{\mu_y + \sigma_y^2/2}}{1-q}(1 - \Phi(\Phi^{-1}(q) - \sigma_y)) \qquad \forall y \tag{3.13}$$

As shown in Eq. 3.13, CVaR calculates the expected value of the 10% worst cost estimates, which are, in terms of this case study, the expected value of the 10% highest costs. Thus, the CVaR calculated here gives the risk of a significantly lower-than-expected benefit/cost ratio. For example, in 2006, the Econometric model gives a 90% BC_y CVaR equal to 0.28; an extremely risk-averse decision-maker may find the risk of such a low benefit/cost ratio unacceptable, even though the mean benefit/cost ratio indicates a favorable cost.

Both VaR and CVaR present the decision-maker with information about the tail of the probability distribution, or what might happen in an extreme case. Along with the probability of the benefit/cost ratio being greater than one ($P(BC_y \geq 1)$), information about the uncertainty associated with the cost estimate provides added value to the decision-maker. Risk metrics are such an important tool in decision-making that recent research is bringing them directly into the optimization problem [105][106].

3.6 Conclusion

A well-performing model for early cost prediction of submarine cable projects has been developed. While the model framework, MARS, is a complex statistical learning model, the data input needed to make a prediction is publicly available. Where decision contexts do not demand the precision accuracy given by the MARS model, the Econometric learning curve model, with less input data, may suffice as reasonably accurate.

Both models output the uncertainty around the predicted cost value, giving decision-makers the ability to calculate risks and assess investment decisions based on those risks. The cost prediction models developed give valuable information to decision-makers in industry, policy analysis and academia, when cost estimation is an integral component of alternatives assessment.

3.7 Addendum

3.7.1 Probabilistic Prediction Normality Assumption

The graph below illustrates the applicability of the normality assumption of the probabilistic prediction in Section 3.4, comparing the residuals of the MARS model to a standard normal distribution.

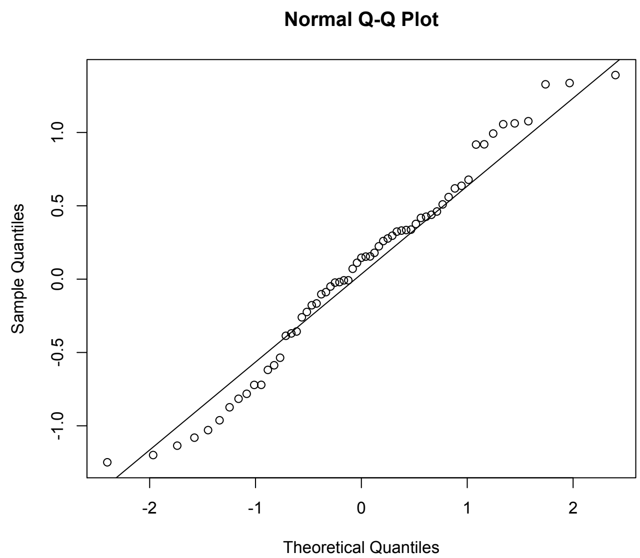


Figure 3.2: Verificiation of normal probabilistic prediction assumption.

While both left and right tails appear, general adherence to the zero deviation line demonstrates that the assumption of a normal distribution is reasonable.

3.7.2 Future Work

The basic idea behind learning curves is that, as experience is gained in the market in deploying a technology such as subsea power cables, competition between suppliers intensifies which reduces cost [97][98]. Learning curve models are routinely utilized within larger energy system models in the United States (US) [107] and the European Union (EU) [108], as well as in climate change integrated-assessment models (IAM) [109]. The assumptions of both learning curve specifications and exogenously utilized learning rates can dramatically affect overall model results, as in [108], where fast-learning assumptions resulted in almost five times the GDP gain in the EU when compared to no-learning. It is imperative to use accurately specified learning curve models, as the overall results of these bottom-up energy and climate change models are often the basis of federal, European Union-level policy designs.

An interesting avenue of future work in this area would be to build statistical learning models for other energy generation technologies (*i.e.* wind, offshore wind, biogas, etc.), and compare cost predictions against their corresponding technological learning curve models. This would verify if the technological learning curves currently being employed in climate change models are resulting in reasonable investment strategies and policy recommendations.

Chapter 4

Complementarity modeling of Renewable Energy Credit (REC) and electricity markets to inform effective renewable energy policy formation

Across the United States (U.S.), at least 2,650 renewable energy incentives and regulations exist at the state level. The most common overarching policy instrument is the Renewable Portfolio Standard (RPS), also known as a Renewable Energy Target (RET), which mandates that a certain percentage of electricity be produced from renewable energy. The highest targets in the U.S. are currently 100% renewable energy production in Hawaii by 2045, and 50% in both California and Oregon by 2030 and 2040, respectively. While the overarching goal of increasing renewable energy production is common among policies, the mechanisms for achieving a given RET vary widely. This study is one of the first to analyze whether an RET is best set as a single or multi-stage goal; at the state level (regionally), or

This chapter is based on Schell et al. [110].

at the firm-level; and whether the mechanism of trading the environmental benefits of renewable energy via Renewable Energy Credits (RECs) aids RET achievement. By modeling both the REC and electricity market, this study finds that an RET policy design of multi-stage targets at the firm-level, without an REC market, is optimal. It not only achieves the highest social surplus, but also the highest renewable investment, as well as the greatest reduction in greenhouse gas emissions.

4.1 Introduction

Policies that incentivize renewable energy have become so commonplace that the U.S. Department of Energy has established a center for tracking policy updates, titled the *Database of State Incentives for Renewables & Efficiency* [22]. Across the U.S., at least 2,650 renewable energy incentives and regulations exist at the state level.

Despite the prevalence of policies that increase the use of renewable energy in the United States, few studies have examined potential policy interference, whether constructive or destructive [111][112]. Even less research has evaluated whether these policies individually, or collectively, are producing the desired results, and at what cost [15][113][35]. Fewer still have been conducted to determine if the predominant policy in most states - an RET - is the best instrument to achieve the primary climate change mitigation goal of greenhouse gas emissions reduction. For example, Bird et al. [30] have shown that, at the federal level, a policy of a greenhouse gas emissions target, known as a *carbon cap*, results in more investment in renewable energy, with higher emissions reductions, and at a lower cost, than either a cap-and-trade policy, an RET policy, or a combination of the two.

4.1.1 Complementarity Modeling for Policy Analysis

With the increasing complexity of electricity markets, "it will be harder to accurately gauge the effects of proposed regulations, policies, or other inputs without tools like" complementarity modeling [114]. Complementarity models allow the representation of several optimiziation problems (such as each individual electricity producer's problem of profit maximization) to be solved jointly with the clearing of the wholesale electricity and ancillary markets. Thus, the main advantage of complementarity models is that both primal and dual decision variables can be directly manipulated. In terms of electricity markets, primal variables refer to the technical decisions, such as how much electricity to produce from a certain generating unit, and which units to invest in or expand. Complementarity model formulations also allow for the dual variables in electricity market optimization models - the prices - to be manipulated [114].

Over the past decade, complementarity modeling has been essential for modeling deregulated electricity markets, which are characterized by an increasing number of agents. For example, Hobbs [115] showed the equivalence of bilateral contracts to pooled electricity markets, and this provided the basis for merger evaluations and market power studies [116][117], transmission congestion effects [118][119] and renewable energy policy evaluation [120][121].

4.1.2 Complementarity Modeling for Renewable Energy Policy Analysis

Recent work with complementarity modeling of electricity systems, markets and regulation has focused largely on the effect of carbon cap-and-trade regulations versus carbon taxation. He et al. [120] show that a cap-and-trade policy is equivalent to a uniform carbon tax, when banking of allowances is permitted. However, a combination of a carbon tax and subsidies could be more efficient than a carbon tax alone. For the European Union Emissions Trading Scheme (EU ETS), an example of carbon cap-and-trade regulation, Bonenti et al. [122] find that strategic generation companies can increase their profits, despite increasing carbon allowance prices. While renewable energy policy is not modeled explicitly, they determined that renewable energy policies or incentives would be needed to force investment and expansion in renewable energy in Italy. Without a policy that incentivized renewables, generating firms preferred and prioritized expansion investment in combined-cycle gas turbines (CCGT), which emits slightly less greenhouse gas (GHGs) than traditional fossil fuels.

Others have utilized complementarity models to analyze both carbon and renewable energy policies. Linares et al. [3] find that an RET policy actually indirectly reduces electricity prices. By increasing the share of renewable energy generation, the carbon allowance price is reduced, and so also is the electricity price. Further, they find that a carbon cap-and-trade policy by itself cannot stimulate much renewable energy investment in the Spanish electricity system; an RET is needed in order to achieve this goal.

