# INCORPORATING ENDOGENOUS DEMAND DYNAMICS INTO LONG-TERM CAPACITY EXPANSION POWER SYSTEM MODELS FOR DEVELOPING COUNTRIES

by
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*“Do not go where the path may lead, go instead where there is no path and leave a trail”*

*-Ralph Waldo Emerson*

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# Abstract

This research develops a novel approach to long-term power system capacity expansion planning for developing countries by incorporating endogenous demand dynamics resulting from social processes of technology adoption. Conventional capacity expansion models assume exogenous demand growth; however, literature suggests that this assumption is not appropriate for developing countries. The planning approach presented in this research explicitly represents the links between the social and technical components of the power system. As potential customers without electricity select between various supply options to meet their power needs and as existing customers alter their consumption in reaction to the price of electricity and the perceived performance of the grid, the demand for grid power is directly impacted. This thesis demonstrates that neglecting these feedbacks and resorting to simplified assumptions can result in suboptimal investment strategies.

By comparing the investment strategies identified using this novel approach to that of more conventional approaches, this research highlights cases in which the incorporation of endogenous demand impacts capacity expansion planning. More specifically, this work proves that incorporating endogenous electricity demand is important when there is a large fraction of the population without access to power or when the improvement in reliability afforded by capacity expansion is large. Employing traditional capacity expansion methods in such cases may lead to the selection of inferior expansion strategies.

This research has both academic and applied contributions. Methodologically, this research extends state-of-the-art power system models by combining two generally separate modeling approaches, system dynamics and optimization. These methods are integrated to capture both the technical details of power grid operation and endogenous electricity demand dynamics in order to simulate the performance and evolution of the electric power grid. This research also demonstrates a holistic approach to centralized power planning that enables a more realistic representation of grid demand in developing countries and the identification of strategies that, in some cases, perform better than the strategies identified using traditional approaches. Finally, while this research was inspired by the case of Tanzania, the approach was developed with the flexibility to be applied to other countries with similar power system structure and contextual features.

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## List of Acronyms

| | |
|---|---|
| DSM | Demand-side management |
| EWURA | Energy Water and Utilities Regulatory Authority of Tanzania |
| kWh | Kilo-watt hour |
| LP | Linear program(ming) |
| MEM | Tanzania Ministry of Energy and Minerals |
| MIP | Mixed-integer program(ming) |
| MW | Mega-watt |
| NLP | Non-linear program(ming) |
| OFAT | One-factor-at-a-time |
| PSMP | Power System Master Plan |
| REA | the Rural Energy Agency of Tanzania |
| RES | Reference Energy System |
| SD | System Dynamics |
| TANESCO | Tanzania Electric Supply Company Limited (Tanesco) |

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# Chapter 1 – Introduction & Dissertation Overview

*"Energy is a fundamental ingredient of modern society and its supply impacts directly in the social and economic development of nations. Economic growth and energy consumption go hand in hand. The development and quality of our life and our work are totally dependent on a continuous, abundant and economic energy supply"*

*- Electric energy systems: analysis and operation, Chapter 1 (Gómez-Expósito et al 2008)*

There are an estimated 1.5 billion people without electricity; one quarter of the world's population. In Africa alone, there are more than 500 million without access to modern energy services (UNDP 2009). The range of impacts that electricity can have on their livelihoods is tremendous, and, while there is still debate surrounding the causal relationship between the provision of electricity and economic growth, access to electricity is agreed to be a necessary but not sufficient condition for economic development (Barnes 2007). As a result, national goals in most developing countries include developing the power system to improve the quality of supply and to provide universal electricity access.

In Sub-Saharan Africa, power system performance is characterized by frequent blackouts, a heavy dependence on hydro power and expensive thermal generators, and unreliable service. Typically, they are "…ridden with shortages and inefficient supply" (Pandey 2002). Industrial, income-generating activities are interrupted, healthcare products and food requiring refrigeration go bad, and according to the World Business Council for Sustainable Development (WBCSD), education, study and evening work are constrained (WBCSD 2007). Economic losses accumulate during periods of load-shedding, and economic growth is often curbed. In 2006, the costs of power outages in Tanzania was 4% of GDP (World Bank 2012), and, in 2011, for example, the economic growth rate in Tanzania fell by more than 1.5% from the previous year due to power shortages resulting from drought (Doya 2011). Power sector efforts in developing countries are therefore aimed at (a) meeting existing and future electricity demand and (b) improving access to electricity. This thesis focuses on the former.

This research develops a novel approach to long-term power planning in developing countries. In a holistic manner, this approach captures the links between the technical operation of the electric power grid and the social processes of technology diffusion and customer choice. The relationships between the social and technical aspects of the system are developed by assuming endogenous demand for grid electricity. Unlike conventional approaches to power planning, the demand for grid power is formulated to depend on the number of people adopting electricity as well as those selecting the national grid as their electricity supply. The selection of the national grid is a function of the relative price, quality and performance of the grid as compared to alternative supply options. In turn, the performance of the grid depends on demand, installed capacity, and investments in new capacity. This dissertation compares the investment strategies identified using this enhanced approach to that of more traditional models, and identifies cases in which incorporating endogenous demand impacts capacity expansion planning.

## 1.1 Motivating Case: the Tanzanian Power Sector

While the approach presented in this thesis was developed to be generalized and applied to various developing countries, the Tanzanian power sector is the motivating case for this research. This section provides background on the structure and performance of the sector and highlights the power planning challenges faced today.

### 1.1.1 Sector Structure & Installed Capacity

In Tanzania, the Ministry of Energy and Minerals oversees the development and utilization of electricity resources and, with regulatory oversight from the Energy Water and Utilities Regulatory Authority (EWURA), the Tanzania Electric Supply Company Limited ("Tanesco") dominates the electricity sector. Established in 1964, Tanesco is a parastatal organization, wholly owned by the government of Tanzania. It is a vertically integrated utility company responsible for the generation, transmission, and distribution of electricity throughout the country of Tanzania. Tanesco operates the national grid as well as isolated generators that supply power to Kagera, Kigoma, Rukwa, Ruvuma, Mtwara and Lindi.

In 1992 the government lifted Tanesco's monopoly in generation to allow the involvement of the private sector. As a result, independent power producers (IPPs) began operating and have, at times, supplied up to 40% of Tanzania's electricity. Private players include Independent Power Tanzania Limited (IPTL), Songas, and Artumas Group. In 1997, the Parastal Reform

Commission of Tanzania spelled out plans to unbundle Tanesco into two generation companies, a single transmission company, and two distribution companies (Gratwick et al 2006). As of late 2005, however, Tanesco was taken off the list of companies specified for privatization due to its poor technical and financial performance. Currently, incremental restructuring has taken place under the Ministry of Energy and Minerals; each core business of the utility is separated to achieve efficiency gains, but they are maintained within a single institutional structure that continues to be owned by the state. Accordingly, Tanesco remains responsible for more than 60% of the electricity generation within the country and holds a government-created monopoly in transmission and distribution (Tanesco 2009, Mwasumbi 2007).

The supply mix in Tanzania consists of hydro and thermal based generation. Tanesco owns and operates 561MW of installed hydro capacity along with 145MW of gas-fired generating capacity. IPPs IPTL and Songas operate a 100MW diesel plant and 182MW OCGT plant, respectively. 10MW is imported from Uganda and 3MW from Zambia. Tanesco also owns 80MW of diesel generating capacity that is connected to the grid but only 5MW is operational; the additional capacity is being decommissioned. Emergency plants totaling 180MW of capacity are also leased. Finally, the isolated regions of the country depend on 8MW of installed OCGT capacity (operated by the IPP, Artumas Group) and 31MW of installed diesel plants.

By the end of 2009, the national grid (excluding isolated centers) was made up of 38 substations interconnected by 2,732km of 220kV lines, 1538km of 132kV lines and 546km of 66kV lines.

### 1.1.2 Sector Performance

While only 14% of Tanzania's population has access[1] to electricity, Tanzania's power system has been increasingly unable to meet growing power demand. The technical and financial performance of the sector is very poor. System losses, comprised of both technical and non-technical losses, have been tremendous over the past decade. Technical losses are caused by various factors, including energy consumed by equipment, poor load management, lack of maintenance, and system overload. Non-technical losses, however, include poor billing, theft, and non-payment by customers (Mwasumbi 2007).

[1] Access drops to 2.5% in rural areas according to the Rural Energy Agency's Annual Report (REA 2010).

| Performance of TANESCO 2004-2009 | | | | | | |
|---|---|---|---|---|---|---|
| Year | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 |
| System Losses (%/year) | 18% | 25% | 24% | 24% | 23% | 26% |

**Table 1.1: Power System Losses reported by Tanesco (World Bank 2007, Tanesco 2009)**

The table above is a combination of the data presented in the World Bank's "Project Appraisal Document on a Proposed Credit to the United Republic of Tanzania for an Energy Development and Access Expansion Project" and in Tanzania's latest Power System Master Plan (Tanesco 2009). Due to poor maintenance and little investment in grid infrastructure, transmission and distribution (T&D) losses of 20% were recorded in 2008, and overall (technical and non-technical) losses totaled 23%. Likewise, in 2009, technical losses in Tanzania slightly increased from 20% to 22.5% (Tanesco 2009). When comparing the T&D performance to that of a developed economy (T&D losses of 6.6% and 6.5% were recorded in the US in 1997 and 2007, respectively), Tanzania's system suffers about three times more losses.

Similarly, the financial performance of the company has suffered. The company has reported severe debt and loss over the past decade. Tanesco's financial reports showed losses totaling 67.2 billion shillings and 21.6 billion shillings[2] in 2007 and 2008, respectively (Tanesco 2008). Poor bill collection and reduced hydro production due to drought has been cited as the cause for such financial performance. In 2006, the shortage of water in reservoirs led to severe load shedding.

### 1.1.3 Sector Planning

Due to the poor performance of the power sector, efforts have been focused on expanding capacity to meet growing demand. In Tanzania, central planning is the responsibility of the Ministry of Energy and Minerals (MEM), and is typically performed by consultants working in a close partnership with Tanesco. However, expanding capacity to meet growing demand in this context is challenging. In addition to a lack of financial resources, predicting demand growth in

[2] In the fall of 2010, 67.2 billion shillings was approximately $46,345,000 USD while 21.6 billion shillings was approximately $14,785,700 USD.

order to understand the capacity required to meet demand is a huge challenge as well. In 2007, Tanesco predicted that the demand for electricity supplied by grid power would increase at 7% per year (Mwasumbi & T 2007). One obtains this estimate growth value when performing trendline analysis of historical consumption patterns since 1997. Unfortunately, historical consumption patterns in a resource constrained country like Tanzania do not paint an accurate picture of demand growth. Increasing demand, according to Meier and Chatterjee, may be caused by increased economic activity (corresponding to Tanzania's growth in mining) or electricity adoption (*i.e.* more residents requesting grid connections). Technology adoption is strongly impacted by sector performance. If historical demand was realized in a system with low reliability, future growth in demand may not follow the same historical trends; this is due to the fact that additional generating capacity and improvements in service may encourage additional residents to request grid connections.

## 1.2 Research Objectives

Power planning is a complex decision problem. In the context of interest, the power sector is centralized and the majority of the population does not have access to the national grid. Various factors impact the evolution of grid demand, including: level of poverty, population growth, willingness to pay for grid connections, the quality of service of the grid, the reliability of the grid, the price per unit of energy, the backlog of customers awaiting a connection, the distance between consumers and the existing grid network, urbanization, and economic development among others. Accounting for such factors is a huge task, making it very difficult to predict electricity demand growth and ultimately making it difficult to make informed capacity expansion decisions.

Investment decisions made within electric power systems have typically been informed by the use of quantitative planning models, and researchers have used modeling to explore policy questions for decades. The literature includes a rich collection of models that address a variety of energy policy concerns for developed countries, including capacity expansion, improvement of operational performance, and the impact of fuel and technology mix on system performance (Turvey and Anderson 1977, Hobbs 1995, Momoh 2001). These models represent the technical details and physical laws of electric power systems. However, such optimization planning models typically assume that electricity demand is an exogenous variable and, in the context of a developing country, this assumption may not be appropriate. System dynamics models have, in the past, incorporated social factors, such as the effect of word of mouth on technological diffusion and the heavy reliance on kerosene, batteries and other more affordable off-grid sources of energy, and represented electricity demand in developing countries as an endogenous variable. These models, however, lack the detailed representation of the power network, which is critical in planning and assessing capacity expansion needs (Steel 2008). Additionally, these models are not typically formulated to optimize or select the best capacity expansion strategy. Unfortunately, no existing approach has captured both endogenous demand and the detailed operation of the electric power grid.

Therefore, this research aims to fill the gap in the existing literature on power system planning in developing countries by addressing the following research question:

> Are the strategies generated when assuming endogenous demand growth different than those generated using a more traditional approach, which assumes exogenous demand?

In order to address this question and the planning challenges described in 1.1.3, this research develops a unique approach to planning. Building upon previous research, a simulation model is developed and focuses on the interaction between local stakeholders and the technical system. More specifically, the model explicitly represents the link between power system performance, in this case measured by the price of electricity and the fraction of served demand to total grid demand, and the choice of consumers to use electricity from or connect to the national grid. This contrasts existing literature and previous research as it explicitly models both endogenous demand and detailed power system operation, including the production of generators in a hydro-thermal coordination model of the electric power network. Finally, the improved simulation model, incorporating endogenous demand, is used to inform capacity expansion planning. To demonstrate this approach, a model inspired by the Tanzania power system is developed.

## 1.3 Research Approach & Methodology

Electric power systems are not simply physically complex with a large number of nodes and connections (combinatorial complexity); they are also dynamically complex as well, with many agents within the system interacting over time (Sussman 2000). Thomas P. Hughes states, "The evolving Power Systems were not, metaphorically speaking, driverless vehicles… [it is] necessary to reach out beyond the technology, outside the history of technical things, to explain the style of the various systems…" (Hughes 1983).

Early on, Hughes recognized that power systems are large-scale socio-technical systems; they span regions and nations, and the consumers, regulatory authorities, power companies and other stakeholders all make decisions that affect the operation of this huge technical system. Power planners in developing countries face a unique challenge as their power systems have fewer technical components than most industrialized countries, but have arguably more social factors acting on and within the systems (Steel 2008). Although the electric power grid is a technical system, its design and management is an engineering systems problem (Moses 2004).

Therefore, this research employs a holistic systems approach, drawing on both the system dynamics methodology and mathematical programming to simulate power system operation and evolution. System dynamics is an approach, based on theories of nonlinear dynamics and feedback control, which is used to represent and understand the structure and dynamics of complex systems (Sterman 2000). The relationships and feedbacks between the stakeholder groups and the technical system are explicitly represented. In this case, customer adoption and the feedback between customer choice and power system performance is modeled using this approach; electricity demand is endogenous. To simulate annual power system performance, a mixed-integer linear program is used to create a deterministic hydro-thermal coordination model that determines the commitment and production of generators operating in the system as well as and non-served power and energy. Figure 1-1 shows the key elements of the simulation model developed in this research. Details are discussed in Chapter 3.

The planning approach uses the simulation model in order to make capacity expansion decisions that minimize total investment and operational costs over time. For this implementation of capacity expansion planning, all possible strategies are systematically enumerated to identify the optimal investment strategy. Details on implementation are described in Chapter 5.

One of the major contributions of this dissertation is the identification of cases in which investment strategies identified by the model developed in this thesis differ from that of more traditional approaches. In order to make such a comparison, a capacity expansion model assuming exogenous demand was developed using the mixed-integer linear programming approach. Details on this formulation are found in Chapter 5 as well.

## 1.4 Thesis Outline

Chapter 2 provides a detailed literature review on existing methods used to address long-term power sector planning in developing countries. Chapter 3 provides a detailed description of the integrated simulation model developed in this research, while Chapter 4 discusses model testing and calibration, and highlights standard model behavior. Chapter 5 demonstrates how the capacity expansion method developed in this thesis results in an investment strategy that is different than that of conventional planning with exogenous demand, and Chapter 6 describes the testing performed to identify cases in which the incorporation of endogenous demand impacts capacity expansion. Chapter 7 presents conclusions with recommendations for future work.

