

Advanced Modeling of Renewable Energy Market Dynamics

May 2006

M. Evans, R. Little, K. Lloyd, G. Malikov,
and G. Passolt
Harvey Mudd College

D. Arent, B. Swezey, and G. Mosey
National Renewable Energy Laboratory

Technical Report
NREL/TP-640-41896
August 2007

NREL is operated by Midwest Research Institute • Battelle Contract No. DE-AC36-99-GO10337



Advanced Modeling of Renewable Energy Market Dynamics

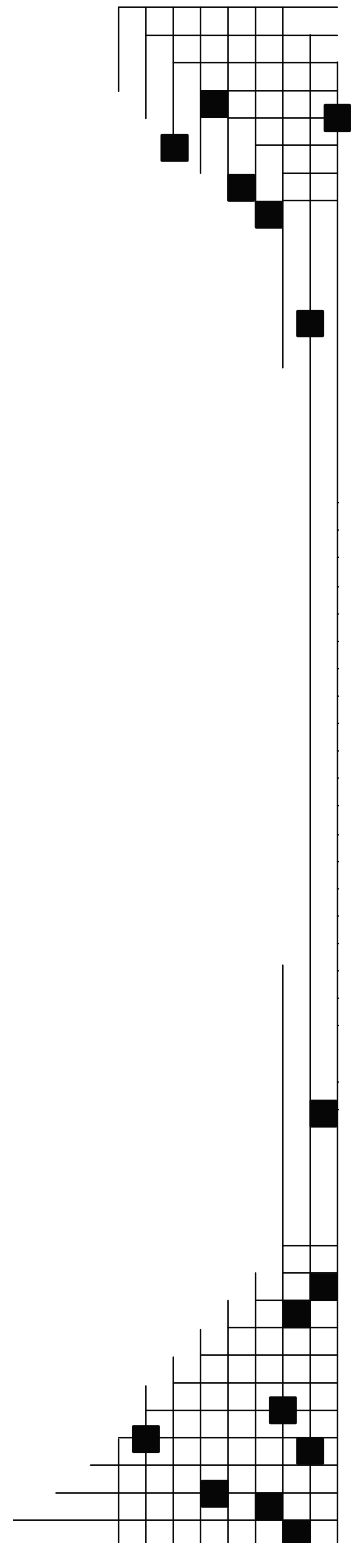
May 2006

M. Evans, R. Little, K. Lloyd, G. Malikov, and G. Passolt
Harvey Mudd College

D. Arent, B. Swezey, and G. Mosey
National Renewable Energy Laboratory

Prepared under Task No. 6400.1040

Technical Report
NREL/TP-640-41896
August 2007



National Renewable Energy Laboratory
1617 Cole Boulevard, Golden, Colorado 80401-3393
303-275-3000 • www.nrel.gov

Operated for the U.S. Department of Energy
Office of Energy Efficiency and Renewable Energy
by Midwest Research Institute • Battelle

Contract No. DE-AC36-99-GO10337

NOTICE

This report was prepared as an account of work sponsored by an agency of the United States government. Neither the United States government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States government or any agency thereof.

Available electronically at <http://www.osti.gov/bridge>

Available for a processing fee to U.S. Department of Energy and its contractors, in paper, from:

U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831-0062
phone: 865.576.8401
fax: 865.576.5728
email: <mailto:reports@adonis.osti.gov>

Available for sale to the public, in paper, from:

U.S. Department of Commerce
National Technical Information Service
5285 Port Royal Road
Springfield, VA 22161
phone: 800.553.6847
fax: 703.605.6900
email: orders@ntis.fedworld.gov
online ordering: <http://www.ntis.gov/ordering.htm>



Abstract

This report documents a year-long academic project, presenting selected techniques for analysis of market growth, penetration, and forecasting applicable to renewable energy technologies. Existing mathematical models were modified to incorporate the effects of fiscal policies and were evaluated using available data. The modifications were made based on research and classification of current mathematical models used for predicting market penetration. An analysis of the results was carried out, based on available data. MATLAB versions of existing and new models were developed for research and policy analysis.

Contents

Abstract	iii
Acknowledgments	xi
1 Introduction	1
2 Fiscal Policy	7
2.1 Introduction	7
2.2 Income Tax Credit	8
2.3 Investment in Renewable Energy Facilities	11
2.4 Current State Programs	14
2.5 Policy Timeline	14
2.6 Funding	19
2.7 Conclusion	20
3 Classification	23
3.1 Introduction	23
3.2 Definitions, Concepts & Terms	23
3.3 Classification	25
3.4 Conclusions	35
4 Model Modification	37
4.1 Introduction	37
4.2 Understanding the Original Bass Model	37
4.3 Understanding the GBM	39
4.4 Modifying the GBM	41
4.5 Hypotheses for the GBM	42
4.6 Understanding the NUI	43
4.7 Modifying the NUI	44
4.8 Hypotheses for the NUI	45

4.9	Summary of Modifications	45
4.10	Conclusions and Recommendations	46
5	GUI	49
5.1	Overview	49
5.2	Key Features	50
5.3	Software Structure	51
5.4	Display of Data	53
5.5	Implementing the Models	53
5.6	Data Inputs	59
5.7	Layout & Design	59
5.8	Deployment	61
6	Data Analysis and Results	63
6.1	Motivation and Approach	63
6.2	Examined Models and Appropriate Data	64
6.3	Regression Results	73
6.4	Conclusion	82
7	Conclusion	89
A	Abbreviations	91
B	Sample GUI Input File	93
C	Bass, Generalized Bass, and NUI Forecast Plots	95
	Bibliography	105

List of Figures

2.1	Electricity Generation from Wind, 1989–2004	12
2.2	Electricity Generation from Wood, Waste, and Geothermal Sources, 1989–2004	13
3.1	Innovation diffusion research approaches (Frank, 2004). . .	26
5.1	Data Flowchart of GUI	52
5.2	Screen Shot of GUI	53
5.3	Graph of clothes dryers data using NUI.	56
5.4	Screen Shot of GUI. This illustrates the results of multiple regressions, the last of which used points 0 through 7 as indicated by the grayed outpoints after 7.	60
6.1	Wind power generation in Spain with fixed and regressed market sizes	72
6.2	United States Hybrid Vehicle Sales	80
6.3	Four year projections for global PV module shipments with a fixed market size and regressed market size.	81
6.4	Four year projections for global PV module shipments with a fixed market size. The model predicts the first three years very well.	83
6.5	Two year projections for US PV module shipments with a fixed and regressed market size.	84
C.1	Global Photovoltaic Modules Shipments (MWp)	96
C.2	United States Photovoltaic Modules Shipments (KWp) . . .	97
C.3	United States Aggregate Thermal Collector Shipments (Units) 98	
C.4	United States Low Temperature Thermal Collector Shipment (Units)	99

viii List of Figures

C.5	CA Grid-Connected Photovoltaic Modules Shipments (kW)	100
C.6	CA Grid-Connected Photovoltaic Modules Shipments (Units)	101
C.7	United States Hybrid Vehicle Sales	102
C.8	Wind Energy Installed in Spain	103

List of Tables

1.1	Behavioral Motivations for Purchasing Renewable Energies	2
2.1	Summary of Renewable Energy Fiscal Policy.	9
2.2	Summary of Credit for Electricity Produced from Certain Renewable Resources.	10
2.3	State Renewable Energy Programs as of Dec. 31, 2003 (Petersik, 2003)	15
2.4	Acceptable Technologies and Resources for State Renewable Energy Requirements as of Dec. 31, 2003	16
2.5	Acceptable Alternatives to and Cost Support for Renewable Technologies for State Renewable Energy Requirements as of Dec. 31, 2003	20
5.1	This table compares the results from the GUI with results from literature. The italicized values are those obtained in the original papers.	57
5.2	Required data for each model.	59
6.1	Part 1.Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: No Prediction with Regressed M.	74
6.2	Part 2.Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: No Prediction with Regressed M.	75
6.3	Part 1.Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Regressed M.	78
6.4	Part 2.Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Regressed M.	79

6.5	Part 1.Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Fixed M.	85
6.6	Part 2.Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Fixed M.	86

Acknowledgments

This report concludes nine months of research, modeling and analysis conducted with the assistance of many individuals.

The team would like to thank the following for support and assistance throughout the 2005/2006 academic year: Dr. Doug Arent, NREL Liaison; Harvey Mudd College (HMC) Professors Patrick Little and Michael Raugh, advisors; Blaire Sweezy, NREL; Gail Mosey, NREL; Professor Seema Nanda, HMC visiting professor; and Professor Susan Martonosi, HMC Mathematics Department.

The team would also like to extend their gratitude to the individuals on the administrative and computer services side of the Mathematics and Engineering Departments at HMC, in particular Barbara Schade and Claire Connelly, for help throughout the year.

Chapter 1

Introduction

As politicians and scientists debate the future of fossil fuels and question the remaining supply, two things are certain: prices of crude oil are rising and the environment is suffering. Whether it be through political imposition or the laws of economics, the world has begun to look for alternative forms of energy. Increasing attention is being paid to renewables, a group of resources used to generate electricity that are capable of being replaced naturally (e.g., solar, wind, biomass).

The speed with which the world economy transitions from fossil fuels to renewable energies is dependent on several factors. Understanding these factors will ease the process of switching technologies, and can help the government intervene wisely. The goal of this project is to generate models and a GUI (graphical user interface), that can be used to help policy makers understand the potential impacts of their actions. Such a tool could have profound impacts on the energy market.

This report explains the origins of this project and presents the findings, beginning with a classification of fiscal policies affecting renewable energies (Chapter 2) and also existing mathematical models for representing market penetration (Chapter 3). Then, an explanation of modified models to account for differences in modeling renewable energies versus more traditional products is given (Chapter 4). Next is a description of the GUI, including its implementation and features (Chapter 5). Finally, the results of this project are presented, along with suggestions for future work, as the needed data becomes available (Chapter 6).

To provide additional insight into background, a list of behavioral motives involved in consumer decisions to invest in renewable energies is presented below (Table 1.1). The first column lists the motives, followed by

2 Introduction

explanations in the second column. The third column describes how the variables are captured by suggested modifications to selected mathematical models, or the difficulties with incorporating such variables.

Table 1.1: Behavioral Motivations for Purchasing Renewable Energies

Motive	Description	Model Implications
Alternative Price	The price and availability of the current alternatives to renewable energy.	Alternatives typically include fossil fuel-derived electricity. This is incorporated in baseline price and savings.
Availability of Resource	Are the natural resources available in the area of interest?	This should be taken into consideration when estimating market size.
Convenience	How much effort must be made by the consumer to make a switch in energy sources?	Initial data points should capture this and calibrate p and q appropriately (for definitions see §3.3.7). This could also be accounted for in the price variable.
Cultural Implications	Could be directly tied to environmental concerns . The social implications of renewable energies as they vary by geographical and political boundaries.	Difficult to capture mathematically. It is assumed that the constants incorporate such implications.

Continued on next page.

Motive	Description	Model Implications
Education	One step further than familiarity . The ability to understand that the alternatives may provide benefits (long term or short term) other than price differentiation and consider the entire scope of benefits collectively.	Experimenting was done with education, making innovators out of imitators, but it does not make sense mathematically. This should be accounted for as familiarity , possibly through innovation and savings constants as well.
Efficiency of the Source	As efficiency increases, the number of pieces of infrastructure and/or the size of the infrastructure needed decreases.	See R&D funding .
Environmental Concerns	The benefits to the environment (typically long term) of not using fossil fuels and instead using renewable energy.	Very hard to estimate and collect data on. Presumably, this is influence by education and culture . Within the model, our constants, p , q , and the weights on advertising, price, and savings, account for environmental concerns.
Familiarity	Understanding that renewable energy is available. This is typically directly affected by advertising.	Assumed that this is covered by word-of-mouth estimations and advertising.
Price	The cost of the renewable energy as seen by the consumer, therefore including some fiscal policies.	Inversely related with rate of diffusion. Incorporated (as data) into models.

Continued on next page.

Motive	Description	Model Implications
R&D Funding	Financial contributions to push the technological advantages of renewable energies. Could be tied to familiarity, education, and efficiency.	Presumably, effects of R&D are lowered price and higher efficiency (more savings). R&D funding could be modeled as such, but expert judgment is needed on when and how much these effects show up.
Risk	Are the tax incentives and long-term savings guaranteed? Or do they need to be reaffirmed by congress occasionally?	A guaranteed market for renewable energy, with initial prices held artificially high, can be constructed by the government to promote investment. This is partially accounted for in computing savings data.
Savings	The financial benefits of the renewable energy not directly included in the price (i.e. tax rebates, annual tax savings, etc.).	Directly related with diffusion rate. Estimates (as data) incorporated into models.
Sustainable Economy	The benefits of reducing dependency on imported energy and becoming a self sufficient economy.	Same as environmental concerns and cultural implications.
Visibility	The physical beauty of the renewable energy. Some are concerned about having windmills nearby, as they can be an eyesore.	Can be incorporated into environmental concerns.

Continued on next page.

Motive	Description	Model Implications
Variable Pricing	In the case of incremental tax savings, what is the likelihood of receiving the maximum savings.	See Risk .

As can be seen, the factors that influence adoption of alternative energy sources, and renewables in particular, are complex and present a difficult challenge. The following six chapters make progress towards addressing these challenges.

Chapter 2

Fiscal Policy

2.1 Introduction

Beginning with the energy crises in the 1970s, many countries, including the United States, have become increasingly interested in renewable energies. The motivation for transitioning to renewable energy is twofold: to decrease dependence on fossil fuels and to protect the environment. The ability for a society to transition to renewable energies, however, differs greatly among states and throughout the world. Natural resource endowments, political and economic systems, and cultural traditions aid or inhibit the incorporation of renewable energies (Energy Information Administration, 2005). The government's involvement with this transition can greatly affect the degree to which renewable energies become a staple in the economy and also the speed with which the transition occurs.

There are various methods through which fiscal policy can impact innovation, consumption, and ultimately market penetration. These methods include tax breaks, subsidies for purchasing renewable energy or installing one's own source, and income through contributing back to the power grid (see Table 2.1 for a few examples). These policies affect renewable energies at various levels, including the consumer, business, and even government.

Tax breaks refer to the reduction of taxable income based on investment in a developing technology (commonly referred to as a "credit"). Subsidies reduce the consumer price of the good by aiding in the cost of the product, before it reaches market, or through a rebate. Mandates, standards, and punitive pricing refer to legislation requiring that goals be met with respect to particular technologies. Of the various policies currently in place, income tax credits have been selected for further discussion within

this chapter.

2.2 Income Tax Credit

Income tax credits are given for the production of renewable electricity sold by a taxpayer (private company/individual) to an unrelated person (customer) from a qualified facility. The United States government has produced standards for qualified facilities (e.g. a solar facility which was placed in service between Oct 22, 2004 and Jan. 1, 2006). The base credit is currently 1.5 cents per kilowatt-hour of electricity produced, indexed for inflation. For 2005, the credit is 1.9 cents per kilowatt-hour. This credit can be claimed for the first 10 years the qualified facility is in service. Credit is reduced for facilities with funding through grants, tax-exempt bonds, and subsidized energy financing. The total credit claimed by a taxpayer is reduced as the market price of electricity exceeds acceptable levels.

A summary of the credit rate and credit period by facility, showing how the rates change based on the resource, is given in Table 2.2 (Staff of the Joint Committee on Taxation, 2005). The table shows that electricity produced from wind energy yields a 1.9 cent credit (in 2005) per kilowatt-hour of electricity produced. This credit is only valid for a ten year period, beginning with the year the facility was placed in service. The table also provides information about “closed-loop” and “open-loop” biomass systems. A closed loop biomass resource is any organic matter from a plant which is planted for the exclusive purpose of being used to produce energy. This does not include wood, agricultural waste, or standing timber (which is commonly referred to as open-loop biomass) (Darling, 2005).

To a taxpayer, the value of this credit is equivalent to the price of the electricity sold as well as the subsidy paid for each kilowatt-hour of electricity produced. A credit that reduces the taxpayer’s liability has the same effect as a subsidy. The equivalent subsidy is $c/(1 - t)$, where c represents the credit rate per kilowatt-hour and t is the taxpayer’s marginal tax rate. For example, a taxpayer with a marginal tax rate of 30 percent receiving a credit of 1.9 cents per kilowatt-hour for energy produced, would have an equivalent subsidy of $1.9/.7 = 2.7$ cents per kilowatt-hour (Staff of the Joint Committee on Taxation, 2005).

The average price of electricity in 2004 for industrial customers was 5.11 cents per kilowatt-hour. A credit of 1.9 cents per kilowatt-hour for renewable energy produced would be equivalent to a subsidy of over 37 percent of this price ($1.9/5.11$). Or, alternatively, the equivalent subsidy could be

Consumer Level	Business/ Entrepreneurial Level	Government Level	Overarching Economic Policy
Tax Breaks: Purchase of hybrid cars, property tax breaks for installation of photovoltaic or wind RE sources.	Tax Breaks: Incentives on income (or losses) due to work in renewables. Tax reduction on profits. Loss write offs.	Mandates: States using specified technologies and quantities of renewable energies.	Punitive Pricing: For pollution units at consumer and business levels.
Subsidies: Purchase of renewable energy equipment.	Subsidies: Purchase of renewable energy equipment.	Standards: Specified percent of total energy supplied by renewables.	Funding: For RE technology (NSF, DOE, NREL, SBIR).
Opportunities for income: PV, fuel cell, wind energy sold back to the power grid.		Transit Systems: Fuel Celled Vehicles	

Table 2.1: Summary of Renewable Energy Fiscal Policy.

Electricity produced from renewable resources	Credit amount for 2005 (cents per kilowatt-hour; dollars per ton)	Credit period (years from placed-in-service date) ¹
Wind.....	1.9	10
Closed-loop biomass.....	1.9	10
Open-loop biomass..... (including agricultural livestock waste nutrient facilities)	0.9	5
Geothermal.....	1.9	5
Solar.....	1.9	5
Small irrigation power.....	0.9	5
Municipal solid waste..... (including landfill gas facilities and trash combustion facilities)	0.9	5
Refined Coal	5.481	10

¹ For eligible pre-existing facilities and other facilities placed in service prior to January 1, 2005, the credit period commences on January 1, 2005. In the case of certain co-firing closed-loop facilities, the credit period begins no earlier than October 22, 2004.

Table 2.2: Summary of Credit for Electricity Produced from Certain Renewable Resources.

analyzed as a stream of receipts across the life of the investment in the project. Using this method, the subsidy would be equal to the value of the payments the taxpayer would receive annually, per kilowatt-hour, over the life of the project, computed at present value. Using a 20 year facility life (while receiving the credit for only the first 10 years), the 1.9 cents per kilowatt-hour tax credit is equivalent to a 1.66 cent cash subsidy per kilowatt-hour over the 20-year life of the investment. This produces a subsidy of 22 percent of the average retail price of electricity (Staff of the Joint Committee on Taxation, 2005).

Tax incentives for renewable energies are designed to match the return on investment for the forms of energy the government is encouraging users to transition out of. The idea is to promote research in the underdeveloped technology source.

2.3 Investment in Renewable Energy Facilities

For an individual to invest in the production of renewable energies, aspects other than return on investment must also be considered. For example, the location of the site may be a factor—it would be better to build a photovoltaic facility in Southern California than Northern Washington because of the amount of annual sunlight. The amount of time required to design and build a facility is an important consideration—a geothermal facility takes much longer to design and construct than wind facilities.

Recent investors in renewable energies have found that wind facilities are the most profitable investment when considering the previously mentioned factors. Over the last 10 years, since wind facilities have been eligible as qualified facilities, the annual production of electricity from wind has increased fourfold (Fig. 2.1), while other energies also eligible as qualified facilities, such as wood, waste, and geothermal have not seen significant growth (Fig. 2.2) (Staff of the Joint Committee on Taxation, 2005).

At the same time, however, in 2004 wind energy accounted for less than four-tenths of one percent of all electricity generated in the United States, while wood, waste, and geothermal accounted for 1.9 percent of all electricity produced. Although wind energy is currently the best investment, state governments are setting up programs that require the use of a broad range of technologies.