Similarly, Chen and Wang [121] model carbon cap-and-trade policy in conjunction with RET policy and voluntary green pricing of renewable electricity. While their model takes into account the operational and transmission constraints of the electricity system, they do not model the possibility of renewable energy expansion, and thus do not fully account for the effect of RET policies on the market. Analyzing various policy formulations for RETs and green pricing premiums, it was found that the social surplus is highest when renewable energy production is allowed to count towards an RET, as well as sold as green power.

Fewer studies have employed complementarity modeling solely for renewable energy policy analysis. Siddiqi et al. [123] analyzed the difference that market structure (i.e. such as centrally planned, perfectly competitive and a Cournot oligopoly) makes on the endogenous determination of an optimal RET. Although neither the production nor the transmission system technical constraints are accounted for, it was concluded that the type of market structure must be considered when policymakers regulate RETs, or substantial welfare loss could occur.

4.1.3 Paper Aims and Structure

This study is one of the first to use complementarity modeling to analyze RET policy formation. It investigates whether it ought to be a single goal, or one that is increasingly stringent over time. It also explores whether it should be set at the regional or the firm-level, and how the mechanism of trading the environmental benefits of renewable energy - via Renewable Energy Credits (RECs) - impacts RET achievement and the broader social goals of renewable energy policy. In Section 4.2, we discuss our complementarity model in detail. Section **??** presents our results, and Section **??** both summarizes the main outcomes and explores policy implications.

4.2 Methods

A market equilibrium model is employed to represent the interaction of market agents, the electricity market and the renewable energy credit market [114]. Fig. 4.1 illustrates the interaction of the strategic generating firms' profit maximization problem, which is subject to technical constraints, with the clearing of the electricity and renewable energy credit markets.

The market equilibrium problem can be presented as a mixed linear complementarity problem (MCP) via the expression of each firm's optimization problem as its corresponding Karush-Kuhn-Tucker (KKT) conditions, along with the market clearing equations. Solving this system of equations simultaneously gives the equilibrium solution to the problem.

The sets, parameters and variables of the MCP model are presented below.

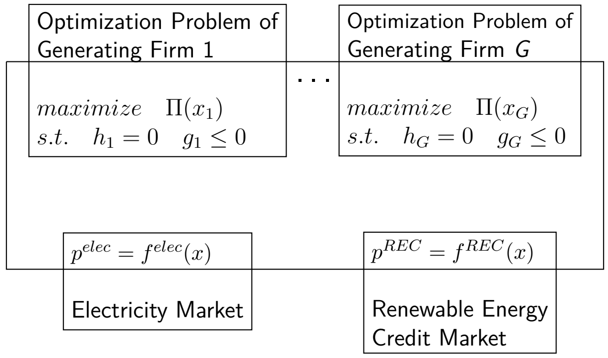


Figure 4.1: Schematic of the market equilibrium problem, adapted from [3].

Table 4.1: Model sets, parameters and variables

Sets	Description	
$\mathcal{I}$	set of nodes *i, j* $\in \mathcal{I}$	
$\mathcal{L}$	set of transmission lines *l* $\in \mathcal{L}$	
$\mathcal{B}$	set of load blocks *b* $\in \mathcal{B}$	
$\mathcal{F}$	set of generating firms *f, g* $\in \mathcal{F}$	
$\mathcal{H}$	set of generating units *h* $\in \mathcal{H}$	
$\mathcal{T}$	set of time periods *t* $\in \mathcal{T}$	
Parameters	**Description**	**Units**
C_{fih}	generator *f*'s marginal cost of technology *h* at node *i*	[$/MWh]
I_{fih}	generator *f*'s investment cost of technology *h* at node *i*	[$/MW]
K^0_{fih}	initial capacity of technology *h* at node *i* owned by generator *f*	[MW]
K^{max}_{fih}	maximum capacity expansion of technology *h* at node *i* owned by generator *f*	[MW]
CF_{fih}	capacity factor of technology *h* at node *i* owned by generator *f*	[%]
RE_h	renewable classification of technology *h*	[0/1]
B_{hb}	availability of technology *h* for demand block *b*	[0/1]
D_b	duration of load block *b*	[hours]
P^0_{itb}	price intercept at node *i* in time *t* and demand block *b*	[$/MWh]
Q^0_{itb}	quantity intercept at node *i* in time *t* and demand block *b*	[MW]
$PTDF_{il}$	power transmission distribution factor, node *i* to interface l	dimensionless
T_l	maximum capacity of power flows through line *l*	[MW]
RET_t	renewable energy target in time *t*	[%]
β	discount factor	dimensionless
M	sufficiently large number	dimensionless
Decision Variables	**Description**	**Units**
x_{fihtb}	production of generator *f*'s technology *h* at node *i* in time *t* and demand block *b*	[MW]
K_{fiht}	total capacity expansion of technology *h* at node *i* in time *t* owned by generator *f*	[MW]
s_{fitb}	sales from generator *f* at node *i* in time *t* at demand block *b*	[MW]
r_{ft}	renewable energy credits (RECs) purchased by generator *f* in time *t*	[MWh]
a^{REC}_{ft}	renewable energy production sold as a REC, by generator *f* in time *t*	[MWh]
a_{ft}	renewable energy production *not* sold as a REC, by generator *f* in time *t*	[MWh]
y_{itb}	power injected at node *i* in time *t* and demand block *b*	[MW]
Market Clearing Dual Variables	**Description**	**Units**
w_{itb}	payment from generator *f* to send power from generation node*i* to consumption node *j*	[$/MWh]
p^{REC}_t	price of renewable energy credit (REC) at time *t*	[$/MWh]
Dual Variables	**Description**	**Units**
θ_{ftb}	dual variables for constraint 4.2	[$/MW]
ρ_{fiht}	dual variables for constraint 4.3	[$/MW]
γ_{fiht}	dual variables for constraint 4.4	[$/MW]
μ_{fihtb}	dual variables for constraint 4.5	[$/MW]
δ_{ft}	dual variables for constraint 4.6	[$/MWh]
η_{ft}	dual variables for constraint 4.7	[$/MWh]
λ^+_{ltb}	dual variables for constraint 4.10	[$/MWh]
λ^-_{ltb}	dual variables for constraint 4.11	[$/MWh]

4.2.1 Generating Firm's Problem

Each generating firm is modeled as a strategic producer, vying to maximize its own profit. We assume that each firm knows the inverse demand curve of the entire market and uses this knowledge to assess how a change in its own production would affect the equilibrium price of electricity. Here, the inverse demand curve is further specified per node, time period and demand block (see Eq. 4.1). Under the Cournot assumption, each generating firm assumes fixed values of production for the other firms (all s_{gitb} for $g \neq f$). This is coupled with the Nash extension that each firm assumes the others' production decisions are beyond its control, resulting in a Nash-Cournot equilibrium [115].

Each generating firm's problem is formulated as a generation expansion planning (GEP) problem, allowing the firm to invest in new generation capacity (Eq. 4.3) if it is either profitable or necessary to meet a renewable energy target (RET) (Eq. 4.7). The first term in the firm's objective function (Eq. 4.1) calculates the firm's profit from electricity sales, minus the cost of transmission; the second term subtracts the marginal cost of generation from the firm's profit, but adds transmission revenue; the third and fourth terms subtract investment cost in new generation, as well as the cost of any renewable energy credit (REC) purchases to meet an RET.

Eq. 4.2 balances the sales of electricity to all nodes with actual production. Eq. 4.3 ensures electricity production is less than total capacity, times a capacity factor, CF_{fih}. This capacity factor incorporates the variability associated with renewable energy resources, as well as the expected down-time of fossil fuel generators for maintenance and repairs.

$$\max \quad \sum_{jtb} \beta^{t-1} D_b \left[P^0_{jtb} - \frac{P^0_{jtb}}{Q^0_{jtb}} \left(\sum_{g} s_{gjtb} \right) - w_{jtb} \right] s_{fjtb} - \sum_{ihtb} \beta^{t-1} D_b \left[C_{fiht} - w_{itb} \right] x_{fihtb} \tag{4.1}$$

$$- \sum_{iht} \beta^{t-1} I_{fih} K_{fiht} - \sum_{t} \beta^{t-1} p_t^{REC} r_{ft}$$

$$\text{s.t.} \quad \sum_{j} s_{fjtb} = \sum_{ih} x_{fihtb} \quad (\theta_{ftb}) \quad \forall t, b \tag{4.2}$$

$$x_{fihtb} \leq (K_{fih}^{0} + \sum_{\tau=1}^{t-1} K_{fih\tau}) CF_{fih} \quad (\rho_{fihtb}) \quad \forall i, h, t, b \tag{4.3}$$

$$\sum_{t} K_{fiht} \leq K_{fih}^{\max} \quad (\gamma_{fih}) \quad \forall i, h \tag{4.4}$$

$$x_{fihtb} \leq B_{hb} M \quad (\mu_{fihtb}) \quad \forall i, h, t, b \tag{4.5}$$

$$a_{ft} + a_{ft}^{REC} = \sum_{ihb} D_b \, \mathrm{RE}_h \, x_{fihtb} \quad (\delta_{ft}) \quad \forall t \tag{4.6}$$

$$a_{ft} + r_{ft} \geq RET_{ft} (\sum_{ihb} D_b x_{fihtb}) \quad (\eta_{ft}) \quad \forall t \tag{4.7}$$

$$s_{fitb}, x_{fihtb}, K_{fiht}, a_{ft}, r_{ft} \geq 0 \quad \forall i, h, t, b \tag{4.8}$$

Generation capacity expansion is limited by both estimates of natural resource availability and available siting area (Eq. 4.4). Further, each generating unit is limited by its availability to reasonably serve a load type (Eq. 4.5). For example, intermittent wind cannot be used to meet baseload demand.

