Managing Distributed Information:

Implications for Energy Infrastructure Co-production

by

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ABSTRACT

The Internet and climate change are two forces that are poised to both cause and enable changes in how we provide our energy infrastructure. The Internet has catalyzed enormous changes across many sectors by shifting the feedback and organizational structure of systems towards more decentralized users. Today's energy systems require colossal shifts toward a more sustainable future. However, energy systems face enormous socio-technical lock-in and, thus far, have been largely unaffected by these destabilizing forces. More distributed information offers not only the ability to craft new markets, but to accelerate learning processes that respond to emerging user or prosumer centered design needs. This may include values and needs such as local reliability, transparency and accountability, integration into the built environment, and reduction of local pollution challenges.

The same institutions (rules, norms and strategies) that dominated with the hierarchical infrastructure system of the twentieth century are unlikely to be good fit if a more distributed infrastructure increases in dominance. As information is produced at more distributed points, it is more difficult to coordinate and manage as an interconnected system. This research examines several aspects of these, historically dominant, infrastructure provisioning strategies to understand the implications of managing more distributed information. The first chapter experimentally examines information search and sharing strategies under different information protection rules. The second and third chapters focus on strategies to model and compare distributed energy production effects on shared electricity grid infrastructure. Finally, the fourth chapter dives into the

literature of co-production, and explores connections between concepts in co-production and modularity (an engineering approach to information encapsulation) using the distributed energy resource regulations for San Diego, CA. Each of these sections highlights different aspects of how information rules offer a design space to enable a more adaptive, innovative and sustainable energy system that can more easily react to the shocks of the twenty-first century.

DEDICATION

This dissertation is dedicated to everyone who

struggles with societies categorical boxes

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INTRODUCTION: GETTING ELECTRICITY INFRASTRUCTURE

TO TRANSFORM; FASTER

1.1 Introduction

The need to transform our energy system is a core sustainability challenge. The complexity of the challenge is such that the drive to transform it may arise from needs that can be described as economic, physical well-being, environmental, socio-political, cultural and a myriad of complexities and compounding dynamics (Holdren, 2006). In order to meet this challenge, society must innovate, both technically and socially (Nill and Kemp, 2009; Verbong and Geels, 2010). This challenge requires both remaking a mountain of existing inertia, inherent in the current state, as well as exploring unknown terrain, filled with of uncertainty.

Exploring this unknown terrain has been described as crossing a valley of death. The term ‘valley of death’ has been used to describe the difficulty of mitigating risk and uncertainty for new innovations as they move out of basic science labs towards commercialization. When a new idea or technology is in its formative stages it is usually supported by research funding intended to demonstrate a limited prototype or proof of concept. The commercialization phase requires demonstration of a potential market, which requires design iterations and feedback. Between the two stages there is both high risk of failure and high uncertainty of eventual success which makes attracting financing problematic (Lerner, 2000). The severity of the valley of death is particularly severe in the energy industry due to 1) the lack of competitive niches in which new technologies and social systems can be tested, improved and take root, 2) the enormous information asymmetry between producers and consumers, 3) the scale of capital and risk tolerance required for any innovation, 4) the status as a regulated infrastructure which must provide reliability and affordability for dependent users (Beard et al., 2009; Murphy and Edwards, 2003).

While many initiatives have sought to mitigate the high risk associated with energy innovation research through public funding of research and demonstration projects, others have stressed the importance of developing networks to re-organize the scope, scale and benefits of testing, learning and potential failure to be better supported and inline with evolutionary theories of adaptation (Kemp, Rotmans, & Loorbach, 2007; Rennings, 2000; Wallner, 1999). Observations from strategic niche management, research on innovation clusters, and ecological economics have all pointed to the fact that, for sustainable innovations, context and networks matter. The premise of this work is that co-production of energy infrastructure can help to illuminate more pathways through the valleys of uncertainty, thereby allowing society to more quickly reduce the uncertainty needed to transition our energy system.

1.2 Why Co-production?

In this work I consider how energy infrastructure may become more adaptable by enabling co-production at additional scales to those levels of organization that have been dominant over the past century (Bakke, 2016). Elinor Ostrom defined co-production as, "The process through which inputs used to provide a good or service are contributed by individuals who are not "in" the same organization" (Ostrom, 1996). Since then the use of the term has expanded to include newer vernacular such as the "peer-production" or "prosumption" which has become especially popular with the advent of open source software, blockchains, wikipedia, sharing businesses, hacker and maker spaces and other mixed or distributed production and consumption models (Benkler, 2006; Benkler et al., 2013; Humphreys and Grayson, 2008). While some researchers find it useful to distinguish between planning, governance, and production as well as the relative contributions of both government and external parties to each process (Alford, 2014; Bovaird, 2007), a more general distinction is between the co-creation of a product or service, and the co-production which produces and delivers it to users (Etgar, 2008; Lusch and Vargo, 2006). A shift towards co-production is characterized by relatively lower centralization and higher connectedness, in which relationships with clients or co-producers see increased management effort and decision making autonomy (Verschuere et al., 2012).

The development and emergence of distributed business models requires an initial stage of research, development, deployment and testing. This stage faces high uncertainty and may require spreading the innovation costs across a large group of innovators. By sharing information innovators can mitigate this uncertainty by pooling multiple smaller commitments, information and feedback streams. Many of these emerging co-production regimes therefore may exist in a state that can be considered an innovation commons (Potts, 2017). Innovation commons are a type of co-production in which the product produced is knowledge. These innovation commons exist to share information and knowledge, thereby minimizing risk to any individual participant. As uncertainty dissipates, and business models become more apparent, these innovation commons collapse to make way for more fixed asset ownership with clear (co)production rules. Because a switch to prosumer (co-production) from consumer requires that users change from being users to also becoming involved in production, there is significant uncertainty that accompanies this transition. This high uncertainty is an important characteristic of an innovation commons, which are, by default, comprised of knowledge co-producers. Many systems of co-production may therefore initiate in an innovation commons. When there is high uncertainty about a production function and benefits, it is possible that an innovation commons will form as a type of co-production.

This dissertation is concerned with dilemmas in emerging co-production arrangements. The focus is on tradeoffs inherent in transitions from a hierarchical organization (firm or government) provisioning energy to a co-production regime. Depending on factors such as production uncertainty, access to capital, and the ability to access and share information between distributed actors, this co-production regime may take the form of an innovation commons, at least for a short time. There is some reason to think that energy blockchain initiatives are, at the time of this writing, in a type of innovation commons. Tradeoffs for co-production decisions include questions about feedback and interconnection with the centralized non-coproduced infrastructure, as well as questions about assets ownership and information and knowledge sharing. Participants in emerging co-production, as used here, intend not just to receive a different product, but to change the nature and configuration of the producer-consumer relationship altogether such that the feedback between users and producers is more tightly coupled.

To understand why co-production may be appropriate for sustainable energy transitions it is useful to think about the motivations and conditions that enable co-production. In this work, the focus is on both theoretical aspects of co-production and the linking of co-production theories to evolving dynamics in distributed energy resources as an emerging realm for co-production in the energy sector. Distributed energy resources

(DERs) includes energy technologies that are located behind a customers electricity meter such solar photovoltaics, batteries, electric cars, demand response and smart meters, smart inverters, and emerging technologies such as combined heat and power systems (chps), fuel cells, and others that continue to be developed. Given the distributed nature of these energy technologies and potential management systems, it is logical to consider how new management and production regimes may continue to emerge and how theory, models and experiments can inform the development and design of policies and practices that can produce a more sustainable and adaptive future.

Etgar proposes there are 5 stages of emergent co-production: 1) Development of antecedent conditions 2) Development of motivations 3) Calculation of co-production cost-benefits 4) Activation when consumers become engaged 5) Generation of outputs. The antecedent conditions include a perception that an improved product/service is possible, and the desire for improved quality (not quantity), that users have some resource or capacity to participate in production, and diminished transaction distance between producers and consumers (Etgar, 2008). I consider each of these factors in turn.

A desire for improved quality: The desired outcomes that a co-production system often defines include: increasing effectiveness and efficiency, increasing involvement, improved customer satisfaction, strengthening social cohesion, and democratizing public services (Voorberg et al., 2015). That is to say that the social dilemma is not the provisioning of scale or quantity of product, but rather a better product. Better quality within the energy sector may include electricity that generates less local pollution, decreased water usage, improved robustness to storms, less carbon intensity, or better electric vehicle charging pricing. In developed countries the challenge of having enough a sufficient quantity of energy available for users has been achieved through supply side investment in which the rationale for a fair price is determined and regulated by the cost of the total production costs over a fixed period (Frischmann, 2005). While this logic has historically been extremely productive, it becomes problematic when 1) demand flattens or decreases and 2) users desire increases in it the quality, not quantity, of a good, which are instead felt on the demand side (Frischmann, 2007). Marvin and Guy summarize:

> "A new logic of infrastructure provision is emerging in contrast to the old-certainties of supply-oriented logic. Infrastructure providers are no longer able simply to extend infrastructure networks in response to demands even if developers are willing to fund extensions. New limits are emerging which are creating a shift to a more demand-oriented logic of infrastructure provision." (Marvin and Guy, 1997)

Naturally these demand side values vary between locations and user groups. It is essentially a type of customization that may occur if the values of different users could be observed. Customization not only may allow for people to value different aspects of energy, but co-creation of energy products can allow for synergistic benefits to be realized through design. Classic examples of this include solar shingles or solar parking structures, which can provide additional value to the user. However, solar parking structures or solar shingles will not provide an intelligent return to utilities who must re-coup their investments through power sales and not the provision of shade and housing. The ability to customize an energy product for different user groups opens up potential niches for competitive development. This can allow multiple ways to cross the previously mentioned "valley of death". This means that rather than attempting to "buy-down" the cost of clean energy through tariffs and incentives that can make renewables cost competitive at scale, that many types of values can create competitive niches in which fledgling technologies may find the ability to grow, get feedback and improve.

It also improves the likelihood of being able to use local resources, such as design expertise, in product development and management. Products that achieve economies of scale through production size cannot be reactive to local conditions because they become competitive from the baseline of cost improvements and learning upon commodity prices material inputs and competitive labor. This challenge is linked to the challenge of realizing the theory of industrial symbiosis. While the theory of industrial symbiosis has been proposed as a sort of emergent ecology of human derived flows, in reality human institutional arrangements and networks are often largely separate such that the opportunity for cycling industrial flows into new products has not produced the theoretical potential of emergent technical and social innovations (Boons and Janssen, 2004; Rennings, 2000). In the instances where they have been successful, detailed work has been invested in creating and designing local and regional network and clusters that can enable this type of innovation (Deutz and Gibbs, 2008; Mirata and Emtairah, 2005; Wallner, 1999).

Resources and the capacity to contribute: In addition to the desire to have a better product designed for a more specific user, and not just more of it, a second antecedent condition focuses on the factor that potential prosumers must have some resource to contribute to the production process. This can vary widely depending on if co-production is aimed at: 1) having users co-develop a product directly e.g.: open source software, 2) gaining user experience feedback e.g.: Fluevog shoes, or 3) users themselves producing the product e.g.: Airbnb.

The level and type of expertise, fixed assets, and financial capital, and time that users can contribute dramatically affects the feasibility of any co-production regime. Facilitating infrastructure for such a system must assess 1) what type of assets potential prosumers may be willing to contribute 2) how prosumers will be compensated for their contribution. Determining the rules and incentives for contribution is an important intentional activity that changes the basis for determining what is both "good" and what is "fair". Many co-production frameworks, most famously open source software, have standards and rules that enable any contribution to be modularly connected to the system, such that it can be added and removed from the system without changing the ability of others to contribute (Chesbrough and Prencipe, 2008). This enables modular competition, but more integrated design can lead to more efficient and responsive overall system functioning as transaction costs are aligned within a firm. Additionally, the cost of attaining this capacity can dramatically shift the ability of users to shift into the role of producers. A classic examples of this come from the maker movement in which the cost of small scale production equipment such as 3d printers have enabled groups of individuals to produce complex items that are modified and designed for their own unique needs and desires (Williams and Hall, 2015). Firms and governments must consider how the rules for contribution, the alignment of system benefits, as well as the ability to access productive capital will impact the users' opinion of both whether the system is fair and whether it is good.

Decreased transaction costs between producers and consumers: Many novel co-production initiatives have emerged due to the ability of the internet to reduce transaction costs and therefore connect users and producers in new ways (Prahalad and

Ramaswamy, 2004). Interfaces and architectures that enable users to take on new creative or productive behaviors have been foundational to the proliferation of co-production (Ordanini and Pasini, 2008).

In the world of electricity the fabled idea of co-production is called the 'smart grid' (California ISO, 2010). However perhaps a better term than a smart grid, is to discuss a smart*er* grid. Through the many levels of automation, customer participation, distributed devices, local balancing, islanding and balancing, the goal of a smarter grid is to add functionality that can enable distributed participation. Many locations, companies, and governments throughout the U.S. and the world are working on different approaches and strategies for this.

While all of these antecedent conditions suggest that co-production may be a useful tool for change in the energy sector, this transition is easier proposed than implemented, and there is an incredible amount of design space that may impact the success of a co-production initiative. Co-production represents a radical transition of the user into a prosumer; from a person who pays a bill and turns on the lights to one that considers multiple aspects of their energy use within a more complex system. Co-production regimes face design challenges associated with 1) How to manage ownership and benefits from co-produced goods 2) How to structure and integrate different levels and sectors of expertise, time and abilities to contribute and 3) Issues of fairness and equality. In the following section I discuss why a focus on information as a good can help mitigate these dilemma and outline several research questions that follow.

1.3 A Focus on Information

It is not coincidence that the Internet has enabled many new co-production regimes around the world. All of the antecedent conditions can be favored through design of a system that gains value through the production and shared management of system and user information as a good, as opposed to the bulk sale of energy. However, without intentional design, these antecedent conditions can also be diminished or may not produce fair or sustainable outcomes. The desire to diminish the electricity sectors' reliance on quantity of sales (supply side valuation) can be seen as actually beginning with the historical trend towards "deregulation" of the energy sector, although not in the language of co-production. As the sophistication of information management and co-production continue to evolve, so too do the opportunities to manage complex resources with information tools beyond, however still including, price driven markets.

The focus on information and systems management as a value proposition can allow for 1) a focus on how to share and improve feedback about emerging idea configurations as well as to build consensus about them 2) the identification, creation and engagement of emergent user groups at previously unmanaged scales 3) the ability to identify a evaluate additional and synergistic design values that an infrastructure may provide 4) improved adaptive capacity through the creation of new arenas for prosumer relationships to develop and be maintained. While this research expects that co-production can offer benefits for the energy industry to be more adaptive, there is also a danger that the term co-production, the smart grid, or the power of the prosumers becomes a panacea that does not meet the expectations of its advocates. Avoiding this outcome requires that co-production is viewed not as a fit all solution but as a tool for co-production that can be used, not as a panacea, but a design space should enable the ability to find better and equitable outcomes. In the following section several design dilemmas are delineated along with the resultant research question and methods that are explored in this dissertation.

1.4 Chapter Overview

Challenges in co-production design space include: 1) how to incentivize and manage production and benefits from co-produced goods 2) how to structure and integrate different levels and sectors of expertise, time and abilities to contribute and 3) issues of fairness and equality. While there are many important questions and tradeoffs that should be further developed, this dissertation focuses on just a few aspects of these.

One of the difficulties with co-production networks is that they are not straightforward to interpret who should be able to enjoy the benefits of the production. This is especially difficult with co-creation of novel combinations, or innovations. As Isaac Newton said: "If I have seen further, it is by standing upon the shoulders of giants". The first section looks at how incentives to own or patent combinatorial information, as an innovation, changes people's willingness to share it. Standard practice for innovation systems is to privatize innovation information in order to incentivize larger scale returns (Hall and Helmers, 2010). However, in networks in which peer or coproduction is encouraged, the patent doctrine or ownership of intellectual knowledge can be problematic (Strandburg, 2008). This is especially relevant for energy innovations commons, such as energy-focused blockchains or demonstration micro-grids. In many of these people are willing to share information about their system, how it functions, and code they use for managing the system. It is worth observing that these examples do not include the sharing of artifact asset risk but may share facility and information risk. In these systems, reputation within a relatively small innovation network, and the potential to have future benefits without large individual asset risk may be an important driver, with the expectation of future benefits based on high expertise (Schweik, 2012).

Using an experimentally simulated search environment, I ask the question: How may exclusion rights impact the search strategies of innovators? Findings suggest that innovators find better solutions when they do not have the ability to exclude others, but this is likely due to the increase signaling that occurs from the ability to copy what appears to be a good solutions, thereby enabling local searching around good solutions in addition to use of a good solution. Coupling the experimental results with modeled agent-based strategies suggests that people often search by creating thresholds for determining what is a good strategy and tend to share even when others copy them. The results of this study are limited in scope, but related experiments and extensions of it may be used to further knowledge on how incentives in co-production may lead to shifts and patterns in strategic innovation behavior, and therefore the ability to be adaptable.

The second chapter tackles the question of: at what scale should co-production occur at in regard to electricity systems? It builds on the logic that electricity infrastructure provisioning is built upon cost valuations of the grid. If novel co-production arrangements continue to proliferate they will require a clear and simple rationale for defining what is fair that does not rely solely on comparison of supply side cost projections. In chapter 3, I examine how a probabilistic agent-based model can be used as a basis to compare co-production rules for distributed energy resources (DER) in the electricity grid. The results suggest that the cost of co-production in the electricity grid is much more sensitive to differences in demand side assumptions (e.g. seasonality of demand profile) than supply side assumptions (e.g. cost of generation). Therefore, the ability to design useful co-production depends primarily on the ability to understand the contextual needs of users, rather than supply side technologies. In chapter 4 I use the aforementioned model to study how local balancing of DER at different geographic scales within the grid has the potential to produce feedbacks that can impact grid costs. I find that while the highest level of local sufficiency is attained by balancing at the individual level, that if these investments are sized to provide more than modest backup, that they can produce harmful system stresses and costs. I suggest that useful rules will focus on the extent of variability. By incentivizing and managing small variability at small scales and large variability at large scales, rules may strike a healthy balance that escapes the confines of supply side logic investment logic.

In the final section I propose the need to connect the engineering concept of modularity to co-production. I test a method to identify modularity in legal decisions about distributed energy resources and apply it to a case study: the set of rules emerging for distributed energy resources in San Diego, California. Designing an infrastructure to enable co-production requires decisions about the scope and scale of user participation, and these rules are designed with a set of emerging rules. Coding of legal decisions that govern user participation allows for the identification of rule statements that govern distributed users. These statements are then analyzed for co-occurrence to detect the emerging co-production modules. Identified modules are then analyzed with the Institutional Grammar Tool (IGT) to allow for the classification of rules into a typology that clearly provides some conceptual clarity to defining types of co-production. I demonstrate the use of the tool and demonstrate how different rule types can elucidate the design space of co-production. I suggest that selection of rules for co-production is highly related to the challenges of matching users capabilities and expertise with conceptions of fairness and that rule types can be used to make theoretical progress on co-production of foundational infrastructures.

In the final chapter I summarize the how the diverse hypotheses explored in this dissertation represent several aspects of the co-production design space. I make recommendations for future research and comment on how this research can help produce a more sustainable and adaptable energy future and can help mitigate the innovation valley of death.

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CHAPTER 2

DO PATENTS IMPROVE THE INNOVATION PROCESS?

2.1 Introduction

As our society becomes increasingly complex and interconnected, it is critical that we create better institutions, practices and infrastructure to advance our collective ability to innovate and promote improved solutions (Clark et al., 2016). Improving this will require that we understand how rules effect the types of strategies and decisions involved in combinatorial searching, testing, sharing, refining and distributing of innovative ideas, artifacts, and facilities (Hess and Ostrom, 2003; Kauffman et al., 2000).

The act of innovation is a social dilemma since individual efforts by the innovator are beneficial to a larger group. The justification for patent and trade secret laws is that they allow innovators to avoid freeriding (Nard, 2014). This solution is in line with a common approach to solve collective action problems, namely by defining property rights (Hardin, 1968). However, Ostrom (1990) demonstrated that long-lasting solutions are possible without private property rights or external governmental regulations. Similarly, there has been controversy regarding the benefits and appropriateness of these property solutions (Bessen, 2004; Boldrin and Levine, 2008; Gallini and Scotchmer, 2002; Heller and Eisenberg, 1998). Furthermore, the proliferation of open source software and other knowledge commons has made it clear that an expanded understanding of the diversity of strategies used in innovation is both necessary and underdeveloped (Bessen and Nuvolari, 2011; Schweik and English, 2007; Strandburg, 2008; von Hippel, 2004).

The useful knowledge that patent law supports is considered a public good (Hess & Ostrom, 2010). Innovation knowledge can refer to two types of useful information, embodied (tacit) and blueprint (explicit) information. Embodied information is the knowledge that comes from gaining experience with a new technology or process and improving practices and related techniques (Madhavan and Grover, 1998). This knowledge is difficult to transfer between people and as such is less responsive to enforceable property rights. In this paper we focus on the second type of innovation information, which can more easily be ascribed into ownership, explicit or blueprint type information. This type can more easily be described and disseminated as a combinatorial formula and can therefore be copied and traded.

In order to improve our understanding of innovation as a social dilemma a behavioral experiment was used to test the effect of using patents in an innovation task. Furthermore, an agent-based models was used to test alternative mechanisms that may explain the observed patterns from the experimental data (Poteete, et al., 2010, Janssen & Baggio, 2015). This combination of methods enabled insight into the relative contribution of behavioral mechanisms in the innovation process.

The rest of the article is organized as follows. First we describe how innovation is studied as a costly combinatorial search task and how this multi-agent problem intersects with research on reciprocity, secrecy and cooperation. We then describe the behavioral experiment and present the results. From there we define several unique strategies and implement these strategies in an agent-based model in order to compare the well-defined strategies of the agents with the experimental results. Finally, we discuss the implications of these findings.

2.2 The Innovation Environment

The cumulative nature of learning can be conceptualized as a goal oriented search process (Simon, 1979). Because innovators do not search in isolation there can be cumulative effects in which innovators' choices to share and copy others can affect group level outcomes (Scotchmer, 2014). Studying the dynamics of the search process therefore requires an understanding of 1) how agents within groups search (including when they copy others) and 2) when agents share information with others.

In the search process actors can manipulate a string of components. Each string, made up of different combinations of components combined in a specific order, has a value. Innovations are new configurations of the string and can have different values, which is often described as an innovation's 'fitness' (Gallini and Scotchmer, 2002; Kauffman and Levin, 1987; McNerney et al., 2011). The varying fitness levels of different combinations represent a 'fitness landscape' upon which innovations are selected. The legitimacy of the use of a fitness landscape relies on commonalities between technological innovation and biological evolution, from which the concept of the fitness landscape is derived (Kauffman and Levin, 1987). Research focusing on searches of a fitness landscape has gravitated towards understanding when people engage in exploration (global search) vs. exploitation (localized search or benefiting from a selected innovation) (Fang et al., 2009; March, 1991). Landscapes can vary from being described as being smooth, meaning it has a single optimum, to rugged, which means there are many internal interdependencies and many local optima from which local search is unlikely to result in a global optima (Kauffman and Levin, 1987).

Both models and experiments have been used to explore different aspects of innovation as an exploration and exploitation process. A basic dilemma exists in which exploitation of a solution found early on can produce short turn gains but may also render an organization obsolete in the longer term (March, 1991). Organizations, firms and individuals attempt to solve this dilemma by employing strategies and heuristics to decide when and how they balance these activities (Fang et al., 2009; Suzuki, 2014).

Models have been used to study how diversity in agent attributes and search heuristics (e.g. constraint satisfaction and internal satisfaction) affect the ability to search optimality under diverse conditions (Hong and Page 2004). An increase in the number of agents searching with diverse heuristics was shown to improve the overall ability of a group to find global optima on a search landscape (Hong and Page, 2001; 2004). However, more searchers is not necessarily better, as inter-agent communication is costly, especially when agents have diverse knowledge bases and perspectives (Frigotto and Rossi, 2012). Designing the structure of knowledge networks can offer solutions to some of the challenges of multi-agent exploration/exploitation search. Although it is a well known idea that transmission occurs most effectively in small world networks (Watts and Strogatz, 1998), several models showed that when searching on rugged networks, inefficient network connections produce higher scoring group findings (Lazer and Friedman, 2007; Fang, Lee, and Schilling, 2010).

Experiments allow researchers to confirm the reality of distinct models of human behavior by examining how searchers, in a defined search environment, impact the selection and success of search strategies. Experimental results by Mason et al. (2008) confirmed the inefficiency hypothesis; they found that a search on a smooth, single optima landscape was facilitated by complete information sharing, while a more rugged landscape was better searched with a small-world network (Mason et al., 2008). However, Mason and Watts (2012) found the opposite in an analogous experiment; that even for rugged landscapes, well-connected network participants found better solutions. This difference could be attributed to differences in the experimental environment as the two experiments differed in 1) the search task, 2) the information sharing networks, and 3) differing definitions of what qualifies as a complex search space. However, other experimental research has observed that landscape complexity does not affect search behavior and focuses on a more generalizable pattern in which successful searches lead to more local searches, whereas unsuccessful search results foster global search (Billinger et al., 2014).

2.2.1 Reciprocity and secrecy

In studies of agents searching on a fitness landscapes it is typically assumed that agents share information with those in their network. This sharing of information generally leads to the observation that when more agents explore the better fitness scores they will derive in their searches. However, as discussed earlier, innovation institutions often rely on the ability to exclude others from their innovation either through patent protection or through trade secrecy (Nard, 2010). Wisdom and Goldstone (2010) demonstrated in a group search experiment that social learning, implemented as the condition to share information with the rest of the group, contributed to the ability of the group to find better solutions (Wisdom and Goldstone, 2010). However, to the best of our knowledge, there have not been any experimental search tasks that have observed what strategies people choose regarding whether or not to share information.

Searchers may share their search information with others even if it will not directly or immediately be beneficial to them. An instance of reciprocal altruism requires that an action is possible which does not directly or immediately provide benefits to the actor, but which the actor expects will be returned over time (Ostrom and Walker, 2003). In a single round search agents will receive no benefits from sharing their findings with others. A rational non-cooperative agent will therefore not share their findings with others, but a conditional cooperator, that has a normative view of sharing, may be inclined to share. While rational actor strategies are an important comparison, most public goods experiments find there are high levels of initial contributions (Chaudhuri, 2011).

Searchers do not only make decisions about sharing/hiding information. They also make decisions to copy others and how to search. Wisdom and Goldstone (2010) found in their group-search experiment that imitation actually benefited the whole group by providing a signal of benefit and increasing the average group score. It could therefore be considered an arbitrary assessment as to whether copying is considered a cooperative or non-cooperative behavior (Wisdom and Goldstone, 2010). However, based on the assumption that an innovator may have to share their payout when copied, we will describe sharing information as a cooperative behavior, such that conditional cooperator actors will be defined as those who share unless a non-cooperative behavior is witnessed.

2.2.2 Institutional Impact on Cooperation

New institutions can impact existing normative strategies that are based on trust and reciprocity. Studies have shown that rules can replace existing normative mechanisms, which can result in unintended consequences (Vollan 2008; Camillo et al 2000). In the experimental results presented below we hypothesized that in an experimental innovation search environment the introduction of a patent institution may have the effect of crowding out the inherent value for sharing innovation information.

2.3 Experimental Design

To study how patenting effects 1) innovation information provisioning, 2) copying behavior and 3) the ability to find good solutions, a controlled behavioral experiment was conducted. The decisions players had to make were analogous to the processes of searching for a string configuration with a high value. The player who selected the highest scoring combination during a round won a dollar for that round. The players experienced a social dilemma in their decision of whether to disclose information about their search. We hypothesized that the introduction of the patent would have the following effects:

1) Crowding out of an existing preference for sharing search findings (decrease in sharing), due to the internalization that only patented information should be shared as discussed above.
2) Decrease in copying behavior because a patent will nullify the free-rider effect of signaling (Nard, 2010).
3) Decreased rates of exploration in patent condition due to improved ability to gain profit from high scoring combinations and an incentive to search solutions that are highly similar to the patented option (Bessen and Maskin, 2009).

2.3.1 Search Landscape

The search landscape was rugged, so that the value of local incremental search would have less value compared with exploration and copying than in a smooth landscape. This type of landscape was chosen to isolate the dynamics of copying and searching the unknown from the ability of participants to find patterns, which could make interpreting results more complex. The values of the rugged landscape were created by summing 6 subcomponent values. Each innovation choice has 3 singleton values (a randomly generated number between 1 and 10 associated with each shape) and 3 duopoly values (randomly generated value taken from a normal distribution with mean = 15 and standard deviation = 7) that make up the 6 subcomponents. This results in 216 possible innovations, with a maximum score of 109. A representative section of the landscape is shown in table 2.1.

The players received information about their own score, whether they won, and a visual display of the shared choices. Each player was able to decide each round whether to make their choice visible to the group. The experiment was conducted using Netlogo's Hubnet software, which creates participatory simulation environments. The model code and ODD protocol are available at:
https://www.openabm.org/model/5769/version/1/view.

Players were assigned randomly to one of the groups (at least two groups participated in each session). Once everyone had read and demonstrated that they understood the instructions by answering two questions about the reading, the experiment was loaded onto the networked computers. Teams of four played and competed together (best performer wins a dollar), but each team member was unaware of who else was on their team. In each round of the game, participants selected three symbols (e.g., a wheel, a star, a plant etc.,) in an order of their choosing (see Fig. 1). Each combination of symbols had an unknown score, determined by the sum of the subcomponent scores, and the instructions explained that a participant could win a dollar by choosing the combination with the highest score. Ties split the dollar evenly. Half the participants were placed in Treatment 1 and half were placed in Treatment 2, as shown in Table 2.2. Depending on which treatment the player was in, they could also choose to allow or prevent (block) other players from choosing the same combinations during either the first or the second sixteen rounds. Blocking was analogous to patenting the innovation. A block prohibited everyone except the blocker from choosing that combination of objects for the next 5 rounds. A block cost the blocker a one-time fee of $0.10.

Table 2.1 Example of innovation combination scores

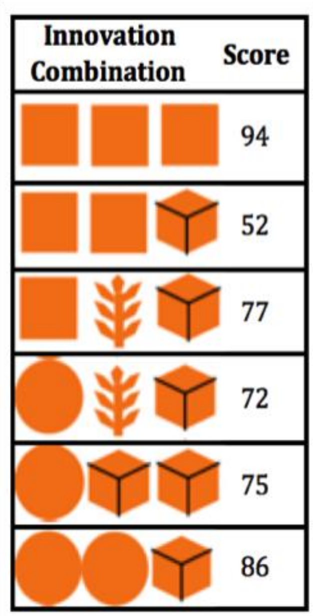

Table 2.2 Experimental Design

Treatment	Rounds	Rounds 17-
1	No Blocks	Blocks
2	Blocks	No Blocks

During the rounds with blocking, players could only select one combination to block at a time. The cumulative scores of the search space were flipped between which shapes they corresponded to so that, unbeknownst to the participants, the search space was the mirror image for the second 16 rounds. In rounds with blocks anyone was able to block a desired combination, but because only the initial explorer of a successful combination knew they had a high scoring combination, it was unlikely that someone would block a combination before it was patented. An example of how the screen might look after two rounds of play, with full sharing chosen by the participants is shown in Figure 2.1. A block is shown at the bottom of the screen in black.

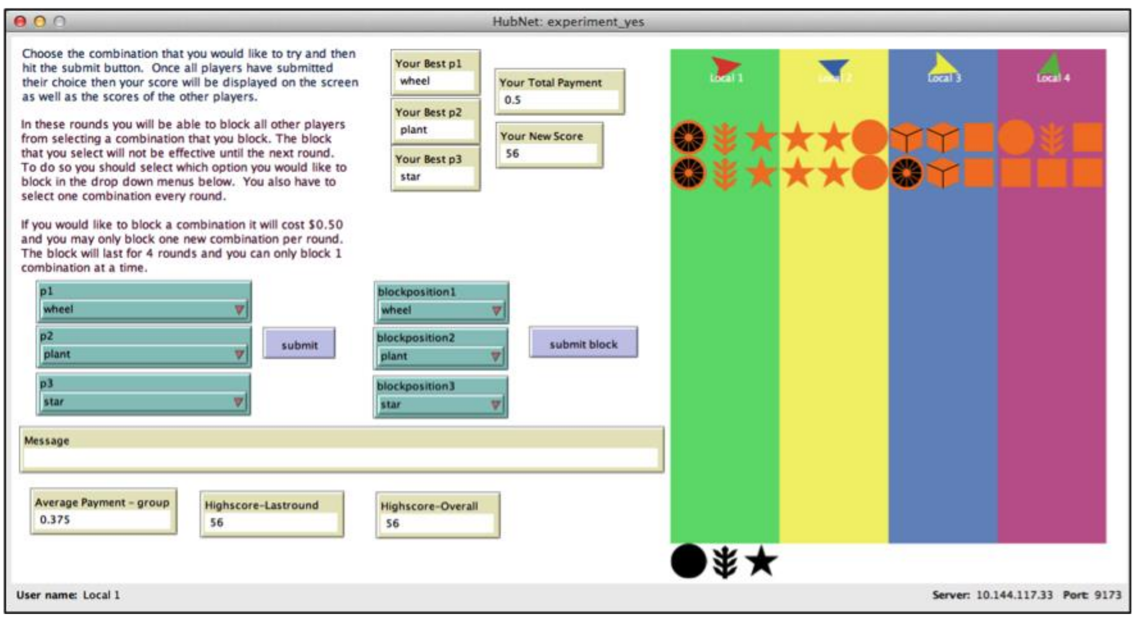

Figure 2.1 Experiment screen after 2 rounds of selection with blocking/patenting

To choose a combination of symbols, the players selected a symbol for position 1 (p1), position 2 (p2) and position 3 (p3). A round finished once everyone selected a combination, and all the choices then appeared on the screen (as shown in orange in Fig. 2). After each round, the previous selection moved down the screen so that the new selection was directly under the user ID of the player. Any active blocks appeared in black at the bottom of the blocker's column (as shown in Fig. 2.1).

During the game, each player had information about what everyone else has chosen, but not what score the choices earned. They also knew how many points they had earned, what their own score was in the previous round, what the highest score was in the last round, and what the highest score in the game so far had been. They did not have information about which combinations earned the highest scores. Combination scores remained the same throughout each condition (blocks or no blocks). At the end of the game, each player learned how much money he or she won, but not the other players' winnings. After the game was completed, players filled out a survey (on paper – see Appendix A) about the game and their experience.

Data was recorded on all the combinations that each player chose, and how many points each won. This data was analyzed statistically to understand how the patent condition (i.e., blocking allowed) influenced players' choices, earnings and ability to find better solutions (i.e., highest-scoring combinations).

2.4 Experimental Results

The goal of the experiment was to find out how patenting influenced: 1) copying, 2) voluntary sharing of information about the "innovation," and 3) players ability to find higher scoring “innovations.” These independent variables are analogous to choices innovators can make in the real world. Copying is analogous to profiting from an innovation that another person has shared. Sharing information is analogous to openly sharing know-how about an innovation. The ability to find higher scoring innovations is analogous to a search strategy in which more innovators find better solutions by exploring new ideas, which will result in better innovations.

A Mann-Whitney test was performed on the average cumulative data in each for each period between both the patent (P) and no patent (NP) condition. Table 2.3 shows the order effect of the ordering (NP to P and P to NP) as well as the non-ordered effect (Total NP vs P). The results of the experiment exhibited both expected and unexpected results. Differences between the P and NP treatments are significant for the amount of coping and the ability of searchers to find high scores. The patent rounds had significantly less copying than the condition without the patent. This is inline with the goals of the patent: to discourage copying and protect the rights of the original discoverer to profit from a discovery. The amount of copying may explain the ability to find good solutions of individuals, as we see that the individuals in the NP treatments were consistently able to find higher scores. However, the significantly higher scores in the NP treatment were not accompanied by a significant difference in the amount shared with other participants, which therefore may enable strategic copying. This not only led to a higher average score across all participants in the NP treatments, but also led to the ability to find higher total solutions on a group level, suggesting that copying led to more efficient local searches which therefore allowed for better search behavior. This trend is shown in 2.2 in which the dark line depicts the no patent condition both for the average of all participants as well as the average of the highest scores that each group was able to find.

Figure 2.2 not only demonstrates that the no patent treatment led to higher scores and better search abilities, it also shows that participants improved their guesses over the rounds which suggests that they were exhibiting strategic behavior, that may have benefited from copying. Given that the stakes of the game remain the same we suggest it is unlikely that this is due to a lack of motivation in the non-patent condition. 2.3 shows the main effect of the patent on copying behavior throughout the experiment. Since there are no overall significant effects of either sharing information or exploration behavior (number of changes), it is highly likely that the ability to find better solutions is due to the increased amount of copying in the non patent condition and its role in signaling better solutions and areas for search. This is consistent with the findings of Wisdom and Goldstone (2010) who found that the copying signaled value, which improved the success of innovation searchers.

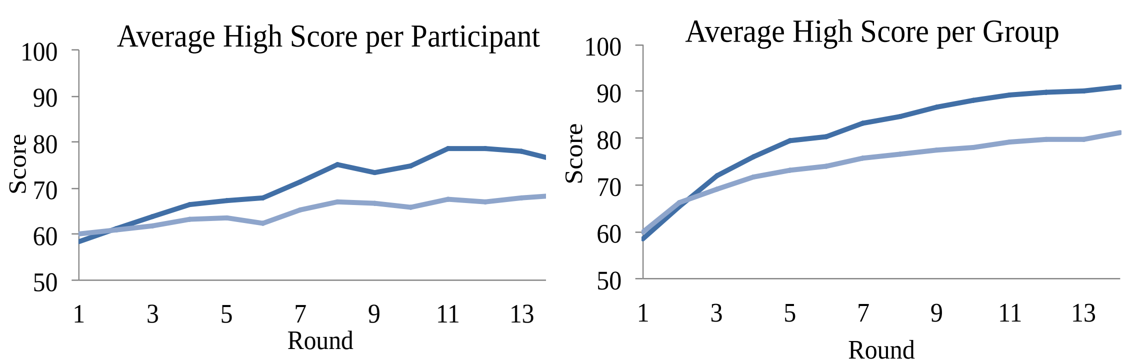

Figure 2.2 Main treatment effect of the patent. The patent treatment led to significantly lower scores, both for the individuals as shown in the Average Score plot and on a group level, as shown in the Max Score plot. The no patent treatment is shown with the darker line and the patent treatment with the lighter line.

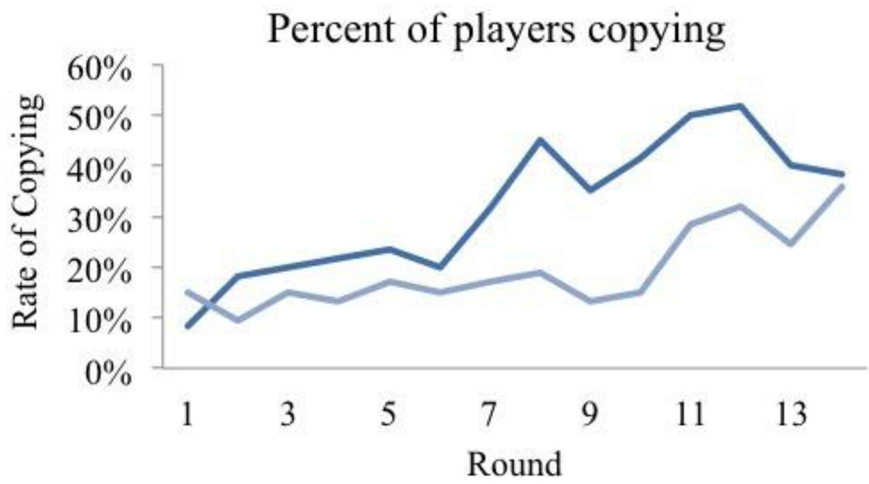

Figure 2.3 Main effect of patent in significantly reducing copying behavior. There is a trend towards more strategic copying in later rounds. NP treatment =dark; P=light

Table 2.3 Mann-Whitney Test Results. Columns show the difference between the No Patent (NP) followed by the Patent (P), P to NP and effect regardless of treatment order.

Total Number of Changes					
NP to P		P to NP		Total NP to P	
Median NP	21	Median NP	16.2	Median	18.5
Median P	18.5	Median P	23	Median P	19.5
n1	32	n1	28	n1	60
n2	32	n2	28	n2	60
W	611.5	W	534	W	1690.5
p (2-tailed)	0.183	p (2-tailed)	0.020*	p (2-	0.567
Total Number of Rounds Shown to Others					
NP to P		P to NP		Total NP to P	
Median NP	13.5	Median NP	9.5	Median	12
Median P	11.5	Median P	6	Median P	10
n1	32	n1	28	n1	60
n2	32	n2	28	n2	60
W	562.5	W	416	W	1861.5
p (2-tailed)	0.478	p (2-tailed)	0.6937	p (2-	0.74
Percent of Final Rounds (R10-14) Shown to Others					
NP to P		P to NP		Total NP to P	
Median NP	100%	Median NP	0%	Median	100%
Median P	100%	Median P	100%	Median P	100%
n1	224	n1	196	n1	420
n2	224	n2	196	n2	420
W	25792	W	21756	W	84256
p (2-tailed)	0.137	p (2-tailed)	0.009**	p (2-	0.439
Total Number of Rounds Copied					
NP to P		P to NP		Total NP to P	
Median NP	2	Median NP	7	Median	4
Median P	2	Median P	1	Median P	1
n1	32	n1	28	n1	60
n2	32	n2	28	n2	60
W	459	W	183.5	W	2295.5
p (2-tailed)	0.476	p (2-tailed)	<0.001**	p (2-	0.008**
Maximum Individual Score Found					
NP to P		P to NP		Total NP to P	
Median NP	92	Median NP	98	Median	93.5
Median P	78	Median P	80	Median P	78
n1	32	n1	28	n1	60
n2	32	n2	28	n2	60
W	687	W	155	W	2626.5
p (2-tailed)	0.019*	p (2-tailed)	<0.001**	p (2-	<0.001**
Individual Score Each Round					
NP to P		P to NP		Total NP to P	
Median NP	64	Median NP	81	Median	71
Median P	64	Median P	65	Median P	64
n1	512	n1	448	n1	960
n2	512	n2	448	n2	960
W	12370	W	63642	W	533000
p (2-tailed)	0.766	p (2-tailed)	<0.001**	p (2-	<0.001**

One of the most interesting findings is the lack of difference in strategies concerning local versus global searches and how much they shared with other participants. In addition to the lack of significant differences in total number of changes, figures 2.4 and 2.5 shows that the average number of positions decreased steadily across treatment conditions. Participants trended towards searching more locally as they gained experience and that they showed less in the final rounds. This is evidence that a threshold type of search strategy may have been used, which we discuss more when we examine how an agent-based model is used to understand the strategies employed. Although there was a significant difference in the total number of changes when the patent was removed, there was not a significant difference overall, when a patent became available. Over both treatments the median amount of changes was approximately 1.3 changes per round and participants showed their choices with a median value of 79% of the time. This is consistent with the theory that most people are conditional cooperators.

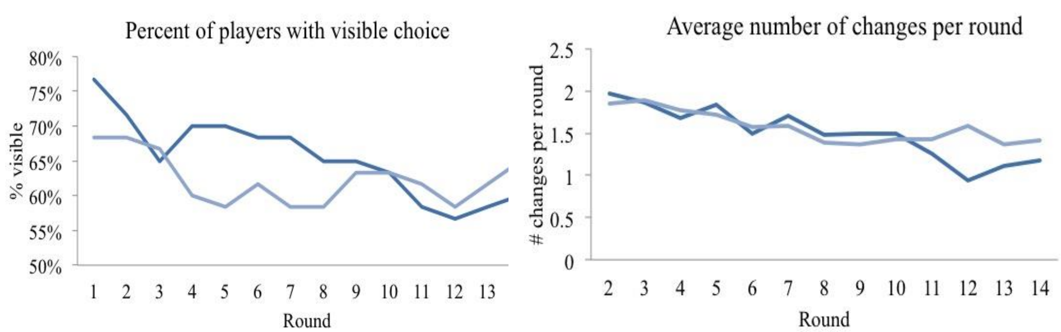

Figure 2.4 Lack of major effect of patent treatment on exploration and information sharing. Darker grey is the no patent treatment (NP), light grey is the patent treatment (P).