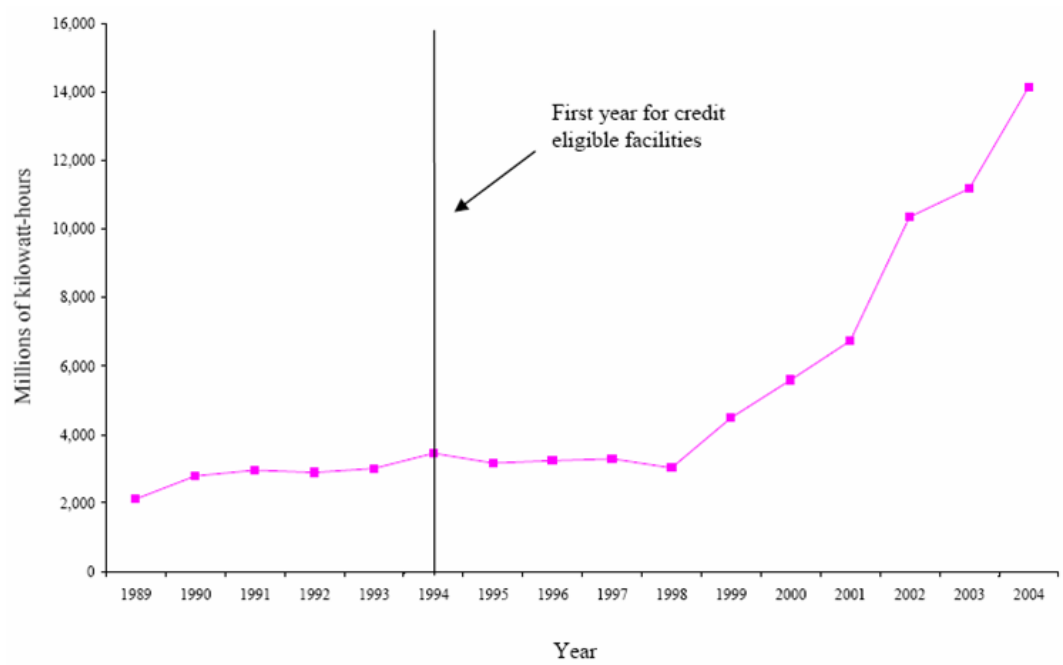


Figure 2.1: Electricity Generation from Wind, 1989–2004

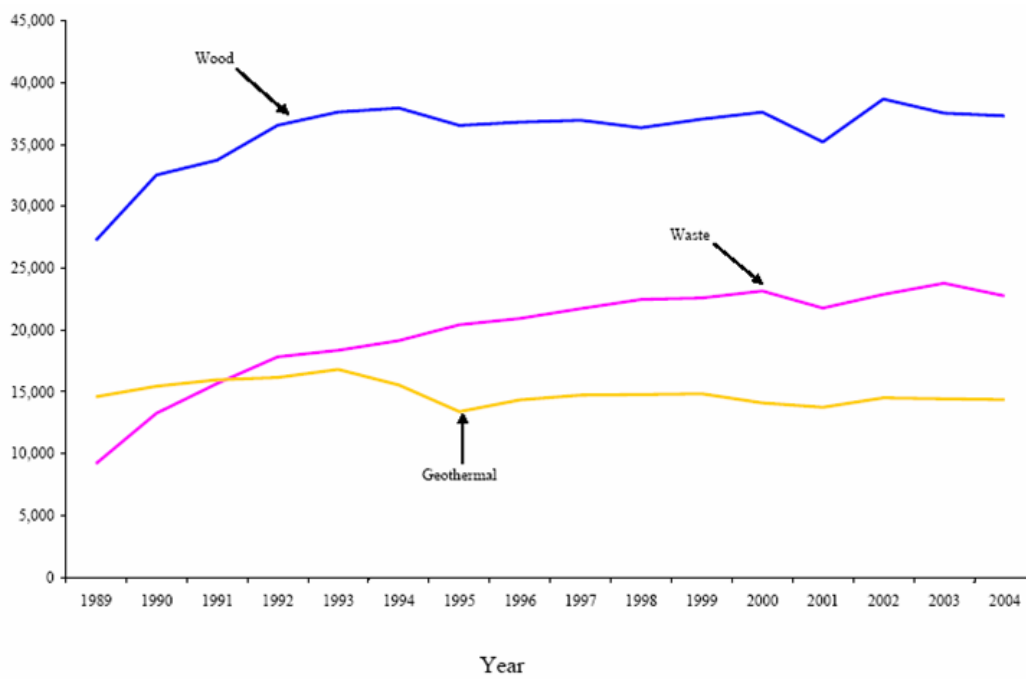


Figure 2.2: Electricity Generation from Wood, Waste, and Geothermal Sources, 1989–2004

2.4 Current State Programs

By the end of 2003, there were 17 renewable energy programs in 15 states encouraging the development of renewable energy for generating electricity. Since then many more states have added similar programs. These programs can be categorized into three types: renewable energy mandates, renewable portfolio standards, and renewable energy goals (Table 2.3 breaks down the different categories by state). Renewable energy mandates require the construction of specific quantities of new renewable energies using specific technologies. This is the most stringent of the governmental programs requiring the generation of new facilities at a specific rate. Renewable portfolio standards require that generation of renewable energies account for a specific share of overall electricity generation and/or sales. The third type of programs, goal-based, are voluntary and may be met with a mix of renewable energies (Petersik, 2003).

As of the end of 2003, mandates resulted in the majority of new renewable energy sources (86 percent of the 2,335 megawatts of renewable energy capacity constructed in the 15 states with programs). Although this behavior may be expected, it should be noted that renewable portfolio standards and goal-based programs are newer to the renewable energy scene than mandates. Also, renewable portfolio standards include output from existing renewable energy sources, decreasing the current impact they have on comparison calculations. Table 2.4 gives a refined breakdown of the types of energy programs per state. For example, it shows that technologies such as wind and solar are widely represented when compared to technologies such as municipal solid waste.

The flexibility that states allow in choosing technologies for investment varies widely. In Hawaii, for example, renewable energy development is a voluntary goal, not a mandate. Therefore, investors have more control over the type of renewable technologies developed in Hawaii when compared to states such as Arizona with stricter mandates (Petersik, 2003).

2.5 Policy Timeline

The policy timeline captures major events in renewable energies policy in the United States, with an emphasis on California's progress in adopting renewable energy technologies (Administration, 2005). With reliable data for a particular area and time, it should be possible to measure the effect of a policy change by fitting a diffusion curve to the data provided before the

<i>Renewable Portfolio Standard Program</i>	
Arizona California Connecticut Maine Massachusetts	Nevada New Jersey New Mexico Wisconsin
<i>Mandate Program</i>	
Iowa Minnesota	Texas Wisconsin
<i>Goals Program</i>	
Hawaii Illinois	Minnesota Pennsylvania

Table 2.3: State Renewable Energy Programs as of Dec. 31, 2003 (Petersik, 2003)

State	Biomass	Biomass Co-firing	Biomass Cogen-eration	Geo-thermal	Conven-tional Hydro-electric	Landfill Gas	Municipal Solid Waste	Ocean or Tidal	Solar	Wind
Renewable Portfolio Standards										
Arizona	Yes	NS	NS	Yes ^a	No	Yes	NS	No	Yes	Yes
California	Yes	NS	NS	Yes	Small only	Yes	Yes	Yes	Yes	Yes
Connecticut	Yes	NS	NS	No	Small only	Yes	Yes	Yes	Yes	Yes
Maine	Yes	Yes	Yes	Yes	Small only	Yes	Yes	Yes	Yes	Yes
Massachusetts	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes
Nevada	Yes	NS	NS	Yes	Small only	Yes	No	No	Yes	Yes
New Jersey	Yes	Yes	NS	Yes	Small only	Yes	No	Yes	Yes	Yes
New Mexico	Yes	Yes	NS	Yes	Small only	Yes	No	No	Yes	Yes
Wisconsin	Yes	Yes	NS	Yes	Small only	Yes	No	Yes	Yes	Yes
Mandates										
Iowa	Yes	NS	Yes	NS	Small only	Yes	Yes	NS	Yes	Yes
Minnesota	Yes	NS	NS	No	Small only	Yes	Yes	No	Yes	Yes
Texas	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Wisconsin	Yes	Yes	NS	Yes	Small only	Yes	No	Yes	Yes	Yes
Goals										
Hawaii	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Illinois	NS	NS	NS	NS	NS	NS	NS	NS	Yes	Yes
Minnesota ^b	Yes	NS	NS	No	Small only	Yes	Yes	No	Yes	Yes
Pennsylvania	Yes	NS	NS	Yes	No	Yes	No ^c	Yes	Yes	Yes

^aAccepted by waiver only.

^bSpecific characteristics are being determined. See web site www.puc.state.mn.us, Docket 03-889.

^cYes by exception, for General Public Utilities (GPU) only.

NS = not specified in the State requirement.

Source: Energy Information Administration, Office of Integrated Analysis and Forecasting.

Table 2.4: Acceptable Technologies and Resources for State Renewable Energy Requirements as of Dec. 31, 2003

policy goes into effect, and measuring the difference between the predicted and actual curves after the policy change.

1970 The cost of producing solar cells drops, decreasing the price from \$100/watt to \$20/watt.

1976 California 10% investment tax credit for installation of renewable technologies, mainly solar energy.

1977 Solar Energy Research Institute is created (later becomes NREL).

1978 California's investment credit was increased to 55%, and extended for wind energy until 1986 and into the 1990's for other alternative energy sources.

1978 California sets a goal of 500 MW of wind capacity installed by the mid 1980's with the Wind Energy Program.

1978 National Energy Act, including PURPA (Public Utility Regulatory Policies Act) was passed. This sought to improve and develop alternative energy sources. Required utility companies to buy electricity from qualified facilities that provided alternative methods of producing electric power. Purchasing cost was left to state regulation. "California based its avoided cost calculations on forecasts of natural gas and oil prices, which were higher than prices actually turned out to be, resulting in favorable investment conditions for renewable power." (Administration, 2005).

1978 Energy Tax Act (part of NEA) provided a 30% investment tax credit for solar/wind energy in residential consumption, and 10% for solar/wind/geothermal/ocean thermal energy in business consumption. These tax credits varied From year to year and expired in 1985.

1980's California starts several demonstration projects for wind.

1982 California purchase cost for wind power drops significantly after returning to the actual avoided cost. California's Public Utilities Commission (CPUC) created 10-year contracts that agreed on a power purchase rate of 6.9 cents/kWh, for both utility companies and qualifying alternative energy facilities.

1985 California has installed 1000 MW of wind capacity.

- 1986** The Tax Reform Act extended tax credits for businesses for solar, ocean thermal, geothermal, and biomass property.
- 1990** California has installed 1799 MW of wind capacity.
- 1990** Clean Air Act Amendments (CAAA). This was the introduction of a new emissions-reduction program.
- 1991** NREL is established by the DOE.
- 1992** Energy Policy Act (EPACT) included "... a 10-year 1.5 cents per kWh inflation-adjusted production tax credit (PTC) for tax-paying privately and investor-owned wind projects and closed-loop biomass plants brought online between 1994 and 1999" (Administration, 2005). It was renewed in 1999, 2001, and the end of 2004, after it expired at the end of the previous year.
- A Renewable Energy Production Incentive (REPI) was part of EPACT, and included a tax credit for biomass/geothermal/solar/wind energy, but since the funds are appropriated annually by Congress, such a credit is variable and cannot be counted on with certainty.
- 1995** Federal regulations passed to determine purchase cost for alternative energy resulted in lower incentives than before in some states (including California).
- 1995** California introduces net metering law, allowing alternative energy projects up to 1 MW of net metering for wind/solar projects, limiting net metering to .5% of a utility's peak demand.
- 1996** California begins residential net metering for solar/wind energy up to 1 MW. It is interesting to note that "the buyback rate for net metering in California is equal to the retail electricity price, and State law prohibits the utilities from charging net metering consumers interconnection fees." (Administration, 2005).
- 1997** Kyoto Protocol negotiated. All countries that ratified the Kyoto protocol committed to reduce their emissions of greenhouse gases, including carbon dioxide. The emissions trading program agreed to in Kyoto allows countries to maintain emissions through a process of emissions trading, as long as collective emissions levels decrease. The treaty was brought into force in 2005, and the United States did not ratify the treaty.

- 1998** California starts the Emerging Renewables Buydown Program to help residential and small businesses invest in renewable energy projects. Rates vary between \$2000/kW and \$3600/kW.
- 1999** California offers a 1.5 cent/kWh credit for consumers of renewable electricity. Tax Relief Extension Act is passed, extending the production tax credit from EPACT for wind, closed-loop biomass, and poultry waste systems.
- 2000** The California 1.5 cents/kWh credit is reduced to 1 cent/kWh with a maximum of \$1000 per year.
- 2001** Home Energy Generation Act allows consumers to sell excess energy back to local utility companies.
- 2002** California lets residential net metering laws include biogas energy.
- 2002** California sets a mandatory target for utility purchases - 20% of electricity must be purchased from renewable sources by 2017.
- 2003** California net metering permits wind energy to net meter up to 50kW.
- 2005** "As of March 2005, California's net metering rules had enticed nearly 600 projects to interconnect with the state's 3 investor-owned utilities totaling 25.1 MW. Nearly 100 percent of the projects were using solar photovoltaic technology." (Administration, 2005).

2.6 Funding

Although some fiscal policies are designed to encourage development of renewable technologies on a consumer or business level, other policies, such as mandates, are requirements for development at the federal level. Funding for these programs comes from three primary sources: passing the costs on to all utility users (called "ratebasing"), applying a fee to specific categories of sales, or encouraging users to voluntarily pay a premium for renewable energy (known as "green power" programs). Additionally, some states reduce their requirements if costs for renewable technologies become excessive (called "cost outs"). Other states allow for reduction in requirements for non-cost reasons ("non-cost outs"). Table 2.5 shows some of the differences in how states address these funding issues (Peter-sik, 2003). For example, this table shows that states such as Arizona and

State	Fuel Cells	Non-electric Alternatives	Favored Technologies	System Benefits Charges	Green Power	Cost Outs	Non-Cost Outs/Delays	Penalties
Renewable Portfolio Standards								
Arizona	No	Yes	Solar	Yes	Yes	Yes	No	No
California	Renewable fuels only	No	No	Yes	NS	Yes	Yes	Yes
Connecticut	Renewables and natural gas	No	No	No	No	Yes	Yes	Yes
Maine	Renewables and natural gas	No	No	No	Yes	No	Yes	Yes
Massachusetts	Renewable fuels only	No	No	No	No	Yes	Yes	Yes
Nevada	No	Yes	Solar	No	NS	Yes	Yes	Yes
New Jersey	Renewable fuels only	No	No	Yes	NS	Yes	Yes ^a	Yes
New Mexico	Renewable fuels only	No	All but wind/hydro	No	Yes	Yes	Yes	Yes
Wisconsin	Renewable fuels only	No	No	No	Yes	Yes	No	Yes
Mandates								
Iowa	No	No	No	No	NS	No	No	NS
Minnesota	Yes	No	Wind, biomass	No	NS	No	No	Yes
Texas	Renewable fuels only	Yes	No	No	Yes	Yes	Yes	Yes
Wisconsin	Renewable fuels only	No	No	No	Yes	NS	Yes	NS
Goals								
Hawaii	Renewable fuels only	Yes	No	No	NS	No	Yes	No
Illinois	No	No	No	NS	NS	Yes	No	No
Minnesota ^b	Yes	No	NS	No	NS	NS	Yes	No
Pennsylvania	No	No	No	Yes	NS	Yes	Yes	No

^aDelays only.

^bSpecific characteristics are being determined. See web site www.puc.state.mn.us, Docket 03-869.

NS = not specified in the State requirement.

Source: Energy Information Administration, Office of Integrated Analysis and Forecasting.

Table 2.5: Acceptable Alternatives to and Cost Support for Renewable Technologies for State Renewable Energy Requirements as of Dec. 31, 2003

Nevada, while having similar choices in favored technologies and allowing non-electric alternatives, have different funding options and different laws with respect to “non-cost outs” and penalties.

2.7 Conclusion

For the United States, transitioning to renewable energies is less likely to be impacted by cultural traditions or natural resource endowments, and more likely to be impacted by the political and economic system. As the United States and the world become more environmentally conscious, there will be greater interest in transitioning to renewable energies. Additionally, as the cost of petroleum increases, there will be more interest in finding alternative energy sources, with renewable energy at the heart of the search. Currently, this transition is most greatly affected by fiscal policies that both require the gradual development of renewable energies and encourage pri-

vate investment in such technologies through financial incentives. Consequently, it is important that those who create the policies understand the affects of their decisions on the economy and the environment.

Chapter 3

Classification

3.1 Introduction

This chapter provides a classification and analysis of existing technology penetration models. Comments on the potential applicability to the renewable energy market and on how well it lends itself to modification for fiscal policy considerations follow the examination of each model.

3.2 Definitions, Concepts & Terms

Notation: Throughout this chapter when dealing with penetration as a function of time the default will be $F(T) = \int_0^T f(t) dt$, where $F(T)$ is the cumulative distribution function of market diffusion—the proportion of the market penetrated at time T , and $f(T)$ is the probability density function—the instantaneous rate of change of penetration.

These following are terms that will be useful to in understanding the the description of the models. They are presented alphabetically.

Decision Variable: Any characteristic of a product that influences a consumer's decision to purchase. Examples include, price, advertising, environmental friendliness, efficiency, maintenance cost, expected life, etc.

Direct Network Effects: Essentially, as more people purchase a technology, the better it is to have. Classic examples are telephones and fax machines, where the machine is useless until it is popular. By nature, models that use contagion or imitation parameters model some inherent network effects. In some cases, however, network effects are much stronger, perhaps having demand increasing exponentially with penetration. To deal with

strong network effects, models require more specific adaptations (Berndt et al., 1999; Saloner and Shepard, 1995).

Hedonic Pricing: This refers to letting a price function account for more than just the price of a product. For example, as a product's quality increases it becomes more desirable, thus hedonic pricing would have the price function be adjusted to below the actual price to account for the greater appeal of the higher quality product. Hedonic pricing modifies the time-dependent price variable and can be easily included in any model that uses such a variable. There are numerous reasons to use hedonic pricing. Adjusting the price of a product can serve as a proxy for the effects of many decision variables such as product quality and advertising, and the same principle can be extended to any decision variable.

Indirect Network Effects: These occur when several financial entities interact as a result of a single consumer. ATMs are a popular example, whereby different banks operate with each other as a result of one person's transaction. It is probable that indirect network effects are involved in renewable energies, especially in cases where consumers may buy green energy from their local power company, which then in turn buys energy from a renewable energies producer. The effects on technology diffusion of indirect network effects must be evaluated on a case-by-case basis. It is unknown if a model could believably incorporate indirect network effects (Knittel and Stango, 2004).

Innovation and Imitation: Many technology diffusion models, starting with the 1969 Bass Model (Bass, 1969), rely primarily on two parameters: the coefficient of innovation and the coefficient of imitation. The reasoning is that when a new product enters a market, there are two types of individuals who will (eventually) purchase it: (1) The innovators, who purchase the product because they are excited by the new technology, and (2) The imitators, who are influenced by the product's success and by those who have already purchased it. Another name for imitation is "word-of-mouth effect" (Easingwood et al., 1983).

Innovation Diffusion Theory: When a new product is introduced to a market, its initial sales start at a level below those that it may achieve. A typical durable good, when first introduced, is only purchased by a few people. Later, as it catches on, more and more people will purchase it, and so on, until there are only a few people "holding out" that will eventually purchase the product, but have not yet done so. This process is called technology diffusion. Technology penetration is the measure of diffusion, usually given in a percentage of a known or expected fully penetrated state or cumulatively as a number of customers, households, etc. that have pur-

chased the product.

Logit function: Very common in technology diffusion models due to the prevalence of s-curves, a logit function is “Simply an exponential function that creates an s-shaped curve representing a market share growth process” (Gilshannon and Brown, 1996).

Point of Inflection: An important qualitative characteristic of an s-curve, the point of inflection is a point, usually near the middle of the curve, where the slope of the curve is maximal—where the rate of penetration is highest.

S-Curve: One typical graphical representation of percentage of technology penetration displays time on the horizontal axis and percent of penetration on the vertical axis. The curve that results is referred to as an *s-curve* because of its shape. It starts at zero, grows slowly, with highest rate of growth near the middle, and then slowly approaches full penetration at the end.

3.3 Classification

3.3.1 Organization

A classification of approaches to innovation diffusion research is given by Figure (3.1). This chapter concentrates on the macro-approach to diffusion models, in both subcategories of epidemic contagion and mixed models as presented in the article by Frank, due to the empirical nature of the problem (Frank, 2004). Epidemic and mixed models are accurate for many innovation models, but a successful renewable energy model will require parameters to include policy effects on adoption. Such parameters may be incorporated into the growth rate of diffusion, as well as the coefficients of innovation and imitation.

Many models produce a symmetric s-curve, where the inflection point is in the center and the curve after it is a reflection through the inflection point of the curve before it. Other models allow more flexibility.

Every model that has imitation or word-of-mouth parameters can begin to simulate direct network effects. Some models, however, have increased flexibility in this area, allowing for a more accurate simulation of direct network effects.

An evaluation of each model follows. They are ordered according to increasing complexity and also grouped based on style and mechanics. Thus, the first model presented is most simple model, the Basic Logistic Model,

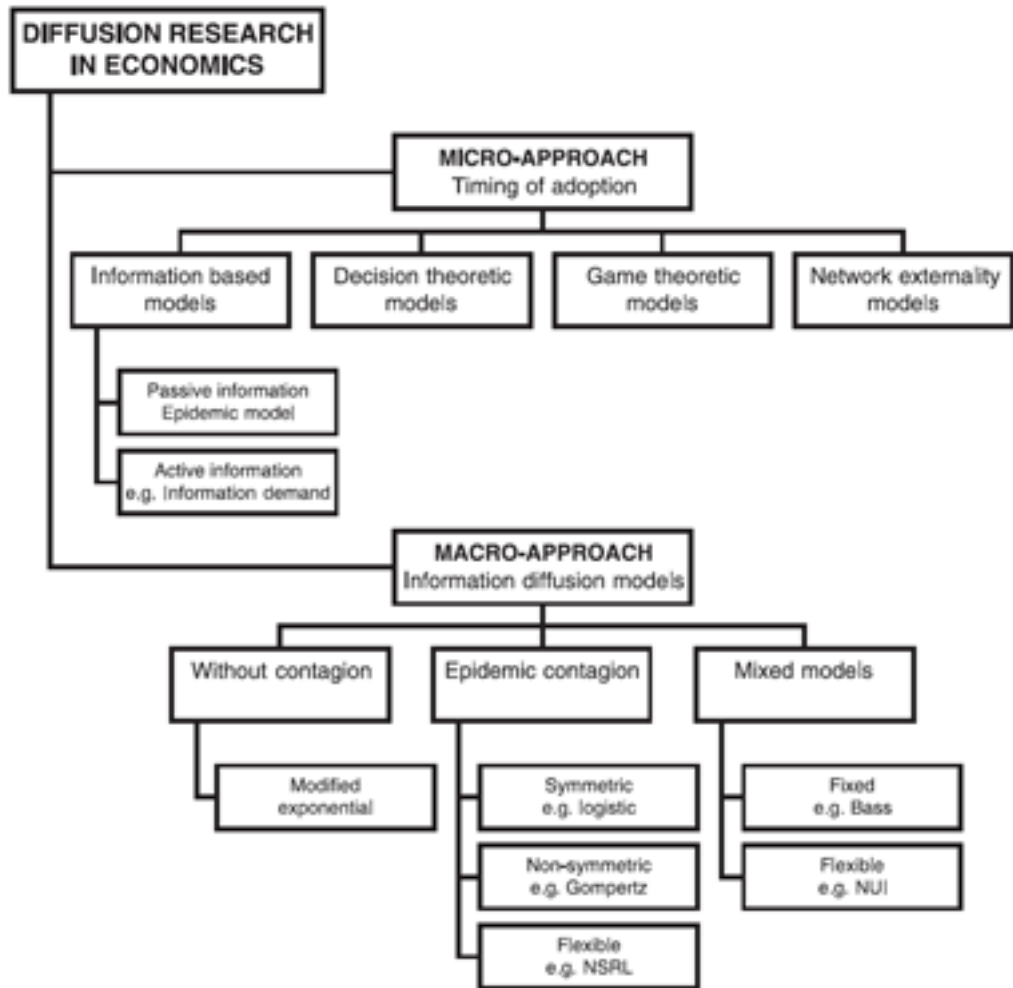


Figure 3.1: Innovation diffusion research approaches (Frank, 2004).

and the section proceeds to examine the specific characteristics of increasingly complex models. The Bass Model, on which the modified models are based, is presented near the end, as its strengths are most apparent after a discussion of many other models' strengths and weaknesses. The Bass Model is followed only by two models that extend it, the Nonuniform Influence Model and the Generalized Bass Model, both of which are explained in detail in the next chapter and modified to tailor them specifically to the renewable energy market.