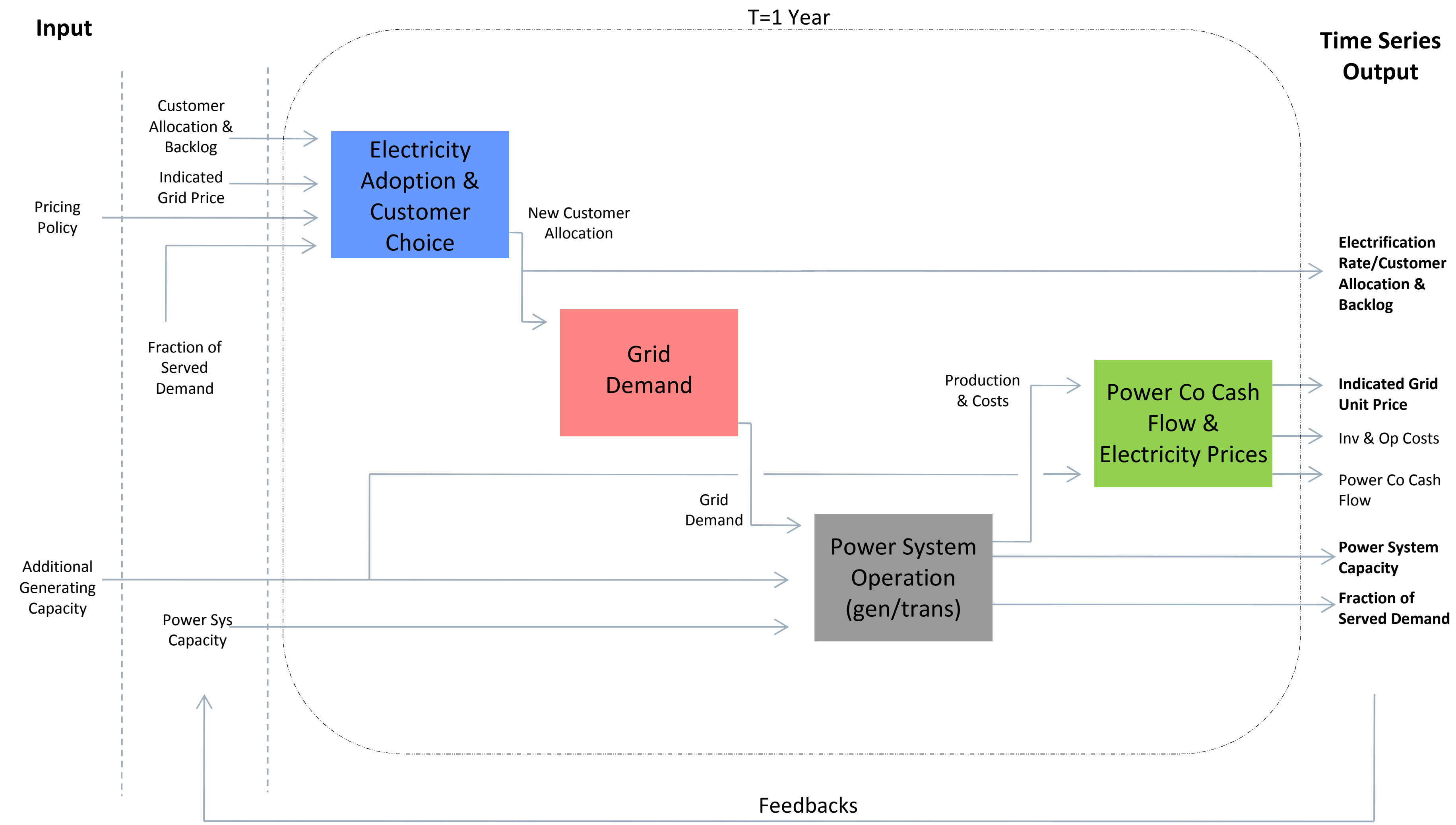


**Figure 1-1: Key Simulation Model Elements**

# Chapter 2 – Literature Review

Power systems are large-scale socio-technical systems. The operation of the electric power system requires the delicate balance of electricity supply and demand. Supply results from management decisions made by power system operators to transmit and distribute electricity throughout the grid network, and demand results from the complex decisions of numerous residents and industries to connect to the grid and to consume electricity. In the context of developing countries, the majority of the population typically lacks access to the grid, and the new grid connections realized depend on various factors, including social processes of technology diffusion.

Extensive research exists on the development of models to address power system concerns and these models often represent the technical details and physical laws of power systems very well; however, a missing piece in addressing power systems is conceptualizing them as complex systems. Accordingly, literature fails to address capacity expansion planning from a holistic systems point of view and commonly neglects to incorporate non-technical aspects of the system. This chapter demonstrates the need to develop an improved approach for capacity expansion planning and policy concerns for power systems in developing countries. It outlines existing policy and planning models for developing countries, identifies the areas in which they can be improved, and motivates the focus of the research described in subsequent chapters.

## 2.1 Power Planning in Developing Countries

Long-term power planning, also called resource, power generation expansion or capacity expansion planning, attempts to determine the minimum cost capacity expansion plan to meet growing demand over a long-term horizon, approximately 10 to 40 years. According to Anderson (1972) and Hobbs (1995), these costs are typically the sum of the capital cost of newly constructed capacity and the ongoing operational system costs of meeting demand during the horizon of the model. Demand, system parameters (generating capacities of existing and new units, for example) and costs (new capacity costs, operating costs, and fixed costs) are assumed to be exogenous, while typical decisions[3] include: the timing of investments, the type (nuclear, thermal, hydro, etc.) and size of newly constructed capacity, and the optimal mode of operation (*i.e.* the power generated and the demand going unserved at every time period within the horizon of the model). The typical constraints include (1) supply-demand balance requirements (2) reserve margin constraints and (3) capacity and annual energy production limits for each generator.

Capacity expansion models have been used for resource planning in the electricity sectors of developing countries for decades, and papers were published describing such applications to Nigeria and Northern Indian as early as 1977 (Meier and Mubayi 1983). The rest of this section outlines how capacity expansion models have been used for developing countries throughout the decades that followed.

### 2.1.1 Capacity Expansion: 1970s

Electricity planning models that utilized optimization methods, such as dynamic programming, linear programming, and mixed-integer programming, were used by developing countries worldwide during this period. In particular, many developing countries performed capacity expansion using the Wien Automatic System Planning Package[4] (WASP) model, which was developed between 1972 and 1973 by the Tennessee Valley Authority and Oak Ridge National Laboratory (Foell 1985). WASP was used for electric power system capacity expansion, employing linear programming to determine optimal dispatch and dynamic programming to determine the optimal investment strategy (Hamilton and Bui 2001).

WASP was one of many models that were developed for such applications. For example, the Brookhaven Energy System Optimization model (BESOM), developed in 1974 by Brookhaven National Laboratory, was a linear program capacity expansion model that was applied to both Mexico and India (Bhattacharyya and Timilsina 2010). Unlike WASP, BESOM analyzes the evolution of the whole energy system, including the electric power sector. Power plants are taken as identical elements of the model and economic dispatch is ignored. BESOM is the

[3] The location of new plants is sometimes a decision variable in generation planning. According to Hobbs, this allows electricity planners to reduce the costs of required transmission expansion.
[4] WASP was developed originally for the IAEA to assess the nuclear market in developing countries (Foell 1985).

predecessor of the widely used MARKAL model described in Section 2.1.3 (Fishbone and Abilock 1983).

In a paper entitled "An Investment Planning Model for the Electricity Sector in Nigeria", Iwayemi formulates a mixed-integer linear program that identifies both the optimal plant capacity expansion from a set of thermal and hydro generators as well as the transmission network expansion required to meet growing demand over 30 years. Unlike WASP and BESOM, Iwayemi's model explicitly represented the grid network. Iwayemi captured three major regions in Nigeria, and he was able to incorporate transmission planning into the standard capacity expansion model. He showed the importance of fuel prices on investment strategy, and demonstrated (using dual variables) that the pricing scheme prevailing in Nigeria at the time was insufficient to recover costs (Iwayemi 1978). Iwayemi provides an early example of the usefulness of capacity expansion models in determining investment strategy as well as sector policy in developing countries.

### 2.1.2 Capacity Expansion: 1980s

As national priorities changed, electricity planning models were more frequently embedded in the broader-scoped, integrated planning of energy systems. The increase in international oil prices caused many developing countries to use such energy system models with the aim of carefully allocating energy resources, promoting economic development and improving the livelihood of residents (Murphy 1988, Foell 1985, Munasinghe 1980)

In these models, macro-economic elements are linked to detailed end-use energy sector activities, including that of petroleum, electricity, and transportation. The Reference Energy System (RES) was developed during that time and often utilized in such energy models to capture the activities in the energy supply chain in a network representation of the energy system. These models were classified as either "top-down", with an aggregate focus on price and markets, or "bottom-up", which emphasized the technical characteristics of the energy sector. Finally, these models used econometric methods to forecast economic growth and demand, and investment strategies were identified for each energy subsector, often using energy accounting (Hoffman and Wood 1976), optimization (Meier and Mubayi 1983), or scenario analysis (Munasinghe and Meier 1993).

During this same period, early critics of energy system models and optimization-based models arose. Some argued that the limitations of commonly used energy models for developing countries were the lack of detail in the petroleum sector, the large data requirements to run the models, as well as the inability to model the transition from non-commercial to commercial energy use, resulting from urbanization and migration (Meier and Mubayi 1981). Similarly, many held the belief that optimization was not appropriate for developing country applications and that energy simulation models were more appropriate. According to Foell (1985), "a developing country's choice of an energy supply system should be based upon a broad range of attributes such as operating and investment costs, impact on balance payments, foreign exchange requirements, self-sufficiency, national security and environmental impact." During that time, optimization-based models identified plans by minimizing costs, and multiple criteria decision making[5] (MCDM) had yet to be widely applied to capacity expansion. Simulation models allowed more flexibility for planning to be based on expert judgment, decision-makers' preferences and also the incorporation of features that could not be represented in the standard models (Munasinghe 1980).

The discussion surrounding the limitations of energy planning models for developing countries has been an ongoing debate for decades. This is the topic of Section 2.3.

### 2.1.3 Capacity Expansion: 1990s

Moving into the 90s, national priorities shifted once again to focus on energy and the environment. Regional and global models became popular, and emissions abatement and climate change was the focus of energy planning models, which continued to incorporate capacity expansion for the electricity sector. Although models like LEAP and MARKAL were developed in the 1980s, they were used heavily in developing countries during this period as a result of the ease with which they evaluated environmental impacts.

Analysts began to incorporate environmental issues into energy supply planning by performing scenario analysis on a set of alternative power development strategies. For example, greenhouse

[5] MCDM constitutes an advanced field of operations research that is devoted to the development and implementation of decision support tools and methodologies to confront complex decision problems involving multiple criteria, goals, or objectives of conflicting nature. (Helms 2006).

abatement strategies were identified for both Sengal and Zimbabwe using this approach. The former study utilized LEAP to select the least-cost mitigation options (Amous et al. 1994), while the latter employed a spreadsheet accounting model to assess costs and emissions reductions for various interventions (Maya and Fenhann 1994).

Energy models also began to incorporate environmental costs and constraints. For instance, MARKAL enabled planners to specify costs and limit sector or system-wide emissions on an annual basis or cumulatively over time (Seebregts 2001). Accordingly, alternative carbon abatement strategies for Brazil were identified using a simplified MARKAL model (La Rovere et al 1994). A similar study was performed for China using ETO, an optimization model developed by INET that was used to determine the structure of energy supply (Wu et al 1994).

Finally, planners considered environmental implications in power system models by minimizing costs (excluding environmental costs) and performing impact calculations after the fact. Models were typically executed numerous times to observe how investment strategies changed with various restrictions (Markandya 1990). For example, Shretha et al used the third version of the WASP model to assess the environmental and generation capacity expansion implications of carbon taxes and technology constraints within the power sector of Pakistan (Shrestha et al 1998).

## 2.2 Capacity Expansion: the Conventional Approach

Capacity expansion represents one of the fundamental problems in power systems, and mathematical programming has been used to solve such problems since the early 1950s (Massé and Gibrat 1957). In their seminal 1977 book “Electricity Economics”, Turvey and Anderson present methods to solve the aforementioned decision problem, and describe the benefits and challenges of using marginal analysis, load duration curve integration, dynamic programming (DP) and linear programming (LP) to solve this problem type. They formulate the LP model as described in Table 2.1 and include extensions to incorporate capacity replacement, transmission, and water storage (extensions are not included in Table 2.1).

| | |
|---|---|
| **Objective Function** | $Minimize \sum_{v=1}^{T}\sum_{j=1}^{J} C_{jv} \times X_{jv} + \sum_{t=1}^{T}\sum_{v=-V}^{t}\sum_{j=1}^{J} F_{jvt} \times U_{jvt} \times \theta_t$ |
| **Constraints** | |
| Demand Balance | $\sum_{j=1}^{J}\sum_{v=-V}^{t} U_{jvt} \geq Q_t \qquad for\ t = 1, \dots, T$ |
| Thermal Production | $0 \leq U_{jvt} \leq a_{jv} \times X_{jv} \qquad for\ j = 1, \dots, J; v = -V, \dots, t; t = 1, \dots, T$ |
| Hydro Production | $\sum_{t \in season\ s} U_{jvt} \times \theta_t \leq H_{vs} \qquad for\ j = hydro\ plant; v = -V, \dots, t$ |
| Reserve Margin/<br>Guarantee Conditions | $\sum_{j=1}^{J}\sum_{v=-V}^{t} a_{jv} \times X_{jv} \geq Q_t(1+m) \qquad for\ t - 1, \dots, T$<br>$\sum_{t=t'}^{t''}\sum_{v=-V}^{t}\left(\sum_{j \neq hydro} a_{jv} \times X_{jv} \times \theta_t + \sum_{j \neq thermal} \beta_{jv} \times U_{jvt} \times \theta_t\right) \geq \sum_{t=t'}^{t=t''} Q_t \times \theta_t$ |
| **Definitions** | |
| | j type of plant<br>v vintage of plant (year of commissioning)<br>$X_{jv}$ power capacity of plant j and vintage v<br>$U_{jvt}$ power output of plant j and vintage v at time t<br>$C_{jv}$ capital costs per unit of capacity of plant j, vintage v<br>$F_{jvt}$ discounted operating costs for each unit of energy output for plant j, vintage v at time t<br>$\theta_t$ the width of the time interval considered at time t<br>$Q_t$ instantaneous power demand at time t<br>$a_{jv}$ the availability of plant j, vintage v<br>$\beta_{jv}$ the ratio of the energy output of hydro plant j, vintage v, in the critical period of the dry year to its mean expected output in this period of an average year<br>$H_{vs}$ hydroelectric energy to be delivered in season s by the hydro scheme of vintage v<br>m the margin of spare available capacity required to meet demands over the mean expectation<br>t',…t" represents the critical period (dry season) |

**Table 2.1: Generation Capacity Expansion Formulation, adapted from Turvey & Anderson (1977)**

Interestingly, Anderson described these models (LP and NLP) as being less utilized in practice due to the computing power available at that time. Practitioners instead used marginal analysis and load duration curve integration. As computing power has increased, however, the use of such models has become standard practice in electric utility resource planning.

As the priorities and concerns of resource planning have changed over the years, so have the models, but not by much. The formulation presented in Massé and Gibrat in 1957 and later by Turvey and Anderson in 1977 represents the basis of most capacity expansion models that have been developed over the last 60 years. For example, in the 1990s, the impact of demand-side management (DSM) programs on capacity expansion became a focus of analysis. In 1995, Hobbs presented a mixed-integer linear program (MIP) to incorporate these DSM programs. The model included a binary decision variable indicating whether or not DSM programs are implemented, but was based on Turvey and Anderson's 1977 formulation (Hobbs 1995).