The sale of renewable energy credits is tracked by variable r_{ft}, while the production of renewable energy expressly for the purpose of being put into the REC market is tracked by variable a_{ft}^{REC}. Equation 4.6 ensures that there is no double-counting: the renewable energy produced and used by the firm itself (a_{ft}) is not available for sale as RECs (a_{ft}^{REC}).

The RET policy described in the model presented here (Eq. 4.7) represents a firm-level attribution of a renewable target. This model specification corresponds to *Scenarios 1c* and *3c*, which are further elaborated upon in Section 4.2.

4.2.2 Transmission System Operator's (TSO) Problem

The grid owner (TSO) is assumed to be a price-taker for the cost of transmission services, w_{itb}. The TSO maximizes profit by maximizing the amount of power transmitted through the grid (y_{itb}).

$$\max \quad \sum_{itb} w_{itb} y_{itb} \tag{4.9}$$

$$\text{s.t.} \quad \sum_{i} PTDF_{il} y_{itb} \leq T_l \quad (\lambda^{+}_{ltb}) \quad \forall l, t, b \tag{4.10}$$

$$-\sum_{i} PTDF_{il} y_{itb} \leq T_l \quad (\lambda^{-}_{ltb}) \quad \forall l, t, b \tag{4.11}$$

$$\tag{4.12}$$

Transmission through the grid is subject to: the specific network topology; the physical constraints of Kirchhoff's laws, via the Power Transfer Distribution Factor matrix (PTDF); as well as the capacity limits on the transmission lines (T_l) [124].

4.2.3 Market Clearing

In addition to simultaneously solving the Generating Firm's and the TSO's optimization problems, the following market clearing conditions must also simultaneously be met:

$$\sum_{f} a^{REC}_{ft} \geq \sum_{f} r_{ft} \quad (p^{REC}_{t}) \quad \forall t \tag{4.13}$$

$$y_{itb} = \sum_{f} s_{fitb} - \sum_{fh} x_{fihtb} \quad (w_{itb}) \quad \forall i, t, b \tag{4.14}$$

The REC market clearing equation, Eq. 4.13, requires that the total amount of RECs sold in the market cannot exceed the total amount of renewable energy actually produced, for that purpose. The dual variable of this equation gives the market price of an REC. Eq. 4.2 ensures equilibrium in the electricity market when the TSO's power injection decision is balanced with all firms' decisions on sales (s_{fitb}) and power (x_{fihtb}) (Eq. 4.14).

4.2.4 Karush-Kuhn-Tucker Optimality Conditions

The Karush-Kuhn-Tucker optimality conditions of all generating firms' optimization problems, together with the TSO optimization problem, represent the necessary and sufficient conditions for a market equilibrium. These are outlined in Eqs. 4.15 - 4.31 below.

$$0 \leq s_{fjtb} \perp -\beta^{t-1} D_b \left[P^0_{jtb} - \frac{P^0_{jtb}}{Q^0_{jtb}} \left(s_{fjtb} + \sum_g s_{gjtb} \right) - w_{jtb} \right] + \theta_{ftb} \geq 0 \quad \forall f, i, t, b \tag{4.15}$$

$$\begin{aligned} 0 \leq x_{fihtb} \perp \beta^{t-1} D_b \left(C_{fiht} - w_{itb} \right) - \theta_{ftb} + \rho_{fihtb} \\ + \mu_{fihtb} + D_b(\delta_{ft} RE_h + \eta_{ft} RET_{ft}) \geq 0 \quad \forall f, i, h, t, b \end{aligned} \tag{4.16}$$

$$0 \leq K_{fiht} \perp \beta^{t-1} I_{fih} - CF_{fih} (\sum_b \sum_{\tau=t+1}^{T} \rho_{fih\tau b}) + \gamma_{fih} \geq 0 \quad \forall f, i, h, t \tag{4.17}$$

$$\sum_i s_{fitb} = \sum_{ih} x_{fihtb} \quad \forall f, t, b \tag{4.18}$$

$$0 \leq \rho_{fihtb} \perp CF_{fih} (K^0_{fih} + \sum_{\tau=1}^{t-1} K_{fih\tau}) - x_{fihtb} \geq 0 \quad \forall f, i, h, t, b \tag{4.19}$$

$$0 \leq \gamma_{fih} \perp K^{\max}_{fiht} - \sum_t K_{fiht} \geq 0 \quad \forall f, i, h \tag{4.20}$$

$$0 \leq \mu_{fihtb} \perp B_{hb} M - x_{fihtb} \geq 0 \quad \forall f, i, h, t, b \tag{4.21}$$

$$0 \leq p^{REC}_t \perp \sum_f a^{REC}_{ft} - \sum_f r_{ft} \geq 0 \quad \forall t \tag{4.22}$$

$$a_{ft} + a^{REC}_{ft} = \sum_{ihb} D_b RE_h x_{fihtb} \quad \forall f, t \tag{4.23}$$

$$0 \leq a_{ft}^{REC} \perp -\delta_{ft} - p_t^{REC} \geq 0 \quad \forall f, t \tag{4.24}$$

$$0 \leq a_{ft} \perp -\delta_{ft} - \eta_{ft} \geq 0 \quad \forall f, t \tag{4.25}$$

$$0 \leq \eta_{ft} \perp a_{ft} + r_{ft} - RET_{ft}(\sum_{ihb} D_b x_{fihtb}) \geq 0 \quad \forall f, t \tag{4.26}$$

$$0 \leq r_{ft} \perp \beta^{t-1} p_t^{REC} - \eta_{ft} + p_t^{REC} \geq 0 \quad \forall f, t \tag{4.27}$$

$$w_{itb} = -\sum_l PTDF_{il}(\lambda_{ltb}^- - \lambda_{ltb}^+) \quad \forall i, t, b \tag{4.28}$$

$$0 \leq \lambda_{ltb}^+ \perp T_l - \sum_i PTDF_{il} y_{itb} \geq 0 \quad \forall l, t, b \tag{4.29}$$

$$0 \leq \lambda_{ltb}^- \perp T_l + \sum_i PTDF_{il} y_{itb} \geq 0 \quad \forall l, t, b \tag{4.30}$$

$$y_{itb} = \sum_f s_{fitb} - \sum_{fh} x_{fihtb} \quad \forall i, t, b \tag{4.31}$$

4.2.5 Scenarios

The base model described in Sections 4.2.1 - 4.2.4 depicts an electricity market faced with a mandatory renewable energy target (RET) policy. In order to facilitate achievement of this policy goal at least cost to all market participants (producers, TSOs and consumers), the regulators have introduced an REC market. A producer may choose to buy an REC in lieu of investing in or producing from its own renewable energy generation. Whether or not the introduction of this REC market would increase social welfare is one of the main research questions of this study.

We address the efficiency of an REC market through the analysis of eight different RET policy scenarios. These scenarios are outlined in Table 4.2 below. They are broadly defined by three characteristics: 1) whether the renewable energy target is a single, ambitious one to be met in the future, or a series of increasingly stringent targets; 2) whether an REC market is in place to facilitate RET achievement; and, 3) whether the RET must be achieved collectively at a regional level, or individually at the firm-level. Analyzing the market outcomes of these eight scenarios will highlight the tradeoffs between the eight different policy designs.

Table 4.2: Description of model scenarios.

	RET - single goal		**RET** - multiple goals	
	REC market	No REC market	REC market	No REC market
Regional	1a	1b	3a	3b
Firm-level	1c	1d	3c	3d

Mathematically, specifying these different scenarios requires slight changes to the RET and REC market clearing equations (Eqs. 4.7 and 4.13). These changes are enumerated in B.1.

4.2.6 Case Study and Data

The model, modified for the eight scenarios in Table 4.2, is applied to a case study of the Azores Islands, a Portuguese archipelago in the mid-North Atlantic. To make model results tractable, only two islands are studied (São Miguel and Santa Maria), over a load duration curve divided into three blocks (base, middle and peak), for a time period of ten years (2015, 2020 and 2025).

