Distributed Generation Systems Planning & the Ecosystem of Electricity Technological Learning

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Distributed Generation Systems Planning & the Ecosystem of Electricity Technological Learning

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Abstract

Distributed Generation Systems Planning & the Ecosystem of Electricity Technological Learning

Across the world, energy policies are promoting distributed generation systems in order to (1) improve the resilience of the energy infrastructure, (2) to mitigate the incidence of CO_2 induced climate change, and (3) to improve cost effectiveness. When these three objectives are combined, a strong case is made for understanding how energy technologies have evolved. Planning for distributed generation systems is complicated by demand and supply volatilities because of the increase in the scale of renewable, intermittent technologies. Therefore, it is imperative to unpack the mechanism of how these technologies have evolved within the electricity ecosystem. As a result, this research seeks to address two critical issues:

(1) How would modern distributed generation systems meet increasingly fluctuating demands while adequately utilizing more renewable, but intermittent energies?

To address this question, we modify and apply a stochastic optimization framework that captures the randomness of supply and demand, and the effects of policy, simultaneously. Specifically, we modify the Benders' decomposition model to explore the optimal scheduling of supply from different technology units in a microgrid system.

(2) Given the growth of distributed generation systems, the question becomes: What can we learn from the ecosystem of energy technologies evolution to guide future investments decisions?

To answer this question, we effectuate a longitudinal study of 5,573 U.S. electricity firms operating from 1998 through 2010. We gauge the strains created by regulatory policies through their susceptibility to induce uncertainties. We consecutively explain the transfer of learning and how organizations learn from the experience of others or from their own experience. We link these two frameworks to another model so as to capture the knowledge acquired through production and technological change.

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Chapter 1 Introduction

1.1 Statement of the Problem

A report recently published by [7] reveals that to avert climate change, funding in low-carbon electricity and energy efficiency is expected to surge by several hundreds billion dollars in 15 years. Moreover, in January 2015, after the governor of California, Vermont Governor proposed a legislation to enact a new program that prioritizes community-scale renewable projects. The program is expected to create economical incentives for energy innovation projects that help customers adopt more intense energy efficiency strategies. This program and the battle for renewable energy technologies are creating a big boost for electricity demand and supply. But, given the increasing demand for electricity and the mounting costs of electricity supply associated with maximizing system performance through an optimal economic scheduling of distributed generation systems, electricity firms and policymakers are already facing the problem of sketching electricity management strategies for localized operation and grid penetration. Besides, since firms' priority is to maximize profits and effectively face competition, they are still facing questions surrounding the dominant forces driving technological learning in an electricity industry with heterogeneous technological sets.

1.2 Background

In general, a distributed generation is conceived as a small-scale electricity generation. [8] define a distributed generation as "an electric power generation source that is connected directly to the distribution network or on the customer side of the meter." Under this frame of reference, [9] defines a microgrid as a "discrete energy system consisting of distributed energy resources and loads capable of operating in parallel with, or independently from the main grid." Understandably, the foremost aim of a microgrid is to ensure a reliable and affordable energy security for all consumers. Monte Carlo estimates have been successful

in modeling aspects of electricity generation. Yet, their results have been approximate and unable to capture uncertainty in electricity demand and supply. The most frequently used decomposition technique in microgrid integration is the Benders' decomposition developed by [10]. The Benders' decomposition model is a notable algorithm for finding solutions to wide-ranging optimization problems including mixed-integer programs. It has been implemented with success to unravel the principal structural questions surrounding many optimization problems such as the restructured microgrid system. The latter has been a valuable prototype for finding how learning in energy generation technologies is achieved.

The study of how learning takes place between and across firms is crucial for firms planning for the start-up of multiple facilities. The role of organizational learning through technological knowledge acquisition in improving firm performance is well documented. There have been numerous models of learning curves that link future technological learning to major frameworks within firms. An example of such a framework is the installed power plant capacity, which has been a major factor of innovation in many electricity firms. The transfer of learning and the process whereby organizations learn internally or externally are part of the two applicable effects of the four types of vicarious learning. Vicarious learning in this context applies to learning by watching others. Some of its effects have combined to shape technology adoption decisions.

1.3 Organization of the Document

This dissertation is organized in the following manner. In chapter 2, we review the general literature of our research. This review prepares us to familiarize ourself with the essence of a more profound analysis of our subsequent topics. We examine our first subject matter in chapter 3. We present an initial literature review on the Benders' optimization as applied to the modeling of the operation of distributed generation systems in an uncertain environment. We clarify the texture of our modified Benders' model and proceed with a numerical application. We stage our results. In chapter 4, we address the topic of asymmetric knowledge acquisition. We review the literature on the evidence of heterogeneities in technological learning in the U.S. electricity industry. We herein analyze the role of policy instruments such as policy mandates and financial incentives. We formulate the theoretical framework and hypotheses. We characterize the main data. We also derive the econometric analysis. We subsequently present our results. In chapter 5, we conclude and discuss the

main findings in the study.

1.4 Purpose of the Study

The first objective of our research is to formulate a model that assesses the economic and policy implications of the adoption and operation of microgrids. Our second goal is to examine how technological heterogeneity influences knowledge acquisition across evolving intrafirm and competitive interfirm ecosystems.

1.5 Significance of the Study

Microgrids are progressively bringing into play a combination of distributed generation systems in order to mitigate the incidence of CO_2 induced climate change. This is all the more necessary as the frequency of hurricanes, floods, and tornadoes, is making our world a dangerous place to live in. The latest example is hurricane Matthew, considered as one of the most powerful hurricanes in recent history. The deployment of distributed generation systems also refines the resilience of the energy infrastructure. This results in a better access to power during emergencies and grid outage. Distributed generation systems located near consumers are having a positive effect on minimizing risks and costs associated with operation and maintenance. As illustrated in Figure 1.1, one of the most important undertakings of electricity demand and supply management is to preserve a constant match between electricity generation and consumption. Thus, there is a mounting desire to develop energy strategies to inform decision making on investment on technology innovation.

1.6 Scope and Limitations

Implementing the Benders' optimization model in the operation of distributed generation systems does not lead to a conclusive argument as to the best way to mitigate CO_2 emissions while ensuring satisfactory economics of operation under uncertainty. Moreover, our investigation is only for a 24 hour periods. An interesting research question would be to look at what happens in a week or month period. Another potential problem is that, across states, regulation policies differ in terms of their percentage targets, fines for non-compliance, and many other factors. So, given the many fluctuating variables governing regulatory policies, it is extremely difficult to precisely measure the level of uncertainties these policies create. This all the more evident as policy mandates greatly affect technolog-

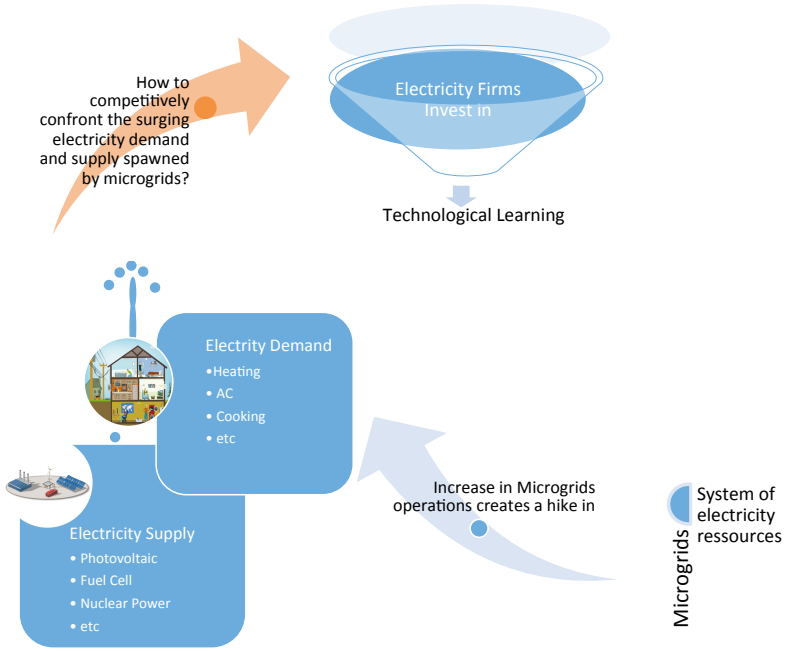

Figure 1.1: From Microgrids to Technological Learning

ical learning within and across electricity firms.

Chapter 2 Review of the Literature

2.1 Microgrids Through the Integration of Distributed Energy Resources

The definition of a distributed generation is ambiguous and subject to several contextual factors. It is abundantly clear that there is no unanimity on an accurate definition. In general, a distributed generation is conceived as a small-scale electricity generation. A point of consensus is that a distributed energy resources or DER is the use of small-scale power generation technologies located close to the load being served. Conventionally, the DER marketplace consists of energy companies, equipment suppliers, regulators, and energy users. As discussed above and as we will consider later, in using microgrids, there exist benefits that extend to utilities and to the community at large. For the purpose of our study, we hold that a microgrid is an energy delivery system that is powered by distributed energy resources in a decentralized manner over a limited geographic environment. We deem that a microgrid can operate in an existing distribution network or in an islanding mode[1].

In either islanding or grid-connected mode, there is a great amount of research related to the integration of distributed energy in microgrid. Case in point, [11] reports that there were approximately 53 GigaWatt of distributed generation in the US as far back as 1998. This approximation covers facilities that generated up to 50 MegaWatt though most installations were undersized in comparison. It is notable to point that through the interconnection of low and medium voltage consumers on a grid, the microgrid shares the property of aggregation in conventional systems. But, the fusion of the newly operating network with the area main utility distribution grid is contingent on the microgrid operational parameters. The main differences between DERs and the centralized energy system can be dually categorized. First, the power rating and modularity of design of DERs vis-a-vis their supply and demand-

[1]Island mode operation relates to the microgrid operating in isolation from the local electricity distribution network.

side portfolio of technologies is small. Second, DERs are usually located in the vicinity of energy consumption sites. In a microgrid setting, the portfolio of technologies can be made of photovoltaic (PV) cells, fuel cells, natural gas engines equipped with CHP technology, microturbines, energy storage devices, humidity control equipment, demand management devices, geothermal energy systems, ... The energy generated from these technologies can be consumed in a variety of low to medium voltage levels and as back-ups. These technologies are dissimilar to one another in several key performance measures: physical vulnerability, cost, intermittency and cogeneration capability. [12] organizes the key performance measures of some generating units. On the other hand, [8] point out the essential advantages of some other technologies.

2.2 Distributed Energie Resources Models

Research on the consolidation of distributed energy resources into a microgrid has been prolific since the early 2000s. As costs of operating onsite generation and CHP systems sky-rocket, the question of minimizing such costs has become a major academic concern. [13] forge the first DER model by setting forth the Distributed Energy Resources Customer Adoption Model or DER-CAM. They explore the economic costs and benefits of DERs in the microgrid. These costs are investigated vis-a-vis the consumers of the energy from the system. The dominant inputs of the model are the customers' load profiles, the customers' electricity purchasing technology option, the fuel costs of the various available DER technologies, and the basic physical characteristics of alternative generating technologies. In addition, the authors put in as parameters the capital, operation, and maintenance costs ($O\&M$) of the DER technologies under consideration. Via these inputs, the authors work out the optimal cost-minimizing capacity of each technology to be installed as well as the total cost of supplying electricity. They equally determine the volume and the running limits of the installed capacity. They use market prices that prevailed during California restructuring market. However, it is worth noting that at the same period, [14] bring about an integrated framework for forecasting the adoption of distributed energy resources both by electricity customers and by the various institutions within the industry itself. Their model evaluates the effects of DER adoption on the power system, particularly on the overall reliability and quality of electrical service to the end user. Altogether, the most seminal DER model remains the DER-CAM. Building on this model, [15] derive a DER

model that encapsulates heat recovery and storage with the inclusion of CHP technology under the influence of carbon tax. Yet, [16] distances himself a little bit by proposing some additional considerations. He explores the path dependence of introducing distributed generation into an existing generation plant. By combining the established DER-CAM model with a geographic information system (GIS) under constraints on local land use, [17] make a substantial contribution to the literature of DER models. Erecting on the GIS model, [18] capture the diffusion of DER in the US commercial building sector. As pointed by [19], the use of DERs both in utility networks and downstream of the meter is skyrocketing not only in the US but also in developed countries worldwide.

While [20] acknowledge the observation above, they find out that still much research works must be done in the fusion of DER technology into the electricity market in most developed countries. They further describe the operation of microgrid in the market environment. They also review numerous researches and studies on microgrid technology. More recently, [21] used the DER-CAM to analyze the annual load of an existing hotel in Athens choosing the optimal combination of installed technologies and their operating schedule. In this context, [22] indicate that traditional power plants are facing competition from new sources. The latter encompass energy efficiency programs run by utilities and distributed generation systems. Interestingly, they observe that falling costs of distributed energy resources are expected to challenge and transform the electric utility industry in the USA. In Appendix B, they summarize over 60 reports related to the future of the utility industry.

Actually, some researches have dug into specific technology of the distributed generation resources. For example, [23] find that net metering rules and the 30% ITC[2] are key determinants of the market for solar panels and batteries. They offer three scenarios for the U.S. residential and solar market. They conclude that higher fixed charges are likely to drive more customers to buy batteries and leave the grid. In parallel, [24] discuss the impact of 30% federal ITC on the market for photovoltaics in 2017. [25] review the latest literature on key components of the distributed generation system. However, they limit their analysis to photovoltaics power generation, its economic analysis, and its environmental impact. In due course, they derive the most applicable policies. From their review, they find that photovoltaic is an easy way to capture solar energy and thus one of the most efficient components

[2]The solar Investment Tax Credit or ITC is a federal policy mechanism that supports the deployment of solar energy in the United States. It provides business certainty to project developers and investors in solar energy.

of DER technologies. As technologies get innovated and economic and regulatory environment varies, it is expected that enthusiasm for distributed energy resources will build up. Nonetheless, the anticipated potential of DER penetration is usually not amply evaluated. Hence, numerous programming models have been initiated for a decomposition scheme and assessment of DER systems.

2.2.1 Microgrid Models under the Bender's Decomposition Framework

The most frequently used decomposition technique in microgrid integration is the Benders' decomposition developed by [10]. The Benders' decomposition model is a notable algorithm for solving large-scale programming problems including mixed-integer programs. It has been implemented with success to unravel underlying problem structures for many optimization problems such as the restructured microgrid system. For instance, [26] alter the basic Benders' decomposition framework to make it fitting for solving two-stage stochastic programs. They first assume that the latter have purely binary first-stage variables and mixed-integer second-stage variables. In their technique, the partial convex hull[3] of the second-stage feasible solutions is constructed using a convexification[4] process. The generated Benders' cuts are functions of the first-stage variables. These cuts are subsequently and repeatedly used each time the first-stage solution values are changed. But, their algorithm theoretically converges only under the assumption that the first-stage variables are purely binary. Another limitation of their method is that the different feasible first-stage solutions generated are not necessarily optimum with respect to the defining constraints. Hence, the decomposition of the second-stage subproblem must be established with respect to non extremal first-stage variables. Still, the second-stage solution is not guaranteed to satisfy the binary restrictions. Their work is nonetheless very stellar in that it serves as the basis for further Benders based models in DERs integration. [27] formulate a new approach of unit commitment scheduling problem based on the Benders' optimization technique.

Although in the context of a microgrid, in an effort to solve the same unit commitment problem, [28] develops a linear programming model for cost minimization. The minimized cost corresponds to the commitment of generating a system of units and storage within a

[3]The convex hull of a set X of points in Euclidean space is the smallest convex set that contains X. A set is said to be convex when, for two points contained therein, any point on the string that makes up these points is equally in the set.

[4]Convexification is a process for defining a local convex approximation of a nonconvex problem.

microgrid. He presents a mixed-integer linear programming model for the integrated plan and evaluation of DER systems. He first selects specific DER technologies on a given site. He examines the site's energy loads, local climate data, and utility tariff structure on the technologies. He equally accounts for the technical and financial information on the latter. He subsequently derives a model that minimizes the overall energy cost for a test year by selecting the units to install and determining their operating schedules. He further evaluates the economic, energetic, and environmental impacts of the DER system. As a case study, he conducts an investigation on the economical optimality of a DER system for an an eco-campus in Kitakyushu, Japan. Compellingly, his results show that gas engine is currently the most popular DER technology from the economic point of view. In addition, he discovers that under reasonable economic merits, the introduction of DER technologies may result in marginal or even adverse environmental effects. After conducting a sensitivity analysis of his results, he observes that the optimal system combination and corresponding economic and environmental performances are more or less sensitive to the scale of energy demand, energy prices[5], and carbon tax rate. On the other hand, via the Benders' decomposition, [29] quantifies the cost reductions related to storage devices in a simulation model of a simplified stylized medium-voltage grid under uncertain demand and wind output. He applies the Benders' decomposition technique to create a two-stage stochastic optimization program. Solving a quite similar problem, [30] formulate an optimal operation scheduling of a microgrid laboratory system. The system consists of a wind turbine, a solar unit, a fuel cell, and two storage battery banks. They propose an optimization algorithm that takes into account the minimization of active power losses. To justify the losses, they forge the problem as a mixed-integer quadratic programming model and solve it through a deterministic optimization technique implemented in GAMS[6]. Even though they do not fully apply the Benders' decomposition technique, their algorithm accounts for it in the GAMS implementation. Within the context of ISO[7] and employing the Benders' technique, [31] suggest a model that considers the uncertainty in customers responses to time-varying prices. They put forth a two-stage robust optimization model that maximizes the social welfare under unit commitment constraints. They then use the Benders' decomposition

[5]Energy prices encompass both electricity and city gas.

[6]General Algebraic Modeling System used to model high-level mathematical programming problems.

[7]Independent System Operators manage customers' electricity consumption behaviors in order to handle the demand response program. It was created to decrease electricity consumption or shift it from on-peak to off-peak periods.

method to handle the two-stage robust optimization problem. They ultimately evaluate the performance of their approach through several case studies. They observe that the power system obtained by their robust optimization approach is more efficient in terms of reliability.

More recently, addressing the same issue regarding reliability in demand response programs, [32] implement the Benders' optimization technique to bring about a new stochastic energy scheduling method for a microgrid. They assume that residential, commercial, and industrial customers can participate in demand response programs in energy or reserve scheduling. They model the uncertainties related to renewable distributed generation using proper probability distribution functions. The uncertainties are managed using reserves provided by both distributed generators and loads. They assess their method on a typical microgrid system comprising different type of loads and distributed generation units. They observe that the adoption of demand response programs can reduce the total operation costs of a microgrid. They further find that the same adoption can determine a more efficient use of energy resources. On a more complex aspect, [33] introduces a model for microgrid optimal scheduling considering multi-period islanding constraints. He aims at minimizing the microgrid total operation cost. This cost incorporates the generation cost of local resources and cost of energy purchase from the main grid. Specifically, he decomposes the microgrid optimal scheduling problem into a grid-connected operation master problem and an islanded operation subproblem. He uses an integer T_τ to scrutinize the microgrid capability in operating in the islanded mode for multiple hours. Through numerical simulations, he perceives the effectiveness of his proposed microgrid optimal scheduling model. Furthermore, he explores the economic and reliability merits of the latter. It is noteworthy to point that, for the first time, [34] have set forth a novel Matlab toolbox for GridLAB-D. This toolbox supports modeling, simulation, grid impact analysis, and the validation of power and control systems of a residential microgrid. Accounting for solar uncertainty, [35] apply the Benders' decomposition to compare solar scenarios. They let a mixed-integer unit commitment problem be the master problem and the subproblem be a stochastic optimal power flow problem. Thus, they put forward a co-optimization framework for a micro-grid with solar photovoltaic generation, emergency generation, and transmission switching. The specificity of their model lies in that it incorporates the ability to trade energy and ancillary services with the main grid. Thus, they capture the ability to allow for reserve sharing

between the two systems. They validate their commitment schedule with solar scenario analysis and test the resulting dispatching solution via several Monte-Carlo simulations.

2.3 Technological Learning and Knowledge in Electricity Firms

Numerous studies have proposed different definitions of organizational learning. The consensus is that organizational learning alludes to the transformation an organization meets while it faces new realities. But, [36] contend that factors such as cognitions and behaviors should be included in the definition of organizational learning. On a different aspect, [37] classifies firms' learning as depending on technical, commercial, and social capital. He defends that organizations that acquire these assets have more leverage when it comes to interdependence learning. [38] use a concrete example, a Toyota case study, to show that "institutionalized knowledge sharing routines" positively affect learning within an organization. Examining Canadian biotech startups, [39] find that they greatly improve their effectiveness by splitting into productive networks. They also observe that the latter open the way to new firm innovation with the least costs of "redundancy, conflict, and complexity." We should also point that, analyzing the effects of cumulative knowledge in organizations, [40] find that cumulative experience is actually a critical factor in predicting the learning potential of organizations. Although breakthrough and cumulative knowledge tends to have separate effects on organizations, it has been proved that the former have a more acute effect. Case in point, [41] develop a model that describes the way organizations can generate breakthrough inventions, thus stimulating an internal organizational transformation. They contend that by operating with "novel, emerging, and pioneering technologies," firms can innovate and generate breakthrough knowledge. A recurrent question in this area of research has always been whether the rates at which firms innovate in operational performance have a causational or correlational effect on firms' operational performances. To tackle the issue, [42] holds that it is well possible to spur the "rate of operational performance improvement of firms" by accumulating and sustaining the technological capabilities of the firms. This type of procedures greatly enhances intrafirm learning although [43] indicates that firms differ in their perceptions and approaches to intrafirm learning or external knowledge acquisition. The author also observes that integration promotes learning-by-doing when environmental volatility increases. This has an effect on firms' behaviors. For instance, to influence market

success, institutional mechanisms must be deployed to drive the diffusion of new technologies. Several studies also show that institutional change reshapes industrial boundaries and shifts the scope of permissible activities. These mainly apply for incumbents and entrants with changes in incentives for behavior ([44]). Whether learning opportunities are spurred by interfirm competitive behavior is discussed in [45]. As learning opportunities enhance network structure, the capacity of firms to penetrate the actual networks is very contingent on the network structure ([46]). But [47] also observes that the disparity of competence in a network structure is hugely affected by the appearance or nonappearance of connections within the members of the network. An issue that the technological knowledge literature constantly contends with has to do with uncertainty as government deregulation impacts firms' productivity.

Over a period spanning the past four decades, R&D as well as empirical interests have created a tremendous enthusiasm for technological learning and knowledge. Correspondingly, the prosperity and achievement of firms have always depended on their capacity to learn and adapt quickly. Through the years, as workers retire from firms, concerns about knowledge detainment are invariably at hand. Competition and globalization are more and more coercing firms to focus on learning transfer through technology. This has led to numerous technological improvements within firms. Consequently, a greater number of research articles on the the issue of knowledge and technological learning has blossomed. In particular, as learning curves capture technological advances, [48] has observed that each curve represents the decrease in unit cost as firms increase production. Yet, there is still a limited understanding of the mechanisms driving learning, how and why it takes place. For instance, after remarking that the variation of firms is proportional to their learning curves, [49] infer but do not explain why some firms are very good at learning while others are not. By the same token, some firms differ in their perceptions of learnings to disparities in absorptive capacity ([50]). Expounding on the notion of disparities within a firm, [51] proposes that cooperation within a firm can be enhanced to the point that profitable knowledge is shared, and consequently leverages the firm intra learning. It is quite well established that organizations learn not only from their own internal experiences, but also from the innovative experiences of others ([52]). After defining the "classic learning curve model" wherein "productivity is an exponential function of the experience", [53] find that the learning mechanism can be complicated in an intrafirm learning environment.

They further observe that limited attention has been given to learning differences and the wide range of learning rates across firms. We must also point how [54] use technological learning aggregation in advanced countries to brighten the understanding of learning in the agricultural precincts of poor countries. A problem facing both poor and rich countries is that of regulatory uncertainty, which occasionally impinges on investment decisions.

The real options approach has been used to lend credence to how regulatory uncertainty leads to delay or cancellation of learning investment decisions. For example, [55] note that the mean-preserving volatility in interest rates increases the expected value of a project, though also creating an incentive to delay adoption or investment. Concurrently, the resource-based view argues that environmental uncertainty supports firm investment decisions. Thus, it is generally agreed that in acquiring strategic capabilities to gain competitive advantage, the diffusion of homogeneous innovations has been quite rapid ([56]). By and large, as pointed by [57], the study of how learning takes place between and across firms is crucial for firms' planning for the start-up of multiple facilities or capacity additions to existing technologies. The understanding of the underlying drivers of technological adoption equally depends on a rigorous analysis on how intrafirm and interfirm learnings occur. However, in the scheme of interfirm or intrafirm learning in generation technologies, limited integration between firms exists, thus creating a wide spectrum for innovation to flourish. For that matter, [58] perceives that the structure of the electricity industry promotes interdependence between generation, transmission and distribution of electricity. In order to justify, for example, how generation capabilities for various firms, vary in terms of competitive abilities, [59] suggest a rather interesting model. They create geographical clusters and contend that firms in these newly created groups have better probabilities to preserve their connections. The latter subsequently facilitate the firms abilities to procure current opportunities, ideas, and information. Since information is so critical to firms' abilities to produce and compete, organizational learning is at the core of firms' investments in R&D.

2.4 Regulatory Policy and Firms' Productivity

After analyzing 177 U.S. electric utilities from 1998 to 2001, [60] find that retail deregulation negatively affects firms' productivity. Precisely, they observe that organizations that depend on the market for their electricity supply are more productive than organizations

that do not. They subsequently highlight the importance of joining in different knowledge structures in the presence of uncertainty. Besides, [61] point that regulatory prescriptions such as mandates for specific technologies should be introduced in the absence of incentives to innovate or to decrease the uncertainty in the environment. They equally provide evidence that deregulation in the electric utility industry stimulates environmental differentiation through greater levels of renewable generation. But, as uncertainty impinges on learning avenues, firms are subject to equal but often opposing forces on the values of external versus internal knowledge. This problem is even exacerbated when an innovation has heterogeneous values as described by [62]. Thus, on one side of the learning fulcrum is the modeling effect that supports the adoption of emerging knowledge external to the firm. Similarly, the heterogeneity of experience as well as technical and organizational experience across firms have had different impacts on innovation adoption ([63]). Even [62] extends the theory of adoption decisions to include how information gained from past adopters either promotes the knowledge or leads to abandonment. However, he argues that uncertainty delays diffusion giving early adopters a competitive edge. Closely related to his study is the ambiguous influence of the increase in volatility in the market environment. In substance, the many dimensions of policy uncertainty ranging from timing to the stringency affect investment decisions ([64]). Nonetheless, we must note that the success of innovation or of a new technology still depends on market success. For example, while internal competition unfreezes firms to overcome inertia, the resulting superior technology may not be commercially competitive ([65]). In a network of firms, individual firms are usually identified according to their aspiration to fit with the network. To that effect, a new model of knowledge acquisition that takes into consideration the many features of knowledge is warranted. Thereupon, [66] put forward a system of knowledge acquisition that accounts for "knowledge-productive practices", knowledge content, and knowledge as it relates to a "knowing subject." Interestingly, [67] remark that since time is the measure on which organizational learning takes effect, understanding organizational learning will necessitate longitudinal data. This explains why we have amassed a large amount of data for the sake of our analysis. Another illustration is given by [68], who uses data from the product innovation and technological collaboration of 944 Chinese firms to study the possible consequences of technological collaboration on product innovation. Alluding to technological collaboration, via the field of semiconductor manufacturing, [69] study the possible impact

of technological and organizational advances. They find that the latter can be reconciled with technological learning through collective practices to generate innovation. Variations of technological structures can also have an effect on interfirm learning in network relations ([70]). Then, the issue becomes whether interfirm learning can successfully address the development of complex products systems. On that very note, [71], using military aircraft development programs, observe that technology acquisition procedures can have numerous effects on learning-by-doing. It is also important to point that experiential learning in an environment marked by creativity can have a very positive impact on a firm's survival in the presence of different technology structures ([72]).