3.3.2 Basic Logistic Model

The basic logistic model is expressed by the equation

$$f(t) = r * t(1 - t) \quad (3.1)$$

Here, r is the rate of diffusion or growth. This simple model is the basis for most of the advanced models examined later. It assumes a carrying capacity (size of market) that places a ceiling on the rate of growth, and is symmetric. This model is too simplistic to be of much use in forecasting renewable energy market penetration, but it is a basis for some of the modifications to come.

3.3.3 Normal Noncumulative Adopter Model

The normal noncumulative adopter model assumes that an innovation's adoption over time is based on a normal distribution curve. The equation for the density function is:

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} * e^{-\frac{(t-\mu)^2}{2\sigma^2}} \quad (3.2)$$

where σ is the standard deviation and μ is the mean time of adoption (Gilshannon and Brown, 1996). Though this is an easy equation to model, it is not very accurate. It is too rigid—it is symmetric and does not take into account any external factors such as innovation, price, or advertising.

3.3.4 Fisher-Pry Model

The Fisher-Pry model is based on a logit function, but with several underlying assumptions. The curve it gives is based on expert knowledge of the growth rate of the market, and the diffusion equation is given by

$$F(t) = \frac{1}{2}[1 + \tanh(\alpha(t - t_0))] \quad (3.3)$$

Here, α is half of the annual growth in the early years of adoption, $t = 2.2/\alpha$ is takeover time, and t_0 is an estimate of the time of peak diffusion, when penetration is half complete (Gilshannon and Brown, 1996).

The model works by taking the standard s-curve produced in the graph of the hyperbolic tangent function, which normally goes from -1 to 1, adding 1 and multiplying by 1/2 so that it goes from 0 to 1, and shifting it over so that it is near 0 when time is slightly above 0. The shape of the curve is determined only by the tanh function.

The need to estimate the growth rate requires knowledge of the market penetration during the early years of introduction. More difficult to estimate is the time where the market penetration will reach the point of half completion. It is hard to predict the overall level of penetration that renewable energy technologies will achieve, and it seems that the adoption for renewable energy will be more heavily weighted in the direction of later adopters rather than earlier adopters. Since this model is symmetric and simple, it is easy to use, but less accurate than other models based on a logit function. Also, it is hard to see where policy parameters could be incorporated into the model.

3.3.5 Stochastic Gompertz Model

The Gompertz model is a variant of the basic growth model, where the growth of a population is determined by the size of that population. The equation governing the behavior is:

$$f(T) = b F(T) \ln \frac{1}{F(T)} \quad (3.4)$$

where b is the coefficient of imitation (Easingwood et al., 1983).

The parameters must be estimated in some way, most likely by iterative approximation when given initial data. The parameters are much more accurate when more initial data points are known, but the earlier inflection point allows for accurate results when presented with even a few points of data. (Jukic et al., 2004).

Unlike most of the models, the Gompertz model is nonsymmetric; its point of inflection is before the halfway point. This might be useful, but the point of inflection is still fixed, just at a different location. This model would likely be useful even if only given as a foil to the other models. Some

renewable energy markets might have a varying point of inflection due to fiscal policy causing the diffusion curve to be weighted in the earlier years of diffusion, thus making the Gompertz model a good possibility for study (Easingwood et al., 1983).

3.3.6 Mansfield-Blackman Model

Though it was Mansfield that developed this model in 1961, Wafe Blackman refined the model and applied it to the market penetration of jet engines, finding that the results agreed well with historical data. He concluded that:

“The rate at which a new product innovation displaces an existing product in a given market appears to be an increasing function of: (1) the proportion of firms already using the new product, and (2) the profitability of the new product relative to the old product and a decreasing function of the size of the investment required to adopt the new product.” (Blackman, 1971).

The model uses a logit function to determine a smooth s-curve for the cumulative market penetration. A simple version of the Mansfield diffusion equation is

$$\frac{f(T)}{1 - F(T)} = b F(T) \quad (3.5)$$

However, the cumulative diffusion equation modeled by Blackman incorporates many different parameters and requires many inputs. Using a Taylor series expansion, Blackman solves for market share

$$F(t) = \frac{L(e^{[I+(Q+\Phi)t]} - Q/\Phi)}{(1 + e^{[I+(Q+\Phi)t]})}. \quad (3.6)$$

Here, Q and Φ are terms determined by the Taylor expansion for market share change. This, in turn, is determined by profitability as well as investment size. L is the maximum market share that the product can hope to garner, and I is a constant of integration.

In Equation (3.6), it is Φ that is used to capture most of the information about the market, since it can be determined by the equation

$$\Phi = Z + 0.530\Pi - 0.027S$$

where Z is an industry-specific risk-association constant, S is an investment index variable, and Π is a profitability index. S can be determined

by dividing the initial investment in the innovation by the total assets of the businesses introducing the innovation. Π can be determined by dividing the average rate of return by the cost of capital. The constants in the equation are dependent on industry averages and the published values are likely not valid for today's innovation markets (Gilshannon and Brown, 1996).

Although this is an interesting model that incorporates many parameters, it seems to rely too heavily on expert judgment to compute the parameters upon which determine its accuracy. Elements of the Mansfield-Blackman model may be useful to help determine the final model, but having to compute parameters at the level of expert judgment is not within the scope of this project. The issue of risk assumed by investors is a good point to bring up, however, and might be incorporated into the final model as either an external parameter or a modification to existing parameters through hedonic pricing.

3.3.7 Bass Model

This is the classic model that, since it was published in 1969, most technology diffusion models have been based on and tested against. Intended for consumer durable goods, such as freezers, televisions and room air conditioners, it is a simple and very successful model relying solely on an estimated market size and coefficients of innovation and imitation. Derived from the logit function, its accuracy depends on expert information of the factors determining the innovation and imitation parameters (Gilshannon and Brown, 1996).

The Bass Model has two parameters, p , the coefficient of innovation, and q , the coefficient of imitation. It requires, as an input, an estimate of the total number of initial purchases to be made. The likelihood that an innovator will purchase the product at any given time is given by p , and the probability that an imitator will purchase the product at any given time is q multiplied by the fraction of initial purchases already made.

The main equation governing the Bass model is the likelihood of purchase at time T given that no purchase has yet been made:

$$\frac{f(T)}{1 - F(T)} = p + qF(T) \quad (3.7)$$

where $f(T)$ is the probability of a purchase being made at time T and $F(T)$ is the number of purchases made at time T . The solution to the equation is the cumulative logit function

$$f(T) = \frac{(p+q)^2}{p} \frac{e^{-(p+q)T}}{\left(\frac{q}{pe^{-(p+q)T}} + 1\right)^2}.$$

A derivative test shows that the peak sales occur at time T^* where

$$T^* = \frac{1}{(p+q)} \ln\left(\frac{q}{p}\right).$$

Required Inputs and Parameters: Input: m , the expected total number of initial purchases (i.e. the market size, less replacements). Parameters: p , the coefficient of innovation; q , the coefficient of imitation.

Characteristics: Estimating the coefficients of innovation and imitation requires three of:

- time at which adoption is at its maximum rate
- noncumulative number of adopters at that time
- cumulative number of adopters at that time
- total population of adopters.

The success of the Bass Model will be limited by the accuracy of these predictions. Its simplicity is one of its greatest advantages, but in the case of renewable energy this may also prove to be a weakness. The Bass model has no way of capturing the subtle characteristics of renewable energy technology diffusion; it always produces a symmetric s-curve, and as p is generally much smaller than q , a Bass Model point of inflection is almost always centered (Bass, 1969; Gilshannon and Brown, 1996).

The Bass Model is included in the final GUI because it is a simple yet well-known and often accurate model. Curves predicted by the Bass model provide a point of reference to see how other models perform relative to it. As several of the models to be examined are derived from the Bass Model, any modifications made to the Bass Model will very likely be adaptations of existing modification methods.

3.3.8 Generalized Bass Model (GBM)

This is a more flexible version of the Bass model that allows for time-dependent decision variables (such as price and advertising). Recall the original Bass Model (Equation (3.7)):

$$\frac{f(T)}{1 - F(T)} = p + qF(T)$$

where f is the density function and F is the cumulative function.

The GBM seeks to modify the right hand side of this equation, and by influencing the effects of the coefficients of innovation and imitation, to simulate the effects of decision variables in a time-dependent fashion. By doing this in a general manner, the GBM allows what is essentially hedonic pricing. Any factor that changes with time and has a predictable effect on the demand for a product can be modeled by the GBM. The resulting equation is:

$$\frac{f(T)}{1 - F(T)} = [p + qF(T)] x(T) \quad (3.8)$$

where $x(T)$ is the “current marketing effort.” (Bass et al., 1994).

In the end, this yields solutions

$$F(T) = \frac{1 - e^{-(X(T)-X(0))(p+q)}}{\frac{q}{p}e^{-(X(T)-X(0))(p+q)} + 1} \quad (3.9)$$

$$f(T) = \frac{x(T) \left[\frac{(p+q)^2}{p} \right] e^{-(X(T)-X(0))(p+q)}}{\left[\frac{q}{p}e^{-(X(T)-X(0))(p+q)} + 1 \right]^2} \quad (3.10)$$

where p and q are the standard Bass innovation and imitation coefficients, and $X(T)$ is the cumulative effect of the decision variables. When $x(T)$ is constant, the GBM reduces to the Bass Model. For many products which the Bass Model successfully models, price and advertising changes are small, which makes the GBM consistent with the Bass Model in these cases (Bass et al., 1994). Handling $x(T)$ can be tricky. The equations above are designed with a positive valued function in mind, but $x(T)$ must be chosen carefully. Bass, Krishnan, and Jain recommend a function that weights the decision variable, in this case price and advertising - the price at time T denoted by $Pr(T)$ and the advertising by $Adv(T)$. Of course, these numbers are arbitrary in relation to the model, but it is the change in price and change in advertising that the model keeps track of, both short term changes and changes in relation to a baseline function denoted for price and advertising as $Pr_b(T)$ and $Adv_b(T)$, respectively. This results in a complicated mapping function first shown in discrete time:

$$\begin{aligned}
x(T) = 1 + \frac{Pr(T) - Pr_b(T)}{Pr_b(T)}\beta_1 + \frac{Adv(T) - Adv_b(T)}{Adv_b(T)}\beta_2 & \quad (3.11) \\
+ \frac{\Delta Pr(T)}{Pr(T-1)}\beta_1 + \frac{\Delta Adv(T)}{Adv(T-1)}\beta_2
\end{aligned}$$

where β_1 and β_2 are the respective weights of price and advertising. Taking the limit as $\Delta T \rightarrow 0$, the continuous time version is

$$\frac{dX(T)}{dT} = 1 + \frac{dPr(T)}{dT}Pr(T)\beta_1 + \frac{dAdv(T)}{dt}Adv(T)\beta_2.$$

Integrating, the continuous cumulative marketing effort, $X(T)$, is

$$X(t) = T + \ln \frac{Pr(T)}{Pr(0)}\beta_1 + \ln \frac{Adv(T)}{Adv(0)}\beta_2.$$

Inputs: Coefficients of innovation and imitation, market size, decision variable functions (could include fiscal policy variables).

Characteristics: Requires more information than the Bass; believable estimates for functions representing decision variable are crucial. However with different decision variable functions GBM can “produce any desired time of peak and can accommodate a great variety of shapes for the density function f ” (Bass et al., 1994).

The Generalized Bass Model is flexible, and can be accurate, although complicated to work with. It has proven itself to be as good as or better than the original Bass model in almost every case (Bass et al., 1994). The control it gives over inputting decision variables into the model may lend itself well to approximating fiscal policy. Further modifications, however, may render the model too unwieldy for any practical purposes.

3.3.9 Nonuniform Influence Model (NUI)

The NUI is a Bass-extension. It allows for a time-variant coefficient of imitation, which can produce an asymmetric s-curve with a variable point of inflection.

The difference between the NUI and the Bass Model is the replacement of the coefficient of imitation with a function. Easingwood, Mahajan and Muller say that “indirect evidence from several studies is available” showing that in many cases the word-of-mouth effect decreases as the diffusion

process progresses (Easingwood et al., 1983). However, in some situations such as those with strong direct network effects, the coefficient of imitation may need to increase with diffusion, either for a realistic portrayal of the word-of-mouth effects, or as a proxy for other results of the network effects (or both). The NUI model allows for all of these possibilities: increasing, constant, or decreasing coefficient of imitation. In the constant case it reduces to the Bass Model.

Let $w(T)$ be the coefficient of imitation. In the NUI model, it is a function of penetration:

$$w(T) = b [F(T)]^\alpha \quad (3.12)$$

where $F(T)$ is cumulative penetration at time T , b is the coefficient of imitation at full penetration, and α is a constant. When $w(T)$ is substituted into the original Bass Model (Equation (3.7)), taking the place of q , the Bass Model's coefficient of imitation, the result is

$$\frac{f(T)}{1 - F(T)} = a + b F(T)^\delta \quad (3.13)$$

where the nonuniform influence factor $\delta = 1 + \alpha > 0$, $F(T)$ is the percent of cumulative diffusion at time T , a is the NUI's coefficient of innovation, and b is a the coefficient of imitation at full market penetration.

The change in the coefficient of imitation is determined by the value of the nonuniform influence factor, δ . When $\delta > 1$ the word-of-mouth effect increases with time, when $\delta = 1$ it is constant as in the Bass Model, and when $0 < \delta < 1$ it decreases.

The nonuniform influence factor can delay or accelerate the influence leading to an early and high peak or a late and low peak in the rate of adoption. There is no closed form solution for F^* , the point of inflection, but it can fall at any percent of penetration.

Inputs: Coefficient of innovation and function for coefficient of imitation.

Characteristics: The NUI becomes flexible like the Generalized Bass Model (GBM) allowing for asymmetric curves and more flexibility in peak time than the Bass Model. Intuitively it is quite different from the GBM because its adaptability comes from entirely different reasons. It is a step towards a Network Effects Model.

The Nonuniform Influence Model provides flexibility in a cleaner way than the GBM. It is unknown how the accuracy of those two models compare, though the NUI does do well against the regular Bass. (Easingwood

et al., 1983) Possible modifications of the NUI Model involve giving a fiscal policy rationale for putting limits of the choice of α . If somehow price could be incorporated into the NUI, with hedonic pricing techniques, this could be a very robust model.

3.4 Conclusions

The most promising models for modeling fiscal policy are the NUI and the GBM. It will be interesting to see how both of these perform in renewable energy situations, especially as they have yet to be compared directly. The NUI is of particular interest because it is still simple enough for modifications, perhaps such as those described by Dalal, Ho, and Sherman (Dalal et al., 2001), which would incorporate price in a simpler manner than the GBM.

The GBM can perhaps best be dealt with as a study in hedonic pricing, for which it seems to be designed. It already is unwieldy, and more parameters could overcomplicate the model and make unreasonable data demands for a reliable fit. Built as it is, it ought to be practical to incorporate several different factors to consider, proxied as separate decision variables. This has the potential benefits of being able to clearly illuminate the different effects of several different fiscal policies.

Many approaches to modeling and many methods of modifying models have been reviewed (Bass, 1969; Bass et al., 1994; Easingwood et al., 1983; Gilshannon and Brown, 1996; Blackman, 1971; Jukic et al., 2004). Furthermore, various methods of incorporating other information into models have been examined, from network effects and hedonic pricing to explicit fiscal policies. (Rana, 2003; Berndt et al., 1999; Grubler and Nakicenovic, 1999) The main goal of this project is not to classify diffusion models, but to find or create a model that works well for renewable energy technology. Learning about the existing models has been a crucial first step in this process.

Chapter 4

Model Modification

4.1 Introduction

This chapter documents modifications to the Generalized Bass Model (GBM) and Nonuniform Influence Model (NUI). The chapter begins with a more detailed explanation of the mechanics of the models than that which was included in the previous chapter, beginning with the original Bass Model, on which the GBM and NUI are based. This chapter then explains and justifies the modifications for each of the GBM and the NUI in turn, as well as hypotheses for each. Closing the chapter is a summary, conclusions, and recommendations for future work.

4.2 Understanding the Original Bass Model

The Bass Model is given by the equation

$$\frac{f(T)}{1 - F(T)} = p + qF(T) \quad (4.1)$$

where p is the coefficient of innovation and q is the coefficient of imitation (Bass, 1969). For all models in this document f is the rate of diffusion and F the cumulative penetration, mathematically $f(T) = \frac{d}{dT}F(T)$. Assuming the initial condition of 0 market penetration, the solution to Equation (4.1) is

$$F(T) = \frac{1 - e^{-(p+q)T}}{1 + (q/p)e^{-(p+q)T}} \quad (4.2)$$

with the density function

$$f(T) = \frac{\frac{(p+q)^2}{p} e^{-(p+q)T}}{(1 + (q/p)e^{-(p+q)T})^2} \quad (4.3)$$

(Bass et al., 1994).

4.2.1 Market Size, m

Notice there is no m in this equation, the solution is purely proportional; the market penetration begins at 0 and goes to 1. For this proportion to be converted into units, one would simply multiply by m , which is the estimated total number of cumulative sales. However, units do not have any mathematical effect on the equation. Although they may effect the way in which it is intuitive to think about the equation, it works whether the data units, and therefore the units of m , are households, kilowatts, or square-footage of PV, as long as m is a reasonable estimate of “full penetration.” Although the value of m is not significant mathematically, for any data fitting whatsoever, just to be able to use the data an estimated value for m is necessary, for every single data set and market segment.

A good fiscal policy question is whether these policies are expected to simply change the speed of penetration or if m should be adjusted for certain policies, and if so by how much. An attempt to create a function that adjusts m based on fiscal policies could be made, but this creates many conceptual problems. Such a model would require base-case estimates of m assuming no policy, and then a decision would need to be made on how much to change m based on various fiscal policies. As no renewable energy technology has ever completely penetrated a market, calibrating these adjustments would be essentially guesswork. The paper introducing the GBM examined the possibility of letting m grow proportionally with the inverse of price (as price goes down, m goes up) (Bass et al., 1994). With renewable energy, it is desirable to be able to examine scenarios where an m value is mandated by the government, another reason to keep m as an input, rather than an output of the model. Bass, Trichnan, and Jain agree, saying “when no data are available for estimation, we think that it is probably best to treat m as fixed because guesses about a fixed m are probably intuitively more feasible than guesses about the influence of decision variables on m ” (Bass et al., 1994).

4.2.2 The Left-Hand Side

What is $\frac{f(T)}{1-F(T)}$? As explained in the previous chapter, $f(T)$ the *probability density function*, it is the instantaneous rate of adoption, the slope of the market penetration curve. From this equation, the Fundamental Theorem of Calculus gives $F(T) = \int_0^T f(T) dT$, called the *cumulative distribution function*, the proportion of units that have been purchased so far, the proportional level of penetration. Thus $1 - F(T)$ is the proportion of the m yet to be purchased, and the quotient that is the left-hand side of Equation (4.1) is the conditional rate of adoption given the market penetration.

Analysis confirms that the solution in Equation (4.2) does exist and that it goes from 0 to 1. Heuristically, the reasons for this are that keeping $1 - F(T)$ in the denominator on the left guarantees that solutions will approach 1, which when multiplied by m , will ensure that the cumulative solution will approach m . Multiplying both sides by $1 - F(T)$, $f(T) = (p + qF(T))(1 - F(T))$. The values of p , q , and F are always non-negative, and p and q are greater than zero. Thus, as total penetration, F , approaches 1, the slope, f , approaches 0.

4.2.3 The Coefficients

The right-hand side of equation (4.1) is similar to a sum of probabilities. For innovation, p is the proportion of the market size seen as innovators, and for imitation, q is the proportion of the market size seen as imitators. The coefficient of imitation is scaled by F , as the more units that have been sold, the more people there are to imitate. The sum of these terms yields a probability density function, given by $q * F(T)$, which is the probability density of a purchase at time T for those who have not yet adopted (Bass, 1969).

4.3 Understanding the GBM

The GBM is an extension of the Bass Model,

$$\frac{f(T)}{1 - F(T)} = [p + qF(T)]x(T), \quad (4.4)$$

where $x(T)$ is made up of a sum of time-dependent decision variables, standardized so that relative changes in these factors effect the curve. To understand why relative changes are tracked by the model, consider this

example: If purchase price goes from \$100.00 to \$105.00, the numbers are meaningless by themselves, as the model has no concept of what a dollar is, or how much it is worth. But, a 5% change in price is meaningful, and this is how the model understands the change. Graphically, $x(T)$ horizontally stretches and squishes the s-curve, but as it is time-variant, it does not do so uniformly.

Another conceptual way of thinking about the effects of $x(T)$ is that it is a way of moving between solution curves. When thinking of fiscal policy, it is easy to imagine a data set where price is relatively constant, then there is a sudden large change, and the new price remains constant. In such a case, it is mathematically somewhat intuitive to imagine two complete solution curves, one for the new price and one for the old price, and at the time when the price change occurs, x (continuously) jumps to the appropriate curve.

The standardized changes are also weighted by variables $\beta_1, \beta_2 \dots$, so that the relative importance of the decision variables can be accounted for. For example, one might expect a 10% increase in advertising to effect sales less than would a 10% price cut. If this were actually the case, then the β corresponding to advertising would be smaller than the β corresponding to price.