We model the islands as linked with a single submarine power cable so that renewable production on one island can be sold to the other. The transmission line is assumed to have unlimited capacity. Each island is modeled as one firm, and has generation capabilities only on its own node (i.e. f equals i in this case study). São Miguel island, the largest in the archipelago, correspondingly has the highest population with the highest demand. It is also endowed with the most exploitable geothermal resources. Santa Maria island has 4.6% of the demand of São Miguel, but has reasonable wind resources.

This case study represents an application of the model to a two-node network with unlimited transmission capacity, and the ability of both firms to invest in more renewable generation. It is not meant to, nor does it, represent the actual situation of the market on the Azores Islands.

Table 4.3: **Data.** The cost data is from ERSE [5], the International Renewable Energy Agency (IRENA) [6], and the International Energy Agency (IEA) [7].

	K^0_{fih} [MW]		K^{max}_{fih} [MW]		CF_{fih} [%]		Inv_{fih} [\$/MW]	C_{fih} [\$/MWh]	RE_h	B_{hb}		
	f_1	f_2	f_1	f_2	f_1	f_2				Base	Middle	Peak
Wind	0	0.9	18.3	0.6	29.3	32.9	261,000	90	1	0	1	0
Offshore Wind	0	0	50	50	31.3	34.9	562,000	49	1	0	1	0
Hydropower	5.03	0	6.75	0	40.0	40.0	615,000	90	1	0	1	0
Geothermal	27.8	0	47.7	0	72.1	72.1	397,000	22	1	1	0	0
Solar	0	0	50	50	11.6	11.6	569,000	325	1	0	1	0
Wave	0	0	50	50	30.0	30.0	629,000	50	1	0	1	0
Diesel	0	5.68	50	50	79.1	79.1	130,000	42	0	1	1	1
Fuel Oil	98.1	0	50	50	79.1	79.1	137,000	43	0	1	1	1
Biogas	0	0	12.8	0.53	79.1	79.1	574,000	80	1	1	1	1

Table 4.3 shows the current generation capacity, as well as the natural expansion and production limits per generation technology and island. The same table also shows the investment and operating costs by technology type; in this case study, the costs are the same for both firms. The islands are distinguished as f_1 and f_2 (firm 1 and firm 2) for São Miguel and Santa Maria, respectively.

Table A.2 gives the demand data per island via the inverse demand curve.

Table 4.4: **Data.** Inverse Demand Function.

		P^0_{itb} [\$/MW]		Q^0_{itb} [MW]	
		f_1	f_2	f_1	f_2
2015	Base	563	1,171	0.56	1.17
	Middle	923	1,920	0.92	1.92
	Peak	1,013	2,108	1.01	2.11
2020	Base	621	1,293	0.62	1.29
	Middle	1,019	2,120	1.02	2.12
	Peak	1,118	2,327	1.12	2.33
2025	Base	686	1,427	0.69	1.43
	Middle	1,125	2,341	1.12	2.34
	Peak	1,234	2,569	1.23	2.57

The RET profile we employ throughout this study is summarized in Table 4.5. When an RET is designed as a single goal, it is set at 75% in 2025.

Table 4.5: **Data.** Renewable energy target (RET).

Time Period	**RET** [%]
2015	20
2020	40
2025	75

4.3 Results

The model results for each scenario described in Section 4.2 are analyzed with respect to the overarching policy goals of incentivizing new renewable energy investment, decreasing greenhouse gas (GHG) emissions, and increasing economic efficiency. These results, presented in Tables 4.6 - 4.12, are discussed in this section.

4.3.1 RET Achievement: Renewable Energy Investment vs. REC Trading

The highest investment in renewable energy occurs in *Scenarios 1d* and *3d*, when the RET is set at the firm-level and there is no REC market. The increased renewable energy investment in these scenarios is driven by compounding factors: 1) because the RET is set at the firm-level, *each* firm must meet an RET; and 2) because there is no REC market, the RET must be met by each firm, using either existing or new renewable energy production. In all scenarios, the new renewable investment comes from Firm 2 (Santa Maria), which does not have enough existing renewable energy generation to meet the middle RET of 40%, or the highest RET of 75%.

As Table 4.6 shows, the Azores Islands case study involves very small electricity systems. Hence, the limited amount of generation expansion required to meet the RETs.

In fact, even in the case where the RET is regional, Firm 2 still invests in renewable energy when there is no REC market (*Scenarios 1b* and *3b*). This is due to the fact that

Table 4.6: **Total renewable energy investment** [MW] per scenario, across time periods.

Renewable Investment [MW]	**RET** - single goal				**RET** - multiple goals			
	REC market		No REC market		REC market		No REC market	
Regional	*1a*	0.38	*1b*	0.38	*3a*	0.38	*3b*	0.38
Firm-level	*1c*	0.39	*1d*	0.53	*3c*	0.39	*3d*	0.53

each firm has knowledge of the entire market demand, via the inverse demand curves. Thus, both firms are strategically managing their own production and investments to meet demand while keeping prices (and therefore profits) as high as possible. With the implementation of an RET policy, renewable generation becomes the most valuable asset. In order to stay competitive in the electricity market, Firm 2 must invest in renewable energy. It makes the strategic decision that maximizes its profit, which results in a rather modest investment in 0.38 MW of biogas. The choice of biogas is also strategic, as this is the only renewable energy generator that can operate to meet all demand levels - base, middle and peak.

Table 4.7 shows the total amount of RECs traded per scenario. Because Firm 2 must invest in renewable energy to stay competitive, this necessity precludes the usefulness of an REC market, under a regional RET policy (*Scenarios 1a* and *3a*). Both firms produce renewable energy to meet the regional RET, but there is no advantage to purchasing RECs in order to meet the RET.

Table 4.7: **Total renewable energy credits traded** [MW] per scenario, across time periods.

RECs Traded [MW]	**RET** - single goal				**RET** - multiple goals			
	REC market		No REC market		REC market		No REC market	
Regional	*1a*	0	*1b*	n/a	*3a*	0	*3b*	n/a
Firm-level	*1c*	1,152	*1d*	n/a	*3c*	4,115	*3d*	n/a

When the RET policy is applied at the firm-level, however, REC purchasing becomes attractive to the firm with fewer renewable energy assets (Firm 2). It sells its renewable energy production in the electricity market because the prices are considerably higher than the price of a renewable energy credit, even at a high RET. Because Firm 1 has sufficient renewable energy assets to meet its own RETs, it seizes the opportunity to overproduce renewable energy and sell that overproduction as RECs to Firm 2.

An REC is only valued when an RET is being enforced. Table 4.8 shows how the price of the credit, p_t^{REC}, changes with each RET and time period. As the target becomes more stringent, the price of the REC increases.

Table 4.8: **REC price** [\$/MWh] per scenario, per time period.

REC Price [\$/MWh]	**RET** - single goal				**RET** - multiple goals			
	REC market		No REC market		REC market		No REC market	
Regional - 2015	*1a*	0	*1b*	-	*3a*	7	*3b*	-
2020		0		-		15		-
2025		38		-		38		-
Firm-level - 2015	*1c*	0	*1d*	-	*3c*	11	*3d*	-
2020		0		-		22		-
2025		38		-		38		-

Even though the price of the REC is lower than the wholesale electricity price, it does not negate Firm 2's need to invest in renewable energy in order to compete in the electricity market at high RETs.

4.3.2 Greenhouse Gas Emissions

The price of an REC is never high enough to warrant renewable energy investment simply for the purpose of participating in the renewable energy credit market. Thus, while the presence of an REC market might facilitate small, fossil-fuel based firms in achieving a firm-level RET, its existence does not encourage as much GHG reductions as an RET policy. The total GHG emissions per scenario are shown in Table 4.9.

Table 4.9: **Total greenhouse gas emissions** (GHG) [tons] per scenario, across time periods.

Greenhouse Gas Emissions [tons]	**RET** - single goal				**RET** - multiple goals			
	REC market		No REC market		REC market		No REC market	
Regional	*1a*	26,078	*1b*	26,078	*3a*	23,032	*3b*	23,032
Firm-level	*1c*	26,070	*1d*	26,040	*3c*	22,988	*3d*	21,162

Scenario 3d results in the lowest total GHG emissions because the multi-stage targets require investment in, and production from, renewable energy earlier than any other scenario. Due to the absence of an REC market, Firm 2 must meet the RET via its own renewable energy production. This requires an increase in renewable energy investment, compared to scenarios without a REC market. While the increased production from renewable energy generation contributes to a reduction in GHG emissions, its main cause is a decrease in overall production (Table 4.10).

Table 4.10: **Total electricity production** [MW] per scenario, across time periods.

Total Production [MW]	**RET** - single goal				**RET** - multiple goals			
	REC market		No REC market		REC market		No REC market	
Regional	*1a*	42,970	*1b*	42,970	*3a*	42,898	*3b*	42,898
Firm-level	*1c*	42,937	*1d*	42,696	*3c*	42,800	*3d*	41,904

Table 4.10 shows how, as the RET policy becomes more restrictive by moving to firm-level achievement and eliminating the REC market, total electricity production decreases. This is a supply and demand issue. The RET policy mandates an increase in renewable generation, which forces the producers to decrease generation from other technologies in order to maintain high prices. As Table 4.11 shows, the more restrictive an RET policy, the less profitable a firm with few renewable assets becomes.