Chapter 3 Commitment Strategies for Distributed Generation Systems

3.1 Introduction

The Lima Accord adopted in December 2014 in Peru saw the culmination of two-decade efforts to create a serious international protocol to combat climate change. For the first time in history, over 200 nations concurred to the first treaty pledging every country in the world to bringing down CO_2 emissions that induce climate change. The arrangements from every nation, known within the United Nations as "Intended Nationally Determined Contributions," would shape the foundations of a far-reaching new treaty that was signed in Paris in December 2015. In addition, president Obama announced in November 2014 a historic consensus between the U.S. and China on curtailing greenhouse gas emissions.

The identification of energy efficiency measures and technologies is at the center of grid-connected generation. A particular case is the integration of distributed energy resources. Energy policies across the world are promoting microgrids as a way to effectively manage the increase in the share of distributed energy. Thus, we deduce an economic optimization framework that enables us to address some policy options for the operation of the microgrid while it fuses with the grid. Although scenarios analyses have been used to examine electricity demand, they very often forgo uncertainty in supply. Monte Carlo estimates have been successful in modeling aspects of electricity generation. Yet, their results have been approximate and unable to capture uncertainty in electricity demand and supply. Thus, as a means to apprehend the particulars of demand and supply uncertainties in electricity generation, we use a modified Benders' decomposition to explore the optimal scheduling of supply from different technology units in the microgrid. We ensure that the power generated by the units meets systemic load while satisfying all the operational and technological constraints. We evaluate the adoption of microgrid technologies in an optimal model for

decision processes based on a least operating and emission costs due to energy consumption. The derived optimal policy is aligned with the maximum penetration of the microgrid into existing distribution systems. In this project, we want to develop a streamlined computational model that integrates the operation of the microgrid in the existing grid. We implement our model in a quantitative numerical analysis to investigate the operational schedule under the lens of a public environmental policy. A seminal implication of our results lies in the cost-effectiveness of microturbines and climate friendliness of fuel cell and natural gas generators. This informs microgrids operators that the most viable way to simultaneously reduce O&M costs is to invest in microturbines technology. Yet, to contribute to a cleaner environment in the face of demand and supply uncertainty, the operator would opt for fuel cells and natural gas generators technologies.

A significant challenge facing modern distributed energy systems is that of meeting the mounting demands for electricity and at the same time making an effective use of renewable energies. Resolving this issue calls for a broad uncertainty model that would answer the following concerns: How could consumers and operators handle simultaneous uncertainties in demand and supply? What are the best cost-effective and climate friendly technologies? How is the storage technology critical in reducing CO_2 emissions? Is there a consensual strategy for a proper mitigation of the effects of emissions?

To answer those questions, we develop a streamlined computational model that integrates the operation of the microgrid in the existing grid. First, we extend prior research on this subject by uncovering a greater reliance on the grid under simultaneous uncertainties in demand and supply. By the same token, we define a strategy for a proper mitigation of the effects of emissions. We find that carbon abatement policy can be used to motivate microgrids operators to invest in fuel cells and natural gas technologies when dealing with uncertainty. We loosen the assumption of continuous output from some technologies. By carrying out our model in a quantitative numerical analysis, we perceive that under simultaneous stochastic demand and supply, fuel cells and natural gas technologies are optimal in terms of reducing costs and CO_2 emissions . Second, by adding storage, we observe a greater reduction of costs and CO_2 emissions. Third, we unpack the intricacies of demand uncertainty to find that it negatively affects climate-friendly policies. For instance, we find that when demand is uncertain, diesel and microturbines units have a greater chance of being scheduled at on-peak hours, which is very unlikely to contribute to the reduction of

emissions. Before discussing in ample details the Benders' decomposition model, we first would like to consider a few examples of microgrids integration.

3.2 Examples of Microgrids

Since the initiation of the DER-CAM, several localities and universities have decided to adopt their own micrigrids. In all cases, microgrid central controller must always be connected to all existing technologies via a given power system.

New York University

By building a new cogeneration plant in 2010, New York University intended to achieve its own commitment to reducing greenhouse gases by 5,000 tons/year. NYU is thus transitioning towards a modern natural-gas fired combined heat and power facility. Its ultimate goal is to carry out microgrid capabilities, better reliability, and a better control of its energy expenditures. The microgrid consists of two 5.5 MW gas turbines for producing electricity paired with heat recovery steam generators. The system is also made of 2.4 MW steam turbine ([73]). The entire system is tied to Con Edison distribution grid. One of its particularities lies in that it purchases electricity when demand is superior to the on-site generating capacity. The upfront capital cost of the upgrade was $126 million not including tax-exempt bonds arranged through the Dormitory Authority of the State of New York. Low-cost financing sources were also provided by the NYU tuition and fees. The CHP system has an output capacity of 13.4 MW. We should observe that this is actually twice as much as the old plants capacity. The NYU microgrid became operational in 2011. It presently supplies electricity to 22 buildings and heat to 37 buildings across the entire campus. In contrast to its original mode of operation, the NYU microgrid now operates in islanding mode in that it does not have to depend on the distribution grid. Interestingly, during Hurricane Sandy, the NYU microgrid successfully islanded from the local distribution. Furthermore, it continued to provide reliable electricity to much of the NYU campus. On an economical and environmental standpoint, much savings and emissions reductions have been effectuated by the NYU microgrid. In fact, NYU has evaluated savings on total energy costs to be $5 to $8 million per year. In addition, the modernization of the plant has drastically reduced NYU's local emissions with an estimated 68% decrease in EPA criteria pollutants (NO_x, SO_2, and CO emissions) ([73]). Moreover, there have been a 23% decrease in greenhouse gas emissions with the adoption of the NYU microgrid. This has

been a critical step towards the pledge that the university made to the City of New York to decrease its greenhouse gas emissions by 30%.

Illinois Institute of Technology

The Illinois Institute of Technology (IIT) used to average three or more power outages per year. The outages had caused a series of teaching and research disruptions with an estimated cost of $500,000 annually and a growing demand for better energy ([74]). Given that upsetting situation, IIT decided to build its own electricity pattern.

The development and the validation of smart grid technologies for IIT microgrid are conducted by IIT in cooperation with the Galvin Electricity Initiative and other key investors. The collaboration has led to the adoption of new policies aimed at improving customer service. The peak load of IIT's campus is around 10 MW. The on-campus DER is made of CC gas units and a wind turbine. It is also of rooftop PV as well as of a 500 kWh battery. The system performance is within the ranges of 9 MW. This enables the campus to rely on itself and thus operating in islanding mode most of the time. The IIT microgrid is sponsored by a five years grant of $7 million of government funding and a $5 million of private support. Ultimately, the IIT microgrid gears towards the creation of its own smart grid. Its main functions would be to single out systems dysfunctions and re-direct electricity to satisfy loads. It also intends to decrease electricity demand brought about by higher electricity prices and grid disturbance ([74]). The latter reference also reports that the IIT prototype is the first "integrated microgrid system that provides for full islanding" of an entire sited "load based on market signals."

Santa Rita Jail

Santa Rita Jail is in Dublin, 40 miles east of San Francisco. It is a 4,500 inmate facility. [75] show that in the past years, several Distributed Energy Resources installations have operated in the jail. Numerous efficiency measures have also been undertaken. This has led to the transformation of the 3.0 MW facility into a litteral Green Jail. The Santa Rita Jail microgrid is made of a 1.5 MW of PV cells, a 1.0 MW molten carbonate fuel cell, and back-up diesel generators. It can function both in islanding mode or in grid-connected mode using a 2 MWh – 4 MWh Lithium Iron battery. Thanks to the battery and a switch, the Jail can easily island and reconnect whenever needed. The CERTS Microgrid technology controls the entire power system while being embedded in the battery and switch power

electronics.

It is expected that the jail seamlessly disconnect from the grid and self-performs in case of any disturbance. The jail can automatically reconnect again once the disturbance has dissipated. Interestingly, [76] point out that the extent to which that jail is capable of islanding is principally dependent on the energy capacity of the battery. By and large, for many researchers, "Santa Rita Jail is one of the" world most successful "microgrid demonstrations."

Kythnos Island

The Kythnos Island microgrid system was initially created to electrify 12 houses in a small valley on Kythnos. Kythnos Island is close to Athens, Greece. The microgrid system is made of 10 KW of PV cells at two locations, a nominal 53 KWh battery bank, and a 5 KW diesel genset. There exists a second PV array of about 2 KW mounted on the roof of the control system building. The PV system is connected to an inverter and a 32 KWh battery bank to provide power for monitoring and communication ([77]). The loads are mainly related to lighting and water. In case there is more power demand than the microgrid can furnish, there is an automatic activation of the batteries. A special characteristic of this microgrid is that it can function in droop condition. This feature constrains the loads in case storage is fully charged. ([77]). In the Kythnos region, the "grid" is "made of overhead power lines and a communication cable running in parallel to serve monitoring and control requirements." The "Kythnos Island Project was" originally "funded by the European FP 5 Microgrids program." The initial goal of the project "was to test centralized and decentralized control strategies for islanding."

We can swiftly observe that none of the microgrids discussed above is capable of keeping a consistent compatibility between electricity supply and consumers demand. A critical feature of electricity resources in microgrids is that the renewable energies therein are very fluctuant. Hence, a significant challenge facing modern microgrids is that of fulfilling consumers' demands while adequately utilizing renewable energies. Solving this problems requires a framework that captures the changeability of supply and demand, simultaneously. The Benders' model happens to be just such a framework.

3.3 The Benders' Decomposition Model

The Benders' decomposition algorithm constitutes one of the most employed techniques in applied optimization. It was introduced by [10] for solving large-scale mixed-integer programming (MIP) problems. After [78] extended the initial Benders' decomposition, it began to find applications in power system decision-related problems. Subsequently, the Benders' decomposition model has been wielded with triumph to exploit underlying problem structures for numerous optimization problems. Among the latter, we can name generating unit planning, transmission planning, optimal generation bidding and valuation, reactive power planning, optimal power flow, hydro-thermal scheduling, generation maintenance scheduling, transmission maintenance scheduling, long-term fuel budgeting and scheduling, long-term generating unit scheduling and valuation ([79]).

The essence of the Benders' decomposition lies in solving large-scale problems via a chain of smaller ones. This explains why the Benders model is convenient when it comes to integrating the many power system asset management decision algorithms. Basically, in implementing the Benders' model, the original problem is decomposed into a master problem and several subproblems (Figure 3.1). The master problem must be an integer program while the subproblems are linear programs. It is possible that the lower bound solution of the master problem involves fewer constraints.

The subproblems examine the solution of the master problem to check whether it satisfies the remaining constraints. When the subproblem is feasible, the upper bound solution of the original problem is determined by producing a new objective function (Figure 3.1). The new objective function is subsequently used for the continuous optimization of the master problem solution. When one of the subproblems is infeasible, an infeasibility cut embodying the least satisfied constraint is introduced to the master problem (Figure 3.1). Recomputing the master problem with more constraints generates a new lower bound solution of the original problem. Several iterations between the master problem and the subproblems may be needed in order to achieve the final solution derived from the Benders' decomposition algorithm. The optimal solution of the original problem is reached only if the upper bound and the lower bound are sufficiently close. In order to get into the particular of the Benders' model, it is adequate to unravel the notion of duality in linear programs.

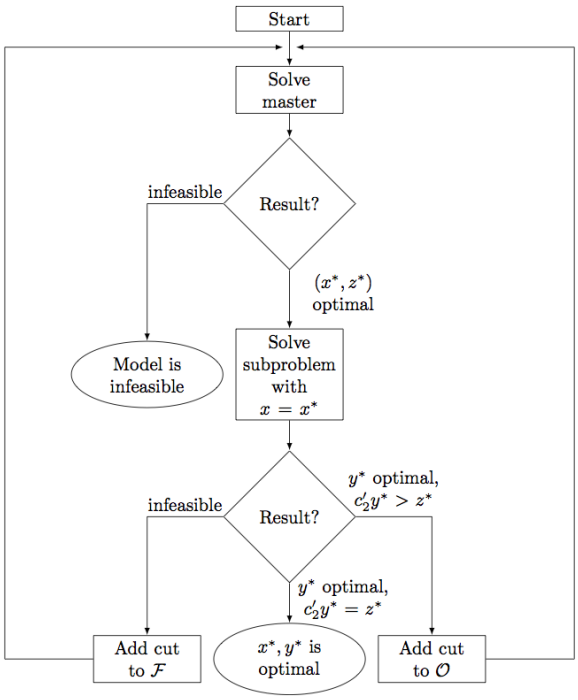

Figure 3.1: General Benders' Algorithm
Source: [1]

3.3.1 Duality in Optimization Theory

Let τ and x be n-vectors. Let β be an m-vector and Δ be an $m \times n$ matrix. We let the linear function $\tau^T x$ be the objective function with linear inequalities representing the constraints. The inequalities form a feasible region for minimizing the objective function. $\{x \in \mathbb{R}^n | \Delta x \geq \beta, x \geq 0\}$ expresses the solution characteristics of the primal problem in the feasible region. For any linear program (LP), (3.1) represents the primal problem in the optimization problem.

$$\begin{aligned} &\text{minimize } \varphi = \tau^T x \\ &\text{s.t.} \quad \Delta x \geq \beta \\ &\qquad x \geq 0 \end{aligned} \tag{3.1}$$

It is possible to find an equivalent expression in another LP form. It is the dual problem and is given by (3.2).

$$\begin{aligned} &\text{maximize } \varphi = \beta^T y \\ &\text{s.t.} \quad \Delta^T y \leq \tau \\ &\qquad y \geq 0 \end{aligned} \tag{3.2}$$

Typically, the quantity of inequalities in the primal problem gets to be the quantity of variables in the dual problem. Equivalently, the quantity of variables in the primal problem comes to be the quantity of inequalities in the dual problem. We can thus speak of a dimensional difference between the primal and the dual problem. Traditionally, it is more uncomplicated to solve an LP with fewer constraints. Hence, we would solve the LP problem that has a less amount of constraints. In case where the primal problem has m constraints and he dual problem has n constraints, we would solve the primal problem if $m < n$. In the same logic, we would solve the dual problem if $m > n$.

3.3.2 Original Benders' Decomposition Concept

Let's assume that Δ is an $m \times n$ matrix, Γ an $q \times p$ matrix, and $\digamma$ an $q \times n$ matrix. We let τ and x be p-vectors with y and η be n-integer vectors. We equally let β be an m-vector and υ be a q-vector. We consider $\mathbf{S}$ as an arbitrary subset of Γ^p with integral-valued components. Thus, we define a mixed-integer program as

$$\begin{aligned} &\text{minimize } \varphi = \tau^T x + \eta^T y \\ &\text{s.t.} \quad \Delta y \geq \beta \\ &\qquad \Gamma x + \digamma y \geq \upsilon \\ &\qquad x \geq 0, y \in \mathbf{S} \end{aligned} \tag{3.3}$$

We hold that (3.3) is a mixed-integer problem only if x is continuous and y is an integer. It is possible to transform (3.3) into a linear program in x by fixing the y values. So doing, we obtain the new problem

$$\min_{y \in \mathbf{Z}} \left\{ \eta^T y | \Delta y \geq \beta + \min\{\tau^T x | \Gamma x \geq \upsilon - \digamma y, x \geq 0\} \right\} \tag{3.4}$$

$$\mathbf{Z} = \{y; \exists x \geq 0 | \Gamma x \geq \upsilon - \digamma y, \Delta y \geq \beta, y \in \mathbf{S}\} \tag{3.5}$$

We are now able to split off (3.3) into a master problem and a subproblem. Let MP be the master problem and SP the subproblem. We recall that the principle of the Benders' model resides in MP being an integer program and SPs being linear programs. The optimal solution of (3.3) will be achieved when the upper bound and the lower bound of the ultimate solution are sufficiently close to each other. Let φ_U be the upper bound of the ultimate

solution of (3.3) and φ_L its lower bound. Thereupon, we can now defined MP as

$$\begin{aligned} &\text{minimize } \varphi_L \\ &\text{s.t.} \quad \varphi_L \geq \eta^T y \\ &\qquad \Delta y \geq \beta \\ &\qquad y \in \mathbf{S} \end{aligned} \tag{3.6}$$

Having specified the master problem, let y^* be its solution that will be used to define the optimality subproblem. In order to verify the optimality of MP (3.6), the Benders subproblems are introduced. These are derived from (3.4). Hence, SP1 can be expressed as follow:

$$\begin{aligned} &\text{minimize } \tau^T x \\ &\text{s.t.} \quad \Gamma x \geq \upsilon - F y^* \\ &\qquad x \geq 0 \end{aligned} \tag{3.7}$$

It is possible to introduce a second subproblem SP2 by taking advantage of the dual subproblem of (3.7) although it can be obtained otherwise. For instance, we used the derivation in [79] where (3.7) is taken as a primal subproblem. So, SP2 can be presented as

$$\begin{aligned} &\text{maximize } (\upsilon - F y^*)^T q \\ &\text{s.t.} \quad \Gamma q \leq \tau \\ &\qquad q \geq 0 \end{aligned} \tag{3.8}$$

Originally, [10] based the Benders' decomposition on the fact that the partition theorem for mixed-variables programming problems imparts a critical optimality rule. To define the latter, we must obtain the optimal solution (φ_L^*, x^*) of the master problem and the optimal solution y^* of the optimality subproblem. In case the upper bound

$$\varphi_U^* = \tau^T x^* + \eta^T y^*$$

satisfactorily matches the lower bound

$$\varphi_L^*$$

obtained in the MP step, the tripartite

$$(\varphi_L^*, x^*, y^*)$$

becomes the optimal solution. We must however remark that [79] do not take this important observation into account. All in all, the Benders' procedure can be summarized in basically three main stages.

3.3.3 Benders' Procedure

Solving Master Problem (3.6) In this stage, we first solve (3.6). We subsequently acquire an initial lower bound, namely φ_L^* at (x^*, y^*). The original problem (3.3) will be infeasible if (3.6) is infeasible. Assuming that the latter is feasible, if it is rather unbounded, we let $\varphi_L^* = \infty$ for some $(x^*, y^*) \in \mathbf{S}$ and try (3.7) or (3.8).

Solving Suproblem (3.7) or (3.8) In this phase, we have the latitude to solve (3.7) or (3.8) in order to verify that the optimal solution from the master problem is feasible. Using subproblem (3.7), it is possible to determine an upper bound solution of the original problem (3.3) for the optimal solution x^* as

$$\varphi_U^* = \tau^T x^* + \eta^T y^*$$

We can also deduce an upper bound solution of the original problem (3.3) corresponding to the optimal dual (dual multiplier vector) q^{*p} of (3.8). We let that upper bound solution be

$$\varphi_U^* = \eta^T y^* + (\upsilon - F y^*)^T q^{*p}$$

$\forall \epsilon$ very small, if $|\varphi_U^* - \varphi_L^*| \leq \epsilon$, the bounds converge to the optimal solution. We have attained our goal. If instead, the upper and lower bounds do not converge, our original problem becomes infeasible again. Happily, it is possible to create a feasibility check subproblem by generating a new constraint. We just have to generate a feasibility cut for (3.8) by ensuring that

$$\varphi_L \geq \eta^T y + (\upsilon - F y)^T q^{*p}$$

Then, we will have to forward that feasibility cut back to the master problem so that the MP can remove the infeasible solution set. To do so, we engender a new MP as we will show in the last phase.

If (3.7) is infeasible, then (3.8) is unbounded, we initiate a new cut, which is the infeasibility cut. It allows the creation of a new MP. This infeasibility cut encapsulates

$$(\upsilon - F y)^T q^{*z} \leq 0, z \in \mathbf{Z}$$

where $\acute{q}$ can be seen as an optimal dual pseudo solution for the sake of the infeasibility cut. In order to determine $\acute{q}$, we use (3.8) to introduce the following feasibility check subproblem. For that matter, let I be the unit vector and consider some $a \in \mathbf{S}$ such that

$$\begin{aligned} &\text{minimize } I^T a \\ &\text{s.t.} \quad \Gamma x + Ia \leq (\upsilon - F y^*) q^{*z} \\ &\qquad x \geq 0, a \geq 0 \end{aligned} \tag{3.9}$$

We should point here that the original problem (3.3) will have no feasible solution or even an unbounded solution if (3.8) if unbounded.

Solving the Second Master Problem This phase applies if the upper bound φ_U^* and the lower bound φ_L^* do not converge, making the original problem (3.3) infeasible. We then use the feasibility cut $\varphi_L \geq \eta^T y + (\upsilon - F y)^T q^{*p}$ and the infeasibility cut $(\upsilon - F y^*) q^{*z} \leq 0$ to obtain a new lower bound φ_L^* along y^* for (3.3) . We call the new problem a second master problem or MP^2.

$$\begin{aligned} &\text{minimize } \varphi_L \\ &\text{s.t.} \quad \Delta y \geq \beta \\ &\qquad \varphi_L \geq \eta^T y + (\upsilon - F y)^T q^{*p}_i, i = 1 \cdots n_p \qquad \dashrightarrow MP^2 \\ &\qquad (\upsilon - F y^*)^T q^{*z}_i \leq 0, i = 1 \cdots n_z \\ &\qquad y \in \mathbf{S} \end{aligned} \tag{3.10}$$

By letting $A(y^*)$ be the optimal solution of (3.7) and $B(y^*)$ the optimal solution of the feasibility check subproblem (3.9), we can generalize the expression of the Benders cuts in

(3.10) in the following manner:

$$\begin{aligned} &\varphi \geq \eta^T y + A(y^*)_i - (y - y^*)^T F^T q^{*p}_i, i = 1 \cdots n_p \\ &B(y^*)_i - (y - y^*)^T F^T q^{*z}_i \leq 0, i = 1 \cdots n_z \end{aligned} \tag{3.11}$$

We can find more discussion on this alternative form of the Benders' cuts in [79]. They further point that $\varphi \geq \eta^T y + A(y^*) - (y - y^*)^T F^T q^{*p}$ denotes the decrease of the objective value of the original problem (3.3) when y^* is updated to y. The article also remarks that the dual multiplier vector q^{*p} represents the incremental change in the optimal objective. By the same token, the Benders' cut $B(y^*) - (y - y^*)^T F^T q^{*z} \leq 0$ signals the fact that y^* given in the master problem (3.6) is updated to a new value so as to eliminate the constraint violations in subproblem 1 (3.7). The dual multiplier vector q^{*z} symbolizes the incremental change in the total violation. After posing (3.11), we can solve SP1 (3.7) for the second time. If MP^2 defined by (3.10) or (3.11) is unbounded, we let $\varphi^*_L = \infty, y^* \in \mathbf{S}$ and solve SP2 (3.8). If we find that MP^2 is infeasible, then (3.3) is also infeasible.

3.4 Distributed Generation Technologies

3.4.1 Microturbines

Microturbines are small electricity generators that are capable of burning gaseous and liquid fuels. Once air enters the microturbine, it is compressed and mixed with fuel. The resulting premix is burned and used to spin the electrical generator through a high-speed rotation. Microturbines take on most commercial fuels such as gasoline, natural gas, propane, diesel, and kerosene. They can equally adopt renewable fuels such as E85, biodiesel, and biogas. Microturbines models normally consist of a single stage radial compressor, a single stage radial turbine, and a recuperator. This is shown in Figure 3.2.

One of the most essential parts of the microturbine is the recuperator. It transports a portion of the waste heat in the exhaust to the compressed air. Through such an operation, the recuperator preheats the compressed air before it enters the fuel burner stage. The entire process results in less fuel being needed to heat the gases. Given that microturbines recover exhaust energy to preheat compressed air, they greatly increase electrical efficiency. All things considered, microturbines meet great utility interconnection requirements. In effect, most microturbines use power electronics with digital processor controls.

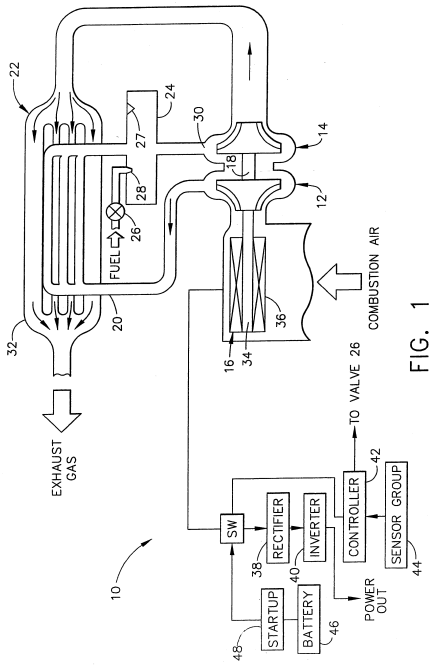

Figure 3.2: Microturbine Power Generating System
Source: [2]

This capability streamlines the integration of the units protective relaying functions into the microturbine. Just about, [80] remark that the modern microturbines technology is the result of development work in small stationary and automotive gas turbines, auxiliary power equipment, and turbochargers. The majority of turbochargers was pursued by the automotive industry beginning in the 1950s. It was not until around 1997 that microturbines entered field testing. Three years later, adequate technology and initial commercial service began expanding.

By and large, Microturbine systems have seen a jump from "30 kW to 70 kW". According to [81], "today's systems can have individual ratings of 200 kW to 250 kW. Packages up to 1 MW are now available that can be assembled into multipac units for projects of 5 MW to 10 MW." The popularity of microturbines lies in the fact that they are more efficient in comparison to other turbines of similar types. In fact, as observed by [82], "the recuperator that recycles a portion of the exhaust energy back into the energy conversion process produces the efficiency advantage." Microturbine technologies have the potential of attaining low emissions when used in combination with combined heat and power (CHP). Microturbines operators are often eligible for federal incentives. This is only possible when

the operation is on a renewable fuel. In that case, a federal "10% investment tax credit" can be secured as a grant.

Dealing with generation solutions, there have been several attempts to create mathematical models for microturbine generators. For instance, [83] demonstrates the "use of power electronics in conditioning the power output of a generating system" that enfolds a microturbine. He uses MATLAB/Simulink to simulate different load conditions. This is the case because most microturbines use power electronics. The latter are used "to convert the high-frequency output from the generator to 50 or 60 Hertz or from 400V to 480V three-phase AC". These parameters are more useable and practical for customers. Thus, [84] observe that "one of the factors that could enable feasible and economic viability for installation of microturbines is the supply of fuel with characteristics appropriate to DG designs." They succeed in managing the "performance indices of microturbines DG units" and analyzing "their dependency on fuel characteristics for economical and optimal performance."

In line with our work, the most important advantage of microturbines resides in that they make integrated systems possible. Given that "a single power system controller can manage multiple engine packages to synchronize their voltage outputs", several components can incorporated into a microgrid. This offers numerous advantages to owners via a secure power source and long operations with minimal probability of outage.

An interesting feature of microturbines is the "maintenance-free air bearings." These constitute the "lowest emissions of any non-catalyzed fossil fuel combustion." [85] observes that "digital power conversion" can be combined to maintenance-free air bearings to develop the optimal "small-scale generator." An example of such systems can be found in New York where they "are highly efficient sources of distributed generation that provide customers with low cost and reliable power with low emissions ([85])." "The carbon dioxide emissions of microturbines burning natural gas will be worse or better than those of the existing utility grid" when used for electricity generation alone. This is actually contingent on the location. "At an efficiency of 31%, microturbines produce approximately 1.29 lbs of CO_2/kWh ([86])." Compared to that, the California's electricity "grid is much cleaner, with emissions of 0.49 lbs of CO_2/kWh. Microturbine emissions for non-CO_2 sources are actually better than" the grid's. As reported by [87], "Capstone microturbines" NOx emission are 0.00015 lbs/kWh and their CO emissions are 0.00010 lbs/kWh." On the other hand, emissions from the grid are 0.00062 NOx lbs/kWh.