The solution to the GBM is as follows:

$$F(T) = \frac{1 - e^{-(X(T)-X(0))(p+q)}}{\frac{q}{p}e^{-(X(T)-X(0))(p+q)} + 1} \quad (4.5)$$

$$f(T) = \frac{x(T) \left[\frac{(p+q)^2}{p} \right] e^{-(X(T)-X(0))(p+q)}}{\left[\frac{q}{p}e^{-(X(T)-X(0))(p+q)} + 1 \right]^2} \quad (4.6)$$

where $X(T) = \int x(T) dT$ (Bass et al., 1994). The standard application of the GBM is to use both price and advertising in $x(T)$. In this case, the equation for $x(T)$ is

$$x(T) = 1 + \frac{Pr(T) - Pr_b}{Pr_b} \beta_1 + \frac{Adv(T) - Adv_b}{Adv_b} \beta_2 + \frac{Pr(T) - Pr(T-1)}{Pr(T-1)} \beta_1 + \frac{Adv(T) - Adv(T-1)}{Adv(T-1)} \beta_2. \quad (4.7)$$

Here $Pr(T)$ and $Adv(T)$ are price and advertising functions (data), respectively, and Pr_b and Adv_b are baseline values. The expected sign of β_1 is negative, because a negative change in price ought to positively effect the

slope, and the expected sign of β_2 is positive for similar reasons (Bass et al., 1994).

4.4 Modifying the GBM

To incorporate fiscal policy into the GBM $x(T)$ was modified, making it the sum of three decision variables: purchase price, advertising, and savings/benefits.

The savings/benefits function is some measure of the benefits of owning the product. For some examples, for a hybrid car it could be engine efficiency multiplied by gas price, so if a model is improved and efficiency increases, or if gas prices climb, the benefits of owning one increase. Alternatively, for a PV or other power source installation, a good choice for the savings/benefits data would be the estimated power produced in month or a year multiplied by the estimated cost of this power through conventional means. If there are fiscal policies giving tax credits or other associated benefits, they should be incorporated. It is important that these are decision variables, so what matters more than accuracy in these estimations is what the consumer perceives their value to be. The ideal source for these numbers would be consumer reports, widely available studies, or even advertisements for the products.

The three decision variable functions will be referred to as $Pr(T)$, $Adv(T)$, and $Sav(T)$, for purchase price, advertising, and savings/benefits, respectively. Many fiscal policies may be incorporated into the price function, such as rebates, subsidies and taxbreaks—anything that occurs once, only at the initial purchase. Other fiscal policies involving education and advertising campaigns will be accounted for in the advertising variable. Benefits associated with owning the product will be part of the savings function. As mentioned in another section, fiscal policies mandating a certain level of market penetration should factor into the choice of m .

A significant amount of data is needed for these functions to be effective. For any given market segment, all of the following are necessary:

- Sales data (initial points of $f(T)$)
- Market size estimate (m)
- Price data ($Pr(T)$)
- Advertising data ($Adv(T)$)

- Savings data ($Sav(T)$)
- Fiscal policy data (included in all above)

Data can be very hard to come by; creativity is encouraged in this area. Any reliable measure is adequate. For advertising, the ideal data would be an exact measure of the influence of advertising. This is unfeasible, so good hard data would be the monetary amount spent on advertising, but when that is not available, the annual number of advertisements placed in some representative set of magazines could be a good proxy. Again, units do not matter, so long as they are consistent.

Bass, Krishnan, and Jain in the GBM paper cite Simon as recommending that advertising be treated as a non-decreasing function. Simon presents a strong argument; he shows numerous examples of sales drop-off lagging far behind a cut in advertising spending, so the models have been coded into the GUI with this assumption (Simon, 1982). However, this assumption does rely on advertising resurfacing, if advertising drops completely and does not return, the assumption is inappropriate.

The baseline values have a standardizing effect. As recommended, they are, by default, the first non-zero values taken by each decision variable. An alternate method would set them as the price, savings, and advertising for a close alternative to the product, but this increases the already large data demands, so the easier option was implemented in the GUI.

The modified model now is that given by Equation (4.4), but with

$$\begin{aligned}
 x(T) = 1 &+ \frac{Pr(T) - Pr_b}{Pr_b} \beta_{Pr} + \frac{Sav(T) - Sav_b}{Sav_b} \beta_{Sav} \\
 &+ \frac{\max\{0, Adv(T) - Adv_b\}}{Adv_b} \beta_{Adv} \\
 &+ \frac{Pr(T) - Pr(T-1)}{Pr(T-1)} \beta_{Pr} + \frac{Sav(T) - Sav(T-1)}{Sav(T-1)} \beta_{Sav} \\
 &+ \frac{\max\{0, Adv(T) - Adv(T-1)\}}{Adv(T-1)} \beta_{Adv} \tag{4.8}
 \end{aligned}$$

4.5 Hypotheses for the GBM

If these models are accurate representations, then β_{Pr} , β_{Sav} , and β_{Adv} , the weights placed on the decision variables, ought to be nearly the same for a given product across different market segments—even in different fiscal policy environments. It is reasonable to assume that a buyer in L.A. County

would go through a similar decision-making process to someone in New Jersey when deciding whether or not to install photovoltaics, or whether to buy a hybrid vehicle, at least as far as weighing the price relative to the expected savings. It is, of course, expected that the data will be different in different areas. But the relative effects that changes in price, benefits, and advertising ought to be similar.

It is plausible that the β 's would be different in different cultures. It could be quite interesting if reasonably consistent United States β 's exist, to see how they compare to averages across Germany, Spain, or Japan. Cultural differences are expected to effect the values to some extent.

The advertising weight, β_{Adv} , may be a slightly different matter. It is reasonable to assume that β_{Adv} will be constant across market segments when advertising methods are consistent. The effect of advertising relies heavily on its effectiveness. If, however, vastly different methods of advertising are used in different market segments, say, for example, education in one and TV commercials in another, the value of β_{Adv} ought to depend on the effectiveness of the advertising itself.

4.6 Understanding the NUI

The Nonuniform Influence Model accounts for a common phenomenon observed by Easingwood, Mahajan, and Muller: that word-of-mouth effect tends to drop off as full penetration is approached. To account for this, they add one parameter, δ , called the "nonuniform influence factor," to the original Bass Model (Equation (4.1)) resulting in:

$$\frac{f(T)}{1 - F(T)} = p + q(F(T))^\delta. \quad (4.9)$$

The nonuniform influence factor is always greater than 0, but, as F goes from 0 to 1, if $\delta < 1$, the point of inflection is achieved sooner, and vice versa for $\delta > 1$ (Easingwood et al., 1983). When $\delta = 1$ the NUI is identical to the Bass Model. Theoretically, for different values of δ , the point of inflection could occur at any time $t > 0$, though values that are extremely close to 0 or arbitrarily large would indicate that innovation/diffusion modeling is inappropriate.

Unfortunately, unlike the coefficients in the Bass Model, there is no behavioral explanation for why δ takes the values it does. As noted earlier, in many cases the word-of-mouth effect is observed to decrease with penetration, that is, $\delta < 1$, but the reasons for this are not well understood. In their

paper testing the NUI, Easingwood, Mahajan and Muller tried 5 data sets, 4 of which had $\delta < 1$, but for dishwashers $\delta = 1.5$. No explanation was offered, though the NUI clearly outperformed the Bass Model (Easingwood et al., 1983).

4.7 Modifying the NUI

The word-of-mouth effect is very similar to advertising. In a way, advertising is simulating a word-of-mouth effect, attempting to create one without selling products. Dalal, Ho, and Sherman say that “promotions are likely to strengthen the innovation tendency” (Dalal et al., 2001), however advertising could theoretically be effectively modeled as an increase in the word-of-mouth effect. Therefore the NUI has been modified just as the GBM for price and savings, but $Adv(T)$ is moved into the exponent for imitation.

The resulting equation is:

$$\frac{f(T)}{1 - F(T)} = [p + q(F(T))^{\delta(T)}]x(T), \quad (4.10)$$

where $\delta(T) =$

$$\alpha - \frac{\max\{0, Adv(T) - Adv_b\}}{Adv_b} \beta_{Adv} - \frac{\max\{0, Adv(T) - Adv(T-1)\}}{Adv(T-1)} \beta_{Adv} \quad (4.11)$$

and

$$\begin{aligned} x(T) = & 1 + \frac{Pr(T) - Pr_b}{Pr_b} \beta_{Pr} + \frac{Sav(T) - Sav_b}{Sav_b} \beta_{Sav} \\ & + \frac{Pr(T) - Pr(T-1)}{Pr(T-1)} \beta_{Pr} + \frac{Sav(T) - Sav(T-1)}{Sav(T-1)} \beta_{Sav}. \end{aligned} \quad (4.12)$$

This makes sense theoretically, because initial increases in advertising will have a strong effect early on, observationally equivalent to faster penetration in the innovation stage, or artificially inflating F when calculating imitation. Regarding the δ function, initial modifications put a 1 in place of the α , but this would force $\delta(T) < 1$ if any advertising is present, so the subsequent modifications are superior. Renewable energy does not seem to penetrate a market rapidly, so it is very possible that then net value of $\delta(T)$ will still be greater than 1. Hence, α is a constant designed so that the inflection point still has flexibility, but advertising can hurry its approach.

The $x(T)$ function is taken straight from the modified GBM, with advertising omitted. The multiplicative quality, so that both coefficient of innovation and imitation are equally effected by savings and price, still seems appropriate. The addition of the savings/benefits function, described in §(4.4), is a valuable innovation, so it would be negligent to leave it out of the modified NUI.

The earlier discussion of data and fiscal policy (§4.4) is equally valid for the modified NUI.

4.8 Hypotheses for the NUI

Much like the GBM, it is expected that for a given market, β_{Pr} , β_{Sav} , β_{Adv} , and α will be consistent. Some variation is expected in β_{Adv} if different advertisements and education methods are implemented. The emphasis put on price and savings may also be a cultural phenomenon and therefore vary geographically, but not much between similar (e.g. all urban American) market segments. Perhaps most interesting will be to see how values of α compare to values of δ in the plain NUI, and how β_{Pr} and β_{Sav} compare with the corresponding values in the modified GBM.

4.9 Summary of Modifications

The GBM modification is innovative in the introduction of a new decision variable, the savings/benefits function. This does not effect the mechanics of the model, but instead fine-tunes it to the renewable energy market.

The NUI modification is a hybrid, part modified GBM and part NUI. The change from the NUI is transforming the nonuniform influence factor into a function of advertising. Essentially, this proxies advertising as an artificially increased word-of-mouth effect. The constants involved allow this to be a large change, but a small β_{Adv} , constant advertising or constantly increasing advertising, it reduces to a pure hybrid. As the NUI can reduce to the Bass Model when $\delta = 1$, the modified model can reduce to the modified GBM, which, if price and savings are constant, reduces to the original Bass Model.

The modified NUI is very similar to the work done by Zachary Bratun-Glennon over the summer of 2005 during his internship at NREL. There are, however, several key differences between his work and these recommendations. First, he recommends using data on renewable energy subsidies in the $x(T)$ function (Bratun-Glennon, 2005), whereas here they are

incorporated directly into the appropriate decision variable to more accurately reflect consumer decision-making. This is because $x(T)$ is intended to be a sum of decision variables (Bass et al., 1994), and subsidies have direct effects on decision variables, but do not by themselves compose a decision variable. In fact, a subsidy in many cases will primarily effect one decision variable in particular. Including both needlessly adds a variable, whereas in these recommendations utilizing hedonic pricing techniques by incorporating policy into the decision variable, the effect of fiscal policy is modeled in a more elegant and believable manner. Also, the creation of the savings/benefits function is new in this paper. This decision variable will hopefully capture an aspect of the renewable energy market that has thus far been ignored. Shifting advertising out of $x(T)$ and into $\delta(T)$ makes the nonuniform influence factor less arbitrary, and is a major qualitative change in how the model works. Together, these changes result in a model quite different from the one recommended by Bratun-Glennon.

4.10 Conclusions and Recommendations

The modified NUI retains the flexibility of the NUI while incorporating important decision variables, giving advertising the potential for a very strong effect, while the modified GBM is a revision of the GBM tailored specifically for the renewable energy market.

4.10.1 The Advertising Choice

Advertising can greatly influence consumer's knowledge about a product and related fiscal policies. The team has several relevant examples where experts maintain that a strong advertising campaign has strongly influenced market penetration. Careful consideration was given to modifying the NUI to retain its independence from advertising, but advertising is a variable too influential to ignore.

Unfortunately, exhaustive research has turned up no useable advertising data. This has left us unable to fully test the modified models. They do work when advertising is assumed constant, but that nullifies one of the modifications to the NUI and hurts the believability of both. Advertising data is needed to examine the market penetration of renewable energies, and currently it does not exist.

4.10.2 Recommendations

One of the toughest parts of this modeling is the small size of data sets. Beginning with an equation that will generally produce the correct shape without any help, and using non-linear regression to estimate five parameters for the modified GBM and six for the modified NUI, on a data set with only six points. In actuality, two of the β 's could be ignored while still providing and numerically good fit, but that fit would be essentially a Bass Model or NUI fit. There are two good methods to take advantage of the modified models, and both involve getting more data.

First, using the assumptions about the values of the various β 's being the same for different data sets of a given product, the difficulty of the number of parameters can be ameliorated by analyzing many data sets to obtain estimates on some of the parameters. The first goal is determine values of β_{Pr} , β_{Sav} , and β_{Adv} for various markets. Once those have been found, if a small confidence interval can be generated around them and they seem consistent (as stated before, this depends on the truth of the hypothesis that they are in fact the same), they may be input into the model for new market segments, effectively reducing the number of parameters. This simply requires multiple data sets for a given product.

The other method is to find more frequently occurring data. So far, some yearly sales data has been found, but if quarterly data could be obtained, the number of points would be quadrupled, and the confidence of fit would greatly improve. Alternatively, when data is not available, it is possible to spline the data and assume trends throughout the year to create biannual or quarterly data. This is a risky practice though, because the confidence intervals on the parameters will be improved, but it is based on fictional data. One would want to research carefully what sort of spline would be appropriate.

As mentioned earlier (§4.4), if it can be confirmed that the values of β_{Pr} , β_{Sav} , and β_{Adv} are relatively constant over different market segments, a good step towards validating the modified models will have been made. If, however, they parameters do not meet these criteria, then it would indicate that the theory behind the model is flawed. As stated above (§4.10.1), the most valuable thing that could be done is to gather advertising data, for without it, progress seems to be stalled.

Chapter 5

GUI

5.1 Overview

The team has developed an application with a graphical-user-interface for two reasons: 1) to visually demonstrate to end users the effects fiscal policies have on the renewable energies market, and 2) to serve as a tool to qualitatively and quantitatively explore the characteristics of the various models. These two different driving forces create an interesting interface challenge: the application must be intuitive to someone with “average” computer experience while allowing for advanced features that allow for comparing the different models.

The application can apply the following models: Bass, Generalized Bass, Nonuniform Influence (NUI), the modified Generalized Bass and the modified NUI model. Every model requires at least historical yearly sales data however some are dependent upon pricing, advertising and savings (see Table 5.2). The application also can export results obtained to common formats (thus allowing for the sharing of results through various media).

The team chose MATLAB as the development platform. The reasons are: the entire team had experience with MATLAB, it has an extensive statistics toolbox and the GUI development environment (GUIDE) is well supported.

5.2 Key Features

5.2.1 Multiple Models

The GUI permits multiple regressions to be applied to a single data set and the results displayed simultaneously. Regressions may vary in both model and data subset size (i.e. user may choose to only use a selection of the total supplied data). This feature allows the user to compare the difference in projections amongst the models and to test the predictive capabilities of the models.

5.2.2 Manage Market Size

Each model is heavily dependent upon the estimated total market size, m , which is often hard to determine. For this reason the GUI allows a user to specify m or regress a value for m . The regression for estimating market size is discussed in the Implementing the Models section.

The user specified m can be quickly scaled up or down by adjusting the *scale market size* value (represented in percentage points). This feature is useful when working with a percentage of a known market. An example of this would be anticipating the market size of hybrid vehicles, the total market size could be estimated as a percentage of total consumer vehicles. Should it be anticipated that hybrid vehicles eventually account for 30% of consumer vehicles the user would input the total number of consumer vehicles for *market size* and 30 for *scale market size*.

5.2.3 Manage Scope of Time

An additional feature is the ability to predict the future penetration of a technology/product. The scope of the time axis can be controlled through the use of the “Expand Time” button, which allows the user to choose how much time he/she wishes to display on the x-axis, thus allowing for the model to plot beyond the regressed data set.

The user may limit the number of data points used. This is most applicable when there is a large data set and the user wishes to test the predictive capabilities of the models. For example, if the user has a 20 point data set, he or she may run the regression on the first 10 data points and see how the model predicts the remaining 10 data points. To select the subset the user right-clicks on the large plot at the last data point to be included. The application will then grey out the remaining points (This feature is limited

to omitting only end points). To quantify this there is an output of the R-squared value for both the data subset (1 through 10) and the entire data set (1 through 20). See section 6.2.6 for the definition of R-squared.

5.2.4 Import / Export

To make the GUI more dynamic and user-friendly data may be imported and results may be exported. Data sets are imported through the standard windows file-open interface and are stored in the .ini file format (see Appendix C).

The graphs and log of results are easily exported via the 'Export' menu item in the top toolbar. The graphs (yearly adoptions and cumulative penetration) are exportable to either a .jpg or .gif image file. The history of the current plot and the results of the regressions are exportable as text files. The actual predicted results of the models may be predicted as well. The annual sales data for each model may be exported by selecting the model in the model-history, right clicking on the same item and selecting 'Export Predicted Sales.' The sales can then be exported to either a text file or to the clipboard (that way the user can paste it into another program).

5.2.5 Error Handling

Because the regression methods are not always successful, error handling has been implemented to notify the user of problems. The errors can often be rectified by changing parameters, such as allowing the model to regress for m , changing the seed market value, or changing the regression method.

5.3 Software Structure

The GUI is modular and it is easily expandable. The code for each model is stored separately in its own MATLAB m-file and all share a common format for input and output. Each model accepts a specially structured input file that contains the information pertinent to the model. Upon completion each model returns its coefficients estimated by regression and the predicted sales/adoptions yearly data computed by using the coefficients. A strong effort to isolate repetitive code into separate modules has been made so that when making a functional change there will be minimal changes in the code.

The GUI works by selecting a data set containing sales/adoptions data and any other relevant data (e.g. pricing, advertising or savings). The data

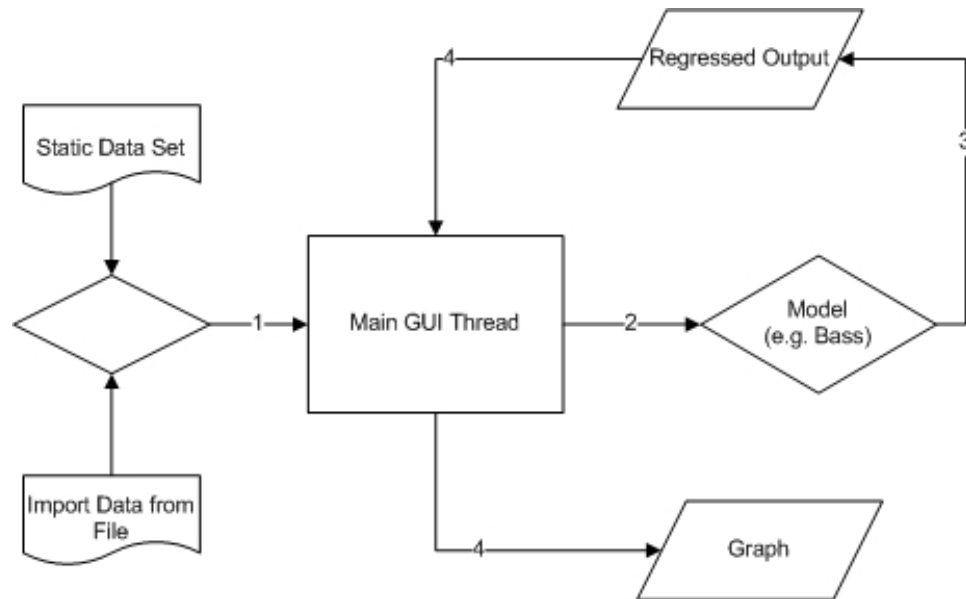


Figure 5.1: Data Flowchart of GUI.

set is processed by the selected model which, as previously mentioned, outputs the regressed coefficients and predicted data. These data are then displayed on the screen of the GUI. Fig. 5.1 illustrates the data path.

There are two main global structures throughout the main application (`NREL_GUI.m`), `appData`, and `mainData`. The purpose of `appData` is to store preferences and variables that are used by the interface (e.g. axis labels, and log parsing information). The `mainData` structure contains all data relevant to running the models, for example the Bass model would require `mainData` to have the following information: the specified length of time to evaluate, the sales data, what regression method to use, and the total market size. The reason the information was split into two structures is that MATLAB does not support pointers, so whenever data is passed to a model a copy of the entire structure is made. The isolation of the data pertinent to modeling to a single structure yields minimal extraneous memory usage.

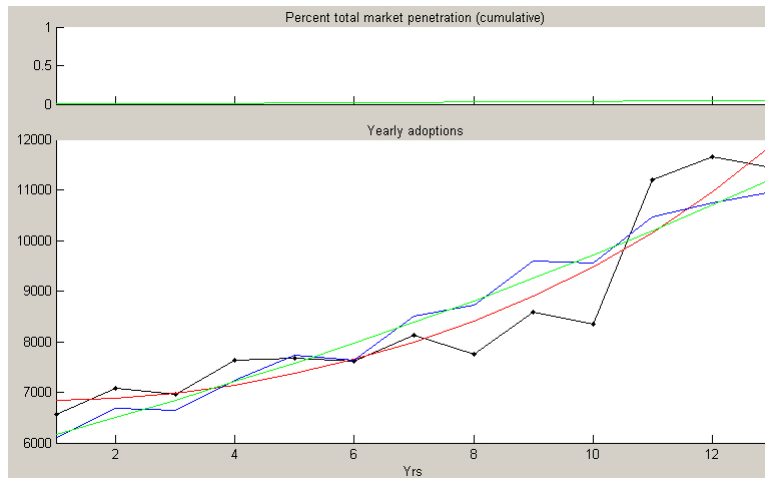


Figure 5.2: Screen Shot of GUI. This illustrates the results of multiple regressions. The green line is the Bass model, the blue line is the GBM and the red line is the NUI model.

5.4 Display of Data

When analyzing the sales/adoption data there are two ways of displaying it: 1) the yearly adoption data, and 2) the cumulative data (also known as market penetration or the S-curve). The yearly adoption data is displayed in the large main graph, while the cumulative data is displayed in a smaller plot. As previously mentioned a main feature is the ability to plot multiple regressions of a data set onto a common graph. The results of an example are displayed in Fig. 5.2.