Table 4.11: **Total profits** [$] per firm, per scenario, across time periods.

	Total Profits [$]	**RET** - single goal				**RET** - multiple goals			
		REC market		No REC market		REC market		No REC market	
Regional	Firm 1	*1a*	5,294,257	*1b*	5,294,257	*3a*	5,290,642	*3b*	5,290,642
	Firm 2		4,752,461		4,752,461		4,721,452		4,721,452
Firm-level	Firm 1	*1c*	5,291,751	*1d*	5,356,619	*3c*	5,337,060	*3d*	5,769,298
	Firm 2		4,741,049		4,685,323		4,648,031		4,345,306

Firm 2's profits are a case in point, as they are always decreasing with the increasing stringency of a renewable energy policy. While this is also the case for Firm 1 under a regional RET policy, a firm-level policy generally works in favor of the firm that already has significant renewable energy assets. This is because, as described in Section 4.3.1, Firm 2 must invest in renewable energy in order to stay competitive in the electricity market. It makes the smallest investment necessary to meet the RET in order to minimize supply and keep prices as high as possible. In *Scenario 3d*, because of the timing of the multi-stage RETs, and the inability to meet them with credits, Firm 2 makes the strategic decision to slightly decrease production. This minimizes the renewable investment needed to meet the RET. Since consumers remain willing to pay for more electricity, Firm 1 is able to supplement the load at node 2. Given this opportunity to over-produce and supply consumers at node 2, Firm 1 is able to maximize its profits under this RET policy.

4.3.3 Economic Efficiency of RET Policy

While the profits per firm may be decreasing, the most restrictive RET policy in terms of goals and achievement mechanisms (*Scenario 3d*), actually results in the highest social surplus (Table 4.12).

In Equation 4.32, the social surplus, or economic efficiency, is defined as the consumer surplus, less the cost of investment and generation.

$$\sum_{fitb} \beta^{t-1} D_b \left[P^0_{itb} s_{fitb} - \frac{P^0_{itb}}{2Q^0_{itb}} \sum_g \left(s_{gitb}\right)^2 \right] - \sum_{fihtb} \beta^{t-1} D_b C_{fiht} x_{fihtb} - \sum_{fiht} \beta^{t-1} I_{fih} K_{fiht} \tag{4.32}$$

Table 4.12 shows that *Scenario 3d* maximizes social surplus. As discussed in Section 4.3.2, the most stringent RET policy (*3d*) results in the less efficient firm reducing its production to meet the RET, so the remaining demand is met by the more efficient firm with the larger renewable energy assets.

Not only does this policy result in the highest social surplus, it also results in the largest reduction in GHG emissions (see Table 4.9).

Table 4.12: **Total social surplus** [$] per scenario, across time periods.

Social Surplus [$]	**RET** - single goal				**RET** - multiple goals			
	REC market		No REC market		REC market		No REC market	
Regional	*1a*	10,046,718	*1b*	10,046,718	*3a*	10,012,093	*3b*	10,012,093
Firm-level	*1c*	10,046,702	*1d*	10,041,941	*3c*	10,025,655	*3d*	10,114,604

4.4 Conclusions

This study used complementarity modeling to investigate eight scenarios for renewable energy target policy achievement. These scenarios apply to strategic generating firms with the resource capacity to expand renewable energy generation. They can also transmit electricity over a transmission network without congestion. The surest way to increase renewable energy generation and reduce greenhouse gas emissions is to enforce a multi-stage RET at the level of individual firms, and to eliminate the renewable energy credit market. The increasingly stringent target stimulates early investment in renewable generation, and its imposition on the firm-level forces individual agents to invest in low-carbon assets to remain competitive in the electricity market. When an RET policy is set at the regional level, a renewable energy credit market is never used to facilitate the target's achievement. Renewable energy investment occurs in all scenarios, as the imposition of an RET policy requires firms with fewer renewable energy assets to invest in more renewable generation in order to stay competitive in the electricity market. Our results show that the aforementioned optimal policy formulation results in the highest social surplus, since the most efficient investment in, and production of, renewable energy is achieved under this policy.

It is clear that renewable energy policy imposition is a fundamentally political affair, as opposed to a mathematically optimal one. Albeit, policymakers could use the results of studies like this to recognize that not all policies are equally efficient. In fact, this paper is part of a nascent but growing literature that demonstrates how destructive interference is possible, even among policies that are well-intentioned and, individually, theoretically favorable. Despite our model's necessary simplification of extremely complicated market dynamics, policymakers should investigate the renewable energy policy portfolio they wish to implement carefully and holistically. In the case of electricity markets similar to the ones modeled in this case study, for example, policymakers seeking to maximize social welfare should consider implementing an increasingly stringent RET at the firm-level, and forego the introduction of an REC market entirely. Our model does not account for REC transaction costs, nor certificate verification, both of which would further decrease the social welfare.

There is much room for further research in this space. Future studies using this method might investigate, for example, the optimal policy in cases where firms are fossil-fuel-dependent and have limited capacity for renewable generation expansion. This would better reflect the case of many electricity systems today. Moreover, it is worthwhile to explore the optimal strategy in electricity systems with substantial transmission constraints, such as the state of California. These are but two examples of future work we plan to undertake; much additional work is needed to ensure that the political decisions being made about renewable energy policies today rest on solid technical sound.

4.5 Addendum

4.5.1 Future Work

Future work for this model involves broadening and extending the case study analysis to one with constrained transmission and less renewable energy expansion options. Comparing the results of this and the previous case study will allow for more generalizable policy recommendations.

Chapter 5

Conclusions

The main conclusions from this thesis provide insights into renewable energy target (RET) policy formulation. It is shown that the geographic attribution of an RET policy has a significant effect on the local economic, social and environmental tradeoffs. For the case study of the Azores Islands, Portugal, a regional geographic attribution of an RET results in: generally, both the lowest cost and the lowest emissions on the archipelago, along with a reasonably diverse distribution of renewable energy investments across the islands. It is also shown that the optimal generation portfolio needed to meet an RET can change dramatically from one RET percentage point to the next. Thus, setting an RET initially too low could result in over-investment of certain renewable energy generation and possible future unuse. It is strongly recommended that decision makers investigate the optimal portfolio generation at the highest considerable RET, to avoid over-investment in renewable generation that may be contrary to what is optimal for higher RET goals.

While one way of achieving a given RET policy is to directly invest in renewable energy generation, another achievement alternative for isolated systems such as islands, is to interconnect to an area with greater renewable resources. In order to assess whether interconnection is a better alternative than direct investment, consistent and accurate cost estimates for submarine power cable projects are needed. Using a global database of 61 submarine power cable projects across application areas, a well-performing model for probabilistic cost prediction of submarine power cable projects was built. The utility of having probabilistic cost predictions is demonstrated via a case study of submarine power cable replacement to Vancouver Island, Canada. Uncertainty in decision making is further illustrated through the calculation of three different types of risk measures: 1) a probability; 2) a quantile - the 90% Value-at-Risk (VaR); and 3) a tail expectation - the 90% Conditional Value-at-Risk (CVaR). A probabilistic cost estimate gives the decision maker the ability to assess investment decisions based on calculated risks. Accurate cost estimation is an integral part of alternatives assessment, which, in turn, is integral to informed decision making.

The final major alternative in RET achievement is through a renewable energy credit (REC) market. When neither direct investment, nor interconnection are feasible or attractive, a firm faced with an RET obligation may choose to buy RECs to do so. Whether or not an REC market is actually helpful in RET achievement was studied via complementarity modeling of both the electricity market and the REC market. In an oligopolistic electricity market, where firms have the ability to meet an RET either through direct investment or by purchasing RECs in an REC market, small, fossil-fuel based firms will invest directly in the minimum amount of renewable energy generation needed to stay competitive in the electricity market. It is only when an RET policy is at the firm-level that REC markets are utilized. In the case study of uncongested transmission, with the possibility to expand renewable generation capacity, the RET policy the ensures the greatest decrease in greenhouse gas emissions (GHG), while also incentivizing investment in renewable energy and resulting in the highest economic efficiency of the eight policy scenarios studied. Thus, if the main goal of a regulator is to maximize the traditional definition of social welfare, the aforementioned RET policy may be the best, given the player and market circumstances of the case study.

This thesis provides insights into RET policy formulation. While it is recognized that the policymaking process is fundamentally political, the models developed in this thesis are an attempt to ground the political discussion in technical analysis, and to move toward evidence-based policymaking.