3.4.2 Solar Photovoltaic (PV)

Notwithstanding a certain amount of general denials about global warming, the solar PV industry in the United States has received billions of dollars of subsidies at the federal and state level. Practically, Solar PV operation can seem a little complex. It entails "using crystalline panels to convert energy from the sun into electricity for" domestic or industrial use. The basic "unit is a solar cell made up of thin layers of silicon. Electrical charges are generated as direct current (DC) at the" moment "photons falling from the sun interact with the silicon. The PV modular panel is made up of multiple PV cells and is the principal building block of the PV system." Once in conjunction with each other, "PV modules produce a direct current (DC) that is transformed into alternating current (AC) by an inverter." The latter in turn forwards the AC to "the home's electrical panel" as shown in Figure 3.3, thus converting sunlight into electricity. The latter is subsequently supplied to appliances, lights and other electrical devices. "In case there is more electricity that is being produced than consumed, the excess is rerouted from the utility meter into the utility grid." Thanks to net metering, this excess electricity is credited to the consumer for later use in storage. For consumers' purpose and in an effort to investigate "cost reductions due to learning using comprehensive data on all solar PV installations, " [88] have put forth "a model of installer firm pricing behavior that allows for learning-by-doing" in Solar PV installations.

In the strict sense, a solar array usually does not include all the necessary hardware. It only encapsulates "the ensemble of solar panels and the visible part of the PV system." It is critical to point that PV systems that "convert light directly into electricity should not be confused with other solar technologies such as concentrated solar power and solar thermal." In general, "PV systems range from small, roof-top mounted to building-integrated systems. The capacities vary from a few to several tens of kilowatts to large utility-scale power stations of hundreds of megawatts." For instance, [89] remark that global installations of Solar PV technology "increased from 26 MW in 2000 to an estimated 21,000 MW in 2011." They explain the "rapid increase in installations by steep declines in cost and by policies favoring renewable energy." They observe "that in the United States", policy interventions along "with property tax assessment programs and clean energy standards" have immensely contributed to the usage of Solar PV skyrocketing. While a great majority "of PV systems are connected to the electrical grid", many systems exist in stand-alone or off-grid modes.

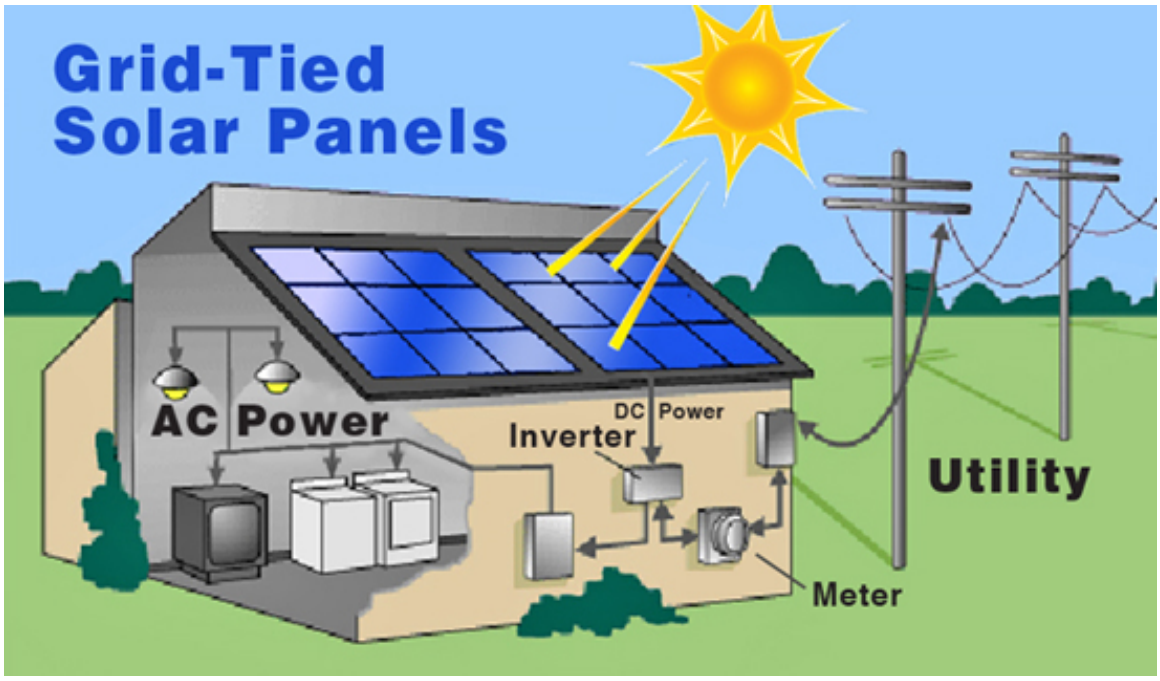

Figure 3.3: Solar Photovoltaics
Source: [3]

"A grid-connected photovoltaic power system, or grid-connected PV system refers to an electricity generating solar PV system that is connected to the utility grid. Usually, a grid-connected PV system is composed of solar panels, one or several inverters, a power conditioning unit, and a grid connection equipment. PV systems range from small residential and commercial rooftop systems to large utility-scale solar power stations. In contrast with off-grid systems, a grid-connected system sporadically includes an integrated battery solution. Whenever conditions are ideal, the grid-connected PV system supplies the excess power beyond consumption through the connected load to the utility grid." This contributes to cost reduction for grid consumers. According to [90], Solar "PV system prices in the United States display considerable heterogeneity both across geographic locations and within a given location." They explain that this "heterogeneity" arises "due to states and federal policies, differences in market structure, and other factors that influence demand and costs." Compellingly, they examine "the relative importance of" federal policies "on Solar PV system prices in the United States using a detailed dataset of roughly 100,000 recent residential and small commercial installations."

As grid-connected Solar PV systems become ubiquitous, the desire and interest "to track the cost and price of these systems have increased." To that occurrence, [91] develop

a report that summarizes "trends in the installed price of grid-connected PV systems in the United States from 1998 through 2012, with preliminary data for 2013." Their "analysis is based on project-level data for more than 200,000 individual residential, commercial, and utility-scale PV systems, representing 72% of all grid-connected PV capacity installed in the United States through 2012." In several occasions, decision-makers have not been able to take notice "of current PV costs and their associated market and technological adjustments in the microgrid industry." Hence, there is still a general perception that PV is preventively overpriced and still has not reached competitiveness. On that account, [92] examine "the recent dramatic reductions in the underlying costs and market prices of Solar PV systems and their implications for decision-makers." The study "finds that the commonly used analytical comparators for" PV with respect to other power generation options can be confusing.

Electricity production "from Solar PV has long been seen as a clean sustainable energy technology." It draws upon the sun, which is the "planet's most plentiful and widely distributed renewable energy source." The greatest allure of Solar PV resides in that while sunlight is converted into electricity, there are no environmental emissions during the operation.

There are several elements that affect "the exact carbon footprint of any particular solar panel." Such factors vary from "the source of the materials" to "the distance to which they have to be transported." Another important element is the energy source used by the manufacturing plants. By and large, "the carbon footprint of a solar photovoltaic (PV) panel has an average level of greenhouse gas emissions of about 72 grams of carbon dioxide-equivalent per kilowatt-hour of electricity generated (CO_2/kWh) ([93])." Thus, the study asserts that "generating electricity using solar PV panels does not produce greenhouse gases directly." But, it is important to remark that manufacturing some components of solar PV panels is an energy-intensive process. These components are made from crystalline silicon and can account for "60% of the total energy used to make solar panels. "

3.4.3 Diesel Generator

To produce electricity, a diesel generator must be combined to a diesel engine with an alternator. The latter usually plays the role of the electric generator. There are other types of generators such as the diesel compression-ignition engine and some "that are adapted for

liquid fuels or natural gas." Diesel generators can work with a full spectrum of crude oil distillated from gasoline, fuel oils or diesel oil. The engines "must be heated to enable the oils to flow down a fuel line." The process is carried out by setting into motion the gas with the "intake air and by using a small amount of diesel fuel for ignition. "

Typically, as reported by [94], "a diesel generator consists of an internal combustion (IC) engine and a synchronous generator coupled on the same shaft. It is mostly used as backup or emergency power in commercial as well as industrial installations. Diesel generators are also heavily used in rural communities where it is very expensive to connect to utility power. It is worth noting that diesel generators used in prime and continuous power applications are often designed to operate at huge efficiencies. This is because, in long term, fuel costs will have mastery over initial capital costs." On that account, [94] note that the "presence of a power electronics front end increases the overall cost" of diesel generators systems "and decreases its fault tolerance." The authors further observe that the "presence of the inverter enables" the "non-synchronous operation of the engine." As an effect, this "makes it possible to achieve increased power density and higher efficiency."

Diesel generators can be operated in places where there is no connection to a power grid. They can also be used "as emergency power-supply if the grid fails" (Figure 3.4). When the constructed diesel generator is a component of a microgrid project, [95] shows that the voltage and power stability of the microgrid can be tested under various load conditions and faulted islanded conditions to help maximize performance. For microgrids, fuel consumption represents the most important cost "when it comes to operating power" applications with a diesel generator. All in all, capital cost remains the chief concern for backup diesel generators.

It is evident that the control of the diesel generator heavily "depends on the amount of the power demand." In order to effectuate such controls, "online monitoring systems" such as "passive load models or active load models" have been studied. To emphasize this reality, [96] remark that "online monitoring systems are absolutely the most accurate" methods for controlling diesel generators systems. Nonetheless, as they further point, the costs of such systems as well as the complexity of their designs remain critical disadvantages. It is noteworthy that the authors allude to "passive mathematical models of load demand" as possibly being the "simplest and cheapest but least accurate" methods for controlling diesel generators systems. It is equally important to remark that although stand-alone

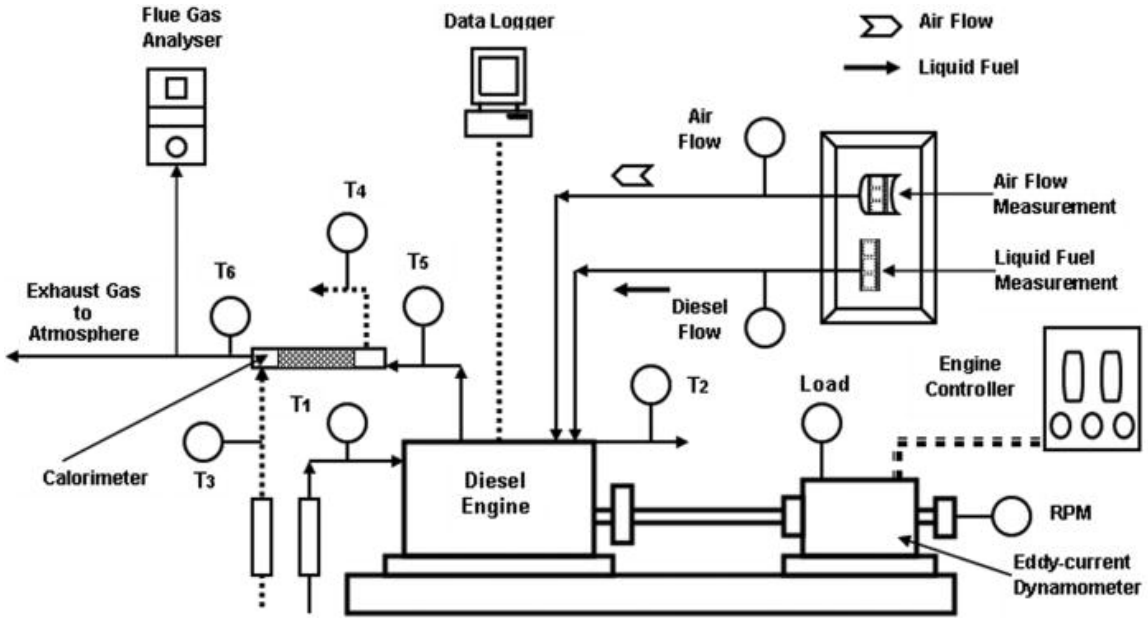

Figure 3.4: Diesel Generator
Source: [4]

diesel generators seem inexpensive to buy, their O&M costs can be overwhelming. That is why, [97] recommend that the "diesel generator must be operated above a certain minimum load level in order to maintain efficiency and to reduce the possibility of premature" outage. By all means, in order for diesel generators to reliably provide the anticipated power without damage to the engine, the manufacturer must provide "one or more ratings of the specific generator set model." Sometimes, "a specific model of a generator operated as a standby generator may only need to operate for a few hours per year." There have been "many research studies on the optimization" of diesel generator systems whereby it is possible to optimally select the diesel generator capacity. For example, using loss-of-load probability "and a mathematical model of a diesel generator system", [98] examine the optimization of "building integrated hybrid diesel" generators systems "for zero load rejection for Malaysia."

It is essential to mention that diesel generators are accountable for releasing substantial levels of Nitrous oxide (NOx), carbon monoxide (CO), and hydrocarbons. These emissions contribute to the poor air quality in the United States and elsewhere. That is why adequate regulations ought to be designed to help states become compliant with the Clean Air Act [1] and its requirements on certain levels of pollutants A recent government study shows "that

[1]This is a government mandate set "to control air pollution on a national level. It requires the EPA to develop and enforce regulations to protect the public from airborne contaminants known to be hazardous to human health."

diesel emission levels of NO_x, carbon monoxide (CO), hydrocarbons, and particulate matter" substantially contribute to "poor air quality in the United States ([99])." Commonly, diesel exhaust is made of a complex mixture "of gases and fine particles. The primary pollutants emitted from diesel engines include particulate matter (PM), carbon monoxide (CO), Nitrogen oxides (NO_x), Hydrocarbons (HC), Volatile organic compounds (VOCs) ([100])." There are "other chemicals that are classified as hazardous air pollutants under" the Clean Air Act, which are emitted by the diesel generator. Numerous health studies have shown "that exposure to exhaust primarily affects the respiratory system and worsens asthma, allergies, bronchitis, and lung function ([100])." This study also points to "some evidence that diesel exhaust exposure can increase the risk of heart problems, premature death, and lung cancer. " Several states governments have encouraged the lowering of the sulfur content of diesel fuel so as to reduce the levels of certain exhaust pollutants. Some other policies favor the use of electronic engine controls in order to more efficiently operate the engines.

3.4.4 Fuel Cells

Steven Chu, the former United States Secretary of Energy declared in 2012 that he saw fuel cell cars as very economically practical given the improvement of hydrogen reforming technologies. This statement emphasizes the importance and growing popularity of fuel cells technology. In fact, several studies have "estimated that the stationary fuel cell market will reach 50 GW by 2020. " Furthermore, [101] indicate that "due to high efficiency and low emission and" noise, fuel cell is among the most promising sources of electrical and thermal energy for distributed generation. According to the same article, alongside "cost effective operational strategies, the use of" fuel cells "is expected to become widespread in the near future" notwithstanding "their current high capital costs."

Classically, "fuel cells are different from batteries in that they need continuous source of fuel and oxygen to sustain the chemical reaction. For that reason, fuel cells can produce electricity continuously for as long as the correct inputs are supplied. In a nutshell, a fuel cell is a device that converts the chemical energy from a fuel into electricity through a chemical reaction with oxygen or another oxidizing agent (Figure 3.5)." Fuel cells are primarily employed "for backup power for commercial, industrial and residential buildings." As seen above, they can also be "used to power fuel-cell vehicles." Although there exist many types

of fuel cells, most are "made of an anode, a cathode, and an electrolyte." The latter allows charges "to move between the two sides of the fuel cell." In order to produce electricity, "electrons are drawn from the anode to the cathode through an external circuit." In most cases, "fuel cells are classified by the type of electrolyte they use." Fuel cells are produced in different sizes. For instance, "individual fuel cells produce about 0.7 volts. Cells are stacked or placed in series so as to increase the voltage and meet applications' requirements." Fuel cells productions are not limited to electricity. They also encapsulate water and heat. Depending on the fuel source, fuel cells productions can include "very small amounts of nitrogen dioxide and other emissions." A special and very popular "type of fuel cells" is the "proton exchange membrane" or "PEM fuel cells". In a research of "PEM fuel cells", [102] find that they "possess a good start up and shutdown performance and as" such can be the best "back-up generator for powering a greenhouse." On the whole, "the energy efficiency of a fuel cell is generally between 40 to 60%, or up to 85% efficient in cogeneration if waste heat is captured for use."

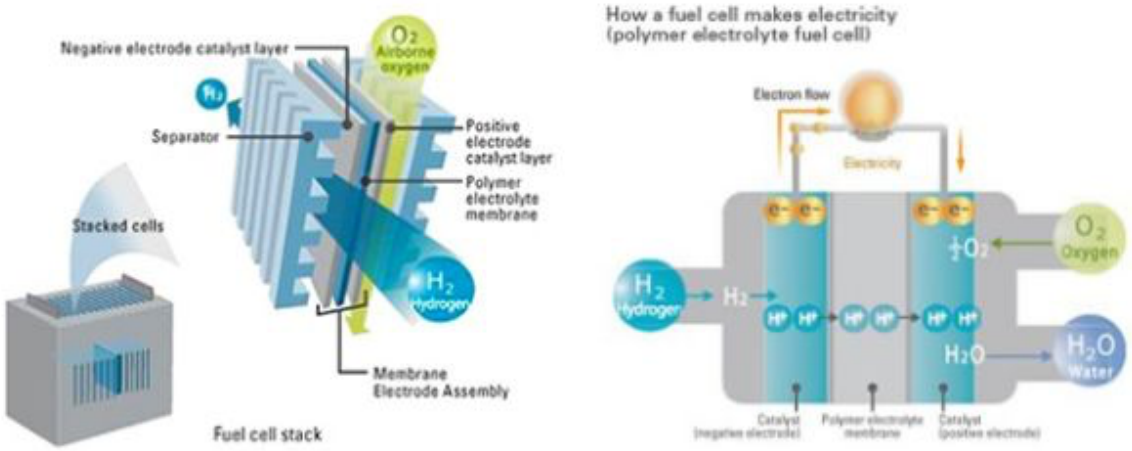

Figure 3.5: How Fuel Cells Generate Electricity
Source: [5]

Fuel cells combined with hydrogen via a chemical reaction have a high probability of emitting carbon dioxide (CO_2). In fact, according to recent studies, fuel cells on average emit 884 pounds of (CO_2) per megawatt-hour of electricity produced. By the same token, "solid-oxide fuel cells produce exothermic heat from the recombination of the oxygen and hydrogen." Thankfully, "this heat can be captured and used to heat water in a micro combined heat and power application." On that account, [103] show that "because the

exhaust from the heat of the fuel cells is stored in the heat storage tank, heat can be supplied as demanded" though "with a time delay." In a study case, the authors indicate that "when electric power is insufficient, it is necessary to increase the output from the fuel cells or increase the capacity of the solar cell and the battery." That is why it is becoming increasingly trendy to operate "combined heat and power (CHP) fuel cell systems in order to generate both electricity and heat for homes." While the system generates constant electric power, it has the ability to sell "excess power back to the grid when it is not consumed." Additionally, the system has the ability to produce "hot air and water from the waste heat." Hence, "CHP systems have the potential to save primary energy as they can make use of waste heat." It is important to note that heat "is generally rejected by thermal energy conversion systems." As pointed to by [104], "when distributing a fuel cell and the photovoltaics to a distant location, the distributed installation of DC – DC converters and inverters is required." The authors also recommend that "it is necessary to consider the auxiliary power consumption of machines including a compressor for the hydrogen and oxygen produced from water electrolysis." Interestingly, in addition to considering different start-up times of different fuel cells technologies, [105] examine the operation scheduling of fuel cells generators. They found that the operation scheduling of fuel cells generators must be made with the consideration of their dynamic operating constraints.

Given that they are for the most part emission-free, fuel cells surpass internal and external combustion engines. As discussed above, fuel cell efficiencies are as high as 40 percent to 60 percent. For cogeneration, fuel cell efficiencies can even increase from 80 percent to 95 percent. Thus, it is evident that fuel cells devices that transform chemical energy into electricity with no combustion are an excellent generating source for microgrids,

Generally, Fuel cells generate electricity by burning natural gas. They have emissions approximating 0.75 TO 1.00 lbs of CO_2/kWh and can be as high as 50% efficient. Hence, they tend to generate electricity more efficiently. [106] shows that a fuel cell usually operates on pure hydrogen and emits zero emissions at the source. There exist some stationary fuel cells that use natural gas or hydrocarbons as a hydrogen feedstock. In general, stationary fuel cells produce far fewer emissions than conventional power plants. [106] observes that, based on measured data, a stationary fuel cell power plant creates less than one ounce of pollution per 1,000 kilowatt-hours of electricity produced. On the other hand, the Grid generates about 25 pounds of pollutants for the same amount of electricity. By all means,

emissions from fuel cells are usually very low. This state advantage has led several states to exempt fuel cells from air permitting requirements all the more so as fuel cells reduce noise emissions. There exist other types of fuel cells such as fuel cell electric vehicles or FCEVs. These are the least polluting of all vehicle types that consume fuel directly. They emit zero emissions during use. Fuel cells can also be used as auxiliary power units to power air conditioners and accessories in Class 8 trucks. In this instance, tractor trailers have been used to reduce emissions by up to 45% ([106]).

3.4.5 Natural Gas Generator

Numerous reviews have shown that shifting from oil-based fuels to alternative ones such as natural gas are environmentally and economically very beneficial. It has been demonstrated that natural gases burn more cleanly than many other fossil fuels. Natural gases thus contribute to reducing greenhouse gas emissions that cause global climate change. Natural gas generators use natural gas such as propane or methane to generate electricity. They normally run by burning a gaseous fuel with a carburetor. At first, an internal combustion engine injects a mixture of fuel and air into a combustion chamber. After a piston compresses the mix in the chamber, a spark plug ignites the fuel. This process drives the piston down and turns a crankshaft. The latter subsequently spins the generator's rotor in an electromagnetic field. The rotation process then generates an electric current that can charge batteries and other power appliances (Figure 3.6). [107] indicate that natural gas is very often conveyed to its consumers with the help of pipes at high pressure. They further point that before it is conveyed to customers, the natural gas is pressure-reduced by means of a regulator. In general, natural gas generators are sold in sizes from portable to industrial. Some prefer to transform a gasoline/diesel generator into propane with a conversion kit. On that point, [108] observe that in the case of a cogeneration system, hydrogen production unit can be designed to transform regular natural gas following various stages. The authors distinguish three types of reforming processes for producing hydrogen from methane by the use of natural gas. By all means, the use of natural gas generators has been a little controversial.

[109] acknowledge that among all the fossil fuels, natural gas has the lowest greenhouse effect in terms of carbon dioxide emissions. Yet, it has recently been found that emissions of methane, the main component of natural gas, are likely 50 percent higher than the U.S.

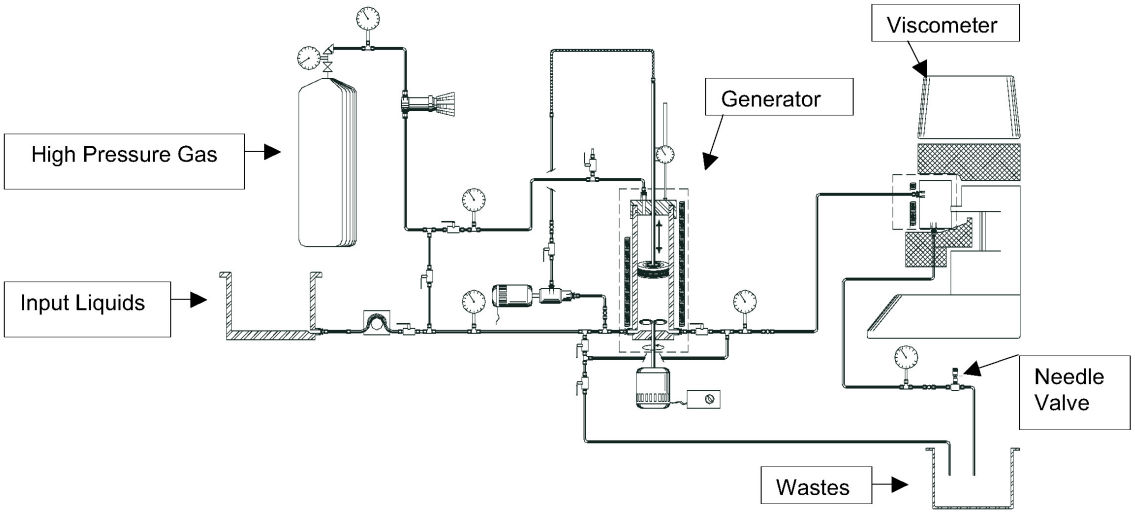

Figure 3.6: Illustration of a Natural Gas Generator at Work
Source: [6]

government has estimated in its official greenhouse gas inventory. It is however important to recognize that natural gas can be easier to access during a disaster because it is carried underground. Moreover, natural gas is readily available wherever gas grills are sold. It is equally more undemanding to store natural gas than diesel or gasoline. Interestingly, another advantage of natural gas is highlighted by [110]. They show that heat released from the combustion of natural gas inside a gas water heater can be used to raise the water temperature in extremely cold regions. It is important to point that there also exists the possibility of convenient production of natural gas. For instance, [111] examine a case where natural gas is reformed locally to produce hydrogen. Nonetheless, natural gas generators have gotten some inconveniences. Some companies in the natural gas generators business claim that the up-front cost of selling natural gas for home use may be 10 to 20 percent higher than that of a comparable liquid-fueled model. This makes sense since the price of natural gas fluctuates quite a bit albeit less than that of petroleum for an equivalent amount of energy.

As global governments turn away from oil-based fuels to a broad array of more sustainable energy sources, a greater amount of institutions are incorporating natural gas into their energy plans. One of the main components of natural gas is methane. As shown in [112], greenhouse gas can also be emitted into the air when natural gas is not burned completely. Typically, the burning of natural gas produces nitrogen oxides and carbon dioxide though

in lower quantities than burning coal or oil. Similarly, methane can be emitted as the result of leaks and losses during transportation. While natural gas burns, sulfur dioxide and mercury compounds can be emitted although they are negligible. According to [112], the average emissions rates in the United States from natural gas-fired generation are: 1,135 lbs/MWh of carbon dioxide, 0.1 lbs/MWh of sulfur dioxide, and 1.7 lbs/MWh of nitrogen oxides. When compared to the average air emissions from coal-fired generation, natural gas produces half as much carbon dioxide. They produce less than a third as much nitrogen oxides as coals. Natural gas generates one percent as much sulfur oxides at the power plant as coal-fired generation. It is worth mentioning that the process of extraction, treatment, and transport of the natural gas to the power plant can generate additional emissions ([112]).

3.4.6 Storage

The fast expansion of microgrids is creating a boom in demand of energy storage systems. One of the core merits of energy storage in a microgrid lies in refining the payback period of the system. Ideally, every microgrid must constitute a distinct response to a customer need. Microgrid systems are getting more and more advanced, thus creating a need for sophisticated batteries. Storage systems can provide resource optimization and efficient load management to microgrids. This is critical as the equipment of onsite generation systems are easily susceptible to damage. Besides, maintenance and fuel costs of operating renewable generation can rapidly increase because of intermittency. For those reasons, [113] note that microgrids are well-positioned to benefit from battery-based storage systems for maintaining reliability and power quality. In likewise, Mariesa Crow, director of the Energy Research and Development Center at the Missouri University of Science and Technology, observes that "Efficient storage is critical because microgrids or onsite generation systems with islanding capabilities can operate without being connected to a utility grid." She also maintains that a full reliance on renewable energy or intermittent energy without a grid connection makes it compulsory to adopt storage. A recent report by [114] contains very informative details about the global market for energy storage in microgrids. It explains the different types of microgrids with respects to storage. Furthermore, it reviews the main technologies related to microgrid controls while emphasizing advanced batteries.