5.5 Implementing the Models

At the conclusion of the project there are five models implemented; the Bass, the generalized Bass (GBM), the NUI, the modified GBM, and the modified NUI. As mentioned in the Software Structure section the models all share a common format for input and output.

The models themselves are constructed in two parts. The first part is the 'run-function' (the controller function), which is what is called by (NREL_GUI.m). The 'run-function' parses the input data then performs any manipulations needed (e.g. adjusting the advertisement data for the GBM model), and the proper regression method is invoked (more than one

regression method available, see the Nonlinear Regression section below). The second portion of a model is the actual mathematical implementation of the model, referred to as the 'modeling-function' in this document. The 'modeling-function' is constructed in a format compatible with the regression methods (see comments in code for particular formatting), and outputs a vector of yearly sales. For more details see sections 5.5.4 through 5.5.8.

5.5.1 Nonlinear Regression

Each of the models available to the GUI uses one of two nonlinear regression algorithms built into MATLAB; 'nlinfit' and 'lsqcurvefit'. The former implements the Gauss-Newton algorithm and the latter implements the Levenberg-Marquardt algorithm. For information about these algorithms, see MathWorld Weisstein (2006a and 2006b) and texts on nonlinear optimization, e.g. Fletcher (1993). Each algorithm has its own advantages and disadvantages. Experience shows the Levenberg-Marquardt algorithm to be more reliable (Gauss-Newton method uses complex numbers that make the process more complex and occasionally fail) however it often finds results local to the initial guess.

The 'lsqcurvefit' method allows specifying bounds on the coefficients being regressed, so it is possible to define a more precise range than the bounds $[0, \infty)$ specified in the GUI. The reason the current range is so large is because different data sets have different magnitudes and we did not want to impose arbitrary limits on the values.

5.5.2 Sensitivity of Market Size

The most sensitive coefficient is m , the total market size. The reason it is so sensitive is because while the other coefficients describe the shape of the curve, m scales the curve to the proper magnitude. For example if a hybrid-car sales dataset were to be evaluated in thousands sold and millions sold, all coefficients other than m would be the same between the two because the curve is the same shape. The market size however would differ by a factor of 1000.

When looking at a data set with a dip at the end one could interpret the dip as the beginning of the decline of sales. In this situation a small market size would correlate with the sales declining; however if the user suspected a much larger market size (relatively) the predicted trend would continue to rise through the dip.

Ideally the market size coefficient should be supplied by the user as an expert opinion. However should the user be unsure of the value, he/she does have the ability to regress for m by selecting the particular option in the user interface. When regressing for m the regression algorithm starts searching around a seed value, which in this implementation uses the user defined *adjusted - m - value* (the inputted m value multiplied by the scalar).

5.5.3 Validation

In order to validate the coding of the models the results reported in the GBM and NUI papers (Easingwood et al., 1983) were compared with the results obtained from running the GUI. The datasets were obtained from (Bass et al., 1994). The published results gave different m values for each regression. The same m values were used as the static m values for our corresponding regressions. As can be seen in Table 5.1 the values match nearly exactly in most cases. The team believes that slight variations are explained by the difference in regression methods.

The most notable differences in the validation results are the β_1 and β_2 values returned from applying the GBM to the clothes dryer dataset. β_1 is the coefficient which scales the affect that pricing has on sales data and is generally negative (lower prices normally yield higher sales) and thus the Levenberg-Marquardt regression limits the upper-bound to zero. If there had not been an upper-bound β_1 would have regressed to .3896 (opposite sign than expected). In this particular data set the price actually increases in the first three years as does the sales data thus temporarily creating a positive correlation between price and sales. The team believes this anomaly is one of the main reasons that the regressed β_1 is not negative. Furthermore when the graphs are compared they closely follow the original sales data points (see Figure 5.3). The team feels confident attributing the difference in values to the difference in regression methods.

5.5.4 Bass Model

There are two options for estimating the coefficients of the Bass model: the first is to use Bass's quadratic approximation method and the second is to apply a non-linear regression. The quadratic approximation is what Bass, (Bass, 1969) used to estimate the p , q , and m coefficients. Unfortunately the team was not able to match the results using this method and instead had to modify the discrete modeling approach.

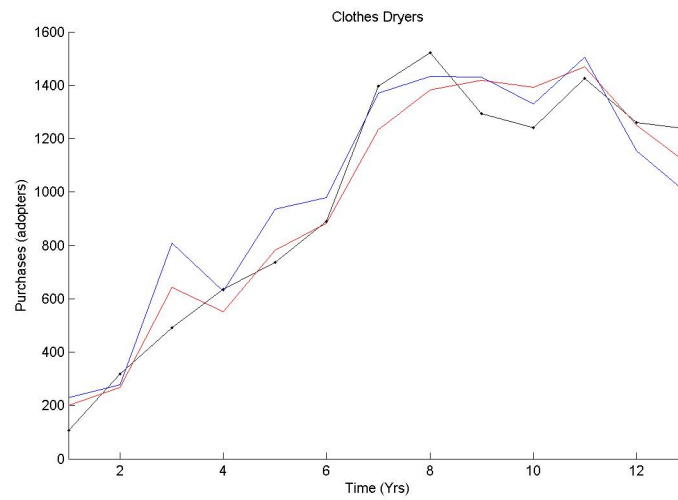


Figure 5.3: Modeling of clothes dryer data using NUI. The magenta curve uses the coefficients reported in the NUI paper and the Cyan curve uses the coefficients regressed by the GUI.

	p	q	δ	β_1	β_2	m
Room Air Conditioners						
Bass	0.00801	0.3845	-	-	-	18,321
	<i>0.00930</i>	<i>0.3798</i>	-	-	-	<i>18,321</i>
GBM	0.00536	0.3343	-	-1.3040	0.5737	19,502
	<i>0.00516</i>	<i>0.3309</i>	-	<i>-1.3691</i>	<i>0.6186</i>	<i>19,502</i>
NUI	0.000172	0.2300	0.6179	-	-	22,389
	<i>0.000168</i>	<i>0.2013</i>	<i>0.4954</i>	-	-	<i>22,389</i>
Color TVs						
Bass	0.00419	0.6432	-	-	-	39,524
	<i>0.00490</i>	<i>0.6440</i>	-	-	-	<i>39,524</i>
GBM	0.00407	0.6009	-	-5.0440	-0.0158	39,754
	<i>0.00416</i>	<i>0.5965</i>	-	<i>-4.8130</i>	<i>0</i>	<i>39,754</i>
NUI	0.00088	0.5207	0.8046	-	-	41,678
	<i>0.01091</i>	<i>0.4121</i>	<i>0.6000</i>	-	-	<i>41,678</i>
Clothes Dryers						
Bass	0.01181	0.3353	-	-	-	16,239
	<i>0.01340</i>	<i>0.3317</i>	-	-	-	<i>16,239</i>
GBM	0.01004	0.3157	-	0.0000	0.4632	16,756
	<i>0.01180</i>	<i>0.2959</i>	-	<i>-0.8117</i>	<i>0.6583</i>	<i>16,756</i>
NUI	0.00816	0.2671	0.7901	-	-	17,233
	<i>0.00879</i>	<i>0.2494</i>	<i>0.7179</i>	-	-	<i>17,233</i>

Table 5.1: This table compares the results from the GUI with results from literature. The italicized values are those obtained in the original papers.

When trying to duplicate Bass's discrete modeling of color television sales with the first three data points the team perfectly duplicated all results except for the value of q (Bass, 1969). Instead of using the long-range forecasting adjustment for q' that Bass described, the team calculated the correction factor, k , from the results of p (see Bass's paper for further explanation of discrete approximation). Then, by applying k to q' the team is able to match Bass's results. The team has yet to identify the reason for this discrepancy and for this reason does not recommend using the implemented discrete model.

The continuous model is the original unaltered Bass model, and the 'modeling-function' is implemented using the ODE toolkit in MATLAB (specifically *ode45*). The regression method used is the Gauss-Newton method.

5.5.5 Generalized Bass Model (GBM)

The Generalized Bass Model uses the Levenberg Marquardt method (with the option to use the Gauss-Newton method) and regresses for p , q , β_1 , β_2 and for m if specified. As explained in the model section the GBM is dependent upon pricing, advertising and sales data.

5.5.6 Nonuniform Influence Innovation Model (NUI)

The NUI Model uses the Levenberg Marquardt least-squares algorithm by default but has the option to use Gauss-Newton. Because the NUI model does not have a closed-form solution MATLAB's ODE (ordinary differential equation) toolkit was used (specifically *ode45*). This function uses an explicit Runge-Kutta formula, the Dormand-Prince pair. The coefficients that are regressed for are p , q , δ and m if specified. The NUI does not depend on any other input variables other than previous sales data.

5.5.7 Modified GBM

The modified Generalized Bass Model uses a Levenberg Marquardt or, optionally a Gauss-Newton algorithm to regress for p , q , β_1 , β_2 , β_3 and m if specified. The modified GBM is dependent upon pricing, advertising, savings and sales data.

5.5.8 Modified NUI

The Modified NUI Model uses a Levenberg Marquardt or, optionally a Gauss-Newton algorithm combined with Euler's method for solving the

<i>Model</i>	<i>Sales</i>	<i>Price</i>	<i>Adv.</i>	<i>Save</i>
Bass	x			
GBM	x	x	x	
NUI	x			
Modified GBM	x	x	x	x
Modified NUI	x	x	x	x

Table 5.2: Required data for each model.

ODE. The coefficients regressed for are p , q , δ and m if specified. The NUI does not depend on any input variables other than previous sales data.

5.6 Data Inputs

As previously mentioned (see Key Features section) there are two options for the source of the data to model: 1) built-in data sets, or 2) import data. The built-in data sets are useful for quickly varying models to see the differences among them and getting acquainted with various features.

All of the models require sales data. As previously discussed (in the Implementing Models and Model Modification sections) some of the models require additional data. These additional data (pricing, advertising and savings) must not only extend to the length of the pricing data but they must extend to the total forecasting time (i.e., beyond the pricing data). Table 5.2 illustrates the data required by each model.

5.7 Layout & Design

The user interface was designed for ease of use. The layout and functionality is intended to mimic similar programs (e. MATLAB), and use popular generic features. For example “tooltips:” when the mouse hovers over an object an encapsulated description of the object appears. The layout (Figure 5.4) is divided into six distinct sections.

Section A acts as the control center coordinating the data and model to use. The data portion allows for selection of hard coded data or imported data and allows the user to increase the time axis so that the models predict into the future. The model portion allows for the various models, choosing among toggling the display of error bars and selection of graph color (which automatically cycles after every plot). The choice of colors is

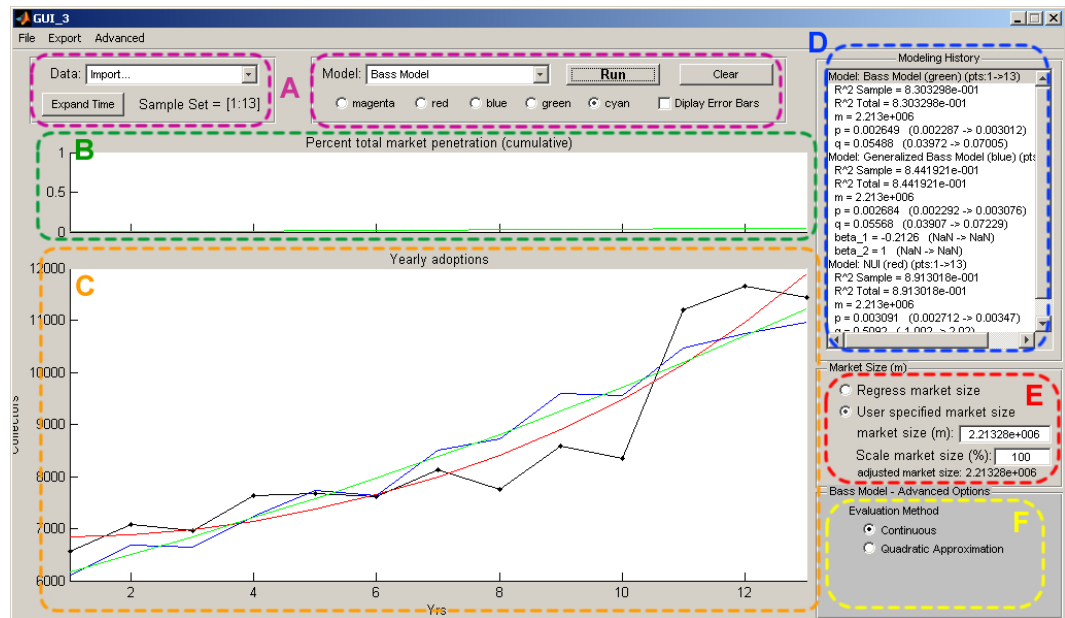


Figure 5.4: Screen Shot of GUI.

allowed to differentiate among regressions on the same plot.

Sections B & C are where the regression curves are displayed. There are two panels, the upper one (B) is the cumulative adoption curve (S-curve) and the lower panel (C) is the yearly adoptions/sales graph. The bottom graph as previously mentioned (in Key Features) permits the user to crop-out the end data points by right clicking on the chosen endpoint.

Section D displays the results of the displayed regressions. Each regression listed is accompanied with the line color, regression error data, model parameters, and what points the regression was applied to. The textual data recording all the results is exportable via the export menu at the top of the program. The curves may also be removed by selecting a model in the history list, right clicking and then selecting "remove curve." The annual sales data corresponding to a particular regression may be exported by selecting a model in the list, right clicking and then selecting 'Export Predicted Sales'.

Section E of the GUI controls whether or not the model is to regress for the market size or to use the specified market size.

When regressing for the market size the 'adjusted market size' is used as an initial guess for m . As previously mentioned regressing for m is prob-

lematic since the regression algorithms tend to find a local minimum and which is an unreliable estimate.

Section F is where all of the model-specific parameters are specified. For example, when the Bass model is selected the user can choose between the discrete and continuous model.

5.8 Deployment

Since one of the goals of the project was to create a program for use by users of average computer skill, the team had to make sure it is easily compiled and deployed. MATLAB's development platform utilizes proprietary libraries, even when compiled into an executable the program still depends on the MATLAB libraries. For use by individuals without MATLAB, the application must be packaged with the MCRInstaller, a program that installs the MATLAB necessary codes. The installer is packaged on the CD supplied by Harvey Mudd College. The MATLAB license does not allow for public distribution of the executable, but it does allow for distribution to the developers clients.

5.8.1 System Requirements

The GUI was developed on a computer running Windows XP Professional, an Athlon 64 3200+ processor with 1 GB of memory. The recommended system requirements are: 300 MB of hard drive space, Windows XP (Home or Professional), 1 GHz processor and 512 MB of memory.

Chapter 6

Data Analysis and Results

6.1 Motivation and Approach

An essential aspect of developing an accurate model for predicting the market penetration of renewable energy technologies is the analysis of renewable energy product data with the currently available market diffusion models. It is evident that the characteristics of the products that are applied in the current models (i.e. televisions, clothes dryers, refrigerators, etc.) are significantly different from the characteristics of products related to renewable energies (i.e. wind turbines and photovoltaic modules). Yet there are various fundamental factors affecting the market penetration of both renewable energy technologies and more traditional products that may deem the current models as an appropriate starting point for this analysis. The introduction of a black and white television may have been just as shocking as the development of a photovoltaic cell that would supply electricity to an entire household. The psychological factors that explain the adoption of such products and thus influence their market diffusion curves may be similar. This would include the risky nature of the innovators who search for novel products that may improve their lives. This would also account for the safety-seeking characters of the imitators, who only consume a product if others have done so before them. The basic drivers behind any market diffusion curve suggest the applicability of the current models to the renewable energy datasets.

The existing models were applied to numerous renewable energy technology datasets and their accuracy and forecasting ability were analyzed. The existing models fit most of the historical datasets for various technologies well. This does not imply that these models are good forecasting tools.

Due to the fact that most renewable energy technologies are in their early stages of development, it is difficult to test their predictive ability. As the consumption of alternative energy resources is steadily increasing, the peak of renewable energy consumption is yet to happen. Although most of the models do predict an increase in consumption, it will only be feasible to fully test their accuracy after the peak occurs.

The validation of the modified market diffusion models designed to account for fiscal policy variations was a challenging task. The modified models required historical and future pricing, advertising and savings data for the specific renewable energy technology. Dedicated search showed that such data is difficult, if not impossible, to obtain. Specifically, historical advertising data for these products was not found leaving a significant gap between the theoretical and the empirical work. The data collection aspect of this project creates an opportunity for future research since a completed dataset would allow for the validation or refutation of the modified models.

6.2 Examined Models and Appropriate Data

6.2.1 Analyzed Models

A crucial aspect of the project was to modify the existing diffusion models to make it possible to see the effects that certain fiscal policies may have on market penetration of renewable energy technologies. The team determined the following models to be the most appropriate as potential candidates for modification:

1. Bass Model: requires historical adoption data
2. Generalized Bass Model (GBM): requires historical adoption, advertising, and pricing data
3. Nonuniform Influence Model (NUI): requires historical adoption data

It can be seen that these models require various levels of data, dictating the data collection aspect of the project and creating a filter for appropriate datasets. Exhaustive effort was made to gather historical data for renewable energy technologies.

6.2.2 Data Classification

Market segmentation is the driving force behind the consumption and pricing of products that in turn determine the diffusion of various products.

According to Nagle (Nagle, 1987), “Market segmentation is the division of buyers into distinct subsets, or segments, that enable a company to tailor marketing programs more appropriate for the buyers in each segment.” In forecasting renewable energy technology penetration the pricing of the products will be an important determinant of market diffusion.

It is important to distinguish between market segmentation and data segmentation. Ideally, we want to be able to obtain data that is segmented the same as the market. In reality, the available data for renewable technologies is not perfectly market segmented. Thus a significant amount of the available data is not directly applicable to the forecasting of technology diffusion.

There exist numerous fiscal policy options, renewable energy products, geographic regions, and consumer sectors throughout the world. In our analysis all of these dimensions of segmentation need to be applied to identify datasets applicable to this study. Segmentation by purchase location is important to consider because various policies regarding the implementation of renewable energy technologies differ on the international, national, state, and local levels. Segmentation by buyer identification is necessary because different fiscal policies apply to different consumer sectors. Segmentation by technology is necessary because the various models analyzed focus on a specific consumer product. Segmentation by fiscal policy is essential to the underlying purpose of the analysis: the effect of various fiscal policies on technology diffusion.

6.2.3 The Ideal Dataset

We have seen numerous ways of segmenting the data. A focus of our project is to study and forecast the impact of fiscal policy on renewable energy technology development and use. Therefore segmentation of comparable data by alternative policies is required in order to see the effects of policy differences. For instance, it would be ideal to consider residential, grid-connected PV systems, in the sun-belt states of the United States. Assuming that fiscal policies vary by state, their effects on the diffusion of grid-connected PV systems may be analyzed. Even here, however, a problem is encountered. It is possible that fiscal policies vary by county (i.e. differing policies in various counties in California) leading to a lack of homogeneity in the data sample. The “ideal” dataset must satisfy the following requirements in order to be useful for diffusion modeling:

1. fiscal policy data must exist for the analyzed dataset;

2. historical data must exist for the analyzed dataset;
3. data must exist for a geographical region within which there is little variance in terms of fiscal policy;
4. if the data corresponds to units acquired or sold ("consumed"), the units must be directed at a single sector (i.e. residential, commercial, etc.);
5. if the data corresponds to energy consumed, the consumption must occur in a single sector and a method of converting energy consumption to product consumption must be determined;
6. if the data corresponds to the consumption of a mix of products (i.e. residential vs. utility-level consumption) the different products should be disaggregated.

The goal is to obtain datasets that are as "pure" as possible.

6.2.4 Gathered Data

The Bass, Generalized Bass, and Nonuniform Influence models were applied to eight different datasets relating to renewable energies over the following time intervals:

1. Global photovoltaic module shipments: 1990-2004. The dataset includes global photovoltaic module shipments measured in peak megawatts (MWp) of energy production for the stated period. Average PV module price for each year in the stated period is measured in current dollars (as of 2005).
2. United States photovoltaic module shipments: 1994-2003. The dataset includes all annual shipments of photovoltaic cell and modules over the stated period measured in peak kilowatts (KWp). The data excludes shipments of cells and modules for space or satellite applications. The global PV pricing data discussed in the global PV modules shipments dataset is taken as a proxy for US prices (due to lack of data for the US).
3. California grid-connected photovoltaic installations capacity (in kW): 1990-2004. The dataset includes all annual grid-connected installations of photovoltaic cells and modules over the stated period in California measured in peak kilowatts (KWp). The global PV pricing

data discussed in the global PV modules shipments dataset is taken as a proxy for California prices (due to lack of data for California).

4. California grid-connected photovoltaic systems installations (in units): 1996-2004. The dataset includes all annual grid-connected installations of photovoltaic cells and modules over the stated period in California measured in the number of units installed. The global PV pricing data discussed in the global PV modules shipments dataset is taken as a proxy for California prices (due to lack of data for California).
5. United States aggregate thermal collector shipments: 1991-2003. The dataset includes the aggregate shipment values for low-temperature, medium-temperature, and high-temperature solar thermal collectors measured in thousands of square feet shipped. Pricing data is available for the corresponding period measured in dollars per square foot.
6. United States low-temperature thermal collector shipments: 1989-2003. This dataset is a subsample of the previous dataset and includes the aggregate amount of low-temperature thermal collectors shipments in the US measured in thousands of square feet. Pricing data is available for the corresponding period measured in dollars per square foot.
7. United States hybrid vehicle sales: 2000-2005. The dataset uses annual new hybrid vehicle registrations as a proxy for annual sales. The pricing data is based on the MSRP of the new Toyota Prius models over this period. This is the only hybrid vehicle model with pricing data corresponding to the time span of the sales data. It is assumed that the 2001 Prius was available in 2000, 2002 Prius was available in 2001, etc.
8. Spain wind energy generation: 1990-2004. The dataset documents all wind power generated in Spain measured in megawatts. This dataset is assumed to be appropriate to the study because it corresponds to a specific renewable energy technology: windturbines.

None of these datasets are "ideal". There is a great deal of fiscal policy variation and product type variation on both the global and the national levels for most of these datasets. Furthermore, four out of the eight sets are

in units of energy produced, not units installed, leading to an inconsistency with the examined diffusion models.