2.4.1 *Effect of Treatment Order*

The order in which the patent rule was either added or taken away had an impact on the effects found. While the total amount shown by round fourteen was not significantly different in either direction, the removal of the patent led to significantly less information being shared during the final rounds than when they had started with the patent, significantly more copying, and more local exploration. This suggests that the removal of the patent resulted in more competitive behavior, as participants were more likely to copy and locally optimize their searchers. The fact that the scores were lower in the patent round even though they searched more widely and shared the results of their searches more suggests that signaling by copying was a more important factor for success than was sharing of information. This is consistent with the fact that participants did not know the scores of the other players, so the primary indicator of a good combination was repetition.

Interestingly, this dynamic was not seen when the treatments were reversed. The only significant difference was that the no patent treatment was able to find higher scoring solutions. The lack of agreement between the treatment-order suggests that by removing the patent, more competitive behavior was interpreted to be acceptable. In the case of the non-patent condition in the first round, the participants had not been primed with the concept of the patent, so there was no relative assessment about whether or not it was okay to copy. The figure above shows how the averaged metrics for the ordered treatments changed over the rounds.

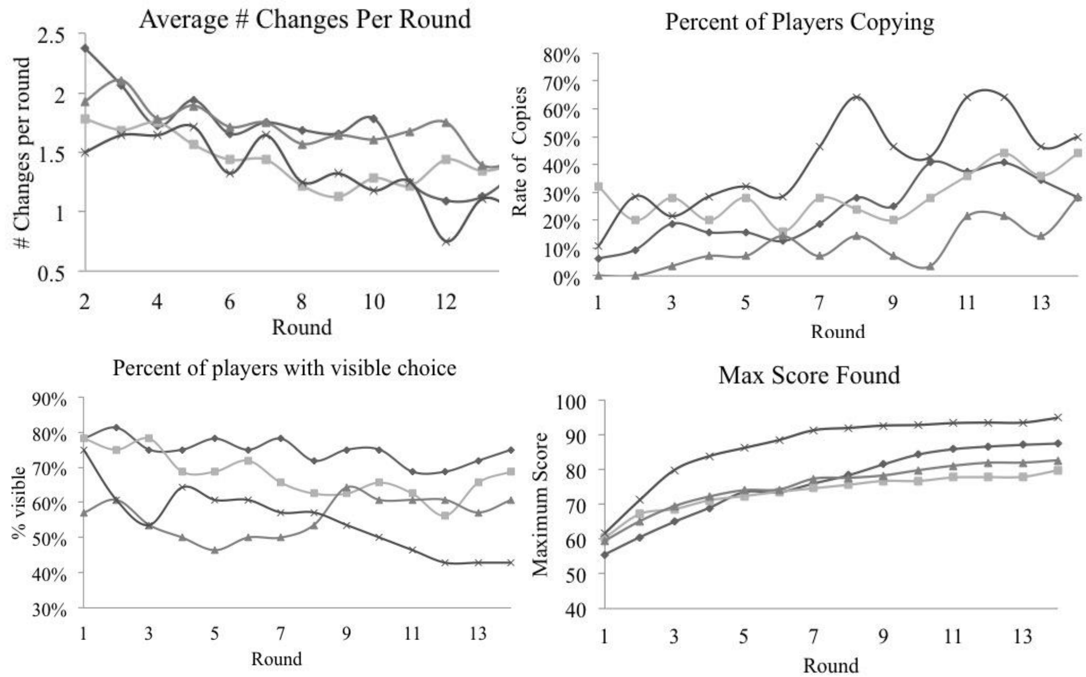

Figure 2.5 Average metrics per round for individual treatments. Diamonds are NP as the first treatment; X is NP as the second treatment; Squares are the P as the second treatment; Triangles are the patent as the initial treatment.

2.5 Modeling strategies from the experiment

We developed an agent based model to test different possible strategies that the players could have used in this innovation environment. We define some simple heuristics and systematically compare the model with the experimental data to evaluate which heuristics are most likely to explain the data. We define two primary decisions that must be made each round: search strategy and a group-orientation strategy. Agents have both search strategy (random or threshold) and a group-orientation strategy (selfish, cooperative, or conditionally cooperative). The search strategy is concerned with how many shapes to change each round (amount of exploration) whereas the group-orientation strategy is concerned with: sharing their searches with others, copying other players, and if they should block (patent) their combination. The possible combinations of behavior are shown in table 2.4.

Table 2.4 Modeled agent strategies

Search Strategies	Group Orientation Strategies
Random	Selfish
	Cooperative
Threshold	Conditionally - Cooperaitve

2.5.1 Search Strategies

Search strategy focuses on the individuals dilemma of whether to explore or exploit (Billinger et al., 2014; Bocanet and Ponsiglione, 2012; Fang et al., 2009; Levinthal and March, 1982; March, 1991; Suzuki, 2014). Two primary search strategies are tested: random sampling strategy (R) and a threshold strategy (T). All searchers will have either the random or threshold strategy such that: $\%R_{searchers} + \%T_{searchers} = 100$

- *Search strategy 1 (R -Random):* In a random search strategy agents randomly change 1,2, or 3 of their component choices, and do not change when they had the winning strategy in the previous round.
- *Search strategy 2 (T- Threshold):* Threshold behavior, meaning a preponderance to start with a global exploration strategy and then to move to exploitation once a sufficiently "good" combination has been identified, has been demonstrated to be an important search strategy in situations with high uncertainty (Seale and

Rapoport, 1997; Walden and Browne, 2009). The strategy relies on the logic that search is a costly feedback process, and that the benefits of widely surveying and testing options should be balanced with the desire to gain the benefits of sticking with a preferable option. Thus, in conditions of uncertainty, people often make assumptions about the underlying distribution of options based on their experience and observations of a subset.

Threshold model agents set an internal threshold after random initial sampling for a minimum of *n* rounds, with a probability of ending exploration p_{stop} in the following round, the threshold α is defined as: $\alpha = \max(\{S(i): i = 1, \dots. n\})$. This represents an internal definition of what is a "good" combination. Once the internal threshold is set, the probability of exploring for each of the three shape positions decreases the higher the score is relative to the threshold, such that the independent probability of changing each component position is defined as:

$$p_{change} = 1 - (S_i\ )/\alpha \qquad (1)$$

Accumulating the knowledge to set an internal threshold is costly since the more a searcher continues to sample globally, the less they can gain the benefits of a good selection. Searchers set an internal threshold randomly but less than or equal the maximum threshold parameter, *n*.

2.5.2 Group-orientation Strategies

The group-orientation strategy refers to an individuals choices about sharing, copying, and blocking combinations. Three group strategies are identified: selfish (S), conditional cooperator (CC), and cooperator (C). All searchers have the selfish, cooperator or conditional cooperator strategy such that: $\%S_{searchers} + \%CC_{searchers} + \%C_{searchers} = 100$

- *Selfish (S)* - The selfish agent assumes there is no benefit to sharing information and therefore does not share information, but will copy information if there is repetition indicating success.
- *Cooperator (C):* A cooperator will share their information and only sticks with a choice when that choice was found by them. They do not copy or block others.
- *Conditional cooperators (CC):* This model is based off of the theory that people cooperate when they expect others to also cooperate (Fischbacher et al., 2001; Janssen et al., 2010; Rustagi et al., 2010). This has been shown to be a dominant strategy in many multi agent social dilemma experiments. Conditional cooperators share information and only copy, block or hide their information when others are displaying uncooperative behavior.

Since agents can search either randomly or with the threshold model we assign search strategies based on a probability, p_r for random searcher or with an internal threshold model with a probability $p_t = 1 – p_r$. Agents keep their strategy throughout the 14 rounds of the experiment. Similarly, agents are assigned a group orientation strategy based on a probability to act selfishly, cooperatively, conditionally cooperatively $p_{cc} = 1-(p_s + p_c)$. For more detail see the ODD and model code.

We first analyze these scenarios with homogenous groups of agents that all have the same strategies throughout the rounds and then combinations of agents with diverse strategies that are calibrated to the experimental data. Homogenous scenarios look at the outcomes of the search interactions when all the agents utilize the same strategy. There are a few trends from the homogenous strategy simulations that are worth observing, as they help to understand the possible implications of an individual strategy. Figure 2.6 shows the results of homogeneous runs that allow patenting which are the averaged values from 500 runs in which either p_t or p_r is 100% and the p_s, p_c, or p_{cc} is 100%, such that the all the agents are either random(R) or threshold (T) searchers with a group orientation strategy of cooperative (C), selfish (S) or conditionally cooperative (CC). A first observation is that without a diversity of strategies there is no benefit from being either completely C or SS. Comparing S versus the C strategies using either the random or threshold strategy shows almost identical results when all the agents are the same. This is expected since in homogenous conditions no one takes advantage of the shared information, so it has equivalent outcomes as if nothing was shared.

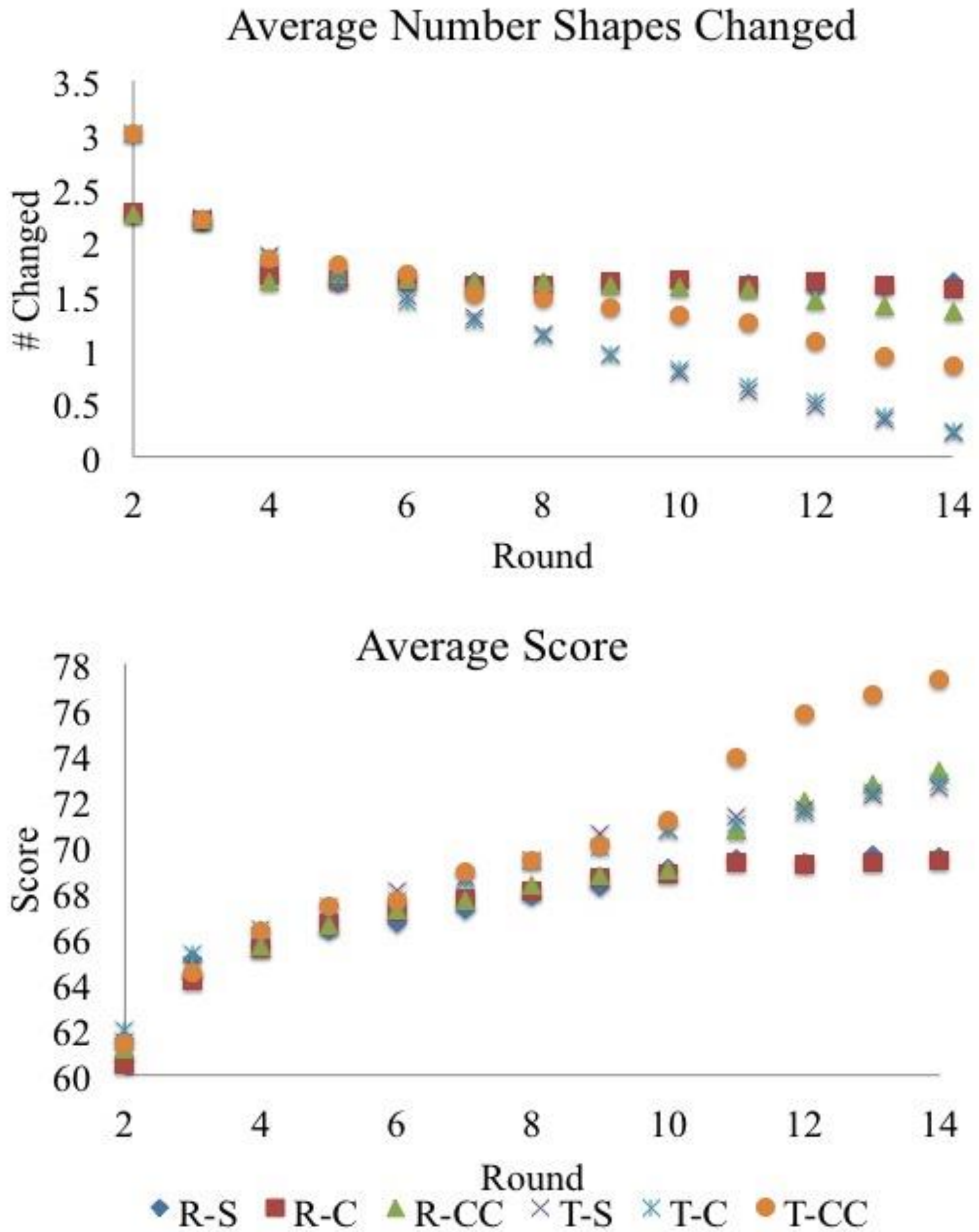

Figure 2.6 Homogeneous agent strategy runs averaged values for score and number of changes

There is no effect of the patent for the homogeneous C or S condition because they will not be copying or sharing information, respectively. In conditions with homogeneous conditional cooperators the patent critical to enabling people to share their findings. However, in the case of a homogeneous set of conditional cooperators, the patent dramatically changes the strategies, as shown in figure 2.7. Random searchers quickly respond to copying by hiding their random guesses, where as threshold searchers continue to optimize around good solutions so that they have less copying, share more, and are able to find high scoring solutions. While the patent does not affect the behavior of the random searcher because they hide their guesses as soon as someone copies, it does increase the amount of searching that a threshold searcher undertakes.

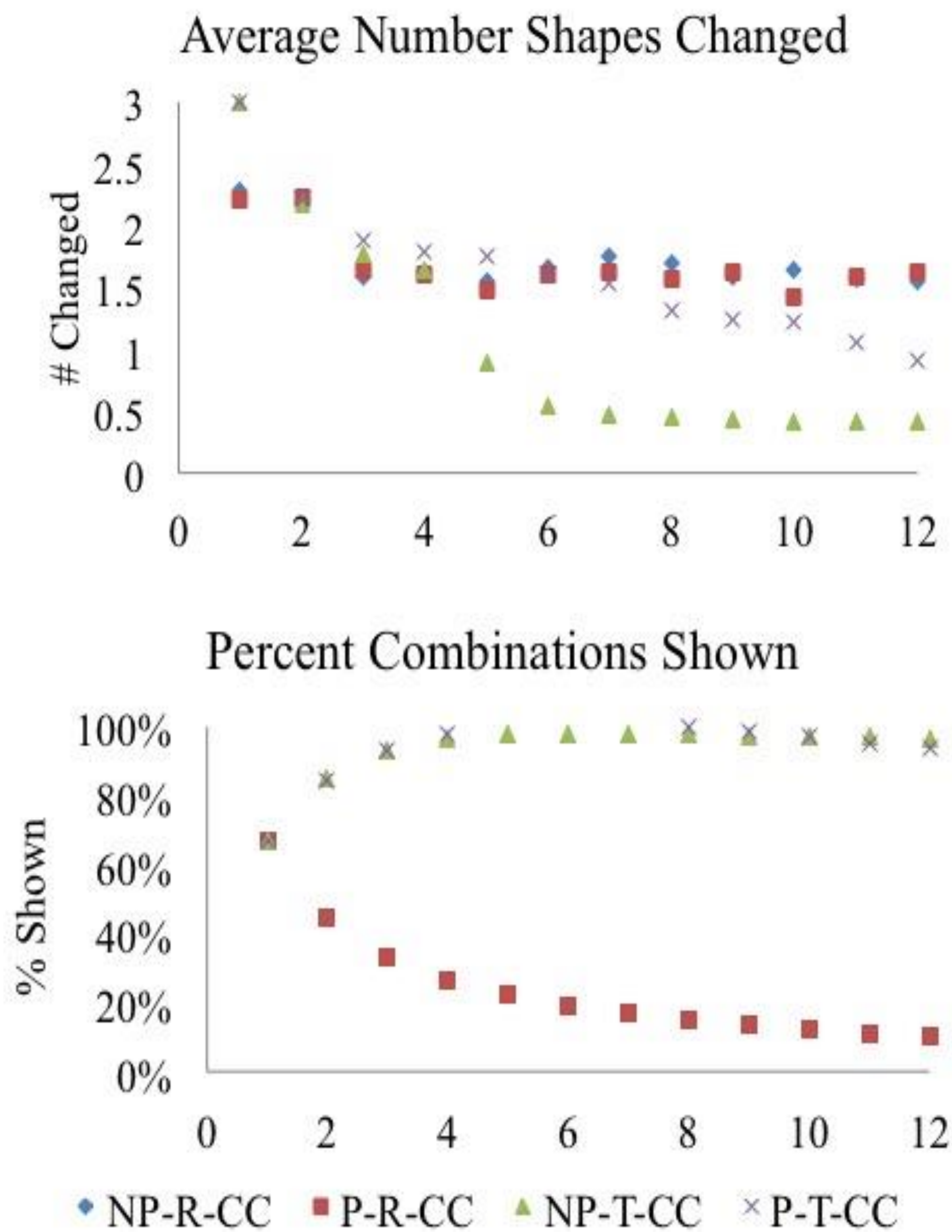

Figure 2.7 Effect of patent on homogeneous CC strategies

The use of threshold and a conditional cooperator strategy produces significantly higher scores on average, there is a middle range of homogeneous strategies that achieve very similar scores: T-S, T-C and R-CC. This is interesting because it suggests that random conditional cooperators may appear to be very similar to unconditional threshold strategies. This is in line with research on the secretary problem; which finds that setting a simple threshold for the number of sampling actions offers a cognitively simple heuristic that can achieve high results (Seale and Rapoport, 1997). R-CC searchers are almost identical to threshold behavior in terms of the average score chosen by searchers, although this is the result of a higher level of exploration (less efficient) than the threshold cases. Combining the threshold search strategy with conditional cooperation group strategy, while potentially cognitively demanding, increases the searchers effectiveness at finding high scoring solutions.

To better understand both the optimal and observed strategies that searchers used in non-homogenous conditions, search strategies were tested using Netlogo's behaviorsearch application to find the variable values that minimize the difference between the simulated and observed data. This search function tests a range of parameter values by using a genetic algorithm to improve on average run parameters that maximize an output fitness score. Comparison between the model runs in which searchers implement the defined strategies and reference data allows for calibration to the distribution of the type of strategies being employed by the group. The fit between the model and the data is a normalized square-root deviation between simulated and observed data, averaged across all treatments, NP, and P separately, for the selected metrics. To compare with what we define as an optimal strategy we compare only a single metric, the maximum score found by the group. This follows from the idea that we do not predefine what is the best way to explore, but rather suggest that the ability of the group to find high scores represents success. Additional metrics could be included to look at equality of payments between the players, or the amount of information shared, but to avoid controversy we stick with the maximum score as an indicator of success. Alternatively, when comparing with the experimental data, the fitness variable is defined by comparing the average model run results with the average experimental results. The output measurements that we used for calibration with the experimental results are:

1) The average maximum score found by the group per round

2) The average % shared by searchers per round

3) The average # of changes by searcher per round

4) The average % copied by searchers per round

The fit score is calculated with the equation below (shown with the four metrics used for comparison to experimental conditions) in which s_{ij} is the average from the data, d_{ij} is the average from the similations, n_{ij} is the number of observations and $d_{j,\,max}$ is the maximum possible value, which normalizes the different metrics. Therefore, a fitness score of 1 means that the averaged values of the simulation perfectly matched the averaged experimental observations. Because the fitness values are multiplied by each other to create a single fitness score for the genetic algorithm to optimize in comparison with, the addition of multiple metrics highly reduces the likelihood of having a high fit.

$$f = \prod_{i=1}^{4}\left(1 - \sqrt{\frac{\sum_{j=1}^{n_{ij}}(s_{ij}-d_{ij})^2}{n_{ij}}} \Big/ d_{j,max}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

2.5.3 Calibration for Optimal Search

Before we compare with the experimental data, we use the fitness score to comment on the question: What strategies lead to the most successful searches? A single metric was used to evaluate the performance of a succesful search: the ability of each searcher to find the highest possible combination value (110). Table 2.5 below shows the top five best fitting calibration values of the variables R,T,Average Threshold,S,C, and CC (the probability of being a random/threshold searcher, average threshold length, and the probability of being selfish, cooperative, or conditionally cooperative).

The calibration for optimal search strategies shows that both a random-conditional cooperative strategy and a threshold-conditional cooperative strategy, results in an average standard deviation from the optimal solution of less than 1% of total score. The fact that both of these search strategies perform similarly is well supported by the homogenous agent runs described above.

2.5.4 Calibration with Experimental Results

Calibrating the strategies with the four fitness metrics against the experimental data, instead of the ideal scenario, imposes three additional degrees of constraint in addition to score. Tables 2.6 and 2.7 below show the parameter calibrations and best fit for the runs that did not have patents (NP) and did have patents (P) respectfully. In order to diminish ordering effects while maintaining sufficient data points the data are averaged between both NP conditions, but NP first and then NP second. The fit for both conditions was about 40%, which is likely due to the use of multiple metrics being included in the fitness metric.

Table. 2.5 Calibration Fit with Optimal Search

Calibration with Optimal Search

Ranking	Fit	R	T	Avg. Threshold	S	C	CC
1	0.998	70%	30%	6	0%	0%	100%
2	0.998	80%	20%	2.5	0%	0%	100%
3	0.997	90%	10%	7	0%	0%	100%
4	0.997	40%	60%	4	0%	10%	90%
5	0.997	40%	60%	6.5	0%	10%	90%

Table 2.6 Calibration Fit with No Patent Condition

Comparison with No Patent Condition

Ranking	Fit	R	T	Avg. Threshold	S	C	CC
1	0.396	70%	30%	4	20%	64%	16%
2	0.387	90%	10%	0.5	20%	40%	40%
3	0.384	60%	40%	1.5	20%	48%	32%
4	0.378	80%	20%	3	10%	54%	36%
5	0.375	80%	20%	3.5	10%	54%	36%

Table 2.7 Calibration with Patent Condition

Comparison with Patent Condition

Ranking	Fit	R	T	Avg. Threshold	S	C	CC
1	0.382	90%	10%	2	30%	70%	0%
2	0.356	70%	30%	2.5	20%	72%	8%
3	0.349	90%	10%	3.5	40%	54%	6%
4	0.343	70%	30%	3.5	20%	48%	32%
5	0.335	50%	50%	3	10%	54%	36%

Both conditions show that a random strategy was the dominant search strategy, and when a threshold was used, it was set very early. This is consistent with the experiments that found that people tend to set their thresholds earlier than optimal, and has been suggested that it is due to the costly nature of search (Seale and Rapoport, 1997). Additionally, in comparison with an optimal search strategy, people are much more cooperative. The patent does seem increase the extent to which people are cooperative at the expense of conditionally cooperative behavior.

This fits with the intended purpose of the patent institutions; that is, to get people to share their knowledge while also innovating. However, this may be counter-productive to having a better innovation system, which may benefit more from the ability to signal and copy than it does from the provision of information without signals.

2.6 Discussion

The results demonstrate mixed findings with regard to the initial hypotheses. The first hypothesis, that the patent would decrease sharing of non-patented choices, was not supported. The patent seems to not only have provided for the sharing of information through the patent, but to have increased confidence in sharing information in general such that participants shared more freely with less fear that people would copy the information. This assumption appears well founded, and brings us directly to the second hypothesis, that the patent would decrease copying. This hypothesis is supported by the experimental results, but also points to a larger looming question: should a rule to encourage innovation have as its' aim incentivizing copying or the sharing of information? This is supported by observations about user innovations and co-production, in which socially embedded knowledge of user values and needs has been demonstrated to be a critical driver of innovation, as opposed to supply side information provisioning and rights (Potts et al., 2008; von Hippel, 2004).

If the patent does not signal value as efficiently as copying, then the question of the value of shared information, which cannot be copied is worth asking. This is highlighted by the fact that better scoring solutions were found on both a group and individual level in the non-patent conditions. The calibration of the agent-based model to study the different underlying strategies suggests that this may be explained by a decrease in conditional cooperation under the patent condition, which was replaced with more sharing but less signaling.

While this study highlights the important tension between sharing and signaling, the generalizability and external validity of this observation is contingent upon many important factors. These include 1) the artificial nature of the experiment 2) questions about how the underlying landscape may have affected the relative value of copying versus local experimentation 3) the small group size and 4) the mandatory submittal of an innovation combination each round.

The final hypothesis, that the patent would decrease exploration as people attempt to exploit their solutions, while signaling to others a combination of high value around which local search may be beneficial, did not show significant difference between the treatment conditions. The data did suggest that people act as random conditional cooperators or create internal thresholds for determining what is a good solution, and that these strategies may appear quite similar and may be difficult to distinguish between, but that the use of both of them may help searchers to find better scoring solutions. One theory that arises in the literature is that a threshold can be helpful when the alternatives are cognitively difficult or ambiguous, such that one might expect that the use of an internal threshold will increase when the number of participants, or combinatorial options increases, and that conditional cooperation will dominate when the number of competitors is low.

Future extensions of this research could explore different landscapes, using a more realistic proxy for an innovation, increasing the group size, and changing the reward structure from testing a combination each round, to one in which participants make a decision about when to get score feedback. This last area is especially important since the rationale for the patent is to incentivize to people to take on innovative behavior.

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CHAPTER 3

PROBABILISTIC SUPPLY-SIDE VALUATIONS OF DISTRIBUTED RESOURCES: CAN WE GENERALIZE?

3.1 Introduction

There are multiple competing typological visions of the future of the electricity grid (EPRI, 2011; Lovins, 2011; MIT Energy Initiative, 2016; The Brattle Group, 2010). Conceptualizations of these visions are substantiated in different reports, analysis, and models, but I will summarize them as: 1. business as usual accompanied with eventual carbon capture 2. increased large-scale renewables and intensive transmission interconnection 3. high penetration of distributed energy resource (DER) [1], smart grids and local management (Geels et al., 2017; Verbong and Geels, 2010).

In many ways all three of these visions are advancing simultaneously, and it is unknown which configurations will stand the test of time, or to what extent mixed visions will continue to co-exist. Vision three, the DER intensive future, represents the largest social-technical reorganization in our time, and therefore it is the least well understood (Verbong & Geels, 2010). Historic investments were not designed with DER in mind. This creates systemic inertia in today's electricity system and can diminish the likelihood of a total reorganization of electricity systems around DER. A distributed architecture introduces many unknowns, such that it is hard to imagine and compare with the existing system, which relies on a centralized architectural structure. The number of possible grid

[1] Distributed energy resources can include technologies and management methods such as: small scale photovoltaic arrays, combined heat and power generators, fuel cells, batteries, demand response program participants, electric vehicles, and home energy management systems among others.

configurations, spatial/temporal variation, variation in user demands, and DER adoption and use patterns are several categories that are often assumed fixed in stochastic grid investment optimization models. This complexity makes answering the question: *What is the value of the DER intensive future?* non-trivial; as extensions of existing methods are insufficient. It is also one that is highly salient to many research initiatives, policies, and businesses.

The fact that the U.S. grid infrastructure is at an age at which a large portion of it must be replaced (Harris Williams and Co., 2014a) presents an opportunity for comparing alternative future investment schemes. The choices that are made in the upcoming years will continue to generate systemic inertia for decades (Bertram et al., 2015; Markard, 2011). This is coincident with a prominent fear from electricity utilities that if consumers use less electricity from the grid (due to DER, energy efficiency and demand response programs) that the utility will not have enough capital to invest in necessary grid balancing, maintenance, and upgrades (Kind, 2013). This has been politically termed the "Utility Death Spiral", and has played a role in many regulatory decisions, and rhetoric often makes it difficult to have a transparent and thoughtful discussion about such a complex subject. Decisions today about infrastructure will have long-term effects, and therefore deserve careful attention with an open and level basis for comparison. This research investigates tradeoffs about the assumed basis for comparison in order to be able to have a better conversation in the future.

Quantifying and comparing the value of infrastructure investments is an important tool for 1) justifying to the utility rate structures and fees that will provide certainty over the life of infrastructure 2) crafting effective policy that is in the publics' interest and 3) decision-making between alternatives (Taylor et al., 2015). Although, there are many important demand side values that electricity infrastructure can provide, in addition to access to electricity[2], the publically sanctioned method for public utility investments is almost entirely based on supply side valuation (Frischmann, 2012). For example, since 2010, many regulating bodies including those from Arizona, California, Florida, Georgia, Hawaii, Massachusetts, Maine, Mississippi, North Carolina, Nevada, New Jersey, New York, Pennsylvania, Texas, Utah and Vermont have all commissioned value of solar studies to quantify the relative supply side value of higher penetration of distributed energy over five to ten years, primarily from building sited solar panels, to inform regulation[3]. While there is some variation between studies, the dominant conceptual basis for valuation in these studies is the avoided cost of providing reliable electricity, with little to no inclusion of other demand side benefits (Taylor et al., 2015).

It is clear that conceptions, about the relative value of DER, play a critical role in the debate about electricity grid futures. It is also clear that decisions about grid investments are made with relatively little effort to envision the future without the limits of path-dependency. The best example of this is that avoided costs are often calculated on timescales of five or ten years, thereby inheriting onto future decisions the structure and constraints of the present. This is in no way illogical, since societies lack other data points to compare with, but it does present a major limitation to our ability to create a better future. Extrapolation from existing investments can make modeling and prediction of short-term futures easier, while concurrently making alternative structural investments

[2] Including, but not limited to: improvements to air quality, climate change mitigation, local resiliency and innovation and economic development.

[3] http://www.seia.org/policy/distributed-solar/solar-cost-benefit-studies

incur increasing uncertainty (Grubler, 2004). When considering alternative scenarios, the vast number of future options (due to the lack of path dependency, variability, stochasticity and other sources of uncertainty) that exist for DER make comparative future analysis difficult, and contributes to socio-technical lock-in (Verbong & Geels, 2010). Alternatively, valuations of status quo scenarios, and minor deviations from it, are abundantly modeled and are relatively well understood. Sensitivity testing of pattern oriented and probabilistic models can help understand what variables can be more easily generalized, and which ones produce path-dependency and potentially divergent futures. Additionally, because DER futures have many types of uncertainty, and lack data for validation, modeling must rely on transparency and accessibility as a prerequisite for comparability (DeCarolis et al., 2012).

3.2 Premise

In 2010 The Edison Foundation contracted The Brattle Group to quantify the scale of investment needed for the electricity grid (and in turn its' members, investor owned utilities (IOUs)), from 2010 to 2030. The report, *Transforming America's Power Industry*, has been widely cited and highly influential. It suggests that the U.S. electricity system will require between 1.5-2 Trillion dollars over a twenty-year period (The Brattle Group, 2010). They provide several scenarios, which vary between the business as usual (BAU) scenario and increased levels of large-scale renewables, as shown in table 1 below. These scenarios, while useful, do not consider changes in: transmission and distribution grid costs (the largest cost category), any scenarios that include high adoption of DER, the effects DER adoption may have on transmission and distribution costs, or any additional values that may come from the provisioning of energy at more localized scales. Increasing the breadth of understanding to include these aspects was a primary motivation for this research.

The report finds that grid costs (both transmission and distribution) is the largest future cost. Although the report notes that the scope and scale of transmission and distribution (T&D) investments could be equal to or larger than investments in generation, the report focuses the entirety of their analysis on variations in centralized generation, such that there is no attention paid to distributed generation in their model. However, distributed generation may have an important impact on transmission and distribution, while lessening the potential need for utility funding of generators (Poudineh & Jamasb, 2014). Additionally, the costs associated with T&D are underestimated because they are a direct extrapolation from historical investments. Since the electricity grid is aging and will need more investment in the future than it did in the past twenty years (Brown & Humphrey, 2005; HarrisWilliams&Co., 2010; Pfeifenberger, Chang, & Tsoukalis, 2015).

Table 3.1 Transforming America's Power Grid Future Scenarios. Reference scenario is based on the U.S.DOE Annual Energy Outlook. The Realistically Achievable Potential (RAP) scenario includes advanced metering infrastructure (AMI), energy efficiency (EE), and demand response (DR) projections. The Maximum Achievable Potential (MAP) scenario assumes more aggressive EE and DR projections. The Prism RAP scenario adds a federal carbon policy to the RAP efficiency scenario. T&D costs are not only constant across these scenarios; they do not account for grid aging. Not only is this unrealistic, but there were historically low levels of grid investments over the last twenty years and therefore extrapolation from these low costs further biases the estimations.

	Scenario Cost Projections ($Billion)			
Cost Category	Reference: No Carbon Policy	RAP Efficiency: No Carbon Policy	MAP Efficiency: No Carbon Policy	Prism RAP: Carbon Policy
Generation	$697	$505	$455	$951
Transmission	$298	$298	$298	$298
Distribution	$582	$582	$582	$582
AMI, EE/DR	$0	$85	$192	$192
Total	$1,577	$1,470	$1,527	$2,023

We will return to these estimated costs, when we discuss the validity of the modeled results.

3.2.1 A Focus on Distributed Energy Resources

Distributed energy resources may, not only, provide value through changing the costs associated with the shared grid infrastructure. They also have the potential to improve local electricity autarky and resilience to different shocks. Resiliency is often characterized as the "capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks" (Walker, Holling, Carpenter, & Kinzig, 2004). Comparing alternative scenarios can help answer the question: is an increase in resiliency worth/cause additional investment? While it is clear that the supply side value of infrastructure is the dominating historical metric for decision making, it is not clear that it is either 1) the most desirable metric nor 2) that it is the only one that is relevant. For example, in charting a new course for its energy future, New York also considers local reliability, customer knowledge and tools, market animation, system wide efficiency, fuel and resource diversity, and carbon reduction (NY State, 2015). All of these goals seek to provide greater resiliency to the electricity system.

Furthermore, it has been demonstrated that designing based on efficiency will make a system more susceptible to eventual failure. While the most classic examples of this comes from fishery science, in which catchment quotas are set at the maximum sustainable yield, the concept is fairly intuitive: when a set of infrastructures are designed to optimize known conditions, deviations in conditions can cause cascading failures throughout the system that are difficult to recover from (Allenby and Fink, 2005; Anderies and Janssen, 2011; Beddington et al., 2007; Chang et al., 2014; Vespignani, 2010). It is for this reason that the concept of adaptive management has become a popular concept in managing natural parks and other natural infrastructures.

Adaptive management requires multiple and nested levels of organization, management and information processing (Anderies, 2015; Brehmer, 1992; Janssen and Hohman, 2012; Messick et al., 1983). In chapter 3, we extend the model presented here to look at how introducing new levels of information and management may alter feedbacks and the resiliency of electricity systems. One intended use of this model is to explore how multiple and novel scales of management can provide local resiliency while also quantifying the salient metric of the shared system cost. To do so we use this chapter to understanding the applicability and generalizability of this probabilistic grid model as a basis for further application and utilization. We focus on understanding how a probabilistic grid model aligns with existing grid investment predictions and what type of sensitivity it has to assumptions, before introducing local management heuristics.

The scale of capital needed for the electricity grid weighs heavily on society. The many studies attempting to value distributed solar in different locations are evidence of this. Unfortunately, the conclusions are difficult to compare and generalize. Each study is specific to the unique conditions and assumptions, physical assets, and policy time horizons used. Analyses based on specific assets, short time horizons, and fixed local production and demand assumptions can produce heterogeneity and potentially path dependency, as specific arrangements and existing investments weigh heavily on future preferences. Because DER is small and distributed its' adoption and use patterns do not lend themselves to optimization in the same way that historical grid investments have, and so it is critical to examine to what extent or when is asset optimization, specific to a given location, a useful method in a more distributed energy future? Conversely, when might a less specific model basis produce a more adaptable, healthy and competitive future? As DER becomes more relevant utility regulators and policy experts are increasingly proposing the importance of probabilistic future projections:

> "As utilities shift toward integrating increasing amounts of DERs into their systems, they will be relying upon these resources to complement energy procurements from the wholesale market. The nature of these DERs and associated properties with respect to intermittency and various levels of reliability, however, need to be integrated into the planning process. Therefore, the Guidance Proposal recommends that the utilities identify a process to move from deterministic to a probabilistic modeling approach for distribution system planning."[4]

[4] State of New York Public Service Commission Case 14-M-0101 -Proceeding on Motion of the Commission in Regard to Reforming the Energy Vision. Order Adopting Distributed System Implementation Plan Guidance. Issued and Effective: April 20, 2016

This model incorporates approaches to probabilistic modeling of future electricity grid costs and benefits by drawing from multiple interdisciplinary fields including geography, economics, complexity science, and engineering. As such we devote considerable attention to model elaboration.

3.3 Model Overview

3.3.1 Model Rationale

Before elaborating on the construction of the model itself, it is important to consider the question of why use an agent-based model (ABM). While historically electricity system models have used engineering optimization models (Bazmi and Zahedi, 2011), and this may continue to be relevant for some shorter term operations, that is no longer sufficient when evaluating DER futures. Most electricity softwares use optimization models and rely on detailed assumptions about technical components. Solving optimization problems requires simplifications to be made in terms of spatial and temporal data. Given the small spatial scale of DER, the temporal variability, and incorporation of human preferences, optimization modeling of DERs is problematic (Pfenninger et al., 2014). To cope with the number of variables and new types of uncertainty that are presented by a distributed future, it has been well documented that a probabilistic approach to modeling more distributed energy futures is desirable.

ABMs are well suited to modeling the future of a DER intensive electric grid. Existing models are quite diverse, ranging from market analysis of DER adoption, demand management, grid operations, agent preferences, learning and decision support, environmental issues, capacity management and macro-economic aspects (Sensfuß et al., 2007). ABMs have been used to study smart grid design, control and operation such that local islanding may also provide local resiliency (Pipattanasomporn et al., 2009). While ABM modeling has flourished and increased in recent years, continued and expanded work is needed to answer many new and existing questions, especially in areas such as local markets, storage systems, intermediaries, and distributed operations and control procedures (Ringler et al., 2016; Rumley et al., 2008). ABMs that focus on decentralized structures and market integration have been categorized by Ringer et al into four types: demand response, distributed generation markets, local control methods, and holistic models such as EMMAs, CASCADE, and GRID LAB-D (Chassin et al., 2014; Ringler et al., 2016; Snape, 2011). The focus of existing models, even holistic ones that include combinations of distribution, transmission and market systems, assume a set of hard or soft infrastructures which are specific to a location, and are therefore over-specified when attempting to generalize about the range of outcomes with such a high degree of uncertainty as to how people may adopt and manage DER in the future.

Pfenninger et al recognize four main issues for modeling challenges: 1) Resolving time and space (variability an detail), 2) addressing uncertainty, accessibility and reproducibility, 3) complexity and optimization across geographic and temporal scales, and 4) inclusion of the behavioral and social human dimensions. They suggest that there is a need to take tools that are well suited to cross scale analysis and continue to search for developing new methods better suited for the twenty-first century (Haller et al., 2012; Pfenninger et al., 2014). Modeling frameworks, such as CASCADE, include distributed prosumer agents, which may take DER adoption decisions. The focus is on understanding adoption patterns or effects of a specific pricing rationale, but stops short of imbuing physical parameters, such as age, distance, and loading of the distribution system (Snape, 2011). One reason for this is a lack of data about physical distribution assets, both in their arrangements and how the location of adoption may impact stresses on the infrastructure. Utilities often develop short and medium term investment comparisons, but these are usually unavailable to the public, consider short timelines, and do not focus on understanding the significantly different future scenarios, in which they may play a different or reduced role. Therefore, results are more likely to reflect the feedback from existing infrastructure assets and arrangements. An ABM of a probabilistic grid, one that is realistic but not real, can help integrate feedback between DER adoption and use futures with physical investments in the grid.

One important feedback in this model is the incorporation of DER loading onto the distribution grid assets and the incorporation onto their replacement plan. Many physical assets in the grid have fairly well understood probability of failure and retirement relationships. DER has the opportunity to cause new strains on the grid as well as reduce congestion. Congestion reduction can be improved by creating more strategic investment incentives and DER management practices. This model can be extended to examine how strategies and scales for smarter investments affect these costs. In this paper we the focus on how model assumptions impact supply side costs without including local management heuristics. The probability of failure, and therefore the need for replacement, are included for: distribution lines, transformers (distribution and substation), as well as for generation units. This is dependent both on the loading as well as the age of an asset. An in-depth discussion of the probability of failure and replacement relationships is provided in appendix B.

A second DER feedback is the potential to defer large investments, such as substations, transmission and generation. New investments may be required due to load-growth, variability, or the retirement of old generation. DER has the potential to decrease large investments by reducing the demand needed by the transmission grid. Section *3.3.3.4* discusses in greater depth the lumpy nature of centralized investments and the investment logic that underlies this pattern. Conversely, increasing levels of DER require increased integration costs so that the grid is sophisticated enough to cope with increasing levels of DER. These costs are required for a “smarter” and more distributed grid. While some locations are moving ahead with smarter grid capabilities and management systems, the extent to which distributed entities desire to participate in electricity grids is unknown (Dave et al., 2013). For example, while battery storage can engage in time of use price arbitrage with the aim of leveling demand (Zheng et al., 2014), the extent to which society desires this outcome, as well as the type of policies, that should be used to encourage this behavior, are unknown.

This leads directly to a third type of uncertainty, which entails uncertainty and variation inherent in DER adoption preferences and patterns. This includes: use and risk preferences, future discount rates, existence of DER adoption incentives, DER sizing and design, and location specific DER interactions with the built and natural environment. While ABMs are viewed as an important tool for building, forecasting, and operating a more distributed and adaptive energy grid, these categories of uncertainty entail added challenges as far as verification, simplicity/complexity tradeoffs, and generalizability (An et al., 2005; Heppenstall et al., 2012; Lustick and Miodownik, 2009). Given the lack of knowledge about agent preferences, a probabilistic model based on distributions of preferences in a physical grid is a logical solution.

In order to combat these types of uncertainty we define four model design criteria: 1) use accessible and transparent software and data to enable continual improvement and feedback, 2) construct system scope and scale boundaries based on identifiable patterns of decision making 3) utilize nested patterns and distributions of attributes, rather than existing fixed assets as the model basis, 4) produce outcomes consistent with top down centralized system model predictions under conditions of minimal DER adoption. These outcomes should be compared as distributions, such that the results may be broadly compared and interpreted. The following sections discuss the model design concepts with regard to each of the design criteria as well how it has been implemented, and opportunities for improvement.

3.3.2 Model Design Concepts

3.3.2.1 Accessibility, transparency, and openness

A partial solution to the challenge of having a valid and comparable model is to have openly accessible models, data and standards for describing models (Grimm et al., 2006). This has been especially problematic in the electricity sector, in which models have historically been developed commercially with proprietary business models (DeCarolis et al., 2012; Pfenninger et al., 2014). Most electricity system modeling environments, used to inform policy decisions, suffer from issues of accessibility to both to source code and input data. This dramatically limits reproducibility by others, creates information asymmetry, and decreases researchers' ability to collaborate. Additionally, complex energy system models face verification challenges due to the timescale over which they take place. When coupled with the lack of access to most of these models it is difficult to understand to what extent results are driven by 1) flaws in code 2) subjectivity of assumptions and 3) the sensitivity to parameter selection (DeCarolis et al., 2012).

Publishing models in open online repositories is one way to improve the likelihood that other researchers can test, validate, replicate and find sensitivities or artifacts in model code that may skew findings. Similarly, the choice of software and whether a GUI is used can alter the likelihood that a wider or interdisciplinary group of people are able to interact and evaluate the model. The model code, along with input data for this model, and ODD are available here: www.openabm.org/DERelectricitygrid.

3.3.2.2 Model boundaries, scope, and scale

One of the most difficult aspects of any modeling process is determining the boundaries, scope and scales to be included in a model. Central to this process is the consideration of the feedback between agents at different scales and the types of variability encountered. Because this is a model that focuses on DER, two scales of agents, buildings and utilities, participate in making investment decisions. They participate in both hourly and yearly energy behaviors and shown in figure 3.1.