$\Delta - m \times n$ constraint matrix	$P_{i,t}-$ electricity output
$\zeta - n$ -integer cost vector	$\dot{P_{i,t}} - P_{i,t}$ as random variables
$U - n$ -vector electricity generation	Π_t^D- electricity price
$x - p$ -demand vector	$p_\omega-$ probability of occurrence
$\tau - p$ -integer cost vector (G_l)	$\Lambda^\omega-$ decisions related to the realizations of $\dot{P_{i,t}}$
$y - n$ -supply vector	$CO_{2i,t}-$ carbon dioxide emission
$\eta - n$ -integer cost vector (G_d)	$\alpha_{t,CO_2}-$ cost of carbon dioxide emission
$\varphi-$ cost function	C_i- cost of generating electricity (G_d)
$\mathbb{E}-$ expected value of total cost	C_i^O- operating costs (G_d)
$\omega-$ scenarios (high, medium, low)	$\Upsilon-$ profit
$(\Omega, P)-$ probability space	$\mathbf{E}(\Upsilon)-$ expected profit
$\Gamma - q \times p$ constraint matrix	$\xi-$ emission threshold
$\digamma - q \times n$ constraint matrix	$E_{i,t}-$ energy output (G_d)
$\vartheta - q \times n$ constraint matrix	x_i^c- efficiency factor as battery charges
$v - q$ -vector	x_i^d- efficiency factor as battery discharges
G_d- dispatchable units	$E_i^{\max}-$ capacity of storage device
G_l- flexible loads	$P_{i,t}^c-$ charging electricity (G_k)
G_k- battery storage unit	$P_{i,t}^d-$ discharging electricity (G_k)
G_s- stochastic unit (PV)	$x_{i,t}-$ on/off indicator (G_d)
$i-$ technology unit	$P_i^{c,\max}-$ upperbound (charging electricity)
$t-$ time period	$P_i^{d,\max}-$ upperbound (discharging electricity)
P_t^D- electricity exchanged	$E^{\min}-$ minimum storage capacity

Table 3.1: Nomenclature – Optimization Model

3.5 Texture of the Optimization Model

3.5.1 Preamble

We consider Δ an $m \times n'$ constraint matrix, ζ an n'-integer cost vector, and a power generation vector U an n'-vector. We further examine an energy demand vector x, a p-vector associated with the cost based p-integer vector τ. By the same token, we look at an energy supply based n-vector y associated with the cost based n-integer vector η. We let $\mathbb{E}[\varphi(U, x, y, \omega)]$ be the expected value of the total cost. φ is a cost function and ω is a scenario of possible outcomes with respect to the probability space (Ω, P). For any λ an m-vector, the linear program is framed as

$$\begin{aligned} \text{minimize} \quad & \zeta^T U + \mathbb{E}[\varphi(U, x, y, \omega)] \\ \text{s.t.} \quad & \Delta U = \lambda \\ & U \geq 0 \end{aligned}$$

We now consider Γ a $q \times p$ constraint matrix, $\digamma$ a $q \times n$ constraint matrix, and ϑ a $q \times n'$ constraint matrix . For each scenario ω and υ a q-vector, we then define

$$\begin{aligned}\varphi(U, x, y, \omega) = \min_{x,y} (\tau_\omega^T x + \eta_\omega^T y) \\ \text{s.t. } \vartheta_\omega U + \Gamma_\omega x + \digamma_\omega y = \upsilon_\omega \\ x \geq 0, \quad y \geq 0\end{aligned}$$

Accounting for discrete probability distributions p_ω, we have that

$$\mathbb{E}[\varphi(U, x, y, \omega)] = \sum_{\omega=1}^{N_\Omega} p_\omega \varphi(U, x, y, \omega)$$

We can now derive the following stochastic linear program (LP) problem

$$\begin{aligned}\min \zeta^T U + \sum_{\omega=1}^{N_\Omega} p_\omega (\tau_\omega^T x_\omega + \eta_\omega^T y_\omega) \\ \text{s.t.} \quad \Delta U = \lambda \\ \vartheta_\omega U + \Gamma_\omega x_\omega + \digamma_\omega y_\omega = \upsilon_\omega \\ U \geq 0, \quad x_\omega \geq 0, \quad y_\omega \geq 0\end{aligned} \tag{3.12}$$

3.5.2 The Objective Function

We resolve to operate the microgrid system by allocating the electricity output from a selection of flexible loads G_l, stochastic technology G_s, dispatchable technologies G_d, and storage devices G_k. All technologies operate in real time. To that instance, we must resolve all uncertainties in order to proceed with the operational decisions. The latter represent a two-stage stochastic problem with recourse. In the first stage, the microgrid operator indicates the initial amount of electricity consumed by the loads as well as any potential electricity made available by the stochastic or PV unit. This information allows the microgrid operator to evaluate how much electricity he can prospectively trade in or purchase from the market at a given price level at time t. As discussed in [115], the law authorizes electricity markets to permit such maneuvers. In the second stage, we subsequently undertake the uncertainties as they affect both supply and demand. We let P_t^D be the quantity of electricity exchanged at the marketplace and Π_t^D the electricity

market price at time t. We note that $P_t^D > 0$ if the electricity is sold in the market and $P_t^D < 0$ if power is bought from the market. The consumption of electricity by the flexible loads unit within a set of scenarios is used to model demand uncertainty. Each scenario $\{P_{i,\omega,t}, i \in G_l\}, \omega = 1, 2, \cdots N_\Omega$, corresponds to a probability of occurrence p_ω with respect to the probability space (Ω, p), $p_\omega \geq 0$, $\sum_{\omega=1}^{N_\Omega} p_\omega = 1$. $\{P_{i,\omega,t}, i \in G_l\}$ is the electricity consumed by the load at each scenario ω. To reproduce supply uncertainty, we take into account the electricity generated by the stochastic unit $i \in G_s$. We use this electricity to characterize each dispatchable unit $i \in G_d$ through a set of scenarios $\{P_{i,\omega,t}, i \in G_s\}, \omega = 1, 2, \cdots N_\Omega$. $\{P_{i,\omega,t}, i \in G_s\}$ is the electricity supplied by the Solar PV unit at each scenario ω.

We let $CO_{2_{i,t,\omega}}$ be the CO_2 emission of each dispatchable technology unit i at time t corresponding to each scenario ω. The cost of CO_2 unit emission at time t is given by α_{t,CO_2}. We maintain that $P_{i,t}$ is the electricity output at time period t from any technology unit i. $C_i, i \in G_l, G_d, G_k$ represents the costs (variable and fixed) associated with the maintenance and operation of the flexible loads, dispatchable, and storage units. We reason that the microgrid can bring in much capital by maximizing its profit Υ. Thus, we estimate the expected profit $\mathbf{E}(\Upsilon)$ by setting the following simultaneous stochastic problem:

$$\max_{\Lambda^\omega} \mathbf{E}(\Upsilon) = \sum_{t=1}^{T} \sum_{\omega=1}^{N_\Omega} p_\omega \left[\sum_{\omega=1}^{N_\Omega} (P_{t,\omega}^D, \Pi_{t,\omega}^D) - \left(\sum_i C_{i,t} P_{i,t,\omega} + \alpha_{t,CO_2} \sum_{i \in G_d} CO_{2_{i,t,\omega}} \right) \right] \tag{3.13}$$
$$\forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega$$

Λ^ωencloses all the decisions conditional on the subsequent realizations of all supply and demand scenarios. In practice, these decisions are taken as the electricity consumed by the flexible loads and the electricity output from the dispatchable units become known.

3.5.3 The Optimization Constraints

Emissions Constraint

First, we must take into consideration an emission threshold, namely ξ. As we seek to minimize CO_2 emissions at all scenarios ω, we must hold that

$$\sum_{i \in G_d} \sum_{t=1}^{T} CO_{2_{i,t}} \leq \xi \tag{3.14}$$

Kirchhoff's Law of Power Flow

The quantify of energy that is produced by the dispatchable and Solar PV units as well as the quantity of electricity pumped (discharged) from the battery (storage) have to correspond to the quantity of energy disposed of by the flexible and the quantity of electricity employed to charge the battery (storage) added to the quantity of electricity exchanged with the electricity market at each scenario. We consider all periods $t = 1 \cdots T$ of length $\bar{\tau}$. Letting $E_{i,t}, i \in G_d$ be the energy output from the dispatchable unit, $P_{i,t}, i \in G_s$ the electricity output from the PV unit, $E_{i,t}, i \in G_l$ the energy consumed by the flexible load, and P_t^D the quantity of electricity traded in the electricity marketplace, for all scenarios ω, we must have that

$$\sum_{i \in G_d} E_{i,t,\omega} + \left(\sum_{i \in G_s} P_{i,t,\omega} + \sum_{i \in G_k} P_{i,t,\omega}^d - \sum_{i \in G_k} P_{i,t,\omega}^c \right) \bar{\tau} = \sum_{i \in G_l} E_{i,t,\omega} + P_{t,\omega}^D \bar{\tau}$$
$$\forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega$$

where $P_{i,t}^c$ and $P_{i,t}^d, i \in G_k$ are respectively the charging and discharging electricities that respectively reflect how fast the storage device charges and discharges. Narrowing the premise to some special case where all periods are of equal length, we let $\bar{\tau} = 1$ so that:

$$\sum_{i \in G_d} E_{i,t,\omega} + \sum_{i \in G_s} P_{i,t,\omega} + \sum_{i \in G_k} P_{i,t,\omega}^d - \sum_{i \in G_k} P_{i,t,\omega}^c = \sum_{i \in G_l} E_{i,t,\omega} + P_{t,\omega}^D \tag{3.15}$$
$$\forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega$$

Dispatchable Power Units

The functional state of the dispatchable technology unit is represented by a binary variable $x_{i,t}$. This variable takes on values 1 or 0 as the unit is on or off, respectively. For $P_{i,t}^{\min}$ the minimum power output from the dispatchable unit and $P_{i,t}^{\max}$ its power capacity, the disjunctive operating region of the unit, for all scenarios ω, is framed as

$$x_{i,t,\omega} P_{i,t,\omega}^{\min} \leq P_{i,t,\omega} \leq x_{i,t,\omega} P_{i,t,\omega}^{\max}, \quad x_{i,t,\omega} \in [0,1]^T, \tag{3.16}$$
$$\forall i \in G_d, \forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega$$

Flexible Loads

The flexible load is defined by individual households that form the consumers demand. The latter commonly comprises refrigeration, cooking appliances, lighting, air conditioner,

computers, etc. Practically, there always exists an upper bound to the amount of electricity domestic consumers can utilize. Consequently, we let $P_{i,t}^{\max}$ be the maximum electricity that could be demanded by the flexible loads and $P_{i,t}^{\min}$ the minimum. For any electricity consumed by the load $i \in G_l$ at time period t, namely $P_{i,t}$, for all scenarios ω, it is required that

$$P_{i,t,\omega}^{\min} \leq P_{i,t,\omega} \leq P_{i,t,\omega}^{\max}, \quad \forall i \in G_l, \forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega \tag{3.17}$$

Storage Units

To define the energy content of the storage technology $i \in G_k$, we account for the quantity of electricity charged into or drawn from the device. To ensure that the state-transition equation at each time period t is met, for all scenarios ω, we must have that

$$E_{i,t,\omega} - E_{i,t-1,\omega} = x_{i,\omega}^c P_{i,t,\omega}^c - \frac{1}{x_{i,\omega}^d} P_{i,t,\omega}^d, \quad \forall i \in G_k, \forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega \tag{3.18}$$

$E_{i,t}$ and $E_{i,t-1}$ are the energy levels in the battery set at periods t and $t-1$, respectively. $x_i^c < 1$ and $x_i^d < 1$ are the efficiency factors that stand for the energies lost while the storage device charges and discharges, in that order. Realistically, the charging and discharging electricities of the storage device although always positive, are restrained by the upper bounds $P_i^{c,\max}$ and $P_i^{d,\max}$ such that for all scenarios ω

$$0 \leq P_{i,t,\omega}^c \leq P_{i,\omega}^{c,\max}, \quad \forall i \in G_k, \forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega \tag{3.19}$$

$$0 \leq P_{i,t,\omega}^d \leq P_{i,\omega}^{d,\max}, \quad \forall i \in G_k, \forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega \tag{3.20}$$

It is important not to forget that any storage device is marked by a specific capacity $E_i^{\max}$. The prespecified threshold $E_i^{\min}$ is a lower bound, which is applied to avert the reduction of the lifetime of the storage device. Hence, the energy level $E_{i,t,\omega}$ in the device must always be kept above $E_i^{\min}$ so that, for all scenarios ω

$$E_{i,\omega}^{\min} \leq E_{i,t,\omega} \leq E_{i,\omega}^{\max}, \quad \forall i \in G_k, \forall t = 1, 2, \cdots T, \forall \omega = 1, 2, \cdots N_\Omega \tag{3.21}$$

3.5.4 The Problem Position

Accounting for the objection function 3.13 and the constraints 3.14 – 3.21, the complete optimization problem becomes

$$
\begin{aligned}
\max_{\Lambda^{\omega}} \mathbf{E}(\Upsilon) = & \sum_{t=1}^{T}\sum_{\omega=1}^{N_\Omega} p_\omega \left[\sum_{\omega=1}^{N_\Omega} P^D_{t,\omega}, \Pi^D_{t,\omega} - \left(\sum_i C_{i,t}P_{i,t,\omega} + \alpha_{t,CO_2}\sum_{i\in G_d} CO_{2_{i,t,\omega}}\right)\right] \\
\text{s.t.} \quad & \sum_{i\in G_d}\sum_{t=1}^{T} CO_{2_{i,t,\omega}} \le \xi \\
& \sum_{i\in G_d} E_{i,t,\omega} + \sum_{i\in G_s} P_{i,t,\omega} + \sum_{i\in G_k} P^d_{i,t,\omega} - \sum_{i\in G_k} P^c_{i,t,\omega} = \sum_{i\in G_l} E_{i,t,\omega} + P^D_{t,\omega} \\
& x_{i,t,\omega}P^{\min}_{i,t,\omega} \le P_{i,t,\omega} \le x_{i,t,\omega}P^{\max}_{i,t,\omega}, \quad x_{i,t,\omega} \in [0,1]^T, \forall i \in G_d \\
& P^{\min}_{i,t,\omega} \le P_{i,t,\omega} \le P^{\max}_{i,t,\omega}, \quad \forall i \in G_l \\
& E_{i,t,\omega} - E_{i,t-1,\omega} = x^c_{i,\omega}P^c_{i,t,\omega} - \frac{1}{x^d_{i,\omega}}P^d_{i,t,\omega}, \quad \forall i \in G_k \\
& 0 \le P^c_{i,t,\omega} \le P^{c,\max}_{i,\omega}, \quad 0 \le P^d_{i,t,\omega} \le P^{d,\max}_{i,\omega}, \quad \forall i \in G_k \\
& E^{\min}_{i,\omega} \le E_{i,t,\omega} \le E^{\max}_{i,\omega}, \quad \forall i \in G_k, \forall t = 1,2,\cdots T, \forall \omega = 1,2,\cdots N_\Omega
\end{aligned}
\tag{3.22}
$$

3.5.5 Model Algorithm

The scheduling problem is separated into the grid-fused and the islanded operations. The Benders' master problem is equivalent to the microgrid operating in association with the grid. It aims to minimize the microgrid costs and emissions by identifying the optimal schedule of all units under uncertainty. The units are made of the adjustable loads, the dispatchable units, and the electricity storage system. The Benders' subproblem denotes the islanded microgrid operation. It applies the optimal schedule determined by the master problem to investigate the microgrid generation sufficiency under each supply and demand scenario. Dual variables are designed to derive the Benders' cuts by appropriately substituting the master problem parameters, which subsequently affects the Benders' subproblem. Hence, practically, the dual variables represent the progressive scaling down of the objective function of the Benders' subproblem. The microgrid can operate in islanded mode with no disruption in load supply. Yet, this is only possible if the microgrid is sufficiently equipped in generating and storage units so as to autonomously furnish the loads at each scenario. In order to guarantee this, we introduce a zero-disruption condition for the subproblem. If the

objective of the Benders' subproblem operation does not meet the zero-disruption condition, the microgrid will not have enough potential to supply the facility load at each scenario. In this case, the islanded microgrid operation becomes unfeasible. As a consequence, an islanding or Benders' cut is produced and combined to the Benders' master problem.

This is the first Benders' cut. It points out that electricity disruption in the islanding step can be remedied by readjusting the dispatchable units and battery system in the grid-fused operation. This first cut is then relayed to the master problem for it to evaluate the result. Afterwards, the Benders' islanded subproblem examines the evaluated solution, at each scenario, in the succeeding iterations until a feasible solution is reached.

We must point that all electricity disruptions for all Benders' subproblems must be zero at all scenarios in order for the microgrid to fully operate. Thus, the iterations will not stop until the zero disruption condition is met. In practice, this is not always possible. There exist situations where the islanding mode fails to converge to the optimal solution after numerous iterations. For example, a null disruption for the the scenarios within the subproblems can collapse upon revamping the dispatchable units and the battery system. In other words, the change in the commitment and schedule of the generating units and the battery systems is not always able to yield the optimal required online capacity necessary for a feasible islanding.

To remedy the problem, a second Benders' cut is needed to recast the schedule of adjustable loads. This cut certifies the convergence of a feasible islanding operation by allowing a concurrent adjustment of the loads, generating units, and the battery system. As shown by [116], in reality, the second Benders' cut recasts the adjustable loads by "shifting or curtailing" the load to ensure feasible islanding. The complete schematization of the algorithm can be seen in Figure 3.7.

1-M: Microgrid transacting with the Grid (Master problem)

2-M: Microgrid in self-generating mode (Sub problem)

3-H: High scenario for supply and demand

3-M: Medium scenario for supply and demand

3-L: Low scenario for supply and demand

4-?: Is there enough electricity supply to meet the flexible loads demand?

4-N & 5-NCut1: If no, islanding operation is unfeasible. Generate Benders' cut 1

8-DS: With cut 1, reevaluate the dispatchable units commitments and the storage

4-Y: If yes, the microgrid islanding operation is feasible

6-?: Does the feasible operation converge to the microgrid optimal scheduling?

6-Y: If yes, the microgrid optimal scheduling is attained

6-NCut2: If no, generate Benders' cut 2

7-L: With cut 2, reevaluate the flexible loads

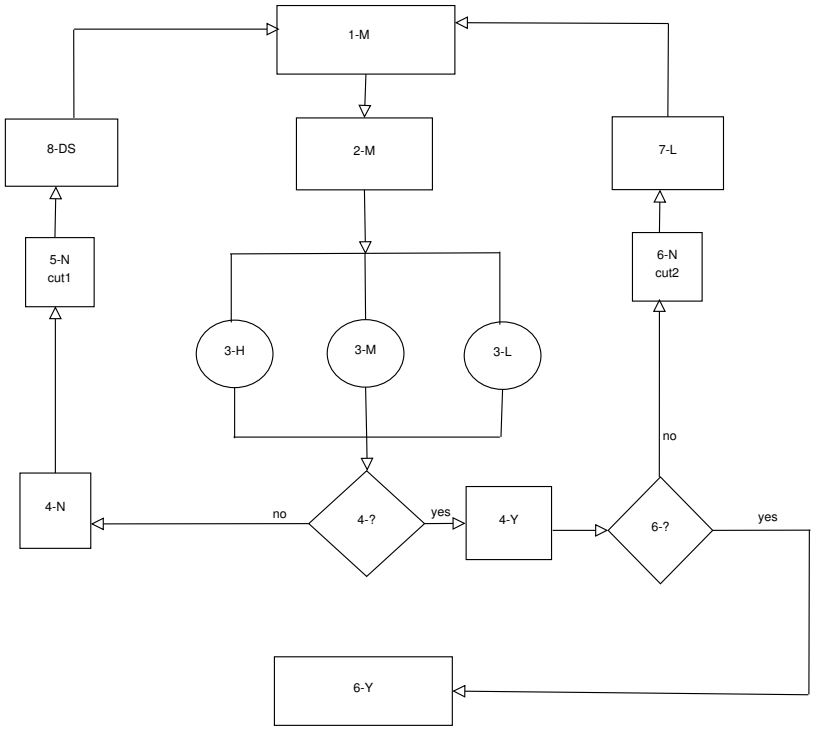

Figure 3.7: Model Algorithm

3.6 Numerical Application

3.6.1 Original Data

To conduct an in-depth numerical analysis of the simultaneous model, we examine a microgrid with one adjustable load, a PV unit, four dispatchable units, and one energy

storage system (Figure 3.8).

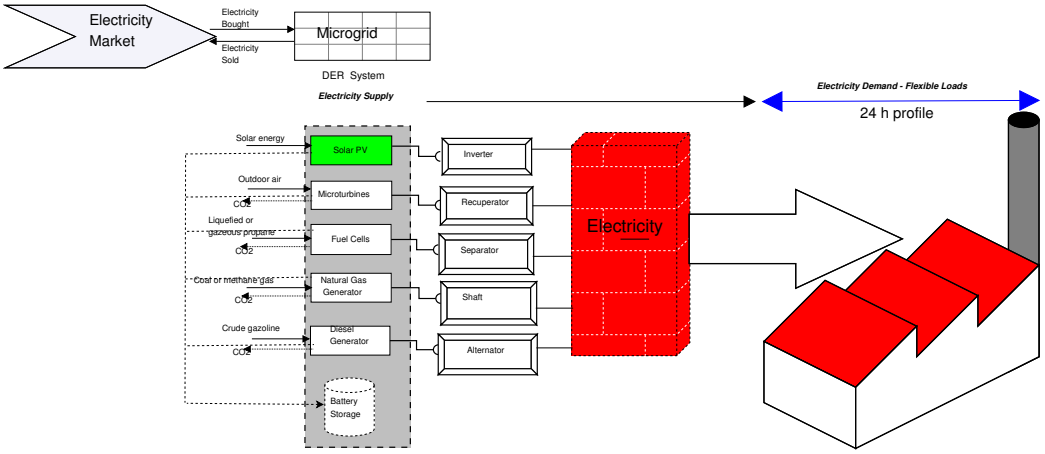

Figure 3.8: Microgrid Structure in the Model

The dispatchable units should accommodate their electricity output in order to meet demand. They represent power supply made available upon demand from the microgrid operator. We seek to single out the most economically favorable fusion of utility, power generation, and storage equipment in terms of costs and emissions. All loads are dependent on the lowest and highest rated electricity. Whenever a load consumes electricity, the associated scheduling state is one or zero otherwise. The features of the flexible loads unit can be seen in Table 3.2.

Ramp rate	1.000
Capacity	47.758
Installation costs ($/kWh)	11.940
Electricity Market Price	35.819

Table 3.2: Flexible Loads Unit – Characteristics
Source: [117]

We note that, for the flexible load, the ramping constraints stand for the pace at which the load can intensify or reduce its consumption. The combined equipment is required to meet the facility's end-use loads. Figure 3.9 clarifies all end-use loads. As shown by Figure 3.10, we contemplate three demand scenarios based on needs determined by the end-use-loads.

In order to capture uncertainty in supply, we consider a Solar PV unit in an environment

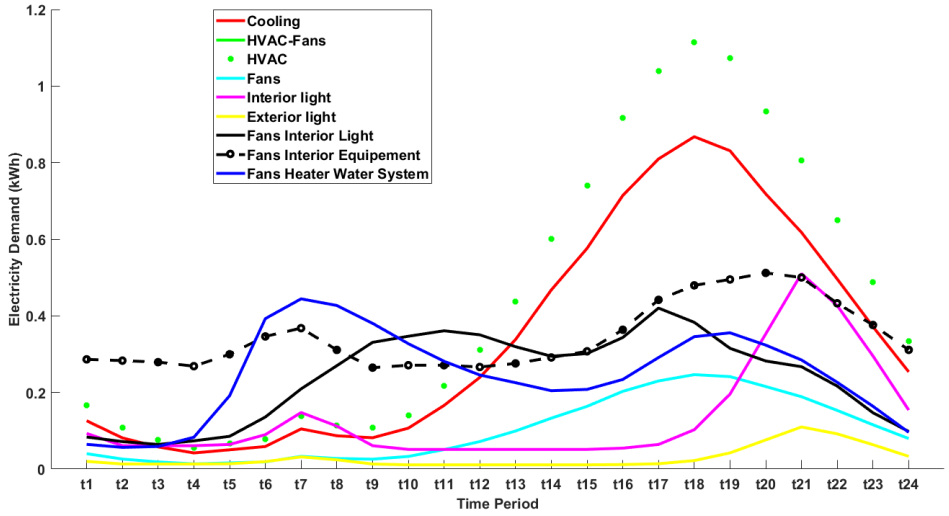

Figure 3.9: 24 h Loads Profile
Source: [117]

closed to the Baltimore area. A comprehensive collection of renewable energy resource data is available at [118]. Our Solar radiation is shown for a fixed PV or solar thermal panel tilt that represents the latitude of the BWI region. All solar data are hourly and in kWh/m^2. Figure 3.11 shows a graphical representation of the collected data for each scenario.

Table 3.3 illustrates the electricity market prices used by the microgrid operator when he decides to deal with the electricity market and not be in islanded mode.

In case the microgrid electricity surplus is put on sale in the electricity market, the cost of electricity transference from the Grid is negative. In this instance, the cost represents a profit for the microgrid. The cost of electricity transfer is set according to the market price. The latter represents the price at which the microgrid buys electricity from the Grid and sells excess electricity to the Grid. This price is derived from the local Baltimore Gas Electric rates ([119]).

On Peak	0.1088
Inter-Peak	0.0742
Off-Peak	0.0719

Table 3.3: Electricity Market Price
Source: [119]

The dispatchable units are made of the microturbine, fuel cells, natural gas, and diesel generators. All dispatchable units depend on some operational constraints such as capacity

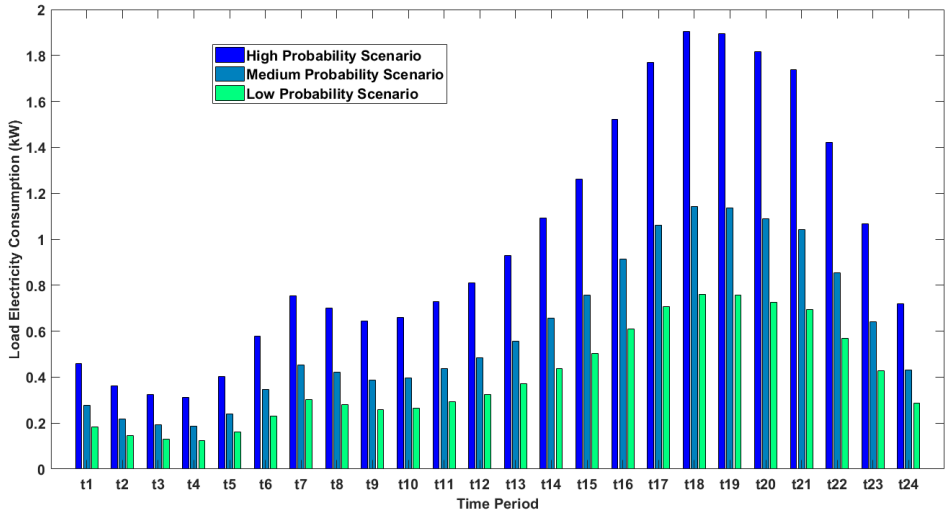

Figure 3.10: Demand Scenarios
Source: [117]

margins and emission thresholds. Table 3.4 displays the characteristics of all dispatchable generating units.

Ramp rate	2.500
Capacity (kW)	110.000
Initial output	44.000

Table 3.4: Dispatchable Units – Characteristics
Source: [120] and [121]

The energy storage system power depends on the charging and discharging minimum and maximum limits. Hence, the power of the energy storage system can take on a positive value, discharging, or a negative value, charging. At value zero, it is idle. Consequently, we must impose a minimum and maximum charging and discharging limits. All the characteristics of the battery system storage unit can be found in Table 3.5. Battery charge efficiency stands for the percent of energy stored by a battery charged at a specified electricity for a unit of time. The overall efficiency of the storage system is considered in both pumping and turbine mode ([123]). There exist three peak periods, namely, on-peak, inter-peak, and off-peak. The summer on-peak hours are 12:00 – 18:00 during weekdays. The summer mid-peak hours are 08:00 – 12:00 and 18:00 – 22:00 during weekdays. All other hours are off-peak ([120]).