In this same article, Hobbs encouraged future capacity expansion modelers to incorporate features into generation planning that consider more realistic aspects of power systems (Hobbs 1995). Before and since Hobbs published his paper, research in the area of power system capacity expansion was and has been aimed at developing models to address each of the listed concerns (see table below).

| Feature | References in which Models Incorporate Suggested Feature |
|---|---|
| Transmission | Turvey & Anderson 1977, Weinberg et al 1993 |
| Uncertainty | Bloom 1983, Stoll et al 1989, Hirst and Schweitzer 1990, Sanghvi and Shavel 1986, Palmintier & Webster 2011** |
| Increasing Competition | |
| - Price response Models | Rutz et al 1985, Hobbs et al 1993 |
| - Market Models | Cazalet 1991, Hobbs 1986, Gately 1974 |
| Multi-Objectives/ Multi-Attribute | Hobbs & Meier 1994, Petrovic & Kralj, 1993, Yang & Chen 1989, Linares 2002**, Pohekar & Ramachandran 2002** |

**References not cited in Hobbs 1995

When capacity expansion incorporates additional features, such as those described by Hobbs, the investment decision problem becomes very complex. Non-linear relationships arise in both the objective function and constraints, some decision variables are discrete, the set of possible solutions becomes very large, constraints may include sub-problems (like market equilibrium), uncertainty increases the number of possible futures, and decisions are taken sequentially (Hernáez 2010).

Methods like LP, MIP, NLP, and DP continue to be used to solve capacity expansion problems; however, additional optimization and heuristic methods have been developed to tackle the high complexity and dimensionality of the problems. These methods include stochastic programming and decomposition techniques, simulation techniques like interactive search, heuristic search or genetic algorithms, system dynamics (SD), agent-based modeling, monte carlo simulation, probabilistic simulation, decision theory, game theory, multi-criteria techniques and real options (Hernáez 2010).

While the methods mentioned above are used for capacity expansion in a variety of settings, this research develops a capacity expansion model for a centralized power system. The following subsection clarifies the difference between centralized versus liberalized electricity markets along with the implications on capacity expansion planning.

### 2.2.1 Centralized versus Decentralized Power System Planning

In what is called traditional planning, a government-controlled centralized coordinator is responsible for operation decisions, control and monitoring of the electric power system. This body is responsible for capacity expansion planning and typically the implementation of such plans as well. The planning criterion in this context is the maximization of social utility in the production and consumption of electric power. More specifically, the aim is to minimize both investment and operating costs while meeting demand with a reasonable level of quality and reliability. Traditional planning often occurs in power systems in which there exists a vertically integrated utility that generates, transmits, and distributes power. This was the predominant approach until recently when it became clear that, as a result of densely interconnected transmission networks, generators at a single location on the network could compete with other generators in supplying power to virtually any location on the grid (Gómez-Expósito et al 2008). It was, therefore, possible to separate transmission and distribution from the generation and supply businesses, which began to operate in a new competitive market.

Liberalization, *i.e.* the introduction of competition between generators and suppliers, has been accompanied by decentralized planning and operation. In this new context, each generator decides when and how much power to produce, and investment decisions are not made centrally by a body guaranteeing supply but by investors. Risk and anticipated returns on investment drive generation expansion and replace the traditional cost minimization criterion (Gómez-Expósito et al 2008).

Nevertheless, centralized planning models continue to be useful in various contexts. It has been proven that the centralized capacity expansion solution and the decentralized profit maximization decisions in a perfectly competitive market are the same (Botterud et al 2005). Therefore, even in liberalized markets, centralized planning models can offer insight on the evolution of the sector. More importantly for the research presented in this thesis, centralized power systems continue to be prevalent in developing countries and island nations throughout the world, such as Kenya, Cape Verde, Vietnam, and Jamaica to name a few.

## 2.3 Limitations to Modeling Power Systems in Developing Countries

### 2.3.1 Distribution and Demand

Research analyzing how well energy planning models were able to capture features of developing countries appeared in the 1980s. In 1987, Meier and Chatterjee published "Electric Utility Planning in Developing Countries: A Review of Issues and Analytical Methods" which demonstrated the first major shift in thinking about electricity planning for developing countries. They emphasized the poor financial state of electric utilities in developing countries and asserted that the traditional planning models used at the time (namely WASP), had become inadequate; they argued for improved electricity planning models.

In this critical paper, Meier and Chatterjee outlined three major deficiencies of traditional planning models. The first was that the loss of load probability metric (LOLP) often used in capacity expansion models did not capture the high frequency of outages experienced in developing countries. Such outages were artifacts of the state of the distribution system, which was typically not represented in these models. The second major concern had to do with demand forecasting; either load forecasting techniques were too primitive or the sophisticated econometric forecasting techniques were misused. Demand was typically assumed to be independent of price and the number of actual customers. They write of demand forecasting practices:

> *Most important is the need to include as many explanatory variables as possible in such models: as noted by Westley … in his study of the Dominican Republic, '. . . many studies "explain" electricity consumption using only a measure of income, a practice that normally inflates the income elasticity and hence exaggerates the importance of this factor . . . a proper perspective requires the inclusion of other factors, such as the number of users, the price of electricity, the price of substitute fuels, and a measure of outage severity'. The inclusion of a variable that captures the number of consumers is therefore of central importance for projection purposes (Meier and Chatterjee 1987)*

The third and "most serious" concern of traditional capacity expansion models was the notion that demand was exogenous to the model. They assert that "…the critical component of demand growth in most developing countries is the rate of growth in new connections…" (Meier and Chatterjee 1987).

### 2.3.2 Salient Features of Developing Countries & the Use of Complementary Approaches

In 2002, Rahul Pandey of the Indian Institute outlined the gaps that exist in energy policy modeling for developing countries, and demonstrated the second critical shift in thinking about policy and planning models. It was a shift from utilizing mathematical models that capture physical and economic laws to the creation of integrated tools that also incorporate the salient features of the countries for which the models were being used.

Developing countries differ significantly from more developed and industrialized countries, and Pandey, along with Urban (2007), Ruijven (2008) and Bhattacharyya and Timilsina (2010), describe the deficiencies of models for developing countries as:

- incorporation of large-scale poverty;
- incorporation of traditional energy (fuel wood, dung, agricultural waste, crop residues, and charcoal) and informal sector activities (non-monetary transactions like bartering);
- incorporation of the transition from traditional to modern sector (due to the migration from rural to urban centers *i.e.* urbanization, the switch from biomass to other fuels, and the change in perception of the benefits of various energy sources), which materializes in the form of increased consumption pattern, rising energy intensity and increased demand for employment;

- characterizing the rural-urban divide, and disaggregating consumers by income groups and spatial distribution for a clearer understanding of locational demand;
- integrated evaluation of decentralized supply options along with centralized options;
- incorporation of structural changes and competition in the emerging markets, and the uncertain and changing patterns of business environment; and
- incorporation of technological change and technology diffusion,  and capturing uncertainties about long-term economic growth.

Since pre-existing models did not incorporate such contextual features, the results and policy prescriptions were unreliable (Pandey 2002). Table 2.2 combines the views and research presented by these authors into a list of features missing from energy planning models.

| | |
|---|---|
| rural - urban divide | decentralized supply options |
| reliance on traditional energy (biomass, firewood) | prevalence of inequity and poverty |
| informal sector activities (barter, in-kind payments) | technological change |
| technology diversity (ability to leapfrog) | technology diffusion |
| transition to modern energy (increased consumption pattern and rising energy intensity due to modernization, urbanization, employment demand) | sector reform/structural change and competition in emerging liberalized markets |
| spatial difference and divergence in consumption/ disaggregated demand by income and location | environmental implications of energy use (sustainability) |
| low data availability for modeling | long-term uncertainties |
| economic growth and corresponding energy implications | demand-side options |
| energy shortage/poor performance of utilities | financial status of utilities |
| low energy access and rates of electrification | resource depletion |
| institutional issues like corruption | |

**Table 2.2: Features of developing countries not commonly included in energy models**

Pandey also highlighted various planning approaches and introduced system dynamics (SD), a method having little previous application in developing countries for electric utility policy and planning.  He noted that bottom-up accounting and optimization methods had been applied in developing countries to determine least-cost technology mix and to assess cost and emissions implications.  However, system dynamic models had been successful in capturing the impacts of changes in market structure and subsequent changes in technology and fuel selection in more industrialized countries (Bunn et al 1997).  Such features were important in the developing country context as well. Therefore, Pandey concluded that models using these different approaches in an integrated or complimentary manner should be developed for the context of developing countries.

*2.3.2.1 System Dynamics and Electric Power Systems*

System dynamics is an approach, based on theories of nonlinear dynamics and feedback control, which is used to represent and understand the structure and dynamics of complex systems (Sterman 2000). System dynamics was developed in the 1950s by Jay Forrester (1961) and has been used to present electric power systems since the early 1970s when Roger Naill developed the FOSSIL2 model to simulate policies that would aid the United States in reducing its dependence on foreign oil (Ford 1997, Naill 1992). Such models are typically implemented with stock and flow software to aid in model construction and testing (Ford 2001), and Sterman (2000) outlines a standard methodology for system dynamics modeling. This includes identifying system elements and their interactions, causal loop diagramming, calibration and sensitivity analysis.

While system dynamics models for power systems are most noted for their ability to represent rapidly changing, deregulated utility markets with high uncertainty and risk (Dyner and Larsen 2001), these models are more generally used to assess macro-level policy analysis by simulating multiple feedbacks, delays, and the behavior of utilities and power companies, consumers, and government. They are equipped to address capacity expansion planning (Coyle 1996), the impact of market structure, market power and competition, and uncertainties on capacity investment, technology-mix and cost to consumers (Bunn *et al* 1993, Sánchez *et al* 2007), and regional utility conservation planning (Ford *et al* 1987).

System dynamics, however, has been applied less frequently to represent power systems in developing countries. Qudrat-Ullah and Davidsen (2001) built the first known system dynamics model of a power system in a developing country to test and understand the power sector reform policies introduced in Pakistan in the early 1990s. Policy was aimed at promoting private sector investments, and the long-term simulation model was used to explore policy impacts on electricity supply, Pakistan's dependence on imports, and the evolution of carbon emissions. The model simulated years 1985 – 2030 and, indeed, assumed endogenous aggregate demand, making it a function of electricity price and intensity as well as economic growth, which was exogenous to the model. While system dynamics models are effective at capturing endogenous demand, they are also effective at capturing unique features of developing countries. The Kenyan power system model developed by Steel (2008) included: the rural-urban divide (using two stocks of residential consumers), the poor performance of electric utilities, decentralized supply options (such as diesel generators, solar home systems, or small hydro), the prevalence of inequity and poverty, hydro and geothermal resource depletion, technology diffusion and customer choice. Unfortunately, these models do not capture the details of power system operation and, since their development, very few system dynamic models representing power systems in developing countries have been created.

System dynamics has been complemented by and combined with[6] various methods to address power sector concerns in industrialized regions. For example, Bunn et al used both system dynamics and linear programming to analyze the effects of privatizing the electricity sector (Bunn et al 1993). The models of this particular analysis remained separate; however, modelers have recently been able to integrate the separate methods within a single model platform. In 2011, Rodilla et al developed a system dynamics-inspired model of the Colombian power system that embedded game theory to simulate generation expansion in the context of a security of supply mechanism based on long-term auctions (Rodilla et al 2011).

Similarly, Dimitrovski, Ford and Tomsovic successfully combined[7] system dynamics and optimization methods to simulate power plant construction in the Western Electricity Coordinating Council while capturing detailed transmission operation (Dimitrovski, Ford and Tomsovic 2007). This particular model captures supplier behavior in a liberalized market and assumes that demand grows at a fixed rate with slight modifications based on consumer sensitivity to retail prices. This model does not capture the growth in demand resulting from new grid connections as this plays less, if any, of a role in the growing demand of developed countries.

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[6] Outside of power system modeling, system dynamics has been combined with decision analysis (Osgood 2005, Hovmand & Ford 2009) and real options analysis (Tan et al 2010).

[7] A similar approach will be utilized in this research to develop a platform that incorporates both the dynamics of customer demand and the detailed operation of the electric power grid in developing countries.

### 2.3.3 Implications for Developing Countries

The use of models that do not adequately capture features of developing countries leads to incorrect investment plans and policy prescriptions. Solutions generated by optimization models may in fact be sub-optimal as such models assume perfect markets and optimal consumer behavior. Such is not the case in many developing countries as large segments of the economy can be non-market-based, and a large fraction of the population (such as those without access to electricity) does not reflect optimal consumer behavior (Urban 2007). Unrealistic scenarios may also be developed in models that do not capture salient features of developing countries (Urban 2007). For example, using average consumption values for a population generates biased results as benefits only reach a small portion of the population due to income distribution (B&T 2010). On the other hand, explicitly accounting for electrification and the number of households connected to the grid may improve demand projections (Ruijven 2008). Similarly, technology transitions often require state intervention, which also requires monetary resources and often involves a large delay in implementation. When models do not capture this delay, they generate an optimistic view of possibilities (B&T 2010). Such models are unable to generate a realistic picture of the future and, as a result, there is the misallocation of resources, inadequate infrastructure development, and poorly adapted development (B&T 2010).

## 2.4 Recent Developments: Improved Models for Developing Countries

In the previous section, characteristic features of developing countries were presented and the limitations of models for developing countries were enumerated. The aforementioned reviews set the agenda for research on electricity planning models for developing countries, including the research explored in this thesis. In this section, state-of-the-art electricity planning models recently created for developing countries are described.

As early as 1996, P. Shukla of the Indian Institute of Management published articles outlining the development of the Indian MARKAL and, in a working paper published in 2001, his team described the integration of three bottom-up models (MARKAL, AIM/ENDUSE, and a demand model) to better represent characteristics of developing countries while identifying energy system mitigation opportunities and investment strategies for India (Garg et al 2001). More specifically, the integrated platform developed by Shukla et al was able to incorporate (1) structural change in the economy, as demand projections were a function of GDP, which was disaggregated into Gross Value Added contributions from estimates of the relative growth rates of various sectors in the economy (2) urbanization and technology diffusion, where demand projections also reflected the increasing demand for electricity over time due to urbanization and improvements in living standards as well as the decreasing agricultural consumption resulting from the adoption of improved practices and (3) natural resource depletion, as exogenous projections of oil explorations and expectations were assumed. While the operation of the electricity sector was not explicitly represented in this model, the same team enhanced the modeling platform by incorporating a power sector model that uses linear programming to minimize system costs (generation, coal cleaning and transport, transmission, and pollution control costs) and determine the amount of new capacity from each type of power plant needed to meet exogenously specified demand (Shukla et al 2003).

The work of Shukla and his team reflected the beliefs of their colleague, Pandey, who encouraged the development of integrated modeling platforms to address energy and environmental policy concerns. Unfortunately, neither version of the model represented distribution nor assumed endogenous demand, features presented by Meier and Chatterjee as major drawbacks to planning models.

In 2008, Beck et al used both agent-based modeling (ABM) and dynamic multi-objective optimization (DMOO) to determine a preferred capacity investment strategy for a regional electricity sector and identify policies that encourage development along the identified path. The objective function is constructed to promote the formation of regional energy networks based on biomass resources in South Africa. While this work captures decentralized supply options, demonstrates a complementary approach to modeling for developing countries, and is appropriate for representing liberalized markets as ABM captures the decision rules of each of the many suppliers in the energy network, electricity demand remained an exogenous variable, and distribution was not represented (Beck et al 2008).

In the same year, Steel developed a system dynamics model of the Kenyan power system (Steel 2008). In this model, she captured the effect of consumer decisions on grid reliability and the effect of consumer decisions on resource depletion and electricity price. She took more of a "macro-approach" to modeling the power system, making simplified assumptions regarding power system operation and new capacity acquisition, instead of explicitly representing the operation of each generator or optimizing to determine the investments required to meet demand. She did, however, capture endogenous electricity demand growth. Elements of the Bass Diffusion model, often used to model the spread of infectious disease or technology diffusion (Sterman 2000), are used to model electricity adoption. Once households adopt electricity, consumers can choose to connect to the grid or use off-grid supply options. Consumer choice is captured using a conditional logit function to represent the boundedly rational weighing of the relative merits of electricity options (Steel 2008). The factors impacting consumer choice are price, unit costs of electricity, perceived reliability, backlog of customers awaiting supply, and perceived supply quality. Steel found that there exists the potential shift from a centralized power system to a decentralized system in Kenya. She also found that, in this context, power system planners should focus on decoupling electricity prices from oil prices as major changes in electricity prices strongly impact grid demand. Moreover, Steel addressed the major concern of Meier and Chatterjee by formulating residential demand in a single year as a function of the number of existing grid customers plus the newly connected customers; demand was endogenous.