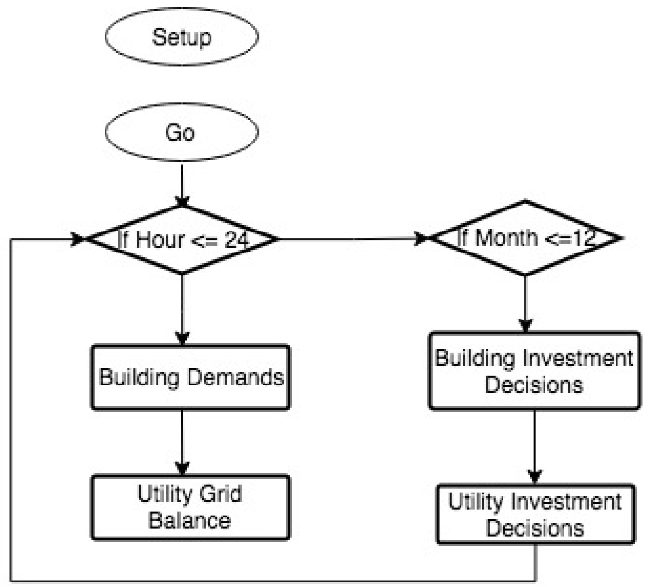

Figure 3.1 High-level model process diagram includes two types of agents: buildings and utilities, which make decisions on two time scales: hourly and yearly

Buildings produce hourly electricity demands and annually consider DER adoption. Similarly, utilities provide hourly grid balancing and take annual grid level investment decisions. This relies on the assumption that investment decisions require more cognitive input than hourly electricity demands and balancing, which are based on average patterns. This notably does not include the political dynamics of bodies that regulate utilities, or which invest in electricity innovation and infrastructure (e.g. public utility commissions and other governing bodies). These actors and dynamics are excluded in order to produce a tool that can illuminate tradeoffs that may be of interest to actors and agencies at these higher governing scales without commenting on the functioning of these higher scales. While we do not discuss it until chapter 4, also included in the model, available online, is functionality to aggregate information and take decisions at novel scales within the grid, such as can be related to neighborhood markets and virtual power plants. Energy balancing can change the feedbacks between DER and grid infrastructure (Pfenninger et al., 2014).

Buildings have hourly demand profiles based on averaged monthly data that is publically available, see appendix B for calculation details. A single hourly-averaged day is simulated for each month in order to reduce simulation time. The utility must provide grid balancing on an hourly basis to meet customer demands. On an annual basis, agents consider whether they should invest in energy infrastructure. Buildings consider their willingness to pay (WTP) for photovoltaics (PV), combined heat and power (CHP) and a battery based on predicted savings from the previous year's energy profile. The utility follows the fixed heuristic that if aggregated electricity demands encroach into their reserve margins (most commonly set at 15%) for both total capacity and quickly dispatchable (model uses the term reactive) energy production facilities that they must invest in additional capacity. A detailed description of these decision processes is available in appendix B. Figures 2 and 3 provide an overview of the subroutines that occur every hour and year respectively.

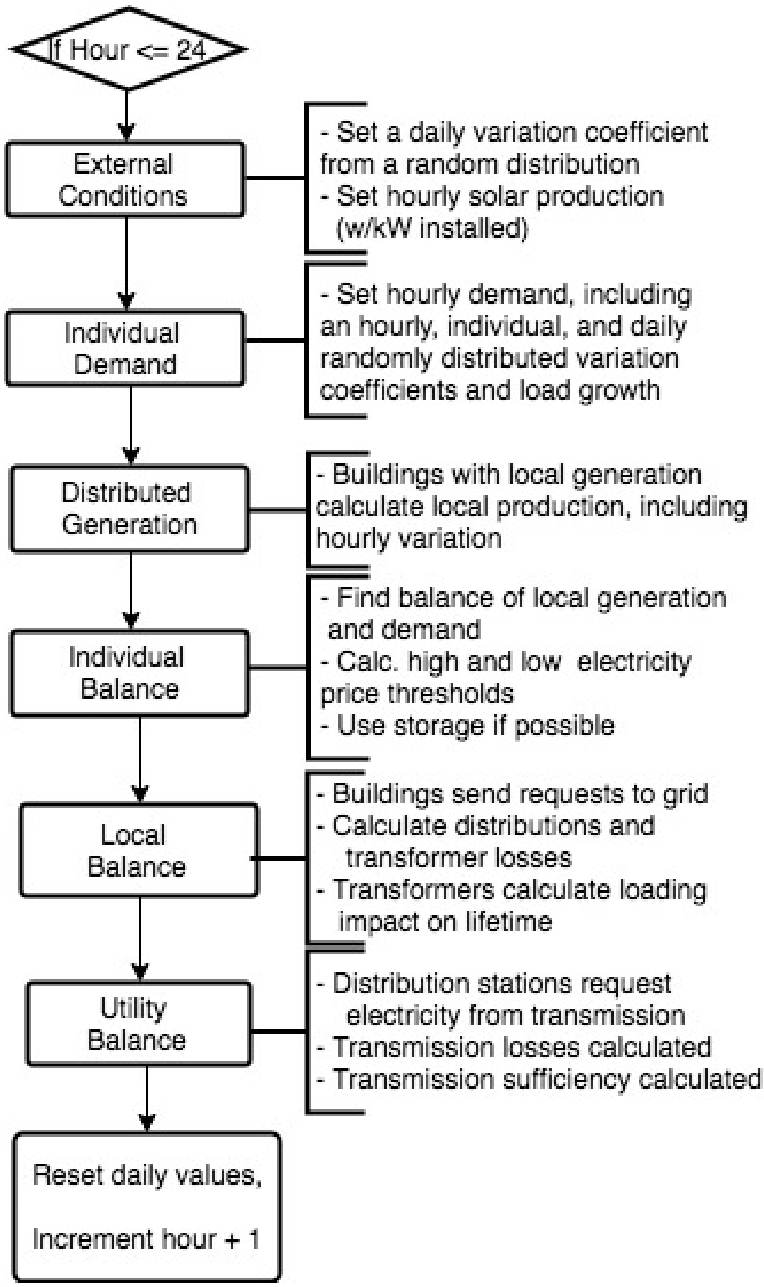

Figure. 3.2 Model subroutines that occur every hour

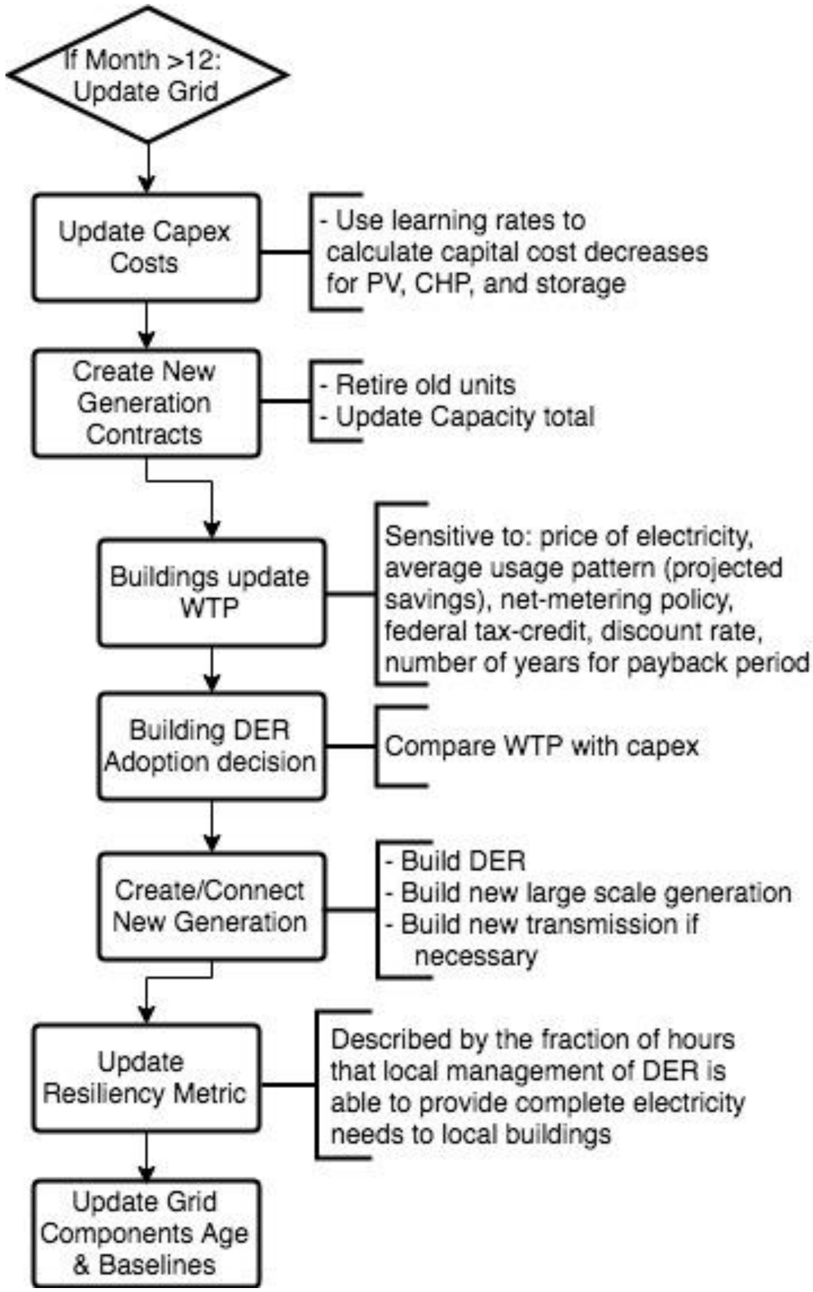

Figure. 3.3 Model subroutines that occur at the end of a year

Hourly demand variation, load growth, and DER energy production can alter the demand profiles and therefore affect the utilities decision to invest in grid infrastructure. While grid level investments do not directly affect DER adoption by buildings, Policy changes such as higher electricity prices, DER incentives such as net-metering (NM), the federal tax-credit (FTC), and financing that extend individual's desired pay-back period or decreases their future discount rate can all affect the adoption behavior.

3.3.2.3 Utilize nested patterns and distributions of attributes

The trend towards open modeling is beginning to take hold as evident by frameworks such as GridLab–D, ReEDS, or OSeMOSYS (Chassin et al., 2014; Howells et al., 2011). However, because these model frameworks are built on a specific set of input infrastructures, thereby imbuing the models with a fixed location and set of assets, which must be imported into the program, it is difficult to understand how the assumptions of the model or a single fixed asset affect the results or to draw comparisons with total investment predictions such as the Brattle report. This can make it difficult to foster dialogue and understand findings more broadly.

Models of the future cannot be validated. However, pattern oriented modeling (POM) and comparisons with other models can provide a useful reality check and basis for calibration. POM emerged as an important tool for validation of agent based models in ecology, but has since spread to other fields (Goldstone and Janssen, 2005; Grimm et al., 2005). POM relies on the observation of multiple patterns at differing scales. This is critical because "bottom up" modeling of individual heuristics and attributes produces emergent patterns at other scales of analysis. This can help mitigate the uncertainty that often accompanies complex systems, as each pattern that is observed at a higher level and is consistent with observed patterns increases the credibility of the overall model structure.

Pattern oriented modeling (POM) can help improve the validity and credibility of agent based models that attempt to move beyond fixed asset optimization towards probabilistic infrastructure investments. POM relies on the idea that if the inputs and mechanisms are sufficient, then known macro level patterns should be observable (Grimm et al., 2005). This can enhance validation when there is otherwise limited data. Emergent patterns can be used as validation for the sub procedures that serve as sub-model components for partial validation. Using this tool requires that causal mechanisms are validated against quantification of the emergent properties. Table 2 below describes each observable pattern, the input data or mechanism that was used and the desired model output system attributes.

Table 3.2 Patterns used for model validation

Component	**Input Data/Mechanism**	**Output Validation**
Demand profiles	Building demand profiles	Residential sector uses ≈40% of electricity
Distribution System	Street GIS files & Grid cost minimization	Scale factors
Transmission and Generation	Transmission connection heuristic	Degree Distribution
Centralized Investment Pattern	Utility investment thresholds	Lumpy investment pattern
DER Adoption Pattern	Building level willingness to pay	Adoption curves responsive to increasing cost of electricity and declining DER prices.

Each of these components is used to build a probabilistic model of the energy grid. We discuss each briefly.

3.3.2.3.1 Buildings as the primary energy demand units

Buildings are a sensible starting point for analyzing DER electricity futures due to the fact that they are the primary electricity users and their owners represent the most logical potential adopters of DER. The average U.S. resident moves almost 12 times[5], making any analysis and data that can be attained based on individual users, quickly irrelevant. Buildings however, have relatively static properties based on use type and area. Average usage patterns for the three main sectors (commercial, residential, and industrial) are well studied. There are several approaches to generating electricity demand profiles: statistical, neural networks, and engineering approaches (Biswas et al., 2016; Fumo and Rafe Biswas, 2015). Much of the research on modeling residential energy use focuses on identifying which factors are more likely to decrease total usage (Hache et al., 2017; Mostafavi et al., 2017; Wahlström and Hårsman, 2015). Models and research into patterns and stochasticity in demand at smaller time scales is difficult due to the fact that occupant behaviors are not well understood (O'Neill and Niu, 2017), and security and privacy concerns pose a challenge to accessing data that is needed for scaling up simulations (Biswas et al., 2016; Diao et al., 2017). This model uses a statistical approach with variability around seasonal averages scaled to buildings size, by using freely available GIS files, which are available from the City of Chicago Data Portal[6]. Buildings size has been shown to be a strong predictor of energy usage (Estiri, 2015; Kipping and Trømborg, 2017).

To create a diversity of buildings, monthly-hour averages are converted into hourly percentages and multiplied by the average intensity of energy usage (kWh/sf) and

[5] https://fivethirtyeight.com/datalab/how-many-times-the-average-person-moves/
[6] https://data.cityofchicago.org/

total area to generate hourly energy profiles. These profiles are taken from average profiles developed by the U.S. Department of Energy[7] and are described in appendix B. To validate the demand generated by the modeled area we compare the total amount of electricity that is used by the residential sector of the modeled area to the U.S. average. Because the input GIS files used for the model basis come from Chicago, the initial input data set used also came from Chicago. However, while on average the residential sector in the U.S. uses approximately 40% of electricity, the demand profile of residences in the Chicago area was only 30%. Therefore, we included a second location's demand profile from a more temperate climate, Houston, with the same input area. As opposed to Chicago, Houston's residential buildings use close to 50% of the total electricity. By averaging these two zones, the total residential demand closely matches the overall U.S. average. Future research for probabilistic modeling may look at how developing additional criteria for comparing and aggregating different demand zones may improve the utility and accuracy of probabilistic modeling. The graph below shows that over time the percentage of electricity used by the residential sector has been increasing. It also shows that, using the input area, that the more temperate Houston climate has a higher percentage of electricity going towards residential (51%) usage than Chicago (30%). Therefore it is more accurate to average the output of both modeled locations to explain the 2016 U.S. average of ≈40% residential usage.

[7] http://en.openei.org/doe-opendata/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states

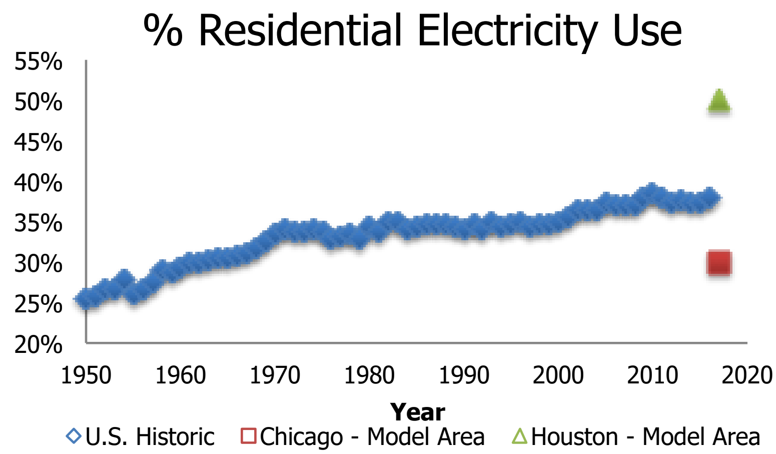

Figure 3.4 Electricity use variation between climatic zones. To have a better approximation of the U.S., as well to be able to compare between different input assumptions, we implement simulations using both a temperate (Houston) and seasonal (Chicago) electricity profiles. Average U.S. results for comparison with other studies compare the average of the two locations.

3.3.2.3.2 A Probabilistic Distribution Grid

Creating a model of all the distribution networks across the United States is computationally problematic (in addition to the fact that such a data set is not available to researchers). Furthermore, utilizing and optimizing a specific distribution system can limit the generalizability of findings to the input data region. Researchers studying cities have found that cities are characterized by self-similarity, or fractal scaling. This means that a subsection of a city will demonstrate the same overall properties as a larger section, as well as other sections (Batty, 1994). The use of the self-similar properties of cities can help, by enabling methods to "grow" realistic energy grids based on GIS inputs. Examples of self-similarity are common in nature (e.g. ferns or arteries) and often demonstrate a branching structure that can efficiently distribute resources. Scaling is evidence of modular evolutionary growth processes under relatively constant constraints.

This concept is foundational to the study of metabolic processes, which now includes urban forms (Samaniego and Moses, 2008). By creating probabilistic grids, a representative section of an urban area can be used as the basis for a distribution grid. This will produce averages and distributions of findings as well as differences between environmental regions that may then be scaled up to comment on larger scale implications. This is helpful as a basis for a distribution grid model because 1) it suggests that the findings from a subsection of urban development may be generalized to other areas 2) by identifying the rules that constrain growth one may arrive at a realistic model of the underlying structure of a system can be compared to known scale factors for real cities.

A generalizable model of a distribution grid requires that basic rules provide constraints for grid construction within an urban environment. Fortunately, researchers are engaging in understanding how a city can be modeled procedurally. This means that, given a growth logic and constraints within a defined area, a set of agents can create a city that is structurally similar, but not identical to the an actual city. Procedural modeling offers a potential solution to both the lack of data and the desire to study patterns instead of locations, as artificial cities are built that "are convincing and plausible" (Lechner et al., 2003). Urban modeling has shifted over time from static, non-spatial and top down models, towards heterogeneity, dynamic and bottom up models that employ the richness of space. Theories of spatial structure demonstrate the importance of optimizing constraints such as profit, cost, distance, agglomeration, and accessibility that provide for explanation of urban patterns (Heppenstall et al., 2012). Although procedural models have been used to study many transport and distribution attributes of cities, they have not been used for electricity distribution systems. "The representation of grids has not been a focus of ABMS so far, in particular not on the level of distribution grids" (Ringler et al., 2016). In this model we implement a procedurally constructed distribution grid based on urban GIS building and street constraints.

GIS data is more available than distribution grid data. It is used in this model to generate a distribution grid based off of streets and building loads and footprints. The U.S. electricity grid has grown incrementally based in part on path dependency generated from previous investments and constrained by the limits of technology and the power of a few expansive institutions. Engineering designs are bounded by the physical reality of the world we live in and have historically inhabited. Randomization of the placement of a few infrastructure components can produce structurally similar but physically distinct grids. Streets provide an outline of potential grid arrangements due to the fact that electricity lines must pass through public spaces to enable access and maintenance. Input data used for the generation of a grid are: energy intensity and GIS data for buildings and roads. Energy intensity is calculated based on the square-footage of buildings, and hourly usage[8]. This data is included in the model for two locations: Houston and Chicago, and all information is taken from Department of Energy sources[9]. The defining design constraints for optimization within the input GIS data are: sufficient space for substation construction, electric lines must follow transportation routes for accessibility, buildings are connected to substations in a radial construction pattern, and most buildings must be

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[8] kWdemand=(max kWh 124kWh*124kWhkWh*kWhsq.ft)*sq.ft

[9] http://buildingsdatabook.eren.doe.gov/default.aspx, https://en.openei.org/datasets/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states, http://pvwatts.nrel.gov/

sufficiently close to a substation so that they do not cause an excessive voltage drop. For additional detail see appendix B.

Optimizing these constraints relies on the branching, or the radial design, of the U.S. electric grid[10]. The U.S. has historically been dominated by a radial distribution grid design that connects building loads to the grid and which makes use of roadways for physical space (Parasher, 2014). This pattern can be used for simplification because it suggests that there is one shortest route between every load center and the closest substation. This greatly simplifies the complexity of building a logical grid. Further simplifying the challenge of grid simulation is the focus of this model on the magnitude of supply side investments and of the logic of total energy demands. This means that more complex energy flows and dynamics are not specified. Extending our understanding of probabilistic grids to energy flow analysis is an important area of future work. It also requires a more temporally granular method of simulating energy demand.

To assess the reasonableness of the procedurally created distribution grid, we compare the results of this design logic with research on scaling in cities. Researchers working on scaling in cities have studied how different urban indicators scale with population (city size) based on the relationship shown below. Y is the indicator of interest, N(t) is the population and β is the scale factor.

$$Y(t) = Y_0 N(t)^{\beta} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(1)$$

A distinctive taxonomy of scale factors is bounded by $\beta > 1$, $\beta \approx 1$, and $\beta < 1$. Indicators for which $\beta > 1$ are quantities for which there are increasing returns to scale. This includes categories such as total energy usage ($\beta = 1.07$ for European cities),

[10] This is in contrast with European electric grids which are often have more connected networks.

research and development employment, patents, crime, and GDP. Indicators that directly scale with human needs have a $\beta \cong 1$, which includes quantities such as jobs, housing, and household energy consumption ($\beta = 1.00$ for European cities). $\beta < 1$ for indicators that have economies of scale, such as gasoline stations, electrical cables ($\beta = 0.87$ for European cities), and road surface (Bettencourt et al., 2007).

By generating grids based on different GIS sections, which vary in population size, we can measure quantities of the model-generated grid and compare to the observed β values above. This allows us to be able to observe whether the model generates realistic scaling across differently sized populations. Table 3.3 below shows the resultant scale factors. They are consistent with the types of relationships expected; the fixed hard infrastructure demonstrates economies of scale, and the energy indicators show increasing returns to scale. Access to better (U.S. and additional measures) for validation data may help improve the accuracy and ability to use scale factors to calibrate urban models in the future, and is an opportunity for future improvements in probabilistic and procedural urban modeling. See appendix B for expanded analysis of scale factors.

Table 3.3 Scale factors from modeled sections

	Total Energy	Count Distribution Grid Sections
β	1.08	0.72
R^2	0.89	0.95
Num. input GIS areas	5	5

3.3.2.3.3 A Probabilistic Transmission and Generation Grid

Since, as we discussed in the section above, we approach the distribution grid by creating a realistic, but not real, grid, a representative subsection of the transmission and generation system is also needed. Agent based models have been predominantly used for analyzing transmission scale electricity markets at different operational time scales and some have included physical constraints that optimize for a fixed set of infrastructures (Fripp, 2012; Li and Tesfatsion, 2009; Sensfuß et al., 2007; Sun and Tesfatsion, 2007; Veselka et al., 2001; Zhou et al., 2007). Similar to the need to have a distribution grid imbued with physical attributes, but which is not specific to a single location, generating a probabilistic transmission and generation grid is achieved by utilizing patterns and constraints.

Because transmission and generation supply large areas, the first critical challenge to answer, is to determine a suitable scale factor that relates the modeled area to the larger region. Here, a scale factor is the percentage of the overall system investment for which a modeled subsection is responsible. If, instead, the modeled subsection was completely supplied by a single generator, then the location would not be responsive to the more gradual process of replacing & retiring generators, having sufficient transmission capacity, and would face difficulty having supply equal demand, as generators are comprised of large turbines which are either ‘on’ or ‘off’. Therefore, a feasible fleet of generators and accompanying transmission system is generated for the larger area. The subsection is allocated a percentage of each generator’s capacity, and therefore a fraction of its’ total cost. In order to have a representative diversity of the types and ages of centralized power plants, it is critical to scale the large investments down so that the percentage of each power generation type is representative of reality. The scale factor is based on the largest capacity generation type, nuclear power plants. Nuclear energy has an average generator capacity of 1.03 GW and is makes up approximately 9% of total U.S. generation capacity, as shown in figure 3.5 below. We assume that a single nuclear plant is allocated to the modeled area. All other centralized plants will be similarly scaled, such that the scale factor (SF) is calculated as shown below.

$$SF_{\%} = \left({Nu_{\%} * kW_{peak} * R_{margin}} \middle/ {Nu_{capacity}} \right) * 100 \ldots\ldots\ldots\ldots\ldots(2)$$

$Nu_{\%}$ is the percent of energy that comes from nuclear, kW_{peak} is the expected peak demand, R_{margin} is the required safety and investment margin (usually 1.15), and $Nu_{capacity}$ is the average nuclear generator capacity.

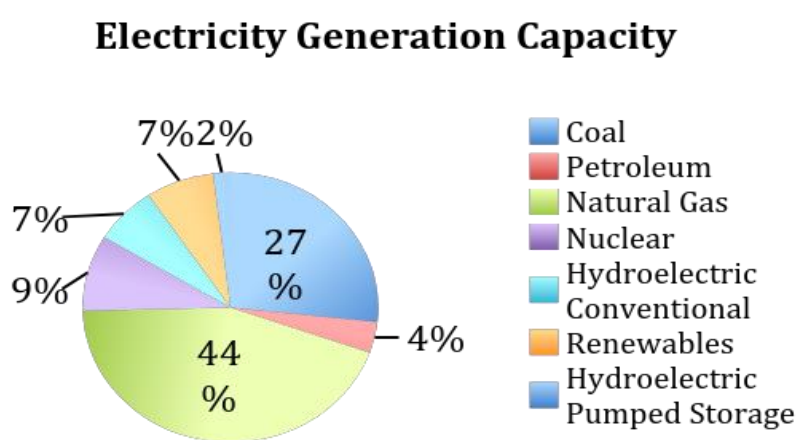


Figure 3.5 Electricity generation capacities by type

A transmission system network can be described by its' degree distribution (a histogram that shows how many nodes have x number of connections) , and its' method of formation, (Chassin and Posse, 2005; Cotilla-Sanchez et al., 2012). Preferential attachment occurs when new nodes are more likely to connect to nodes that are already connected. This attachment pattern leads to a scale free, or power-law degree distribution, which on a log-plot will have linear relationship (Barabási & Albert, 1999). In a study of the network structure of the American electric power infrastructure it was found that the major transmission networks bisect the cumulative degree distributions trends for preferential attachment and random connectivity (Cotilla-Sanchez et al., 2012). To capture this dynamic, substations located at generators connect to other substations using preferential attachment during the setup phase, but additional capacity additions and transmission needs are connected randomly. Figure 3.6 shows the degree distribution of generated transmission systems after the setup phase, which demonstrates that it is scale free.

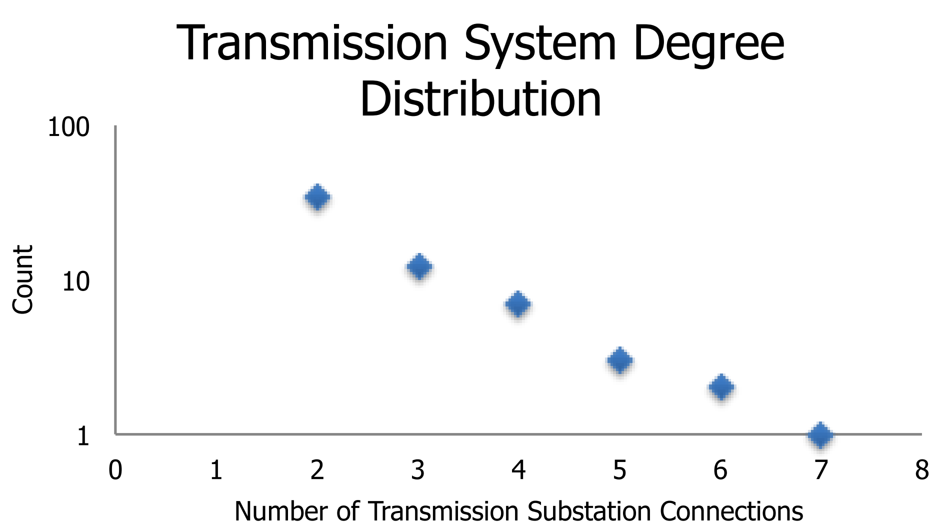


Figure 3.6 Connectivity of transmission grid is scale free

Although analysis of transmission grids shows that they also minimize distance, for simplicity sake we assume that all transmission distances are randomly generated around a normally distributed average distance of 80 miles. Additional description can be found in appendix B.

3.3.2.3.4 Lumpy pattern of utility scale investments

Centralized generation investment guidelines are well defined and are based on the need for sufficient reserve margin. A common reserve margin requirement is 15%. If the generation capacity is projected to fall below this margin, the utility will be required to invest in additional capacity (Maloney, 2013). These investments are large expenses that take many years of planning, with only small grid investments annually. The expenses pattern can be characterized as lumpy, as shown in figure 3.7. These large investments have a similarly large risk. Throughout the twenty-first century this was a successful investment model, as energy consumption continued to rise and large investments offered efficiency savings. However, under low growth conditions, which are common in many locations throughout the U.S., this creates high uncertainty regarding how the investment will be paid for, as it may not operate for the vast majority of each day (Gellings and Smith, 1989).

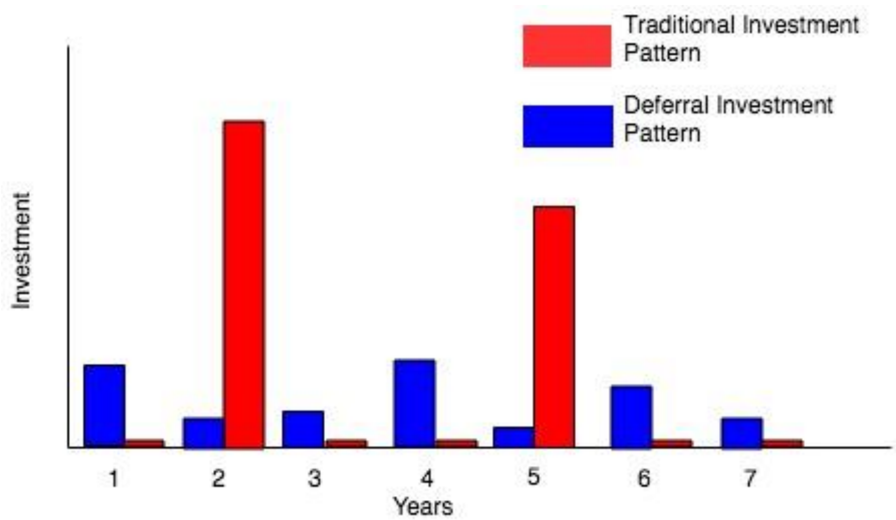


Figure 3.7 Example of idealized traditional and deferral investment patterns

As a reaction to this, some locations aim to defer these large investments by placing more emphasis on managing demand. Policies that seek to shift demand to less congested times or decrease load growth with DER investments can mitigate uncertainty by spreading relatively small investments out. Figure 3.7 above shows both the traditional investment pattern and a theoretical deferral scenario. The lumpy investment pattern of the traditional investment paradigm is an important verification pattern that the model is working logically. The ability of DER to defer these large capital investments is the subject of a great deal of speculation and will depend greatly on the management of the DER operations as well as the shape of load growth and other factors. Figure 8 shows an investment profile from a baseline scenario model run without DER incentives, which shows the lumpy centralized investment pattern.

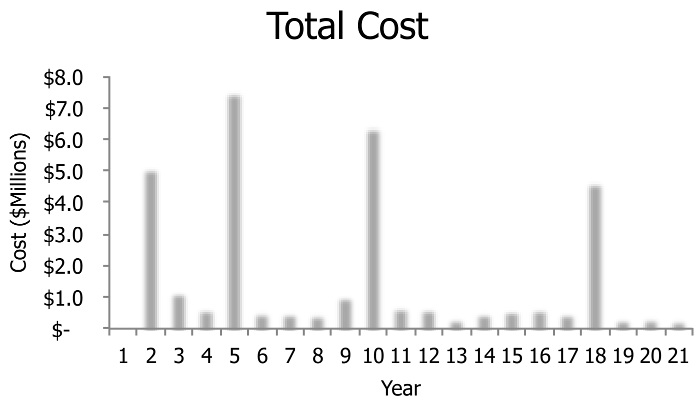


Figure 3.8 Example model output demonstrates lumpy investment pattern

3.3.2.3.5 DER adoption patterns

DER adoption decisions should be responsive to several parameters: the appropriateness of system sizing, the price of retail electricity, any investment incentives, and the cost of the DER itself. Assuming that the system is sized well, as electricity costs rise over time the amount of DER adopted should increase over time. Additionally, DER costs decreases have been well documented as following learning curves that result in cost decreases over time. The willingness of people to adopt DER based largely on the payback period of investment costs results in 'S curves' in which there is there is an increase in the rate of adoption that reaches a saturation level when all potential adopters have adopted it, as shown in figure. 3.9 The fraction of adopters increases as the payback period for the technology decreases (Gagnon, 2015). This price responsiveness and cost trends have been well supported with adoption data (Wang et al., 2013,). Learning curves describe the cost reductions that occur for technologies when more is installed. DER capacity adopted should also increase with time due to price decreases. We will first discuss the DER sizing assumptions and then present DER adoption results.

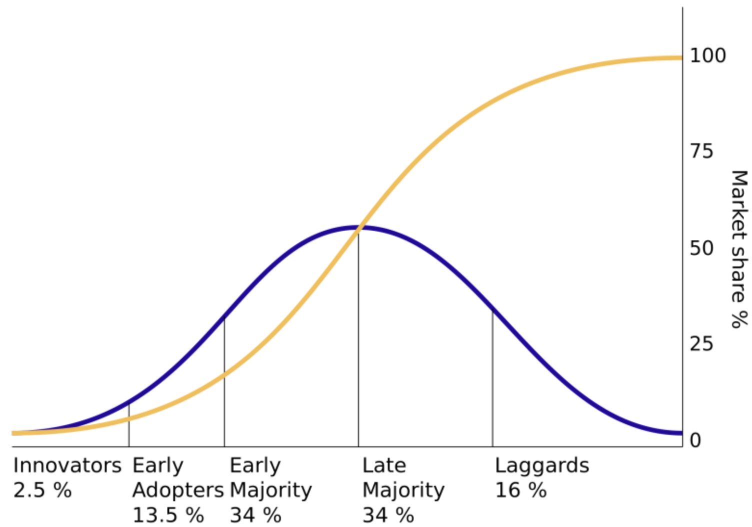


Figure 3.9 Idealized 'S curve' innovation adoption pattern

DER sizing, and therefore estimated yearly building savings, is based on the demand profiles, building area and potential shading effects for each building. GIS data, including building area, height, and location provides a distribution of building attributes, as well as the ability to infer from building location the likelihood of shading from nearby structures. This is important because the physical attributes of a city can dramatically alter the adoption patterns of residents (Gooding et al., 2013). Each structure must assess what are possible DER investments that are potentially beneficial. This is dependent on the physical attributes of the building, as well as the existence of policy, such as whether a net-metering or tax-credit policy is available (California Public Utilities Commission, 2013). Under net-metering policy the electricity production is sized to the yearly electricity consumption, whereas if there is no net metering policy, rooftop solar is sized to the area available. CHPs are sized to summer heat load to mitigate risk (Kok et al., 2010). CHP quickly reaches the saturation rate, due to the sizing constraints for summer heat load. Sizing CHP to heat load is just one sizing assumption that can be used, and this is an important area for future expansion. Batteries are sized to provide backup energy for a set number of hours. Four hours is used for battery size in the baseline condition. Empirical and modeling efforts have demonstrated that while economics is just one of many potential adoption factors, economic willingness to pay may encapsulate these drivers as preferences that may shift the WTP, but do not alter the eventual adoption rationale (Snape, 2015). Therefore we take a stochastic approach to assigning preferences in a multi-agent environment in which a distribution of WTP anticipated future savings[11]. See appendix B for more a more detailed description.

The figure 3.10 below shows that the adoption of PV and CHP by buildings is accelerated when there are increases in the electricity price, and over time due to technological learning which matches the S shaped adoption curve. PV enters the rapid adoption phase and then plateaus. The adoption curves are consistent with recognized global patterns, in which DER adoption increases over time due to both technology and business cost decreases. This suggests that the buildings' willingness to pay function is responsive to logic of increased cost of electricity as well as to technological learning and cost reductions. Increasing the electricity price, creating rules that increase the payback period or discount rate, the existence of net-metering (NM) or the Federal Tax Credit (FTC) are all different ways to shift the adoption behavior. We delve into the interactions

[11] See the appendix B for a detailed description of the method for calculating the projected savings and willingness to pay.

between sizing, incentives and prices in the results section, but it is important to note at this juncture that sizing will affect the willingness to pay of individual buildings, thereby shifting the adoption curves.

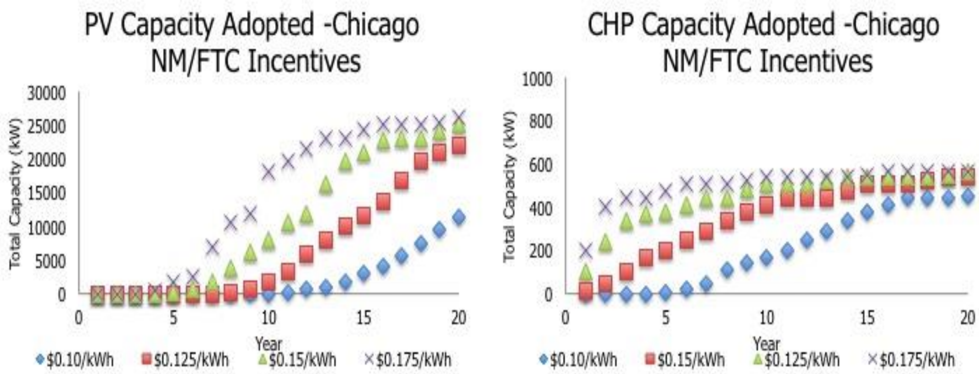


Figure 3.10 DER Adoption curves in baseline condition show that the capacity of DER adopted approaching saturation capacity at different rates. Adoption rates slow when the price of electricity is low. The CHP saturation capacity is relatively insignificant compared to PV.

3.3.2.4 Comparison with Centralized Predictions

In addition to POM verification of sub modules or procedures, an important way to assess a model in its' entirety is by comparing model outputs with those of other models. The Brattle study was an impetus for this modeling effort; it is therefore used to assess the reasonableness of the baseline scenario, in which DER does not receive incentives. This should most closely align with the Brattle scenarios, since they do not include DER. Assumptions such as load growth are set the same levels as the Brattle study. In order to compare the outputs the overall findings of the Brattle study from the entire U.S. to the population size of the modeled area. While the Brattle study is based on the aggregation of four different regions, the comparison results from this model are the average the two different regions. For comparison purposes we do this based on 1) the observation in section 3.3.2.3.1 that a more accurate representation of U.S. energy usage is an average of both a variable (Chicago) and more temperate (Houston) climate and 2) that the results from the two locations are significantly different. Figure 3.11 shows the histogram for both the Chicago and Houston results in the baseline condition.

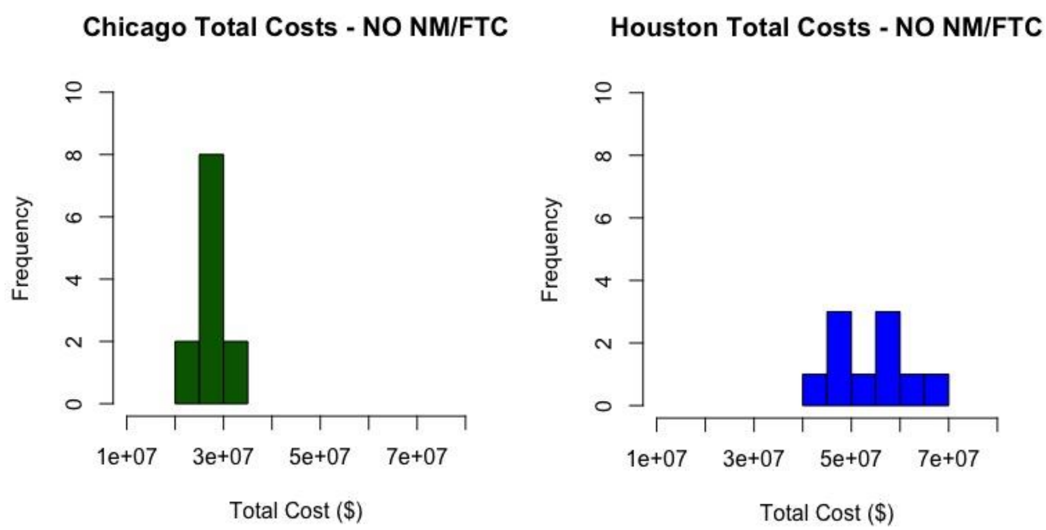


Figure 3.11 Histogram of total cost results for the Chicago and Houston regions demonstrate that the differences in electricity demand profiles has a large impact on results.

The distributions of results from the two locations are significantly different from each other. Future work would benefit from increased research on regional differences. Since this model uses a probabilistic grid as a basis for comparison we look at the distribution of outcomes. In addition to this baseline scenario, that does not include incentives for DER, we compare the Brattle to two scenarios that look at how existing mechanisms, used in different extents in different cities and states, may impact the overall costs. The three scenarios are defined by the implementation of combinations of DER incentive types.

Scenario 1: this baseline condition does not include net-metering (in which a DER owner is paid the avoided cost of electricity generated, inclusive of additional fees that the utility charges in addition to the generation cost) for DER generated electrons. It also does not include the federal tax credit, which has provided a 30% rebate to DER installers in the U.S. since 2006. *Scenario 2:* includes both net-metering (NM) and the federal tax credit (FTC), which incentivizes DER. In scenarios one and two, agents have a discount rate of 0.05 and an average payback period preference of 5 years. *Scenario 3:* a high DER adoption scenario has a discount rate (d) of 0.03, and average payback period (pbp) of 6 years, NM, and the FTC. This high adoption scenario is created as a proxy for access to DER financing, which may include initiatives such as solar leasing, property accessed clean energy (PACE), or other mechanisms that redistribute the capital and investment risk.

As we discussed above in figure 3.11, the distribution of outcomes are reasonably and normally distributed for each location (Chicago or Houston), but are not Gaussian in aggregate. Scenario 1 has a bi-modal distribution with one peak comprised of Chicago data and the other Houston. However, as more distributed energy is adopted (in scenarios 2 and 3), the profile of the total costs for both locations becomes more similar and normally distributed in aggregate, as the costs profile in Houston shifts more towards Chicago. We therefore perform separate cost comparisons between locations when comparing the distributions of modeled output, and then average the two projected futures to compare with the Brattle Study. Figure 3.12 shows the distribution of total costs for three different DER adoption scenarios for both the Chicago and Houston locations.