The variable costs of the flexible load are defined by the operation and maintenance

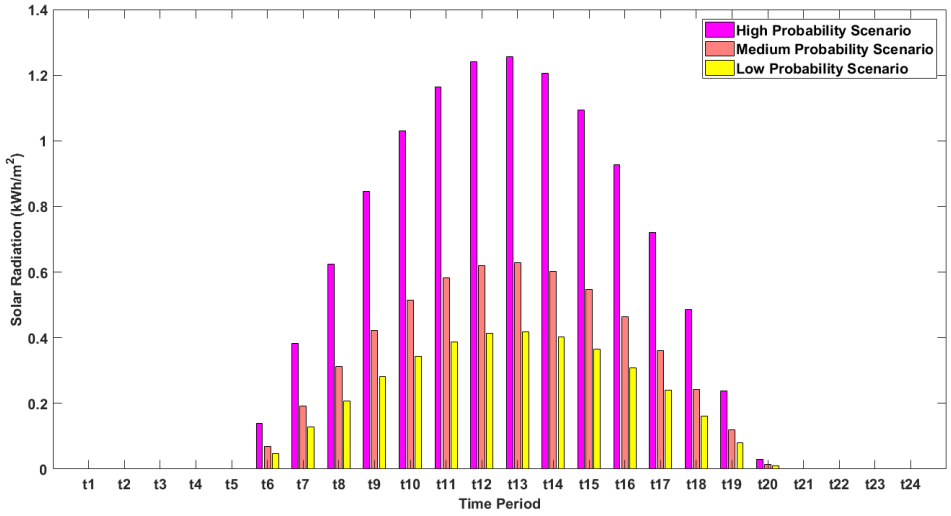

Figure 3.11: Solar Radiation Scenarios
Source: [118]

Equivalent energy capacity (kWh)	24.000
Minimum storage level (kW)	4.800
Initial storage level (kW)	9.600
Charging power limit (kW)	0.100
Discharging power limit (kW)	0.250
Efficiency	0.850
Capacity (kW)	12.000

Table 3.5: Battery Storage – Characteristics
Source: [122]

costs. They are proportional to usage. They vary so far as the hour throughout the day is on-peak, inter-peak, or off-peak. The installation costs related to the loads consist of a necessary cost independent of the capacity. These costs correspond to fixed costs of infrastructure needed to appropriate all the devices within the load. The variable costs of the dispatchable units are obtained from analyses and studies described in [120]. According to [121], the average installation or fixed costs of a normal unit varies between 400$/kW and 1,400$/kW and depends on the capacity of the unit. The variable costs of the storage system are contingent on the age of the batteries ([122]). The fixed costs for the storage system consist of the capital costs of the batteries. Table 3.6 and Table 3.7 show all variable and fixed costs, respectively.

Storage	t1	t2	t3	t4	t5	t6	t7	t8
	0.005	0.001	0.003	0.004	0.004	0.018	0.005	0.001
	t9	t10	t11	t12	t13	t14	t15	t16
	0.003	0.004	0.004	0.018	0.005	0.001	0.003	0.004
	t17	t18	t19	t20	t21	t22	t23	t24
	0.004	0.018	0.005	0.001	0.003	0.004	0.004	0.018

	Loads	Microturbine	Fuel Cells	Natural gas	Diesel
t1, t2, ..., t7	0.072	0.012	0.002	0.004	0.004
t8, ..., t11	0.074	0.015	0.005	0.007	0.007
t12, t13, ..., t18	0.109	0.020	0.030	0.010	0.010
t19, ..., t22	0.074	0.015	0.005	0.007	0.007
t23, t24	0.072	0.015	0.005	0.007	0.007

Table 3.6: Variable Costs ($/kWh)
Source: [122], [120], [121]

	Loads	Microturbine	Fuel Cells	Natural gas	Diesel	Storage
t1, t2, t3, ..., t24	1.990	0.341	0.341	0.341	0.341	0.400

Table 3.7: Fixed Costs ($/kWh)
Source: [122], [120], [121]

Emissions costs are calculated according to the EPA's standards as shown in [124]. To set the emission constraint, we take into account the EPA's threshold under the Clean Air Act. According to [125], the national average carbon dioxide output rate for electricity generated is 1.328 lbs/kWh . Furthermore, the Clean Air Acts goal is to decrease carbon emissions from the electricity sector by 32 percent from 2005 levels by 2030 ([126]). The overview of the GAMS code used to implement the numerical analysis is given in Table 3.8.

EQUATIONS	**SETS**
masterobj – Master objective function	t – Time periods
optcut(iter) Benders' optimality cuts	g – Generating units
EB(g,t) – Energy balance (Kirchhoff's law)	s – Scenarios index
pRL0up(g) – Dispatchable unit ramping limits	iter – Max Benders' iterations
FRLup0(g) – Flexible load ramping limits	dyniter(iter) – Dynamic subset
STE0(g) – Battery system state-transition function	**SCARLARS**
EPAth(g,t) – Emission threshold	Emap – Electricity market price ($/kWh)
subobj – Subproblem objective function	Fop – Installation costs ($/kWh)
VARIABLES	Sop – Generating cost for storage set ($/kWh)
zmaster – Objective variable of master problem	pramp – Unit ramp rate
theta – Extra term in master obj	p0 – Unit initial power output (kW)
zsub – Objective variable of subproblem	Framp – Facility ramp rate
POSITIVE VARIABLES	ESmax – Battery energy capacity (kWh)
p(g,t) – Electricity output	ESmin – Battery minimum storage level (kW)
E(g,t) – Energy production	ES0 – Battery initial storage level (kW)
EL(g,t) – Facility load energy consumption	PScmax – Battery charging limit (kW)
ES(g,t) – Battery system storage level	PSdmax – Battery discharging limit (kW)
SSc(g,t) – Electricity charge (storage)	eff – Battery efficiency
SSd(g,t) – Electricity discharge (storage)	MaxStoset – Battery capacity (kW)
emP(g,t) – CO_2 emissions (lbs/KWh)	emiT – CO_2 emission threshold (lbs/KWh)
PARAMETERS	emTC – CO_2 Clean Air Act target (lbs/kWh)
maxcap(g) – Capacity of each unit	**BENDERS' SOLVERS**
Prob(s) – Probability scenarios	option limrow = 0
EMC(t) – CO_2 emissionts cost ($/kWh)	option limcol = 0
demand(t,s) – Electricity demand scenarios (kW)	subproblem.solprint = 2
PVoutput(g,s) – PV electricity output (kWh/m^2)	masterproblem.solprint = 2
c(g,t) – Variable operating costs ($/kWh)	subproblem.solvelink = 2
cutconst(iter) – Constants in optimality cuts	cutcoeff(iter,g,t) – Coefficients in optimality cuts

Table 3.8: Overview GAMS Code

3.6.2 Sources of Uncertainties

The level of supply side uncertainty depends on whether the DER system is grid-connected or not. Regardless of the mode, the main source of supply uncertainty is on the non-dispatchable unit, which in this case is the solar PV. This is because of the variability of solar radiation, which depends on the intensity of the sun. The variability of the solar radiation can result in the microgrid not satisfying the load. In the island mode, as shown in Figure 3.8, the DER system is not connected to the electricity grid. In this case, one factor affecting supply side uncertainty is intermittency, which is handled in the model with the provision of storage. At times of high demands and low solar radiation, the stored energy is called upon as shown in Figure 3.12 and Figure 3.13. In the evenings, the system uses the stored electricity which reduces costs and CO_2 emissions. In island mode, the electricity from the PV technology is first used if available to meet demand. Otherwise, demand uncertainty is met with the dispatchable technologies. We see this in hours $t_1 - t_5$ in Figure 3.14. If neither the PV unit nor the dispatcable units are sufficient, the DER system faces a possible loss of load expectation (LOLE). To illustrate this loss, we see that demand uncertainty is created when, at $t_{21} - t_{24}$ (Figure 3.9), there is a mid-peak demand and there is no solar radiation (Figure 3.11). In this situation, demand is exceeding electricity supply because of outage of solar radiation.

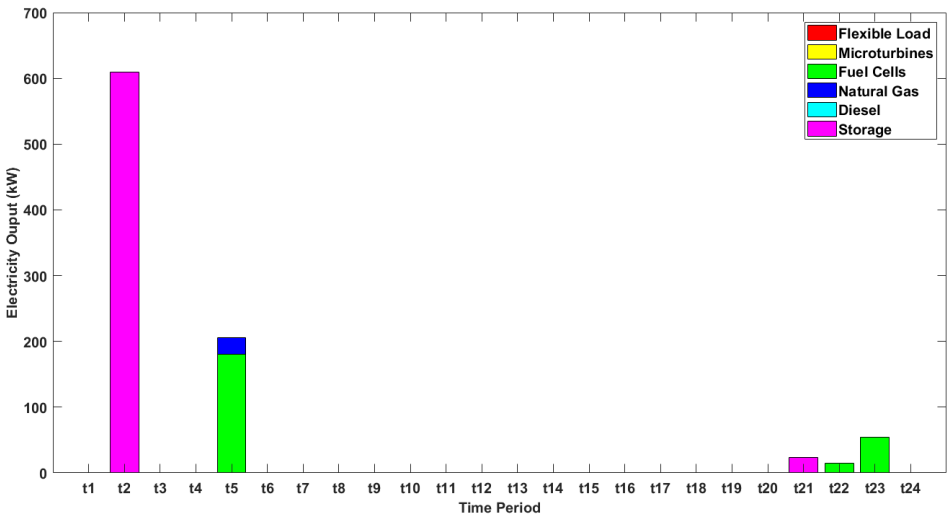

Figure 3.12: Results - Minimizing Costs & CO_2 Emissions
Simultaneous Stochastic Demand & Supply

If grid connected, supply uncertainty is lower because the grid serves as a backup.

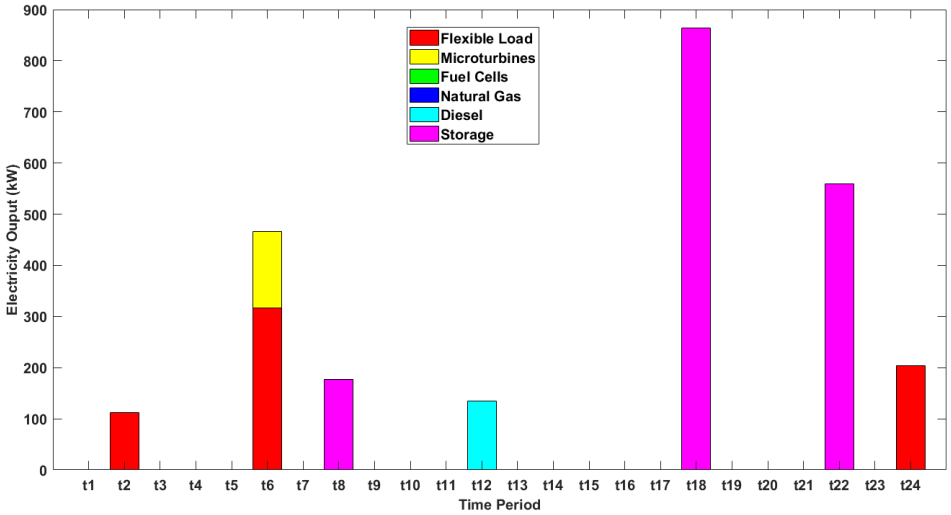

Figure 3.13: Results - Minimizing Costs
Simultaneous Stochastic Demand & Supply

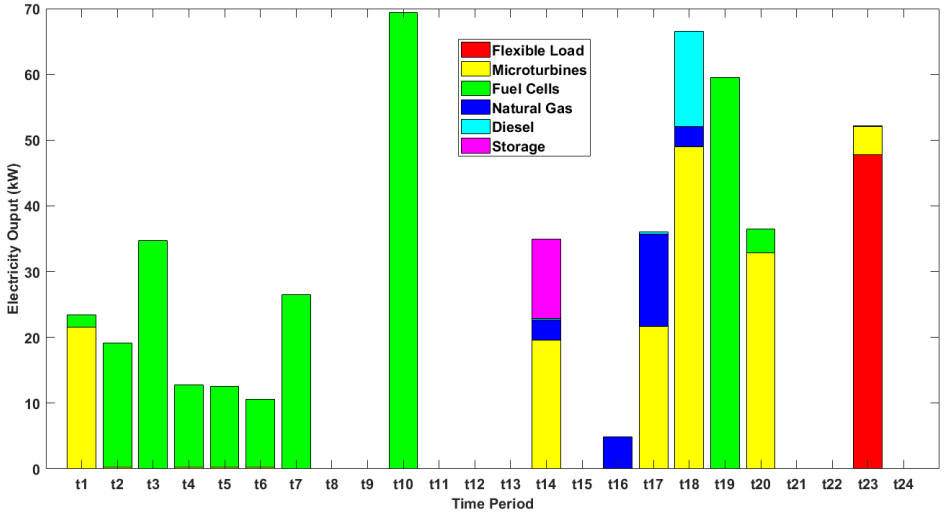

Figure 3.14: Results - Minimizing Costs & CO_2 Emissions
Stochastic Demand

Consequently, the fluctuation problem that comes from the electricity supplied from the PV technology will be resolved even in the absence of solar radiation[2]. The operating costs of the solar PV are zero in the model. The system with the objective of minimizing costs now faces the task to accommodate suppliers from external sources, which comes at a cost. As the system chooses to consume from the grid, another layer of uncertainty is faced. This uncertainty is due to price volatility, but this is not in the scope of this paper.

3.7 Results

3.7.1 Costs and CO_2 Emissions Minimization

Under uncertain demand and supply, the fuel cells unit (Figure 3.12) is committed and dispatched as it emits low CO_2 gas in comparison to diesel and microturbine units. This is all the more notable as [120] indicate that fuel cells are capable of generating clean and efficient electricity. The natural gas unit can also be committed along with the fuel cells unit as both can efficiently mitigate costs and CO_2 emissions. The battery storage must be charged in order to avoid increased costs and CO_2 emissions. Nonetheless, this will highly depend on the flexible load profiles (Figure 3.9) and the solar insulation (Figure 3.11). Interestingly, [122] also observe that "elemental carbon emission reduction is lower with adoption of storages than without it." We also note that, given the great amount of uncertainty, the operator will have to rely on the main grid for a fair amount of times.

When only demand is unknown, the operator commits the fuel cells unit at mid and off-peak hours $t_2 - t_7$, t_{10} , and t_{19} (Figure 3.14). He would rather prefer to commit high CO_2 emitting units at those low consumption hours. The operator also finds that he must commit the microturbine and diesel units at on-peak hours t_{14}, t_{17}, t_{18} and mid-peak hours t_{20}, t_{23}, where the consumption is quite high. Unhappily, this is in direct conflict with his goal to minimize CO_2 emissions. Furthermore, [120] articulate the fact that diesel and microturbines units contain a relatively high amount of CO_2 pollutant. Hence, to his disenchantment, the operator discovers that dealing with uncertain demand is not always conducive to the reduction of greenhouse gas emissions.

When supply and demand are known, looking at the peak hours t_{12} through t_{18} (Figure 3.15), the microgrid must schedule the battery storage system along with dispatching the

[2]See Model Algorithm (Figure 3.7) where the Microgrid is transacting with the Grid (Bender's Master problem)

natural gas and diesel units. It is noteworthy that the diesel unit must be dispatched at t_{19} to compensate the electricity consumed by the loads. To the operator's gratification, the diesel unit must only be committed at t_{17} and t_{18}, which correspond to the transition between mid-peak and off peak hours. Hence, as discussed in [122], CO_2 emissions can effectively be mitigated by scheduling storage units and natural gas unit.

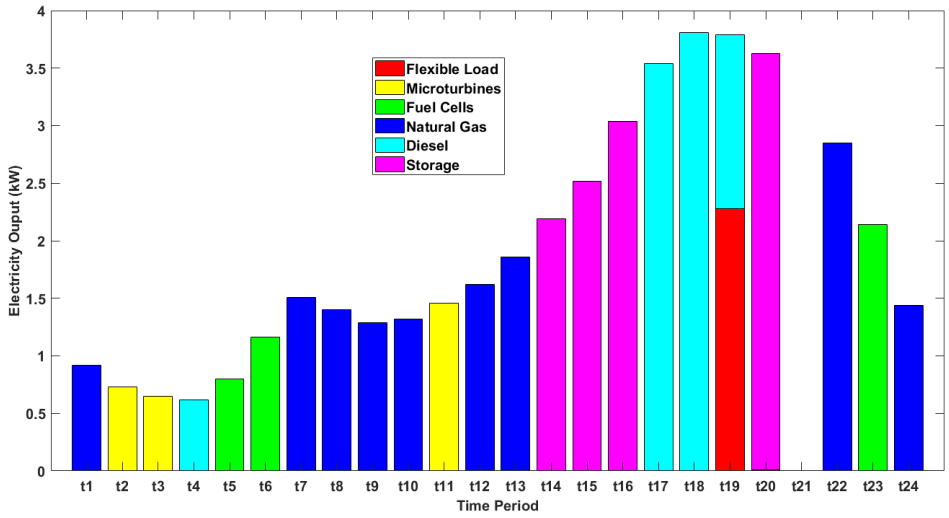

Figure 3.15: Results - Minimizing Costs & CO_2 Emissions
Deterministic Demand & Supply

3.7.2 Costs Minimization

Under uncertain demand and supply, the microgrid charges the battery set at mid-peak hours (Figure 3.13) . Thankfully, the market price is not at its highest at these hours. So, the operator could later sell any potential excess electricity to the main grid and make some profits. The flexible loads are deployed for consumption at t_2, t_6, and t_{24}. They play a role of balancing resource and are allocated for efficiency purpose as the quantities of electricity supplied and consumed by the loads are equal at those time periods. The microturbine unit should be committed so as the meet the loads demand at the off-peak hour t_6. The diesel unit can only be dispatched once at the on-peak hour t_{12} when the electricity price is quite high. That microturbine is dispatched and committed when the electricity price is low is good news for the operator. According to [121], it is more expensive to operate and maintain microturbine units than diesel engines. As pointed in the emissions minimization case, under simultaneous uncertainty, the microgrid operator will have to depend on the main grid for most periods. When only demand is unknown, at

peak hours t_{12} through t_{17} (Figure 3.16), the microturbines, natural gas, and diesel units must be dispatched and committed in order to reduce operating and maintenance costs. That we observe a dominance of microturbine units is not satisfactory for the operator since his intention is to minimize costs. In effect, [121] point out that microturbine units tend to be very expensive to purchase and operate. Hence, in face of demand uncertainty, mitigating costs would be very challenging for the microgrid operator.

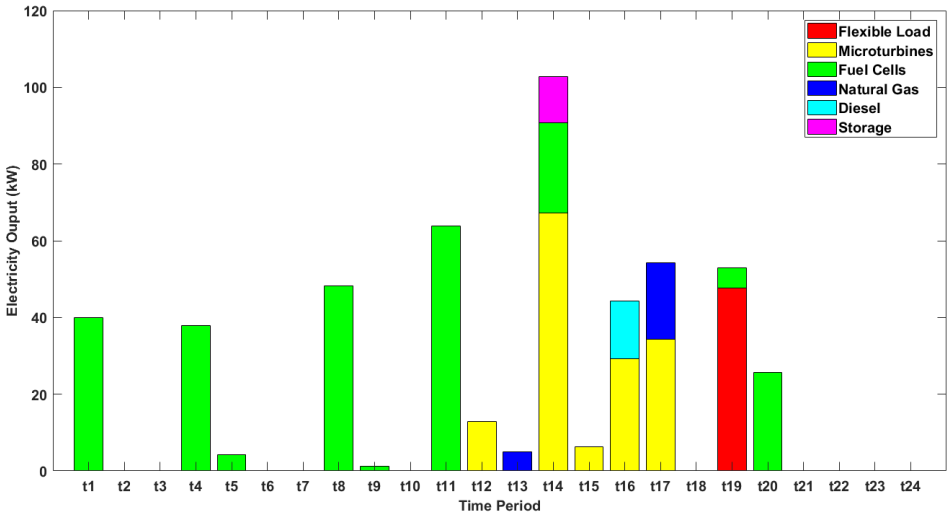

Figure 3.16: Results - Minimizing Costs
Stochastic Demand

When supply and demand are known, the fact that microturbine unit (Figure 3.17) only appears at off-peak hours is elating for the microgrid operator since it can be very expensive to operate and maintain. Meanwhile, the operator is pleased to dispatch the fuel cells unit at t_{21} to compensate the extra amount of electricity consumed by the loads. As in the emissions reduction case, the adoption of the battery system along with the natural gas and diesel units greatly helps in reducing operation and maintenance costs for the microgrid operator. This is corroborated by [121].

3.8 Effects of the Microgrid Scale on Uncertainty

The objective of this section is to address the effects of the microgrid scale on demand uncertainty. Given that the system comes short in meeting demand loads as shown in Figure 3.14 and Figure 3.16, there is value for having a bigger scale system of DER. However, increasing the scale of the DER system comes at a higher capital cost along with increasing

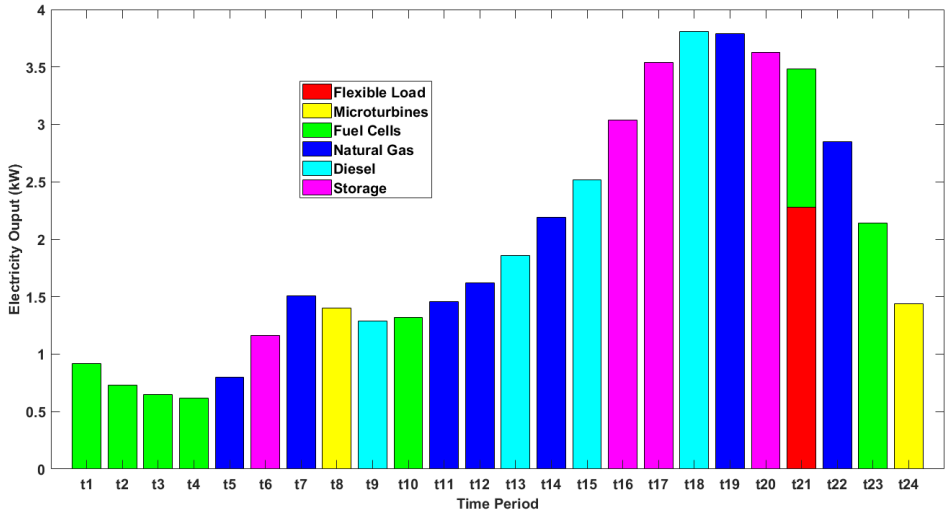

Figure 3.17: Results - Minimizing Costs
Deterministic Demand & Supply

the capacity limits of the system. The higher capacity microgrid is set to minimize costs and CO_2 emissions. Comparing Figure 3.14 in which the system has a smaller scale with Figure 3.18 with a higher scale, the number of hours at which the system does not meet demand is reduced. Thus, with a larger DER system, the effects of demand uncertainties are reduced, culminating in a more reliable system. This is to show that, in a scaled up microgrid, technologies are better allocated to preserve the system stability and alleviate the effects of uncertainties. By the same token, [127] also find that as microgrids become larger, the effects of demand uncertainty are mitigated. Intuitively, larger microgrids entail larger solar PV capacities, and so lower CO_2 emissions. Thus, our results demonstrate that CO_2 emission is reduced in face of demand uncertainty as microgrids get larger.

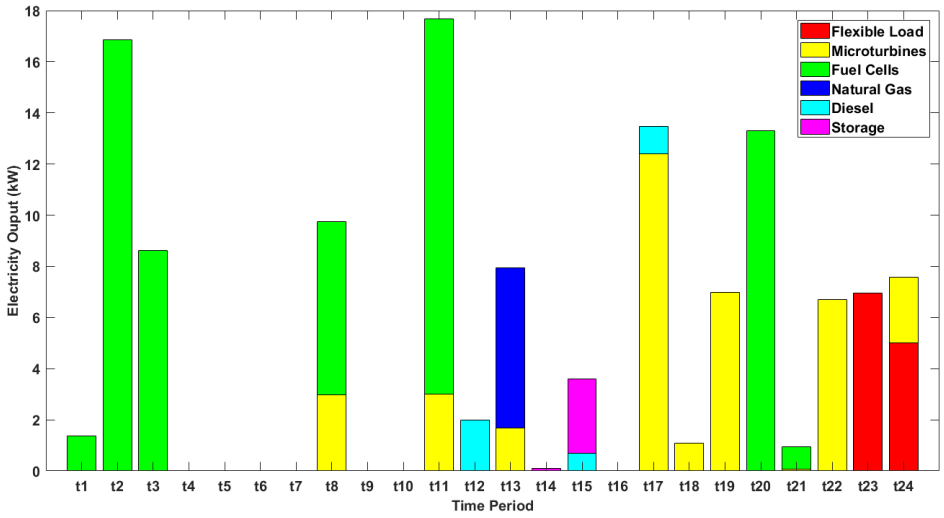

Figure 3.18: Effects of the Microgrid Scale on Demand Uncertainty Costs and CO_2 Emissions Minimization

Chapter 4 The Mechanism of Electricity Technological Learning

4.1 Introduction

Within the past decade, billions of dollars have flowed into investments in clean technologies. Sadly, many of these investments collapsed leaving investors startled and wondering about the difficulty of the problem. It is a fact that U.S. electricity firms have been the least likely to innovate and invest on research and development. However, the unprecedented shape-up in the electricity sector is making technological innovation an unavoidable factor in firms' profit maximization strategies. Case in point, technological innovation is unfastening boundless opportunities that did not exist before. For instance, technological innovation is wielding big data to single out market trends. By the same token, technological innovation is using the Internet of Things to foster energy efficiency. But, these are not coming without challenges created by regulatory policies.

In an effort to alleviate these challenges, we inspect the asymmetries and heterogeneities related to knowledge acquisition within and across electricity firms in the U.S. The issues of environmental regulations and firms' desire to innovate and maximize profits are complex and intricate. Thus, to shed more lights on the mechanisms underlying firm innovation, we borrow two modeling concepts from psychology, namely [128]. This allows us to explain the transfer of learning and how organizations learn from the experience of others or from their own experience. We also avail ourselves of the [57]'s learning curve model. But, we differ from the existing literature on transfer of learning in service organizations by focusing on firms' electricity technologies. We concomitantly carry out a longitudinal study of 5,573 U.S. electricity firms operating from 1998 through 2010. We use a MATLAB object script file to generate seven models of the responses in cost per electricity produced. OLS regressions are more pliable to the addition of control variables such as policy mandates and financial incentives. In contrast, Logit and Probit regressions are restricted and do not give as much

leeway to dependent variables.

This study inspects the asymmetries and heterogeneities in learning dynamics within and across electricity firms in the U.S. We reveal the positive relationship between the acquisition of new knowledge through intra-firm learning in electricity firms and the enhancement of existing technology. We deduce the association between inter-firm learning across electricity firms with radical breakthroughs in knowledge acquisition and technological innovation. We unravel the complexity of complying with policy instruments. This study is also illuminating in that it draws out the criticalness of knowledge collaboration across firms in developing disruptive technologies. We demonstrate that learning rates of some technologies such as solar and wind can be insensitive to republican or democratic leadership. We find that policy mandates and financial incentives should continue to be promoted because they have a positive impact on technological innovation. We also find that, given the economic benefits of pollution emissions reductions, much is yet to be done policy-wise to spur progress in the development of solar technology.

4.2 Theoretical Framework & Hypotheses

4.2.1 Technological Adoption and Uncertainty

[129] develops a model of generic incremental growth in technology adoption. In this model, the decision maker must decide on the adoption of a technology. For that matter, let the adoption decision be denoted by the decision variable t such that

$$\max_{t} \; E_{\omega}\left[B(t,\omega)\right] - c(t) \tag{4.1}$$

ω is a random variable. E_{ω} is the expectation operator on ω. $B(t,\omega)$ is the benefit of the adoption decision while $c(t)$ is its cost. Without loss of generalization, assuming that this problem is well behaved, the first order condition is given by

$$c'(t) = E_{\omega}\left[\frac{\partial}{dt}B(t,\omega)\right] \tag{4.2}$$

Let t^* be the optimal decision, the solution of (4.2). It is equal to the sum of the marginal cost of adoption and the expected marginal benefit of adoption. However, it is conditioned on the change in the probability distribution of ω. That is, any change that increases

(decreases) the expected marginal benefits will cause the optimal decision t^* to increase (decrease). Hence, for all increases in the risk adoption, the expected marginal benefits of the decision will increase and contrariwise. But, this will only happen if the marginal benefits are convex. Unfortunately, the marginal benefits of the decision on technological adoption are neither strictly convex nor concave.