Additional research in the area of power system planning for developing countries has recently emerged. The work of Vijay Modi's research group at Columbia University is focused on methods to estimate the cost of local-level distribution systems for least-cost networks (Zvoleff et al 2009) and the development of spatial electricity planning models to guide grid expansion in regions with little grid coverage (Parshall et al 2009). These models capture detailed spatial population information to guide distribution system planning or grid extension but they do not consider the generation or transmission needs to support the scale-up in distribution. Parshall et al, however, successfully captures the impact of the rural-urban divide on electricity demand, and addresses the concern raised by Pandey regarding the comparison of centralized versus decentralized supply options within a single model. They compare grid electrification to diesel mini-grids and stand-alone solar PV systems for households.

Finally, Howells et al have developed an open source energy system modeling platform (using a subset of AMPL) to provide an analytical toolbox that is accessible to energy planners in developing countries. The latest formulation uses the RES and assumes exogenous demand to determine the energy investment strategy that minimizes operational, investment and emissions costs. They assert that their contribution lies in the fact that the modeling framework requires no upfront investment costs, the learning curve is less steep than that of other models, such as LEAP or MARKAL, and the model can be easily modified for application to various settings (Howells et al 2011).

| Author [Country] Year | Demand as fn(cust) | Solves Capacity Expansion | Solves Economic Dispatch | Power System Representation | | | Electricity Only? | Nodes | Approach | Salient Developing Country Features Represented |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Gen | Tran | Distr | | | | |
| Iwayemi [Nigeria] 1978 | | X | X | X | X | | X | 3 | MILP | - |
| Shukla et al, Garg et al [India] 2001, 2003 | | X | X (Shukla) | X | X (Shukla) | | | - | LP for capacity expansion and economic dispatch; logistic regression for demand projections | structural change in the economy, natural resource depletion, urbanization and technology diffusion |
| Steel [Kenya] 2008 | X | | | X | | | X | 1 | SD | natural resource depletion, corruption, technology diffusion, customer choice, off-grid supply options for individuals |
| Beck et al [South Africa] 2008 | | X | | X | | | | 12 | DMOO + ABM | renewables (biomass); off-grid supply options for communities |
| Parshall et al[i] [Kenya] 2009 | | | | | | X | X | >6000 | combinatorial optimization/ relaxed minimum spanning tree algorithm | spatial distribution of homes (rural versus urban divide); off-grid supply options for individuals and communities |
| Chen et al [China] 2009 | | X | | X | | | X | - | LP | renewables, carbon abatement costs, CO2 allowance trading mechanism, technological change, fuel supply constraints, natural resource depletion |
| Howells et al [RES] 2011 | | X | X | X | possible | | | 1 (more possible) | LP | - |
| **Jordan 2013** | **X** | **X** | **X** | **X** | **X** | | **X** | | | **customer choice, off-grid supply options** |

**Table 2.3: Select Energy Models Created for Developing Countries**

(i) Capacity expansion is not presented in the traditional sense; model identifies the least-cost distribution network for various regions within a country

## 2.5 The Gap in Literature & Current Research Questions

The researchers presented in section 2.4 have made huge strides in incorporating the developing country features outlined by Pandey, Urban, and Ruijven; however, they poorly, if at all, address concerns regarding demand that were raised by Meier and Chatterjee. Many of the main drivers in the electric power sector and other energy sectors, such as demand, technological change and resource parameters, remain exogenous to simulation and optimization models (Urban 2007). The models typically include price or GDP impacts on demand, but only Steel formulated demand endogenously as a function of the number of customers and new grid connections. Unfortunately, Steel's model does not capture the details of power system operation and cannot be used for capacity expansion.

After reviewing existing literature and state-of-the-art power system models, it is clear that there is no model that captures detailed power system operation along with an endogenous representation of demand resulting from technology diffusion and adoption in developing countries (see Table 2.3); this thesis will develop such a model. It is critical that annual power system operations (generator production and unmet electricity demand throughout the grid) are characterized in order to obtain a representative measure of grid reliability, a major factor impacting electricity consumption and the choice to connect to the grid (Steel 2008). In turn, understanding the evolution of electricity demand is critical in order to ensure that power supply meets demand. This is a feedback loop that if omitted, could potentially result in counterproductive investment strategies.

In 1987, Meier and Chatterjee assert that endogenous demand (as a function of the number of new grid customers, the price of electricity, the price of substitutes, and relative measure of power outage) must be considered when planning for developing countries; and in 2008 Ruijven asserted that it is not particularly clear how incorporating these features will impact the output and results of energy models. Therefore, the aims of this research are to (1) incorporate endogenous demand into power system models for developing countries and (2) determine how incorporating such features impacts capacity expansion planning. More specifically, this research aims to bridge the gap in existing literature on capacity expansion planning for developing countries and address the following research questions:

- **Does it Matter?** Are the strategies generated when assuming endogenous demand growth different than those generated using a more traditional approach, which assumes exogenous demand? If so, how and why?
- **When Does it Matter?** When does the incorporation of endogenous demand impact capacity expansion planning *i.e.* when or in what cases are the strategies generated when assuming endogenous demand growth different than those generated using a more traditional approach?

As the aforementioned research questions necessitate the development of a power system model, my secondary research questions are:

- Within a single power system model for a developing country, how do you integrate the technical details of grid operation and endogenous demand dynamics resulting from social processes of electricity adoption and customer choice (such that new grid connections, and subsequently grid demand, are functions of word of mouth and power grid performance)?
- Given a power system model that incorporates endogenous demand, how can you perform capacity expansion?

A holistic systems approach drawing on various methods is employed to address the aforementioned research questions. An integrated simulation model that captures both the technical details and endogenous demand dynamics of power systems is developed. Subsequently, a heuristic optimization decision framework that uses the enhanced simulation model to inform capacity expansion planning is implemented. The details of model development and formulation are presented in Chapter 3.

# Chapter 3 – Simulation Power System Operation

The objectives of this research are to determine how and when incorporating endogenous demand into power system models for developing countries results in capacity expansion strategies that are different than those generated by conventional approaches. As a critical first step in meeting these research objectives, a power system simulation model was developed.

The model, depicted in Figure 3-1, simulates the evolution of a Tanzania-like electric power system from 2008 to 2028. It captures endogenous demand and the salient features of developing countries along with the detailed, technical operation of the grid network. It takes as input policies and investment decisions, and simulates a single year by calling each of four critical modules once. Policies include those concerning price; electricity prices can be fixed[8] or changing, and price changes may come after regulation delays. Investment decisions include the size and timing of generation units that will come online. The simulation model acts as a "calculator" and generates various indicators that are of interest to stakeholders in the electric power sector, including the number of grid and off-grid customers, grid operational costs, the price of electricity, grid demand and consumption, power company cash flow, and the fraction of served energy to total grid demand.

Mathematical programming is employed to determine annual power system operations while system dynamics is primarily used to capture endogenous demand, explicitly representing the number of new grid customers over time and the feedbacks between grid demand and perceived power system performance (signaled to consumers through electricity price and the fraction of served energy to total demand).

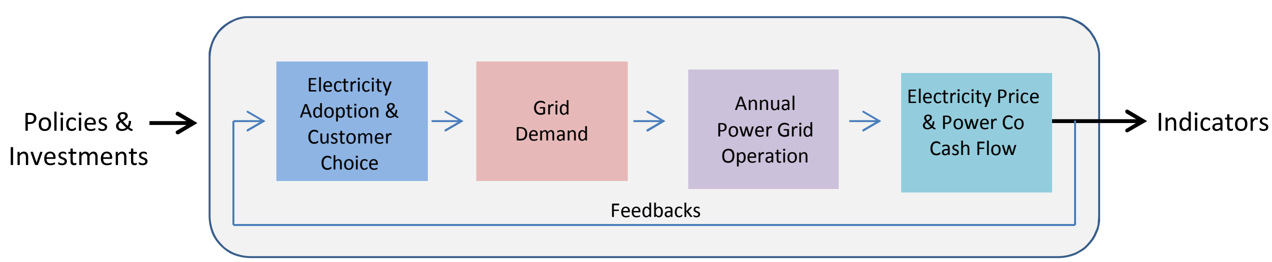


**Figure 3-1: Simplified Simulation Model Diagram**

[8] Electricity price may be fixed for residential or industrial consumers to simulate a subsidy.

This chapter describes the details of the simulation model. It begins with a discussion of each of the four critical modules depicted in Figure 3-1. Next, the process by which the model simulates multiple years of power system operation is explained. A discussion of the software platforms used for model implementation follows, and the chapter concludes with a summary of the simulation model.

## 3.1 Electricity Adoption & Customer Choice

Power systems in developing countries are frequently characterized by high costs and low reliability. Unlike that of industrialized countries, the majority of residents in this context lack access to modern energy sources, have relatively low disposable income and must consider the adoption of both grid and off-grid supply options. As presented by Meier and Chatterjee (1987), technology adoption and the changing number of grid customers is a driving element of grid demand in developing countries and should not be excluded from power system models. Therefore, this module captures (a) the process by which households adopt electricity as a modern source of energy and (b) the choice between grid and off-grid sources of electricity as experienced by both residential and industrial consumers.

Based on the Kenyan power system model developed by Steel (2008), this module consists of the residential and industrial consumer models. It takes as input industrial grid and off-grid consumption for the previous year, the number of residential grid, pv and diesel customers, the number of residential customers awaiting a grid connection, reliability of the power grid, the capacity of the power company to make new grid connections, and the price of grid power. The module determines the number of new residential customers adopting electricity, the number of new residential customers connected to the national power grid, and the number of residential customers purchasing PV systems or diesel systems. It also determines industrial grid and off-grid consumption.

### 3.1.1 Residential Consumer Choice Model

This model consists of 4 subsystems (also called "blocks") depicted in Figure 3-2. In the "Adoption" block, interest in electricity is spread through word of mouth. This block takes as input (i) total households with electricity (ii) households without electricity and (iii) the total household population. Using this information, the word of mouth element of the Bass Diffusion model (Sterman 2000) is employed in equation [1] to determine the number of new households adopting electricity each year *y* as a result of word of mouth.

$$New\_Adopters_y = c \cdot f \cdot P_y \cdot \frac{A_y}{HH_y} \qquad --[1]$$

where *c* is the contact rate of households, *f* is the adoption fraction (*i.e.* the probability that an interaction will result in electricity adoption), *A* is the stock of households that have already adopted electricity, *P* is the stock of potential adopters of electricity, and *HH* represents the total number of households in the region.

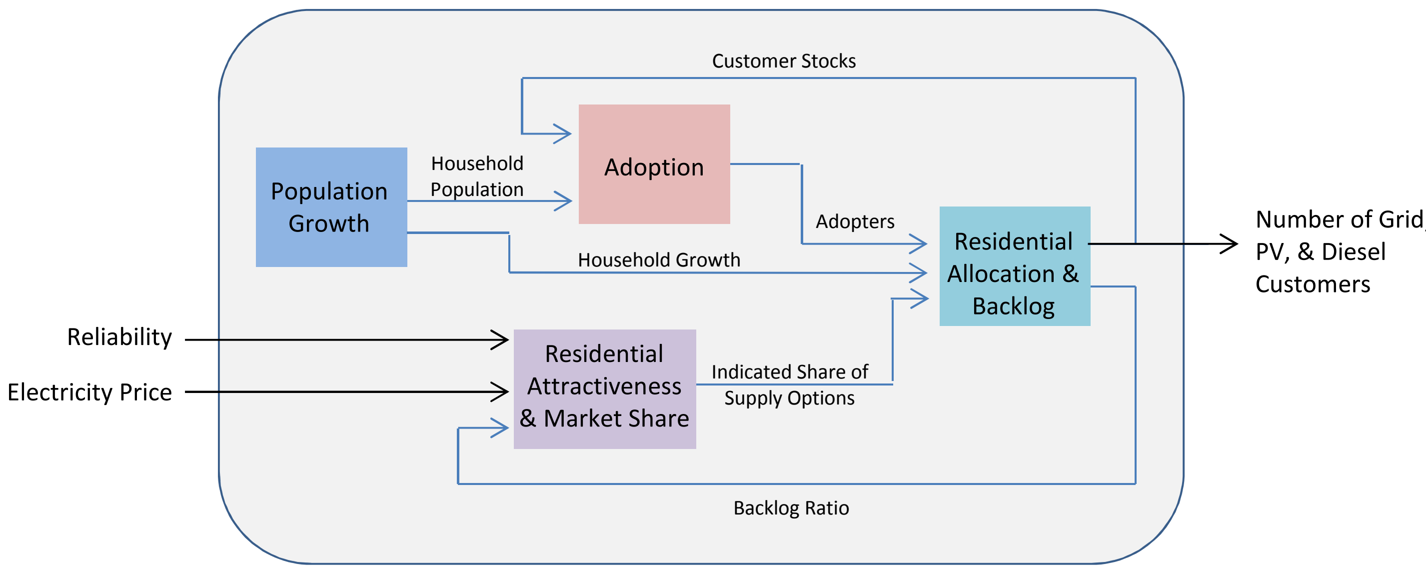


**Figure 3-2: Diagram of the residential consumer choice model**

The total number of households in the region at any time is determined in the "Population Growth" block, which keeps track of the growth in the number of households due to birth and death processes. The number of households accumulates according to

$$HH\_growth_y = pop\_growth\_rate \times HH_y \qquad --[2]$$

$$HH_y = \frac{population_0}{average\_size\_HH} + \int_0^y HH\_growth_y \, dy \qquad --[3]$$

Once households adopt electricity, they must select a power source to supply their needs. Accordingly, the "Residential Attractiveness & Market Share" block determines the indicated market share of each of the electricity options. This subsystem takes as input: (i) the fraction of energy served to total grid demand (for simplicity, referred to as grid "reliability[9]") (ii) grid backlog ratio (the ratio of desired grid connections to the capacity of the power company to connect new customers), and (iii) the per unit energy price paid by customers for each supply option. It uses a multinomial logit choice function (Ben-Akiva and Lerman 1985) to determine the fraction of customers that will choose to purchase a grid connection, a PV solar home system, or a diesel generator.

In this choice model, the market share is determined by weighing the attractiveness of options against one another, where attractiveness is determined by the relative utility of each option. Utility, attractiveness and indicated share are determined as:

$$U_{ij} = \frac{Value_{ij}}{Ref\_Value_{ij}} \times Sensitivity_j \qquad --[4]$$

$$V_i = \prod_j e^{U_{ij}} \qquad --[5]$$

$$Indicated\_share_i = \frac{V_i}{\sum_i V_i} \qquad --[6]$$

where $j$ is the attribute impacting choice (capital cost, unit price[10], reliability, perceived backlog, quality of connection), $i$ is the supply option, $U_{ij}$ is the utility of option $i$ with respect to factor $j$, and $V_{ij}$ is the attractiveness of option $i$ with respect to factor $j$. Utility is determined by multiplying the value of the attribute[11] (normalized by dividing it by a reference value) by the

---

[9] Reliability is typically defined as the ability to meet end-user demand in the face of unexpected failures or reductions in available electricity (NERC 2012); it is often calculated as 1 minus the probability of system failure. However, the term is used in this thesis to represent the fraction of served to total grid demand each year. The reliability of off-grid options is assumed to be 0.95.

[10] The capital costs and unit electricity prices associated with diesel generators and PV systems are exogenously fixed according to data presented in Steel (2008). According to Tanesco, the minimum cost of a grid connection is $500 USD and the price increases with the distance to the national grid. Here, the capital cost of connecting to the national grid is assumed to be fixed at $800 USD per connection.

[11] The levels of some attributes are smoothed so that there is no sudden change in the values of the attributes. $Value_{smooth} = a_0 + \int (value_t - Value_{smooth})/time\ to\ adjust$, where $a_0$ is the initial value of the attribute (Sterman 2000).

sensitivity of adopters to this attribute. The market share of each option, indicated by a fraction from 0 to 1, is used to determine the allocation of residential consumers.