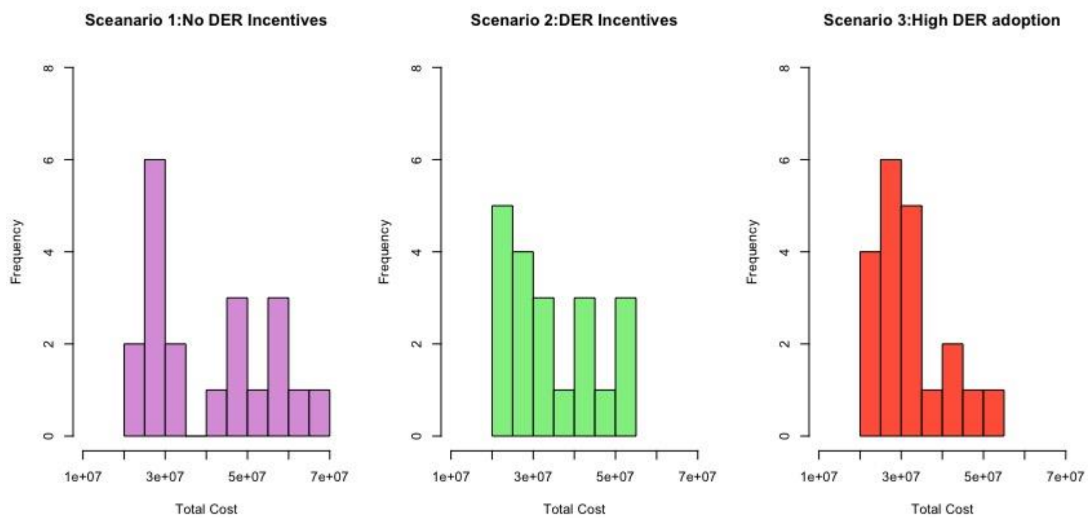


Figure 3.11 Distribution present value of total costs for both Chicago and Houston locations under three DER adoption scenarios

Total cost results, averaged between both the Chicago and Houston distributions, from 20-year runs are compared below with the Brattle studies 20 year projected costs. To compare between studies it is critical to know what is a sufficient number of runs in each environment. The minimum number of runs required can be calculated by observing when the change in the coefficient of variation falls below a threshold (shown in figure 12), or by iteratively solving equation 3 below for a stable n. Finding agreement between the two methods allows for a more rigorous understanding of a representative sample.

$$n \geq \frac{2\sigma^2}{\delta^2}(t_{v;1-\alpha} + t_{v;1-\beta})^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In equation 3 above, n is the minimum number of simulations needed, σ is the standard deviation of the output values, δ is the absolute difference between the mean value and the value at $t_{v;1-\alpha}$, and $t_{v;1-\alpha}, t_{v;1-\beta}$ are the t values for $\alpha = 0.05$ and a power level of 0.9 (Radax and Rengs, 2010). Using this method and the output data from Chicago we find that the minimum number of runs needed stabilizes by n_{min}= 4. This is supported figure in 12, which shows the that, when the model looks at total costs over 20 years, change in the coefficient of variation falls stabilizes by round four in both locations. We use 10 runs as a reliable stable comparison for baseline conditions, but also assert that a smaller n will produce reliable results, which enables less computational time for sensitivity analyses. The use of a twenty-year time period is beneficial for comparison with the results from the Brattle study, but there is further significance in terms of path dependency.

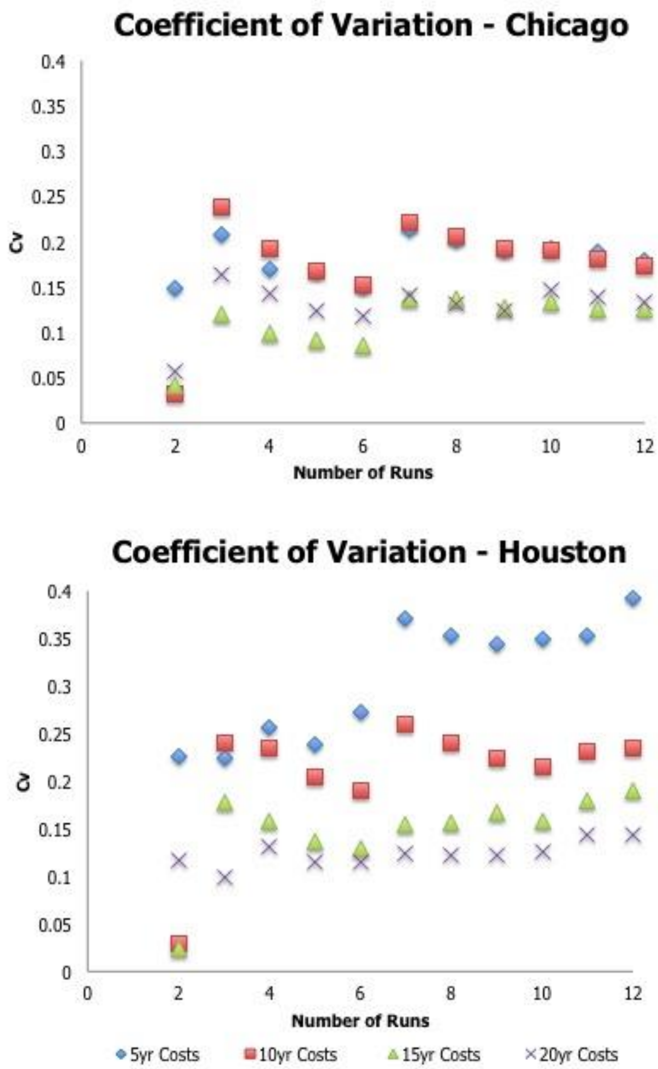


Figure 3.12 Coefficient of variation from results in both Chicago and Houston

A shorter time horizon for comparing costs will require a larger number of simulations to obtain similarly reliable results. This is important because many Value of Solar (VoS) studies for policy making have recognized the sensitivity to time horizons, which based off of optimization of a fixed set of investments. By using longer time horizons, generalizations from a small area simulations will be more robust to path-dependency that may occur from a small n. Short time horizons will produce dramatically different outcomes with large standard deviations, relative to the average. As distributed energy becomes an increasingly important factor, simulations of variation in investments, as opposed to a fixed set, and longer time horizons can mitigate uncertainty and path-dependency.

The results from the Brattle study are multiplied by a scale factor of 0.0002 to make them comparable with the results from the modeled area. This scale factor is calculated by taking the total annual energy used by the subsection of the Chicago grid system in year one (≅75GWh) in the model divided by the average total energy used by the United States in EIAs 2008 Annual Energy Outlook (≅3,755,000 GWh) (EIA, 2008; The Brattle Group, 2010), the basis for the Brattle study.

Table 3.4 Comparison of averaged Chicago and Houston results with Brattle Study

NM/FTC – Cost Type	**Brattle Cost at Local Scale ($Millions)***	**Scenario 1 No NM/No FTC Avg. Model Estimates ($Millions)****	**Scenario 2 NM/FTC Avg. Model Estimates ($Millions)****	**Scenario 3 High Adoption Scenario ($Millions)****
Generation	$9.03-13.8	$ 11.7	$9.2	$7.0
Transmission	$5.9	$ 10.9	$ 10.1	$7.0
Distribution	$11.5	$ 18.2	$18.3	$17.9
AMI, EE/DR	$0-3.8	1.3 MW DER Installed @ year 20	18.1 MW DER Installed @ year 20	32.3 MW DER Installed @ year 20
Total	$26.4-35	$40.8	$38.0	$31.9

*Results are aggregated from 4 U.S. regions

** These results are averaged mean values from the Chicago and Houston location distributions. Location specific results are discussed in results section

The table shows that the total averaged model costs are similar to Brattle's top down future scenarios, however there are higher costs for transmission and distribution investments. It also shows that incentivizing DER decreases overall costs. The higher T&D costs are expected since, as discussed previously, the Brattle study has extrapolated historical costs to determine T&D costs, they do not account for the age profile of the infrastructure or the underinvestment in recent years (Brown and Willis, 2006; Kurtz et al., 2005). Cost differences due to DER adoption can be examined by considering the effect that scenario 2 and 3 had on costs. Although increased DER appears to decrease the costs to T&D, when we consider the averaged results from both Chicago and Houston under the three conditions the only significant effect of DER incentives is between the high adoption scenario (scenario 3) and the baseline, no incentives, scenario 1. Differences in total costs are not significant between scenario 1 and the scenario 2 without any DER incentives $t(35)=1.5328$, $p=0.1343$), or between scenarios 2 and 3 $t(36)=0.854$, $p=0.399$). The high DER adoption scenario, scenario 3 does have a significant cost reduction when compared with the no incentives scenario $t(31)=2.347$, $p=0.026$.

Even in the baseline scenario, without existing incentives, 1.3MW of DER capacity (or approximately 0.13kW/person) has been adopted on average by the modeled area. While this number is not particularly high, it suggests that it is important to incorporate DER in future cost analyses, even though it adds increased complexity. It will be very likely that, given the inevitable cost reductions, especially for PV, from global drivers, that DER will continue to increase in desirability in the near term future.

The averaged results from both Chicago and Houston are largely consistent with the Brattle Study, with the anticipated difference in T&D costs. The comparison of the Baseline scenario with the Brattle study provides a mechanism to validate the model, as well as suggesting that DER savings may have a significant impact on future grid costs. Even when the simulation does not include incentives for DER such as net-metering, federal tax credits, or increases in potential adopter's willingness to pay, cost decreases suggest that DER will be desirable to many buildings by the end of the twenty years. While there may be some inevitability in the affordability of solar in the future, without concerted incentives to accelerate the adoption rate, DER may not dramatically impact the magnitude of future imagined costs.

3.4 Results

Now that the conceptual basis for the model has been elucidated and compared with existing predictions, sensitivity results are used to understand how this probabilistic model basis is sensitive to different types of assumptions. Understanding the sensitivity of a model helps elucidate when a model results are generalizable, and when they are limited. In the results we explore the model's sensitivities to two overarching categories: supply side and demand side assumptions. Examples of supply side assumptions include assumptions about the cost and composition of centralized generation and the age of infrastructure while demand side assumptions include differences in demand profiles, load growth and DER adoption assumptions. This division is made to account for the fact that while supply side variability is often included in market based decisions, variability in demand patterns has historically received less attention, but may be the subject of increased attention as smarter consumer located devices offer new tools to interact with demand.

3.4.1 Demand Side Sensitivities

3.4.1.2 Results Sensitivity: Location and DER Adoption

The Brattle study did not include a sufficient scope to consider DER impacts on costs, potentially due to diversity of initiatives and potential outcomes between locations. Table 3.5 shows t-test comparisons for total costs for both Chicago (C) and Houston (H) for the three DER incentive scenarios (1 – No NM/FTC, 2- NM-FTC, 3 – High adoption). It shows that not only are the costs significantly different between Houston and Chicago, but that there is an important interaction between the location dependent shape of the demand/DER production profile and the grid costs. The costs for the Houston location, without DER, are significantly higher from both the net-metering/federal tax credit scenario and the high adoption scenario. On the other hand, even the high DER adoption scenario does not make a dramatic impact on the expected costs for Chicago.

Table 3.5 Comparison of DER adoption scenarios 1,2, & 3 in both Chicago (C) and Houston (H)

	C-1	C-2	C-3	H-1	H-2	H-3
C-1	M1=$27.7 SD=$3.8					
C-2	t(23)=1.275 p=0.215	M=$25.5 SD=$4.9				
C-3	t(22)=0.023 p=0.982	t(23)=-1.224 p=0.233	M=$27.7 SD=$4.0			
H-1	t(13)=1.61 p<0.001**	t(14)=10.028 p<0.001**	t(13)=9.551 p<0.001**	M=$53.9 SD=$7.9		
H-2	t(14)=4.9505 p<0.001**	t(16)=5.496 p<0.001**	t(15)=4.922 p<0.001**	t(20)=2.976 p=0.007*	M=$42.7 SD=$9.8	
H-3	t(15)=-3.099 p=0.007*	t(17)=-3.755 p=0.002*	t(21)=2.255 p=0.035*	t(20)=5.02 p<0.001**	t(22)=1.729 p=0.098	M=$36.2 SD=8.7

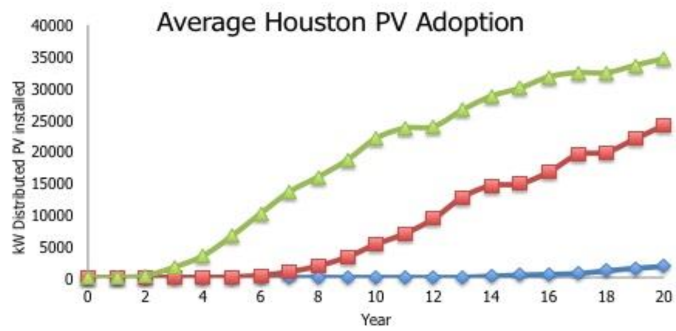
If DER is responsible for generation savings, it is expected to see decreased generation investments as DER adoption reaches appreciable levels. This is the pattern that is demonstrated in the Houston location, but is less straight forward in the Chicago context. The type of generation investments that occur in the two locations explain this difference. Houston investments are almost completely capacity additions, while Chicago must invest in peaking generation. This is interesting because Chicago peaking needs come from the need to rapidly ramp up electricity capacity in the morning, especially in the winter, as well as to meet evening peak needs. A dominant narrative is that places with high solar PV adoption face problematic peaking needs in the evening. However, places such as Chicago have been meeting such a challenge for decades. Since the morning energy needs in Chicago are largely predictable, one possible response to this is that investments in forecasting technology, that can provide certainty about expected production from renewable resources, can help with this challenge. Table 3.6 below shows the average amount of both capacity and peaking resources required in the three scenarios.

Table 3.6 Average amount of centralized generation needed in Chicago (C) and Houston (H) in each of the different DER adoption scenarios (1,2, or 3)

	C-1	C-2	C-3	H-1	H-2	H-3
Capacity (MW)	0.1	0.9	0	12.8	7.4	5.2
Peaking (MW)	10.4	8.2	10.8	0.2	0	0.4
Total (MW)	10.5	9.1	10.8	13	7.4	5.4

The significance of the difference in grid costs in Houston between scenarios one, two and three demonstrate that the FTC and NM are critical drivers for making DER affordable and reducing grid costs. This depends largely on the generation investments that are needed. When capacity additions are needed, PV additions can be helpful, but when peaking reserves are primarily needed, these DER incentives will be insufficient to have a noticeable benefit on grid costs. This is especially true because none of the incentives are sufficient to incentivize batteries.

Figure 13 shows the average PV adoption and average annual centralized generation investments for each scenario. We focus on PV due to the fact that CHP adoption is relatively insignificant, and batteries are not sufficiently incentivized by any of these scenarios. The effect of expedited DER adoption in Houston in both scenario 2 and 3 significantly decreases the total capacity generation investments needed. The case is less clear in the Chicago context. The differences in generation capacity needed with the baseline scenario is significant only for scenario 2, but not for scenario 3. This suggests that there is an important interaction with timing, retirements and load growth for long term planning in the Chicago context, but not in the Houston context. If load growth occurs to a greater extent at certain hours than others (e.g. higher levels of peak load growth), there may be a large impact on the type of costs expected. An examination of how non-normally distributed load growth patterns (e.g. peak load growth but overall growth) interact with potential savings would be a useful extension of the model.



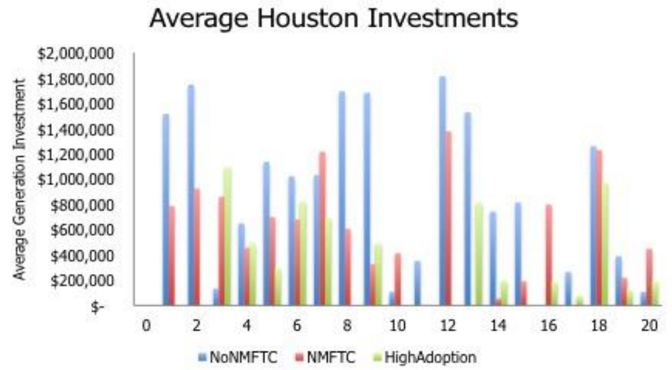


Figure 3.13 Average of PV capacity adopted (top) and centralized generation investments for Houston for each DER investment scenario. Lowest adoption scenario (Scenario 1 – No NMFTC) has the highest centralized generation costs.

While some benefits are realized by adopting DER, without some form of balancing, or battery incentive, the benefits from PV adoption depend on how well aligned the DER production is with the demand curve of a location. Currently existing mechanisms (net-metering, FTC and financing) are not sufficient to incentivize distributed battery investments, which could mitigate peak energy growth. This is consistent with reality; battery investments for local load balancing and savings are insignificant. Additionally, because CHPs are sized to summer heat load, there are a limited number of buildings that have sufficient size to actually consider CHP and therefore CHP does not significantly impact grid costs. As decision-making agents, building owners/managers must make decisions about DER sizing and adoption based on their understanding of their electricity demand profile, incentives/pricing, and risk preference. This conservative sizing heuristic is an example of one of the many aspects of uncertainty and complexity that is added to future analyses of energy futures when DER is included. To understand how these assumptions impact outcomes we look at the total cost's sensitivity to changes in DER sizing and adoption preferences.

3.4.1.2 Results Sensitivity: DER Sizing

Building agents make decisions about whether and what size of DER systems to consider, and this may dramatically impact the amount of DER capacity that may eventually be integrated into the system. Due to the nature of the three technologies considered in this model, different heuristics are required for each. CHPs (or potentially also fuel cells in the future) are sized to the minimum (July) heat load of a building, because the ability to use excess heat is the main advantage that CHPs provide. While CHPs can also be sized to electricity load, we focus our analysis on sizing to heat load, as a more conservative metric, that is less sensitive to gas price volatility. CHPs become less efficient at small scales. A 1kW electric output is considered the smallest feasible CHP that can be installed and even this is not common in most markets. Table 3.7 below shows how changing the reference month for CHP sizing changes both the number of buildings that adopt CHP in both Houston and Chicago in the scenario 1.

Sizing to winter heat load increases both the CHP cost as well as potential electricity savings, as the lack of commensurate heating savings during warmer months can make this too costly. This is evident in the Chicago location, which actually has the highest adoption when sized to spring heat loads (assuming favorable heat prices). By contrast, sizing to winter heat load in warmer climates, such as Houston, can actually produce higher levels of total adoption. This confronts the assumed wisdom that places like Chicago will be the primary markets for CHPs due to their need for heat. However, this presents a sizing dilemma, as heating and electricity needs are not necessarily coincident. It therefore seems that places such a Houston, that have more consistent load patterns are likely to be larger markets for distributed energy that provides local heating.

Table 3.7 Effect of CHP sizing on total adoption pattern

Average CHP Capacity Installed	**CHP size reference month**		
	Jan	**April**	**July**
Houston (MW)	2.0 σ=\$0.1	1.0 σ=\$0.03	0.6 σ=\$0.01
Chicago (MW)	1.1 σ=\$0.2	2.5 σ=\$0.1	0.5 σ=\$0.01

While the capacity of CHP is significantly different for each the reference months, this does not produce any significances differences in grid costs. This is likely due to the fact that, even under the highest adoption scenarios, the capacity adopted is negligible relative to the amount of PV adopted.

Unlike CHPs, Photovoltaic size is constrained by the fraction of the roof that is considered suitable for a PV installation. In the baseline runs, it is assumed that fifty percent of each non-shaded roof area is properly suited for solar panels. Table 3.8 below shows how the amount of adopted PV capacity changes with these assumptions.

Table 3.8 Effect of rooftop area on total PV adoption

Total PV Capacity Adopted in Year 20	Percent of rooftop area suitable for solar panels		
	25%	50%	75%
Houston (MW)	10.0 σ=\$1.6	15.4 σ=\$1.7	17.2 σ=\$3.3
Chicago (MW)	5 σ=\$1.3	8.4 σ=\$2.3	10.8 σ=\$3.3

The amount of PV adopted is significantly different between all scenarios. If **α=**0.075, then there is a significant difference in centralized generation investments for the Houston location only when 25% of the roof is available versus 75% ($t(7)=2.18$, $p=0.065$). No other differences in grid costs are significant. The lack of significant differences in DER sizing parameters increases confidence that results are not an artifact of these parameters.

Additionally, storage is not sufficiently incentivized to be adopted by potential adopters in any of these scenarios. Additional policies are likely necessary to incentivize storage. Storage is evaluated economically in terms of its ability to take advantage of the simplified time of use pricing. It therefore produces no benefit under net-metering. The evaluation of storage is based off of when it can be strategically charged and discharged with a time of use pricing, see appendix B for further details. Batteries storage sizing can be controlled by changing the number of hours which the battery can supply peak load to the building. Expected savings then are the difference between the highest electricity price and the lowest electricity price for each hour of sufficiency.

3.4.2.4 Results Sensitivity: DER Adoption preferences: Discount Rate

Distributed energy entails uncertainty from the lack of information about owner adoption and risk preferences. Potential DER owners' risk preferences are included in their internal willingness to pay (WTP) functions in both the discount rate as well as the number of years that they require for an investment to pay for itself (payback period). For an expanded description of the WTP model, see the appendix B. WTP depends on multiple factors, including the ability to access financing and other programs that can mitigate risk or redistribute risk to larger entities. This can include product quality guarantees, or mechanisms that allow for the transfer of investment liability when DER owners move. It is therefore important that the willingness to pay represents a distribution of preferences, which we assume to be normally distributed for simplicity. Changing the average, normally distributed, future discount rate of agents in the simulation, changes the overall WTP of the potential DER adopters.

Figure 14 show how changes in the discount rate, which may be achieved by combinations of many of the policies mentioned above, may shift the onset of the adoption curve. However, changing the discount rate alone did not significantly alter total grid costs. Implementing a single policy, such as access to financing, that may shift potential DER adopters WTP is unlikely to have a significant impact on the total costs to the grid. However, combining financing with other initiatives such as the federal and state tax credits, the net metering policy, can have a combined effect that can reduce grid cost by expediting higher levels of adoption (e.g. scenario 3).

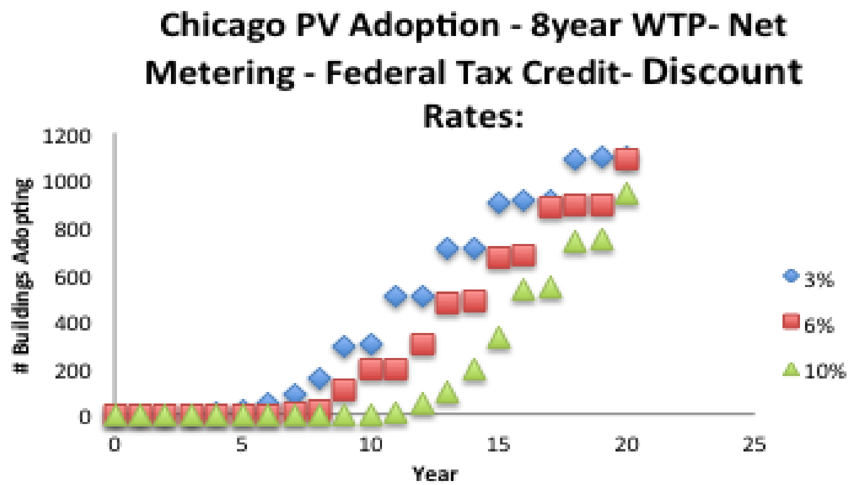


Figure 3.14 Effect of discount rate on PV adoption pattern

3.4.1.3 Results Sensitivity: Load Growth

In addition to regional generation differences, there are also differences in load growth. To be consistent with the assumptions in the Brattle study we model 1.1% load growth in the baseline scenarios. However, many locations are facing flat, or in some places declining, load growth. While many utilities face challenges to their foundational business model, flat load growth has the potential to dramatically decrease the total cost to consumers. The table below shows a comparison of zero load growth scenarios compared with 1.1% load growth without DER incentives (scenario 1).

Table 3.9 Comparison of flat load growth with 1.1% load growth

	Chicago 1.1% LG	Chicago 0% LG	Houston 1.1%LG	Houston 0% LG
Generation ($M)	5.7	4.4	17.6	6.2
	t(1.679)=11.227, p=0.121		t(16)=6.882, p<0.001**	
Transmission ($M)	9.0	5.8	12.9	5.0
	t(17)=2.501, p=0.023*		t(13)=12.438, p=0.001**	
Distribution ($M)	13.0	13.2	23.4	23.4
Peaking Generation (MW)	10.4	7.0	0.2	0
	t(12)=2.283, p=0.04*		t(10)=1, p=0.341	
Capacity Generation (MW)	0.1	0.2	11.8	4.2**
	t(11)=-0.481, p=0.640		t(17)=7.249, p<0.001**	

It is obvious from the figure above that in flat load growth locations that the majority of costs stem from the distribution system, and total costs are much lower, but do not eliminate the need for new generation resources that results from retiring old plants as well as variability. This is consistent with the findings of the Brattle study that *"EE/DR programs could significantly reduce, but not eliminate, the need for new generation capacity….the implementation of realistically achievable EE/DR programs by electric utilities would reduce the need for new generation capacity significantly"* (The Brattle Group, 2010). Although we did not model it here, flat load growth with increasing peak growth is an important trend for future modeling.

3.4.2 Supply Side Sensitivities

3.4.2.1 Results Sensitivity: Centralized Generation Technology Assumptions

To determine how centralized energy technology choices and prices impact the ability to recognize likely costs and savings from DER we compare the baseline scenario with alternative cost projections and generation technology choices. With regard to technologies, we assume that, for the upcoming twenty years, there continues to be a reliance on natural gas peaking plants to integrate variable resources. This is inline with recent critiques of models that do not reasonably consider the feasibility of scaling up battery and hydropower to capacities currently supplied by natural gas combustion turbines (Clack et al., 2017). In the baseline scenarios we assume renewable energy, with an average project installation capacity of 58.9MW and an average of 2 sites per project, is used for capacity additions. Natural gas combustion turbines, which have an average of 6 turbines each with an average capacity of 85.6MW, are used for responsive additions.

Average installation capacities are taken from DOE historical installation data, additional information is available in the appendix B. Since 2008 renewable energy and natural gas have been responsible for more than 95% of newly installed capacity[12], with wind and solar occupying increasingly large market shares as market prices continue to decline relative to more mature fossil fuel technologies.

In the years since the Brattle study was released, renewable energy investments have begun to outpace even natural gas generation investments. We assume renewable energy installations in the baseline scenario for non-peaking installations due to the fact that the learning cost curve for renewable technologies suggest continued additional future savings. Gas turbines are a mature technology whose price competitiveness relies on the price of natural gas, thereby imbuing additional future cost uncertainty to the technology. To understand how generation cost assumptions skew results we compare the expected cost profile using natural gas at three different price points with wind at equivalent price points as the primary capacity adding technology at different costs. Both simulations assume natural gas combustion turbines are used for responsive (non-capacity) generation needs. Table 5 shows the differences in total and generation for the Houston location.

[12] www.eia.gov

Table 3.10 Sensitivity of total costs to changes in cost of generation technology

Average Costs ($Million)	**Gas $1680/kW**	**Gas $1980/kW**	**Gas $2280/kW**	**Wind $1680/kW**	**Wind $1980/kW**	**Wind $2280/kW**
Total	*$48.4* σ=$3.8	*$48.1* σ=$5.3	*$53.2* σ=$8.7	*$44.6* σ=$7.2	*$53.9* σ=$7.9	*$53.1* σ=$6.7
Generation	$16.5 σ=$3.2	$17.4 σ=$3.3	$21.9 σ=$7.1	$12.1 σ=$4.0	$17.6 σ=$3.7	$20.2 σ=$5.5

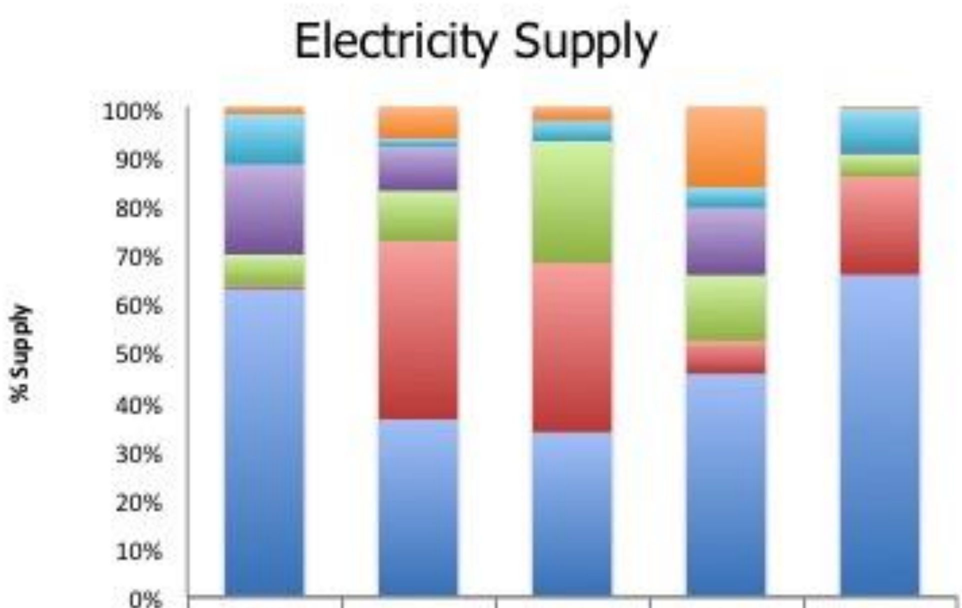
Changing the cost of generation does demonstrate rising average generation prices, but the majority of the differences in the distributions from 8 runs were not significantly different. The differences that were significant (**α** <0.05) for generation costs were $1.68/W Wind and $1.98/W Wind, $2.28/W Wind, and $1.68/W Gas; t(15)=-2.996, p=0.009, (t(13)=-3.388, p=0.005, t(14)=2.484, p=0.027, respectively. Generation costs incur variation in the number of and size of installations, and additional information can be found in appendix B. Total costs had even less significant differences than generation costs. Differences that were significant for total costs were $1.68/W Wind and $1.98/W Wind and $2.28/W (t(16)=-2.603, p=0.02) and (t(14)=-2.44, p=0.03) respectively. The lack of expected differences is due to the variability in transmission distance. Transmission costs are based on an average distance. By installing less large capacity projects transmission costs may be less, making it difficult to directly compare costs. This analysis is limited by the fact that it does not account for the fact that many large renewable projects are located much farther from load centers. Therefore, the generation results show that the cheapest form of centralized generation is renewable, when that may not be the case since transmission costs add variability to the total cost.

However, reality suggests that this may not be an egregious flaw, as the trend towards large scale renewable projects is well represented in reality. This may be caused by laws that designate utilities to pay for (and therefore rate-base) transmission investments while others parties may own generation assets.

The model is also limited by a lack of accurate centralized generation production profiles. Because this analysis looks at a relatively small area, just over a square mile, responsible for only 0.02% of the investment burden of these transmission level investments, it is unclear how a more specified centralized production model should be mapped onto such a small area. Since balancing the transmission markets takes place on a larger scale, we use the simplified investment logic of having sufficient capacity buffer (minimum of 15%) to spur investments and exclude the complex power-flows from this analysis. As demonstrated above, this seems to produce accurate and conservative cost predictions relative to other industry predictions, but we also recommend that this may be an useful area for further analysis and improvement. Overall, the cost of centralized generation produces a more minimal impact on overall costs than we expected due primarily to the variability inherent in transmission investments, which obscures what would otherwise be a fairly straight forward cost comparison.

3.4.2.2 Results Sensitivity: Regional Generation Composition

The baseline conditions presented earlier used a generation mix that was comprised of the average mix of centralized generation, based on the national average. A logical next question is, to what extent does regional variation in attributes such as infrastructure age, load growth, and generation resource diversity significantly change the scale of investments needed? While the baseline scenario considered average generation that was comprised of a total generation capacity that was 44% natural gas, 27% coal, 9% nuclear, 7% hydro-electric, and 7% renewables, there is significant variation in different regions. Figure 15 shows that places like California and Texas have high levels of natural gas and relatively small amounts of nuclear energy, whereas places like Georgia, Illinois and New York have have more baseload power sources such as coal and nuclear[13].



	CA	GA	IL	NY	TX
Oil	1.5%	6.5%	2.9%	16.4%	0%
Renewable	10.2%	1.7%	4.2%	4.2%	9%
Hydro	18.5%	9.0%	0.1%	13.8%	1%
Nuclear	6.3%	10.2%	24.8%	13.3%	4%
Coal	0.6%	36.4%	34.5%	6.8%	20%
Natural Gas	62.9%	36.2%	33.6%	45.5%	66%

Figure 3.15 Differences in regional electrity generation supply

13 https://www.eia.gov/todayinenergy/detail.php?id=26672

The percentage of nuclear capacity is particularly important role due to the fact that it is used to calculate the scale factor for the location. As discussed earlier, the scale factor assumes that the modelled area is responsible for a fraction of the largest grid investment: nuclear generation capacity. Therefore when an area has less nuclear capacity, this logic suggests that the total area over which costs must be dispersed is smaller, and therefore the relative fraction of costs that the modelled area is responsible for is greater. Tables eleven and twelve below show the cost results under the different generation capacity compositions in both Houston and Chicago. Scenario results that were significantly different from the baseline condition are highlighted.

Table 3.11 Houston investment comparison with varied generation composition

	Houston Demand Profile and PV Production					
	Baseline	CA	GA	IL	NY	TX
Generation Cost ($M)	17.6 (σ=$3.7)	16.7 (σ=$2.1)	12.9 (σ=$3.7) $t(9)=2.3$ $p=0.049$*	12.5 (σ=$5.2)	13.4 (σ=$7.6)	19.1 (σ=$1.5)
Transmission Cost ($M)	12.9 (σ=$3.3)	11.0 (σ=$2.2)	9.2 (σ=$4.0)	8.7 (σ=$2.1) $t(9)=2.8$ $p=0.018$*	7.8 (σ=$2.6) $t(7)=3.06$ $p=0.018$*	14.4 (σ=$2.6)
Capacity Generation (MW)	11.8 (σ=$2.5)	11.2 (σ=$1.1)	8.9 (σ=$2.4)	6.6 (σ=$3.4) $t(5)=2.8$ $p=0.044$*	9.5 (σ=$5.6)	12.6 (σ=$0.6)
Peaking Generation	0.2 (σ=$0.8)	0 (σ=$0)	1.6 (σ=$1.6)	6.1 (σ=$2.2) $t(4)=-5.3$ $p=0.01$*	0 (σ=$0)	0 (σ=$0)

The results from the Houston environment simulations show that there are some significant differences between the average baseline results and the locations with more nuclear power. When using the generation capacity of Illinois, which has the largest percent of nuclear generation, a significant fraction of the new generation had to be allocated to peaking generation, as opposed to capacity growth. There also were lower transmission and generation costs in GA, NY, and IL. This is due to the scale factor effect as all three places have larger amounts of nuclear energy, so that the modeled area is responsible for a smaller fraction of centralized grid and generation investments. The difference in transmission costs were only significant for the IL and NY locations, as they the largest reliance upon nuclear. Differences in transmission costs were significant only for the GA generation profile, due to the fact that both IL and NY had a large amount of variation in their generation investments. This variation occurs when a large generation facility must be replaced.

Table 3.12 Chicago investment comparison with alternative generation composition

	Chicago Demand Profile and PV Production					
	Baseline	CA	GA	IL	NY	TX
Generation Cost ($M)	5.7 (σ=$)	9.2 (σ=$3.1)	6.6 (σ=$2.0)	10.4 (σ=$2.6) t(5)=-3.85 p=0.01	7.6 (σ=$1.9)	6.4 (σ=$4.7)
Transmission Cost ($M)	9.0 (σ=$)	8.6 (σ=$3.1)	6.0 (σ=$2.6)	7.0 (σ=$2.1)	8.1 (σ=$2.4)	9.1 (σ=$5.7)
Capacity Generation (MW)	0.1 (σ=$)	4.7 (σ=$1.1) t(5)=-9.27 p<0.001**	0 (σ=$0)	0 (σ=$0)	1.2 (σ=$1.7)	1.6 (σ=$2.2)
Peaking Generation	10.4 (σ=$)	5.7 (σ=$4.6)	11.0 (σ=$3.3)	17.2 (σ=$3.5) t(6)=-3.94 p=0.008	10.8 (σ=$5.3)	8.3 (σ=$4.6)

The results from the Chicago environment generation scenarios also demonstrate how generation profiles may produce significantly different interactions with local environments, which may produce path dependency. Although it does not have a major effect on total generation costs, the California generation composition requires significantly more capacity additions, rather than peaking generation capacity additions. On the other hand, in simulations that matched Chicago with Illinois's own generation composition, the need for peaking capacity was significantly exacerbated, thereby dramatically increasing costs. This is surprising because one would expect that costs would be lowest in a more realistic scenario, due to the assumption that system designers should design a system to minimize future costs. A more accurate model representation of a small scale does not necessarily provide for better generalizations when used as a representation for a larger scale. Illinois and California represent two extremes in terms of being having a generation capacity that has a greater reliance on baseload capacity versus more dynamic and reactive electricity supply, so it is not surprising that they create the most significant differences from averaged supply. As the field of probabilistic DER intensive forecasting continues to mature, it may be important for modelers to be able to define and test outlier scenarios, for comparison with average.

3.4.2.3 Results Sensitivity: Grid Infrastructure Age

One reason often given both for and against implementing DER is the impact on the distribution grid. Distribution grid costs can be divided into three categories in this model: line replacements, transformer replacements and upgrades and substation upgrades as shown in figure 16.

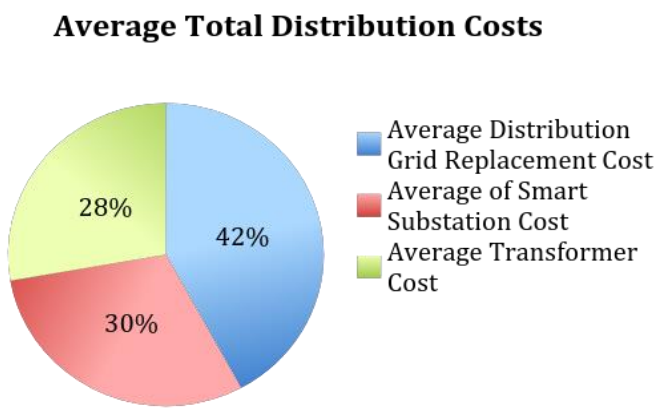


Figure 3.16 Categories of modeled distribution costs

One of the challenges and opportunities for DER in the U.S. context is that many parts of the grid are old and require replacement. This is a challenge due to the fact that lines may require investment to accommodate new load patterns and reverse flow, and it is an opportunity because many investments would be required even without DER to maintain reliability. To test the sensitivity of the model to age we look at the total 20 grid costs when the grid components have an average age profile of 35, 45, and 55 years at the beginning of the simulation. For a more complete description of the load aging interactions, smart upgrade investment and replacement procedures see appendix B. The table below shows the average and standard deviation for both Chicago and Houston in the baseline – high adoption scenario.

Table 3.13 Effect of infrastructure age on distribution costs

		Total Distribution Cost ($Million)		
		35 years	45 years	55 years
Houston:	Average	$20.9	$23.5	$23.6
	Std. Deviation	$2.2	$3.2	$4.1
Chicago:	Average	$12.7	$13.1	$13.8
	Std. Deviation	$0.5	$1.2	$1.3

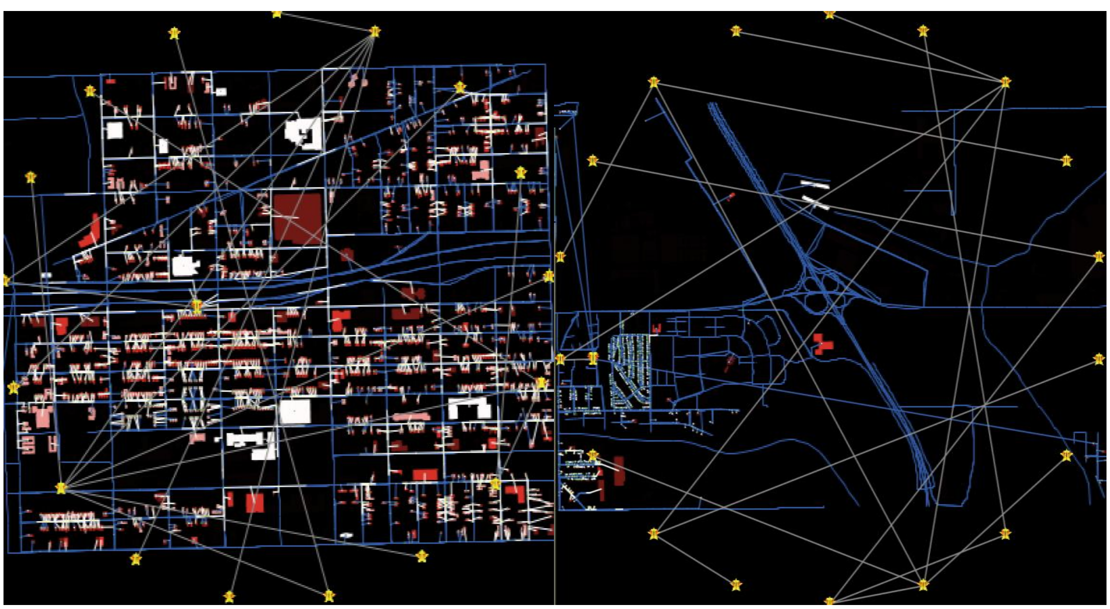
The table above shows that the grid costs are significantly more in Houston than in Chicago. This is due to the fact that there is more solar energy and demand profiles in Houston, more DER is adopted there than in Chicago and it therefore makes sense that there are more significant differences on the grid infrastructure investments to accommodate DER. The only significant different between same location simulation scenarios was between the 35 year and 45 year initialization age in Houston $t(18) = -2.156$, $p=0.045$, all other same location scenarios did not have significant differences in the total distribution costs. This suggests that the 35 year old infrastructure was better able to accommodate the DER and did not require replacement within the 20 year time period, even with the high adoption of DER.

3.4.3 ***Results Sensitivity: Urban Area Selection***

The area selected will affect both supply and demand assumptions, and therefore it is categorized as belonging to neither category exclusively. The fundamentals distribution grid design in the U.S. have not changed dramatically since the regulated utility gained preeminence. However, the density and the age of grid infrastructure may make the economics of different locations sufficiently different. Although most cities are structurally similar, and this is foundational to the design of this model, it is important to examine whether there are differences between locations that are urban versus rural. In this research we highlight this difference by comparing the results from the urban area with a much less dense. Further research is needed that further illuminates how additional development typologies can be used to compare outcomes.

In order to comment on how the nature of the density of a location's impact the expected investments, we compare the original highly urban and dense baseline GIS file and compare it with the results of a more rural and less dense area, although still from the greater Chicago area. The two selected areas are shown below:

Figure 3.17 Urban input area (left) and rural input area (right)



The summarized out from the rural runs are shown below in comparison to the Brattle report costs, scaled down based on the total amount of energy used. For complete calculations see appendix B.

Rural Area Cost Category	Brattle Cost at Local Scale ($M)	Scenario 1: No NM/FTC Estimates ($M)	Scenario 2: NM/FTC ($M)	Scenario 3: High Adoption ($M)
Generation	**$4.5-6.9**	**$5.95**	**$5.15**	**$3.95**
Houston		$6.6 (σ=$2.9)	$6.2 (σ=$4.5)	$3.7 (σ=$2.7)
Chicago		$5.3 (σ=$2.2)	$4.1 (σ=$2.2)	$4.2 (σ=$2.1)
Transmission	**$2.9**	**$9.85**	**$10.55**	**$9.15**
Houston		$9.1 (σ=$8.2)	$10.9 (σ=$3.0)	$7.5 (σ=$4.8)
Chicago		$10.6 (σ=$4.2)	$ 10.2 (σ=$4.3)	$10.8 (σ=$7.5)
Distribution	**$5.8**	**$3.2**	**$4.2**	**$4.75**
Houston		$4.4 (σ=$0.4)	$5.3 (σ=$1.1)	$5.6 (σ=$0.7)
Chicago		$2.0 (σ=$0.6)	$3.1 (σ=$1.2)	$3.9 (σ=$1.1)
AMI, EE/DR	**$0-1.9**	**0.55MW**	**8.7MW**	**11.45MW**
PV Houston		1.0MW (σ=1.4)	11.0MW (σ=2.1)	13.3MW (σ=1.4)
PV Chicago		0.1 MW (σ=0.1)	6.4 MW (σ=1.8)	9.6MW (σ=1.3)
Total Costs	**$13.2-17.5**	**$18.95**	**$19.8**	**$17.85**
Houston		$20.0 (σ=$5.4)	$22.3 (σ=$13.0)	$16.8 (σ=$7.2)
Chicago		$17.9 (σ=$5.2)	$17.3 (σ=$5.7)	$18.9 (σ=$8.1)

Table 3.14 Rural Area Costs

The runs in rural areas show what engineers and planners and developers have known for a long time: providing services to rural areas is expensive. This is because the majority of the costs for rural locations are transmission costs, while generation and distribution costs are relatively small. In practice these transmission costs may often be met with higher voltage distribution networks over relatively large areas, but the model lacks more sophisticated distribution heuristics and therefore shifts the costs to the transmission system. This dynamic still highlights the overall challenge of rural areas, which is small usage over a large area. The relatively large percentage of costs that are dedicated to getting electricity to remote users effectively obfuscates much of the location specific (Chicago versus Houston) savings differences that were so prominent when examining the urban area. Total costs are not significantly different either between locations, or between scenarios. Within the same location, scenarios which had significantly different cost results were distribution costs for scenario 1 and scenario 3 in Houston ($t(12)=-4.45$ $p<0.001$), scenario 1 and 2 in Chicago ($t(10)=-2.25$, $p=0.048$) and scenario 1 and 3 in Chicago ($t(11)=-4.31$, $p=0.001$). Unlike the urban setting the distribution grid costs significantly increased with adoption of DER, however once savings from generation and transmission are included, these costs balance out, suggesting that DER does not provide generalizable costs or benefits in rural areas, but rather cost shifts.