In a two-period learning model, [130] shows that there is learning that yields an improvement over the existing technology. This learning is given by

$$\max_{t_1} \; E_\omega \left[\max_{t_2} B(t_1, t_2, \omega) - c_2(t_2) \right] - c_1(t_1) \tag{4.3}$$

Equation (4.3) is an inter-temporal, but sequential decision making problem. This is because the optimal second period decision t_2^* depends on the optimal first period decision t_1^*. Regrettably, this dependence rather complicates the resolution of the two-period learning model. As a matter of fact, characterizing the marginal benefits is ambiguous given the uncertainty generated by the distribution on ω.

Technological Adoption – An Example

Consider two innovators making discrete and simultaneous improvements on an existing technology T_1 to yield a new technology T_2 at cost C. Either of the two innovators may adopt the new technology. The adoption of this new technology T_2 yields a benefit B. The adoption of technology T_2 is only possible if the payoff of the innovation satisfies $B - C > 0$. In this model, the innovator with the breakthrough technology holds the rights to the new technology T_2. He only leases it to the second innovator. The latter assumes the role of a user. Thus, the user on adopting the technology enjoys benefits B. If the user does not adopt the new technology, then the innovator still enjoys the benefits B because he regains the choice of leasing to a new user.

4.2.2 Intra-Firm Knowledge Transfer

Intra-firm learning deals with the pace at which firms thoroughly utilize the new technology once they have adopted it. It enables teams and departments within the firm to transfer knowledge via an ad-hoc transfer strategy. To determine intra-firm efficiency, one must take into account the firm's efficiency level over time relative to the firm-specific production. The efficiency is empirically translated by the adoption of new technologies. This

eventually leads to technological progress. On that note, [131] provide some "evidence on the factors affecting the speed at which new technologies diffuse within firms."

In our context, learning involves the ability to produce an action and to effectuate the understanding of an experience. [52] deems that learning generally occurs when conduct is altered by virtue of the processing of information exchange. Hence, the acquisition and exploitation of new knowledge are associated with learning new techniques and practices. This process eventually transforms the firm from within. [132] assert that "an organization learns when it acquires knowledge, understanding, or techniques of any kind." A significant component of the transfer and creation of learning is transparency in the firm. For new knowledge to be generated, knowledge must be shared collectively. This will not occur if transparency is not fostered.

It is abundantly argued that the firm's capacity to transfer knowledge has a positive impact on its performance. Studies conducted by [133] and [134] successfully illustrate that knowledge transfer is critical for the firm's long-term survival. A salient characteristic of intra-firm learning is tacit knowledge, which has to do with skills acquisition. As claimed by [135], tacit knowledge is an essential part of people and teams within firms. For that matter, tacit knowledge is inherently implicit in that players outside the firm cannot copy or imitate the techniques used inside the firm. It is noteworthy that [136] associates firm learning with the creation, acquisition, and transfer of knowledge. This refers back to our inference that intra-firm learning germinates in existing technology enhancement.

Intra-firm learning is also achieved by shifting existing knowledge through interaction with different teams within the firm. One of the main metrics of firm learning is learning networks such as groups or teams. Identifying learning networks that share knowledge is capital for the estimation of the effect of learning. Within the electricity industry, amendments of environmental regulation often demand that electricity firms adapt. These factors usually coerce firms to produce and share new knowledge. For example, [137] show that "in response to increased regulatory stringency, electricity generators find technical efficiency enhancements then transfer these enhancements to other units within their fleet." So, after electricity firms have successfully acquired knowledge, innovation in existing technology is sparked thus creating a framework whereby firm learning is improved.

We hypothesize that technological enhancement from intra-firm knowledge acquisition is more evident for renewable technologies such as solar and wind. It is demonstrated that

technological innovation is the foundation of cost reduction and capital efficiency. [138] is the first to study the impact of intra-firm learning on the adoption of new technology. He finds that when firms become accustomed to their own innovation, they are eager to replace it with new technology when given the opportunity. The finding is all the more critical as the level of intra-firm learning of an electricity firm affects the rate of learning within the entire electricity industry. Grasping the intra-firm context of strategic planning among electricity firms requires a network approach of the experience with the existing technology. This explains why [139] point that "as the diffusion process develops, the experience of firms with new technology leads them to update initial estimates of both risk and returns and the level of use of the new technology."

In order to measure the impact of learning and new information on intra-firm diffusion, [140] use the Bayesian mechanism. This method allows the firm to wage between the existing and new technology through optimizing its utility function. In this case, the firm evaluates the potential risk and returns aligned with the new technology. Whenever the degree of adoption of the new technology varies, the firm exposes itself to the cost of adaptation. This cost is actually a part of the utility function. The firm then learns from the experience it acquires with the new technology while adapting to expected returns. As the integration of the new technology takes place, the firm is better able to estimate the risk involved. Given these factors, [141] reveals that the study of the extent of use of a technology within a firm is indeed critical.

Hypothesis 1. The higher the level of intra-firm knowledge acquisition, the higher is the technological improvement in solar technology.

4.2.3 Inter-Firm Knowledge Transfer

Inter-firm learning can be viewed as the combined acquisition and development of knowledge. It requires the refinement of firms' environments and working rules in order for learning to occur. Understanding how radical breakthroughs unfold is central to the development of inter-firm learning. The fundamental generative mechanisms of breakthroughs in knowledge acquisition are difficult to investigate. However, it is easy to observe that, when two firms cumulate experiences, intellectual capital is created. Whenever that association is interrupted, the capital is wrecked and firm's productivity decreases.

There are several variables that influence the adoption of new technologies by firms

operating in the electricity market. Strategic alliances and joint ventures among electricity firms usually form strong inter-firm collaborative networks. These networks, in turn, stimulate learning processes through knowledge synergy. A recent example is the partnership between *Energy Transfer* and *Enbridge*. Both electricity firms teamed up to innovate their pipeline technology. From this example, we perceive that the edification of inter-firm environments creates a collective acquisition and development of knowledge. In his seminal paper, [142] shows that the diffusion of knowledge culminates in growth and measured productivity. Using the Hybrid corn innovation, he hypothesizes and demonstrates that technological change reinforces the economies of scales. This finding catalyzed the work of [143] on the adoption of new technology across firms in the manufacturing and transport sectors. Specifically, [143] found that "larger firms tend to adopt innovations sooner than do their smaller counterparts."

Empirically, the firm's performance is brought to light by inter-firm productivity over time with respect to comparable firms. This productivity is measured by the speed with which the firm can learn. It is echoed by technological differences across firms. Insofar as firms deploy efforts to transfer knowledge within and across them, they create platforms opportunities. These platforms open ways for parties within firms to allocate observations and experiences. The new podium enables firms to boost their store of knowledge by incorporating knowledge not previously available to them. In turn, they are able to formulate brand new knowledge via interaction with other organizations. [144] corroborate our point by remarking that "the opportunities for entry by firms sponsoring new technical sub-systems, which may be either complementary to or substitutes for those already in the field, should be regarded as fostering the options for innovative action." Another example is given by [145] regarding the A.C. Polyphase technology. Speaking of two electricity firms, he reports how their "flexibility and capabilities led to a rapid diffusion of the A.C. Polyphase technology and the integration of smaller urban electricity supply systems into larger networks which eventually formed regional grids." Therefore, inter-firm learning equips organizations with the synergy necessary for learning to occur.

Firms within the electricity industry very often form strategic alliances in order to collaborate and learn from other firms' technological knowledge. This undertaking elevates electricity firms' competitiveness and ability to technologically innovate. [146] highlight the importance of strategic alliances and present "empirical evidence on the effects of knowl-

edge on the degree of inter-firm technology." Interestingly, [147] reports that "inter-firm networks and organizational learning are the source of knowledge updating." Technological capability-accumulation acquired through inter-firm learning has the potential of improving the operational performance of firms. [148] not only elaborates on that reality but also examines firms' efforts on "learning and technological capability accumulation for competitive advantage." By the same token, [149] unveil that "specific learning gives firms an incentive to work with firms with which they have substantial experience, rather than those with which they have worked relatively little." Also, [150] find "evidence that a firm's recent production experience has a stronger impact on productivity than does older experience." Thus, firms' learning relationships are associated with a commensurate gain of capital induced by technological innovation.

4.2.4 Policy Instruments and Firm Learning

It is of general view that governmental authorities use policy instruments to bring about change in behavior. Of particular importance is the choice of a specific policy instrument to target the expected response. It is abundantly clear that the electricity industry, by itself, emits an extremely high percentage of CO_2, SO_2 (sulfur dioxide), and NO_x (nitrogen oxide) into the atmosphere. In an attempt to lower such pollutants, policy instruments often unintentionally induce technical efficiency through transfer of learning within electricity firms. [151] characterize policies instruments as "a set of techniques by which governmental authorities or proxies acting on behalf of governmental authorities wield their power in attempting to ensure support and effect social change." They also emphasize the relevance of policy strategies by observing that "the use of various policy instruments for governance purposes will probably have different consequences on the nature of addressee responses." In our case, we spell out two main policy instruments, namely regulatory mandates and financial incentives.

Regulatory Mandates

Another point of general consensus is that the 1963 Clean Air Acts initiated an array of environmental regulations. Gauging the impact of the latter on electricity firms' capital and productivity is essential. Besides, such an endeavor will enlighten policymakers on the relevance of future viable amendments. On such an effort, [137] discuss "how firms

respond to an increase in regulation at one plant and how efficiency enhancing knowledge is transferred within the firm." We discuss renewable portfolio standards or RPS mandates and examine the ramifications of a republican state controlled legislature and democratic governorship.

Financial Incentives

Financial incentives frequently accompany regulatory policies for far reaching clean energy designs. Hurdles to successful and efficient operations of renewable energy technologies can be tackled with financial incentives. Financial incentives boost access to capital and decrease the load of high initial operation costs. As a result, the creation of new electricity markets and the innovation in better energy-efficient technologies are spurred. Pointing to the different types of financial incentives, [152] notes that "energy efficiency financial incentives include: tax measures, rebates, grants, and performance-based incentives and loan programs, guarantees, and credit enhancements." In our study we spell out and apply the following three main financial incentives: Renewable Electricity Production Tax Credits, Qualified Energy Conservation Bonds, and the Federal Appliance Standards.

We infer that electricity firms gaining from tax credits to invest in wind technologies see more radical breakthroughs in innovation from inter-firm knowledge acquisition. It is well established that one of the econometric implications of firm's learning is that unit costs decrease with cumulative production. A key observation is that technological innovation is both incremental and cumulative and even more so in the electricity industry. In the latter environment, technological innovation is chiefly determined by its context. It is necessary to point that knowledge acquisition has considerably helped drive down unit cost and even effectuated scales in the renewable, wind and gas industries. Our endeavor in this inference is to show that some of these innovations have been driven by inter-firm learning and have increased faster availability of electricity ([153].)

Hypothesis 2: The higher the financial incentives for clean technologies, the higher is technological improvement in clean technologies under inter-firm learning.

4.2.5 Technological Progress in the Electricity Industry

Progress in electricity generation technologies is a key factor behind productivity and growth in the electricity industry. Intensified competition from merchant electricity generators has stimulated progress. The latter is seen through the development of numerous technologies within the electricity industry. For instance, cost competitive wind and solar panels as well as cheap natural gas have significantly lowered the cost of electricity generation. But the question whether technological progress will continue to grow as policy makers contemplate alternative regulatory instruments remains. To that effect, [154] observes "It is also of interest to improve the process of learning and identify those technologies that are likely to achieve most progress during a given period. Further, it is important to determine whether resources allocated to promotion of a given technology are better spent on research and development (R&D) or on capacity promotion policies." So, grasping the importance of learning in technological progress is relevant for innovation and policy adaptation.

We contemplate that, in the process of complying with policy instruments, the progress of the electricity sector in terms of knowledge acquisition in solar technology will be asymmetric. By asymmetric, we hold that the progress induced by technological change within and across electricity firms, does not automatically translate into identically declining and increasing economies of scale. This rationale is supported by [155] who after surveying firms in the Turkish electricity industry found "existence of scale economies throughout the period of analysis, hence declining long-run average costs." Yet, he indicated that "this effect was reduced largely after 2002" leading technological progress to deteriorate "from 1984 – 1993 to 1994 – 2001." Whatever the case, the electricity industry is always set on adopting new efficient technology and business models. This allows them to simultaneously ascertain profits maximization while meeting policy requirements. Hence, we predict a high likelihood of heterogeneity in learning patterns among those electricity firms. By the same token, while investigating asymmetries in learning across different domains, [156] discovers that "learning differs in the gain and the loss domain, and that, on average, it is worse in the loss domain." Interestingly, she further points that "within-individual domains, learning in the gain vs. loss domain, passive conditions are not perfectly correlated, indicating that there may exist heterogeneity across people with respect to the context or type of information to which they are the most sensitive." Given the intense competitiveness among electricity firms, the fact that knowledge asymmetry create a relative amount of heterogeneity is not

a new phenomenon.

Hypothesis 3. The more stringent policy mandates are, the more diverse is the effect of progress on technological change in clean technologies.

4.2.6 Policy Instruments and Uncertainty

Economic uncertainty added to uncertainty in technological cost makes decisions in technological learning not only necessary but complex. It is quite evident that electricity firms revise their investment decisions as they seek to adapt to regulatory mandates. RPS Policies, for example, have spurred electricity firms to invest in non-carbon technological learning. Since short terms investments in technological learning could decrease future environmental costs, federal and state policies instruments are looking for strategies to promote such investments. But investment in a current technology is essentially based on an uncertain learning factor that could potentially increase the future cost of that technology. So, the interaction between policy instruments and investments within and across electricity firms can have a clashing effect if not shaped appropriately. Case in point, looking at more than 1,592 electricity firms in the U.S., [157] "find that regulatory mandates dampen the effect of competitors' new resource investments on a focal firm's new resource investments." It is likely that this could be due to uncertain economic parameters policy making cannot exactly capture. As [158] investigate "socially optimal near term electricity investment decisions under uncertainty," they realize that "uncertainty about the future policy increases the expected cost of policy by over 45% in future policy." Using a two stage stochastic programming with recourse, [159] find that carbon abatement policy can successfully be used to mitigate uncertainties. [160] and [161] apply Monte Carlo analysis along with computable general equilibrium or CGE to "provide probability distributions of climate impacts and economic costs of policies." Examining the implications of policies on U.S. electricity markets, [162] "find that policies that increase the effective competitive pressure on firms, or increase the risk of financial distress lower leverage. However, firms with market power have the ability to counter this competitive threat and take on more debt." These studies reinforce the importance for firms to harness technological learning through learning by doing for example to alleviate the haphazardness created by policy instruments.

The above discussion from the literature enlightens the basis we undertake to infer that regulatory policies generate a non-trivial level of uncertainty. Precisely, we hypothesize

that regulatory policies create uncertainty in the development of wind technologies. But, we hold that intra-firm learning is reinforced for solar and coal technologies. Consequently, the transfer and acquisition of knowledge are curbed, depressing learning investments to develop disruptive technologies. It is well established that open innovation incites collaboration across organizations. This may be explained by the quick and easy access to different resources offered by a broader set of connections. These types of collaborations easily generate new innovative opportunities culminating into disruptive technologies. Nonetheless, because of policies mandates and financial incentives, firms tend to rely more on internal networks to acquire leverage and realize innovations in the face of competitions. As a result, open collaboration is stressed, dampening all the innovative advantages that come with it. In effect, [163] confirm the rationale behind our inference. After analyzing several case studies, they report that "knowledge gaps emerge due to exogenous factors and endogenous factors." In this instance, they specify that "exogenous factors include institutional forces like changes in government policies or regulations and industrial forces like competitive forces and industry specific changes."

Hypothesis 4. More regulation leads to more diversity in investments across technologies.

4.3 Methodology

4.3.1 Electricity Industry Context

Data on the U.S. electricity industry spanning 1998 through 2010 are used to conduct this study. The enactment of the Public Utilities Regulatory Policies Act or PURPA of 1978 allowed independent power production to sell electricity to utilities ([164], [58]). These included major electric utilities operated as natural monopolies "regulated on a state-by-state basis by public utility commissions." Originally, electricity producers produced, transmitted, and distributed electricity. However, over the last 30 years the electricity generation part of the U.S. energy industry has seen huge deregulation starting with PURPA in 1978. Then, the Energy Policy Act of 1992 followed, allowing independent power producer ownership by both utilities and non-utilities. Currently, there are over 3,000 electricity utilities in the U.S. electricity industry. These utilities encompass private energy firms, investor-owned utilities, and government utilities. The latter include cooperatives and federal utilities.

Private energy firms originate in PURPA. This Act effectively created an entrepreneurial opportunity in the private sector to build power plants for the generation of energy sold to other utilities ([164]). In 2009, the electricity industry supplied 4 million GWh of electricity of which 70.2% was from fossils such as coal, gas, and oil. Nonetheless, renewable energy sources, other than conventional hydroelectric capacity, accounted for the largest capacity additions in recent years. There are three junctures that make up the electricity sector. Energy generation defines the first stage. It necessitates a fuel supply like coal or gas and a power plant to transform the fuel supply into energy. The second juncture is energy transmission. It requires that the generated energy be converted into electricity that can be easily distributed by power lines. The third stage is distribution. In this stage, the transmitted electricity is transformed to voltage levels for consumption. Our study focuses on the first stage and the percentage of renewable in a firm's energy generation mix.

Presently, the distribution of energy from renewable resources such as solar, biomass and geothermal technologies is more costly. This is in comparison to conventional to coal and gas technologies. To spur investments in renewable technologies, a total of 29 U.S. states had enacted energy policies as of 2011. These policy instruments can be grouped into two categories, namely financial incentives and policy mandates. Financial incentives are made of tax incentives, production credits, and rebates. Policy mandates encompass Renewable Portfolio Standards (RPS). In this study, we focus on specific financial incentives and policy mandates. Some policy instruments are less uncertain and more "durable" whereas other are either temporary or currently phased out.

4.3.2 Data Characterization

We effectuate a longitudinal study based on data collected from archival sources found in the [165]'s database. We focus on design data for 5,573 electricity firms operating from 1998 through 2010. They comprise regulated utilities, private power companies, and industrial auto-producers. The actual study is conducted across 57 U.S. states and territories. All firms operate 26 different technologies that include Internal Combustion, Steam, Fossil-Fired, Photo-voltaic, Fuel Cell,..., etc (See Table 4.1). Our data requirements are constrained on 1,372,544 entries on electricity output by firm, technology, and state (Table 4.2).

The PLATTS dataset is extremely large and unstructured. Hence, we streamline the

IC/H	Internal combustion engine w/heat recovery
HY	Hydroelectric
IC	Internal combustion
GT	Gas turbine
ST	Steam, nuclear-powered
ST/S	Steam, fossil-fired w/steam sendout
WTG	Wind turbine generator
GT/S	Gas turbine w/steam sendout
GT/C	Gas turbine w/ combustion
ST/C	Steam, nuclear-powered w/ combustion
CC	Combined-cycle
PV	Photovoltaic
CCSS	combined-cycle single shaft configuration
IC/S	Internal combustion w/ steam sendout
FC	Fuel cell
COL	Coal

Table 4.1: Technologies in the Model
Source: [165]

Firms	5,573.00
States, US Territories, Canada	57.00
Technologies	26.00

Year	**Reported Electricity Output**
1998	20,626.00
1999	21,441.00
2000	21,997.00
2001	23,278.00
2002	24,907.00
2003	25,257.00
2004	26,509.00
2005	27,088.00
2006	28,109.00
2007	29,163.00
2008	30,252.00
2009	31,584.00
2010	32,925.00
Total	343,136.00
Grand Total	1,372,544.00

Table 4.2: Data Distribution
Source: [165]

electricity output for each firm in each state. We extract and structure all the data using the R application. It allows us to create dictionaries of smaller datasets. We subsequently specify all the data requirements we need to estimate all coefficients within the different regression models. Our final data extraction lays an aggregate of panel data with different intercepts. We formulate OLS regression models where dependent and independent variables are set in form of matrices. To carry into effect our analysis, we create and execute a MATLAB object script file.

Dependent variables are evaluated using data from [165]. Technology costs over time are taken as U.S dollars per MWh. They represent the costs of generating electricity using

the coal, gas, solar, or wind technology. Specifically, each dependent variable defines the logarithm of the allotment between the electricity cost and the unit electricity produced. A more detailed discussion on how these variables interface in our models is found in the Econometric Analysis section. Data on cumulative electricity output make up the independent variables. We substitute the cumulative electricity output for knowledge acquired through production. Precise characteristics are given in the Econometric Analysis section. Independent variables are lagged by one time period with respect to the logarithm of the electricity cost over the unit electricity produced. The control variables are factored by the year and the state. They encompass data on policy mandates and financial incentives.

Renewable Portfolio Standards

A renewable portfolio standard, also known as renewable electricity standard, is one of the largest state-level policies for the promotion of renewable energy. According to [166], a renewable portfolio standard or RPS is "a regulatory mandate to increase production of energy from renewable sources such as wind, solar, biomass and other alternatives to fossil and nuclear electric generation." Basically, states devise RPS mandates to promote the use of a specific technology through "carve out" provisions. The latter require that a limited percentage of produced electricity originates from non-fossil or nuclear technologies. Several states have already carried through this mandate. However, there are various factors that affect their implementation. For example, each state uses its own criteria to stipulate the technologies found eligible to count towards RPS requirements. Another instance is that state policies diverge when it comes to the sources deemed eligible for RPS effectuation. Some states implement RPS requisites to all its utilities while other states to only its investor owned utilities or IOUs. Besides, ensuring compliance can be a daunting procedure. In some states, enforcement for RPS policies materializes in terms of financial penalties like alternative compliance payments. In other states, it comes in terms of procurement of renewable energy credits for the utilities by a state central agency. All well considered, there are many aspects of RPS mandates that have contributed to the adoption of renewable energy technology within electricity firms. RPS data are shown in Figure 4.1.

This adoption has empirically been translated into knowledge acquisition culminating into job creation and reduced emissions. This explains why many advocates allude to gains in knowledge acquisition for championing RPS policies. Corroborating this point, [168] de-

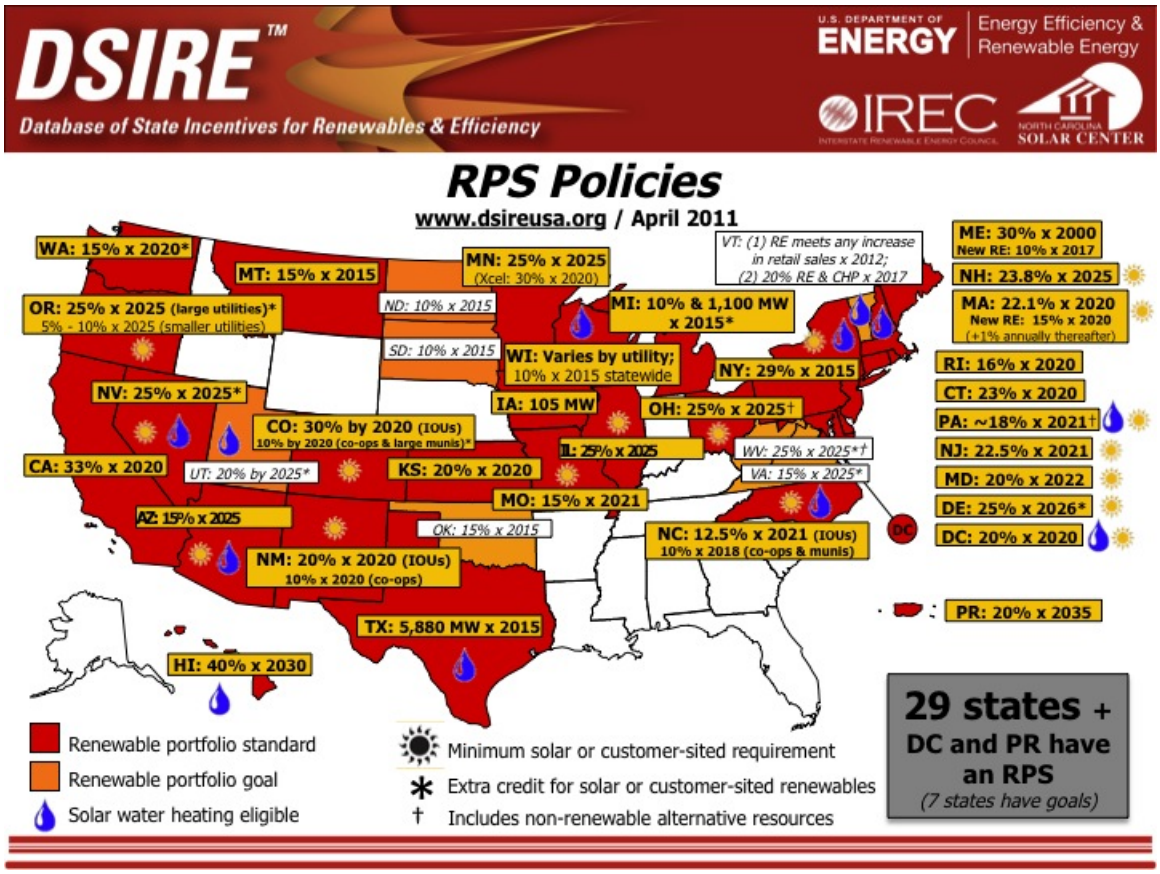

Figure 4.1: Renewable Portfolio Standards
Source: [167]

clares that "one of the key benefits of renewable portfolio standards is to stimulate technology development and provide vital opportunities for learning cost reduction." Some studies have found a positive correlation between RPS policies and the development of new technologies. For that matter, [169] found that RPS mandates have contributed to the growth of wind technologies in Illinois, resulting in electricity firms giving customers more choices with respect to their electricity supplier. Thus, it is evident that the implementation of RPS mandates results in significantly improved and efficient electricity delivery methods and production. A rationale for this could be that RPS regulatory stringency affects how regulated and unregulated generators convolute inside electricity firms. For that matter, process innovation through intra-firm learning is instrumental to electricity generators' increased efficiency. It is tangible that RPS mandates had had positive effects on firm learning as shown by [170] and [171]. They found that Clean Air Act Amendments on environmental regulation have had positive effects "on employment, capital, output, and total factor

productivity." Given that learning occurs across a relative long period of time, assessing RPS impact on learning can be complicate. Moreover, the benefits of learning are usually gradual and take time to emerge. Among others, RPS mandates make up our main control variables.

Republican State Controlled Legislature

State governments have a substantial amount of authority over electricity restructuring in their jurisdictions. In particular, state regulatory mandates over electricity markets have been quite conspicuous in state constitutional provisions and anti-trust laws. However, the challenge for state legislatures has been and still is its capacity to reflect the political preferences of its constituents. Referring to this political dilemma, [172] remarks that "the goal is not to impose a right policy (e.g. promoting efficiency) through a rhetorical back door, but to set up rules that would best reflect constituent views." The question of how much state legislators affect environmental regulations remains and should stay relevant. Consequently, of equal importance is whether states still have the right to dictate the process whereby local retail electricity markets are operated. By and large, the deployment and operation of electricity markets ought to take into consideration localized experimentation in order to mitigate uncertainty and efficiency. To illustrate, [173] recently reported that "a new measure submitted to the Wyoming legislature this week would forbid utilities from providing any electricity to the state that comes from large-scale wind or solar energy projects by 2019. It's an unprecedented attack on clean energy in Wyoming, and possibly the nation. And it comes at a time when such resources are becoming cheaper and increasingly in demand as the world seeks to transition to clean energy to prevent the worst impacts of climate change." Given this state of affairs, admittedly, the political leaning of state legislators cannot be overlooked when examining the role of regulatory mandates.

Inasmuch as the political inclinations of state public utility commissions are weighed, learning dynamics within electricity firms are impacted. Case in point, [174] and [175] both observe that "the ideological makeup of state PUCs (public utility commissions) influences utility management because PUCs with a larger proportion of Republican commissioners tend to make regulatory decisions that are relatively more favorable to utility profits as opposed to consumer welfare and tend to be lax in monitoring utility behavior." Given the effects of republican legislatures on firms' profits, executive salaries and the distribution of

capital within the firms are likely to be affected. A significant repercussion will be observed in the firm's R&D investments strategy. This explains why we hold that, as policy makers, republican state controlled houses and senates are likely to depress learning investments to develop disruptive technologies.