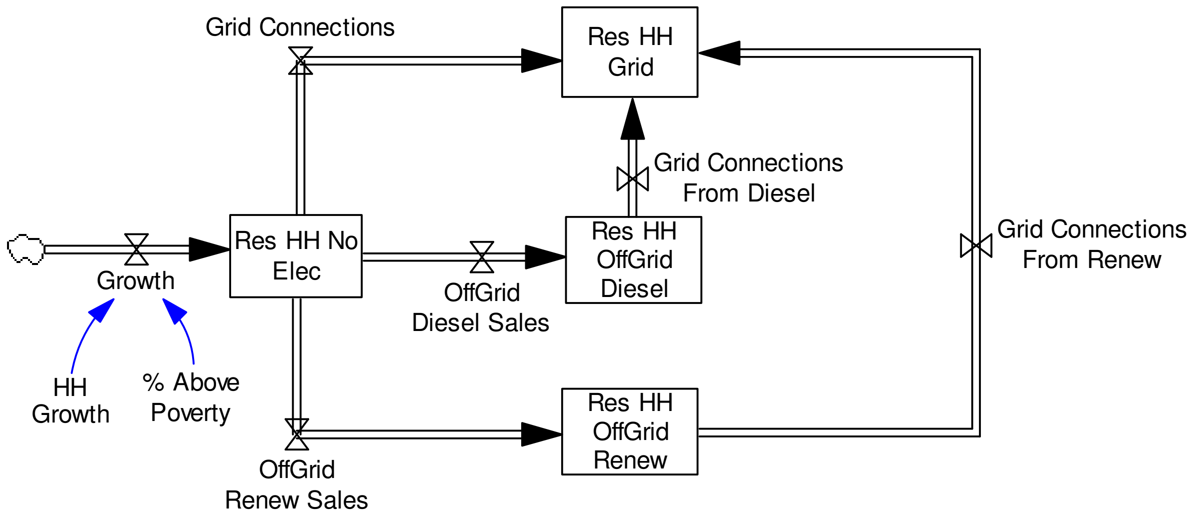


**Figure 3-3: Basic Structure of Residential Allocation Model (adapted from Steel 2008)** [12]

The "Residential Allocation & Backlog" block keeps track of the stock of grid, diesel, PV, and off-grid customers. This subsystem takes as input the number of electricity adopters and the indicated market share for each supply option, and residential consumers are allocated to stocks as depicted in Figure 3-3. The stock of households without electricity accumulates as the number of households grows. The growth in this stock, however, is restricted by the percent of the population that lives below the poverty line. For Tanzania, this has been approximately 35% from 2000-2010 (WDI 2011). The fraction of the population living in poverty is assumed to be constant, and households that live in such poverty are assumed to remain non-connected *ie* they never enter the stock of customers labeled "Res HH No Elec" (Steel 2008).

The supply of PV systems and diesel generators is assumed to be adequate to meet the demand for these sources[13], and the number of grid connections made each year is based on the capacity of the electric utility to perform new connections. The capacity of the electric utility to connect

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[12] "Renew" indicates PV solar home systems.
[13] As observed during fieldwork in Tanzania, the supply of off-grid electricity supply options is typically limited in developing countries. For simplicity, the model neglects this reality; however, this formulation can be simply modified and improved in future work.

new customers is exogenously specified; the value is initialized at 60,000 per year (the connection goal for all of Tanzania in 2008 (Tanesco 2009)) and gradually increases over time. There can be no more connections than this limit and obviously no less than zero. The customers who desire a grid connection but are not connected are assumed to resort to kerosene and dry cell batteries, *i.e.* sources other than PV and diesel, to meet their electricity needs until they are connected. The stock of grid customers is initialized at 2008 levels and the initial stocks of PV and diesel customers are estimated.

The total number of desired grid connections in a single year is comprised of new adopters of electricity as well as previous adopters of electricity that selected off-grid sources. When adopters of electricity select off-grid supply options, they are initially content with their choices. Over time, however, a fraction of off-grid customers are assumed to desire grid connections as their demand and use of appliances grows. The fraction of customers wanting to shift from PV systems and diesel generators to the grid is assumed to be fixed over time. There is no shift from grid to off-grid supply options as residential consumers in this context perceive the grid to be the superior option[14] (Steel 2008).

### 3.1.2 Industrial Consumer Choice Model

Industrial customers are treated as a separate population from residential households. Steel (2008) observed that the industrial customers in Kenya were extremely sensitive to grid reliability, there was the potential for them to switch multiple times between electricity sources, and that these customers are likely to split their consumption between several sources. Similarly, Tanesco (2009) reports that, during the most severe periods of load shedding, customers substitute other sources for grid power to maintain a consistent level of electricity supply and minimum energy costs. Thus, in this model of a Tanzania-like power system, industrial consumers are modeled as units of energy instead of firms. Growth in industrial electricity demand is assumed to increase at the rate forecasted by the PSMP; in Tanzania, industrial demand growth is proportional to mining activity and is formulated as function of changing GDP (Tanesco 2009).

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[14] As indicated in numerous reports during the period of sever load shed in Tanzania in 2011, residential grid customers were also found to switch to off-grid supply options. This was observed after the development of the model and is therefore not included.

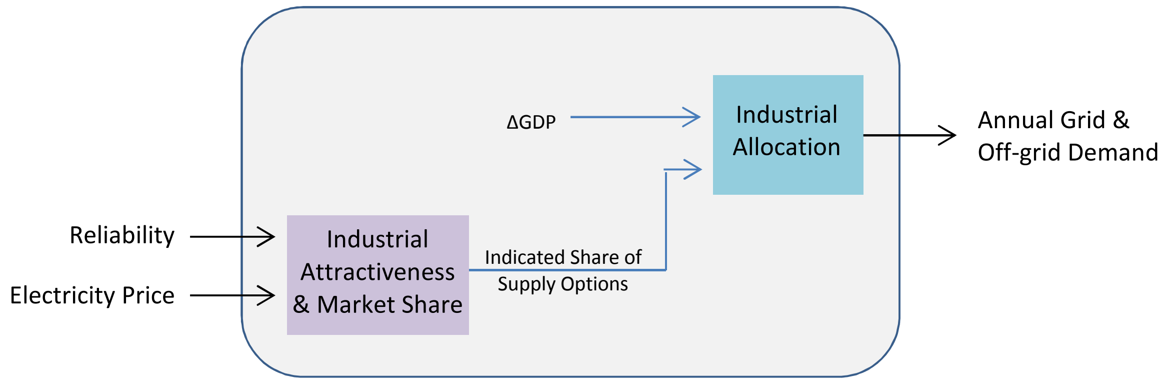


**Figure 3-4: Diagram of the industrial consumer choice model**

The "Industrial Attractiveness & Market Share" block assumes no social dynamics and no questions of ability to pay. This subsystem takes as input[15]: (i) grid reliability and (ii) per unit energy price for each supply option. It uses a multinomial logit choice function as described in equations [4] to [6] to determine the fraction of industrial demand that will be met by the grid, a diesel generator, or a renewable power system (PV or hydro). However those attributes of supply impacting the industrial decision are capital cost, the unit price of electricity and reliability.

The "Industrial Allocation" block keeps track of those energy units met by grid, off-grid diesel, off-grid PV, or off-grid hydro sources, and demand is allocated as in Figure 3-5. The stocks represent industrial electricity demanded from grid and off-grid sources, and the flows indicate the shift in energy units demanded from one source to the other (Steel 2008). This captures the potential of industrial consumers to switch between options to meet demand in a reliable and cost-effective manner.

[15] As in the residential choice model, the capital costs and unit electricity prices of off-grid diesel, hydro and solar are assumed to be exogenously fixed based on data presented by Steel (2008).

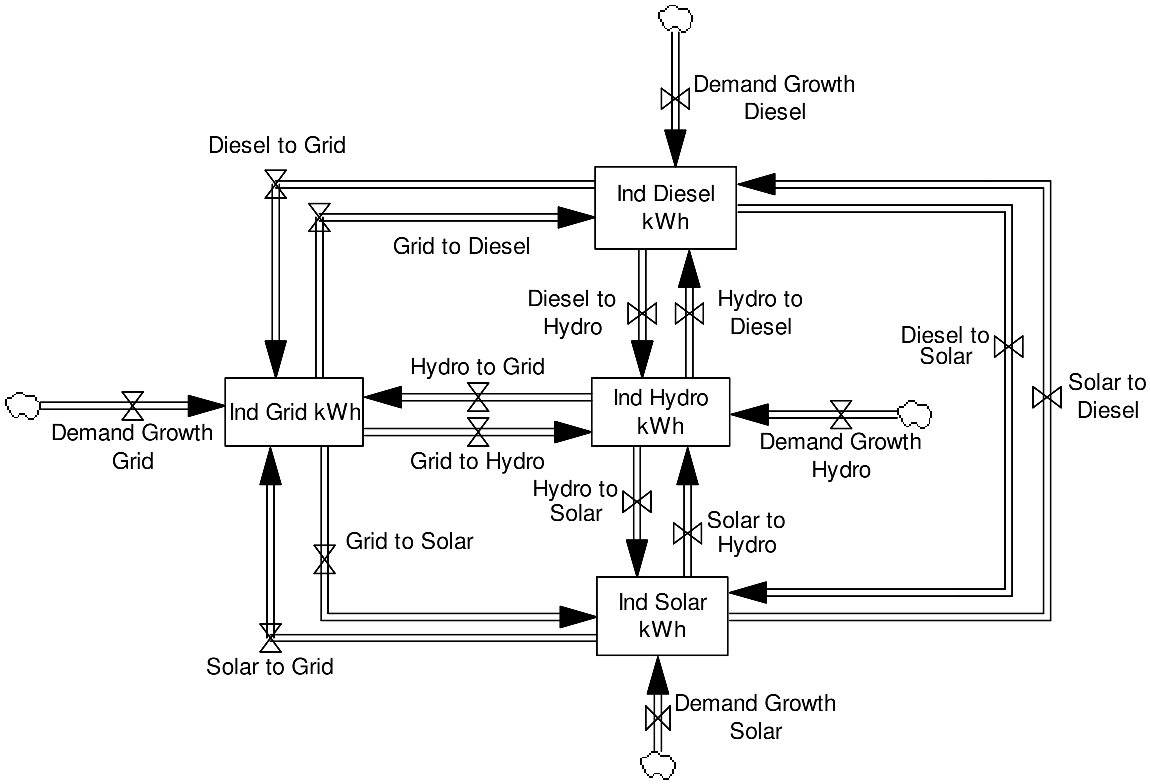


**Figure 3-5: Basic Structure of Industrial Allocation Model (adapted from Steel 2008)**

The growth in energy demanded from each source results from the incremental change in energy demanded due to economic growth, indicated by changing GDP. This is formulated as:

$$Demand\ Growth_l = \Delta GDP\ \times \gamma_{ind}\ \times Demand_l$$

where $l$ is the electricity supply option, $\gamma_{ind}$ is percent increase in industrial demand per the percent increase in GDP, and the percent change in GDP (*ΔGDP*) is exogenously fixed. Additionally, each year industrial consumers consider switching electricity sources and a fraction of the energy demanded from one source will shift to another source. The shifting demand is allocated based on the indicated market shares identified by the logit choice model. For example, in any year *y* the units previously demanded from the grid that will now be demanded from off-grid hydro is defined as:

$$Grid\ to\ Hydro_y = \%Shift_{grid}\ \times\ Demand_{grid,y-1} \times Indicated\_Share_{hydro,y}$$

## 3.2 Grid Demand

The core function of the "Grid Demand" module is to determine annual grid demand for both industrial and residential consumers. It takes input from the "Electricity Adoption & Customer Choice" module, and passes output to the "Annual Power System Operations" module. More specifically, this module determines the power demanded during each demand block of a single year, where each demand block is characterized by period, day type, load level, and duration. This module is divided into two subsystems: "Residential Demand" and "Industrial Demand" (see Figure 3-6).

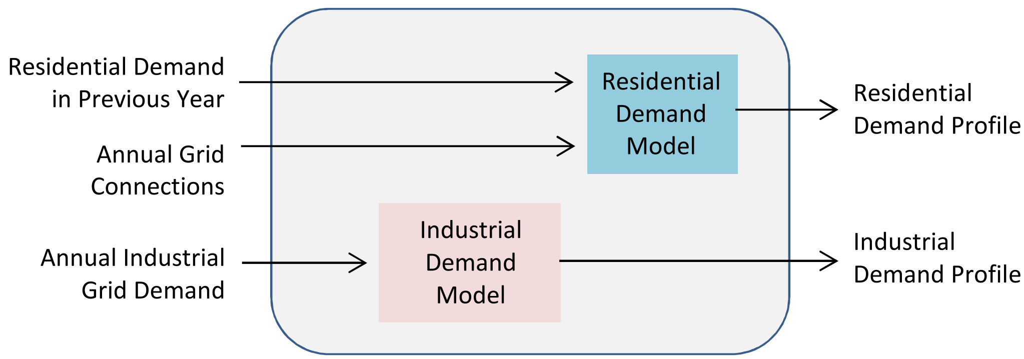


**Figure 3-6: Diagram of the Grid Demand Module**

A single period represents approximately 2.5 months out of the year and is indexed from 1 to 5. A day is defined as either a weekday or weekend, and the load level is defined as peak, shoulder, or base load. The duration (in hours) of each demand block is presented in Table 3.1. The set of demand blocks and associated power demand (in kW) that completely characterize a single year is considered a "demand profile".

| Period | WeekDays | | | WeekEnds | | |
|---|---|---|---|---|---|---|
| | Peak | Shoulder | Base | Peak | Shoulder | Base |
| 1 | 256 | 704 | 576 | 156 | 234 | 234 |
| 2 | 168 | 462 | 378 | 114 | 171 | 171 |
| 3 | 176 | 484 | 396 | 102 | 153 | 153 |
| 4 | 176 | 484 | 396 | 102 | 153 | 153 |
| 5 | 264 | 726 | 594 | 156 | 234 | 234 |

**Table 3.1: Duration (in hours) of each demand block in a year**

### 3.2.1 Residential Demand

This subsystem takes as input the number of new grid customers in a given year and residential demand from the previous year. It then determines the aggregate demand profile (*i.e.* the power demanded in each demand block) of the year.

Individual household grid demand patterns for residents in Tanzania were not available. Instead, historical data and numerous studies specific to the East African context were utilized to predict the electricity demand profile of newly connected grid customers. A newly connected grid customer is assumed to demand 50kWh/month, which is consistent with data and previous research findings (Decon 2008). For weekdays, the daily load pattern of a single customer is assumed to follow that of newly connected Peruvian[16] households as found in data shared by Julio Eisman Valdés. Additionally, according to 2004 data provided by Tanesco along with qualitative information provided in the PSMP (Tanesco 2009), weekend residential consumption is mainly constant except for an evening peak. The electricity demand profile in Table 3.2 captures that of a newly connected residential consumer in Tanzania during 2004 – 2010. These values are assumed in this model.

| Period | WeekDays | | | WeekEnds | | |
|---|---|---|---|---|---|---|
| | Peak | Shoulder | Base | Peak | Shoulder | Base |
| 1 | 0.241 | 0.065 | 0.032 | 0.045 | 0.031 | 0.031 |
| 2 | 0.240 | 0.065 | 0.032 | 0.044 | 0.031 | 0.031 |
| 3 | 0.234 | 0.063 | 0.031 | 0.045 | 0.032 | 0.032 |
| 4 | 0.243 | 0.065 | 0.032 | 0.044 | 0.031 | 0.031 |
| 5 | 0.247 | 0.067 | 0.033 | 0.045 | 0.032 | 0.032 |

**Table 3.2: Residential demand (in kW) of a newly connect grid customer during each period, day type, and load level within the first year**

[16] Please see APPENDIX for the aggregate daily electricity demand of 3335 customers in Peru

Aggregate residential demand in a single year is comprised of two components: demand from existing grid customers and newly connected grid customers. Based on econometric studies found in the PSMP (Tanesco 2009) and the electricity demand profile of new grid customers shown above, the aggregate demand for grid power in a single year is estimated as follows:

$$DT_{y,p,s,n} = DN_{y,p,s,n} + DE_{y,p,s,n} \qquad \forall\, y,p,s,n \qquad --[7]$$

$$DN_{y,p,s,n} = NC_y \times DPN_{y,p,s,n} \qquad \forall\, y,p,s,n \qquad --[8]$$

$$DE_{y,p,s,n} = DT_{y-1,p,s,n} \times \{1 + (\gamma_{res} \cdot \Delta GDP_y)\} \qquad \forall\, y,p,s,n \qquad --[9]$$

Where

| | |
|---|---|
| $y$ | year (ranging from 1 to 20) |
| $p$ | period (ranging from 1 to 5) |
| $s$ | day-type (weekday or weekend) |
| $n$ | load level (peak, shoulder, base) |
| $DT_{y,p,s,n}$ | total grid power demanded in year *y* for each *p*, *s*, and *n* |
| $DN_{y,p,s,n}$ | aggregate electricity demand of newly connected customers in year *y* |
| $DE_{y,p,s,n}$ | aggregate electricity demand of existing grid customers in year *y* |
| $NC_y$ | the number of new grid customers connected in year *y* |
| $DPN_{y,p,s,n}$ | electricity demand of a newly connected grid customer |
| $\gamma_{res}$ | percent increase in electricity consumption of existing grid customers per the percent increase in GDP |
| $\Delta GDP_y$ | percent change in GDP in year *y* |
| $DT_0$ | aggregate grid demand observed in 2008 *i.e.* $y = 0$ |

### 3.2.2 Industrial Demand

Unlike the "Residential Demand" block, the "Industrial Demand" block takes as input the annual grid energy demanded (in kWh) by industrial consumers and determines the aggregate demand profile of the year. Historical hourly consumption data[17] for Industrial consumers in Tanzania is used to estimate the shape of the demand curve[18] in a single year. This is demonstrated in Table 3.3.