Historical consumption data was available for all datasets. Historical pricing data was available for seven out of the eight datasets (excluding Spain wind energy generation). However historical advertising data was not available in all cases. Thus, in order to run the Generalized Bass Model advertising was assumed to be constant. For seven out of the eight datasets the analysis was performed with all three models, and one dataset was analyzed with two of the three models (excluding the GBM).

6.2.5 Validation Approach for Existing Models

Several steps are involved in testing the accuracy of the discussed models as applied to renewable energies. The approach discussed below follows the general method of model verification employed by the authors of the models under consideration (Bass, 1969), (Bass et al., 1994), (Easingwood et al., 1983). The first step is to run the regression on the entire dataset. This approach does not test the forecasting capability of the models; however, it does reflect the models' applicability to market penetration as measured by its goodness-of-fit. If a model does not fit the existing data at all it cannot be relied upon to forecast the future.

The second major step is testing the model's ability to predict the near past based on historical data. That is given a sufficient historical dataset of n points it is useful to see how well the first $n - x$ of the points predict the last x points. If a model is determined to be an appropriate forecasting tool for a specific renewable energy technology, the entire dataset may be applied to determine the technology's future market penetration.

6.2.6 Goodness-of-Fit Measure: R-squared

In identifying a goodness-of-fit measure for the performed regression it is essential to understand how the regressed curve is determined. According to Pindyck and Rubinfeld (Robert Pindyck, 1981), "The R^2 , however, can be applied in its conventional sense to a nonlinear regression." As the regression is performed the following function is minimized in order to determine the best fit (Fletcher, 1993):

$$f(x) = \sum_{i=1}^m [r_i(x)]^2$$

Here, $r_i(x)$ is the residual value for observation i . The value of the residual is the difference between the actual value of the dependent variable for observation i and the fitted value of the dependent variable for the observation i .

In order to determine a goodness-of-fit measure for the regression performed in this study, the approach of the authors of the original papers was used (Bass, 1969), (Bass et al., 1994), (Easingwood et al., 1983). In these articles the R-squared value is used to determine whether a specific model fits the data well. Assume that we have the following data: x_1, x_2, \dots, x_m corresponding to y_1, y_2, \dots, y_m as the dependent variable. Suppose the regression produces the following fitted values of the dependent variable: $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_m$. The R-squared value is calculated as follows and is usually expressed as a percentage:

$$R^2 = 1 - \frac{SSE}{TSS}$$

Here, SSE stands for the sum of squared errors ($f(x)$ above), and is calculated as follows:

$$SSE = \sum_{i=1}^m (y_i - \hat{y}_i)^2$$

TSS stands for the total sum of squares, which is calculated as follows:

$$TSS = \sum_{i=1}^m (y_i - \bar{y})^2$$

Here \bar{y} represents the mean of y_1, y_2, \dots, y_m . Thus there is an inverse relationship between the value of R-squared and the objective function $f(x)$ that is being minimized. As $f(x)$ becomes smaller, the sum of squared errors (or residuals) tends to zero, leading the value of R-squared to approach 1 (100%). As the value for R-squared approaches 1, the squared residuals tend to 0, leading a higher goodness-of-fit.

6.2.7 M-Value Collection and Validation

A parameter in the existing models is the potential market size: the m-value. Although all of the discussed models can be applied without this value so that one of the outputs of the regression is the m-value, such tests may be highly inaccurate. The main reason for this is that the models may treat existing data as having already approached its peak, leading to

a steadily declining market penetration curve. Furthermore, the nonlinear regression algorithms employed by the graphical user interface require an initial guess for the market size, regardless of whether the m -value is an input or an output of the regression. The regression estimate for the m -value as well as the other parameters can be very sensitive to the initial guess for the market size.

Determining a reliable estimate for the potential market size is a difficult task. Due to the limited resources of data available to this project, the derived estimates have to be considered with some skepticism. M -values were calculated for six out of the eight analyzed datasets. Due to the lack of appropriate publications, market size could not be estimated for the two datasets related to thermal collectors. Below is an explanation and justification for the market sizes used in the analysis.

1. Global Photovoltaic Modules Shipments. The European Photovoltaic Industry Association and Greenpeace in a publication on October of 2004, stated that they predict a cumulative photovoltaic systems capacity of 205 GWp by 2020 (Association and International, 2004). Due to the scarcity of comparable publications this number is considered to be a reasonable estimate for the potential market size of the photovoltaic industry. The number is consistent with the units of the analyzed dataset
2. United States Photovoltaic Modules Shipments. The M -value for this dataset is based on the publication by European Photovoltaic Industry Association and Greenpeace referred to above. The journal contains an estimate for the PV market in the US in 2020 for two scenarios: "business as usual" and "take-off scenario". For the purposes of market size the "take-off scenario" is used with the value of 30,209 MWp (Association and International, 2004).
3. California grid-connected photovoltaic module shipments (in kW and Units). These two datasets focus specifically on California which logically asks for an estimate of the state's PV production relative to the rest of the United States. Since an estimate for total PV market size has been already determined for the previous dataset a fraction of this number is taken. It is assumed that future production of the grid-connected PV market of California relative to the rest of the US will remain constant to its current levels. Since the current levels of CA grid-connected PV production is an input of the considered dataset, and the level of aggregate US production is an input of the dataset

above, the ratio of these two values for 2003 is taken. This is assumed to be the fraction of the aggregate United States PV market that California grid-connected PV accounts for in 2020. The fraction is the multiplied by the expected 2020 US market size described above, resulting in 7,394 MWp. In order to estimate the market size in units of modules, an average generating capacity for a module is calculated by dividing the 2004 grid-connected generation of the modules by the number of such systems installed in California (both are inputs of the analyzed datasets). The expected California market size in MWp is divided by an average system generation in MWp, resulting in a potential market size of 996,592 modules.

4. US hybrid vehicle sales. A press release by Exxon Mobil states that the company expects hybrid vehicles to account for 30% of all new sales in the United States by 2030 (ExxonMobil, 2004). This figure is assumed to be the level at which hybrids will eventually saturate in the market. Furthermore, Exxon Mobil provides an estimate for the North America vehicle fleet in 2030. It is assumed that 30% of this number is the market size for the potential hybrid vehicle market in North America. Ward's Automotive Guide is used to calculate the ratio of total registered vehicles in the US relative to all of North America (i.e. US, Mexico, and Canada) and this number is multiplied by the hybrid market size of North America resulting in an M-value of approximately 85 million.
5. Wind energy installed in Spain. An article published by the European Wind Energy Association provides an estimate for the aggregate European wind energy production for 2020. The same article states that it expects Spain to account for approximately 20% of this value (Association, 2003). Multiplying the two values results in a potential market size of 37,080 MW.

6.2.8 Relative Importance of High R-squared and Accurate M-Values

Although the R-squared value is used by the authors of the original papers, it may not be entirely appropriate for the purposes of this study. As will be seen in the following sections, the non-linear regressions will generally have high values for R-squared since the models will fit the historical data well. At the same time, as discussed in the previous section, these results may be unrealistic where the market size value is regressed for. Thus

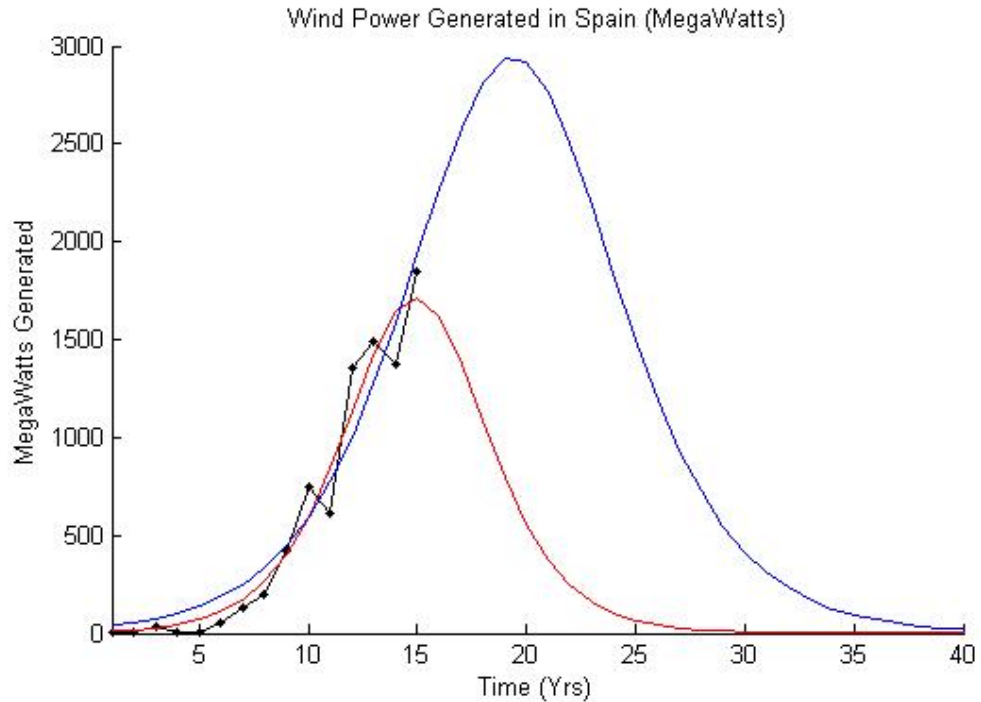


Figure 6.1: Wind power generation in Spain using a fixed m -value (blue) and a regressed m -value (red).

we cannot trust that a high R -squared implies a model's strong forecasting ability.

The identification of an accurate M -value is much more important to this analysis than the determination of a model that results in a high R -squared value for the regression. A high R -squared would be an appropriate benchmark in a setting where there is sufficient data in the time series, that the model can rely on the current points to estimate the future market penetration. In this analysis, the majority of the available data is at the very beginning of the time series (not even past the first inflection point of the market penetration curve) so an inaccurate or even regressed m -value leads to unreliable results.

Figure 6.1 gives an example of the importance of a fixed m -value (data is for wind energy generated in Spain).

In the absence of a fixed market size the Bass model sees the current level of energy generated as the peak. At the same time a fixed m -value results in the peak extending to five years in the future. Both of these predictions occur in the presence of an R -squared close to 1. Of course, the m -value cannot be guessed; it has to be substantiated by an expert opinion. The authors of the models analyzed in this study argue that an accurate market size estimate is essential to the predictive ability of the market penetration curve (Bass, 1969).

In the context of renewable energies, the goodness-of-fit measure (R -squared) is not essential to the accuracy and the predictive ability of the models. The main determinant of the forecasting ability of the analyzed models is an accurate estimate for the market size.

6.3 Regression Results

The discussion of the importance of m -values leads to two scenarios for running the regressions: (1) fixing market size and (2) regressing for market size. Furthermore, the regression can be applied to the entire dataset in order to forecast the future or it can be applied only to the past to see how well it can predict the known recent values.

The iterative method that is used for running the regression may not be accurate based on initial guesses for the parameters. According to Pindyck and Rubinfeld (Robert Pindyck, 1981), "There is no guarantee that this iterative process will converge to the maximum-likelihood estimate of the coefficients. The process may, for example, converge to a local, as opposed to global, minimum of the sum-of-squared-errors function."

6.3.1 Regressed Market Size

Tables 6.1 and 6.2 show the regression results for the entire dataset (i.e. no prediction over the time span of the data) with a regressed market size potential.

The majority of the datasets have high R -squared values (95.6% - 99.9%) implying a high goodness-of-fit. On average, the goodness of fit encountered for the Bass Model in this table is significantly higher than the fits produced by Bass in his original paper (Bass, 1969). Similarly, the R -squared values for the NUI applied to the renewable energy data are greater than those shown in the NUI paper (Easingwood et al., 1983). The Generalized Bass model produces comparable goodness-of-fit values to those modeling the

Table 6.2: Part 2. Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: No Prediction with Regressed M.

Model	Time Interval	R^2	p	q	δ	Guessed m	Regressed m	β_1	β_2
<i>CA Grid-Connected Photovoltaic Modules Shipments (kW)</i>									
Bass	1990-2004	99.9%	3.9×10^{-7} ($1.06 \times 10^{-8}, 7.7 \times 10^{-7}$)	0.97 (0.888, 1.05)	—	7,394,196	152,000	—	—
Generalized Bass	1990-2004	99.8%	1.92×10^{-7} NA	0.676 NA	—	7,394,196	7,350,000	-1.43 NA	1
Nonuniform Influence	1990-2004	98.2%	4.4×10^{-7} NA	0.424 NA	0.946 NA	7,394,196	7,360,000	—	—
<i>CA Grid-Connected Photovoltaic Modules Shipments (Units)</i>									
Bass	1996-2004	97.8%	0.00077 (-0.00039, 0.00193)	0.697 (0.385, 1.04)	—	996,592	29,700	—	—
Generalized Bass	1996-2004	97.0%	6.9×10^{-5} NA	0.507 NA	—	996,592	991,000	-0.76 NA	1
Nonuniform Influence	1996-2004	98.3%	3.16×10^{-5} (-0.000107, 0.000124)	0.412 (-0.873, 1.7)	0.77 (0.00549, 1.54)	996,592	—	—	—
<i>United States Hybrid Vehicle Sales</i>									
Bass	2000-2005	98.5%	1.83×10^{-5} (-0.0115, 0.0115)	0.733 (-0.3, 1.77)	—	85,034,289	135,000,000	—	—
Generalized Bass	2000-2005	98.6%	4.38×10^{-5} NA	0.696 NA	—	85,034,289	85,000,000	1.84 NA	1
Nonuniform Influence	2000-2005	99.4%	0.000149 (-0.962, 0.962)	9.58 (-3070, 3090)	1.44 (0.476, 2.4)	85,034,289	104,000,000	—	—
<i>Wind Energy Installed in Spain</i>									
Bass	1990-2004	96.2%	0.000484 (-0.000139, 0.00111)	0.46 (0.313, 0.606)	—	37,060	14,900	—	—
Generalized Bass	1990-2004	—	—	—	—	—	—	—	—
Nonuniform Influence	1990-2004	95.6%	0.000234 (-0.00033, 0.00376)	0.252 (-0.502, 1.01)	0.858 (-0.00159, 1.72)	37,060	35,100	—	—

traditional consumer goods (Bass et al., 1994). The lower R-squared values may be attributed mainly to the thermal collector shipment datasets, which have volatile shipment values. It can be seen that the R-squared values are much smaller for datasets where consumption is not steadily increasing over the considered time interval. In addition, the m -values for the thermal collector sets were randomly chosen (it was assumed that the current cumulative shipments are 5 % of the potential market size), which may be another source of inaccuracy.

It is also important to consider values and the statistical significance of the coefficients in the various regressions. In value, the p estimates are generally close to 0, which is consistent with values found when running the regression for the traditional durables. The q values are also within the appropriate range excluding a few outliers. Although the goodness-of-fit values are high, the majority of the coefficients are not statistically significant from 0 on a 95% confidence interval (i.e. 0 is included in the interval). As a general trend, the regressed m -value for the Bass Model is a significantly less than the estimated m -value for the GBM and the NUI. This can be explained by the Bass Model's tendency to see the last point of a uniformly increasing time series as the peak of the dataset. Due to the small number of explanatory coefficients, from a computational perspective the Bass Model is less sensitive to the initial guess for the market size. In some instances the GBM and the NUI m -value regression estimates are close to the researched m -values. This is explained both by good research approaches for the market size as well as these models' sensitivity to the initial guess of the market size. Five out of the eight models have δ values greater than 1 for the NUI which indicates increasing influence of the word-of-mouth effect in the market. This is consistent with reality as the popularity of renewable energies is accelerating especially with rising oil prices. The β_1 values are negative for a majority of the goods, which is consistent with theory (Bass et al., 1994). However, it's important to remember that due to a lack of data, advertising is not taken into account with the GBM which may affect the results.

Overall, the results of the regression are both consistent with theory and intuition. At the same time, an accurate estimate for the market size is important. It is also necessary to consider the confidence intervals for the coefficients (which in most cases are not statistically significantly different from 0).

6.3.2 Forecasting Accuracy: Regressed M-value

To compare the predictive ability of the three models, either the last two (datasets with ten observations or less) or the last four (datasets with more than ten observations) data points were removed, and the models were fitted to the truncated data (Easingwood et al., 1983). See the appendix for all of the plots of the regressions. Tables 6.3 and 6.4 show the results of the analysis. The R-squared of the sample refers to the goodness-of-fit of the truncated dataset, and R-squared of prediction refers to the fit of the entire dataset, including predicted values.

Here the results varied significantly among the considered models. Certain datasets “favored” certain models. The lowest average R-squared belonged to the hybrid vehicle dataset; however this may be explained by the small number of data points. While the model fitted the truncated data well, there was high error in predicting the future, see Figure 6.2.

The regressed market size values were generally much smaller than the researched values (section 6.2.7 describes the sources for these values) when using the Bass Model. The GBM regressed market size value greatly differed from the researched estimate only once, being close to it in all other cases. Finally, the NUI varied in accuracy with regards to the regressed m-value.

A regressed value for market size causes the resulting confidence intervals on the fitted values to be much wider than they would if the market potential was an accurate and fixed input. This is caused by the confidence interval on the m-value which is usually extremely wide. Figure 6.3 shows an example of the Bass Model predicting future penetration of global PV shipments.

The red error bars correspond to the bounds on the values with regressed market size, while the blue error bars correspond to a fixed m-value.

In general, when the three models (Bass, Generalized Bass, and Nonuniform Influence) are applied to the analyzed datasets, some show strong predictive ability while others do not. For datasets such as California grid-connected modules shipments (in kW or units), wind energy installed in Spain, or thermal collectors for at least one of the models, the predicted R-squared was low. This suggests that when employing the existing models to predict future market penetration, it is important to consider the models on a one-by-one basis and be very cautious with the results.

A model that may perfectly fit the entire dataset without predictions could easily fail when used for prediction. At the same time, this is in-

Table 6.3: Part 1. Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Regressed M.

<i>Model</i>	<i>Time Interval</i>	<i>N-Total</i>	<i>N-Sample</i>	<i>R² Sample</i>	<i>R² Prediction</i>	<i>Guessed m</i>	<i>Regressed m</i>
<i>Global Photovoltaic Modules Shipments (MWp)</i>							
Bass	1990-2004	15	11	96.3%	96.2%	205,000	1,430,000
Generalized Bass	1990-2004	15	11	97.4%	97.6%	205,000	261,000
Nonuniform Influence	1990-2004	15	11	99.7%	94.0%	205,000	34,400
<i>United States Photovoltaic Modules Shipments (kWp)</i>							
Bass	1994-2003	10	8	97.7%	97.2%	30,209,000	2,010,000
Generalized Bass	1994-2003	10	8	99.3%	93.5%	30,209,000	30,209,000
Nonuniform Influence	1994-2003	10	8	98.6%	80.1%	30,209,000	675,000
<i>United States Aggregate Thermal Collector Shipments (Units)</i>							
Bass	1991-2003	13	9	85.6%	73.2%	1,106,640	419,000
Generalized Bass	1991-2003	13	9	92.9%	80.3%	1,106,640	1,100,000
Nonuniform Influence	1991-2003	13	9	86.4%	74.7%	1,106,640	1,830,000
<i>United States Low Temperature Thermal Collector Shipment (Units)</i>							
Bass	1989-2003	15	11	88.3%	56.9%	1,202,540	164,000
Generalized Bass	1989-2003	15	11	86.0%	90.1%	1,202,540	1,190,000
Nonuniform Influence	1989-2003	15	11	88.9%	72.0%	1,202,540	226,000

Table 6.4: Part 2. Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Regressed M.