Democratic Governors

PURPA and the Energy Policy Act of 1992 represent the main federal energy legislators in the United States. In the past decades, they have unclosed the wholesale electricity market to competition from independent power producers or IPPs. But, by and large, electricity generation is mostly regulated at the state level. Electricity firms' investments decisions are usually sensitive to prospective instability in regulatory mandates. Most firms would align their investment strategies under a platform that swiftly acclimatizes them to regulatory change. In some cases, firms' decisions strategies will cause regulatory policies to be less effective.

Considering RPS policies for example, their repercussions on investments in renewable generation technology are almost insignificant in states with traditional non-democratic governors. With possibilities for repeal, the inference that policy instability discourages electricity firms from investing in new technologies is receivable. After exploring the impact of state political and institutional agencies on policy instability, [176] finds that "the likelihood of repeal increased with the presence of a democratic governor." He further observes that "firms invest less in new assets in states that have previously passed and repealed legislation to restructure the electricity industry, indicating that perceived regulatory instability reduces new investment and undermines policy goals." Since new investments are the cornerstone of technology progress in electricity markets, we can argue that changes in policy mandates in states could dampen firms' reactions to those policies. Under uncertain business circumstances, [177] and [178] notice that "investing in relationship-specific assets exposes a firm to expropriation hazards." Hence, for most part, electricity firms are obligated to find a way to mitigate risk regardless of the political party in control. Looking at several case studies in five countries, [179] show the significant impact of regulations that tend to "reduce the potential for administrative expropriation to foster private investment." Since democratic governors are more likely to recommend regulations and foster private investments in renewable energy, considering policy mandates in such lights would

be illuminating for future investments strategies.

Renewable Electricity Production Tax Credit

The Renewable Electricity Production Tax Credit is often referred to as PTC and was originally enacted in 1992. According to [180], the Federal Renewable Electricity Production Tax Credit "is an inflation-adjusted per-kilowatt-hour (kWh) tax credit for electricity generated by qualified energy resources and sold by the taxpayer to an unrelated person during the taxable year." Practically, PTCs are federal performance-based incentives. As indicated by [152], they are "credits for onsite use of renewable energy for large-scale renewable energy that is fed into the grid." She further observes that "In relation to renewable energy, corporate investment tax credits are based on initial cost of renewable energy systems, while production tax credits are based on actual energy produced. Therefore, production tax credits can be more effective in incentivizing maximization of energy production over the long term." The primary goal of PTCs is to advance the development of renewable energy technologies. Electricity firms like wind farms have greatly benefited from PTCs. However, PTCs have kept wind energy attractive only to other wind firms thus contributing to the development of the wind turbine technology. This explains why, under the platform of financial incentives, we defend that intra-firm learning is reinforced.

Qualified Energy Conservation Bonds

Better known as QECB, a Qualified Energy Conservation Bond is not a grant but a taxable bond. [181] defines QECB as "a bond that enables qualified state, tribal, and local government issuers to borrow money at attractive rates to fund energy conservation projects." The main objective of QECBs is to decrease energy consumption in publically owned buildings. Since they are taxable bonds, electricity investors have to pay federal taxes on interests received from QECBs. There are two options that make QECBs particularly attractive. The first is that investors can structure their QECBs as bonds on which they can receive federal tax credits instead of interest payments tax credit bonds. The second option is that "investors can directly receive cash rebates from the U.S. Department of the Treasury to subsidize their net interest payments." For electricity firms, QECBs are enticing in that profits derived from them can be used to capitalize expenditures on firms' innovation projects. [181] points that QECBs are great incentives for "implementing

green community programs including loans, grants, or other repayment mechanisms such as efficient street lighting replacements and loan programs for residential energy efficiency improvements." In deciding on picking firms that are eligible for QECBs, special consideration is bestowed on firms with projects that "demonstrate feasibility and readiness and expand economic opportunities ([182])." Hence, notwithstanding that QECBs are employed to promote renewable energy-related research, they contribute to the transfer and acquisition of knowledge only within the firms.

Federal Appliance Standards

The Federal Appliance Standards or FAS set minimum standards of energy efficiency for several appliances. Most of these standards "account for 90 percent of residential energy use, 60 percent of commercial, and 29 percent of industrial usage ([183])." The products covered by FAS range from refrigerators, central AC and HP, gas furnaces, to clothe and dishes washers. Commercial and industrial equipment like electric motors and distribution transformers are also covered. FAS was established by the U.S. Congress in the "Federal Energy Policy and Conservation Act (EPCA) of 1975, and have been subsequently amended by succeeding energy legislation, including the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007 ([184])." FAS foster the development of efficiency standards that will culminate into the best energy savings. Since customers are often motivated by costs, by choosing energy savings products, they could achieve costs saving and efficiency at the same time. But, in some cases, appliances with energy-efficient capability are not as cheap. However, if the electricity price is lower, the customer can still be motivated to opt for an energy efficient appliance. We predict that FAS by itself may not have a strong an effect as expected. Yet, we still hold that it would only favor learning within the electricity firm. Ideally, it would be more effective to let electricity firms themselves incentivize energy-efficient products. This would catalyze innovation into cheaper energy options.

4.3.3 Predictive Analysis: Coal, Gas, Solar, & Wind Technologies

An initial analysis of our dataset shows that, between 1998 and 2010, Investor-Own Utilities have maintained a steady increase in electricity production at a rate comparable to private electricity firms. However, municipalities are slacking at an almost low linear scale

as shown by Figure 4.2.

An examination of Figure 4.3, Figure 4.4, Figure 4.5, and Figure 4.6 shows that after 2008, private electricity firms have substantially decreased their investments in the coal technology. It is interesting that, at around the same time, the same private firms sky-rocketed their investments in the Solar technology. This is demonstrated by Figure 4.5. A question we will be interested at looking at would be whether a transfer of learning has occurred and the role of policy instruments on that potential transfer.

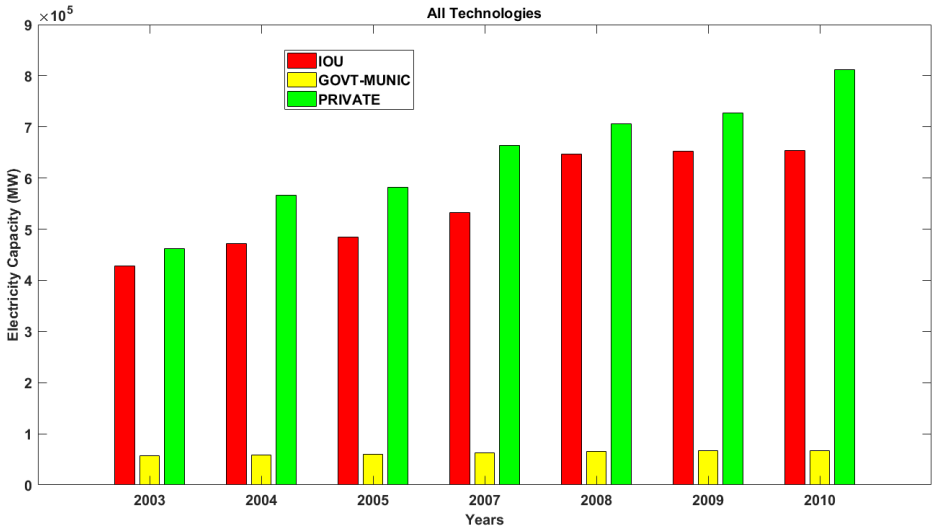

Figure 4.2: Electricity Capacity by Firm Type

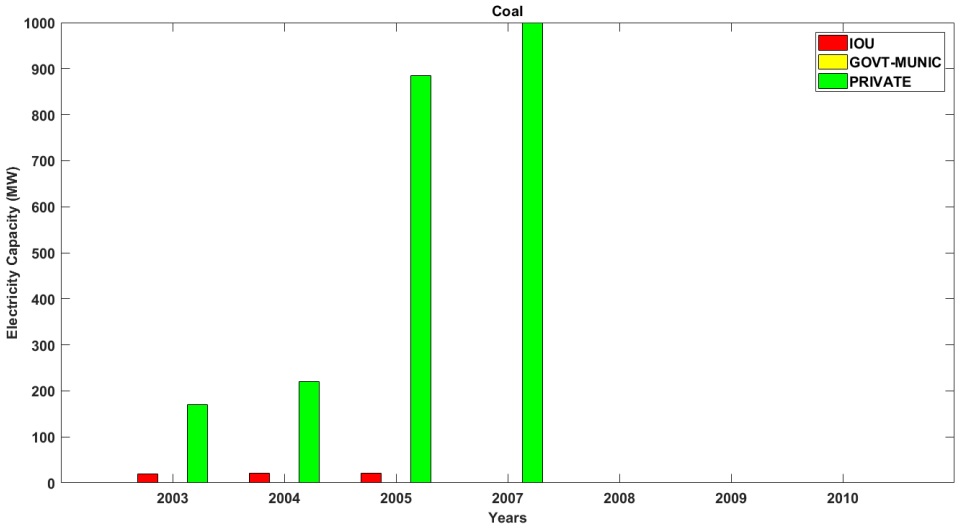

Figure 4.3: Electricity Capacity of Coal by Firm Type

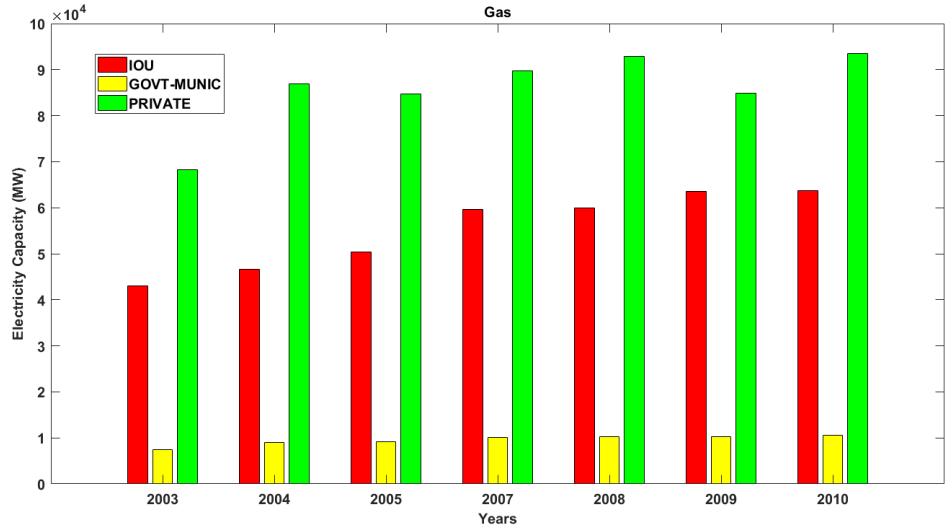

Figure 4.4: Electricity Capacity of Gas by Firm Type

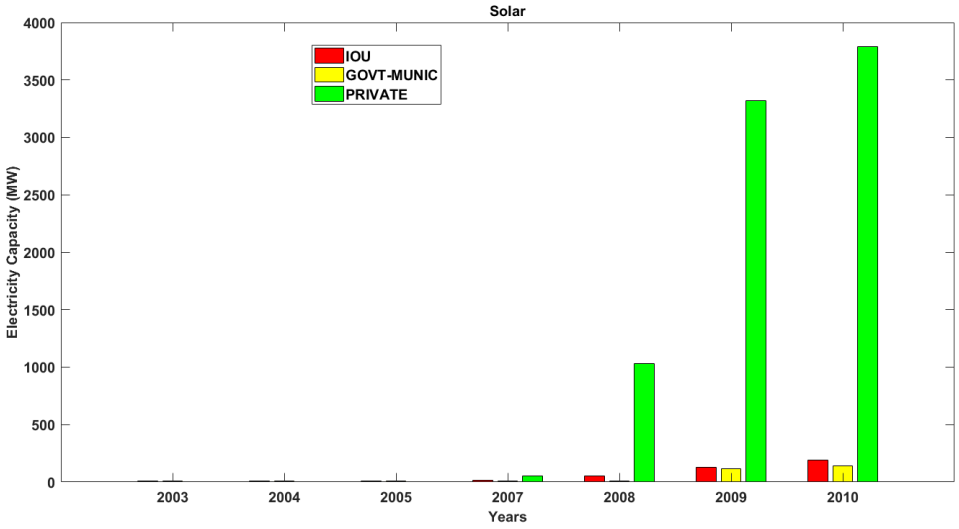

Figure 4.5: Electricity Capacity of Solar by Firm Type

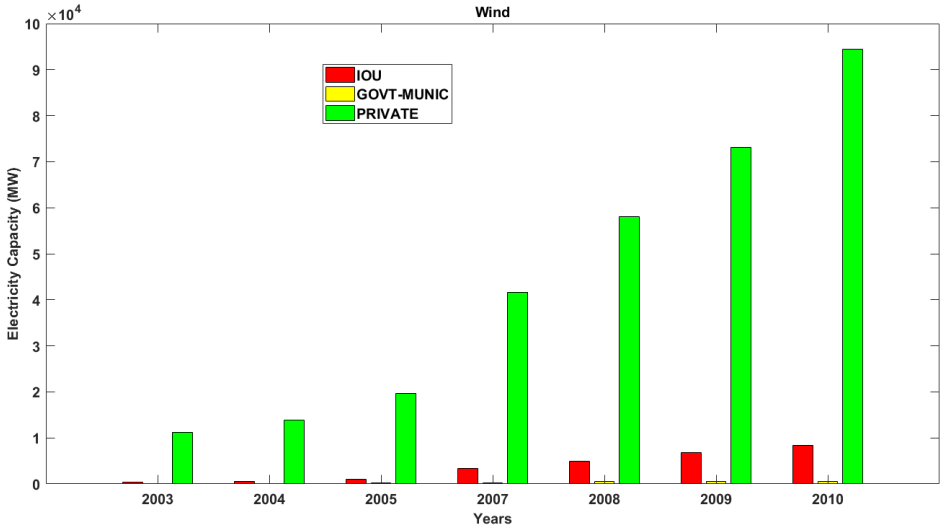

Figure 4.6: Electricity Capacity of Wind by Firm Type

4.4 Econometric Models

We adopt the conventional form of the learning curve ([57]). This framework very well captures the cost reduction in electricity production across different technologies and firms. $\zeta(y)$ is the cost per unit to produce the *y-th* MWh of electricity. It is determined by

$$\zeta(y) = \delta y^{-\beta} \tag{4.4}$$

δ is the cost of producing the first MWh of electricity. y is the cumulative number of electricity units produced. β is a measure of the rate at which costs are reduced as cumulative output increases. β also stands for the learning elasticity. To effectuate the estimation, we linearize equation (4.4) by taking its logarithmic transform such that

$$\log \zeta(y) = \log \delta - \beta \log y \tag{4.5}$$

According to [57], the cumulative output produced is a proxy variable for knowledge acquired through production. Hence, decreasing unit cost can be viewed as a function of organizational knowledge. In this context, the electricity firm's acquired learning is due to technological change. We use this concept to capture the electricity firms' rate of technological learning in specific technologies. The same framework allows us to determine whether the evolution of learning in a given technology is spatial-dependent. The spacial dependency may explain the uncertainties created by policy instruments given their influence on adoption decisions. We will also avail ourself of the [57]'s concept of learning to explain inter-firm and intra-firm franchise learning transfers or spillover effects. Finally, using the formulated framework, we examine the influence of learning on technology adoption decisions.

We capture the electricity industry's specific knowledge in a given technology by aggregating firms' outputs in MW in that technology through time. We explore the impact of state-level policy prescription such as RPS on the learning elasticity for a given technology. According to [185], electricity firms share the properties of franchises. This share-out is explained by the fact that electricity firms operate across their regulated domains. They behave in the same manner in other states where they own independent power plants. Thus, the learning elasticity for a specific firm, the franchisee, may be accounted for by aggregating the cumulative output across all states where that firm has a production plant. This

Nomenclature

$\mathbf{y}$ – cumulative number of units produced
β – measure the rate at which costs are reduced
δ – cost of producing the first MWh of electricity
$\mathbf{k}$ – technology
$\mathbf{i}$ – firm
$\mathbf{s}$ – state
$\mathbf{t}$ – year
$\mathbf{n_{i,t}}$ – number of states
$\mathbf{q_{k,i,s,t}}$ – electricity output
$\zeta_{\mathbf{k,i,s,t}}$ – cost of producing electricity
$\mathbf{R_{s,t}}$ – percentage of RPS mandates
$\mathbf{\Gamma_{s,t}}$ – republican state controlled legislature
$\mathbf{D_{s,t}}$ – democratic governorship
$\mathbf{P_{s,t,k}}$ – renewable electricity production tax credits
$\mathbf{\Delta_{s,t,k}}$ – qualified energy conservation bonds
$F_{\mathbf{s,t,k}}$ – federal appliance standards
$\mathbf{K}$ – number of energy technologies k in the dataset
$\mathbf{N}$ – number of firms i in the study
$\mathbf{Q_{k,i,s,t}}$ – firm-specific knowledge
$\mathbf{FQ_{k,i,t}}$ – proxy for firm-specific knowledge
$\mathbf{FTQ_{k,t}}$ – proxy for inter-firm learning in a specific technology
$\mathbf{CTQ_t}$ – progress of electricity sector in terms of knowledge gained
$\theta_{\mathbf{k,i,s,t}}$ – dummy variable for regression residual
$\xi_{\mathbf{k,i,s,t}}$ – error of the regression estimate

Table 4.3: Nomemclature – Econometric Analysis

approach produces the intra-firm learning elasticity. For inter-firm knowledge estimation, we aggregate the cumulative output across all firms. $Q_{k,i,s,t}$ represents the firm-specific knowledge in a given technology in a given state. It is evaluated using

$$Q_{k,i,s,t} = \sum_{t=0}^{T} q_{k,i,s,t} \tag{4.6}$$

$FQ_{k,i,t}$ is a proxy for firm-specific knowledge in a given technology and is determined by

$$FQ_{k,i,t} = \sum_{s=0}^{n_{i,t}} \sum_{t=0}^{T} q_{k,i,s,t} \tag{4.7}$$

Equation (4.6) captures the cumulative electricity output through year t for a given firm by state of operation s and by technology k. It measures intra-firm learning. We use equations

(4.6) and (4.7) to aggregate a firm's overall output across all states in a given technology k in its portfolio through time t. On the other hand, $FTQ_{k,t}$ is a proxy for inter-firm learning in a specific technology. It represents the knowledge that firms have gained over the years in a specific technology. It also captures the elasticity of knowledge spillover and is given by

$$FTQ_{k,t} = \sum_{i=1}^{N} \sum_{s=0}^{n_{i,t}} \sum_{t=0}^{T} q_{k,i,s,t} \tag{4.8}$$

CTQ_t is a cumulative variable that determines how the electricity sector has progressed in terms of knowledge gained. This determination is done without specific emphasis on the electricity sector technology portfolios. CTQ_t is given by

$$CTQ_t = \sum_{i=1}^{N} \sum_{s=0}^{n_{i,t}} \sum_{k=0}^{K} \sum_{t=1}^{T} q_{k,i,s,t} \tag{4.9}$$

Using least squares regression, we evaluate seven models to probe whether learning has occurred and its associated effects. The matrice equation of the multivariate regression analysis is given by

$$\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \sum_{m=1}^{M} \beta_m \log \overrightarrow{Q} \tag{4.10}$$

The left hand side of (4.10) is the dependent variable. It represents the cost per unit of electricity output by technology, state, and firm. The right hand side is the summation of the appropriate variables in (4.6) – (4.9) .

The basic model is given by

$$\begin{aligned}\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \beta_1 \log(Q_{k,i,s,t+1}) + \beta_2 \log(FQ_{k,i,t+1}) + \beta_3 \log(FTQ_{k,t+1}) + \\ \beta_4 \log(CTQ_{t+1}) + \beta_M \theta_{k,i,s,t+1} + \xi_{k,i,s,t+1}\end{aligned} \tag{4.11}$$

The second model estimates the implications of RPS mandates on knowledge acquisition. It is given by (4.12).

$$\begin{aligned}\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \beta_1 \log(Q_{k,i,s,t+1}) + \beta_2 \log(FQ_{k,i,t+1}) + \beta_3 \log(FTQ_{k,t+1}) \\ + \beta_4 \log(CTQ_{t+1}) + \beta_5 R_{s,t+1} + \beta_M \theta_{k,i,s,t+1} + \xi_{k,i,s,t+1}\end{aligned} \tag{4.12}$$

The third model is evaluated using (4.13). It inquires into the implications of republican state controlled legislatures on learning dynamics within and across electricity firms.

$$\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \beta_1 \log(Q_{k,i,s,t+1}) + \beta_2 \log(FQ_{k,i,t+1}) + \beta_3 \log(FTQ_{k,t+1}) + \beta_4 \log(CTQ_{t+1}) + \beta_5 R_{s,t+1} + \beta_6 \Gamma_{s,t+1} + \beta_M \theta_{k,i,s,t+1} + \xi_{k,i,s,t+1} \tag{4.13}$$

Equation (4.14) assesses the fourth model. It measures the impact of democratic governorships on the acquisition of the learning.

$$\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \beta_1 \log(Q_{k,i,s,t+1}) + \beta_2 \log(FQ_{k,i,t+1}) + \beta_3 \log(FTQ_{k,t+1}) + \beta_4 \log(CTQ_{t+1}) + \beta_5 R_{s,t+1} + \beta_6 \Gamma_{s,t+1} + \beta_7 D_{s,t+1} + \beta_M \theta_{k,i,s,t+1} + \xi_{k,i,s,t+1} \tag{4.14}$$

The fifth model is given by (4.15) and measures the effects of renewable electricity production tax credits.

$$\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \beta_1 \log(Q_{k,i,s,t+1}) + \beta_2 \log(FQ_{k,i,t+1}) + \beta_3 \log(FTQ_{k,t+1}) + \beta_4 \log(CTQ_{t+1}) + \beta_5 R_{s,t+1} + \beta_6 \Gamma_{s,t+1} + \beta_7 D_{s,t+1} + \beta_8 P_{k,s,t+1} + \beta_M \theta_{k,i,s,t+1} + \xi_{k,i,s,t+1} \tag{4.15}$$

Model 6, given by equation (4.16), measures the impact of qualified energy conservation bonds on technology innovation through learning acquisition.

$$\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \beta_1 \log(Q_{k,i,s,t+1}) + \beta_2 \log(FQ_{k,i,t+1}) + \beta_3 \log(FTQ_{k,t+1}) + \beta_4 \log(CTQ_{t+1}) + \beta_5 R_{s,t+1} + \beta_6 \Gamma_{s,t+1} + \beta_7 D_{s,t+1} + \beta_8 P_{k,s,t+1} + \beta_9 \Delta_{k,s,t+1} + \beta_M \theta_{k,i,s,t+1} + \xi_{k,i,s,t+1} \tag{4.16}$$

Finally, the last model is assessed by equation (4.17). It accounts for the effects of federal

appliance standards.

$$\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \beta_1 \log(Q_{k,i,s,t+1}) + \beta_2 \log(FQ_{k,i,t+1}) + \beta_3 \log(FTQ_{k,t+1}) + \beta_4 \log(CTQ_{t+1}) + \beta_5 R_{s,t+1} + \beta_6 \Gamma_{s,t+1} + \beta_7 D_{s,t+1} + \beta_8 P_{k,s,t+1} + \beta_9 \Delta_{k,s,t+1} + \beta_{10} F_{k,s,t+1} + \beta_M \theta_{k,i,s,t+1} + \xi_{k,i,s,t+1} \tag{4.17}$$

4.5 Results

The first three coefficients assess firm-specific learning, intra-firm learning and inter-firm learning, respectively. The fourth coefficient evaluates the degree of innovation in the electricity sector. In this case, innovation is progress measured in terms of knowledge gained without specific emphasis on technology portfolios. The last six coefficients estimate the impact of policies mandates and financial incentives.

4.5.1 Residual Analysis

The examination of the residuals of the coal technology shows evidence of normal distribution. This is shown by the "Normal probability plot" of residuals in Figure 4.7. The

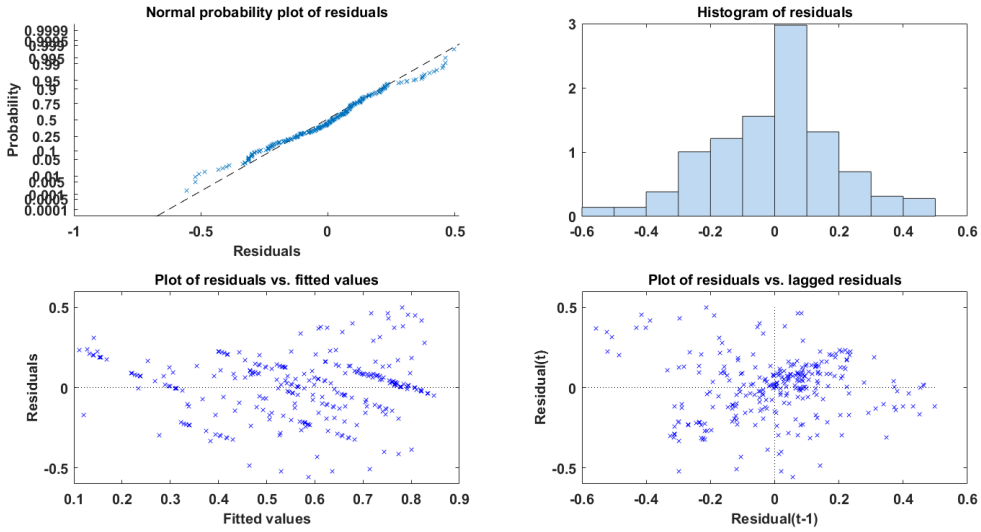

Figure 4.7: Residual Analysis - Coal Technology

"Histogram of residuals" displays symmetric residuals, which confirms a reasonable fit to normally distributed residuals. From the "Plot of residuals vs fitted values", we observe that there are few unusual points in comparison with points that lie together. Hence, the varia-

tion around the estimated regression line is constant. This is confirmation of an acceptable level of homoscedasticity. The "Plot of residuals vs lagged residuals" exhibits no specific pattern in the residuals. This validates independence amongst the residuals. Accordingly, there is no plausible evidence of autocorrelation. This is confirmed by the Durbin-Watson test. For a confidence level of $\alpha = 0.05$, the Pvalue (0.4114) of the residuals in the coal technology is less than the Durbin-Watson t statistic ($1.9381 \approx 2$).

The initial analysis of the residuals of the gas technology does not uncover normality. For remedy, we create a new regression matrix of explanatory variables by lagging the column vector of the original regression matrix. The number of observations is truncated from 24,368 to 9,368. The resulting residuals are analyzed in Figure 4.8. This procedure also

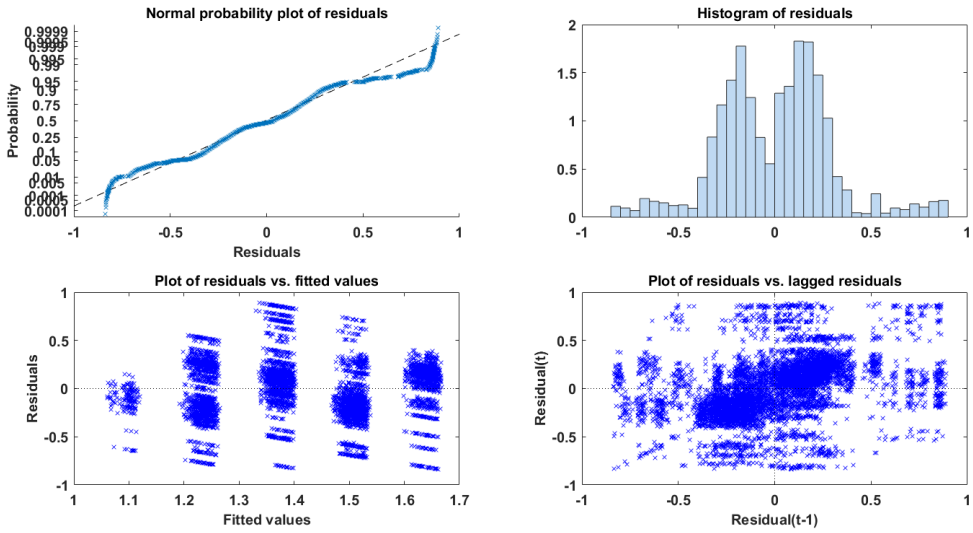

Figure 4.8: Residual Analysis - Gas Technology

rectifies the serial correlation. Using the Durbin-Watson test, we find a t-statistic closer to 2 than the original Durbin-Watson t-statistic. This reduces autocorrelation since the closer to 2 the Durbin-Watson t-statistic is, the less autocorrelation.