Appendix A

Data, Generation Profiles and Costs per Island

A.1 Portugal Data

Table A.1: **Mainland Portugal data.** Data used in *Scenario 3* includes the mainland of Portugal, where generation capacity and costs differ from the Azores Islands. Generation capacity data was gathered from the electricity system operator, REN (Rede Elétrica Nacional) [10]. Maximum capacity expansion is assumed to be unlimited in almost any technology except hydropower and biomass, which we assume can only expand to three times their current capacity. Capacity factor data on mainland Portugal is from [11] for wind, [12] for hydropower and wave in mainland Portugal, and from [13] for all other technologies. Cost data is from the Portuguese electric regulatory agency, [5], and the International Energy Agency (IEA) [7].

			Annualized Costs			
	2008 Generating Capacity, $C0_{gport}$ [MW]	Maximum Capacity Expansion, CM_{gport} [MW]	Capacity Expansion Integer, CEI_{gport} [MW]	Capacity Factor, CF_{gport} [%]	Operating Cost, δ_{gport} [$/kWh]	Investment Cost, α_{gport} [$/kW]
Wind	2,757	50,000	2.30	21	0.0950	276
Offshore Wind	-	50,000	2.30	30	0.0467	896
Hydropower	4,957	14,871	5.20	12	0.0920	339
Solar	50	50,000	0.29	15	0.3400	398
Wave	2	50,000	2.00	10	0.0819	1,138
Coal	1,776	50,000	298	65	0.0621	261
Diesel	1,877	50,000	16.0	70	0.0940	261
Natural Gas	2,166	50,000	9.00	45	0.0809	153
Biomass	1,463	4,389	34.0	45	0.0794	411

Table A.2: **Demand and peak load in 2018.** The annual demand for mainland Portugal, as well as annual peak load, using forecasted growth values from [14][10].

	Annual Demand and Peak Load	
	2018 Demand, D_{port} [MWh]	2018 Peak Load, Pl_{port} [MW]
Portugal	55,000,000	10,757

Table A.3: **Annual load duration curve approximation.** The percentages in the table below divide the annual load duration curve into the amount of base, middle and peak load that must be met by the mainland Portuguese electricity system in 2018 [5].

Load Duration Curve Approximation	
L_l	[%]
Base	29.0
Middle	54.0
Peak	17.0

A.2 Results *Scenario 1 - Isolated* Generation Capacity Expansion Investments

The first bar in the following graphs represent the existing generation capacity on the island.

At zero percent RET, no investments need to be made in renewable energy expansion.

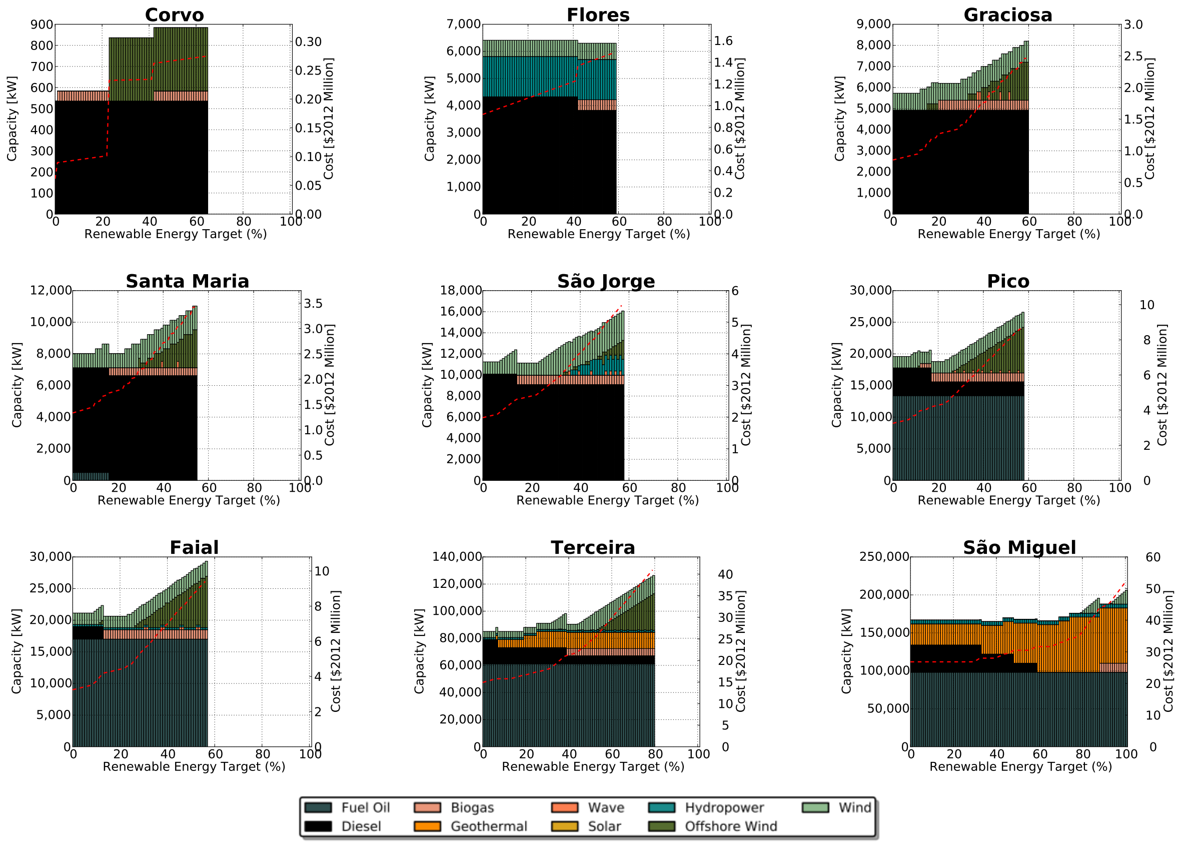


Figure A.1: ***Scenario 1* - *Isolated* Generation Capacity Expansions by Island**. From left to right and down, the islands are listed by increasing electricity demand. This figure shows how renewable energy investment changes by RET. Lumpiness is at play in all cases.

A.3 Results *Scenario 2* - *Regional* Generation Capacity Expansion Investments

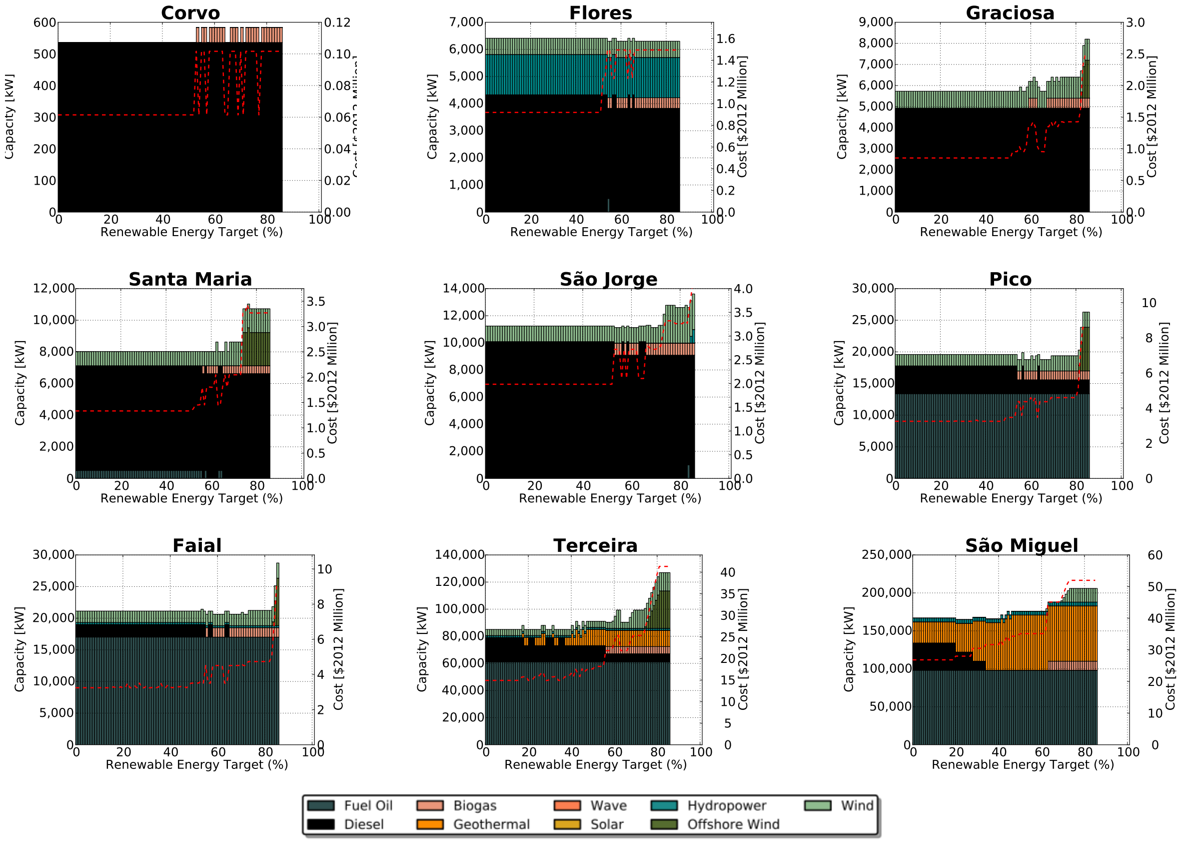


Figure A.2: ***Scenario 2*** - ***Regional*** **Generation Capacity Expansions by Island**. From left to right and down, the islands are listed by increasing electricity demand. This figure shows how renewable energy investment changes by RET. The strategy of RET setting becomes particularly important when the production of renewable energy from the entire archipelago can count towards meeting the regional RET. Natural resource characteristics, lumpiness of turbine investment and differing costs can cause the least-cost investment profile to change dramatically from one RET percentage point to the next. Long-term goals should be considered carefully before the RET is set.