[17] Hourly grid production as well as consumption data for both industrial and residential consumers was provided by Tanesco in July 2010.

[18] It should be noted that, due to load shedding schemes implemented in Tanzania, industrial consumption occurs at the following times: all day except for 8pm – 12am on weekdays, and all day on weekends.

| Period | WeekDays | | | WeekEnds | | |
|---|---|---|---|---|---|---|
| | Peak | Shoulder | Base | Peak | Shoulder | Base |
| 1 | 0 | 1 | 1.096 | 1.329 | 1.103 | 1.064 |
| 2 | 0 | 0.982 | 1.076 | 1.305 | 1.083 | 1.045 |
| 3 | 0 | 0.980 | 1.074 | 1.302 | 1.080 | 1.043 |
| 4 | 0 | 0.995 | 1.091 | 1.322 | 1.098 | 1.059 |
| 5 | 0 | 1.038 | 1.138 | 1.379 | 1.145 | 1.105 |

**Table 3.3: Assumed ratio of industrial demand to demand during a weekday shoulder load in period 1, during each period, day type, and load level in a single year**

Using the annual grid demand (in kWh) generated in the "Industrial Allocation" block, the demand profile of industrial consumers is defined as:

$$ID_{y,p,s,n} = \frac{Demand_{grid,y}}{\sum_{p,s,n} ratio_{p,s,n} * duration_{p,s,n}} \times ratio_{p,s,n} \qquad --[10]$$

Where

| | |
|---|---|
| $y$ | year (ranging from 1 to 20) |
| $p$ | period (ranging from 1 to 5) |
| $s$ | day-type (weekday or weekend) |
| $n$ | load level (peak, shoulder, base) |
| $ID_{y,p,s,n}$ | total grid power demanded in year $y$ for each $p$, $s$, and $n$ |
| $Demand_{grid,y}$ | annual industrial grid demand (in kWh) in year $y$ |
| $ratio_{p,s,n}$ | ratio of power demanded for this $p$,$s$, and $n$ to the power demanded during the weekday shoulder load of period 1; see Table 3.3 |
| $duration_{p,s,n}$ | duration in hours of each $p$,$s$, and $n$; see Table 3.1 |

## 3.3 Annual Power Grid Operation

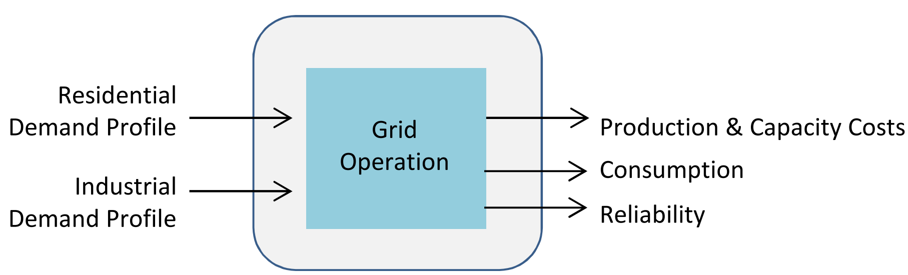


**Figure 3-7: Diagram of Annual Power Grid Operation Module**

The "Annual Power Grid Operation" module is a medium term power system model. Mixed-integer programming is employed to formulate this deterministic model with hydro-thermal coordination and block-wise unit commitment. The model minimizes total variable costs while satisfying demand balance and production constraints. It takes as input the newly installed generation capacity and the grid demand profile of both residential and industrial consumers to determine the production of each generator during every period, day type, and load level of the year[19]. This model also determines total annual operational costs, annual electricity production and consumption, and total non-served energy.

### 3.3.1 Model Objective

The **objective** of the problem is to minimize costs, defined as:

$$Min\,\{vProdC + vNSEC + vCommitC\} \qquad --[11]$$

*vProdC* represents the variable costs of production, *vNSEC* indicates the penalties incurred from non-served energy and power, and *vCommitC* represents the cost of operating thermal units. They are defined as:

$$vProdC = \sum_{p,s,n,g} pDuration_{p,s,n} \cdot pVarCost_g \cdot vProduct_{p,s,n,g} \qquad --[12]$$

$$vNSEC = \sum_{p,s} pPNSCost \cdot vPNS_{p,s} + \sum_{p,s,n} pDuration_{p,s,n} \cdot pENSCost \cdot vENS_{p,s,n} \qquad --[13]$$

$$vCommitC = \sum_{p,s,n,t} pDuration_{p,s,n} \cdot pNoLoadCost_t \cdot vCommit_{p,s,t} \qquad --[14]$$

where

| | |
|---|---|
| $y$ | year (ranging from 1 to 20) |
| $p$ | period (ranging from 1 to 5) |
| $s$ | day-type (weekday or weekend) |
| $n$ | load level (peak, shoulder, base) |
| $g$ | generating unit |
| $t$ | thermal generating unit |
| $h$ | hydro generating unit |

---

[19] The operational model presented in this section does not consider the transmission network; similarly, the analysis presented in Chapters 4 to 6 neglect transmission constraints. However, additional work was performed to formulate a second version of the Annual Power Grid Operation module that includes transmission. See APPENDIX for details on the formulation.

and

| | | |
|---|---|---|
| $pDuration_{p,s,n}$ | duration | [hours] |
| $pVarCost_g$ | variable costs | [M$ per MWh] |
| $pNoLoadCost_t$ | no load costs | [M$ per h] |
| $pPNSCost$ | cost of power non-served | [M$ per MW] |
| $pENSCost$ | cost of energy non-served | [M$ per MWh] |

Model **input parameters** are:

| | | |
|---|---|---|
| $pDRes_{p,s,n}$ | residential demand | [MW] |
| $pDInd_{p,s,n}$ | industrial demand | [MW] |
| $pInstalled_g$ | number of generating units installed of type g | |

and **decision variables** of this model are defined below:

| | | |
|---|---|---|
| $vProduct_{p,s,n,g}$ | production of the unit | [MW] |
| $vCommit_{p,s,t}$ | commitment of thermal unit | [positive integer] |
| $vENS_{p,s,n}$ | power non served | [MW] |
| $vPNS_{p,s}$ | total power non served | [MW] |

The objective must be minimized subject to numerous constraints. The **constraints** are described in the following subsections.

### 3.3.2 Demand Balance Constraint

The sum of electricity generated and non-served energy must equal the demand for all *p*, *s*, and *n*.

$$\left[\sum_g vProduct_{p,s,n,g}\right] + vENS_{p,s,n} = pDInd_{p,s,n} + pDRes_{p,s,n} \qquad \forall p,s,n$$

### 3.3.3 Reserve Margin Constraint

The reserve margin of installed capacity is the generating capacity available in excess of what is required to meet peak demand levels. In most systems, regulators require reserve margins to be approximately 10% to 20% in order to ensure that, during times of generator breakdowns or sudden increases in demand, the power grid is still operational.

$$vPNS_{p,s} + \sum_{h} pMaxProd_h \cdot pInstalled_h + \sum_{t} pMaxProd_t \cdot vCommit_{p,s,t}$$

$$\geq \left[pDInd_{p,s,n1} + pDRes_{p,s,n1}\right] \times (1 + pOpReserve))$$

$$\forall p, s, n1$$

where $pMaxProd_g$ is the maximum production (in MW) of each generating unit and $n1$ is the peak demand level. According to EWURA, the reserve margin is negligible in the Tanzanian power system. Accordingly, $pOpReserve$ is equal to zero.

### 3.3.4 Production & Commitment Constraints

The power generated must not exceed the rated capacity of the unit or, for thermal units, fall below the minimum production capacity specified. Electricity production in the peak load blocks must be greater than that of the shoulder load blocks, and the production in the shoulder load blocks must be greater than that of the base load blocks. Data for each thermal unit was used to determine the maximum annual energy production of the units, and historical hydro production data was used to determine the average maximum and minimum energy production of each hydro unit in a single period. Additionally, the variable production costs of hydro power are assumed to be zero.

$$vProduct_{p,s,n,t} \leq pMaxProd_t \times vCommit_{p,s,t} \qquad \forall p, s, n, t$$

$$vProduct_{p,s,n,t} \geq pMinProd_t \times vCommit_{p,s,t} \qquad \forall p, s, n, t$$

$$vProduct_{p,s,n,h} \leq pMaxProd_h \qquad \forall p, s, n, h$$

$$vProduct_{p,s,n+1,g} \leq vProduct_{p,s,n,g} \qquad \forall p, s, n, g$$

$$pMaxProd_g = pRatedMaxP_g \times \left[1 - pEFOR_g\right] \times pInstalled_g \qquad \forall g$$

$$\sum_{p,s,n} vProduct_{p,s,n,t} \leq 8760 \times pMaxPlantFac_g \times pMaxProd_t \qquad \forall t$$

$$\sum_{s,n} vProduct_{p,s,n,h} \cdot pDuration_{p,s,n} \leq pAPProdhmax_{h,p} \qquad \forall h, p$$

$$\sum_{s,n} vvProduct_{p,s,n,h} \cdot pDuration_{p,s,n} \geq pAPProdhmin_{h,p} \qquad \forall h, p$$

where $pRatedMaxP_g$ is the rated capacity of the generating unit, $pEFOR_g$ is the equivalent forced outage rate of each unit, $pMaxPlantFac_g$ is the fraction indicating the maximum generation that is feasible in a single year for each thermal unit, $pMinProd_g$ is the minimum production of a committed thermal unit, and $pAPProdhmax_{h,p}$ and $pAPProdhmin_{h,p}$ are the maximum and minimum production of each hydro unit in a single period, respectively. Finally, once built and installed, thermal units can be committed as follows:

$$vCommit_{p,s,t} \leq pInstalled_t \qquad \forall p, s, t$$

### 3.3.5 Additional Model Outputs

The "Annual Power Grid Operation" module determines the following values, which it passes to the "Electricity Price and Power Company Cash Flow" module:

$$ACC = \sum_{g} (pAnCap_g + pFixedOM) \cdot pInstalled_g \qquad --[15]$$

$$NSE = \sum_{p,s,n,nd} pDuration_{p,s,n} \cdot vENS_{p,s,n} \qquad --[16]$$

$$TD = \sum_{p,s,n} pDuration_{p,s,n} \cdot \left[pDInd_{p,s,n} + \ pDRes_{p,s,n}\right] \qquad --[17]$$

$$Cons = TD - NSE \qquad --[18]$$

$$FSTD = 1 - \frac{NSE}{Cons} \qquad --[19]$$

where *ACC* is the annualized capacity costs of installed generating units, *NSE* is annual non-served grid demand, *TD* is the total energy demanded over the year, and *FSTD* is the fraction of served to total grid demand. The module also passes along *vNSEC* and *vProdC*, the annual costs of non-served energy and the annual variables costs of electricity production, respectively.

### 3.3.6 Generation Representation

The supply mix in Tanzania consists of hydro and thermal based generation. As described in Section 1.1.1, Tanesco owns and operates units but power is also generated by IPPS. At the time of building the model and writing the thesis, the involvement of IPPs was ambiguous. Due to numerous legal disputes between IPPs and Tanesco, some IPP generating units were left idle. Therefore, only Songas units are captured in the model. Additionally, the relationship between Songas and Tanesco is not explicitly represented. As agreed in the power purchase agreements, Songas is paid (by Tanesco) a fixed tariff for injecting power into the national grid. As described in Section 3.3.1, this fixed tariff appears as Tanesco's variable operating cost of the IPP units.

## 3.4 Grid Electricity Price and Power Company Cash Flow

This module takes as input (i) variable grid operational costs (ii) residential and industrial consumption and (iii) the annualized costs of generation capacity in order to keep track of the cash flow of the utility and to determine the price of electricity. See Figure 3-8.

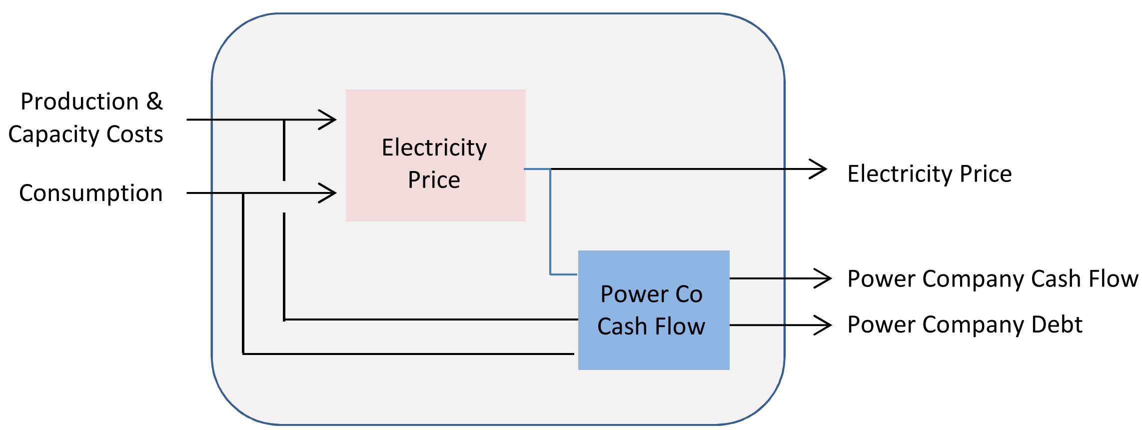


**Figure 3-8: Diagram of Electricity Price & Power Company Cash Flow Module**

Electricity prices are calculated to recover the utility's costs of supplying power. Additionally, the utility must pay taxes on each unit of energy supplied. Government tax is set at 20% and an additional charge of 3% of unit sales must be paid to REA for rural electrification. The taxes are passed directly to the consumer and the price of grid electricity is determined as:

$$el\,price_{grid} = \frac{vProdC + vCommitC + ACC}{Cons} \times (1 + tax_{REA} + tax_{gov}) \qquad --[20]$$

Additional pricing options are built into the model. Prices can be fixed over the horizon of the model or change according to [20]. In Tanzania, however, EWURA regulates the price of grid power. Thus prices change after some regulation delay. Accordingly, an exogenous variable *reg_delay* is introduced to capture this effect. For example, the regulator may revise grid electricity prices once every three years. In this case, the price incurred by customers will change as depicted in Figure 3-9.