We use the same procedure for the solar and wind technologies. The only difference in this case is that we do not lose as much observations as with the gas technology. The analysis are illustrated in Figure 4.9 and Figure 4.10 for the solar and wind technologies, respectively.

A broad analysis of the coefficients of determination R-squared shows heterogeneity among the models across the technologies. For the coal technology, the average coefficient of determination is 0.6. This indicates a non-negligible degree of variability between the

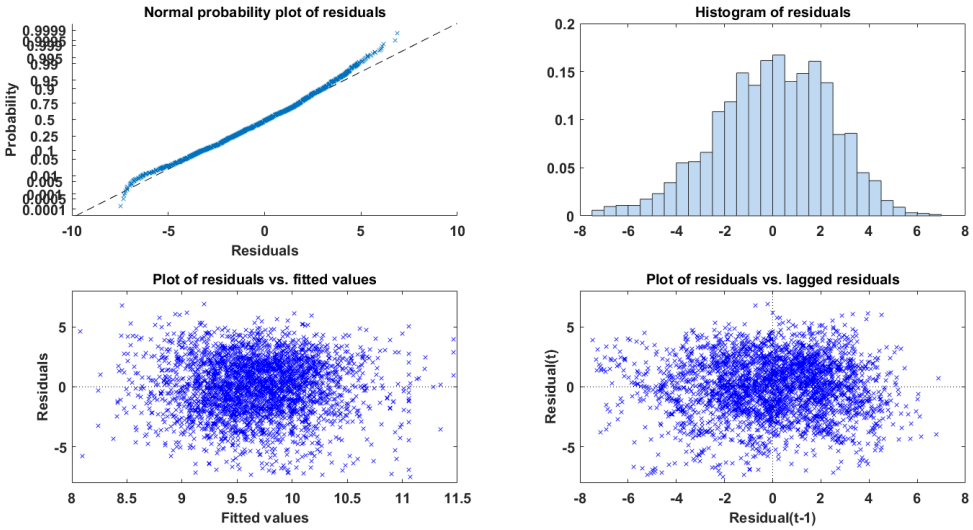

Figure 4.9: Residual Analysis - Solar Technology

response and explanatory variables. The gas technology exhibits an average R-squared of 0.2. For the solar and wind technologies, the average coefficient of determination stands at 0.1. Insofar as R-squared is non-trivial, the regression coefficients correlate to the mean change in the response of a unit of electricity produced. By and large, across all technologies, we see a stronger coefficient of determination when policy instruments are introduced as displayed in Tables 4.4 through 4.7. This indicates that the degree of variability between the response and explanatory variables gets more acute when policies come into play.

We estimate all coefficients in seven main models. The first model is basic while the second model accounts for RPS mandates. The third and fourth model inspect the impacts of republican state controlled legislatures and democratic governorships, respectively. The fifth model examines the effects of renewable electricity production tax credits. The qualified energy conservation bonds are investigated in the sixth model while the effects of the federal appliance standards are analyzed in the seventh model.

4.5.2 Hypothesis 1

β_1 represents the coefficient for firm-specific learning. The results for the solar technology are displayed in Table 4.6. Under the foundational model (Model 1), β_1 is noticeably negative [1]. This simply shows that improvements to existing technology are brought about by the acquisition of new knowledge, culminating into declining costs. In all models, knowl-

[1] 99% confidence interval

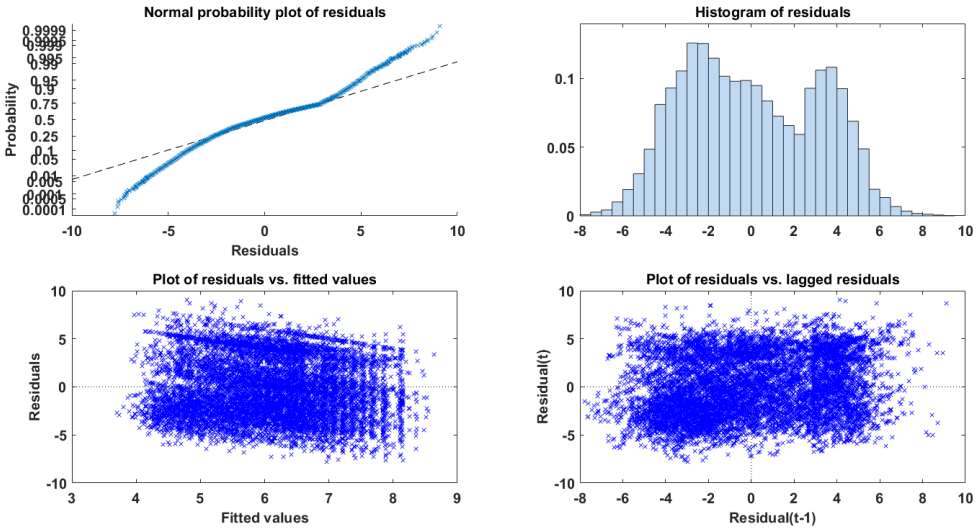

Figure 4.10: Residual Analysis - Wind Technology

edge acquisition occurs through cumulative installed electricity capacities. β_2 stands for the coefficient for intra-firm learning. The negative sign of β_2 indicates that intra-firm knowledge acquisition elucidates the reduction in the unit cost of electricity production. Furthermore, we observe that, as β_1 becomes significantly more negative (model 5 to model 6), β_2 increases[2]. The same finding is verified from model 5 to model 7. Thus, hypothesis 1 is justified all the more as empirical research shows that successful enhancements to current technology are accompanied by declining costs ([186]).The ensuing observation is that electricity firms in the solar technology tend to reinforce learning within themselves. Consequentially, collaborations with other firms investing in the solar technology dampen. However, [187] point that, ideally, cooperation among firms should eventually allow them to successfully mitigate challenges related to technological improvement. Comparably, [163] report how "firms can improve their innovative performance by taking advantage of knowledge residing in networks of external stakeholders." Sorrowfully, by concentrating all their efforts into internal knowledge acquisition, solar firms are least likely to collaborate with other firms.

4.5.3 Hypothesis 2

β_3 is the coefficient for inter-firm learning. From Table 4.6 (Solar technology), we observe that β_3 increases while β_1 becomes more significantly negative from model 5 (production

[2]95% confidence interval

COAL							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1) (p-Values)	-0.0838 (0.0004)	-0.0825 (0.0006)	-0.0700 (0.0006)	-0.0703 (0.0006)	-0.0583 (0.0053)	-0.0555 (0.0083)	-0.0573 (0.0074)
Intra-Firm Learning (β_2) (p-Values)	0.0786 (0.0016)	0.0772 (0.0026)	0.0625 (0.0037)	0.0628 (0.0036)	0.0555 (0.0105)	0.0524 (0.0163)	0.0544 (0.0144)
Inter-Firm Learning (β_3) (p-Values)	-0.1177 (0.3209)	-0.1172 (0.3239)	-0.1042 (0.2948)	-0.1035 (0.299)	-0.1058 (0.2852)	-0.1066 (0.2813)	-0.1079 (0.2765)
Technology Progress (β_4) (p-Values)	0.1578 (0.0878)	0.1579 (0.0882)	0.1531 (0.0483)	0.1522 (0.0505)	0.1573 (0.0421)	0.1599 (0.0387)	0.1603 (0.0385)
RPS Target Percentage (β_5) (p-Values)		0.0173 (0.8208)	-0.3690 (0.0000)	-0.3634 (0.0000)	-0.3343 (0.0000)	-0.1969 (0.1427)	-0.2450 (0.1435)
Republican State Legislature (β_6) (p-Values)			-0.4101 (0.0000)	-0.4103 (0.0000)	-0.4153 (0.0000)	-0.4162 (0.0000)	-0.4174 (0.0000)
Democratic Governor (β_7) (p-Values)				-0.0044 (0.8429)	-0.0070 (0.7546)	0.0101 (0.6967)	0.0115 (0.6613)
Production Tax Credit (β_8) (p-Values)					-0.0000 (0.0326)	-0.0000 (0.0328)	-0.0000 (0.0355)
Qualified Energy Bonds (β_9) (p-Values)						-0.0000 (0.2059)	-0.0000 (0.1941)
Federal Appliance Standards (β_{10}) (p-Values)							-0.0026 (0.6294)
R-Squared (R^2)	0.461	0.461	0.624	0.624	0.63	0.633	0.633
289 observations of 5,573 U.S. electricity firms over a period spanning 13 years							

Table 4.4: Econometric Analysis Results – Coal Technology

tax credits) to model 6 (qualified energy bonds). Model 5 (production tax credits) to model 7 (federal appliance standards) elicits the same result. These findings evoke a reasonable evidence that more financial incentives for solar technology are likely to strengthen technological improvement under the framework of inter-firm learning. From Table 4.7 (Wind technology), β_3 increases from model 5 (production tax credits) to model 6 (qualified energy bonds) and to model 7 (federal appliance standards). Concomitantly, β_1 gets more significantly negative from model 5 (production tax credits) to model 6 (qualified energy bonds) and to model 7 (federal appliance standards). These findings attest that, to a measurable extent, for the wind technology, financial incentives are proportional to the level of technological progress when knowledge is shared across firms. Consequently, hypothesis 2 is corroborated.

GAS							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1) (p-Values)	0.0042 (0.0000)	0.0045 (0.0000)	0.0045 (0.0000)	0.0046 (0.0000)	0.0041 (0.0006)	0.0041 (0.0006)	0.0040 (0.0008)
Intra-Firm Learning (β_2) (p-Values)	-0.0007 (0.4628)	-0.0008 (0.4516)	-0.0007 (0.473)	-0.0007 (0.4713)	-0.0007 (0.4743)	-0.0007 (0.4746)	-0.0008 (0.4417)
Inter-Firm Learning (β_3) (p-Values)	-6.5461 (0.1743)	-6.3964 (0.1844)	-6.5884 (0.1714)	-6.7593 (0.1606)	-6.7703 (0.1599)	-6.7729 (0.1598)	-6.4979 (0.1774)
Technology Progress (β_4) (p-Values)	5.6617 (0.1453)	5.5410 (0.1541)	5.6987 (0.1426)	5.8376 (0.1332)	5.8465 (0.1326)	5.8486 (0.1325)	5.6274 (0.1477)
RPS Target Percentage (β_5) (p-Values)		0.0292 (0.0987)	0.0580 (0.0035)	0.0611 (0.0022)	0.0613 (0.0021)	0.0621 (0.0099)	0.0774 (0.0017)
Republican State Legislature (β_6) (p-Values)			0.0244 (0.0014)	0.0266 (0.0006)	0.0266 (0.0006)	0.0267 (0.0008)	0.0303 (0.0002)
Democratic Governor (β_7) (p-Values)				0.0106 (0.0886)	0.0106 (0.0885)	0.0106 (0.0895)	0.0107 (0.0853)
Production Tax Credit (β_8) (p-Values)					0.0000 (0.4661)	0.0000 (0.4657)	0.0000 (0.5427)
Qualified Energy Bonds (β_9) (p-Values)						-0.0000 (0.9567)	0.0000 (0.3217)
Federal Appliance Standards (β_{10}) (p-Values)							0.0023 (0.0034)
R-Squared (R^2)	0.224	0.224	0.225	0.225	0.225	0.225	0.226
9,368 observations of 5,573 U.S. electricity firms over a period spanning 13 years							

Table 4.5: Econometric Analysis Results – Gas Technology

4.5.4 Hypothesis 3

β_4 is the coefficient for the progress of the electricity sector in terms of knowledge gained. β_5 quantifies the effects of the renewable portfolio standard mandates. In Table 4.6 (Solar technology), we observe that as β_5 gets more exacting (model 5 to model 2), technological progress (β_4) decreases. However, β_4 remains idem in Table 4.7 (Wind technology) as RPS mandates become pronounced (model 6 to model 7). Therefore, in face of RPS stringency, the response of β_4 is versatile. Our hypothesis 3 is supported. [156] and [155] have also uncovered asymmetries associated with progress in technological learning acquisition. However, contexts in which electricity firms seek to adapt to RPS mandates are crucial in achieving technological progress.

SOLAR							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1) (p-Values)	-0.1394 (0.0000)	-0.1288 (0.0000)	-0.1291 (0.0000)	-0.1303 (0.0000)	-0.0995 (0.0000)	-0.1045 (0.0000)	-0.1045 (0.0000)
Intra-Firm Learning (β_2) (p-Values)	-0.0394 (0.0123)	-0.0294 (0.0615)	-0.0295 (0.0605)	-0.0301 (0.0555)	-0.0317 (0.0436)	-0.0316 (0.0435)	-0.0315 (0.0445)
Inter-Firm Learning (β_3) (p-Values)	1.9000 (0.0000)	1.9206 (0.0000)	1.9195 (0.0000)	1.8632 (0.0000)	1.8651 (0.0000)	1.8720 (0.0000)	1.8734 (0.0000)
Technology Progress (β_4) (p-Values)	-1.2515 (0.0000)	-1.2852 (0.0000)	-1.2856 (0.0000)	-1.2633 (0.0000)	-1.2724 (0.0000)	-1.2763 (0.0000)	-1.2778 (0.0000)
RPS Target Percentage (β_5) (p-Values)		1.3785 (0.0000)	1.3157 (0.0000)	1.3512 (0.0000)	1.2521 (0.0000)	-0.0140 (0.9742)	0.0190 (0.9655)
Republican State Legislature (β_6) (p-Values)			-0.0499 (0.7249)	-0.0804 (0.5741)	-0.1234 (0.3892)	-0.3122 (0.0384)	-0.3146 (0.037)
Democratic Governor (β_7) (p-Values)				-0.1454 (0.1075)	-0.1619 (0.0732)	-0.1659 (0.0656)	-0.1663 (0.0652)
Production Tax Credit (β_8) (p-Values)					-0.0002 (0.0006)	-0.0002 (0.0006)	-0.0002 (0.0005)
Qualified Energy Bonds (β_9) (p-Values)						0.0000 (0.0001)	0.0000 (0.0001)
Federal Appliance Standards (β_{10}) (p-Values)							0.0054 (0.6777)
R-Squared (R^2)	0.0371	0.0483	0.0483	0.0491	0.0527	0.0575	0.0575
3,122 observations of 5,573 U.S. electricity firms over a period spanning 13 years							

Table 4.6: Econometric Analysis Results – Solar Technology

4.5.5 Hypothesis 4

We hold that technological progress (β_4) is maximized with firms investments in knowledge acquisition. β_6 measures the impact of clean energy policies ratified by republican state legislatures across all states. From Table 4.4 (Coal technology), we observe that as RPS mandates (β_5) are strengthened, technological progress (β_4) decreases (model 3 to model 4). But, under the same circumstances, the impact of republican state legislatures (β_6) is less acute. Still, in Table 4.6 (Solar technology), as RPS mandates (β_5) get more exacting, technological progress (β_4) becomes greater (model 3 to model 4). The same phenomena is quite reiterated in Table 4.5 (Gas technology) where RPS mandates (β_5) increases from model 4 to model 5. Yet, β_6 is unchanged. The ensuing effects create ambivalence among firms as to whether their investments in learning acquisition will pay off or not. The resulting uncertainty subsequently fosters our hypothesis 4. A forceful consequence is the resulting general state of dubiety. The latter is generated by the complexity of measuring the real

WIND							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1) (p-Values)	-0.2333 (0.0000)	-0.2306 (0.0000)	-0.2381 (0.0000)	-0.2378 (0.0000)	-0.2125 (0.0000)	-0.2327 (0.0000)	-0.2327 (0.0000)
Intra-Firm Learning (β_2) (p-Values)	0.0054 (0.5558)	0.0053 (0.5639)	0.0034 (0.7382)	0.0037 (0.7136)	0.0030 (0.764)	0.0043 (0.6672)	0.0043 (0.6673)
Inter-Firm Learning (β_3) (p-Values)	-1.2220 (0.0000)	-1.2127 (0.0000)	-1.3288 (0.0000)	-1.3098 (0.0000)	-1.2645 (0.0000)	-1.2094 (0.0000)	-1.2094 (0.0000)
Technology Progress (β_4) (p-Values)	0.7520 (0.0001)	0.7445 (0.0001)	0.8378 (0.0000)	0.8250 (0.0001)	0.7968 (0.0001)	0.7429 (0.0003)	0.7429 (0.0003)
RPS Target Percentage (β_5) (p-Values)		0.2160 (0.2025)	0.3392 (0.1259)	0.3390 (0.1261)	0.4137 (0.0622)	-1.5804 (0.0000)	-1.5791 (0.0000)
Republican State Legislature (β_6) (p-Values)			0.0792 (0.3945)	0.0979 (0.2984)	0.1215 (0.197)	-0.0900 (0.3443)	-0.0899 (0.3472)
Democratic Governor (β_7) (p-Values)				0.0863 (0.2137)	0.0949 (0.1712)	-0.0210 (0.7627)	-0.0209 (0.7655)
Production Tax Credit (β_8) (p-Values)					-0.0000 (0.0000)	-0.0001 (0.0083)	-0.0001 (0.0083)
Qualified Energy Bonds (β_9) (p-Values)						0.0000 (0.0000)	0.0000 (0.0000)
Federal Appliance Standards (β_{10}) (p-Values)							0.0001 (0.9886)
R-Squared (R^2)	0.0854	0.0856	0.0932	0.0933	0.0958	0.106	0.106
10,333 observations of 5,573 U.S. electricity firms over a period spanning 13 years							

Table 4.7: Econometric Analysis Results – Wind Technology

effects of policy instruments on learning dynamics. Among other things, [176] indicates that histories of policies adoptions and reversals increase uncertainties and hazards in electricity markets. In such an environment, learning investments are likely to be depressed, which ultimately affect the capacities of electricity firms to develop disruptive technologies.

4.5.6 Technologies Learning Rates

We compute the learning rates for the coal, gas, solar, and wind technologies using formula (4.18) from [188]. In (4.18), 2^{β_1} is the technology progress ratio where β_1 is the coefficient for firm-specific learning. All results are illustrated in Figure 4.11.

$$1 - 2^{\beta_1} \tag{4.18}$$

Learning rate is a fundamental concept in technological learning. As shown by [188], it represents "the fractional reduction in cost for each doubling of cumulative" production of

electricity. We find that RPS mandates, more than some financial incentives, have a positive effect on the solar technology learning rate. This is shown in Figure 4.11. The finding isn't as surprising since the market penetration for solar technology is not as considerable as other technologies. For that matter, [186] reveal that, with relevant policies, renewable such as solar can achieve higher learning rate. They further point to possible decreases in electricity costs that such policies could bring about. Furthermore, in a notable study, [189] observes that solar technology was the largest source of RPS mandates in recent years. The study points to the creation of successful "residential solar program funded through RPS" as being the main reason behind this attainment. However, as shown in Figure 4.11, compared to wind, much as yet to be accomplished to boost learning rate in solar technology. Interestingly, we saw in Figures 4.5 and 4.6 that investments in the solar and wind technologies have skyrocketed since 2008. Therefore, policy instruments could successfully be wielded to speed up transfer of learning from some technologies to others.

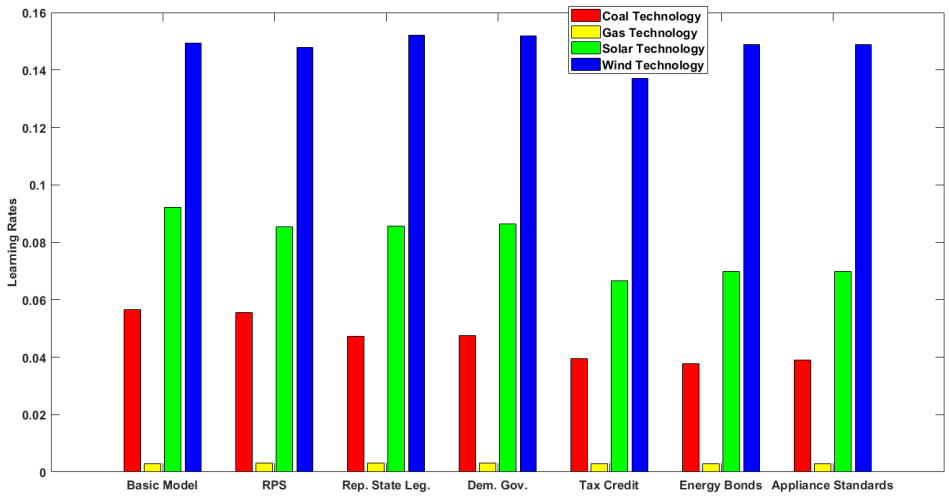

Figure 4.11: Technology Learning Rates

Also, as demonstrated by Figure 4.11, we observe that Republican State Controlled Legislature and Democratic Governorship do not significantly affect the learning rates of clean technologies such as solar and wind. [190] recently published a study demonstrating that "solar adoption rate among the two parties" is about the same. The study reports that in some states, "Republicans were even more likely to have solar installed than their democratic neighbors." Additionally, we perceive that financial incentives are quite successful in boosting learning rate in the wind technology as shown in Figure 4.11. Particularly,

qualified energy conservation bonds and federal appliance standards are the most efficient incentives in that regard.

Chapter 5 Conclusion

5.1 Discussion

It is noteworthy that, in the face of uncertain demand and supply, fuel cells are attractive when it comes to minimizing Costs & CO_2 emissions. Ideally, a combination of fuel cells and natural gas generates a clean and cost-efficient electricity. The adoption of storage contributes even to a greater reduction of CO_2 emissions. Interestingly, [191] shows that some of the most effective ways to decrease CO_2 emissions consist in installing onsite generators that possess less carbon emissions rates than the grid. Fiscal incentives can be used to encourage the adoption of DER technologies such as fuel cells and natural gas. So, government agencies should investigate the impact of carbon tax on the microgrids decision to invest in DER technologies such as fuel cells given uncertainty. However, [192] remark that associating CO_2 emissions with electricity consumption encounters several major complications.

One of these lies in the fact that electricity can be produced out of numerous energy sources. Some of these actually emit a substantial amount of CO_2 emissions like coal combustion. Our work shows that, when dealing with supply and demand uncertainty, with fuel cells and natural gas, it is well possible to minimize costs and CO_2 emissions when using electricity for consumption. On the other hand, in our model, we find that microturbines are appealing when the objective of the microgrid operator is to reduce costs under uncertain demand and supply. In effect, we saw that microturbines are likely to be dispatched when the electricity price is low. It is worth pointing that [15] obtains the same results although they deal with a more deterministic approach within the DERCAM. We also saw that batteries must be charged during mid-peak hours in order to reduce electricity costs. This is also attested by [193], who observe that battery charging satisfies the operator's objective to minimize electricity costs.

The potential of microturbines to inflate CO_2 emissions is quite high compared to fuel

cells and natural gas. According to [194], some microturbines emit about 2,000 lb/MWh of CO_2 emissions while natural gas produces about 800-900 lb/MWh. In the interval, we saw that, for lesser capital and maintenance costs, the microgrid operator could dispatch microturbines. Even [195] have observed that further reductions of CO_2 emissions will be realized at the price of economic growth. Hence, mitigating CO_2 emissions while ensuring satisfactory economics of operation under uncertainty remains a conundrum. A potential solution could lie in technological learning.

But the question as to whether technological innovation is the main driver behind decreasing costs of electricity productions is still abridged. [196] carefully examine this problem. They indicate that "technical change unrelated to economies of scales deserves the primary attribution for declines in the cost of production." If that was true between 1955 and 1970, it may not necessarily be so today. An even more compelling query is whether empirical data proves it. That is a relevant question left for future study.

All the while, we find that financial incentives are good motivators when it comes to implementing renewable energy technologies. Nonetheless, as discussed in [152], a key challenge facing policy makers is to align each financial incentive with each state's, county's, and city's circumstances. This is rather intricate yet necessary for better efficiency and risk management. An unintentional consequence of policy mandates is its likelihood to be repealed under a different administration with opposed priorities. The uncertainties created by the adopt-repeal push-pull dampen firms' ability and willingness to invest into new renewable technologies. Hence, designing models that would bring about strategies that are immune to changes in policies are needed. Our study has not been successful in deriving such a model. [176] elaborates on the problem and offers some hints for future works. Finally, as pointed by [137], although we find asymmetries in learning acquisition in some electricity technologies, we do not propose a solution to those asymmetries. The burning issue of environmental regulation and firms' fundamental desire to maximize profits may always collide on the altar of knowledge asymmetries in the electricity market.

5.2 Conclusion

We modify the Benders' model to investigate the policy and economic effects of the management of microgrids in the face of simultaneous uncertainties in demand and supply. We consider a microgrid made of a unit of flexible loads, 4 dispatachable units, and a bat-

tery system for storage. We ascertain that the power generated by the units fulfills all the operational and technological constraints. Applying the outcomes of a quantitative numerical analysis, we illustrate the practicality of our proposed solution procedure to minimize costs and CO_2 emissions. Equally, we employ the same modified Benders' approach to the microgrid O&M costs reduction. We show that the fuel cells and natural gas technologies are cost-efficient and climate friendly, and that microturbines could be economically viable technologies under simultaneous stochastic demand and supply. We discover that, under uncertain demand, diesel and microturbines units are more likely to be committed at on-peak hours, which is not always favorable to the reduction of greenhouse gas emissions. We further observe a greater reliance of the microgrid on the main grid under supply and demand uncertainties for both O&M costs and CO_2 emissions minimization. The main policy implication of our work lies in that carbon abatement policy can be used as a way to motivate investors and operators to include natural gas and fuel cells technologies in microgrids projects in order to successfully manage the risks caused by uncertainty. In a time when the issue of climate change is globally becoming emotionally and politically charged, our work is consequential in that it simultaneously captures demand and supply uncertainties. As such, it unlocks a strategy for a proper mitigation of the effects of CO_2 emissions. In the wake of the climate change summit in Paris, our work provides a quantitative argument as to the very possibility of reducing CO_2 emissions in dispatching fuel cells and natural gas technologies and scheduling storage units in the face of uncertainty. To manage the latter, a more deterministic strategy consists in using regression analysis.

That explains why we also carried out seven regression models within a Matlab object script file. The models enable a longitudinal study of 5,573 U.S. electricity firms operating from 1998 through 2010. Our examination uncovers asymmetries and heterogeneities in learning dynamics within and across electricity firms in the U.S. We bring to light the positive relationship between the acquisition of new knowledge through intra-firm learning in electricity firms and the enhancement of existing technology. We consequently deduce the association between inter-firm learning across electricity firms with radical breakthroughs in knowledge acquisition and technological innovation. We unravel the complexity of complying with policy instruments. We specifically notice that as electricity firms seek ways to comply with policy instruments, the progress of the electricity sector in terms of knowledge acquisition is asymmetric for solar technologies. Finally, we gauge the strains created by

federal financial incentives and regulatory policies by their susceptibility to induce uncertainties in technologies improvement and development. We thus bring to light the general havoc generated by those uncertainties in depressing learning investments to develop disruptive new technologies.

Our work is illuminating in that it draws out the criticalness of knowledge collaboration across firms in developing disruptive technologies. Moreover, our study demonstrates that learning rates of some technologies such as solar and wind, are insensitive to republican or democratic leaderships. The policy implications of this study can be clustered into four main aspects. First, policy mandates and financial incentives should continue to be promoted because they have a positive impact on technological innovation. Second, states should be given more monopoly in managing financial incentives such as production tax credits for better effects on technological innovation in developing new renewable energies. Third, federal regulators should seek worthier strategies to incentivize electricity firms to collaborate across them in order to foster the development of disruptive technologies while still effectively responding to policy mandates. Fourth, given the economic benefits of pollution emissions reductions, much is yet to be done policy-wise to spur progress in the development of solar and wind technologies.

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