Model	Time Interval	N-Total	N-Sample	R ² Sample	R ² Prediction	Guessed m	Regressed m
<i>CA Grid-Connected Photovoltaic Modules Shipments (MW)</i>							
Bass	1997-2004	8	6	99.6%	92.3%	7,394,196	89,600
Generalized Bass	1997-2004	8	6	99.9%	6.2%	7,394,196	92,500
Nonuniform Influence	1997-2004	8	6	99.9%	0.1%	7,394,196	23,600
<i>CA Grid-Connected Photovoltaic Modules Shipments (Units)</i>							
Bass	1996-2004	9	7	99.5%	25.8%	996,592	6,700
Generalized Bass	1996-2004	9	7	98.4%	51.9%	996,592	993,000
Nonuniform Influence	1996-2004	9	7	97.8%	84.7%	996,592	996,000
<i>United States Hybrid Vehicle Sales (Units)</i>							
Bass	2000-2005	6	4	99.9%	0.1%	85,034,289	180,000
Generalized Bass	2000-2005	6	4	NA	NA	85,034,289	NA
Nonuniform Influence	2000-2005	6	4	NA	NA	85,034,289	NA
<i>Wind Energy Installed in Spain (MWp)</i>							
Bass	1990-2004	15	11	99.1%	3.8%	37,080	36,200
Generalized Bass	1990-2004	15	11	-	-	-	-
Nonuniform Influence	1990-2004	15	11	91.0%	98.0%	37,080	124,000

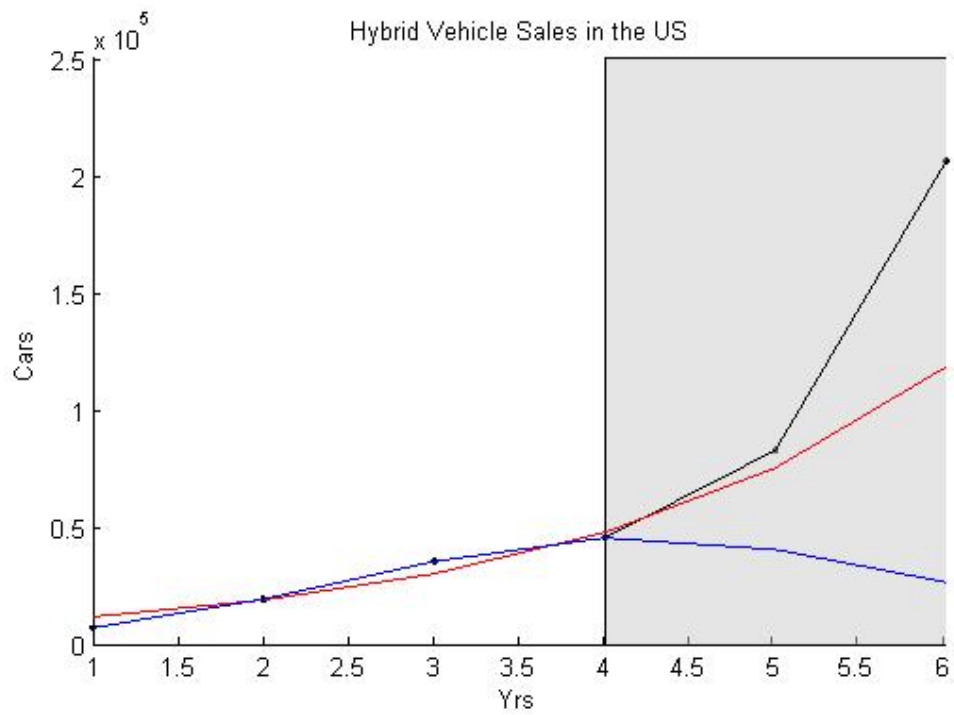


Figure 6.2: The Bass Model is in red, the GBM is in green ,and the NUI is in blue. The grey region is the predicted values. Data time span is: 2000-2005

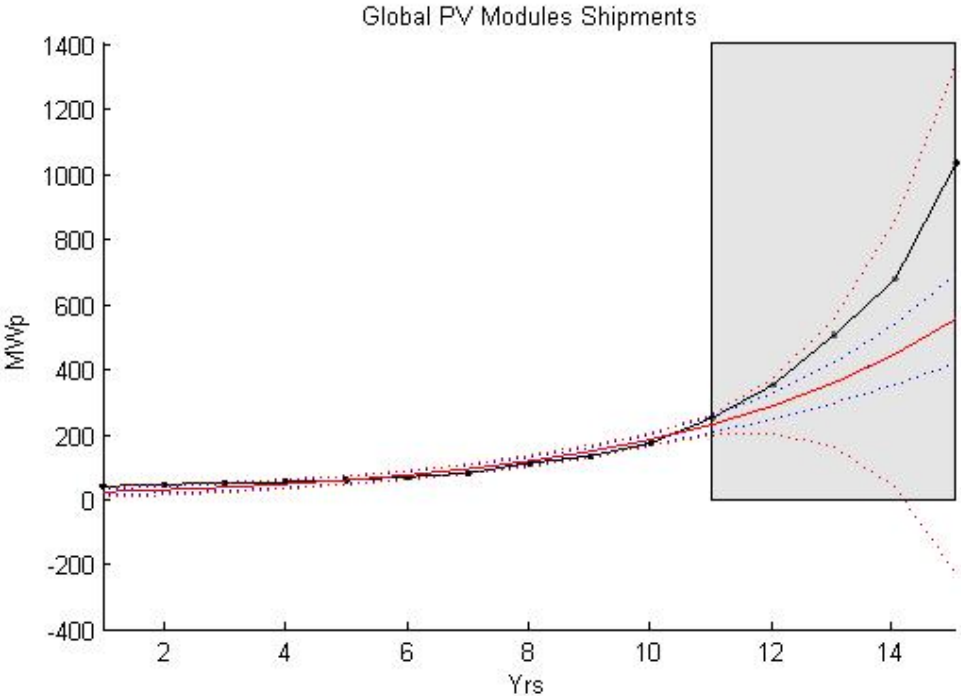


Figure 6.3: Four year projections for global PV module shipments with a fixed market size and regressed market size. The red dotted line corresponds to the confidence interval using a regressed value and the blue dotted line uses a fixed value.

fluenced by the fact that the renewable energy industry is at its beginnings. There is no steady growth as year-to-year jumps in adopters could be highly volatile and the industry is yet to reach its peak. Furthermore, the unpredictability of the data is also explained by the flaws of the datasets discussed above. The data used to validate the existing models as well as the modified models does not seem to exist. Until suitable data is obtained there is no way of measuring the true accuracy of the applied methods.

6.3.3 Forecasting Accuracy: Fixed M-value

Running the regressions with fixed m values creates opportunities for increased accuracy in the predictions. See Figure 6.4 for an example of the NUI applied to global PV module shipments, with four year predictions. The first three years are forecasted well as the actual values fall within the 95% confidence intervals, which remain relatively narrow.

Another example of this situation is shown in Figure 6.5.

It is clear from the graph that although the regressed market size error bars are not as wide as in the example above, they are still much wider than the error bars corresponding to a fixed value of m . This difference becomes even more apparent in the second year's predictions.

Tables 6.5 and 6.6 show the results of the analysis. The R-squared of the sample refers to the goodness-of-fit of the truncated dataset, and R-squared of prediction refers to the fit of the entire dataset, including predicted values.

Finding an accurate m -value does not eliminate the risk of choosing the wrong model for prediction purposes, however it does increase the likelihood of a reasonable forecast.

6.4 Conclusion

One of the main results of this study was the regression analysis of numerous renewable energy technology datasets using various market diffusion models that are typically applied to more traditional consumer goods: the Generalized Bass, Bass, and the Nonuniform Influence models. The analysis produced results which were in many instances consistent with those of Bass and others. Furthermore, the predictive capabilities of the models were tested with the renewable energy data. Although the results varied greatly, certain models were able to predict future market growth accurately. The significance of the fixed input for the potential market size was

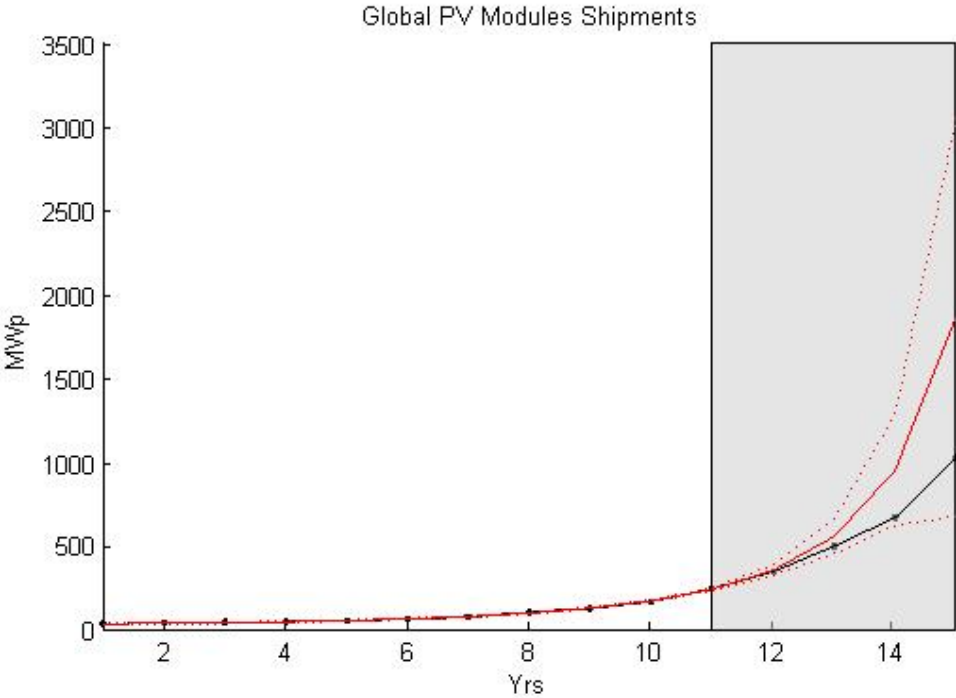


Figure 6.4: Four year projections for global PV module shipments with a fixed market size. The model predicts the first three years very well.

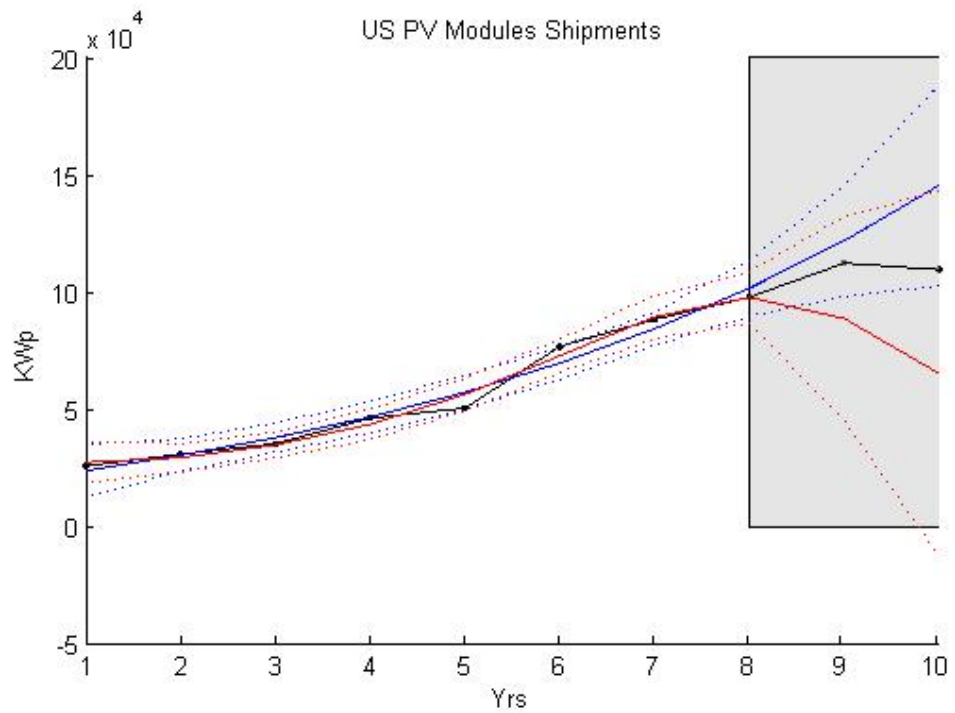


Figure 6.5: Two year projections for US PV module shipments with a fixed and regressed market size. The blue error bars correspond to the fixed m , and red error bars correspond to regressed m .

Table 6.5: Part 1. Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Fixed M.

Model	Time Interval	N-Total	N-Sample	R^2 Sample	R^2 Prediction	Fixed m
Global Photovoltaic Modules Shipments (MWp)						
Bass	1990-2004	15	11	96.2%	95.0%	205,000
Generalized Bass	1990-2004	15	11	95.4%	93.7%	205,000
Nonuniform Influence	1990-2004	15	11	99.7%	95.9%	205,000
United States Photovoltaic Modules Shipments (KWp)						
Bass	1994-2003	10	8	97.3%	92.0%	30,209,000
Generalized Bass	1994-2003	10	8	97.3%	92.0%	30,209,000
Nonuniform Influence	1994-2003	10	8	97.3%	93.4%	30,209,000
CA Grid-Connected Photovoltaic Modules Shipments (KW)						
Bass	1997-2004	8	6	99.5%	89.5%	7,394,196
Generalized Bass	1997-2004	8	6	99.8%	20.7%	7,394,196
Nonuniform Influence	1997-2004	8	6	99.4%	85.9%	7,394,196

Table 6.6: Part 2. Parameter Estimates for Bass Model, Generalized Bass Model, and Nonuniform Influence Model: Prediction with Fixed M.

Model	Time Interval	N-Total	N-Sample	R^2 Sample	R^2 Prediction	Fixed m
<i>CA Grid-Connected Photovoltaic Modules Shipments (Units)</i>						
Bass	1996-2004	9	7	97.9%	87.4%	996,592
Generalized Bass	1996-2004	9	7	98.4%	52.0%	996,592
Nonuniform Influence	1996-2004	9	7	NA	NA	996,592
<i>United States Hybrid Vehicle Sales</i>						
Bass	2000-2005	6	4	93.9%	94.1%	85,034,289
Generalized Bass	2000-2005	6	4	99.4%	22.6%	85,034,289
Nonuniform Influence	2000-2005	6	4	99.1%	77.4%	85,034,289
<i>Wind Energy Installed in Spain</i>						
Bass	1990-2004	15	10	99.6%	87.9%	37,080
Generalized Bass	1990-2004	15	10	—	—	—
Nonuniform Influence	1990-2004	15	10	99.6%	90.1%	37,080

analyzed in detail. A fixed m -value leads to greater precision with much narrower confidence intervals.

At the same time numerous obstacles were encountered in the process of data collection. In order to validate the modified NUI model and GBM, future and historical pricing, advertising, and savings data was required. Extensive searches were performed for this information, however they were mostly futile. This data is difficult to obtain. In addition, the limitations in the availability of data lead to the need for using aggregate data which creates a lack of perfect segmentation. There are sources for well segmented data, but these tend to capture only a certain point in time, whereas a historical time series is necessary for the forecasting of product penetration. Data collection is a logical continuation of this study as it will create a possibility to validate the modified diffusion models for renewable energy technologies.

Chapter 7

Conclusion

This report lays the foundation for what this team believes could become a powerful tool for market forecasting and exploring hypothetical policy decisions. However, further research and development is necessary before such a tool is ready to be placed in the hands of policy makers. Future work includes validating the modified models as the data becomes available, expanding the data sets to include other alternative energies, and continuing development of the GUI.

The modified models presented in Chapter 4 have yet to be validated, due to lack of data. Savings data, although not easily collected, exists. As discussed in §4.3, the savings data does not need to be meticulously calculated; it would be best to take savings data from sources readily available to consumers. Advertising data, on the other hand, has yet to be found. As these technologies become more abundant, this data will likely become available. However, it is unknown how long this will take. A few options to get around this obstacle include a study to collect the data, or, alternatively, creating a hypothetical data set.

Such a data set would need to include pricing, savings, and advertising data of equal length. An existing data set including pricing and savings data could be used, with added advertising data. Both modified models can be tested using the GUI designed for the project. Comparing results to the Bass Model, Generalized Bass Model, and Nonuniform Influence Model will determine if and when the modified models are applicable. Recommendations for making do with small data sets can be found in §4.9.2.

To check the validity of the model, the first $x\%$ of the data set could be used to predict the final $(100 - x)\%$ of the data set, as explained in §6.2.5. Once the validation is complete, the models will be ready to use against po-

tential policy decisions. To do this, use the potential policy changes to predict pricing, savings, and advertising data into the future. Run the models with the data set and examine the predicted market penetration for feasibility, compared to a data set of equal length without the policy changes.

The second area for future work includes collecting data sets for renewable technologies not mentioned in this report. Some examples of such technologies include biomass, geothermal, and fuel cells.

The third area for future work is continued development of the GUI. The GUI will need to be updated to reflect the findings of the validation. Additional features may be added as well. Some ideas include allowing for specification of upper and lower bounds for individual coefficients, allowing for removal of data points at the beginning of a data set and implementing more regression algorithms.

The team recommends further development in these three areas to bring NREL closer to the goal of providing lawmakers and analysts with a powerful, easy-to-use tool for exploring impacts of policy variations on market penetration of renewable energy technologies.

Appendix A

Abbreviations

GBM Generalized Bass Model

GUI Graphical User Interface

NUI Nonuniform Influence (Model)

PV Photovoltaic

RE Renewable Energy

Appendix B

Sample GUI Input File

[Main]

Title = Grid-Connected PV Capacity Installed in California

[Data]

Time = 1 2 3 4 5 6 7 8 9 10

Sales = 10 20 45 80 160

Price = 20 20 19 19 17 16 15 13 10 10

Adv = 5 6 6 8 9 11 15 20 30 30

Sav = 10 10 10 10 10 12 18 24 30 30

m = 10000

[Units]

Time = Years

Sales = KW

Appendix C

Bass, Generalized Bass, and NUI Forecast Plots

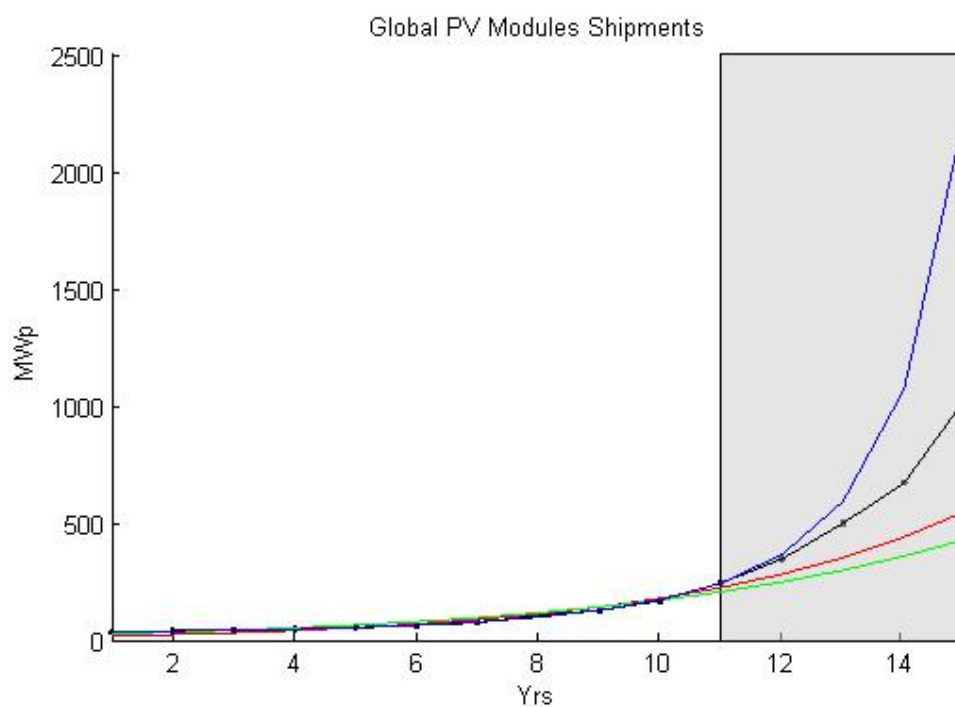


Figure C.1: The Bass Model is in red, the GBM is in green ,and the NUI is in blue. The grey region is the predicted values. Data time span is: 1990-2004

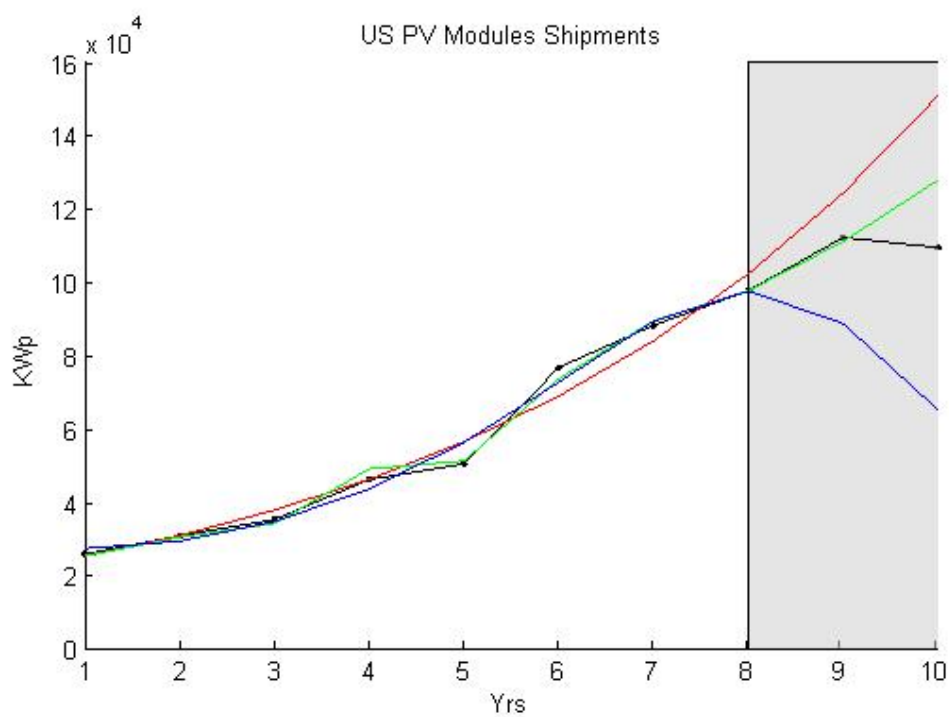


Figure C.2: The Bass Model is in red, the GBM is in green, and the NUI is in blue. The grey region is the predicted values. Data time span is: 1994-2003

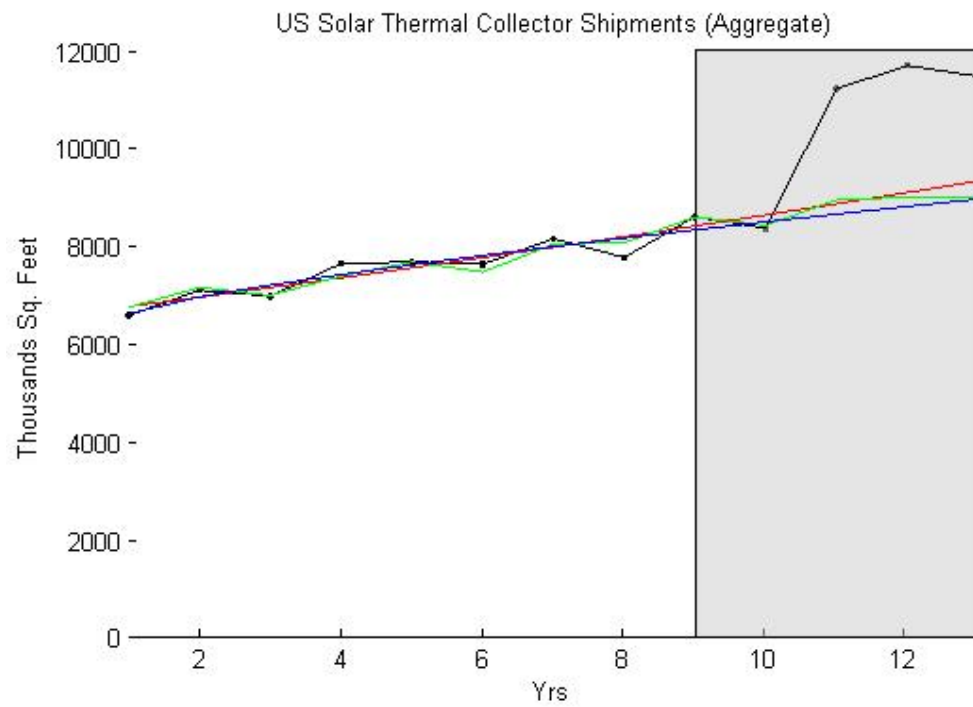


Figure C.3: The Bass Model is in red, the GBM is in green, and the NUI is in blue. The grey region is the predicted values. Data time span is: 1991-2003