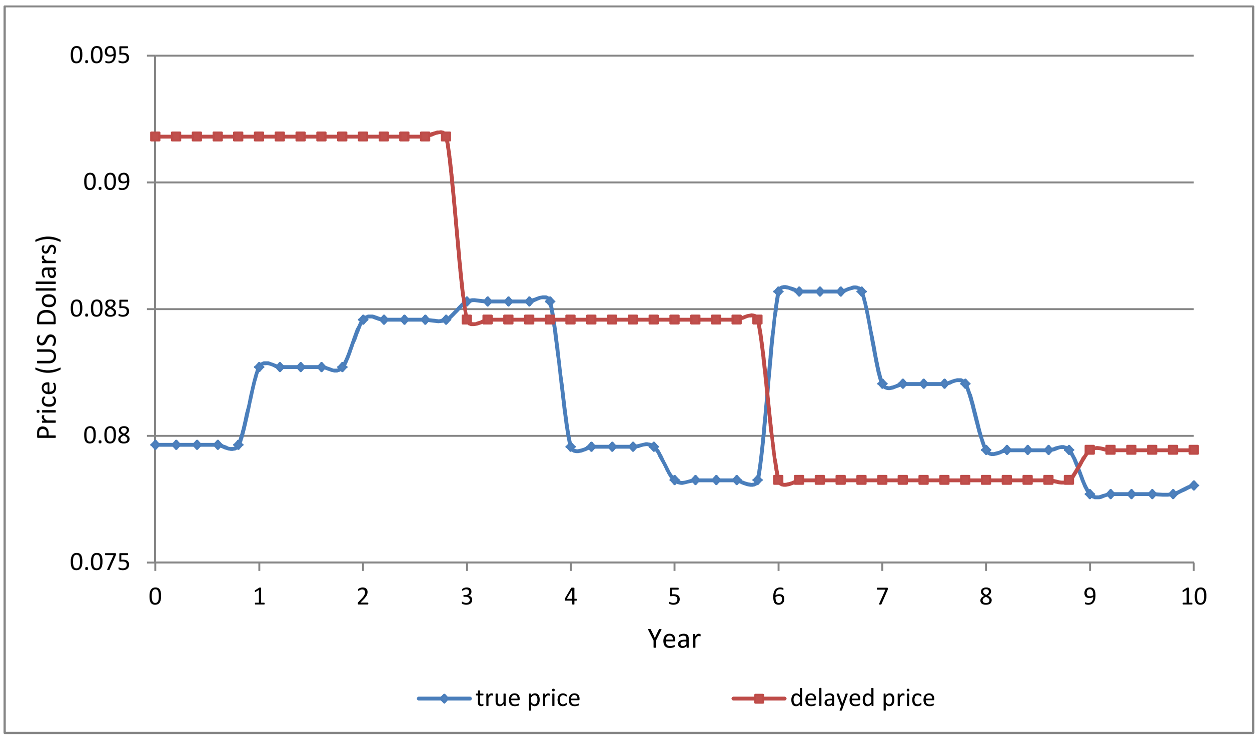


**Figure 3-9: Changing prices of electricity (the "true price" shown in blue) and the price charged to consumers (the "delayed price" shown in red) in the case of a 3-year regulation delay**

The price incurred by grid customers can be adjusted to charge a higher rate to residential customers; this is the case in most East African countries today. This is captured by introducing a residential tariff factor, which is a value greater than 1, that indicates the increase in tariff paid by residential consumers and the decrease in tariff paid by industrial consumers.

$$el\,price_{res} = el\,price_{grid} \times tariff\ factor$$

$$el\,price_{ind} = el\,price_{grid} \div tariff\ factor$$

Power company cash flow is the difference between the utility's sales revenue and costs of electricity supply and new generating capacity. Revenue is calculated as the residential and industrial unit sales multiplied by the prices charged, and the revenue collected by the utility is a function of meters read and bills collected. As described in Section 1.1, Tanesco has historically lost tremendous revenue[20] due to the poor ability of the company to read meters and collect money.

$$revenue_{sales} = \{(cons_{ind} \cdot el\,price_{ind}) + (cons_{res} \cdot el\,price_{res})\} \times \%meters\ read\ \times \%bills\ collected$$

The costs of supply are comprised of variable electricity production costs, annualized capacity costs and taxes. Additionally, funds are often misallocated due to corruption within the utility. As described in Steel (2008), a "corruption tax" is used to capture this reality.

$$utility\ costs_{supply} = vProdC + ACC + TaxC$$

$$TaxC = revenue_{sales} \times \left\{ tax_{corruption} + \frac{tax_{REA} + tax_{gov}}{1 + tax_{REA} + tax_{gov}} \right\}$$

where *vProdC* and *ACC* are as defined in [12] and [15], respectively.

Low or negative cash flow results in the utility having to obtain external funding. As in Steel (2008), this funding is assumed to come from international lending or development aid, which increases debt. Therefore, each year the utility's cash flow is reduced even more by debt repayment. On the other hand, each year the government bails out the utility, covering a portion of its costs. This is due to the close relationship between the utility, Tanesco, and the

[20] The losses in revenue are assumed to be absorbed by Tanesco and do not impact the price of electricity experience by grid customers.

government, the Ministry of Energy and Minerals. Power company cash flow[21] and debt are defined as:

$$Cash\ Flow = revenue_{sales} - utility\ costs_{supply} - interest_{debt} - debt\ repayment \qquad --[21]$$

$$Debt = -\int cashflow + bailout + debt\ repayment \qquad --[22]$$

Power company cash flow and debt are not assumed, in this model, to impact the budget available for capacity expansion. The capacity expansion approach that uses the simulation model to inform planning is presented in detail in Chapter 5.

## 3.5 Simulating N Years

Sections 3.1 to 3.4 describe the four critical modules of the simulation model. Executing the modules in the following order simulates a single year of power system operation:

Electricity Adoption & Customer Choice

↓

Grid Electricity Demand

↓

Annual Power Grid Operation

↓

Power Company Cash Flow & Electricity Prices

In order to simulate N years, the model user enters (a) the pricing policy (fixed or changing price, with or without regulation delay) and (b) the size of and year that new generating units become operational. Next, the simulation model executes the four critical modules N times, each time running the modules in the order described above. Finally, time-series data is generated at the output (see Figures 1.1 and 3.1). This process is facilitated by the software platform on which the model is built. The software is described in the following section, and Section 4.2

[21] This formulation neglects the costs of power company payroll.

demonstrates how to simulate twenty years of power system operation for a particular set of decisions.

## 3.6 Implementation

In order to link the system dynamics subsystems (that capture electricity adoption, changing electricity demand and power company cash flow) to the annual power grid operations module (built using General Algebraic Modeling System[22] (GAMS)), two options were explored: the Vensim® simulation environment and Matlab's Simulink®.

The Vensim environment "emphasizes information feedback and icon-based modeling with a clear portrayal of the 'stocks' and 'flows' ", and it allows one to call external functions during the simulation via a Dynamic Link Library (Dimitrovski, Ford and Tomsovic 2007). Simulink uses icon-based modeling as well; however emphasis is on "explicit mathematical representation of the relations among the system variables". Simulink has been used widely throughout academia to represent coupled sets of first-order differential equations because of its "ease of use, versatility and large library of functions". Simulink allows one to call external functions using either the Embedded MATLAB functions or Embedded S-blocks (these blocks include MATLAB code that generates embeddable C code).

Because the simulation model must be used to inform capacity expansion planning, the Simulink software was employed. This provided access to MATLAB's large optimization and heuristic optimization library of tools as well as the flexibility to develop unique algorithms not available in MATLAB's toolboxes. In order to call the annual power grid operations module from Simulink, an Embedded MATLAB function block was used to make system calls to the GAMS model.

## 3.7 Summary of Simulation Model

The model described in this chapter simulates the evolution of a Tanzania-like power system. It takes as input the size of and years in which new generating capacity comes online; it can also

---

[22] The General Algebraic Modeling System (GAMS) is a high-level modeling system for mathematical programming and optimization. It consists of a language compiler and a stable of integrated high-performance solvers. (www.gams.com)

take various pricing policies as input. By sequentially executing the four critical modules, the model generates time series data, including the changing customer stocks and grid demand, grid supply costs, non-served grid demand, and power company cash flow.

More importantly, grid demand is endogenous to the model. It is comprised of both residential and industrial demand, where residential demand grows as new household connect to the national grid and industrial demand grows with the economy. The choice to select the national grid as a supply source is a function of the price of grid power, the reliability of the grid, *ie* the fraction of served to total demand, grid connection costs, and, for residential consumers, the quality of supply and the backlog of customers awaiting a connection.

Unlike the model presented by Steel (2008), this model neglects urbanization, resource depletion, and the volatility of the exchange rate. This model, however, captures the detailed operation of the electric grid by calling a medium-term operational model that includes hydro-thermal coordination and unit commitment. Chapter 4 demonstrates simulation model behavior.

# Chapter 4 Parameter Definition, Simulation Model Testing and Sensitivity Analysis

The United Republic of Tanzania is the motivating case of this research. This chapter begins with a description of the parameter definition procedure used to fit simulation output to Tanzania's historical data. Basic model behavior is then illustrated by testing various capacity expansion strategies and pricing policies as input. While the parameters were fixed to match Tanzania data, some model parameters remain uncertain. Therefore, the results of a sensitivity analysis are described to demonstrate the impact of changes in these parameter values on model behavior. The chapter closes with a discussion of the limitations of the simulation model and future extensions.

## 4.1 Parameter Definition

Electricity adoption and consumer choice are key features of the simulation model described in Chapter 3. Many of the model parameters used to simulate these social processes are uncertain. For example, electricity adoption depends on the rate at which households with electricity access interact with those without electricity, and the probability that such an interaction will cause a home to start using electricity. Similarly, the fraction of electricity adopters that choose to purchase solar home systems depends on their sensitivity to capital costs, per unit electricity price, the fraction of served demand to total demand, the perceived quality of the supply and the backlog of customers waiting for service. For the case of Tanzania, information on these parameter values was not available during the time of research so they were estimated.

Ideally, a formal statistical calibration would be performed to fit parameters listed in Table 4-1 to at least twenty years of historical data. An example of the approach can be found in Sterman (1984). Data was collected from MEM, Tanzania'a Rural Energy Agency (REA), Tanesco, EWURA and the World Bank during multiple visits to Tanzania. However, information was missing and there was only enough data to completely represent a period of four years: 2006 to 2009. Therefore, model parameters were initially set to values assumed in the power system model of Kenya (Steel 2008), a country bordering Tanzania with a similar population. Next, the

Parameter Estimation[23] tool of MATLAB's Simulink software was used to fit the number of households connected to the national grid and aggregate grid demand to the four years of Tanzania data. During estimation, the number of grid customers and total grid demand were weighted by the standard deviation of respective data.

| | |
|---|---|
| Contact Frequency | ✗ |
| Adoption Fraction | ✗ |
| Demand Profile Scale Factor[24] | ✓ |
| Sensitivity to Capital Costs | ✓ |
| Sensitivity to Reliability | ✓ |
| Sensitivity to Electricity Price | ✓ |
| Sensitivity to Quality | ✗ |
| Sensitivity to Backlog Ratio | ✗ |

**Table 4.1: Model parameters estimated for the case of Tanzania. Entries not checked were fixed to values assumed in Steel (2008)**

In order to estimate these model parameters, the following time-series data was used:

- Residential grid customers
- Annual grid demand
- Electricity price of supply options
- Capital costs of supply options
- Grid generation & transmission capacity

Collecting key data was a challenge. For example, it was difficult to assess the production capacity of the grid over time as Tanzania has experienced reduced hydro availability due to drought and thermal units were forced to sit idle due to legal disputes with the IPPs. Since the available capacity of the grid was not known, the Annual Power Grid Operation module was disconnected from the simulation model, and historical data on load shedding and grid electricity price was exogenously fixed as model input during the estimation procedure.

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[23] The Parameter Estimation was performed using the nonlinear least squares method and the trust-region reflective algorithm. The following settings were assumed: parameter tolerance is 0.001, maximum function evaluations is 400, maximum iterations is 100, and function tolerance is 0.001

[24] The demand profiles of both residential and industrial consumers were estimated based on data gathered in Tanzania (see Section 3.2). Scale factors are multiplied by these demand profiles to improve the estimates and match historical data.

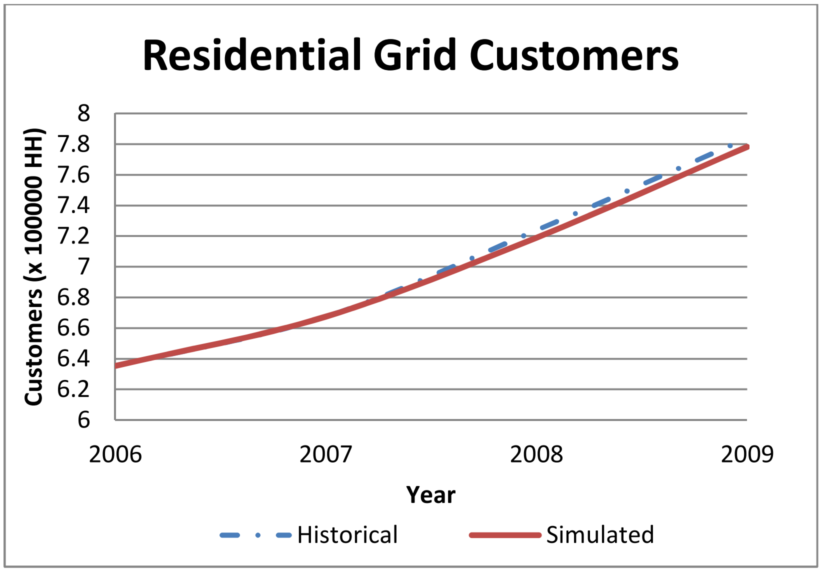


**Figure 4-1: Comparison of model generated and historical residential grid customers**

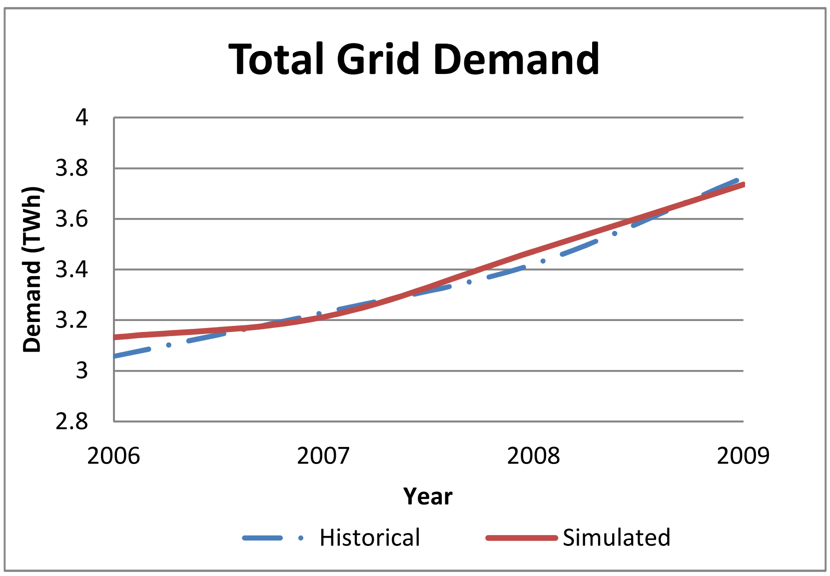


**Figure 4-2: Comparison of model generated and historical grid demand**

The focus of this research is to develop a novel approach to planning and to demonstrate this approach by applying it to a simplified representation of the Tanzanian power system. The results, depicted in Figures 4-1 and 4-2, show that the simulation model reproduces the qualitative trends of the Tanzanian power system. The $R^2$ values for the number of grid connected households and total grid demand are 0.99 and 0.97, respectively. See APPENDIX for a table of final estimated simulation parameter values, hereto referred to as "Base Case Parameter Values".

## 4.2 Simulation Model Testing: System Behavior under Reference Assumptions

The aim of this section is to illustrate simulation model behavior. As briefly described in Chapter 3, the simulation model takes as input a single capacity expansion strategy along with a single pricing policy, and simulates twenty years of power system operation. This section explores the impact of capacity expansion strategies and pricing policies on grid reliability, grid electricity prices, consumer behavior and grid demand. For all simulations presented in this section, parameter values are set to the levels determined during parameter estimation, and all other input data and stocks are set to the 2008 values provided in the PSMP (Tanesco 2009).

### 4.2.1 The Impact of Various Expansion Strategies on Grid Demand

For the purpose of model testing, I assume that new hydro and thermal capacity are added to the grid in years 1 and 11 of the twenty year simulation. The size of new capacity is assumed to be:

| Plant Name | Plant Type | Size per Unit (MW) |
|---|---|---|
| H1 | Hydro | 150 |
| H2 | Hydro | 300 |
| T1 | Thermal | 60 |
| T2 | Thermal | 200 |

Grid electricity prices[25] are assumed to vary over time without regulatory delay, and the electric utility is able to meet all requests for grid connections.

The simulation model takes as input a single capacity expansion strategy. The strategy indicates when and how many additional generating units will become operational. I consider three expansion strategies to illustrate the behavior of the simulation model.