A second important observation is that the variation in costs between runs is much greater. As a percentage of the mean, the standard deviations for the scenarios are between 24-50% of the average values. This type of variation suggests that utilities and electricity cooperatives may be able to realized large returns when DER is implemented to avoid large costs, and that different locations may have very different valuations. Re-investing in rural infrastructure may require a different investment model than in urban areas in order to realize a substantial savings even without selective adoption practices and local balancing. Connecting new generators and running transmission lines over long distance creates enormous costs on small areas, and DER adoption when there is a smaller load base requires additional distribution investments. Distribution investments were higher as DER adoption increased in rural areas, in contrast to urban areas that had lower distribution costs within increasing DER adoption. Even in the high adoption DER simulations the adoption of DER did not significantly mitigate the generation and transmission costs. Local management of the DER, in addition to adoption will be requisite to improve the cost burden on rural locations.

3.5 Discussion

In many ways the current energy and climate crisis is an example of why people should consider path-dependency when considering infrastructure investments. Infrastructure often produces path dependency through investments that can produce stranded costs and an uncompetitive basis for new technologies. This inertia can make systems slow to react to feedback and changes in other parts of the system. Probabilistic modeling and sensitivity analyses can help uncover likely sources of path dependency by demonstrating how initial conditions produces variation in outcomes. Scenarios that have high internal coefficients of variation or are produce significantly different outcomes from other scenarios are areas that would produce path dependency if static conditions were optimized. As researchers and practitioners try to move towards more probabilistic grid models to accommodate the expanded degrees of uncertainty DER produces, an understanding how path dependency may influence their findings is an important step. Not only can it help with comparison between different locations and scenarios, but it can help to identify factors which may require less variation, thereby decreasing the complexity of analyses. In this research we demonstrate and test a probabilistic and pattern oriented method of modeling high DER adoption grid futures. We test this method for four distinct categories of variation and find that:

1) DER adoption demonstrates significant value and should be included in future energy models.

2) Using GIS data can enable pattern-oriented probabilistic models, which are capable of producing results consistent with industry analyses.

3) The utility and accuracy (and therefore generalizability) of these results are highly reliant on the selection of demand side assumptions, and are less sensitive to supply side assumptions.

We discuss each one of these topics in turn.

3.5.1 *DER is worth including in future projections:*

One of the most important observations is the necessity of incorporating DER into future analysis. Scenario 1, the scenario without currently existing incentives for DER, resulted in a significant number of buildings investing in DER by the end of the 20 year simulation period. This means that many upgrades to the distribution system to accommodate DER are more appropriately approached as a question of when and not if. High levels of DER adoption, which were tested with scenarios 2 and 3, improved the grid costs for the Houston environment and had no significant positive or negative effect on grid costs for Chicago. Averaging the results of both locations, DER adoption has an overall positive effect on grid costs. This is due to several factors. First, the load growth in Houston required primarily capacity market growth, as opposed to reactive (dispatchable) capacity in the Chicago simulation. Secondly, the economics of installing DER are better in Houston, due to less variable demand patterns and more incident sunlight. Therefore a greater amount of DER was installed on buildings in Houston, and this increased the benefits from avoiding transmission and generation investment costs.

3.5.2 *GIS data is a good template to model probabilistic (realistic not real) grids:*

To the best of our knowledge, GIS input data and a pattern oriented approach has not been used to model a theoretical grids' value and evolution. We focused on five major sub-modules for model construction and validation: 1) energy demand profiles scaled to GIS floor space data should reproduce global trends in the amount of energy needed by different sectors, 2) the use of streets as a skeleton for optimizing a local distribution grid 3) transmission grid connection reproduce a scale free distribution 4) Utility investment decision based on maintaining sufficient margin making creates a "lumpy" and large investment pattern 5) Building DER investments using a WTP heuristic should be responsive to changes in price and incentives and follow an S shaped adoption curve.

We find that a pattern-oriented approach is capable of producing results consistent with industry analyses, but requires significant attention to the underlying assumptions. For example, by averaging the low DER scenario results from both a cold (Chicago) and warm (Houston) climate the average costs are consistent with the top down models that also do not include DER. The dramatically different results from the locations suggest that balancing these input conditions is critically important, and may bias model outputs. This area can benefit from increased research and sophistication to improve selection methods and tools to decrease biases.

The use of a probabilistic grid that is a subsection of a larger balancing area is perhaps most beneficial for studying DER systems. There are several reasons for this. First, a scale factor can be used to use focus on a smaller, and therefore less computationally problematic, subsection of the grid. Not only can this make DER adoption scenarios more tractable, but it lends itself to the larger discussion about nested responsibilities of individuals and communities to large investments. Secondly, a probabilistic grid can help to avoid reactionary investments that may be a result of path dependency, and help facilitate debate about a wider set of options. Some rationale's for DER investments are built on the idea that they can defer a specific investment. However, it can be difficult to understand if a more universal policy would be beneficial. Modeling a grid probabilistically can identify when variation will create local opportunities/costs and when a larger scale policy would be more effective.

3.5.3 *Demand vs. Supply Side Assumptions:*

The utility and accuracy (and therefore generalizability) of these results are highly reliant on the selection of demand side assumptions, and are less sensitive to supply side assumptions. Demand side assumptions we tested using sensitivity analysis include load growth, location dependent demand curves, and urban density. Scenario runs demonstrated significant differences in cost projections between different parameter selections for load growth, demand curves, and population density. Supply side assumptions include the cost of generation, the composition of the generation, and DER sizing and adoption assumptions.

The majority of these supply side assumptions did not produce significantly different results, although the most extreme differences were significant. For example, the cost of centralized generation did not significantly impact total costs.   This is a non-trivial result; standard logic suggests that when the cost of generation increases this will significantly increase total costs. However, the large variation in transmission costs makes many of the potential differences costs in generation capex prices less important. This is extremely relevant to policy, since a large portion of policy analysis focuses on generation prices. This model suggests that changes in demand patterns may be a much more important sensitivity to understand. Examples of how load patterns may change may include smart meters, electric vehicle charging, the mining of cryptocurrencies, effects of climate change on heating and cooling, and local energy balancing incentives and resiliency oriented smart grids.

This model and analysis represents an initial and crude foray into developing practices for probabilistic modeling of distributed infrastructure investments, and many additional variables, analysis, should be studied both on the demand and supply side. However, we believe that it demonstrates that this is a crucial direction for further work and points to many future analyses. The initial findings demonstrate not only that DER may offer significant future savings, but the use of a probabilistic grid suggests that the regulated utility investment logic built on meeting a supply side metric (reserve margins), rather than a demand side metric implicates enormous path dependencies and vulnerabilities from differences and changes in demand.

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CHAPTER 4

THE SCALE OF SMART: SCALE TRADEOFFS FOR DISTRIBUTED ENERGY RESOURCE MANAGEMENT

4.1 Introduction

As distributed energy resources (DER) become more prevalent, an increasing number of options and questions about how to manage them arise. While many studies look at questions of engineering and transmission market optimization, some areas are not well explored. Pfenninger et al. recognize four main issues for modeling future energy systems: resolving time and space (variability and detail), addressing uncertainty, accessibility reproducibility of optimizations across scales, and inclusion of human dimensions. They suggest that there is a need to use tools such as agent-based models, to perform cross scales analysis, and to search for new methods that are better suited to the 21st century (Pfenninger et al., 2014). Emerging models concerned with DER balancing often assume a single aggregator, which acts as a strategic market participant, however, it is unclear as to how the scale of aggregation within in the physical constraints of a radial grid may impact system wide properties (Kok et al., 2008). Electricity models are built to examine how a set of rules, procedures, constraints, etc., interact and produce outcomes based on fixed assumptions about scale. Although it has been well documented that scale is a critical model feature, the scale at which DER grid investments decisions are made and managed has not, to the best of our knowledge, been compared. This work compares how a set of fixed investment and aggregator balancing rules produce alternate outcomes when applied at different scales and in different locations. We find that there are significant added savings to be gained from local battery markets when paired with DER generation technologies that cannot be realized through transmission level generation and balancing alone. We also introduce and compare an indicator of local sufficiency, as a way to operationalize local resiliency that extends the concept of self-sufficiency to a local network context. Non-linearity emerges both in quantifying local-sufficiency and cost savings, which suggests that multi-scale comparisons are an important decision making tool that should be further developed.

This research compares a how an investment and balancing heuristic, applied at an individual house, between neighbors, at the street scale, and at the neighborhood scale may result in different adoption, investment, and local-sufficiency levels. There are several reasons why this analysis may provide a useful reference for modeling the future of DER systems. First, there is no consensus for combined engineering and market optimizations as to what assumptions should be used for DER forecasting. Second, the degree to which customers are interested in becoming strategic grid participants, even through smart devices, is unknown and users privacy concerns continue to emerge. Third, self or local sufficiency (in contrast to efficiency) may continue to be an increasingly valued as the incidence of external variability continues to increase. Fourth, concerns about security of energy system information, hacking and terrorism, may influence decisions about how centralized electricity information should be. Finally, load flattening and deferral of grid infrastructure are being increasingly implicated as a reason for DER investment. We discuss each of these drivers individually before discussing the model basis.

4.1.1 Tradeoffs in optimizing ABMs for physics, markets, and costs

Design for efficiency, reliability and market competitiveness is not easily resolved when it comes to DER. Utilities, charged with maintaining a reliable and affordable grid, often prefer controllability over the variability and complexity that accompanies the proliferation of DER interconnections. Markets, on the other hand, take as a foundational assumption that sufficient competition exists to drive prices down. While multi-agent systems and agent-based models have been recognized as a promising route to develop distributed operation and control protocols (Rumley et al., 2008), most models have focused on transmission markets that consider DER as an aggregated node that interacts with transmission markets, if at all (Li and Tesfatsion, 2009; Sensfuß et al., 2007; Zhou et al., 2007). Spanning the interdisciplinary divide of engineering and market design is an important area that is making considerable progress, (Fripp, 2012; Li and Tesfatsion, 2009; Praça et al., 2003; Sensfuß et al., 2007; Veselka et al., 2001). However, questions about smaller scale markets, storage and the role of intermediaries, within the physical constraints of a distribution grid, desires increased exploration (Gnansounou et al., 2007; Ringler et al., 2016; Snape, 2015).

The proliferation of distributed generation introduces new sources of power flow stochasticity. This poses enormous computational challenges for optimization and controls as well as security risks that depend on the degree of centralization and nexus of control (Rumley et al., 2008). The largest group of electricity system models, optimization models, relies on detailed descriptions of technical components and reliable demand profiles. Solving these optimization problems require that some simplifications must be made in terms of spatial and temporal data. This becomes more difficult the larger and more variable the DER (Pfenninger et al., 2014). Optimization solving for socially beneficial price signals with agents engaging in demand side management becomes computationally problematic when there are more than eighty agents (Ramchurn et al., 2011), as well as requiring that distributed agents actually act predictably.

The vast majority of demand side management is implemented by medium to large industrial or commercial consumers, which have dedicated personnel to manage smart energy strategies. More ubiquitous adoption of electric vehicles, batteries, residential demand side management, photovoltaics, and other technologies means reaching potential adopters that do not have such management capacity. Ramchurn et al suggest a method to cope with this limitation by having subgroups re-compute cost optimally based on updated conditions that requires sharing of centralized information price signals across distributed locations. Demand flattening is another heuristic that some studies have investigated in relationship to dynamic pricing and decision-making. Researchers have stressed that, not only are there computational challenges related to dynamic pricing and demand flattening, but there are inherent systemic vulnerabilities that loom with a proliferation of distributed agents involved in decision making. (Kahrobaee et al., 2013).

If not well coordinated, load shifting may cause significant grid stress and unexpected peaks, and some coordination queuing rules must emerge that are not based on price, which may cause instantaneous shifting (Ramchurn et al., 2011). One danger of distributed energy generation and storage is that homogeneity of use preferences will create unanticipated peaks, which may make the system worse off (Vytelingum et al., 2010). Similarly, in their study of electric vehicle charging behavior, Dallinger and

Wietschel note the importance of having a controller to mitigate feedback effects that can take place with price information (Dallinger and Wietschel, 2012). One method that is proposed for dealing with this is a forward price mechanism for next day prices. This method requires the ability to predict future demand and preferences in real world scenarios and needs to be tested against real world data and forecasts. Some studies use game theory to study pricing behavior of distributed energy resource providers (DERPs) participating in wholesale markets through aggregations called virtual power plants. Virtual power plants are aggregations of DERs that participate in markets through bundled production. Chalkiadakis et al look at DERP aggregators of between 0-224 participants. They show that when prediction abilities are symmetric, earnings are dramatically increased for DERPs joining an aggregation market. When prediction abilities are asymmetric, the more good predictors join the market, the larger the relative gains for the average predictor. However, each predictor would prefer a poor predictor to join as opposed to a good predictor (Chalkiadakis et al., 2011). This illustrates how important market design, scale, prediction and other aspects related to variability and uncertainty are for designing a beneficial system to manage investments in DERs. Research on DER markets, including demand response, while beginning to illustrate different design criteria, has not offered insight into how the aggregation size may produce feedbacks onto the need for grid investments (Rumley et al., 2008).

4.1.2 Customer behavior

While some locations are moving ahead with smart grid capabilities and management systems, the extent to which distributed entities desire to participate in electricity grids is unknown (Dave et al., 2013). It is not clear from initial attempts to layout building-scale distributed energy markets that sufficient attention is paid to 1) physical constraints of demand preferences both in terms of local grid sufficiency or battery charging behavior or to 2) the extent to which residential units are interested in engaging in strategic energy pricing behavior (Rosen and Madlener, 2013). The assumption that distributed agents will participate in strategic behavior relies on the assumption that smart devices, such as smart thermostats, smart appliances, smart inverters, and smart chargers, will undertake strategic behavior. The assumption here is that the customer reduces the cognitive burden by selecting desired settings and entering into a contract with the utility. However, the extent that smart pricing markets develop to sufficiently incentivize this behavior, or the extent to which people will require flexibility in contracts to meet their changing needs is unknown. While distributed agents may be more strategic when making large investments, they are not necessarily interested in having electricity prices that require them to think about such a dynamic system. Therefore, customers may be more inclined to choose a less complex rate structure along with the agreement to allow a third party to manage specified assets such as a smart thermostat, battery, or other DER assets.

4.1.3 The Emerging Value of Self-Sufficiency

As terrorism, climate change, and the frequency and intensity of major weather events and seasonal stresses increases, it is becoming increasingly important to have infrastructure that is ready to cope with storms and stresses at multiple scales (Executive Office of the President, 2013; National Infrastructure Advisory Council, 2010; NIST, 2014). Adopting DER so that each house has complete energy independence from the grid is enormously costly. Design for energy independence requires each system to be designed to meet the maximum needs and provide multiple days of backup generation capacity. A limited amount of self or local sufficiency, to meet some basic needs under emergency conditions, may be provided by investing in local DER management. This may also contribute to the grid during non-emergency conditions. ABM models studying distributed control structures have begun to look into the topic of zones within which local balancing and islanding may occur (Pipattanasomporn et al., 2009). This requires neighborhood markets or other information exchange protocols by which DER devices in the same zone exchange information production information. The method of incentivizing, balancing and aggregating information, such as prices, can cause drastically different outcomes (Kahrobaee et al., 2014; Rumley et al., 2008).

4.1.4 *Trust and Information Security*

Information security is a critical service (Kok et al., 2005). Many concerns have already arisen about how the smart grid can stay safe, the potential for cascading failures, and how to provide safety and security of user data (NIST, 2014). In a well connected network any single security breach may cascade throughout multiple connected infrastructure systems (Cotilla-Sanchez et al., 2012; Hines et al., 2010; Watson et al., 2014). The hacking of a Ukrainian power plant has been pointed to as a harbinger of times to come[14]. Local management and aggregation, is one way to diminish this vulnerability.

[14] http://www.bbc.com/news/av/technology-35686498/ukraine-power-hack-attacks-explained

4.1.5 Deferral and Cross-Scale Investment Feedbacks

One of the primary drivers of DER adoption is the potential to defer distribution and transmission upgrades, as well as larger scale generation investments that may have low capacity factors due to slow or uncertain load growth. Battery storage has the potential to shift the stresses onto substations, transformers and other components of the grid. With dynamic pricing, batteries can participate in pricing arbitrage, which can flatten loads and may reduce the need to oversize grid equipment or invest in new transmission connected capacity (Zheng et al., 2014). Unger and Myrzik present and describe how a virtual energy market, for a six-node distribution grid in which storage is linked to substations, can balance substation loads. Similarly, the power matcher tool has been used to validate a local pricing mechanism within a distribution network of < 50 houses. Because smart software, like Power Matcher, incentivizes participants to charge when prices are low and conserve or release power when prices are high the effect can be a flattening of demand. While design aspects of market efficiency are debated, the total cost to most electricity customers ultimately depends more on the total cost to the utility to manage and invest in the grid and supporting resources (Frischmann, 2007). DER has the potential to defer grid investments if managed intelligently, but the scale at which these investments are managed is hard to determine a priori (Kok et al., 2010). Changing demand at one scale may have cascading effects at other scales, and neither market nor engineering focused MAS/ABMs have looked at the cross-scale implications of these choices on system wide measures such as total cost or resiliency.

In order to take a step towards understanding the interplay between costs, distribution markets and investment patterns, this research looks at a simplistic investment and management heuristic and compares outcome measures when the heuristic is implemented at different scales. In the next section we build on the foundation we have just provided to discuss the distributed management model and the different scales at which investments are compared.

4.2 Model Explanation

The model, implemented in Netlogo, is available with documentation online including the ODD, at https://www.openabm.org/model/6006/version/1/view. It uses GIS building and street information to generate a probabilistic grid. A picture of a generated urban environment and electricity grid is shown in figure 1.

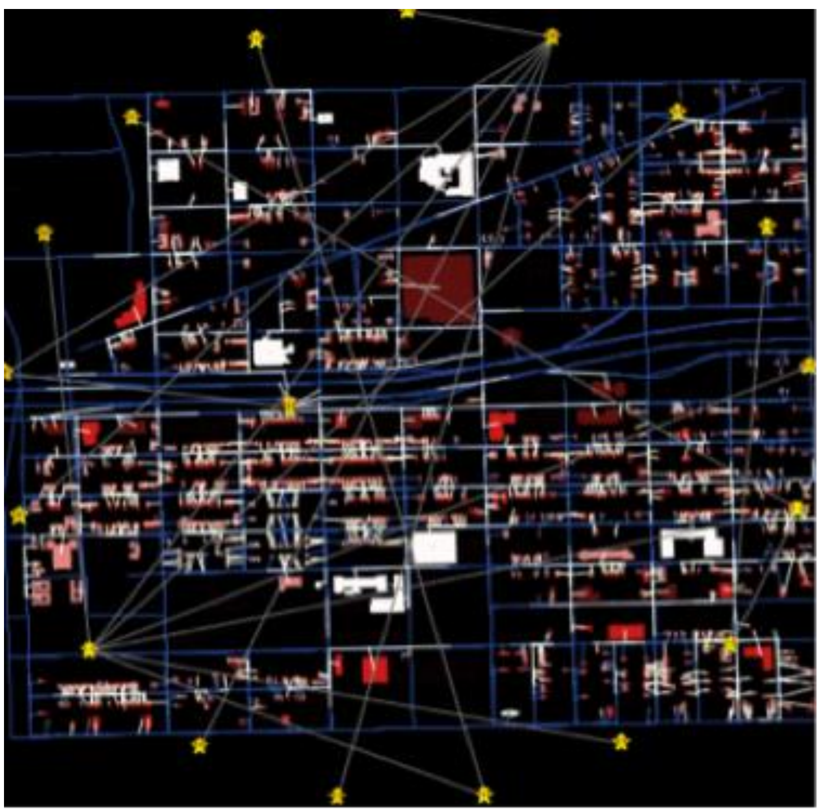

Figure 4.1 GIS generated electricity grid uses roads as a template for the grid. Buildings, shown in red, pink and white connect loads to centralized generation. Centralized generation is shown with yellow; not at scale.

There are two main time scales that generate feedbacks: hourly electricity demand and annual investment decisions. This model builds on the baseline version, presented in Chapter 3, by implementing a local DER investment and management rule. The options for local rules include three market choices: capacity, reactive, or both; and four scales of management: individual, neighbors, street, or neighborhood. Figure 4.2 below shows a schematic of the main processes within the model.

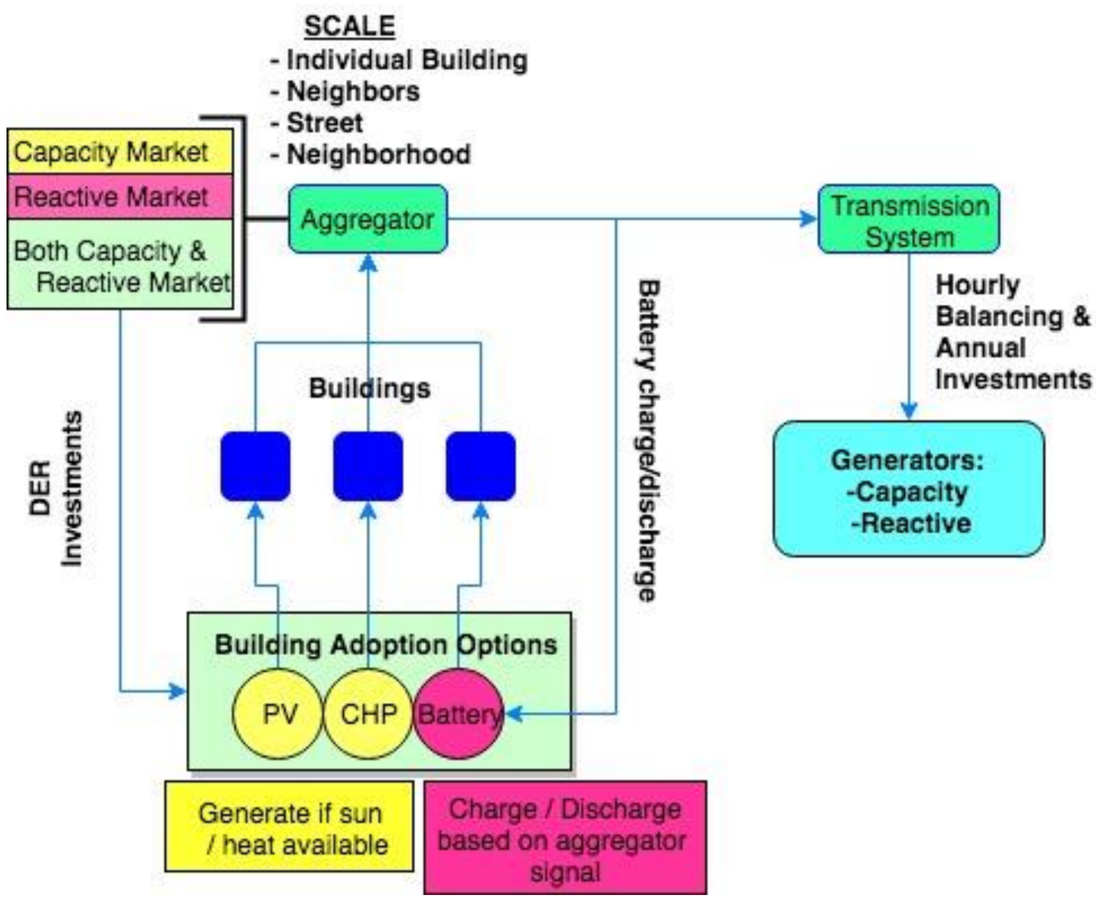

Figure 4.2 Primary dynamics in the model are DER investments that react to capacity and reactive markets based on aggregation scale. PV/CHP always fires when conditions allow. Battery charging behavior depends on aggregator signals. Unbalanced energy needs are met at the transmission scale.

At each scale of aggregation an agent, which represents a component of the distribution system, is deemed to be the local aggregator. At the end of each year the aggregator looks to see whether there was an increase in the maximum amount of energy needed (capacity market) or an increase in the amount of responsive generation needed (change within an hour). If there was, they ask any of the buildings within their aggregation area ("downstream" agents that rely on the aggregator to get electricity) to bid on the capacity difference between the current maximum and the previous years maximum, at the price they are willing to pay. Buildings continue bidding until the desired amount of DER capacity is met or none of the buildings in the aggregation area have additional usable capacity. Buildings always build the maximum capacity that their building is sized for. An incentive is then used to pay for the cost difference between the cheapest bidder and the capital needed to install the project. This reverse auction style is often used for competitive auctions within deregulated transmission markets. This model assumes that building owners may be able to participate in bidding behavior for capital purchases only (not competitive price setting in day ahead markets). Table 4.1 below summarizes the possible market combinations.

Table 4.1 Local management scenario options. Investment market options define whether there is a local requirement for generation capacity (PV or CHP technologies), reactive capacity (battery) or both. Scale of aggregation is the point for DER adoption decision making, balancing and measuring local sufficiency.

	Name	Description
Investment Market Options	Capacity	Buildings will invest in photovoltaics (PV) and/or combined heat and power generators (CHP) through reverse auction market by aggregator
	Reactive	Buildings invest in a battery through reverse auction market by aggregator
	Both	Buildings participate in both capacity and reactive markets
Scale of Aggregation	Individual	Each building acts as their own aggregation point ***Buildings/aggregator:1***
	Neighbors	The closest transformer to each building acts is their aggregation point. ***Average buildings/aggregator: 5***
	Street	Circuit breakers, located at grid branching locations. In the case that no change in load occurs, substations are used as the aggregation point. ***Average buildings/aggregator: 300***
	Neighborhood	Substations are aggregation points. ***Average buildings/ aggregator: 1500***

The conceptual foundation of these market strategies is that at each level of aggregation they are mitigating any increased grid stresses, potentially balancing or flattening demand at this scale and also creating a point of control from which some local islanding could be managed in the event of an emergency. Aggregators set the amount of local investment to be the difference between the maximum capacity ($\Delta C_{max,t}$) or maximum change in hourly demand ($\Delta C_{max,t}$reactive capacity needed) in any year (t), and the maximum in the previous year ($\left(C_{max,t-1}\right)$& $\Delta C_{max,t-1}$) as shown in equation 1 and 2 below. As the scale of aggregation increases, variability between users may cancel others. Dissimilar use profiles may reduce the market size when they are aggregated in the same group.

$$Market\ size\ (kW)_{capacity} = \max\left(0, C_{max,t} - C_{max,t-1}\right) \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$Market\ size\ (kW)_{reactive} = \max\left(0, \Delta C_{max,t} - \Delta C_{max,t-1}\right) \ldots\ldots\ldots\ldots\ldots (2)$$

Once investments have been made in DER they follow the following production logic: PV and CHP will produce the maximum they can at each hour. Batteries base their decisions to charge, discharge, or do nothing on a simple signal from the aggregator and whether they have available capacity to charge/discharge. If distributed demand at the aggregator is more than one standard deviation from the aggregators' historical average demand the aggregator will ask each battery that has charge to discharge until the demand in their area is within one standard deviation from normal. Alternatively, if the distributed demand at the aggregator is less than one standard deviation from average they will direct each battery in their supply area that has empty capacity to charge until the total aggregated demand in their area is within one standard deviation from normal or no additional capacity exists. Each hour aggregators add the previous hour's demand to their memory such that over time a standard deviation from normal becomes smaller.

4.2.1 Local-sufficiency:

Utilities operationalize reliability in terms of the fraction of customer hours that went unserved over a year (SAIDI). In order to create a measurement of local supply an alternate metric was created: the percentage of hours (t) that the generation aggregator did not need to supply energy to their service area from the centralized utility. We call this local-sufficiency (S_L) because it is the corollary of self-sufficiency, but averaged by the local aggregator for the total aggregation area. It is described by equation 3 below.

Local-sufficiency assumes that there is a local aggregation point that can island a sub-network and provide local control which there is sufficient local power. However, if the controller does not have enough local power it would not be able to manage local demands. Therefore, local sufficiency is the fraction time that a local controller is able to provide this back up service, in case of a power outage or other disruption in another location in the grid.

$$S_L = \frac{\sum_h^N I_h}{N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

Scenarios were run using both the Chicago and Houston electric and heating load profiles, solar production and variability profiles. Each scenario was run eight times and output results presented here are averaged across all completed runs. For a discussion of the number of minimum number of runs, see chapter three. Table 4.2 shows the initialization conditions.

Table 4.2 Variable initialization conditions shown in this table are consistent with those used in Chapter 3.

Variable Name	Value	Variable Name	Value
avg_gridage	45 years	pv_cost	$5/watt
seeds?	false	chp_cost	$6/watt
avgloadgrowth	0.011	battery_cost	$1/watt-hour
load_growth_variability	0.1	Average_T_Distance	80miles
gis_area	urban	electricityprice	$0.125/kWh
FTC	false	nat_gas_price	$0.04/kWh
Net-meter?	false	Peaker_type	Gas
battery_selfsufficiency	4hours	Nonpeak_Type	Gas
fraction_roof_available	0.5	Peaker_capex	670
CHP_size_month	7 (July)	Nonpeaker_capex	1980
Coal	27%	Oil	4%
Natural_gas	44%	Renewables	7%
Nuclear	9%	Hydro	9%
WTP_distribution	Random-normal	Discountrate	0.05
Local_Investment_Rule	Rule2	WTP-max	10years
influence-radius	10 buildings		

4.3 Results

Before presenting results from the three different investment markets (capacity, reactive and both) it is important to establish a baseline for comparison. Table 4.3 below shows the results for the same area with the same starting parameter conditions from the baseline study, but without any local markets to require adoption in a specific area. This is comprised of two scenarios. The first scenario, Scenario 1 assumes there are no policies to incentivize DER investments. Scenario 2 includes the most ubiquitous DER incentives in the U.S. as of writing this, both net-metering and the federal tax credit. Chapter three of this dissertation dove in depth into sensitivity analysis and explanation of the baseline condition. For further specification of these policies, model basis and their effect on DER adoption see the DSIRE website, model overview, and the results of baseline runs in chapter three.

Table 4.3 Baseline: 20 year averaged present value of total grid costs

Total 20 year Present Value of Investment Costs ($ Millions)			
Scenario 1: No DER incentives		Scenario 2: DER incentives: NM & FTC	
Chicago	Houston	Chicago	Houston
\$27.7	\$53.9	\$25.5	\$42.7
σ=\$3.8	σ=\$7.9	σ=\$4.9	σ=\$9.8

In both climates (Chicago and Houston) higher adoption of DER decreases the average overall costs. However, with the piecemeal adoption that accompanies customer preferences and net-metering, there is no gain in self-sufficiency that can accompany this investment. If the grid has a failure and there is no local management capacity, all DER must be deactivated to avoid electricity islanding that may accidentally hurt safety personnel or others. For this reason, even though there are cost savings potentials in both locations, there is no gain in robustness, defined here as a local-sufficiency of zero, however with local markets and aggregators at the individual, neighbors, street or neighborhood scale, local DER can provide an additional layer of functionality

4.3.1 Capacity Markets

Investments based on growth in overall demand at any scale may mitigate the need for grid wide investments. However, without storage, and the lack of CHP capacity inherent to sizing CHPs to summer heat loads, it is also possible that peak growth is unaffected, and costs are not significantly different. This will occur when peak growth does not occur during the hours that PV produces energy. Due to the lack of risk adverse potential capacity, we do not display CHP adoption, as it represents an insignificant capacity addition. Figure 4.3 shows the comparison of DER (photovoltaic) adoption in both Chicago and Houston under the different markets.

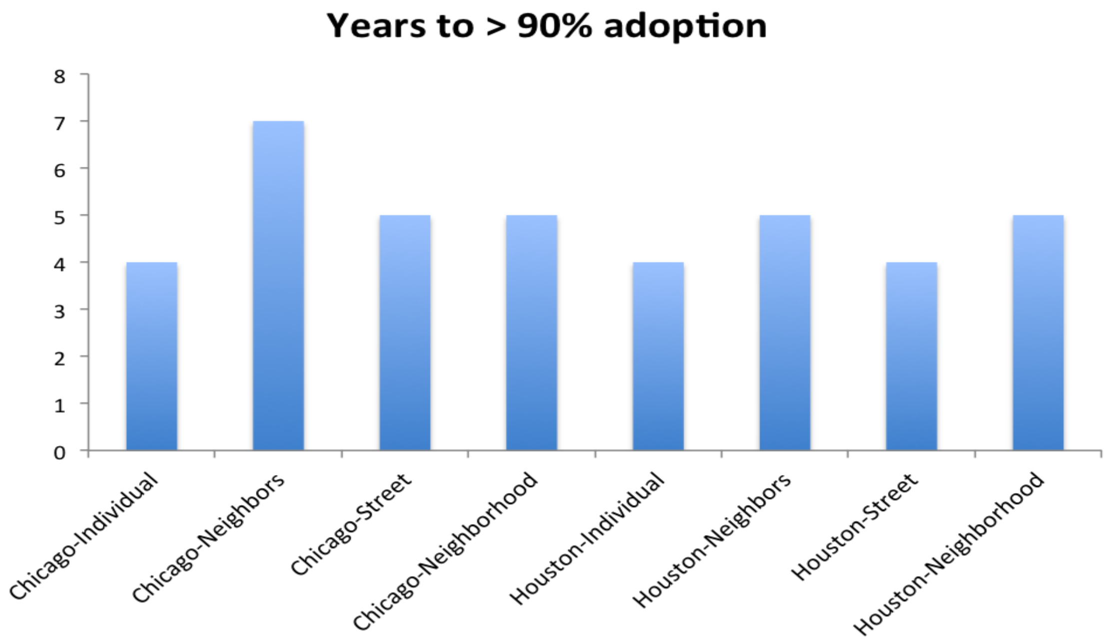

Figure 4.3 The number of years needed to reach 90% maximum PV adoption. Given the assumption of 1.1% load growth, capacity markets at all scales produce rapid PV adoption

The expedient adoption occurs at all scales. The averaging effect of variation between buildings does slow the rate of adoption in Chicago when averaging takes place between neighbors, but after just five years, all investment scales have come close to maximizing the distributed PV potential.

While the adoption patterns occur relatively uniformly between all capacity markets, the resultant local sufficiency has much more interesting variation. A smart control system for a capacity market would be able to island a local grid if it had sufficient energy but the rest of the grid did not. It would not however be able to provide electricity if demands outgrew local supply since there is no storage capacity. Figure 4.4 shows that allowing individual buildings or neighbors to island could provide the highest levels of local-sufficiency. Due to the large excesses of solar energy during the day, averaging between neighbors provides almost equivalent levels of local sufficiency to that of individuals. Managing DER at the individual building level means that only DER adopters would have a back-up power source, a potential source of systemic inequality. However, when adoption levels are high (driven here by increases in load growth), this results in many people having back up for at least part of an average day.

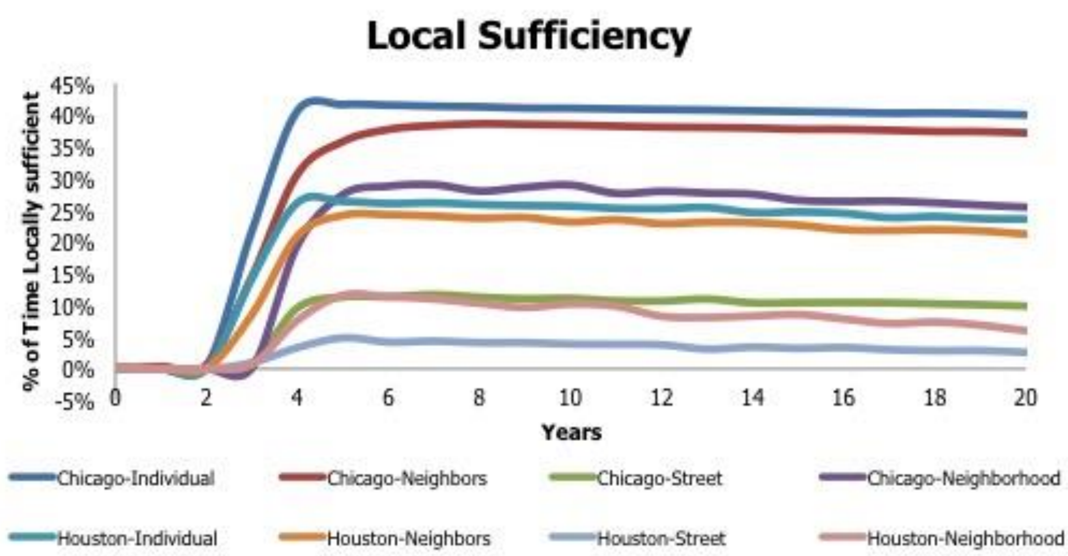

Figure 4.4: Local sufficiency metrics from the different capacity market runs in both Chicago and Houston. Lower electricity usage in Chicago contributes to higher overall local sufficiency. Identical patterns between Chicago and Houston show that individual and neighbor scale adoption/management offers the highest local sufficiency, followed by neighborhood and least of all management at the street scale.

A surprising result is that averaging at the neighborhood level offers more local-sufficiency than when investments are made based on street level signals. This trend is extremely strong in both locations, which suggests that it is a results of aggregation of different building types, which is more likely to occur throughout neighborhoods, but less so streets, so that those loads can balance each other throughout the day. Streets are often comprised of similar buildings, which diminishes averaging effects. In both climates, neighborhood aggregation produced much higher levels of local sufficiency than the street level. Larger aggregation areas can also mitigate potential inequities between people who have the resources to invest in DER and those that don't. In all scenarios once the maximum amount of PV is adopted, local sufficiency decreases as load growth continues to rise. The ubiquity of adoption patterns under load growth leads to very similar cost results. The only same-location significant differences between scales of capacity markets was the neighbors scale market in Houston, which was significantly different from the individual scale market ($t(13)=3.405$, $p=0.005$). The slower adoption of DER with the neighbor market led to significantly higher long-term costs, even though the local-sufficiency levels were similar. Due to the rapid adoption of PV across all scenarios, there are significant cost savings compared to no market, no DER incentive baselines (Baseline Scenario 1 - see appendix for expanded statistical analysis). The average total costs, for each capacity market scenario, are shown in table 4.4 below.

Table 4.4 Average total grid costs for capacity markets at different aggregation scales

Average Costs ($ Millions)	Individual	Neighbors	Street	Neighborhood
Chicago	$24.8 σ=$2.3	$24.0 σ=$2.8	$25.1 σ=$3.9	$23.4 σ=$ 2.5
Houston	$32.8 σ=$4.6	$40.4* σ=$4.1	34.8 σ=$6.1	37.5 σ=$5.9

Comparison of the total costs with the baseline scenarios shows that none of the Chicago scenarios are significantly different from Scenario 2, which assumes net metering and the federal tax credit. However, in the Houston scenario, there are significant savings when compared with baseline scenario 2 for all levels of implementation, except at the neighbor aggregation level, which had higher costs due to the slower adoption curve. Most of the scenarios, in both locations have significant savings when compared with Scenario 1, which has no DER incentives. See appendix B for full statistics. These results suggest that in some locations, existing DER incentives such as net-metering and the federal tax credit provide many of the same savings as a local capacity market. In locations that have abundant solar energy, speeding up local PV capacity deployments, via local capacity markets or adoption targets, may provide additional cost saving benefit.

4.3.2 Reactive Markets

In the same way that solar price decreases result in increasing solar adoption, price drops in storage follow a similar trend. This makes the question of *how* to incentivize storage increasingly salient. Figure 4.5 below shows the adoption patterns for a reactive (in this case battery) market, managed at different scales. The figure shows that there are two different final levels for total adoption in Chicago and Houston. This is a response to the sizing heuristic, in which buildings size their potential battery to meet a set number of hours of their own demand, at peak usage, in this case four hours. Because buildings have higher peak demands in Houston than Chicago, Houston has a higher total capacity. Sensitivity to changes in the battery sizing is presented in section 4.3.4. Figure 4.5 also shows that both locations follow the pattern of having the fastest adoption when managing for reactive needs at the individual level with a slower adoption pattern as aggregation level increases.

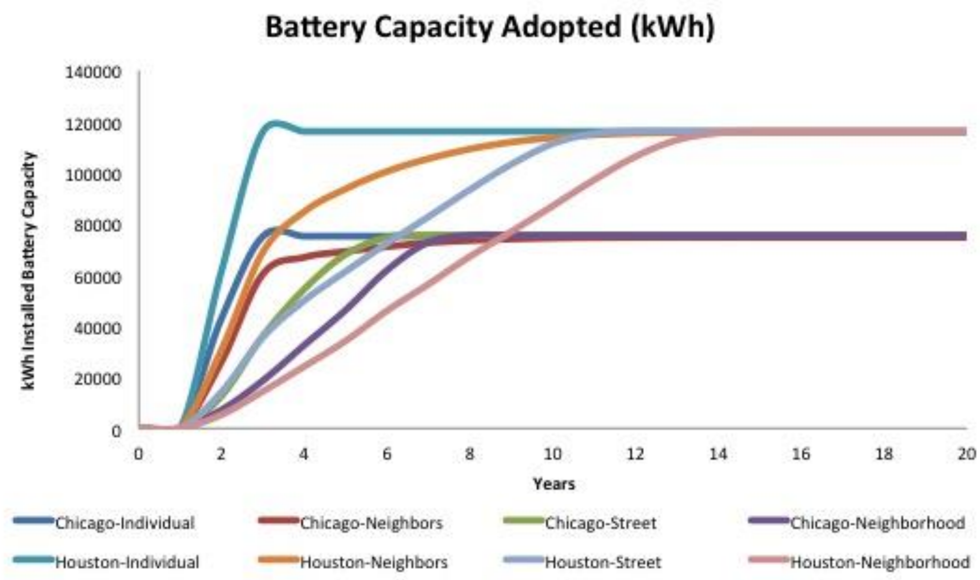

Figure 4.5 Battery capacity adopted in kWh in Chicago and Houston. Reactive markets organized at individual, neighbors, street, and neighborhood scale

PV adoption responds only to price decreases over time since there are no capacity based incentives. PV adoption is shown below in Figure 4.6. Photovoltaics take a longer time to be adopted due to the lack of net-metering and federal tax credit in these simulations, but the adoption in Houston grows faster as a response the higher solar insolation. By the end of twenty years, PV adoption is 3.6% and 1.1% of the solar adoption with a capacity market in Houston and Chicago, respectfully.