A.4 Results *Scenario 3* - *Country*. Generation Capacity Expansion Investments

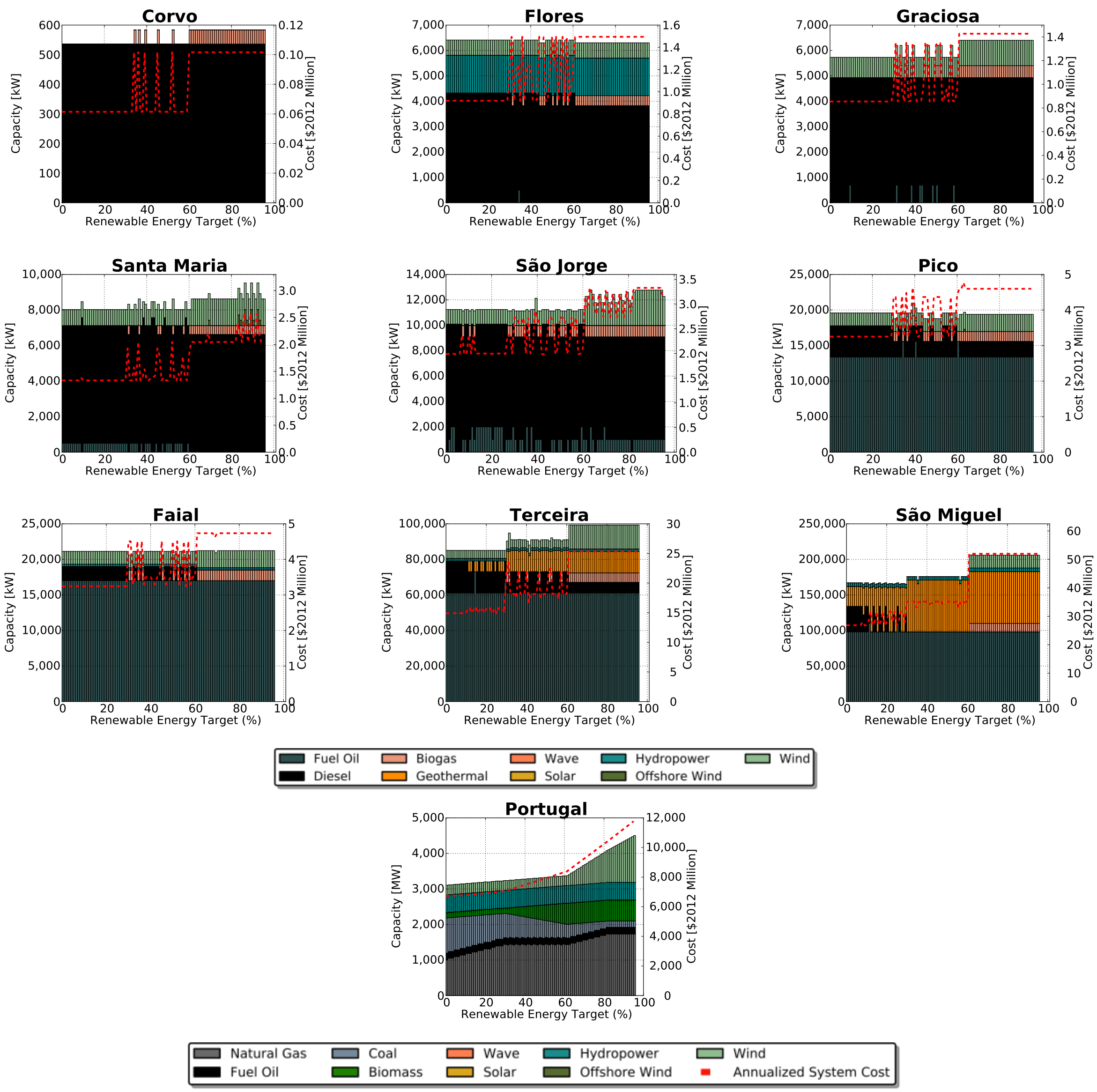


Figure A.3: ***Scenario 3** - **Country***: **Generation Capacity Expansions by Island and mainland Portugal**. From left to right and down, the regions are listed by increasing electricity demand. This figure shows how renewable energy investment changes by RET. When considering the broadest attribution of an RET, investment in local renewable energy still occurs.

A.5 Costs per Scenario, by Island

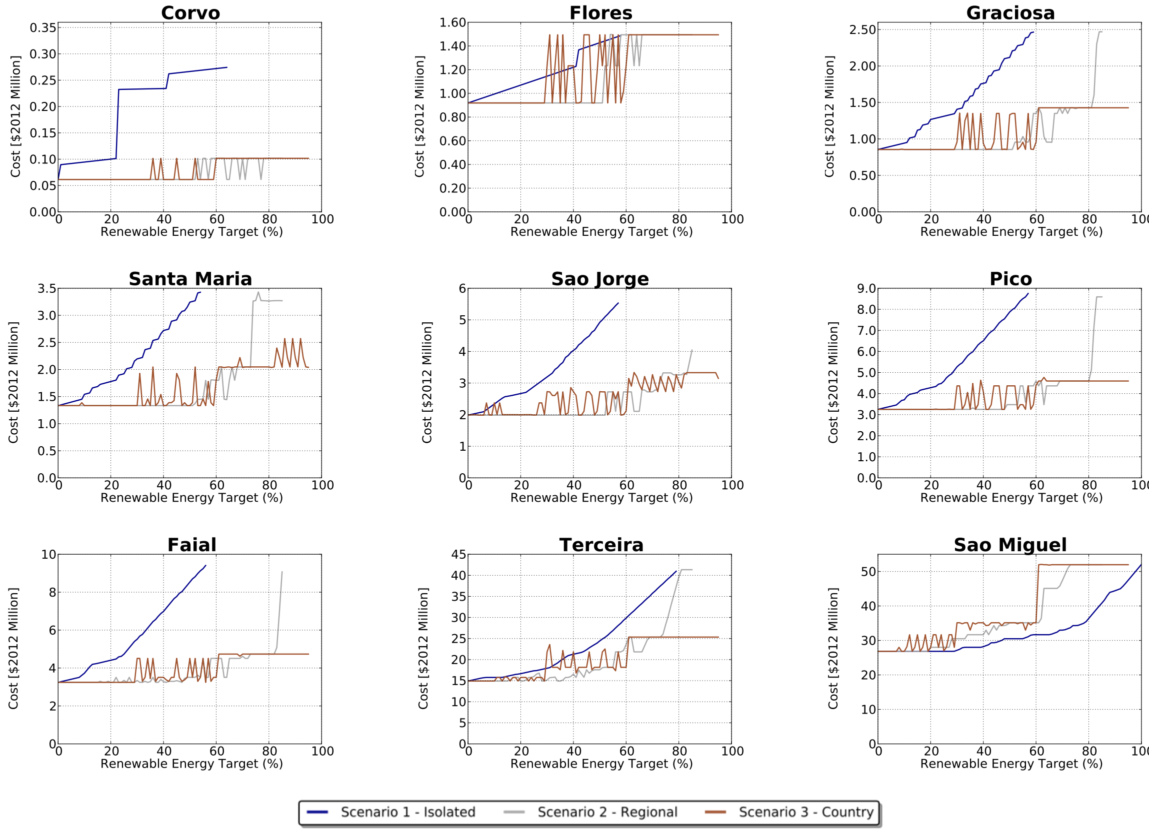


Figure A.4: **Costs per island, per scenario**.