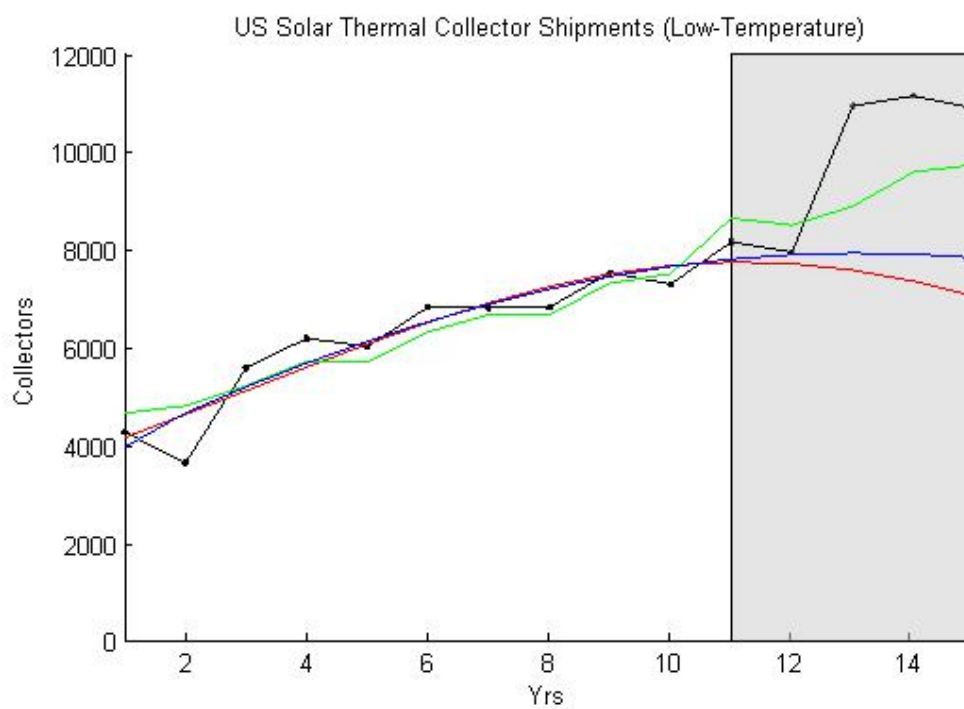


Figure C.4: The Bass Model is in red, the GBM is in green, and the NUI is in blue. The grey region is the predicted values. Data time span is: 1989-2003

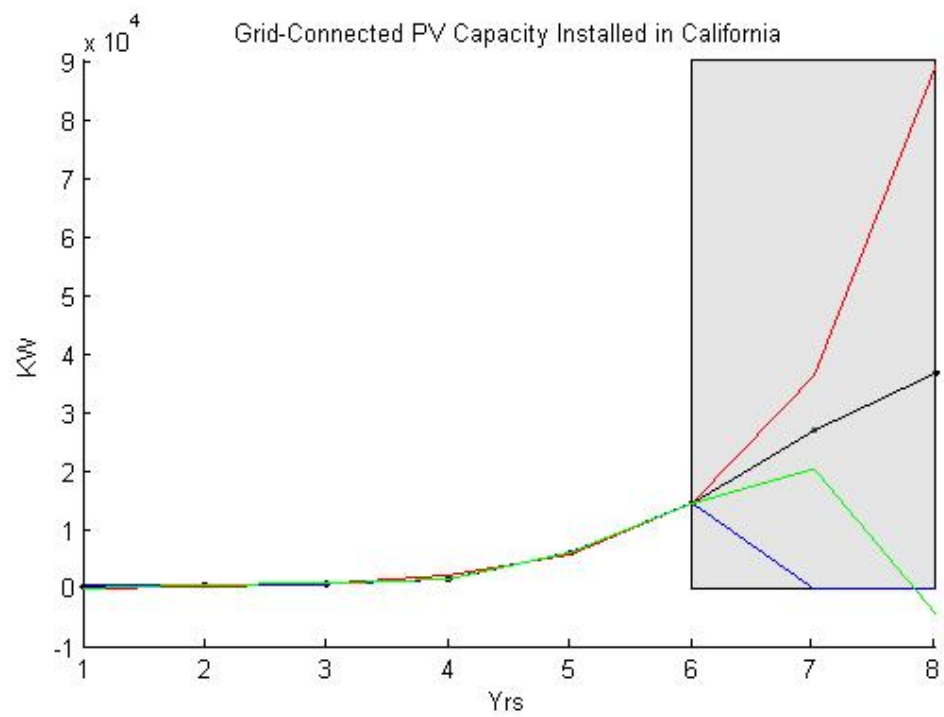


Figure C.5: The Bass Model is in red, the GBM is in green, and the NUI is in blue. The grey region is the predicted values. Data time span is: 1997-2004

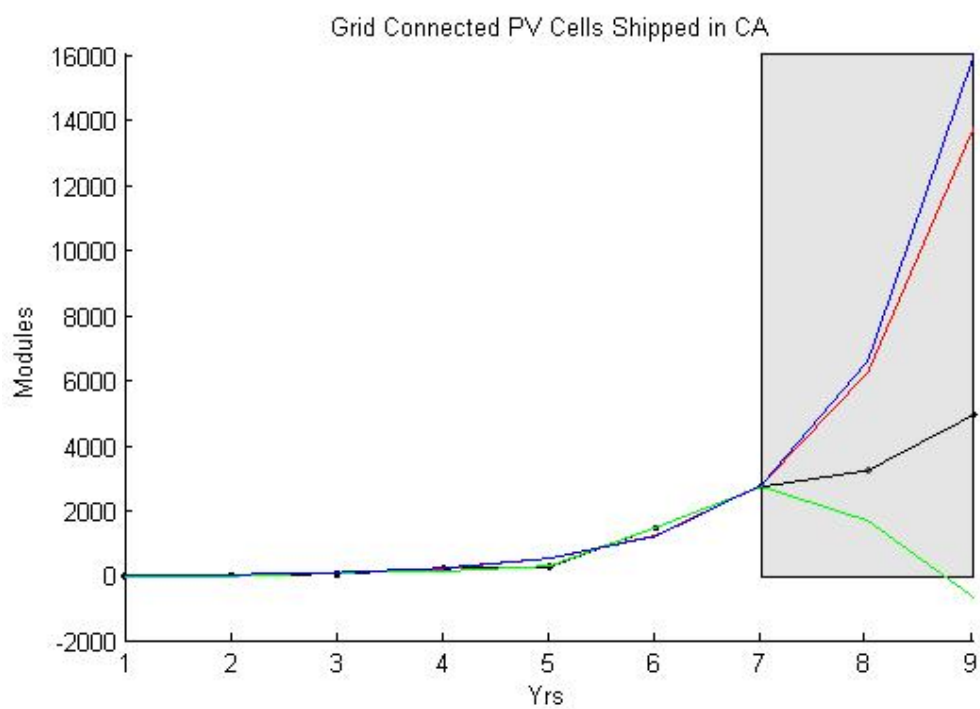


Figure C.6: The Bass Model is in red, the GBM is in green, and the NUI is in blue. The grey region is the predicted values. Data time span is: 1996-2004

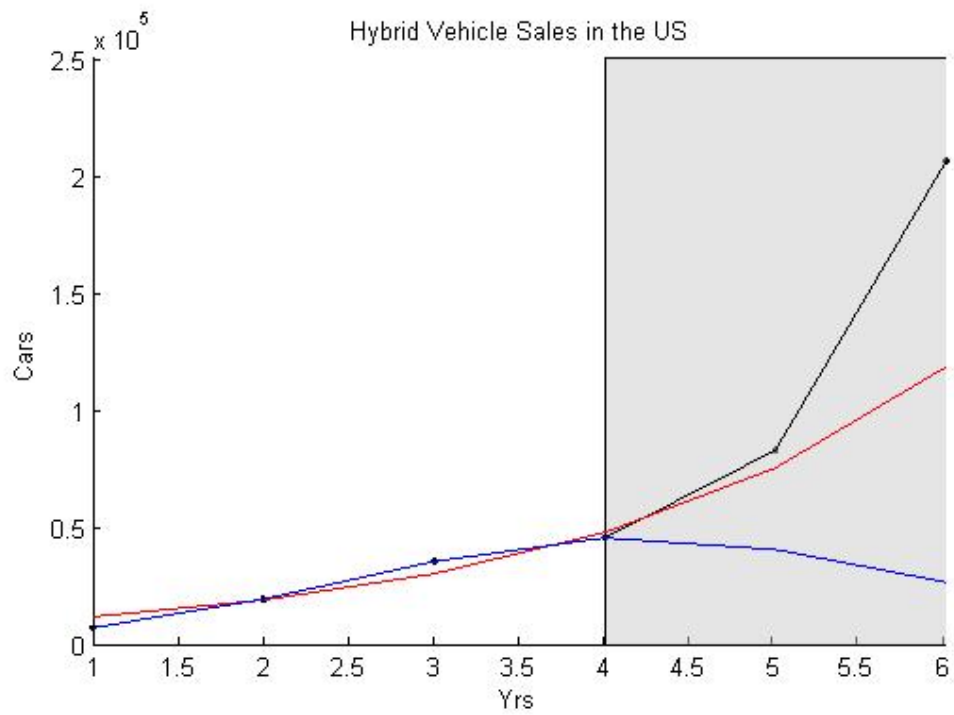


Figure C.7: The Bass Model is in red, the GBM is in green, and the NUI is in blue. The grey region is the predicted values. Data time span is: 2000-2005

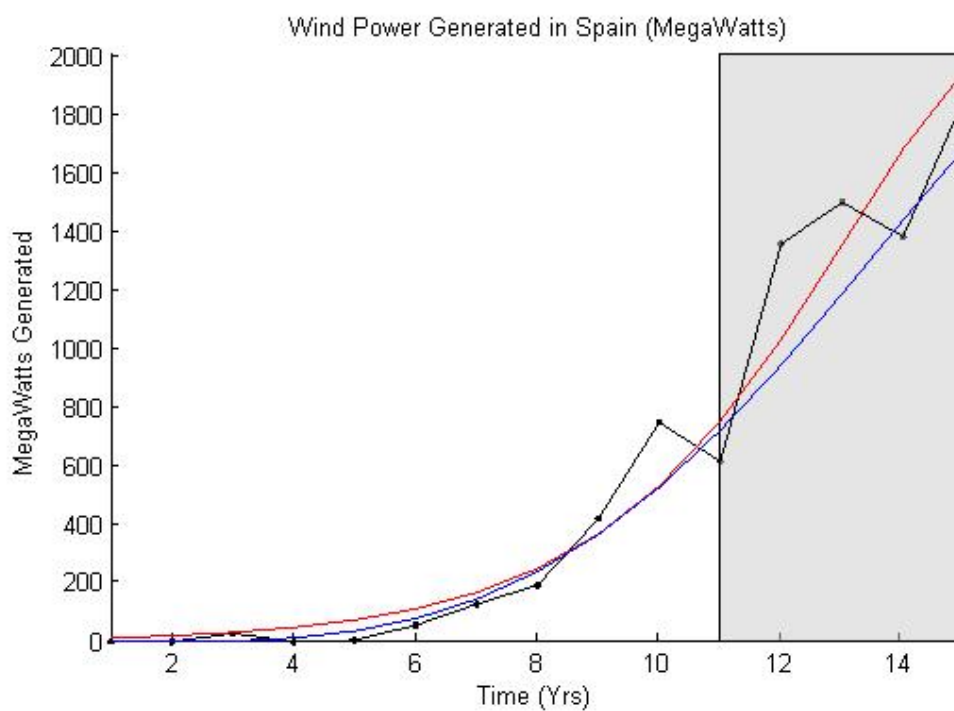


Figure C.8: The Bass Model is in red, the GBM is in green, and the NUI is in blue. The grey region is the predicted values. Data time span is: 1990-2004

Bibliography

Administration, Energy Information. 2005. Policies to promote non-hydro renewable energy in the united states and selected countries URL www.eia.doe.gov/cneaf/solar.renewables/page/non_hydro/nonhydro_toc.html.

Association, European Photovoltaic Industry, and Greenpeace International. 2004. Solar generation: Solar electricity for over 1 billion people and 2 million jobs by 2020. Tech. rep., European Photovoltaic Industry Association and Greenpeace International. URL archive.greenpeace.org/climate/climatecountdown/solargeneration/solargenback.pdf.

Accessed April 12, 2006.

Association, European Wind Energy. 2003. Wind power targets for europe: 75,000 mw by 2010. Tech. rep., European Wind Energy Association. URL www.ewea.org/fileadmin/ewea_documents/documents/publications/briefings/75gw.pdf.

Accessed April 12, 2006.

Bass, F. 1969. A new product growth for model consumer durables. *Management Science* 15(5):215–227.

Bass Model description. Most diffusion models are based on this. There is a detailed explanation of the development of the Bass Model, including the rationale about consumer behavior that justify certain mathematical assumptions. It continues with several pages of tests of the model on technologies that have already diffused; these validate the Bass model nicely.

Bass, F., T. Krishnan, and D. Jain. 1994. Why the bass model fits without decision variables. *Marketing Science* 13(3):203–223.

This paper describes the Generalized Bass Model, potentially more accurate than the Bass Model. It begins by reviewing the Bass Model, and then provides very detailed reasons for wanting to modify it and expectations of a well-modified model. Then it moves into the math of the GBM's derivation, again explained in detail. It also includes a handy chart detailing characteristics of many models that include price or other decision variables, reaching the basic conclusion that of those, the GBM is best. There is a short discussion on how to estimate parameters, and the paper closes with comparisons of the GBM to other models in several situations, where the GBM performs well.

Berndt, Ernst R., Robert S. Pindyck, and Pierre Azoulay. 1999. Network effects and diffusion in pharmaceutical markets: Antiulcer drugs. National Bureau of Economic Research, Working paper no. 7024.

This short paper could be of real use. They say "Our approach could be applied to other products for which information about efficacy and safety is conveyed by the usage of others." They use hedonic pricing models, which modifies the actual price to account for many other factors like consumer demand and, in this case, network effects. They then incorporate this into a modified Bass model. Could be quite useful. This is currently only available as hard copy.

Blackman, Wade. 1971. The rate of innovation in the commercial aircraft jet engine market. *Technological Forecasting and Social Change* 2(3-4):269-276.

This abstract summarizes the conclusions of Blackman in his tests on an altered version of Mansfield's model of product diffusion in the market of jet engines. The model was found to agree well with existing data. It is unclear how much of the Mansfield-Blackman model will be useful because it depends on expertly determined, industry-specific parameters that are out-of-date for current markets.

Bratun-Glennon, Z. 2005. Innovation diffusion modeling: Tests and application to the renewable energy sector. NREL summer intern paper.

This paper was written by a summer intern at NREL. It evaluates several models but has incorrect reasoning in error analysis invalidating the conclusions.

Dalal, Siddhartha, K. Ho Yu-Yun, and R. Sherman. 2001. Learning from experience to improve early forecasts: A posterior mode approach. Tech. rep., California Institute of Technology.

This has interesting methods for estimating model parameter and improving early forecasts by analyzing data from similar cases. Perhaps more interesting is its suggestions for a simple modification of the Bass Model to incorporate price. It is left unsaid how effective a modification it is, and it lacks some logical robustness as it only directly modifies the number of eventual adopters. Still, it is a modification idea to look further into in future work.

Darling, David. 2005. Closed-loop biomass. URL http://www.daviddarling.info/encyclopedia/C/AE_closed-loop_biomass.html.

Accessed December 5, 2005.

Easingwood, C., V. Mahajan, and E. Muller. 1983. A nonuniform influence innovation diffusion model of new product acceptance. *Marketing Science* 2(3):273–295.

Describes the NUI model and discusses three perceived limitations of Bass and similar models that NUI overcomes. Includes the rationale and resulting math behind the NUI. In direct comparison, the NUI performs very well against the Bass Model and another model, the Sharif-Kabir, which generally does quite poorly.

Energy Information Administration. 2005. Policies to promote non-hydro renewable energy in the united states and selected countries. Tech. rep., Energy Information Administration.

Compares fiscal policy among the United States, Germany, Denmark, Japan, and the Netherlands.

ExxonMobil. 2004. The outlook for energy - a view to 2030. Tech. rep., ExxonMobil. URL www.exxonmobil.com/Corporate/Citizenship/Imports/EnergyOutlook05/2005_energy_outlook.pdf.

Accessed April 12, 2006.

Fletcher. 1993. *Practical Methods of Optimization*. Chichester: John Wiley & Sons.

Frank, Lauri Dieter. 2004. An analysis of the effect of the economic situation on modeling and forecasting the diffusion of wireless communications in Finland. *Technological Forecasting & Social Change* 71:391–403.

This has the best conceptual overview of different modeling tactics we have seen.

Gilshannon, S., and D. Brown. 1996. Review of methods for forecasting the market penetration of new technologies. Pacific Northwest National Laboratory report.

Compares and analyzes characteristics of many different models. This will be very helpful. Does not test the models, purely conceptual. Goes into details, pros and cons, etc. for the normal noncumulative adopter distribution method, the Bass Model, the Mansfield Blackman Model, and the Fisher-Pry Model, as well as the broader Renewable Energy Penetration and National Energy Modeling System, and more. Especially valuable for its focus on renewable energy modeling, which is evidenced rarely in the technology diffusion models, but underlies the whole paper.

Grubler, A., and N Nakicenovic. 1999. Dynamics of energy technologies and global change. *Energy Policy* 27:247–280.

Discusses technological improvements within given mathematical models. This will be helpful when considering the economics behind our model, especially the importance of technological advances. It also includes a very lengthy list of references.

Jukic, Dragan, Gordana Kralik, and Rudolf Scitovski. 2004. Least-squares fitting gompertz curve. *Journal of Computational and Applied Mathematics* 169(2):359–375.

This provides a detailed mathematical background for the Gompertz curve, including a good explanation for the estimation of parameters through a least-squares method of approximation.

Knittel, Christopher R., and Victor Stango. 2004. Compatibility and pricing with indirect network effects: Evidence from ATMs. National Bureau of Economic Research Working Paper #10774.

Investigates pricing when a consumer interacts with two (or more) companies simultaneously. Best source found for indirect network effects, but seems to have limited applicability to renewable energy technology diffusion models.

Nagle, Thomas T. 1987. *The Strategy and Tactics of Pricing*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Petersik, Thomas. 2003. State renewable energy requirements and goals: Status through 2003. Tech. rep., Energy Information Administration.

Compares fiscal policy among several states regarding renewable energy.

Rana, Ashish. 2003. Evaluation of a renewable energy scenario in India for economic and CO₂ mitigation effects. *Review of Urban and Regional Development* 15(1):45–54.

Lacks mathematical details, Rana uses a Computable General Equilibrium model which, like the NEMS model deals with the breakdown of the entire energy market and seems to require inordinate work to calibrate for a given region. This calibration for India was taken from a previous paper. Rana then models market share of renewable energy under several different fiscal scenarios including increased R&D funding and tariffs on coal. A nice approach to fiscal policy situations and good presentation of the comparison of different situations.

Robert Pindyck, Daniel Rubinfeld. 1981. *Econometric Models & Economic Forecasts*. United States: McGraw-Hill, Inc.

Saloner, Garth, and Andrea Shepard. 1995. Adoption of technologies with network effects: An empirical examination of the adoption of Teller machines. *RAND Journal of Economics* 26(3):479–501.

This paper does a test for network effects in the adoption of ATMs. The authors avoid prediction; they simply test historical data to see if it is plausible to assume that network effects are applicable to this case. It is hard to determine from this paper if a network model would be useful for predicting the future

from a small number of initial data points. Although a major concern in network effects is geography, the authors do not concern themselves with physical geography, their primary variables are the number of branches a bank has equipped with ATMs and the number of depositors using ATMs, which is promising for the kind of data that might be available for us.

Simon, Herman. 1982. Adpuls: An advertising model with wearout and pulsation. *Journal of Marketing Research* 19:352–363.

This paper shows very convincing examples of the effects of marketing long outlasting the actual run of the advertisements. Because of this paper, the GBM treats advertising as a non-decreasing function, and we have chosen to do the same.

Staff of the Joint Committee on Taxation. 2005. Present law and background relating to tax credits for electricity production from renewable sources. Tech. rep., Joint Committee on Taxation.

Article prepared for a Subcommittee on Select Revenue Measures of the House Committee on Ways and Means.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing the burden, to Department of Defense, Executive Services and Communications Directorate (0704-0188). Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ORGANIZATION.

1. REPORT DATE (DD-MM-YYYY) August 2007		2. REPORT TYPE Technical Report		3. DATES COVERED (From - To)		
4. TITLE AND SUBTITLE Advanced Modeling of Renewable Energy Market Dynamics: May 2006			5a. CONTRACT NUMBER DE-AC36-99-GO10337			
			5b. GRANT NUMBER			
			5c. PROGRAM ELEMENT NUMBER			
6. AUTHOR(S) M. Evans, R. Little, K. Lloyd, G. Malikov, and G. Passolt (Harvey Mudd College); D. Arent, B. Swezey, and G. Mosey (NREL)			5d. PROJECT NUMBER NREL/TP-640-41896			
			5e. TASK NUMBER 6400.1040			
			5f. WORK UNIT NUMBER			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) National Renewable Energy Laboratory 1617 Cole Blvd. Golden, CO 80401-3393				8. PERFORMING ORGANIZATION REPORT NUMBER NREL/TP-640-41896		
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)				10. SPONSOR/MONITOR'S ACRONYM(S) NREL		
				11. SPONSORING/MONITORING AGENCY REPORT NUMBER		
12. DISTRIBUTION AVAILABILITY STATEMENT National Technical Information Service U.S. Department of Commerce 5285 Port Royal Road Springfield, VA 22161						
13. SUPPLEMENTARY NOTES						
14. ABSTRACT (Maximum 200 Words) This report documents a year-long academic project, presenting selected techniques for analysis of market growth, penetration, and forecasting applicable to renewable energy technologies. Existing mathematical models were modified to incorporate the effects of fiscal policies and were evaluated using available data. The modifications were made based on research and classification of current mathematical models used for predicting market penetration. An analysis of the results was carried out, based on available data. MATLAB versions of existing and new models were developed for research and policy analysis.						
15. SUBJECT TERMS NREL; market dynamics; analysis; renewable energy; modeling; market penetration; environment; price; risk; fiscal policy; subsidies; Harvey Mudd College						
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT UL	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON	
a. REPORT Unclassified	b. ABSTRACT Unclassified	c. THIS PAGE Unclassified			19b. TELEPHONE NUMBER (Include area code)	

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18