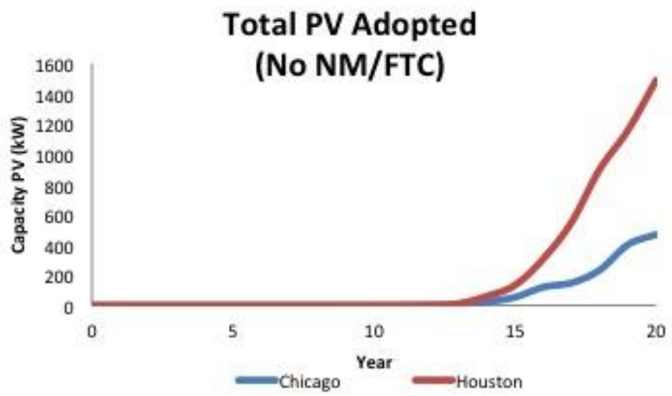

Figure 4.6 PV adoption pattern without incentives

Without sufficient local capacity there is very little benefit in terms of local-sufficiency. Figure 4.7 below, shows the percent of the time that the aggregator can island and provide local supply is less than 10% of the time for all scales, with individual investments having the most self-sufficiency. Because the level of PV is relatively low, even in the final five years, there is no noticeable impact on local sufficiency. Additionally, if batteries are managed on a scale greater than between closest neighbors, there is no benefit in terms of local resiliency.

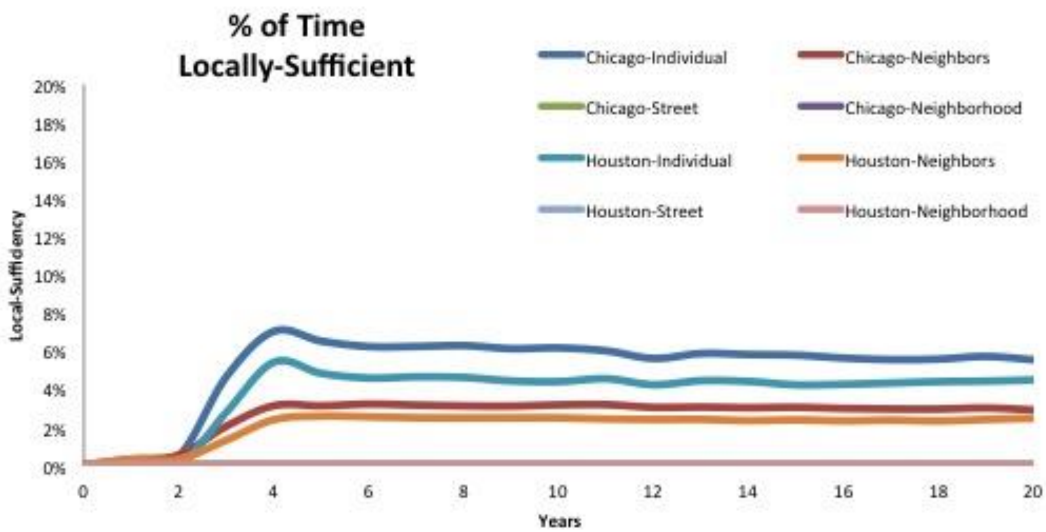

Figure 4.7 Local sufficiency metric for reactive markets shows limited local sufficiency when managed between individuals or neighbors and no local sufficiency when managed at larger aggregation levels

The reactive market, unaccompanied with local generating capacity, at any scale, does not produce significant benefits in terms of total grid costs for either location. The table below shows the averaged results for each simulation. For expanded comparison and significance analysis, see tables in appendix B.

Table 4.5 Total costs for simulations with reactive markets only are not significantly different than the baseline scenario 1 (no DER incentives)

Average Costs ($ Millions)	Individual	Neighbors	Street	Neighborhood
Chicago	\$ 23.9 σ=\$4.7	\$ 26.4 σ=\$5.6	\$22.9 σ=\$3.5	\$ 24.1 σ=\$4.0
Houston	\$49.4 σ=\$4.3	\$50.0 σ=\$8.9	\$48.5 σ=\$6.5	45.3 σ=\$7.2

4.3.3 Both Capacity and Reactive Markets

The next section examines how capacity and reactive markets can work differently in tandem. Figure 4.8 shows the adoption patterns for PV and batteries with both capacity and reactive markets. A main adoption difference, as compared with the single markets, is the slowed PV adoption in Chicago. In Chicago, batteries are capable of mitigating the capacity addition needed in the short term. Therefore, PV capacity additions are not immediately necessary. Since Chicago has a more varied demand profile, times of high demand can be met with a relatively small battery. Conversely in Houston, high demand periods are longer and batteries are less capable of providing sufficient reserves.

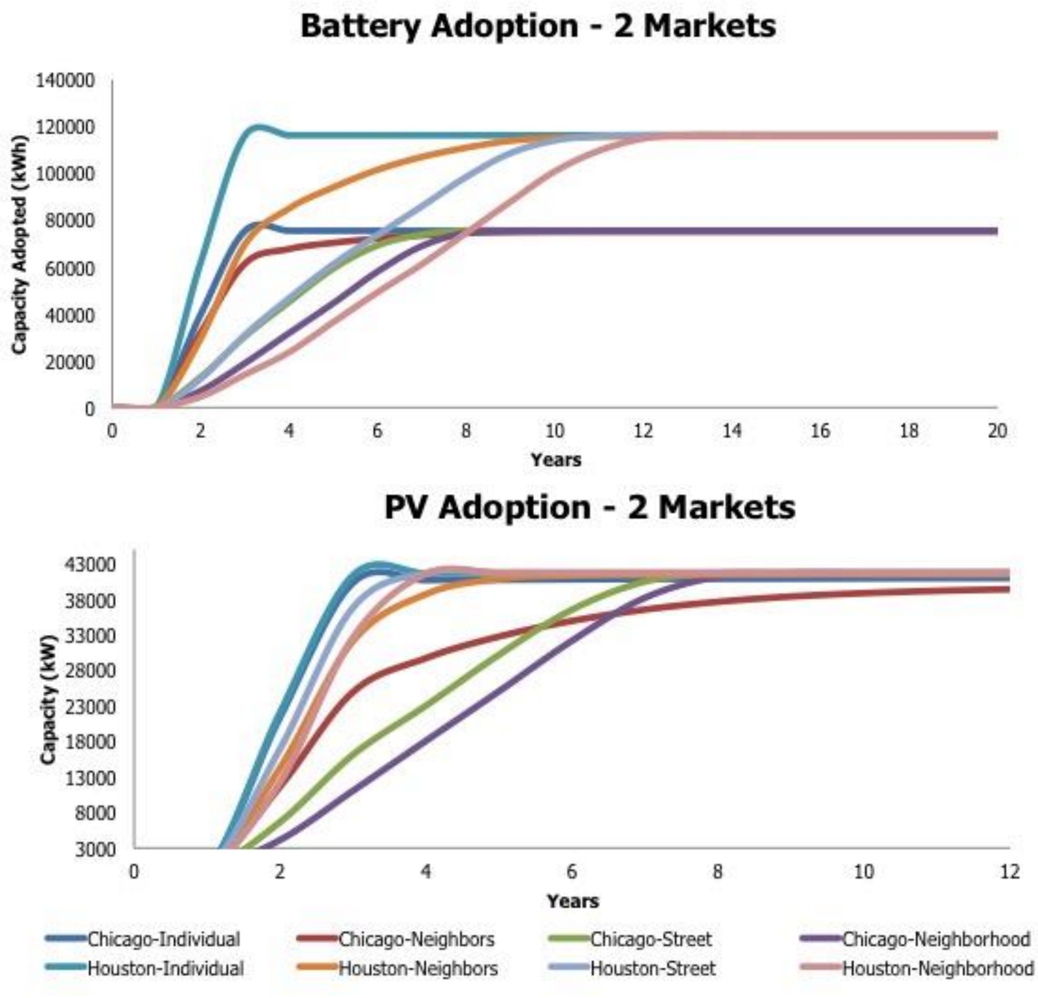

Figure 4.8 Battery and PV adoption patterns with both capacity and reactive market instruments implemented at different scales

These simulations have both expected and unexpected findings. In terms of local-sufficiency, the dual markets do not provide as much benefit as expected. Only when managed at the individual scale was there a significant gain in overall local sufficiency when compared with the capacity market only. This comparison is shown in the table 4.6. In fact, balancing can either increase or decrease the overall percentage of time that the area is completely locally sufficient at larger scales. This is a result of the fact that batteries will charge when local generation is producing more than can be used locally. The table below shows that the percentage of time that an area is locally sufficient is highest when balanced at the individual scale and then decreases as aggregation size increases, with the street level having the least local sufficiency, and then increases again at the neighborhood level. Managing batteries at the neighbors or neighborhood level actually decreases the total amount of time the area is locally sufficient relative to just having a capacity incentive for local generation. Street remains the least locally sufficient aggregation scale.

Table 4.6 Comparison of maximum local sufficiency for capacity and both markets

	Individual	Neighbors	Street	Neighborhood
Chicago				
Capacity	41.7% σ=0.15%	38.6% σ=0.3%	11.8% σ=8.1%	29.7% σ=2.0%
Both	45.3% σ=0.3%	38.6% σ=0.6%	11.4% σ=7.7%	25.8% σ=1.9%
t-test	t(10)=-27.73 p<0.001**	t(10)=0.27 p=0.794	t(11)=0.098 p=0.923	t(13)=12.8 p=0.002*
Houston				
Capacity	26.6% σ=0.3%	24.6% σ=0.5%	5.0% σ=4.9%	12.4% σ=1.8%
Both	28.9% σ=0.3%	21.1% σ=0.8%	2.4% σ=0.6%	9.5% σ=1.6t%
t-test	t(14)=-14.5 p<0.001**	t(11)=10.5 p<0.001**	t(12)=1.35 p=0.223	t(13)=3.29 p=0.006*

This non-linearity that occurs as aggregation scale increases suggests that the interaction with the diversity of buildings in an aggregation area is an important design feature for micro-grids within larger grids. The potential to have local sufficiency has important interactions with the battery size, and load growth for which we perform sensitivity tests in section 4.3.4. However first we comment on the effect that this balancing has upon total costs.

While the gains in local sufficiency are minimal by adding and balancing local battery capacity with DER generation capcity, the larger system savings in term of overall cost are substantial. Comparison of the total system costs that result from only a capacity market with those that result from the dual capacity and reactive markets finds lower average costs at every scale of aggregations and the significantly lower costs at both the individual and street level for Houston, and the individual level for Chicago. The ability to have significantly different results within the twenty year time period is a result of the speed at which locations adopt generating DER. Projecting savings farther into the future would likely demonstrate that other scales have significant savings as the local deferral value becomes larger. From a cost perspective, none of the Chicago dual market scales stand out as significantly better than another scale, but the individual and neighbor level markets have significantly lower 20 year costs than both the street and neighborhood balancing in Houston.

Table 4.7 Comparison of total costs between capacity and dual markets

	Individual	**Neighbors**	**Street**	**Neighborhood**
Chicago				
Capacity	\$24.8 σ=\$2.3	\$24.0 σ=\$2.8	\$25.1 σ=\$3.9	\$23.4 σ=\$ 2.5
Both	\$21.6 σ=\$2.3	\$22.1 σ=\$3.7	\$22.5 σ=\$2.1	\$20.3 σ=\$4.8
t-test	t(11)=2.253 p=0.028*	t(13)=1.202 p=0.251	t(10)=1.534 p=0.156	t(9)=1.515 p=0.166
Houston				
Capacity	\$32.8 σ=\$4.6	\$40.4* σ=\$4.1	34.8 σ=\$6.1	37.5 σ=\$5.9
Both	\$25.6 σ=\$5.6	\$24.8 σ=\$5.0	\$32.4 σ=\$6.3	\$35.9 σ=\$7.3
t-test	t(13)=2.807 p=0.014*	t(13)=6.72 p<0.001**	t(13)=0.735 p=0.476	t(12)=0.457 p<0.657

4.3.4 Sensitivity Analysis

When interpreting these results it is important to consider the impact of assumptions on the results. As was investigated in Chapter 3, supply side assumptions, such as the price of centralized generation have relatively little impact on averaged model results, but variation in demand side assumptions can have large implications. To explore some of these implications we test the battery sizing heuristic as well as the load growth assumption the dual market scenario.

4.3.4.1 Battery Size

To test the effect of battery sizing on results the reference condition of 4 hours of peak battery supply is compared with both two hours and eight hours managed at either the individual or neighborhood level with dual (capacity and reactive) markets. As an example, a house with a peak demand of 2kW, is used to illustrate the sizing heuristic. In the results presented above the battery was sized for four hours of peak demand, or 8kWh of battery, in these sensitivity results the same house would consider investing in either 4kWh of storage (2 hours of storage) or 16kWh (8 hours of storage). Figure 4.9 shows the battery adoption pattern for each scenario (2 or 8 hours of peak storage, Chicago/Houston location, and individual or neighborhood markets).

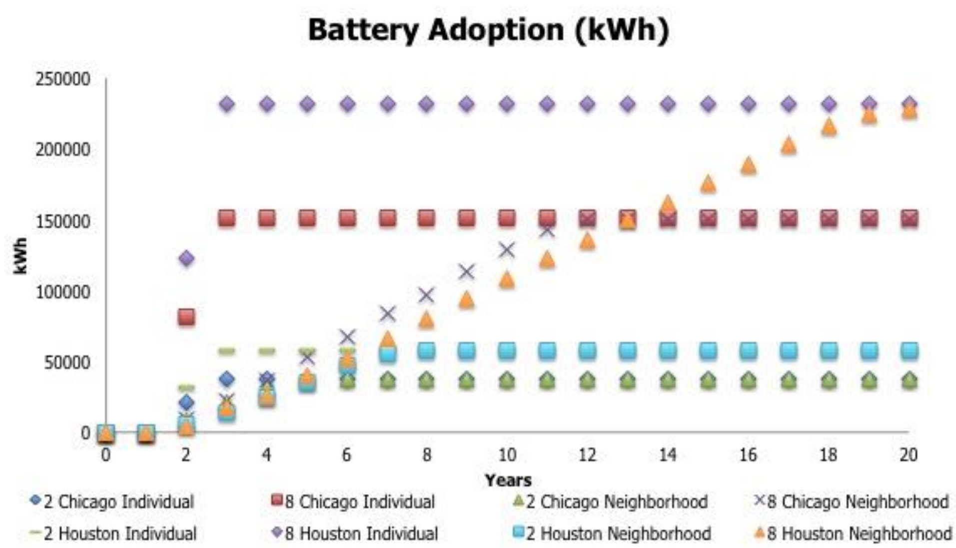

Figure 4.9 Battery adoption pattern in under dual aggregation markets with 2 or 8 hours of peak capacity

It shows that 8 hours of battery capacity results in approximately five times the amount of adopted battery capacity, and a gradual adoption pattern for the neighborhood market and an abrupt adoption when managed at the individual scale. The figure below shows total costs and local sufficiency for the 2,4, and 8 hour battery sizing. The two and eight peak-hour battery condition distributions are compared for significance to the otherwise equivalent 4 hour condition.

Table 4.8 Individual scale markets with batteries sized to provide 2,4 and 8 hours of peak battery supply. The 2 and 8 hours of sufficiency are compared for significance with the 4-hour condition.

	Individual 2 hours	**Individual 4 hours**	**Individual 8 hours**
Chicago			
Average Costs ($ Millions)	$ 22.8 σ=$3.0 t(11)=-0.779 p=0.452	$21.7 σ=$2.3	$19.4 σ=$1.6 t(12)=2.282 p<0.041*
Local Sufficiency	42.8% σ=0.1% t(11)=18.6 p<0.001**	45.3% σ=0.3%	44.4% σ=0.5% t(13)=4.445 p<0.001**
Houston			
Average Costs ($ Millions)	$ 28.2 σ=$6.2 t(10)=-0.826 p=0.428	$25.6 σ=$5.6	$41.2 σ=$7.9 t(13)=-4.558 p<0.001**
Local Sufficiency	25.1% σ=0.5% t(8)=14.998 p<0.001**	28.9% σ=0.3%	31.4% σ=0.4% t(14)=-14.4 p<0.001**

The runs at the individual scale show that, in Chicago, the 8 hour battery installation can significantly reduce total system costs, compared to a 4 hour battery, but that these savings do not necessarily translate to increased time being locally sufficient, as the batteries consume significant power to charge even at off peak hours. This stands in contrast to the simulation results in the Houston context, which show that by rapidly adopting (using an individual scale market) large batteries, a new pressure is created on the grid that actually significantly increases costs compared to the smaller batteries.

Aggregating at the neighborhood level, as shown in Table 4.9, decreases the potential dramatic impact of rapid adoption that takes place with the individual market. This mitigates much of the effect of battery sizing requirements, and makes the overall market more predictable. Although differences in costs are not significant over the twenty years, this is likely due to the fact that adoption of the larger battery size takes place gradually, so much of the potential deferment value is not realized within the time span. It is worth noting that, although the difference in costs are not significant at the neighborhood level within the 20 year time span, the trend is that with increasing battery size managed at the neighborhood scale there are decreasing total costs.

Table 4.9 Neighborhood scale markets with batteries sized to provide 2,4 and 8 hours of peak battery supply. The 2 and 8 hours of sufficiency are compared for significance with the 4-hour condition.

	Neighborhood 2 hours	Neighborhood 4 hours	Neighborhood 8 hours
Chicago			
Average Costs ($ Millions)	\$21.5 σ=\$2.4 $t(8)=-0.544$ $p=0.6$	\$20.4 σ=\$4.8	\$20.0 σ=\$0.8 $t(6)=0.215$ $p=0.836$
Local Sufficiency	27.6% σ=1.5% $t(12)=-2.024$ $p=0.067$	25.8% σ=1.9%	25.0% σ=1.9% $t(13)=0.832$ $p=0.421$
Houston			
Average Costs ($ Millions)	\$36.0 σ=\$7.2 $t(13)=-0.036$ $p=0.972$	\$35.9 σ=\$7.3	\$28.9 σ=\$5.8 $t(12)=1.999$ $p=0.07$
Local Sufficiency	8.9% σ=1.4% $t(12)=0.764$ $p=0.459$	9.5% σ=1.6%	11.1% σ=2.7% $t(10)=-1.364$ $p=0.203$

4.3.4.2 Load Growth

Changing the load growth from 1.1% to 0% did not have a major effect on DER adoption patterns. Tested with both the capacity and reactive market, in both locations the adoption pattern was fastest at the individual scale and slowed as market aggregation scale increased. Final DER adopted capacity, were reached quickly and were not noticeably different than the positive load growth scenario presented in figure 4.8. This suggests that the local variation between houses is a more important driver for this adoption heuristic than load growth.

Table 4.10 below compares the costs and local sufficiency of the zero load growth scenario in Chicago and Houston. The costs are compared to the zero load growth conditions, without markets or DER incentives as presented in Chapter 3. This is a suitable comparison because it suggests what the costs would have been for zero load growth without DER. Local sufficiency is compared with the local sufficiency observed in the 1.1% load growth scenarios, presented earlier in this chapter. When significant differences for the local market is significantly better than the comparison scenario (lower cost or higher sufficiency) the comparison is highlighted in green. Significantly worse results are highlighted in red.

The comparison shows that zero load growth can often be made significantly cheaper by coordinating distributed energy, but that these savings are less dramatic than when there is load growth. In the positive load growth scenarios the neighbors aggregation level had the largest cost savings. In the zero load growth scenario, however, in Chicago the neighborhood aggregation level has the most cost savings.   A second unexpected result at the neighborhood aggregation scale is the fact that the local sufficiency was worse without load growth. This was surprising because less load growth requires less overall electricity used, which in turn requires less electricity to be locally generated. However, in Houston, the relatively flat demand pattern resulted in the batteries not being fired as much, thereby decreasing the local sufficiency.

These results show the important interactions with scale that occur when managing DER locally. The interaction is particularly dramatic here depending on the amount of variability. Defining useful micro-grids or islanding within the larger electric grid should consider the nature of electricity variability when defining rules about scales, sizing and other design decisions.

Table 4.10 Comparison of zero load growth cost and local sufficiency metrics with reference scenarios.

	Individual	Neighbors	Street	Neighborhood
Chicago				
Average Costs ($ Millions)	\$20.0 σ=\$2.5	\$19.1 σ=\$2.9 t(12)=0.047 p=0.047*	\$19.7 σ=\$3.3	\$17.3 σ=\$1.9 t(9)=-3.442 p=0.007**
Local Sufficiency	45.6% σ=0.2% t(12)=2.447 p=0.031*	40.3% σ=0.4% t(11)=6.874 p<0.001**	14.4% σ=14.2%	29.3% σ=1.9% t(13)=3.619 p=0.003*
Houston				
Average Costs ($ Millions)	\$25.4 σ=\$3.5 t(11)=-3.269 p=0.008*	\$23.4 σ=\$3.9 t(11)=-3.936 p=0.002	\$24.4 σ=\$1.7 t(8)=-3.999 p=0.004*	\$24.5 σ=\$4.5 t(12)=-3.386 p=0.005
Local Sufficiency	30.5% σ=0.6% t(7)=5.504 p<0.001**	21.6% σ=0.8%	2.8% σ=3.1% t(4)=0.320 p=0.764	5.4% σ=1.3% t(11)=-5.369 p<0.001**

4.4 Discussion

In the beginning of this chapter it was suggested that there are five main reasons for using a probabilistic model, such as the one here, to study the future value of DER. We now take the opportunity to reflect upon that rationale, in light of the results.

4.4.1 Optimization tradeoffs

Optimization of distributed actors belies the scale tradeoffs that can provide for different values when optimized for different spatial and temporal scales. If the goal is to provide the most local sufficiency, incentivizing generating DER capacity to be managed by each building can provide relatively high self-sufficiency (assuming advances in smart interconnection via smart meters, inverters etc.,), even without storage or small storage capacity at each house. Implementing and increasing storage capacity can increase the amount of time that a house is locally sufficient. For example, in the Chicago location, adding storage, based on household demand fluctuations, increased the amount of time the residence was self sufficient from 41.7% to 45.2%. The results show that implementing larger battery capacities at individual scales may not improve the amount of time that a majority of buildings have back-up, and, conversely, may actually provide a system wide stress that increases systemic costs. If batteries are large enough they can cause system wide strain as opposed to benefits, as the case of adding 8-hours sized batteries to individually managed buildings in Houston, demonstrates.

Adding batteries (through a reactive market) can dramatically improve cost projections for a locale only when paired with a generation incentive. A reactive market alone did not significantly improve system wide costs, and had minimal self sufficiency benefits (less than 8% of the time self sufficient is achieved in the best case scenario, the individual scale market). When generation capacity is paired when small batteries (2-4 hours of peak demand) there are cost savings when managed at all aggregation levels. These savings are significant when compared at the individual and neighbors scale, and if measured over a longer time scale the savings would likely be significant at the other scales of aggregation. Large batteries can be lead to stress and high costs when managed at a small aggregation scale. Conversely both small batteries, managed on small scales (individual or neighbor scale) or larger batteries managed at the neighborhood scale produce the lowest system costs. Significant costs are possible when large batteries are deployed and managed at small aggregation levels, although this also may depend on the demand profile of the location.

Optimizing for costs favors larger batteries implemented at the neighborhood scale. Optimizing for local sufficiency finds that small batteries at the individual scale will produce the best outcomes. A logical next step may be to propose a middle ground that can balance both qualities. However, the results suggest that the opposite is true. The street level of aggregations had both the lowest local-sufficiency and does not demonstrate significant cost savings. Additionally, it had the largest variability in outcome measures. This highlights the importance of analysis for non-linearity's that can occur within an urban context, with some locations seeing much larger benefits than others.

4.4.2 Strategic customer behavior is largely unknown.

Because the extent to which customers are interested in participating in complex energy markets is unknown, the management heuristic does not include a complex pricing model. A smart and variable pricing model would require some knowledge of to what extend customers react to price. Instead, a customer DER adoption model is implemented that requires a certain capacity of DER is adopted based on grid variability. Additionally, battery-charging strategies attempt to flatten load based on load aggregation, not pricing. The finer the scale of market aggregation, the higher the reliance on smart devices must be. The assumption is that smart devices could optimize certain conditions or constraints in order to receive favorable rates. Therefore, we assume that each smart device takes on a fixed heuristic that is not responsive to larger market trends and therefore can function without solving larger market optimization problems.

4.4.3 Valuing local sufficiency

Although the highest local sufficiency occurs with the smallest scale balancing (individual balancing), increasing the aggregation area does not have a linear effect on potential local sufficiency, as street level balancing has lower balancing than neighborhoods. Larger optimization scales (e.g. neighborhood) provide for less overall self-sufficient hours than individual building balancing, but they do allow for the local sufficiency to be more equitably spread between different users within the aggregation area. This is in contrast to individual or neighbor based markets and heuristics, which, although they have the highest overall self-sufficiency metrics, often have high inequality between buildings, with some buildings having zero local capacity and while others have many hours of local robustness. Additionally, if buildings use larger batteries that have sufficient capacity to provide many hours of backup, this can add significant costs to the grid. The topic of equity and the cost burden of self-sufficiency should be further explored and metrics should be further developed.

4.4.4 Trust and information security

The smaller the scale of a market or balancing incentive the less value there is in any one node, and the less an error in a node will have noticeable impacts on other processes within a system. Conversely, a more decentralized system is more difficult to control and predict and optimize. When trust in a system is high people may prefer more centralized structures, as it minimizes the cognitive capacity and investment stress on the more decentralized components. If disruptions or stresses to the system become apparent to the users of a system, or if their values and desires are not sufficiently addressed by the system, there is a likely shift towards less aggregated systems. This also allows for higher information security in the system because there are less centralization points that have high information value content. While these values are not well described by the model, the inclusion of multiple scales of potential organization and management speaks to the potential diverse values and preferences that agents within the model may have.

4.4.5 Deferral and cross scale feedbacks

The baseline conditions suggest that this same area requires between around 28 and 54 million dollars of investment in Chicago/Houston respectively and that, especially in the temperate and less variable Houston demand scenario, simple net-metering can make a significant difference of a more than 20% cost savings. A capacity market, under the modeled high load growth conditions results in rapid DER adoption. This rapid adoption has much of the same effect in terms of cost reductions as incentivizing DER with net-metering and access to financing. However, it assumes that these incentives come with advances in smart management devices. Reactive markets without accompanying distributed generation capacity provide minimal benefits both in terms of cost savings and local sufficiency. Dual market incentives for both generating and balancing DER have the potential to dramatically reduce total system costs in both environments. However, they require additional planning if there is to be both high local sufficiency and low costs realized from pairing batteries with generating DER. Potentially incentivizing small batteries at the individual scale may provide the best in terms of both cost and sufficiency. Aggregating at larger scales and using larger batteries also offers longer term benefits including improved equality for who has access to local backup capacity as well as a more gradual adopt curves. Conversely, creating incentives for large batteries managed at the individual building scale is likely to add more stress than it saves, and does not significantly increase local robustness to storms or threats. Adding batteries without also adding distributed generation will produce minimal benefits.

While these results can help to inform local storage and management policy, there are several model limitations, which limit the ability of these to be interpreted in other situations. First of all, the variability between buildings load patterns, load growth and seasonality was randomly distributed in this model. A more accurate understanding of how variability changes monthly, hourly, by housing type etc., would help make findings more accurate. This may be a particularly egregious error with regard to the pattern of load growth, which, in many locations, is growing at peak times, but not overall. Testing the reaction of these DER investment mechanisms with peak only load growth may demonstrate different patterns. We recommend that researchers, planners and utility developers devote significant resources to understanding how variability changes at different scales and that measures of variability should become endemic in grid planning and governance in the future.

Additionally, these findings are valid in an urban setting where local outflows may provide high benefits to congestion. This model should also be run in different geographies to understand how geography, density and distance interacts with market drivers. One prediction is that, in rural locations, the value of local storage even without commensurate generation investments will be significantly higher than in cities due to the potential avoidance of high transmission costs. Finally, because CHPs were sized to minimum summer heat load, there was limited potential adoption capacity that was available for investment. Looking at changes in CHP sizing logic may results in additional benefits.

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CHAPTER 5

USING THE GRAMMER OF RULES TO EVALUATE MODULARITY AND CO-PRODUCTION IN ELECTRICITY INFRASTRUCTURE

5.1 Introduction

The electricity grid faces several challenges that lead us to ask the question: how can it adapt and innovate faster and still provide reliable service? It is imbued with inertia, embedded from all of the large investments that have been made over a century. It faces increasing uncertainty as to how it will pay for future investments as load growth stagnates and large storms and disruptive events are on the rise. This causes increasing costs, as well as users to increasingly value local resiliency. At the same time that the costs of renewables, including distributed energy resources (DER) continue to fall (Hee Kang and Rohatgi, 2016; Nemet, 2006) new ways to coordinate distributed systems are just beginning to emerge with advances in information systems and smart devices (Chalkiadakis et al., 2011; Pinto et al., 2011; Rahimi and Ipakchi, 2010; Unger and Myrzik, 2013). Although sustainable energy has been percieved as a critical area for change, research and development budgets for energy companies are among the lowest of any industry (Margolis and Kammen, 1999).

The existing set of rules and incentives for creating electricity infrastructure has not resulted in a sufficiently innovative energy sector. One reason the energy sector may innovate slowly is the lockin effect of sunk costs in a hierarchical and centralized industry. This includes both the underlying hard infrastructure as well as the organizations that provide, manage, and regulate it (Gans et al., 2001). A more distributed and modular architecture may enable the industry to innovate at a rate more closely aligned with users desires and needs (Argyres and Bigelow, 2010). It may do so by enabling modules that users can more directly participate in and that minimize complexity to the greater system. Additionally, modularity can offer the ability to test new ideas, copy and experiment with minimal impacts on other parts of the system, as well providing some local self sufficiency. In this paper we take the concept of design modularity from engineering and business and relate it to concepts in co-production through the use of the grammer of rules to identify modules and interdependencies in the evolving rule sets emerging for San Diego, California. We suggest that an analysis of the rules governining distributed energy resources (DER) can help illuminate what it means to design for modularity and co-production in large infrastructure systems that are otherwise slow to change. This is valuable for the ability to improve our understanding of modularity and co-production in infrastructure systems.

5.1.1 Historical Patterns

Historically, the economics of electricity production have been prohibitively expensive and complex for users to participate in production. Utilities were granted the right to be the sole providers within geographical areas in order to avoid duplicative grid infrastructure. In exchange for agreeing to be regulated by elected boards, they were guarunteed a “resaonable” rate of return from the users within their service area. Other factors that shaped the electric utility into the hierarchical and risk adverse institution that it is today include the sophisticated level of technical expertise and coordination needed, economies of scale for large construction projects, and the scale and legal processes requisite to aquire rights-of-way across private lands (Ostrom, 1996).

Making electricity cheap and accessible meant that a single regulated provider could spread the costs across the different user groups in a population. It created a pattern of large risk adverse investments that are centrally managed as part of an integrated system. However, large hierarchical firms and products often have trouble reconfiguring themselves even when new factors become apparent (Henderson and Clark, 1990). The importance of a system to be adaptable may be compared to the rate and scale of shocks or system changes it faces, which continues to grow in the energy sector. A system which faces stable conditions may optimize upon a set of input conditions at a single scale, whereas a more uncertain future will often bias system designers to instead mitigate uncertainty by having by considering multiple scales and production functions (Janssen et al., 2007). A focus on adaptability preferences a diversity of resources and protocals, local niches, learning and memory, and may favor multi-use solutions over the most efficient outcome. Given the increasingly volatile nature of changes in the world, as well as the rise of smaller scale options for investing in the grid, it is likely that the electricity grid of the future favors resiliency, both local robustness and adaptive capacity, in addition to system efficiency.

A more decentralized energy system has the potential to help the grid innovate, adapt and change more quickly due to 1) the ability of new innovators and sectors to become engaged in the industry 2) smaller scale projects to diminish the costs of failure 3) the creation of new niches to test ideas and 4) increased user feedback. However, distributed systems can also be cumbersome, inefficient, poorly coordinated, and rife with inequality. Creating a system that makes sense for distributed energy and avoids these challenges will require that attention is paid to the modularity of design and decision making.

5.1.2 Co-production

Co-production refers to the process by which individuals who are not "in" a shared organization jointly produce goods or services (Ostrom, 1996). Co-production is especially critical for service industries such as health or education. In these industries if users are not engaged in the production of health or education outcomes, no amount of external provisioning can compensate (Ostrom, 1996).

Co-production in the energy sector includes multiple polices and technology options. Technologies include smart meters, building sited photovoltaics, small scale generators and fuel cells, batteries and electric cars. Policies include net-metering of building sited generation, dynamic pricing to encourage different demand patterns, demand response programs and markets, and energy efficiency incentives and standards. All of these options change the aggregated load profile that a utility must match.

The literature on coproduction differentiates between types of co-production and we summarize these according to three types: 1) governance (what to do), 2) planning/design (how to do it), and 3) production (doing it). The question of whether co-production that focuses on what to do and how to do it is authentic co-production seems to be open to disciplinary debate. Alford, who has written extensively on co-production in the health sector, considers production co-production to be true coproduction (Alford, 2014), but others especially those from a business context, consider the other forms as also belonging to the category of co-production.

The extent to which users can contribute to the governance, planning and production depends greatly on the level of expertise needed for that task. Dunston et al suggest that when there are excessive expertise barriers that users may be consulted to provide feedback and commentary as part of the designers process in developing prototypes. (Dunston et al., 2009) Bovaird sees differences in the types of co-production that may occur; ranging from professional to user development and delivery of services (Bovaird, 2007). To understand how a change in the type of co-production may change the outcome we consider the example of an electrification development project. Table 5.1 below gives examples of how co-production may look different depending on the design of enabling rules.

Table. 5.1 Typology of co-production

	What to do	**How to do it**	**Doing it**
User	Users decide on goals	Users decide how goals should be achieved	Users produce outcome
Hybrid: Consultation	Professionals jointly determine project goals with users (e.g. focus group/workshop)	Professionals jointly determine how to achieve a known goal with users (e.g. credit union)	Professionals create a plan for users to implement (e.g. weight loss plan)
Hybrid: User Market Choice	Users select from different ideas about what to do (park re-development competition)	Users choose from professionally developed choices (e.g. competitive bids)	Users select which professionals should do the work (contractors)
Professional	Professionals design a project	Professionals develop work plan	Professionals/ contractors build and maintain

The table above shows that co-production can take many different forms, which differ in the amount of engagement that users must put into a system.

The likelihood that a user will become involved in an available type of co-production can be described in terms of the opportunity costs for participating in different types of coproduction, which will vary with the type of coproduction that is occuring (Ostrom, 1996). Two aspects of a project that can make the opportunity costs for participation high are: 1) the cost of acquiring the expertise and 2) the capital required to build and maintain a reliable system. Figure 5.1 shows the relationship between these factors and the likelihood of co-production.   As systems become increasingly risk adverse due to high capital costs and technical complexity, such as highly engineered infrastructure, there is a tendency to move towards increasing levels of professional development (Verschuere et al., 2012).

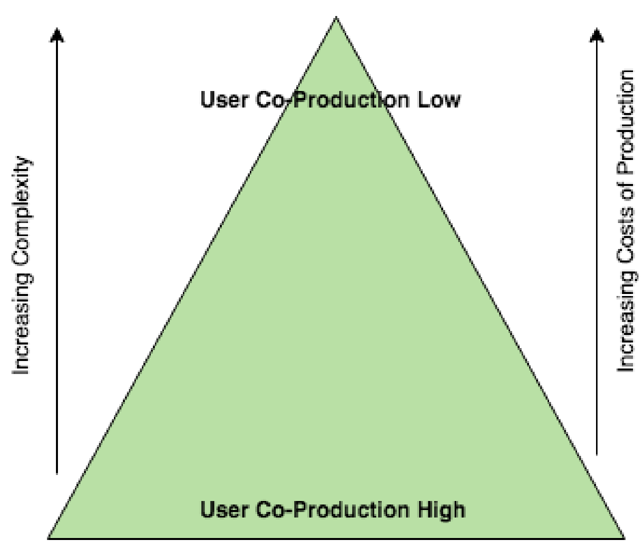

Figure 5.1 Tradeoffs between co-production costs and complexity

The effort to transition towards a less carbon intensive future has long focused on decreasing the costs of carbon free energy production with policies such as funding research and development of renewable energy, production and investment tax credits. The cost of solar energy has continued to fall exponentially. This has had dramatic effects, not just on the investment choices of existing energy producers, but on the cost of participation by new participants. Regardless of whether regulators, utilities, and society are prepared for it, the price of distributed energy continues to decrease at a rate such that people demonstrate increasing desire to be producers as well as consumers of energy(MIT Energy Initiative, 2016). However, the use of renewable energy can, in many ways, increase the complexity of managing an energy system with increased distributed complexity, increasing variability and diminishing balancing supplies. One way of managing complexity is through the use of modularity.

5.1.2 Modularity

Modularity is a concept that is often used in engineering to simplify highly complex design work. The core idea is that different teams can take on different design tasks and components, as long as they know how the different components interact. A simple example is a cell phone charger. By creating a standardized interconnection point Android phones thereby enable many different designers to be able to design different and competing cables that can enable rapid incremental changes. Modularity intentionally creates a high degree of independence which or a loose coupling between component designs by standardizing compenent interface specifications (Sanchez and Mahoney, 1996). The smaller scale the module is, the greater likelihood that users will have both the captial (financial, expertise and other types) to engage in co-production either by designing and producing their own module or by selecting one that a professional has produced. This modularization requires that a fixed information structure is created that can ensure the larger systems based on the knowledge of the interconnections and flows between componenets (Sanchez and Mahoney, 1996).

Designing a technical system to be modular is anything but costless or organic. A modular system requires that an overarching architecture is specified from which interdependencies (such as the charger port) are fixed and specified such that modules can be defined in relationship to those fixed points. Defining what is desirable in a modular system architecture is a difficult process that involves understanding what are the design rules (fixed interdependencies), hidden modules, and system integration and testing.

"Firms arise as islands of nonmodularity in a sea of modularity." (Langlois, 2002). This well describes the history of the utility industry. Traditional engineering design follows a method of constrained optimization which tries to obtain the highest level of product performance within some cost constraint. …. This leads to product designs composed of highly integrated, tightly coupled component designs" (Sanchez and Mahoney, 1996) Unless effort is put into creating a modular system architecture, technical systems will default to hierarchical cost minimization. This will generally require an organizational structure coordinated by a managerial authority and hierarchy. Historically, the energy industry has managed this complexity through the inertia that accompanies large scale projects.

Clark and Baldwin suggest that there are three main purposes of for designing modularity into a system: to make complexity manageable, to enable parallel work, and to accommodate uncertainty (Baldwin and Clark, 2004). All of these drivers appear to be present in the electricity industry. Modularity is one way to deal with burgeoning complexity through encapsulation of levels of inputs and outputs at a given scale. This involves “information hiding”, which is a strategy that encapsulates information within a module. This information does not need to be communicated with other parts (Langlois, 2002). Langlois summaries these costs and benefits of modularity “A well decomposed modular system must pay a kind of fixed cost that an intertwined system need not pay: a system whose environment never changes may not have to worry about modularization.” He goes on to say that “systems that develop slowly in a slowly changing environment may not acquire or require much modularity…. in a world of change, modularity is generally worth the costs. The real issue is normally not whether to be modular, but how to be modular.” (Langlois, 2002)

Modular products allow for “mixing and matching” and can be a source of flexibility as well an opportunity for emergent user desires to be incorporated in the product (Sanchez and Mahoney, 1996). In the electricity industry this may increasingly include the desire for self sufficiency, environmental preferences, and the ability to integrate with other applications, such as electric vehicles. How to design, or even understand the concept of modularity, in a governed system which is both engineered but also regulated by polycentric laws intended to provide fairness, efficiency, and security among other values is inherently different then designing modularity in a cell phone.

Similar to co-production, scholars suggest that there are several different types of modularity: modularity in use, modularity in production, and modularity in design. The table below summarizes the three different types of modularity.

Table 5.2 Modularity Typology

	Description	Example
Use	Customers can mix and match elements of a product	Car can come with spoiler or bluetooth
Production	The same components sourced from multiple competing producers	Honda sources parts from multiple independent manufacturers
Design	Process of designing is distributed product	Open source software

Although there can be debate as to how to draw the lines between these types of modularity, there is a clear parallel between the types of modularity and the types of co-production. These two fields are in a nascent stage of understanding their relationship to one another, and as such it would be inappropriate to suggest that the same drivers for one are relevant for for understanding another. We do however suggest that we should begin to understand the relationships better by 1) using tools from both engineering and governance analysis and 2) applying these tools to systems which are both highly technical and intensively governed. The tools we propose to use to look at modularity in the increasingly distributed electricity system are: 1) Interdependency analysis of the distributed position relationships to detect potential modules and 2) Analysis of the rules that apply to modules using the Institutional Grammer Tool (IGT). These rules can describe whether interdependent distributed actors are acting as modules, capable of information hiding and decreasing system wide complexity. These tools may help with future design architectures that can more easily accommodate and test new innovations and ideas.

5.2 Using the Institutional Grammer Tool to Describe Modularity:

The IGT was developed by Elinor Ostrom and collegues to understand how people engage in feedback system for the making of institutions (meaning rules and norms) through the use of multiple connected action arenas (Crawford and Ostrom, 1995). Action arenas are the spaces in which interactions, exchanges, and competitions occur. Institutional statements, such as rules, norms or strategies, can be analyzed to understand guidelines for interactions. Figure 5.3 below shows several members of a DER action arena, that includes prosumers and DER operators, system engineers, designers, consultants, and financers, electricity utility personnel and regulators. They are composed of actors with preferences, strategies and resources (Poteete et al., 2010). Figure 5.2 below shows the seven rule types that are employed in an action arena. The action arena that this analysis focuses on is the arena in which DER owners and technologies become integrated into existing infrastructure.

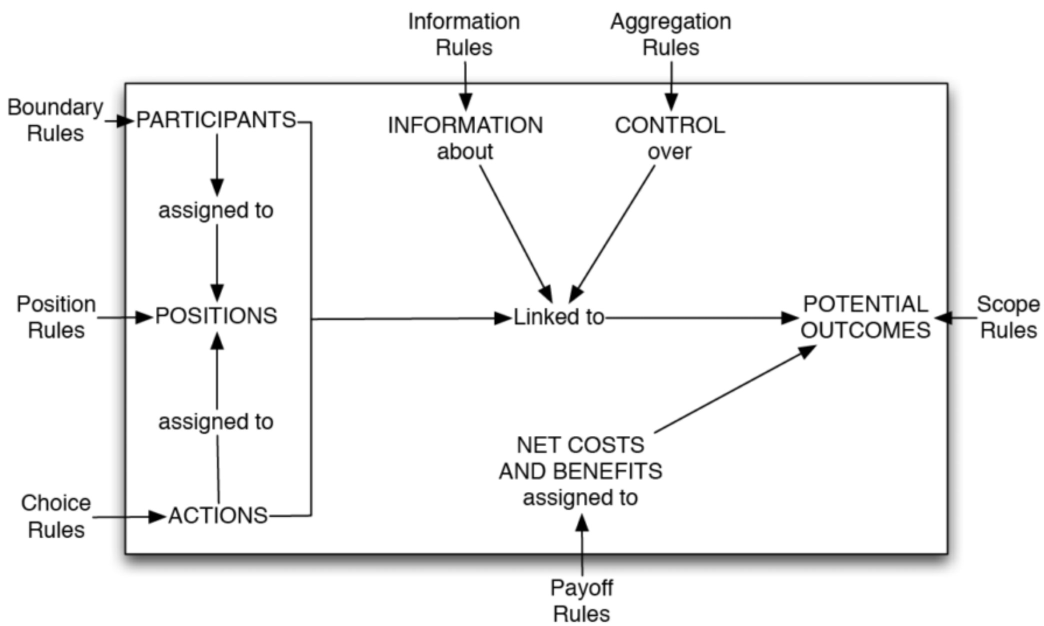

Figure 5.2 Action Arena includes seven different rules that structure interactions.

Desiging/innovating and provisioning the electricity grid can be described as a system of linked action arenas. The focus on modules in this analysis means that we are initially and primarily interested in understanding in what are the distributed (non-firm) positions that a person or component can occupy.   Positions are functionally defined, which is a direct parallel to a module, which is also defined by the function it provides. For example, the position of mailman is defined by the function of delivering mail, which directly relates to the actions that they should take (choice rules).   The boundary rules for a position are those requirements that a person must have in order to qualify for the position.   In terms of the mailman this may include rules such: a mailman must hold a valid drivers license. In coupled infrastructure systems a position may also be held by a technology. For example, a drone may be utilized to deliver the mail instead of a person. When a function is performed by a technology or piece of infrastructure that the choice dilemma can be controlled by installing software or an operational protocol. This may help alleviate the disposition for vertical integration, such as described by Williamson et al (Williamson, 1989), since some types of opportunistic behavior can be essentially programed away.