A.6 Cost savings as compared to *Scenario 1 - Isolated*, by Island

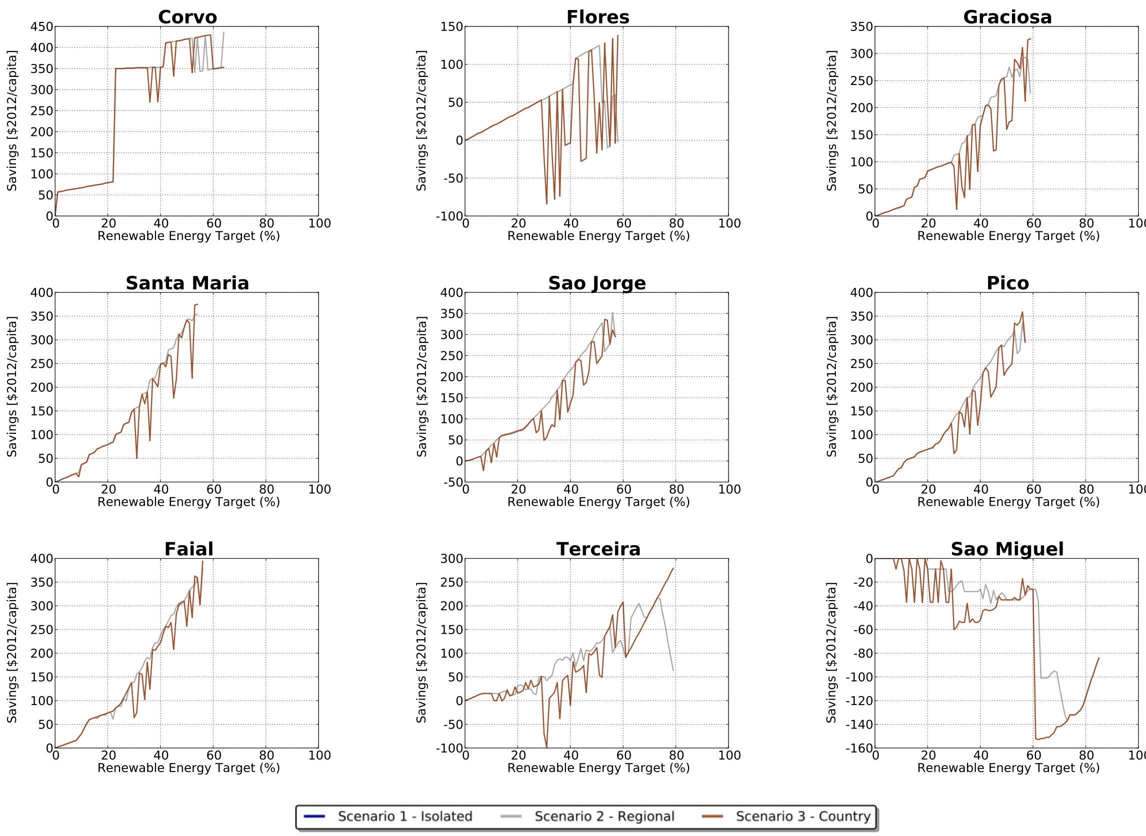


Figure A.5: **Cost savings as compared to *Scenario 1 - Isolated* per island**. There are three islands (Flores, São Jorge and Terceira) where it may be cheaper to be in an isolated scneario, particulary at low RETs. In the case of São Miguel, with large geothermal reserves, it always cheaper to have an isolated RET attribution. The cost to São Miguel of a regional or country RET is more than compensated by the savings incurred on the other islands, as shown in Figure 2.5.

Appendix B

Complementarity Model Specifications Per Scenario

B.1 Mathematical specification of Scenarios

The model presented in Sections 4.2.1 - 4.2.4 represent Scenarios 1a and 3a: a regional RET policy with the possibility of trading RECs. Modeling the six other scenarios described in Table 4.2 require slight changes to the RET and REC market equations (Eqs. 4.6 - 4.13) and corresponding KKT conditions of the complementarity model described in Sections 4.2.1 - 4.2.4. The necessary changes are enumerated in the following sections.

B.1.1 Regional-level RET without REC market: Scenarios 1b & 3b

In these two scenarios, a regional-level RET policy is put in place without the possibility of trading RECs. This eliminates Eqs. 4.6 and 4.13 and the corresponding KKT conditions. Further, the complementarity condition for primal variable x_{fihtb} is updated to:

$$0 \leq x_{fihtb} \perp \beta^{t-1} D_b \left(C_{fiht} - w_{itb}\right) - \theta_{ftb} + \rho_{fihtb} \\ + \mu_{fihtb} + D_b(\delta_t RET_t - \delta_t RE_h) \geq 0 \quad \forall f, i, h, t, b \tag{B.1}$$

and Eq. 4.7 becomes:

$$\sum_{fihb} D_b RE_h x_{fihtb} \geq RET_t(\sum_{fihb} D_b x_{fihtb}) \quad (\delta_t) \quad \forall t. \tag{B.2}$$

As Eq. 4.7 is now an inequality, the dual variable complementarity condition must be added as follows:

$$0 \leq \delta_t \perp \sum_{fihb} D_b RE_h x_{fihtb} - RET_t(\sum_{fihb} D_b x_{fihtb}) \geq 0 \quad \forall t \tag{B.3}$$

B.1.2 Firm-level RET with REC market: Scenarios 1c & 3c

Equation 4.6 remains the same. With the RET set for achievement at the firm-level, Eq. 4.7 becomes:

$$a_{ft} + r_{ft} \geq RET_{ft}(\sum_{ihb} D_b x_{fihtb}) \quad (\eta_{ft}) \quad \forall f, t \tag{B.4}$$

Because Eq. 4.7 has been changed, the corresponding complementarity conditions (Eqs. 4.25 - 4.27) must also be updated:

$$0 \leq \eta_{ft} \perp a_{ft} + r_{ft} - RET_{ft}(\sum_{ihb} D_b x_{fihtb}) \geq 0 \quad \forall f, t \tag{B.5}$$

$$0 \leq a_{ft} \perp -\delta ft - \eta_{ft} \geq 0 \quad \forall f, t \tag{B.6}$$

$$0 \leq r_{ft} \perp \beta^{t-1} p_t^{REC} - \eta_{ft} + p_t^{REC} \geq 0 \quad \forall f, t \tag{B.7}$$

Finally, the complementarity condition for primal variable x_{fihtb} must be updated to:

$$\begin{aligned} 0 \leq x_{fihtb} \perp \beta^{t-1} D_b \left(C_{fiht} - w_{itb}\right) - \theta_{ftb} + \rho_{fihtb} & \\ + \mu_{fihtb} + D_b(\delta_{ft} RE_h + \eta_{ft} RET_{ft}) \geq 0 \quad \forall f, i, h, t, b & \end{aligned} \tag{B.8}$$

B.1.3 Firm-level RET without REC market: Scenarios 1d & 3d

In these two scenarios, a firm-level RET policy is put in place without the possibility of trading RECs. This eliminates Eq. 4.6 and the corresponding KKT conditions. Further, the complementarity condition for primal variable x_{fihtb} is updated to:

$$\begin{aligned} 0 \leq x_{fihtb} \perp \beta^{t-1} D_b \left(C_{fiht} - w_{itb}\right) - \theta_{ftb} + \rho_{fihtb} & \\ + \mu_{fihtb} + D_b(\delta_{ft} RET_{ft} - \delta_{ft} RE_h) \geq 0 \quad \forall f, i, h, t, b & \end{aligned} \tag{B.9}$$

and Eq. 4.7 becomes:

$$\sum_{ihb} D_b RE_h x_{fihtb} \geq RET_{ft}(\sum_{ihb} D_b x_{fihtb}) \quad (\delta_{ft}) \quad \forall f, t. \tag{B.10}$$

As Eq. 4.7 is now an inequality, the dual variable (δ_{ft}) complementarity condition must be added as follows:

$$0 \leq \delta_{ft} \perp \sum_{ihb} D_b RE_h x_{fihtb} - RET_{ft}(\sum_{ihb} D_b x_{fihtb}) \geq 0 \quad \forall f, t \tag{B.11}$$

B.1.4 Nodal Electricity Prices

Table B.1: **Nodal Electricity Prices.** Per Scenario, firm, time period and load type.

			Electricity price [$/MWh]							
		Scenario	*1a*	*1b*	*1c*	*1d*	*3a*	*3b*	*3c*	*3d*
Firm 1	2015	Base	209	209	209	209	205	205	206	245
		Middle	336	336	336	336	338	338	339	372
		Peak	366	366	366	366	368	368	369	402
	2020	Base	228	228	228	228	225	225	228	230
		Middle	368	368	368	368	380	380	383	384
		Peak	401	401	401	401	414	414	416	417
	2025	Base	277	277	280	296	277	277	280	296
		Middle	445	445	449	465	445	445	449	465
		Peak	520	520	510	501	520	520	510	501
Firm 2	2015	Base	412	412	412	412	408	408	409	448
		Middle	668	668	668	668	671	671	671	705
		Peak	731	731	731	731	733	733	734	767
	2020	Base	452	452	452	452	449	449	452	454
		Middle	735	735	735	735	748	748	751	751
		Peak	804	804	804	804	817	817	819	820
	2025	Base	524	524	527	543	524	524	527	543
		Middle	851	851	854	870	851	851	854	870
		Peak	965	965	955	946	965	965	955	946

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