Figure 5.3 below shows some potential positions and sub positions and the concept of a house module, which may include human and technological positions. Some technologies, such as a smart inverter may be programmed by a human position to take on tasks like turning off lights, charging an electric car, or more efficiently cycling cooling. These tasks could be done by a person but can also be automated by a device programmed to complete the task.   Actors on the right and left half of the figure may enter into action arenas that focus on interconnection and payment for DER, based on the rules regulators approve, such as installation applications and payment for electricity. Although there is also a feedback from customers to regulators, this is a long and slow feedback loop, which we do not include in this analysis.

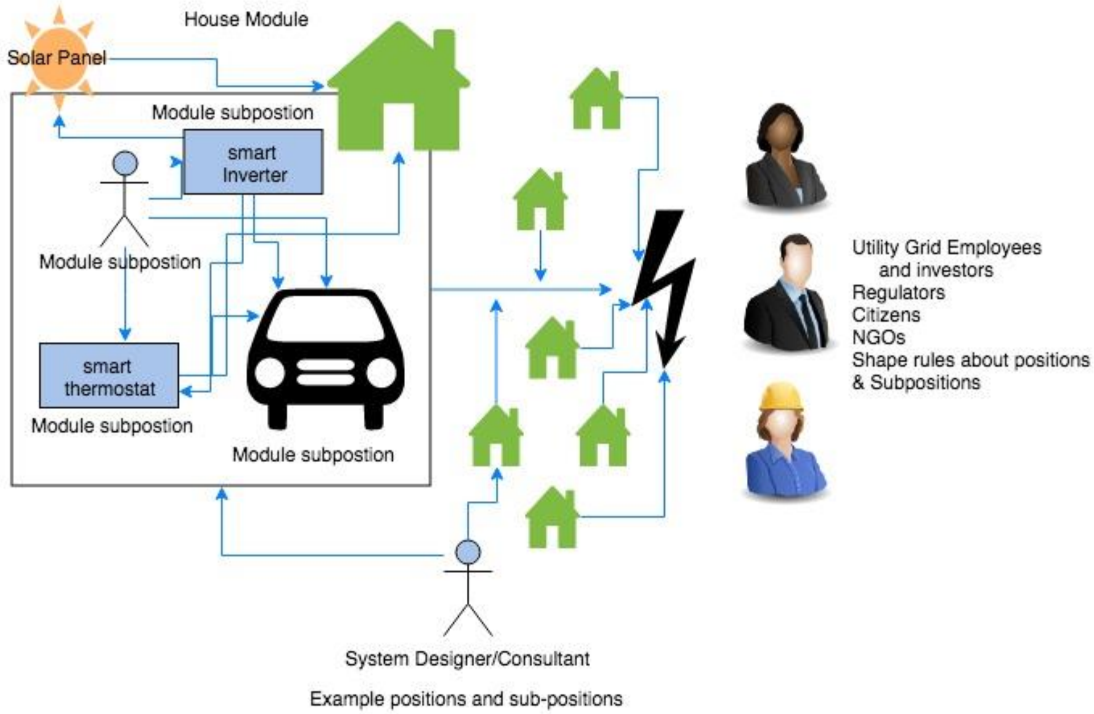

Figure 5.3 Example positions and subpositions within a theorized distributed infrastructure co-production module. Regulations may specify how different distributed positions may interact or function within the grid rules action arena.

Boundary rules can be understood as analogous to design rules (Chesbrough and Kusunoki, 2012), which are fixed requirements for one module to connect with another module. Therefore, in a modular system, clear boundary rules are central design features. In a well-designed and highly modular system, the existence of clear and consistent boundary rules would allow for require minimal information to be communicated between modules with the use of information rules. Instead the information used to manage and design how sub-components interact is contained within the module itself, and as such does not need to be communicated to higher levels.

Modules may be composed of sub-components or sub-modules. The sub-components for the mailman include their mail car, mail-carrier outfit, and list of packages to be delivered. The mailman acts as a module for the postal service because there is no centralized controller who follows and directs her. It is assumed that she will take care of the sub-modules and will report at the end of the day, using information rules, about the total flows completed, thus sparing the Postal Service from having to manage each subcomponent itself. This is directly analogous to the concept of information encapsulation, which is a core component of modularity in engineered systems, that seeks to minimize hierarchical complexity through containment of information within modules, so that only module inflow/outflows are reported to managing systems. Table 5.3 below provides a description of each type of rule and it's hypothesized relationship to modularity.

Table 5.3 Relationship between rule type and modularity

Rule Type	Actions	*Description*	*Modularity Questions*	Modularity Implication
Position Rules	**BE**	Position rules define a function that a person or technology can provide	What module positions exist?	Clearly defined roles for distributed positions will enable modularity?
Choice Rules	**DO**	Define what actions can a person or technology in a position take?	What choice rules exist for distributed positions?	Choice rules describe the type of co-production that a module may be involved in
Boundary Rules	**ENTER / LEAVE**	Define the criteria or attributes for each position	What boundary rules exist for each position?	Clear boundary rules fix the relationships between components.
Information Rules	**SEND / RECEIVE**	Define what information about other modules is available to whom	What information must/may/may not be availableand provided to what positions?	Information sharing should be minimized between modules to encourage modularity.
Aggregation Rules	**JOINTLY AFFECT (Who decides)**	Define how decisions are made when multiple people are involved	What aggregation rules exist?	Evidence of hierarchy; aggregation rules that involve multiple distributed positions will decrease modularity. May be evidence of design (not production) co-production
Scope Rules	**OCCUR**	Define conditions necessary for an outcome to occur	Under what conditions will/should distributed positions be allowed, encouraged, and compenasted for their actions (choice rules)?	Scope rules may serve as selection and operational criteria in a hierarchical organizaiton that does not have strong boundary conditions for modules
Payoff Rules	**PAY OR RECEIVE**	Define how costs and benefits are accrued	Do modular positions have payoff rules that incentize participation?	Describe the benefits/costs for a module

Figure 5.3 below shows some potential positions and sub positions and the concept of a house module, which may include human and technological positions. Some technologies, such as a smart inverter may be programmed by a human position to take on tasks like turning off lights, charging an electric car, or more efficiently cycling

cooling. These tasks could be done by a person but can also be automated by a device programmed to complete the task.

5.3 Methods

A modularity analysis method is proposed and tested to study modularity of regulated infrastructure systems. Modularity analysis focuses on illuminating 1) what the primary modules are within an infrastructure system and 2) how the rules promote or diminish modularity. The proposed method includes 4 different sub-procedures, which are described in turn. The procedures are:

1) Document selection and preparation

2) Position Statement identification

3) Co-occurrence analysis

4) Rule typology coding

5.3.1 Document selection and preparation

The first step is to choose a regulated infrastructure in a location which is likely to require increasing modularity, as evidenced by a shift towards more distributed infrastructure investments. San Diego was chosen as the location due to several factors: 1) The implementation of new distributed energy rules and incentives throughout California 2) The historic deregulation of the electricity industry which can allow for increasing modularity through competitive generation contracts 3) San Diego has high solar insolation, which favors the economics of distributed solar energy 4) The adoption of a 100% renewable goal by 2035. To define which documents should undergo analysis, all the official decisions of the California Public Utility Commission (CPUC) in relevant dockets since 2008 were downloaded from the CPUC's website[15]. Regulatory dockets were chosen based on their inclusion in The California Distributed Energy Resources Action Plan: *Aligning Vision and Action*[16]. The dockets that were included, and total number of decisions analyzed are shown in the table below. Intervenor compensation decisions, which decide whether to provide funding to third parties who submit substantial evidence to a proceeding on behalf of a client, were not included in the analysis.

Table 5.4 Rulemakings included in modularity analysis.

Rulemaking ID	Short Description	Number of Decisions
R.08-12-009	Electric Vehicle Grid Integration	18
R.11-09-011	Rule 21 – Grid Interconnection	6
R.12-06-013	Residential Time of Use Rate	6
R.12-11-005	California Solar Initiative and Self-Generation Incentive Program	31
R.13-09-011	Demand Response Programs	17
R.13-11-005	Energy Efficiency Programs	8
R.13-11-007	Electric Vehicle Charging Pilots	8
R.14-07-002	Net Energy Metering Successor Tarriff	4
R.14-08-013	Distributed Resource Plans	4
R.14-10-003	Integrated Distributed Resources	7
R.15-03-011	Energy Storage Procurement	5
Total	**11 Rulemaking Dockets**	**116 Decisions**

Document preparation requires 1) an initial familiarization with the documents to identify the relevant sections and subsections. 2) Identification and selection of institutional statements (rules, norms, or strategies). Each rulemaking has a number of decisions associated with it, as shown in figure 5.3. Within each decision there are

[15] http://www.cpuc.ca.gov/

[16] http://www.cpuc.ca.gov/uploadedFiles/CPUC_Public_Website/Content/About_Us/Organization/Commissioners/Michael_J._Picker/2016-09-26%20DER%20Action%20Plan%20FINAL3.pdf

multiple descriptive sections that give background, rationale, and summaries of stakeholder comments. After these sections there may be findings of fact, conclusions of law, orders, and attachments. Relevant institutional statements are aggregated into a single rulemaking document. Relevant statements include the order section, and any subsections of the decision referenced within the order section, such as an appendix. An example from Rulemaking R.11-09-011, Decision D.12-09-018 is shown below that requires that the contents of appendix C be included in the analysis. The rule below shows an example of a constitutive rule, which sets the conditions.

IT IS ORDERED that:
1. The Proposed Settlement attached to the March 16, 2012 Motion for Approval of Settlement Agreement Revising Distribution Level Interconnection Rules and Regulations (Attachment A) hereto is adopted in full.

4.2.2 Position Statement Identification

Once the relevant institutional statements have been collated into a single document for each rulemaking proceeding, the next step is to identify each rule statement that involves a distributed position, either as a human position (e.g. customer or contractor) or technological component (e.g. generation facility or vehicle). Distributed positions must occur in multiple locations and do not share joint operational or coordination protocals. This excludes actors such as Distribution Providers, Investor Owned Utilities, or San Diego Gas and Electric (SDG&E). These coded statements are used in step three, co-occurrence analysis, to identify when distributed positions, both human and technological are involved in a regulated statement. A statement is usually only one sentence long, but when the meaning is lost in isolation, such as in a list, it may be coded as longer statement. An example of a coded statement is shown below from rulemaking 14-07-002; human positions are highlighted in yellow and technological positions are highlighted in green.

> Where the VGI Facility site host opts to receive the VGI Rate (i.e., the VGI Rate-to-Host pricing plan), the site host, or its selected vendor, will be required to submit to SDG&E the load management tactics it will implement at its VGI Facility, including the incremental costs and equipment required to implement the load management tactics, the prices or fees that it intends to levy on VGI Facility users (EV drivers), and any vehicle or EVSE communication systems necessary to implement the load management tactics.

Although the above statement appears to have three unique human position codes, and three unique technology codes, most codes imply more general categories which increases the total number of codes per statement.   Through the process of coding variables, it quickly becomes clear that some positions are sub-categories or sub-positions of more general positions. For example, the communications system is a type of electric vehicle supply equipment (EVSE), which in turn is a subposition to charging infrastructure and equipment. The most common example of human sub-positions are the many types of customers (residential, industrial, interconnection, etc.,). Through the process of adding codes each time a new code is encountered that is a subsection of a more general position, it is added as a child code to the more general category. To track the different codes the qualitative analysis software Dedoose[17] was used.

4.2.3 Modularity analysis

[17] http://www.dedoose.com/

The purpose of identifying distributed positions in the same statement is to use co-occurrence of these positions to create a network of relationships between distributed positions. Dedoose is able to output the co-occurrence of each position with the other positions. The assumption in this is that co-occurrence in statements can be a useful way to create a network of relationships between positions. These relationships can help to uncover the modularity in an infrastructure system, as distributed positions that do not interact should have minimal co-occurrence in sentences. When distributed positions have a high interaction, it is likely that they are within the same module. Once the statements are coded for distributed positions the co-occurrence output is downloaded from Dedoose, imported into Gephi software [18], and analyzed for modularity. This algorithm approaches the challenge of nodal partitioning by iterating between nodes that consider adding their neighbors to their module, and then regrouping adjacent communities based on link weightings (Blondel et al., 2008).

4.2.4 Rule typology coding

Once the main modules are identified the rules were categorized for the most centralized, or parent position in each module. To examine modularity in infrastructure the most central node in each of the technological modules was selected and the coded the relevant statements for rule type. The first step consisted of distinguishing between constitutive and regulatory statements. Constitutive statements lack an identifiable agent who may, must, or must not take on an action. Due to the inclusion of distributed technological positions, the majority of statements reference a non-human actor as the

[18] https://gephi.org/

attribute of the statement. However, even constitutive statements have primary aIms (actions or verbs) which indicate the actionable intent of rule is. Constitutive rules that were of the form there is X or X is Y, were primarily categorized as position rules, because they usually were describing a position either through the use of boundary rules that specified a characteristic to be true of a subgroup of a larger group, or through the use of a choice rule about what a position should be able to do. When a technology was used place of an attribute (e.g. smart inverters shall operate at 60 Hz) the main aIm, in this case operate, was used to determine the purpose of the statement, even though the technology lacks its own agency, and agency is implied to it through usage by a person. Therefore, the main task was delineating the primary aIm in a statement. Identifying the aIms of each statement allows for the institutions to be considered by type. For the coding forms and complete coding protocal visit: https://ciscodebook.seslibrary.asu.edu/wiki/Modularity_Codebook. Once all statements are categorized by their rule type they were sorted into rule types so that the main verbs be identified and to allow for a more second IGT coding for consistency.

5.4 Results

5.4.1 Module identification

Coding the 116 documents resulted in 232 distributed position codes. Many positions referred to components of the larger position. For example, a battery is a component of an electric car. The most common positions were: customer, producer, applicant, generating facility, interconnection (applicant), and third parties. The modularity analysis using co-occurrence of positions in the coded staements found that out of 39 modules, four modules contained more than 95% of of the positions. Figure 5.4 shows the size of each module by the number of components it contains. The figure suggests that there are at four main modules.

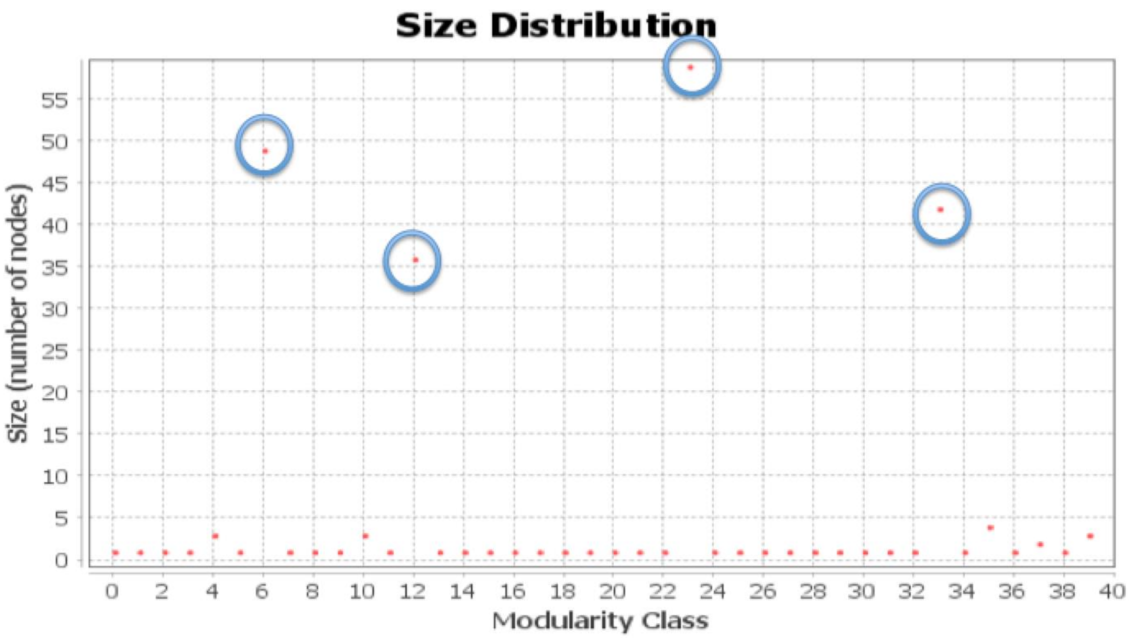

Figure 5.4 Modularity analysis shows four primary modules shown

To conceptualize what each of these modules contains and how it is connected, each modules is depicted visually. Additionally, the most highly connected node is used to refer to the module. The largest module (w/ 25.43% of the node-positions), has 59 nodes and 592 edges is shown in purple in figure 5.4. Rules for this module came primarily from rule makings R.11-09-011 on interconnection rules and R.12-11-005 on the Self-Generation Incentive Program (SGIP). Generating Facility and Producer have the same number of connections (58) and a betweenness centrality score of 1,154.1. Producer is a parent category to generating facility. This suggests that the position of Producer was never included in a rule statement without also including the position Generating Facility. For the purposes of simplicity this module is called the Generating

Facility module. Other components of this module include: metering, interconnection facilities, generator (distribution connected - net-energy metered or non-export), circuit breaker/fuses, point of common coupling, protective function devices and electricity wires.

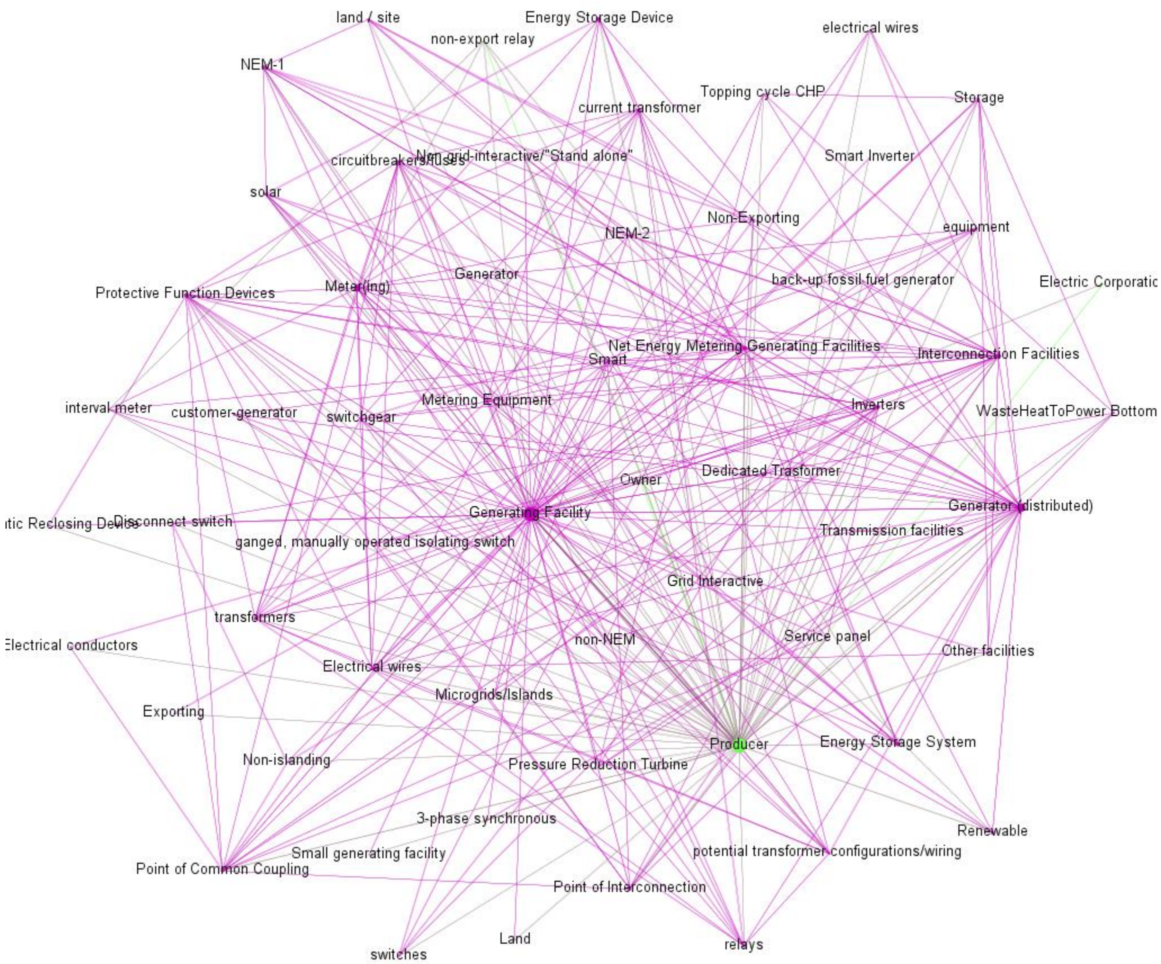

Figure 5.5 Module 1. Central node: Generating Facility. Technological linkages shown in pink; human linkages in green.

The second largest module is shown below in figure 5.4 it has 21.12% of the possible nodes. This figure shows that Customer is the most central node in this module, with a betweenness centrality of of 16,683. Unlike figure 5.3, there are very few nodes (positions) that are not types of customers. Most of the positions within this module are sub-categories of customer such as residential, interconnection, applicant, low-income, or single-family. A few nodes are technologies that a customer could own such as solar pool heating or a smart meter, but there is very little internal connectivity between these components, which suggest they are unlikely to function as a module. This is further demonstrated by the relative lack of connections between components that are not the most central node.

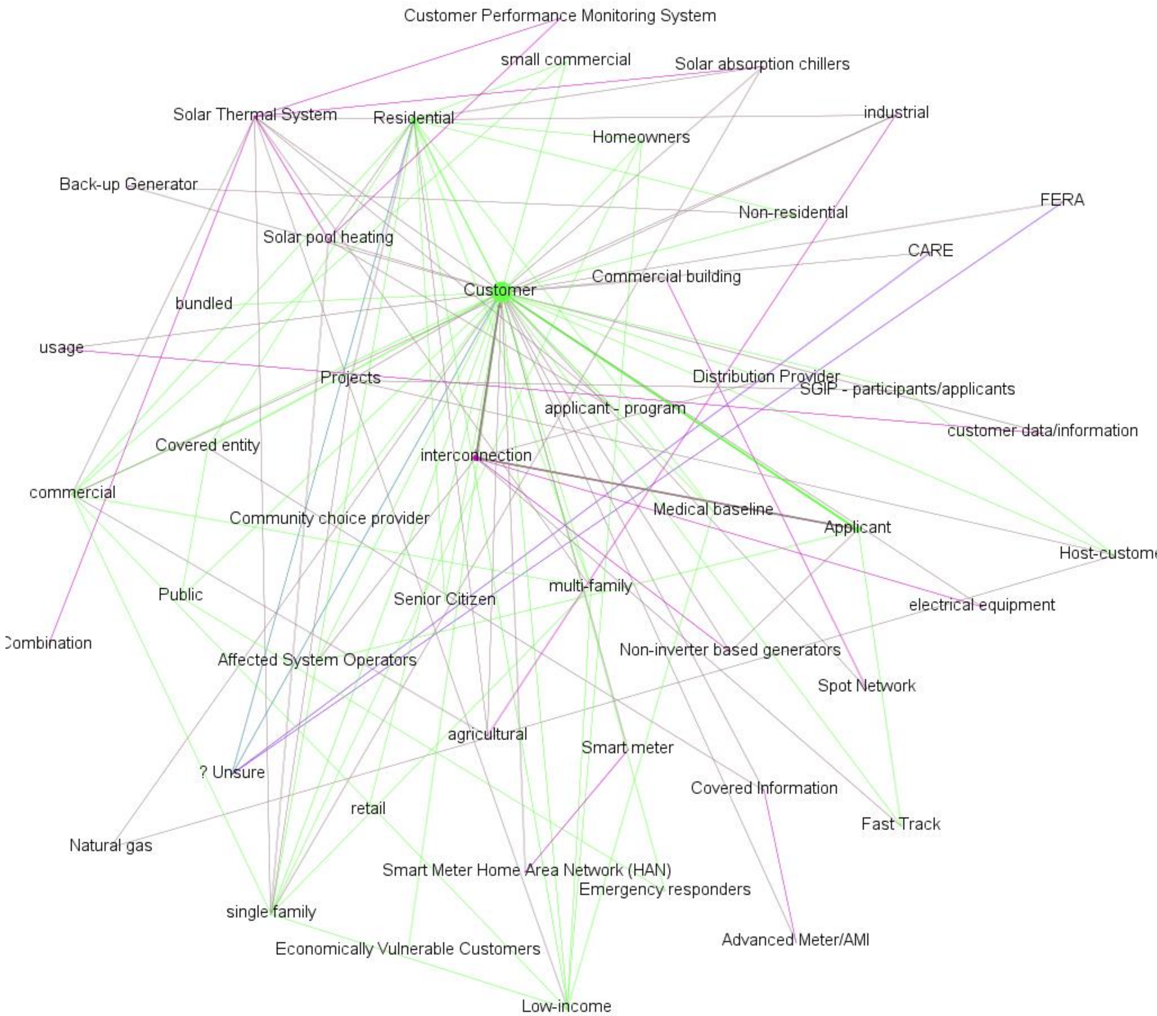

Figure 5.6 Module 2: Central node: Customer. Technological linkages shown in pink; human linkages in green.

The third module is shown below in figure 5.5, it contains 18.1% of the possible nodes. The most central elements are a party/entity and charging infrastructure and equipment. A party/entity is connected to 42 other nodes has a betweenness centrality of 3,167. Charging infrastructure and equipment is connected to 35 other nodes and has a betweenness centrality of 1,263.8. Other important nodes or components of the charging infrastructure include: disadvantaged communities, electric vehicles (EVs), EV charging sites, EV drivers, contractors and authorized third parties, EVSE, and programs. These different components play different supporting roles within the network. And the network is much more connected than the customer module shown in figure 5.4, suggesting that this area is developing modularity.

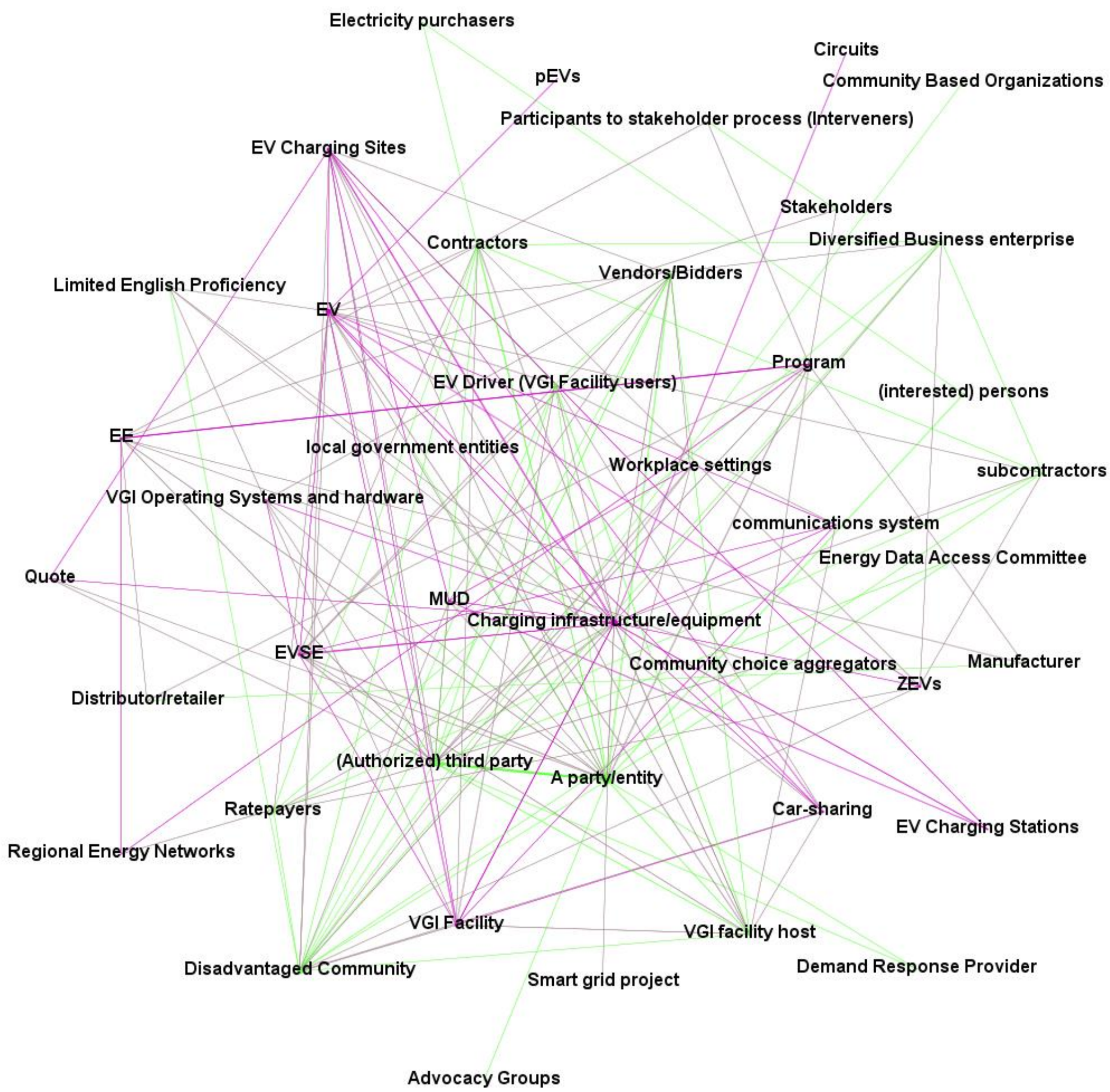

Figure 5.7 Module 3: Central node: Charging infrastructure. Technological linkages shown in pink; human linkages in green.

The fourth module, shown below in figure 5.6, has 15.52% of possible nodes. The most central element is grid technologies and components. It is connected to 65 nodes with and a betweenness centrality score of 3,624. Other primary nodes or components include distribtuion system, smart technologies, consumer devices, distribution circuits, DER, energy efficiency technologies, demand resource, and automation and communication technologies. This suggests that this emerging module focuses on management of local distribution circuits. Unlike the other modules there are almost human positions (only one: consultant) within this module.

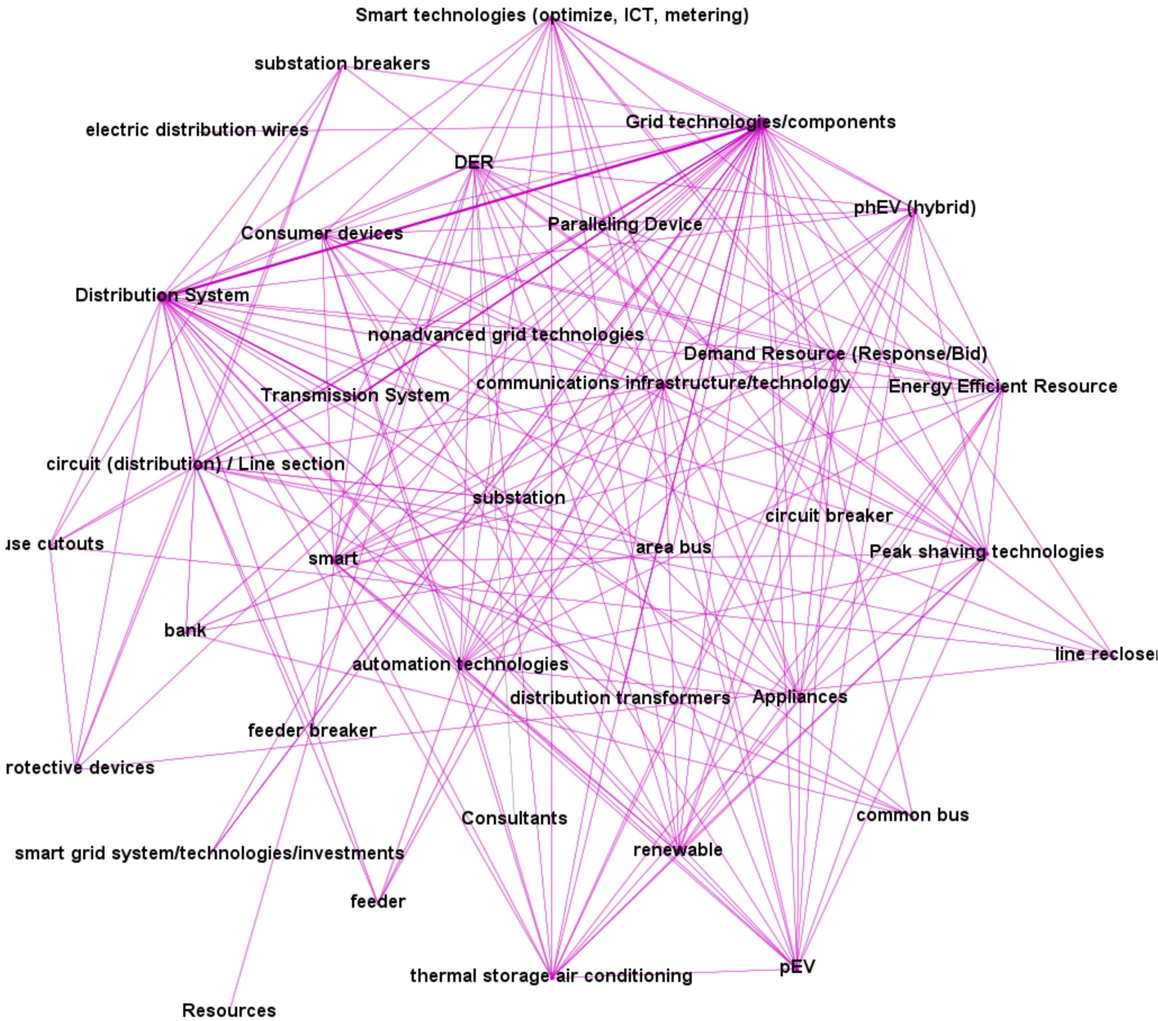

Figure 5.8 Module 4: Central node: Grid technologies/components. Technological linkages shown in pink; human linkages in green.

Comparing these modules suggests that the shape of these different modules is evolving differently. To have a more precise description of these differences, we can use network metrics to compare the modules. Table 5.5 below summarizes several total network statistics for the four different modules. Each module is refered to by the most connected node.

Table 5.5 Module network analysis statistics

Central Node	Network Average Degree	Network Graph Density	Betweeness Centrality
Generating Facility	10.034	0.173	1,154
Customer	4.612	0.096	16,684
Charging Infrastructure	7.238	0.177	1,263
Grid Technologies & Components	10	0.286	3,624

Average degree corresponds to the average number of connections that each node has. Graph density describes the number of connections that exist as a fraction of all possible connections. The betweeness centrality counts the number of shortest paths between any two nodes that go through the central node. As such it is an indication of how central that node is to the network. The customer network stands out from the rest of the modules as being significantly different. Instead of being interrelated components with inter-related functionalities, most of the nodes within this module are actually sub-positions of customers. Rather than the components of this module being inter-related, and potentially being managed as a functional module, the customer sub-components are more hierarchical in nature. This suggests that the customers module should not be viewed as a module that can diminish complexity by managing complexity within itself, as sufficient sub-positions and relationships do not exist. It is therefore excluded from the modularity rule analysis.

While the customer module does not have a sufficient number of inter-related functional and technological components that show evidence of being managed as a distributed module, a strong case is also made for not considering the grid technologies and components module as a distributed module. This is due to an almost inverse reason, there are no human positions, outside of the managing utility, which can interact with the grid outside of the utility. While grid technologies and components may be modular within the utility, there is no evidence that people outside the managing utility can participate in this module. The one human position that is recognized in this module is a consultant, and it has only only one connection, to DER. It is therefore reasoned, although there are many technological modules within the grid infrastructure, that without recognizing human positions that can interact with these technologies, that the current module will only adapt and innovate as a reaction to changes in other modules.

5.4.2 Module Rule Analysis

For the two modules that exhibit emerging modularity (generating facilities and charging infrastructure) the rules associated with the most centralized component are categorized into rule types using the IGT. This categorization is then used to reflect on the modularity questions posed in table 5.3. The table below shows the total number of rule types identified for each module.

5.4.2.1 Position Rules: What distributed positions exist?

Distributed position rules were identified for electric vehicles (EV), electric vehicle supply equipment (EVSE), vehicle grid infrastructure facility (VGI facility), small generating facilities, producers, large generating faciities, exporting generating facility, producers, transfer trips, smart inverter and interconnection facilities. Other position rules were concerned with the number of positions that exist for charging infrastructure. The verbs that were used in these rules included: is, will, is responsible for, will be, be designed, or means. The diversity of functional needs that each sub-component position presents suggests that there are multiple functions or performance capabilities that are required by the larger module. Position rules for technology were either defined by a boundary rule on a larger category (e.g. generating units with less than 20MW capacity) or by the ability to take an action (e.g. a device that converts mechanical energy into electrical energy).

5.4.2.2 Boundary Rules: What boundary rules exist for positions?

Boundary rules define the criteria that are needed for a person or technology to qualify for a position. Boundary rules can enable modularity because they can fix parameters and thereby decrease the uncertainty for interconnecting systems. The largest number of boundary rules exist for generating facilities, but sub-components of the different modules also have boundary rules including: meters, EV charging stations, EVSE metering, renewable generation, net energy metering generating facilities, storage, smart inverters, smart inverter parallel devices, interconnection facilities, producers, applicants and customers, and contractors. Boundary rules delineate requirements and rules for being in a position and therfore have verbs (aIms) such as be installed, be, be studied, include, be eligible, be certified, be studied, be accessible, remain eligible, is subject to, be reviewed. By creating boundary rules for sub-components, these regulations create sub-module design-rules.

5.4.2.3. Information Rules: What information must/may/may not be available and provided to what positions?

Information rules exist both for the managing utility and for distributed positions. Just over half of the rules are focused on information rules for distributed positions, and the other half are focused on the utility. The types of actions required include: review, inspect, report, submit, include, notify, detect, receive, inform, be monitored and tracked, recorded, shared, disclosed, accept, solicit, pass, install (a sign). The utility has rules to keep and protect information, to track and monitor electricity providers and provide explanations and notifications about application proceedings. Distributed applicants submit information reports and studies and are monitored using required metering.

5.4.2.4 Aggregation Rules: What aggregation rules exist?

Aggregation rules, are rules that describe how multi actors in positions will make decisions. Aggregation rules are unlikely to exist in a modular system because aggregation rules imply the involvement of positions in making decisions that are outside of the scope of their own module. In the rules examined, very few aggregation rules were found. Those rules that do exist used concensus agreement to determine when meetings would be held to enable minimal design exceptions to otherwise rigid boundary, scope, and choice rules. All the aggregation rules included both applicants/producers and distribution providers. An example of an aggregation rules is: “No changes may be made to the planned Point of Interconnection or Generating Facility size included in the Interconnection Request during the Fast Track Process, unless such change are agreed to by Distribution Provider”.

5.4.2.5. Payoff Rules: Do distributed positions have payoff rule incentives to participate?

Payoff rules describe the costs and benefits for participating in a system. Most of the payoff rules were accompanied in statements by scope and choice rules, since the costs for interconnecting with the grid depend on design and use features. Payoff rules were more thoroughly covered for generating facilities, which had more than ten times the number of payoff rules. Rules concerted rate setting for energy produced as well as grid upgrade costs and interconnection application costs.

5.4.2.6. Scope or Choice Rules: Under what conditions will/should distributed positions be allowed, encouraged or discouraged for their actions (choice rules)?

Scope and choice rules were coded as a single category. This a recommended IGT coding practice unless there is a specific reason to code them seperately. Scope and choice rules are by far the largest category of rules. These rules are especially important because they delineate both the acceptable actions that generating facilites and electric vehicle infrastructure may provide.

Choice rules determine what actions distributed positions can take, and therefore the type of co-production (governance, planning or production) that may take place. Examples of choice rule aIms that were common in the coded document for distributed positions include: operate, request,provide, apply, install, elect (choose), export, transfer, cease to energize, regulate, use, consist, set, proceed, deploy, disconnect/connect, coordinate, support, become isolated. These suggest that the primary type of regulated co-production that is occuring is production.

Since there are very limited aggregation rules for distributed positions to participate in decision making and management decisions, scope rules, often coupled with boundary, choice, information or payoff rules define the many terms of application for interconnection of distributed positions and modules with the grid. One of the most common organizing logics for these scope rules is the use of a first in time rule (a queue) to evaluate individual modules. This process requires the use of many back and for processes such as submitting, studying, testing and certifying the effects of the module on the larger system.

Scope rules can be used to provide a type of fairness in systems, but they also present dilemmas for modularity in terms of having clear boundaries. Different goals or outcomes can require different boundary conditions both for an individual in a position, but also can change the possibility for others to attain desired outcomes. The following paragraphs demonstrate that the use of scope rules can be used in place of an aggregation rule by providing for a selection procedure that triages approval based on a series of outcome criteria. It demonstrates the a problematic quality of scope rules, in terms of modularity, which is that an impact study when used in a scope rule may alter the boundary rules for others.

"Screen L: Transmission Dependency and Transmission Stability Test.
Is the Interconnection Request for an area where: (i) there are known, or posted, transient/dynamic stability limitations, or (ii) the proposed Generating Facility has interdependencies, known to Distribution Provider, with earlier queued Transmission System interconnection requests. Where (i) or (ii) above are met, the impacts of this Interconnection Request to the Transmission System may require Detailed Study.

If Yes (fail), Supplemental Review is required.

If No (pass), continue to Screen M.

Significance: Special consideration must be given to those areas identified as having current or future (due to currently queued interconnection requests) grid stability concerns.
Screen M: Is the aggregate Generating Facility capacity on the Line Section less than 15% of Line Section peak load for all line sections bounded by automatic sectionalizing devices?
If Yes (pass), Initial Review is complete.
If No (fail), Supplemental Review is required."

5.5 Discussion:

Managing electric vehicles, distribution circuits, distributed generation facilities, and customer demand is a much more complex task in the future than it is currently. One of the primary tools used by engineers to manage complex systems is the concept of design modularity. Even as co-production in electricity systems becomes more ubiquitous this tool has yet to be extended analytically to infrastructure policy. Even without purposefully attempting to provide modularity, this analysis suggests that some areas show evidence of emerging modularity, as well as a number of areas for how rule changes could increase modularity. Modularity can be detected by 1) looking at the whether rules tightly couple multiple functions and 2) identifying how boundary conditions are used to mitigate the amount of information sharing and hierarchical decision tools such as scope and aggregation rules.

While four groups of positions are readily apparent using modularity analysis of position co-occurrence in rules associated with DER implementation and operation in San Diego, CA, only two of the modules, generating facilities and electric vehicle charging infrastructure, show evidence of developing distributed modularity features. The customer module lacks the functional diversity of interconnected parts to be managed as a unit. Instead the central position, customer, is subdivided into many smaller categories, to which a few specialized rules may apply (e.g. a specific rate class for industrial customers, or an permit process for solar hot water heaters for low income residential customers). If customers gain sufficient numbers of devices, programs or strategies so that their demand patterns begin to register a significant change, more rules to manage these functions will likely emerge, thereby creating new internal relationships and constraints and the potential for a customer module to form. Unlike the customer module, the grid technologies and components module had many internal and inter-related functions. However, it did not contain distributed human positions that would allow for interaction with this module outside of the utility.

The generating facility and EV charging infrastructure modules have both internal functional diversity and connectivity as well as distributed human positions capable of investing in, designing, and managing these potential modules. While some clear boundary rules exist (e.g. must show land ownership and have a disconnect swittch), there are also many complex choice and scope rules that require study and approval to test the module's functionality at a specific location in the grid. This includes submitting specifications and paperwork, paying for interconnection studies, and testing . However, many of these boundary rules are nested in scope rules which set different boundary rules depending on different intended outcomes and contextual factors, such as load on a grid segment. This is further complicated by the use of a scope rules that are designed to be fair by using a that queue for most DER application and approval procedures. The queue can create changes in outcome conditions as applicants are approved, disproved, delayed, etc, and this can create uncertainty in the boundary conditions, which could otherwise reduce the complexity of modules.

The failure to set have strict boundary conditions results in the need for significant information flow both to and from these modules. For example, databases that contain information about how much available capacity exists in different sections of the distribution grid must be provided to potential generating facility applicants. Electric vehicle infrastructure facilities are required to monitor and track and submit to the utility its site load managmeent tactics and site usage patterns. This large amount of data from many distributed locations represents an enormous increase in management complexity.

While these two modules show evidence of modularity in their interrelated components, it is clear that modularity could be increased through the use of more fixed boundary conditions. While this may come at a cost to the utility in the form of investing in distribution management devices that can provide more ubiquitous interconnection conditions, it would dramatically reduce the computational cost and would likely provide some local resiliency. Similarly, if the costs of managing increasingly complex and information dense distributed customers and distribution technologies rises significantly, regulations could use this type of analysis to create rules that will allow for more modularity.

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CHAPTER 6

CONCLUSION

This work demonstrates several design tools that may enable co-production to produce distinct outcomes. Chapter two suggests that when uncertainty about potential co-production arrangements are high the best searching outcomes occur when people do not have exclusion rights, such as a patent, for their innovations or arrangements. This may encourage innovators to share their information more widely. Furthermore, innovators are likely to share their information until they find an innovation that they consider good, according to their own internal thresholds. Because keeping track of others decisions and discoveries is demanding, innovators are more likely to use internal thresholds when searching, and may become less willing to share once they have found a combination which they judge to be is good. Although this diminishes the rationale for a patent as an incentive to innovate; as an innovation commons collapses due to decreased uncertainty, the patent, or limited right to exclude, may provide some shared knowledge benefits by reducing the fear of free riding.

As uncertainty dissipates and co-production production functions becomes more well understood, important questions arise about how the new form of co-production will impact the centralized and connecting infrastructure. Modeling to understand these impacts on urban infrastructure requires a different basis for comparison than asset optimization. A procedural and probabilistic model of infrastructure offers a useful research direction, in which emergent urban qualities of the infrastructure can be compared to known patterns and scale factors. Exploring this model for different assumption sensitivities suggests that differences in the demand side assumptions about infrastructure are a much more important basis for analysis than supply side. Applying this same model in chapter four, and focusing on the scale of grid balancing, supports this finding, since different aggregation scales can offer significantly different and non-linear costs/benefits. This analysis shows that diminishing costs requires that both distributed generation and storage are incentivized, but that high local sufficiency can be achieved with generation technologies only. A further important finding suggests that the best cost savings can be achieved when small balancing (battery) capacities are installed and managed at small scales, and larger batteries should respond to larger scale markets. This is an important result that may improve the functioning of local and global future markets.

If this finding about battery sizing was taken into account and implemented in market policies and regulations, it may result in rules that suggest that the size of an investment will dictate the scale of a market into which it should participate. This could be an important boundary rule for distributed generation and future energy co-production. The final chapter seeks to understand how and if rules are resulting in modules that can participate in co-production. This exploration suggests that analysis of institutional statements can be a useful way to quantify emergent co-production modules in regulated infrastructure. The analysis of the distributed energy resource rules relevant to San Diego suggests that while customers and the grid technologies have the potential to engage in modular co-production, they are not currently. Customers continue to participate primarily as users or potentially in governance co-production of infrastructure, which is non-modular. Grid technologies, on the other hand, lacks distributed human positions, which may partake in co-production of a grid module. Two distributed modules that show potential development are generation facilities and electric vehicle charging. Both of these modules show high internal connection of sub-positions and include at least one primary human actor that may engage in co-production. Analysis of these modules suggests that co-production modularity can be improved by relying on more boundary rules and less scope rules as a way to decrease the need for information sharing.

Taken compositely, these chapters demonstrate several different information-centric design aspects of co-production. A final reflection upon the subject suggests that as co-production moves from an innovation commons to a well understood co-production regime, that issues of market information and scale must be reconciled with scales infrastructure demand variability and complexity. Research on variability of demand needs at different urban scales may provide useful heuristics for crafting helpful boundary rules for modular co-production and aggregation rules for non-modular or governance oriented co-production.

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APPENDIX A

RESEARCH PROTOCOL FOR CHAPTER 2: DO PATENTS IMPROVE THE INNOVATION PROCESS?

A1. Experiment Instructions:

Instructions:

Welcome!

You are about to participate in an experiment in which you will have the opportunity to win money based on the decisions you make. You have already earned **5 dollars** for showing up. Payments will be made upon completion of the experiment. Getting up or disturbing the experiment at any point will result in earning only the show up payment of **5 dollars**.

Imagine you are an inventor who is trying to combine different objects to form a new invention. An invention is a combination of 3 objects in a specific order. You are about to play a game with 3 other people who are randomly chosen in this room. Each round you will choose from a set of 6 objects. From these 6 objects you can choose any combination of 3 object shapes to put in each of 3 positions: Position1 (p1), Position 2 (p2) and Position 3 (p3). The objects you will be able to choose from are: Square, Box, Wheel, Circle, Plant, and Star. You can choose the same object for multiple positions and/or repeat the same invention for multiple rounds.

For example you might choose:

p1 – circle
p2 – plant
p3 – plant

Each invention (selection of 3 objects) gets a score that represents its success. You will be playing with 3 other randomly selected people in the room and the highest total score each round will win.

When the experiment begins you will see the screen shown below in Figure 1. Notice at the bottom of the screen left that your player is called Local 1. This means that you are the red arrow at the top of the first column:

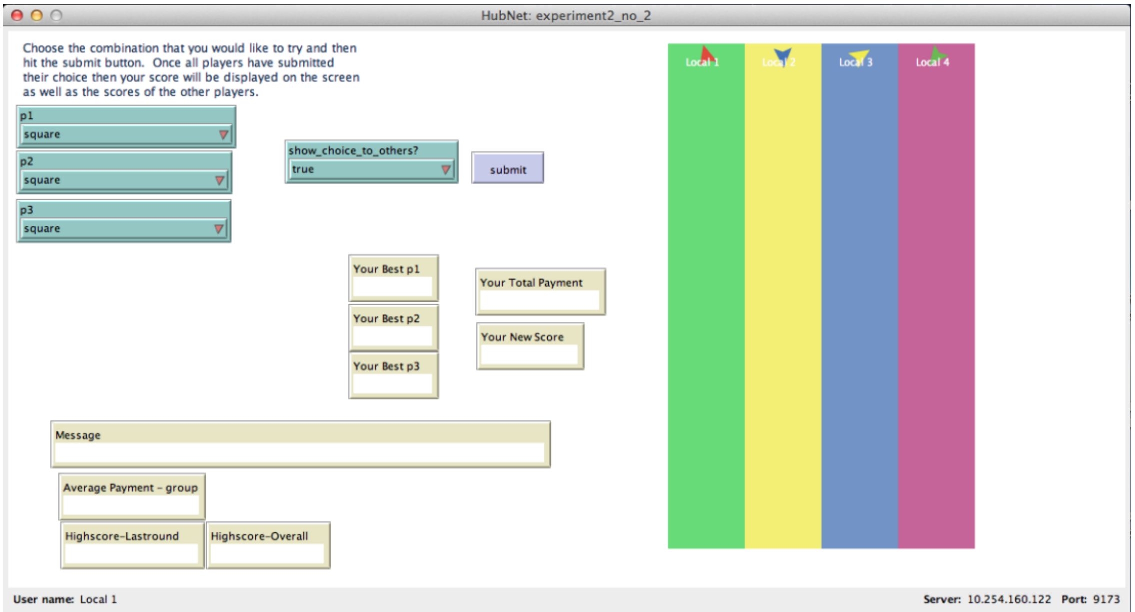
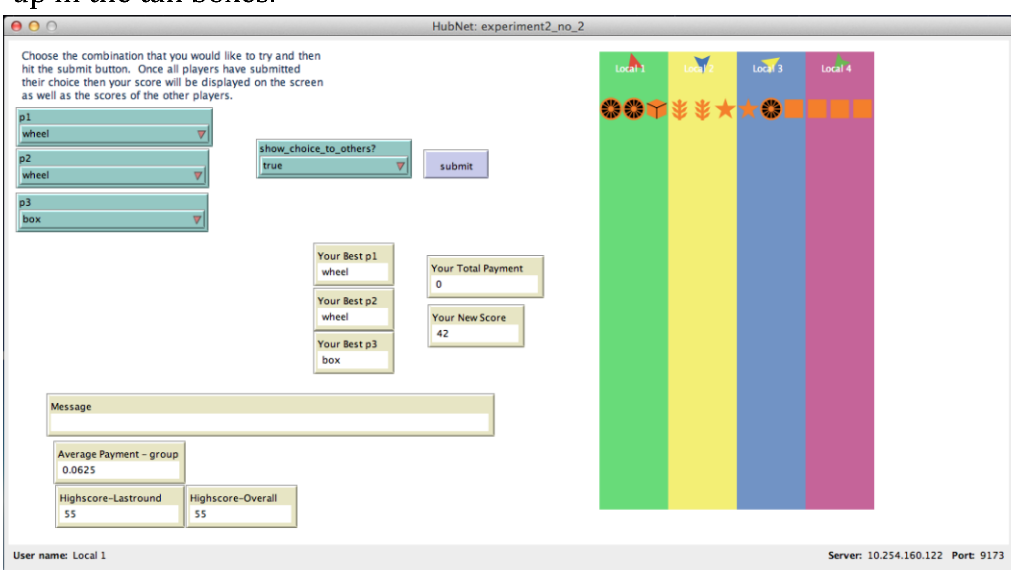


Figure 1 Screen-view. Choices, p1, p2, and p3 are in green. In the other green box you may choose whether others can see your choice. Messages will come back from the computer in the tan boxes. Your player is located at the top of the green column.

You choose which object you would like to put in each of the 3 positions by selecting from the green boxes on the left. Once you select your objects, decide if you want to show others what you chose by selecting true or false from the "show choice to others?" box. If you select true, at the end of the round once everyone has selected, your choices will show up directly below you, as shown below in figure 2. If you select false your choices will not be visible. Messages from the computer server show up in the tan boxes.



The reason you may want to show others what your choices are is because there are secret synergy scores that only apply to choices that are shown. The textbook definition of a synergy is: "the interaction or cooperation of two or more organizations, substances, or other agents to produce a combined effect greater than the sum of their separate effects". What a synergy means in this game is that there is some part of another participants choice that benefited your choice. If you have a synergy with someone you will receive an extra **$0.50.** Synergies are secrets that have to be found out through trial and error. You get them if p1 of your selection is a secret synergy combination with someone else's p3. However you can only get the points if the other player is visible. Your choice does not need to be visible to receive the extra synergy score, but the other person's does. This represents the fact that it is hard to take advantage of synergies if you don't know they exist.

After you select your objects, and decide whether you would like to show the other participants your selection, hit submit. The round will end once all 4 participants in your group have submitted their choice.

If your total score is higher than the other players scores, then you win **$1.00**. If players choose the same combination they will split the earnings. However, in the game you won't know what anything is worth and you will have to find out through experimentation.

Each round either you or one of the other players will earn **$1.** If you find a synergy that will also be added to your score. There will be 32 rounds in total. We may introduce new conditions during the experiment. Your earnings will be added from all the rounds.

The end of the round cannot be completed until everyone has submitted a choice. After everyone has submitted their selection you will see the selections appear on the screen and be able to see whether or not you won. On the screen you can see both your object choices and those of the 3 other players you are competing with, but you can only see the winning score and how much extra credit you made that round. If you are happy with a score you can submit it for multiple rounds, or you can change some or all of it before you submit.

Thank you for participating! Before we get started we would like to ask you a few questions.

What is your

Age:

______

Sex:

M / F

Major:

____

Understanding Questions:

If 2 people get the same high score, how much will they each earn in that round?

ANSWER: ____________________

True or False. If you have a synergy with another player, we both get an extra $0.50.

ANSWER: ___________________

If you do not understand something please raise your hand.

When you have finished answering these you can turn the paper over and wait until everyone is ready.

A2. Patent condition instructions

Blocks

Blocks give you the option to block others from using a combination of 3 (an invention). The block will last for 5 rounds starting with the round after you submit it.

Blocking will make it so that no one else except you can play that invention. However, a block will cost you $ 0.25 to submit, and you can only block 1 invention at a time.

It is recommended that if you want to block an object that you submit your block before you submit your combination for that round because once everyone submits his or her invention choice, the round is over.

If you have any questions please raise your hand and remain seated until the next round begins.

A3. Post Survey

Post Survey

Did you understand the experiment? If not, what was not clear?

What did you think of the experiment?

How could the interface be more clear?

Did you had problems interacting with the software? If so, what kind of problems?

Did the choices of others affect your choices?

How did the change after round 12 affect the experiment?

Any other comments you would like to make:

A4. Debrief

Providing Information about Innovations

Thank you again for participation in this experiment. The experiment is part of a research project that is trying to understand how we can incentivize people to provide information about their innovations. Information can be studied as a resource system in which rules and norms impact how people govern or manage the resource. Information about innovations is primarily incentivized through patent protection. This rule may crowd out existing norms that people have about the value of sharing information based on reciprocity. Crowding out of a norm means that through the implementation of an official rule that people are less inclined to follow the norm (in this case sharing their information without the privilege of being to exclude others)

The experiment you participated in tests how patents impacts when people provide information to others. If people are selfish and rational we expect that nobody will share information with others about when they can patent their innovation. Many open source innovation studies have shown that when reciprocal benefits are possible that people do provide information about their innovations even when another person could patent their idea.

It is in the public interest to have information about new innovations, as it will aid in decision-making, generate societal feedback about innovations, and increase the ability to have new innovations that build from existing ones. How best to incentivize the provision of this information is an important subject for innovators, policy makers and entrepreneurs.

As stated earlier, your responses to all of the questionnaires will be absolutely confidential. Your name will not be attached to any information, and only people who are associated with this research will see your name or your responses. In return, we want you to honor our confidentiality -- please do not tell anyone about the details of this study. If the other students know about the study before they participate, their data will be biased and thus cannot be included.

Your participation in this study is greatly appreciated. If you'd be interested in obtaining a copy of the results once the study is complete, you may contact the primary investigator of this study, Dr. Marco Janssen at Marco.Janssen@asu.edu. If you have a more general interest in this area of research, you may follow our research at csid.asu.edu

Thank you very much for your participation!!

A5. Letter of Consent

LETTER OF CONSENT

Dear Participant,

I am a professor in the School of Human Evolution and Social Change at Arizona State University. I am conducting experiments that investigate how people think, act, and make decisions. You will be given a debriefing at the end of the experiment.

I am requesting your participation, which will involve participating in a computer game. The experiment, including the debriefing will take a maximum of 60 minutes. Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty; it will not affect your compensation for participation up to that point. In this study you can receive up to $47 for participating and a minimum of $5 for showing up.

Society may benefit from this research because an understanding of how people make decisions can help us to design regulations that sustain the use of shared resources. You may benefit from this experience because you learn something about how an experiment is designed and conducted, what issues are of interest to social scientists, and how your own cognitive abilities come into play in decision making situations.

The results of the research study may be published, but your name will not be used or recorded at any point. Your responses will be confidential. However, due to the group nature of this study, complete confidentiality cannot be guaranteed.

If you have any questions concerning the research study, please call me at 480 544-3773.

Sincerely,

Dr. Marco Janssen

By signing below you are giving consent to participate in the above study.

______________________   _________________________   __________

Signature   Printed Name   Date

If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Research Compliance Office, at (480) 965-6788.

APPENDIX B

CHAPTERS 3: PROBABILISTIC GRID MODEL EXPLABORATION

B1. Probability of Failure and Infrastructure Age

Appendix A: Probability of Failure

All infrastructure eventually fails, but equipment fails for different reasons such as aging, overloading, outdated engineering criterion, and old cultural values (Willis et al., 2001). Most of U.S. infrastructure is well passed its prime and needs investment in the short term (American Society of Civil Engineers, 2011). 35-48% of T&D assets in the U.S. are expected to need replacement in the present to near future. EPRI, in evaluating the effects of smart storage, estimates the value avoided T&D upgrades to be 8.3 Billion dollars over twenty years (EPRI, 2011). We therefore focus on the first two main factors in creating a model of failure and replacements for electricity grid infrastructure: aging equipment and overloading. These two factors are jointly estimated to be responsible for between 45-90% of replacements (20-40% of failures are due to aging, and overloading is responsible for 25-50%) (Willis et al., 2001).

The main types of aging infrastructure that are identified in this model are: transformers, substations, distribution lines, transmission lines and generators. These types have distinct age profiles, failure properties, losses and associated costs, and we therefore discuss each aspect separately. Due to the fact that other components such as, switches, circuit breakers, and control relays are often bundled into the cost of larger components, such as substations, we do not explicitly include them.

Transformers:

The average age of a large power transformer is 38-40 years (as of 2014) w/ 70% being 25 years or older (DOE, 2014). However, the distribution demonstrates a bi-model distribution (Harris Williams and Co., 2014b). Such a distribution is generated by the primacy of the initial investment period, which then tailed off under the pressures of market de-regulation throughout many parts of the U.S., resulting in a growing need for investments, especially at new combined cycle power plants during the early 2000s.

Age and Failure:

To quantify the effect of age on failure, probability of transformer failure can be described with a weibull distribution. The cumulative probability of failure is shown in equation 1 below, and the chance of failure within a year, is the difference in the probability of the cumulative probabilities between years.

$$P_f(t,\beta,\eta) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad \text{.....................................(1)}$$

Parameter values are taken from the distributions provided in Southern California Edisons 2015 Rate Case - transmission and distribution investment replacement report, shown in table 1 (Southern California Edison, 2013). If a transformer has not failed and reaches it's maximum life (80 years) it is retired pre-emptively.

Loading:

Loading is an important component to include in the model due to the hypothesis that DER may not actually *decrease* grid costs due to reduced grid stress, but actually *increase* stress especially at higher levels of adoption. DER, when may actually increase the strain on grid infrastructure through reverse flow onto the grid. Loading primarily results in transformer failures by inducing thermal failures that degrade transformer insulation (Hilshey et al., 2011). Loading is operationalized with the logic that loading can cause a transformer to be effectively older (or younger) than it actually is by using an aging acceleration factor (FAA), as shown in equations 2-5 below (Perez, 2010).

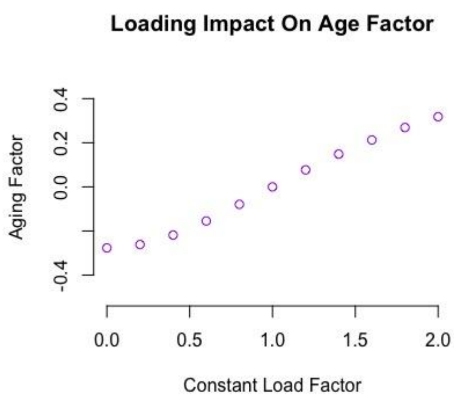


Figure 2 Effect of constant loading pattern on aging factor

$$FAA = \left[\frac{15000}{383} - \frac{15000}{T_{HS}+273}\right]\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$T_{HS} = 110\left({}^{Demand}/_{Capacity}\right)^2\ldots\ldots(3)$$

$$FEQA = \sum_{t=1}^{8760} FAA\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$Aging_{factor} = \frac{\sum FEQA}{L_0 * 8760}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

In equation 2, FAA describes the difference between normal operation with a hot spot temperature of 110, and T_{HS}(hot spot temperature in Celsius). FEQA is the annual list of loading affects on age. $L_0$is the expected lifetime of a transformer under normal loading. The effect of constant loading factors on the aging factor is shown in Figure 2 above. The aging factor is then used to calculate an effective age for the year, as described by equation 6 below.

$$Effective\ Age = Age + (Aging_{factor} * Age)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

The effective age is then used to calculate the probability of failure in based on the weibull distribution from equation 1. This effective age is recalculated each year, based on that year's use profile. Any transformer that is more than eighty years old is replaced.

Table 1 Probability of failure parameter values

Type	Beta	Eta	L_0
Distribution	8.45	39.35	37
Transmission	6.27	62.04	57

Costs:

Transformer costs are based on the size of the transformer. They are shown in table 2 below.

Table 2. Transformer replacement costs

Transformer Type	Cost	Source
Pole mounted	$36.8*Capacity_{kVA}+1758.5$	
Substation <500kVA	$2,000,000	(DOE, 2014)
Substation <750kVA	$4,000,000	(DOE, 2014)
Substation >750kVA	$7,500,000	(DOE, 2014)

Distribution Lines:

Besides transformers, distribution lines are the other main piece of the distribution grid for which maintenance and replacement is considered. Distribution lines are either above or below ground depending on the density of energy use around them. Underground cabling is more expensive, but is often used in highly urban areas due to space constraints and the need for improved reliability. A section of the grid is replaced when it fails with a probability of 0.006/mile for above ground cabling. This is due to the fact that most above ground outages are caused by random events or vegetation. Below ground cabling has a probability of failure described by equation 7 below.

$$P_f = \left(1 - e^{\left(-\frac{age}{40}\right)^{4.2}}\right)/mile \text{.............................(7)}$$

Additionally, any cable section that is more than 90 years old is replaced even if has not failed. The costs for cable replacements are shown in table 3 below.

Table 3. Distribution Grid Cable Replacements Costs

Cable Type	Cost per mile	Source
Above ground	$\$88,000+45,250*Capacity_{MW}$	
Underground	$\$566,000+70,000*Capacity_{MW}$	

B2. Building Demand Profiles

Hourly Demand:

Hourly electricity and heat demand for both residential and commercial buildings come from: https://openei.org/datasets/files/961/pub/ from both Chicago and Houston. The total hourly usage in kWh is totaled for both electricity and heat. The hourly usage is multiplied by the daily usage fraction and monthly usage fraction of total energy and then scaled to the building size by multiplying by the intensity of energy use and total square footage of the building, as shown in equation 1 below.

$$kWh_h = \frac{kWh_h}{kWh_{month-day}} * \frac{kWh_{month-day}}{kWh_{year}} * \frac{kWh_{year}}{sf.area} * sf.area \text{.................................}(1)$$

Because demand data is averaged hourly for each month, only a single average day is modeled per month. Variability is introduced from a normal distribution hourly, individually, and daily.

Values for building areas, and hourly demands are available in the model code, and GIS files available online.

B3. Generation Investments

Centralized investment logic:

New transmission scale generation is needed when a) either the amount of ramping (also called responsive or peaking) generation or total generation is within the safety margin that is set by the utility or b) transmission capacity is insufficient.

Insufficient capacity triggers the need for more investment the amount of generation in less than the required safety margin. Most utilities have a safety margin of 10-15% reserve capacity (modeled variable: investment_sensitivity) that they are required to have available to cope with variability, generator maintenance or outages. In the baseline case this is set to 15%. If both ramping capacity and total capacity are needed the ramping capacity is first calculated and subtracted from any total capacity additions needed. Insufficient transmission capacity is detected by distribution stations, who compare the sum of total generation they are connected to through the transmission grid and compare whether they have access to enough generation. If they do not, additional transmission must be built.

When installing generation after the initial setup stage, generation is classified as either a peaking (natural gas) generator or a non-peak generator. The total number of generators, installed at a new generation site is taken from a distribution based on averaged data from www.eia.gov/cneaf/electricity/page/eia860.html, and is shown in table 1 below.

	Avg. gen Size	Avg. Gen/facility	std. dev gen/facility
Coal	246	4	3
Oil	15	15	18
Natural Gas	86	6	5
Nuclear	1081	2	1
Hydro	19	7	11
Wind	59	2	3
Solar	5	2	1

New generation costs

The costs for new generation are set as input assumptions. They are multiplied by the appropriate scale factor, in order to allocate the percentage of total costs that the modeled area is "responsible" for, and by the number of generators at a facility. Baseline conditions for the model assume that ramping capacity capital costs are: $670/kW and that non-responsive capacity costs $1980/kW. This may appear counter intuitive, as it would be illogical to install non-responsive generation when ramping is both cheaper and more flexible. However, these capital costs do not include operations, maintenance and fuel costs that are calculated as a basis for the levelized cost of energy (LCOE). In order to remove additional uncertainty that does not impact the upfront investment cost burden we do not include LCOE in decision-making and instead simplify by suggesting that responsive and non-responsive have different cost points, which can be set as input conditions. Inclusion of a more complex LCOE decision metric is one potential area for model expansion.

Building Investment Decisions in DER

Buildings invest in DER if their willingness to pay (WTP) is greater than the upfront capital cost. They consider their anticipated annual savings for either pv, chp, or a battery based on the price of electricity and the expected production of a system. Once the have calculated their anticipated savings they calculate their overall willingness to pay (WTP). Each agent has a fixed number of years that they consider savings over (WTP_horizon is the model variable), and these savings are discounted rate of 5% in the baseline scenario. Therefore the total willingness to pay is defined by equation one below.

$$WTP_{DER} = \sum_{1}^{WTP\_horizon} \frac{DER_{savings}}{(1.05)^{year}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

The capital costs of DER in $/watt decreases with a learning rate as defined equations 2-4 below (Nemet, 2006). Learning rate values are given in table 2 (Veatch, 2012).

$$\alpha_{DER} = \frac{DER_{cost\ (t-1)}}{1^{\beta_{DER}}}$$

$$\beta_{DER} = \frac{(\ln(1 - LR_{DER}))}{\ln(2)}$$

$$DER_{cost\ (t)} = \alpha(1 + (DER_{growth\ rate} * t_{years})^{\beta}$$

Table 2. DER cost assumptions

	Learning Rate (LR)	DER global growth rate	Initial cost (t=0)
PV	20%	95%	$5/watt
CHP	15%	10%	$6/watt
Battery	25%	10%	$1/watt-hour

B4. Distribution Grid

The first step in creating a grid is to have each house create a link to their closes road. Because roads are natural conduits for the distribution grid, they are a proxy for the grid itself.

Transformers

Nodes where multiple buildings connect within the GIS shapefiles serve as endpoints for where each link of the distribution must curve or bend, even if slightly. This logic holds true for the distribution grid, which when cabling is above ground, must utilize polls at intervals along the system. When buildings connect to the distribution system they attach to the closest utility poll. Polls that have multiple buildings connect to it become the site for a distribution transformer.

Transformers also occur at substations. Because the design and sizing of transformers depends on pricing and site design, the number of transformers at a substation is randomly distributed around an average number of large transformers at step down substation, or is directly related to the generating capacity, if the transformer is a step up transformer.

Substation Placement

Substations are created at two places, as step up substations at generators, and step down substations within the distribution system. Setting up the distribution system first identifies places that can hold a substation based on two factors: 1) a sufficient amount of open space 2) that is also close to buildings. Once a substation is placed, all the buildings find the distance to the closest substation near them. If more than 80% of the buildings are within 2.5 miles of a substation, then the distribution substations procedure ends, based on the logic that a majority of the buildings are within sufficient distance that the voltage drop will be acceptable. When distribution substations are initiated they do not have smart grid investments such as additional disconnect switches, IEDs, additional transformer capacity, monitoring and communications equipment. However, as the adoption level of DER within it's service area increases, these investments must be made.

System Upgrades:

"Findings suggest that wholesale photovoltaic projects (from 500 kW to 5 MW) have low or manageable affects even at high penetrations without major system upgrades if their point of connection are at sufficiently strong network locations that consider upstream equipment ratings and avoid certain circuits with unusual sensitivity." (Peter, 2012). As the total adoption capacity increases points the following costs are also assumed to be needed at the substation as DER thresholds are crossed (EPRI, 2011):

Table 2 Distribution system upgrades for DER

Upgrade Type	Substation DER Capacity	Cost
Disconnect switches	$\sum \mathrm{kW}_{DER} \geq 0$	$5,000/feeder
Sensors & Intelligent Electronic Devices (IEDs)	$\sum \mathrm{kW}_{DER} \geq 10$	$425,000/substation
Dedicated Transformers	$\sum \mathrm{kW}_{DER} \geq 100$	$2,000,000/substation
Monitoring Equipment	$\sum \mathrm{kW}_{DER} \geq 500$	$75,000/substation
Communications Equipment	$\sum \mathrm{kW}_{DER} \geq 1000$	$75,000/substation

B5. Transmission Grid & Generation

Centralized Generation

The model requires that each type of generation is supplied by an appropriate number of generators such that each generator is partially allocated to the modeled area. To do this the largest capacity generation technology is scaled down to meet the peak demand plus safety margin of the model area. This a scale factor for centralized generation, such that the modeled area is responsible for the portion of each centralized investment. The equation for calculation of the scale factor is shown in equation 1 below.

$$SF_{\%} = \left({Nu_{\%} * kW_{peak} * R_{margin}} \middle/ {Nu_{capacity}} \right) * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Because nuclear energy has the largest size generators, shown in table 2 it is the technology that the model is scaled for. Figure 1 shows that Nuclear energy makes up 9% of available electricity capacity and table t.   Generators also have step up substations and transformers.

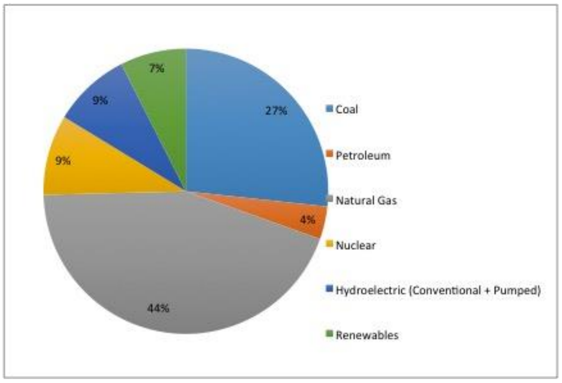


Figure 3 Total amount of generation capacity in. the U.S.

Table 3 Operable Generating Units in U.S. Source: U.S. Energy Information Administration, Form EIA-860, "Annual Electric Generator Report."

	Avg. gen Capacity	Avg. Gen/facility	std. gen/ facilit y	# facilitie s	Total Gen size (Capacity * # gen/facility)
Coal	246	4	3	1400	877
Oil	15	15	18	3731	232
Natural Gas	86	6	5	5493	488
Nuclear	1081	2	1	104	2089
Hydro	19	7	11	3992	128
Wind	59	2	3	781	106
Solar	5	2	1	326	11

Age profile:

Table 4 Age of Generators Source: U.S. Energy Information Administration, Form EIA-860, "Annual Electric Generator Report

	Average Age (years)	**Stdev (years)**
Coal	48	16
Oil	35	19
Natural Gas	28	17
Nuclear	37	7
Hydro	66	30
Wind	12	6
Solar	8	5

http://bv.com/docs/reports-studies/nrel-cost-report.pdf

Transmission Distance

In 2011 there was an estimated 184,707 miles of transmission lines. Generators are connected by transmission power lines that each have a length, which is normally distributed around 80 miles. This average distance is given by Eighty miles is used because

Transmission miles: 184,707 See EPRI figure (EPRI, 2011) – now more than 200,000 miles

Transmission Line Miles

Voltage (kV)	Miles
230 AC	85,048
345 AC	59,767
500 AC	32,870
765 AC	4,715
250-500 DC	3,307
Total Miles	**184,707**

Costs for Generation and Transmission

Type	Capital Cost ($/kW)	Fixed O&M ($/kW-yr)	Variable O&M ($/MWh)	Ramp Rate (%)
Coal	2890	23	3.71	2
Natural Gas CT	671	5.26	29.9	22.2
Natural Gas CC	1250	6.31	3.67	5
Nuclear	6,100	127		5
Conventional Hydro	3,500	15	6	0
Wind	1980	60	0	0
Solar	3480 *declining	50	0	0
Pumped Hydro	2230	30.8	0	50

B6. Distributed Energy Resource (DER) Production

Photovoltaics (PV)

Solar production estimates were generated using PV-watts by NREL for a 1 kW system in Houston TX and Chicago, IL http://pvwatts.nrel.gov/ using standard assumptions. Variation around this average is introduced based on variation in global tilt irradiance (GTI) data compiled by NREL (Wilcox and Gueymard, 2010).

Combined Heat and Power (CHPs)

CHPs, sized to summer heat load, operate when there is sufficient heat need. Standard baseline conditions assumptions are shown in table 1 below.

Table 5 CHP production assumptions

Variable Description	Model variable name	Baseline Value
CHP size (heat load)	chp_size_month	July
Electric capacity	capacity	
Capacity factor	chp_capacity_factor	90%
Electric efficiency	chp_efficiency	40%

Battery

Batteries function when a local aggregator signals that there is a need for battery supply or charging, because there is no dynamic pricing for included in this model for building level agents to interact with the transmission system, there is no logic for building balancing without aggregation points.

Aggregation points tell a battery (with available capacity) when to charge or discharge based whether the electricity demand they interact with is less than or greater than a standard deviation from the mean. The charge threshold allows for a multiplier to be applied to the standard deviation to make the battery operation more/less sensitive to variation. The charge rate is assumed to be a third of total battery capacity per hour. A battery must wait at least one hour after charging to discharge and vice versa. Standard baseline assumptions are shown in table 2

Variable Description	Model variable name	Baseline Value
Battery building sizing heuristic	battery_selfsufficiency	4 hours
Sensitivity to local variation at aggregator	charge_threshold	1
Expected capacity factor (for estimation of ROI only)	battery_capacity_factor	80%
Depth of Discharge	depthofdischarge	90%
Efficiency	battery-efficiency	0.9

APPENDIX C

ADDITIONAL FIGURES FOR CHAPTER 4

Capacity Market:

Total Cost: Chicago	C-Individual	C-Neighbors	C-Street	C-Neighborhood
C-Individual	\$ 24.8 σ=\$2.3			
C- Neighbors	t(12)=0.587 p=0.568	\$ 24.0 σ=\$2.8		
C-Street	t(10)=-0.169 p=0.869	t(11)=0.620 p=0.548	\$25.1 σ=\$3.9	
C-Neighborhood	t(11)=1.069 p=0.308	t(14)=0.436 p=0.669	t(10)=0.976 p=0.352	\$ 23.4 σ=\$2.5

Baseline Comparisons: Chicago Total Cost	C-Individual $ 24.8 σ=$2.3	C-Neighbors $ 24.0 σ=$2.8	C-Street $25.1 σ=$3.9	C-Neighborhood $ 23.4 σ=$2.5
S1: No NM/FTC $27.7 σ=$3.8	t(15)=-2.000 p=0.064	t(18)=-2.507 p=0.022*	t(12)=-1.416 p=0.181	t(18)=-3.04 p=0.007*
S2: NM/FTC $25.5 σ=$4.9	t(17)=-0.401 p=0.693	t(19)=-0.872 p=0.394	t(15)=-0.184 p=0.857	t(19)=-1.260 p=0.223

Local Sufficiency: Chicago	C-Individual	C-Neighbors	C-Street	C-Neighborhood
C-Individual	41.6% σ=0.2%			
C- Neighbors	t(11)=24.409 p<0.001**	38.6% σ=0.3%		
C-Street	t(6)=9.738 p<0.001**	t(6)=-8.746 p<0.001**	11.8% σ=8.1%	
C-Neighborhood	t(7)=17.069 p<0.001**	t(7)=12.643 p<0.001**	t(7)=5.692 p<0.001**	29.7% σ=2.0%

Total Cost: Houston	C-Individual	C-Neighbors	C-Street	C- Neighborhood
C-Individual	$32.8 σ=$4.6			
C- Neighbors	t(13)=-3.405 p=0.005*	$40.4 σ=$4.1		
C-Street	t(11)=-0.712 p=0.491	t(10)=-2.043 p=0.067	$34.8 σ=$6.1	
C- Neighborhood	t(13)=-1.766 p=0.101	t(12)=1.147 p=0.273	t(13)=-0.862 p=0.405	$37.5 σ=$5.9

Baseline Comparisons: Houston Total Cost	C-Individual $32.8 σ=$4.6	C-Neighbors $40.4 σ=$4.1	C-Street $34.8 σ=$6.1	C-Neighborhood $37.5 σ=$5.9
S1: No NM/FTC $53.9 σ=$7.9	t(15)=-7.083 p<0.001**	t(14)=-4.601 p<0.001**	t(15)=-5.643 p<0.001**	t(16)=-5.061 p<0.001**
S2: NM/FTC $42.7 σ=$9.8	t(17)=-3.031 p=0.008*	t(16)=-0.701 p=0.494	t(17)=-2.169 p=0.045*	t(18)=-1.487 p=0.154

Local Sufficiency: Houston	C-Individual	C-Neighbors	C-Street	C-Neighborhood
C-Individual	26.6% σ=0.3%			
C- Neighbors	t(10)=9.503 p<0.001**	24.6% σ=0.5%		
C-Street	t(6)=11.425 p<0.001**	t(6)=-10.374 p<0.001**	5.0% σ=4.9%	
C-Neighborhood	t(7)=22.03 p<0.001**	t(8)=18.627 p<0.001**	t(7)=3.722 p=0.007*	12.4% σ=1.8%

Reactive Market:

Total Cost: Chicago	R-Individual	C-Neighbors	R-Street	R- Neighborhood
R-Individual	$ 23.9 σ=$4.7			
R- Neighbors	t(12)=-0.907 p=0.383	$ 26.4 σ=$5.6		
R-Street	t(11)=0.474 p=0.645	t(10)=-1.419 p=0.186	$22.9 σ=$3.5	
R- Neighborhood	t(12)=-0.086 p=0.933	t(11)=0.907 p=0.384	t(13)=-0.642 p=0.532	$ 24.1 σ=$4.0

Baseline Comparisons: Chicago	R-Individual $23.9 σ=$4.7	R-Neighbors $26.4 σ=$5.6	R-Street $22.9 σ=$3.5	R-Neighborhood $24.1 σ=$4.0
S1: No NM/FTC				
$27.7 σ=$3.8	t(11)=-1.820 p=0.097	t(9)=-0.534 p=0.606	t(14)=-2.806 p=0.014*	t(15)=-2.010 p=0.063
S2: NM/FTC				
$25.5 σ=$4.9	t(13)=-0.700 p=0.497	t(11)=0.376 p=0.714	t(16)=-1.373 p=0.189	t(17)=-0.697 p=0.495

Local Sufficiency: Chicago	R-Individual	C-Neighbors	R-Street	R-Neighborhood
R-Individual	7.0% σ=0.2%			
R- Neighbors	t(10)=33.157 p<0.001**	2.9% σ=0.2%		
R-Street	t(6)=64.991 p<0.001**	t(6)=-46.114 p<0.001**	0% σ=0	
R-Neighborhood	t(6)=64.991 p<0.001**	t(6)=46.114 p<0.001**		0% σ=0

Total Cost: Houston	R-Individual	C-Neighbors	R-Street	R-Neighborhood
R-Individual	$49.4 σ=$4.3			
R- Neighbors	t(10)=-0.197 p=0.848	$50.1 σ=$8.9		
R-Street	t(10)=0.309 p=0.764	t(13)=-0.401 p=0.695	$48.5 σ=$6.5	
R-Neighborhood	t(12)=1.344 p=0.204	t(13)=1.170 p=0.262	t(13)=0.886 p=0.392	$45.3 σ=$7.2

Baseline Comparisons: Houston	R-Individual $49.4 σ=$4.3	R-Neighbors $50.1 σ=$8.9	R-Street $48.5 σ=$6.5	R-Neighborhood $45.3 σ=$7.2
S1: No NM/FTC $53.9 σ=$7.9	t(14)=-1.515 p=0.151	t(14)=-0.942 p=0.362	t(14)=-1.541 p=0.145	t(16)=-2.398 p=0.029*
S2: NM/FTC $42.7 σ=$9.8	t(16)=2.063 p=0.056	t(16)=1.747 p=0.100	t(17)=1.545 p=0.141	t(18)=0.697 p=0.495

Local Sufficiency: Houston	R-Individual	C-Neighbors	R-Street	R-Neighborhood
R-Individual	5.4% $\sigma=0.3\%$			
R- Neighbors	$t(13)=19.566$ $p<0.001$**	2.6% $\sigma=0.3\%$		
R-Street	$t(6)=54.837$ $p<0.001$**	$t(7)=-25.305$ $p<0.001$**	0% $\sigma=0\%$	
R-Neighborhood	$t(6)=54.837$ $p<0.001$	$t(7)=25.305$ $p<0.001$		0% $\sigma=0\%$

Both Capacity and Reactive

Total Cost: Chicago	B-Individual	B-Neighbors	B-Street	B- Neighborhood
B-Individual	\$21.7 σ=\$2.3			
B- Neighbors	t(12)=-0.261 p=0.798	\$22.1 σ=\$3.7		
B-Street	t(11)=-0.694 p=0.502	t(11)=0.274 p=0.788	\$22.5 σ=\$2.1	
B- Neighborhood	t(8)=0.643 p=0.537	t(11)=0.753 p=0.466	t(9)=1.046 p=0.325	\$20.4 σ=\$4.8

Baseline Comparisons: Chicago	B-Individual $21.7 σ=$2.3	B-Neighbors $22.1 σ=$3.7	B-Street $22.5 σ=$2.1	B-Neighborhood $20.4 σ=$4.8
S1: No NM/FTC				
$27.7 σ=$3.8	t(18)=-4.415 p<0.001**	t(16)=-3.321 p=0.004*	t(16)=-3.720 p=0.002*	t(10)=-3.434 p=0.006*
S2: NM/FTC				
$25.5 σ=$4.9	t(18)=-2.407 p=0.027*	t(18)=-1.819 p=0.086	t(17)=-1.850 p=0.082	t(13)=-2.240 p=0.044*

Local Sufficiency: Chicago	B-Individual	B-Neighbors	B-Street	B-Neighborhood
B-Individual	45.3% σ=0.3%			
B- Neighbors	t(11)=27.047 p<0.001**	38.6% σ=0.6%		
B-Street	t(5)=10.782 p<0.001**	t(5)=-8.642 p<0.001**	11.4% σ=7.7%	
B-Neighborhood	t(6)=26.5 p<0.001**	t(7)=16.872 p<0.001**	t(6)=4.468 p=0.005*	25.8% σ=1.9%

Total Cost: Houston	B-Individual	B-Neighbors	B-Street	B-Neighborhood
B-Individual	\$25.6 σ=\$5.6			
B- Neighbors	t(14)=0.293 p=0.774	\$24.8 σ=\$5.0		
B-Street	t(14)=-2.306 p=0.037*	t(13)=2.708 p=0.018*	\$32.4 σ=\$6.3	
B-Neighborhood	t(11)=-3.050 p=0.011*	t(10)=-3.417 p=0.006*	t(12)=-0.975 p=0.349	\$35.9 σ=\$7.3

Baseline Comparisons: Houston	B-Individual $25.6 σ=$5.6	B-Neighbors $24.8 σ=$5.0	B-Street $32.4 σ=$6.3	B-Neighborhood $35.9 σ=$7.3
S1: No NM/FTC $53.9 σ=$7.9	t(16)=-8.885 p<0.001**	t(15)=-9.566 p<0.001**	t(16)=-6.418 p<0.001**	t(14)=-4.858 p<0.001**
S2: NM/FTC $42.7 σ=$9.8	t(18)=-4.956 p<0.001**	t(17)=-5.389 p<0.001**	t(18)=-2.845 p=0.011*	t(16)=-1.725 p=0.104

Local Sufficiency: Houston	B-Individual	B-Neighbors	B-Street	B-Neighborhood
B-Individual	28.9% σ=0.3%			
B- Neighbors	t(9)=25.206 p<0.001**	21.1% σ=0.8%		
B-Street	t(11)=105.1 p<0.001**	t(13)=-52.497 p<0.001**	2.4% σ=0.6%	
B-Neighborhood	t(6)=31.397 p<0.001**	t(9)=17.324 p<0.001**	t(8)=10.983 p<0.001**	9.5% σ=1.6%