[25] Prices are calculated to cover capacity and production costs as described in Section 3.4. Under this pricing policy, power company debt does not accumulate.

| Expansion Strategy | Year 1 | | | | Year 11 | | | | Summary |
|---|---|---|---|---|---|---|---|---|---|
| | H1 | H2 | T1 | T2 | H1 | H2 | T1 | T2 | |
| None/No | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | No new capacity is added to the grid. |
| Gradual | 3 | 0 | 1 | 0 | 0 | 1 | 10 | 0 | 450MW of hydro and 60MW of thermal capacity is added in year 1. 300MW of hydro and 600MW of thermal capacity is added in year 11. |
| Delayed | 0 | 0 | 0 | 0 | 2 | 1 | 15 | 0 | 600MW of hydro and 900MW of thermal capacity is added in year 11. |

**Table 4.2: Capacity expansion strategies used to demonstrate simulation model behavior. Columns 2-9 of the table indicate the number of additional generating units that become operational in the specified year**

Expanding generating capacity directly impacts grid reliability (Figure 4-3). Grid reliability is considered to be the fraction of served grid demand to total grid demand. Under all three capacity expansion strategies, total grid demand increases over time. If no new capacity is added to the system, the fraction of served to total grid demand will decline. This dynamic is depicted in the "No" expansion case. On the other hand, when new generating units are added to the system, the additional capacity can supply more power to meet demand, and reliability will remain at or approach one before gradually declining. This trend is demonstrated in Figure 4-3 under the "Gradual" and "Delayed" expansion strategies.

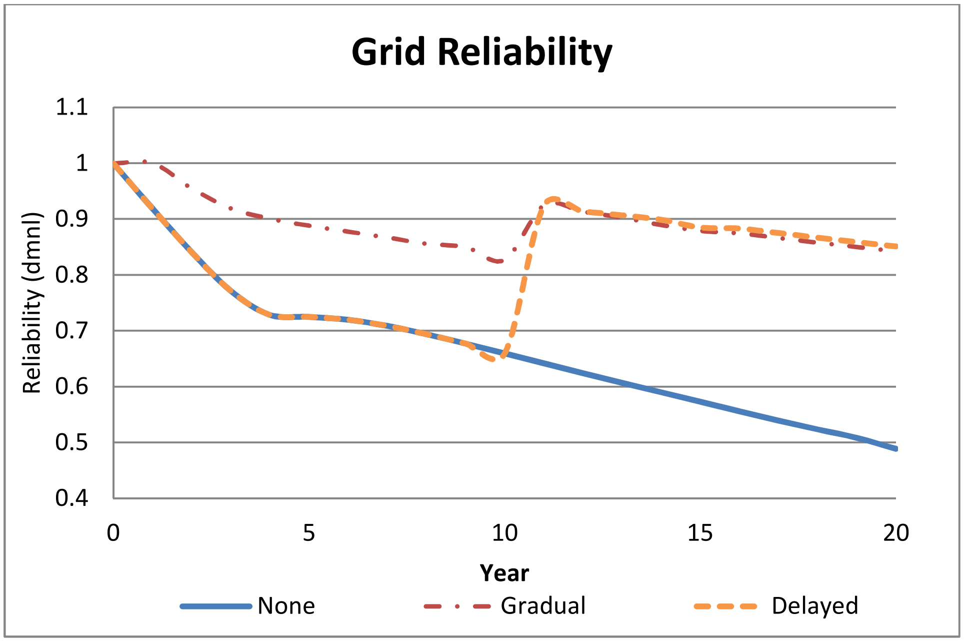


**Figure 4-3: Grid reliability under three expansion strategies. Since demand is increasing, reliability declines when no new capacity it added to the grid. Reliability remains at or increases closer to one as new capacity is added under the "Gradual" and "Delayed" expansion strategies.**

Expanding generating capacity also directly impacts electricity prices through more complicated power grid dynamics. Electricity price is driven by annualized capacity costs and the variable cost of power production. As demonstrated in equation [15], annualized capacity costs include the fixed O&M costs of all units as well as the fixed investment costs amortized over the lifetime of the plants. The addition of new generating capacity increases annualized capacity costs but the total variable cost of power production depends on the sum of previously installed and newly installed generating capacity as well as the amount of energy production required to meet demand.

More specifically, the ratio of grid-wide hydro to thermal power production can have a significant effect on total variable costs. Hydro is dispatched before thermal power because it is produced at zero variable costs; thermal power is produced at non-zero costs to account for the cost of fuel. Once new hydro is introduced to the grid, the substitution of new hydro production for previous thermal production reduces total variable costs. When the reduction in the total variable cost of power production is larger than the annualized investment costs, electricity prices decrease. This dynamic occurs in year one under the "Gradual" expansion strategy, depicted in Figure 4-4. On the other hand, when the reduction in the total variable cost of power production is less than the annualized capital costs, electricity prices increase. This is demonstrated under the "Gradual" expansion strategy during years ten to eleven (Figure 4-4).

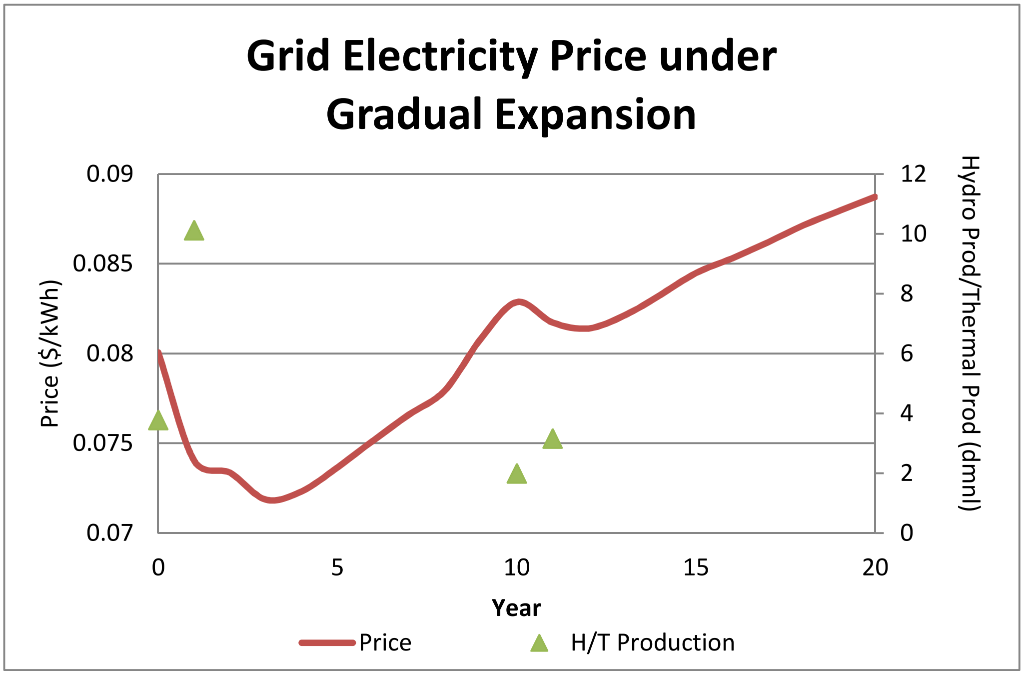


**Figure 4-4: Grid electricity price under "Gradual" expansion. The ratio of hydro to thermal power production increases with the introduction of new generating capacity in years 1 and 11. Electricity price decreases in year 1 as the reduction in variable costs exceeds the increase in annualized capacity costs. Electricity price increases in year 11 as the reduction in variable costs is less than the additional costs of new capacity.**

The amount of production required to meet growing demand also has an effect on total variable costs. If no additional generating capacity is added to the system and demand exceeds hydro production, then thermal production will increase with growing demand. This increase in thermal production causes the total variable costs of production to rise. Subsequently electricity prices increase. This dynamic can be observed in the first five years under "No" capacity expansion (Figure 4-5). Similarly, if demand declines then the ratio of hydro to thermal power production increases. Total variable production costs decrease and so do electricity prices. This is depicted in years five through ten under "No" expansion (Figure 4-5).

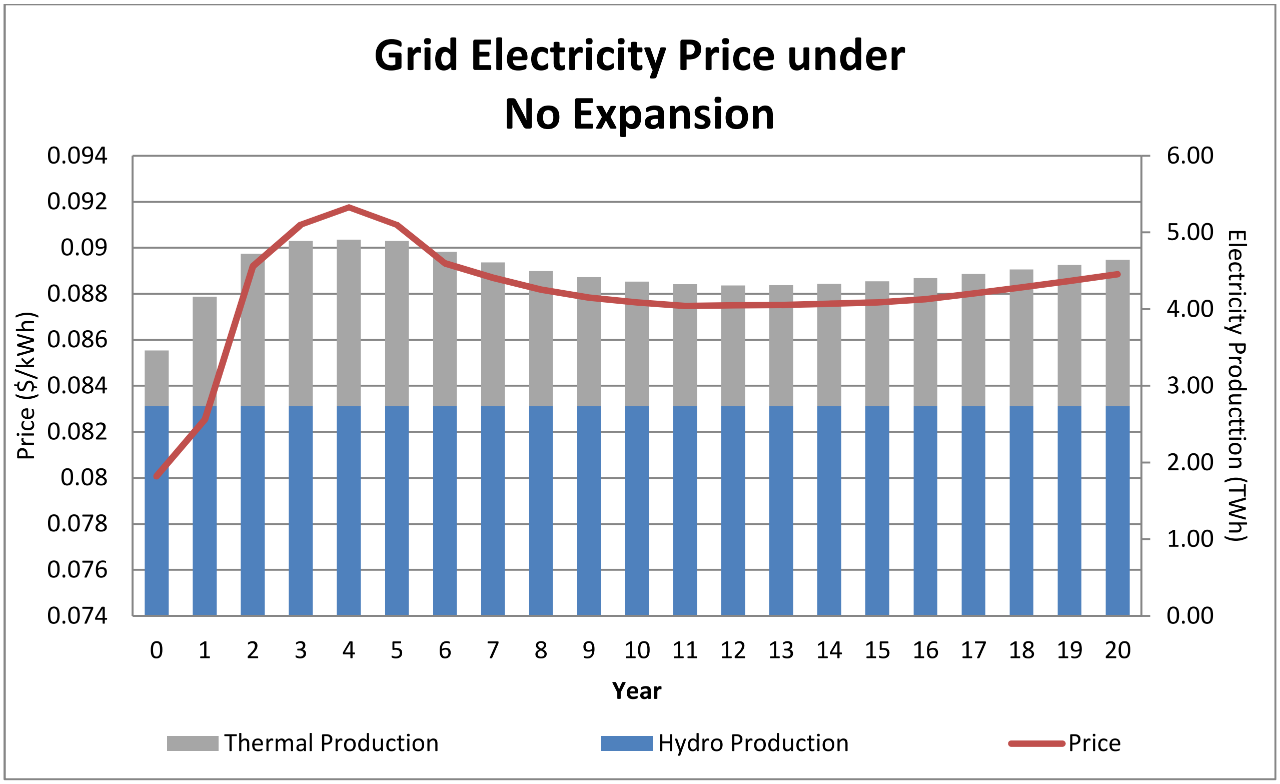


**Figure 4-5: Grid electricity price under "No" expansion. As thermal production increases and decreases to meet changing grid demand, grid price also changes.**

The grid price observed under the "Delayed" expansion strategy can also be explained by the dynamics described above. When additional generating capacity is added to the system in year eleven, there is a sharp increase in price resulting from the increased capacity costs. At the same time, electricity production rises to meet demand. Figure 4-6 depicts this jump in electricity price as well as an increase in electricity consumption. As demand continues to grow beyond year eleven, consumption rises and, with the addition of new hydro production capacity, the ratio of hydro to thermal production also increases. This decreases the average costs of production and electricity prices begin to decline. This decrease in price is observed until demand grows so large that the ratio of hydro to thermal production starts to decrease.

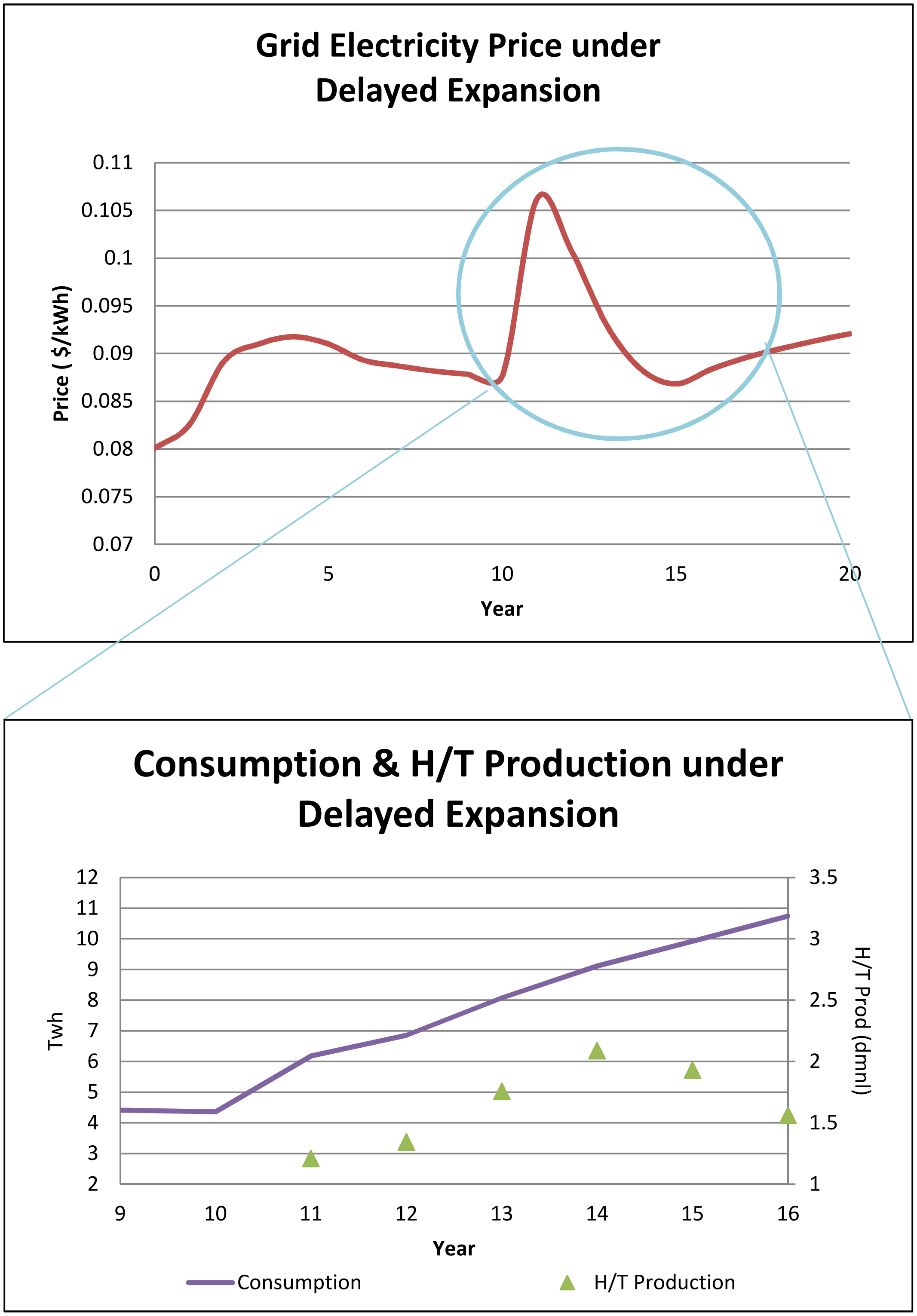


**Figure 4-6: Grid electricity price under "Delayed" expansion. The sharp increase in price results from the addition of new generating capacity. The decrease in price follows as the ratio of hydro to thermal production increases.**

Changing reliability and electricity price in turn have an impact on consumer choice, *i.e.* the fraction of residential electricity adopters requesting a grid connection and the fraction of industrial demand served by the grid. As described in Chapter 3, the fraction of residential adopters requesting a grid connection and the fraction of industrial demand served by the grid is determined using the multinomial logit choice model. This model calculates the fraction of consumers choosing grid power as the ratio of grid attractiveness to the sum of the attractiveness of all supply options, and high electricity prices and low reliability reduce the attractiveness of an electricity supply option.

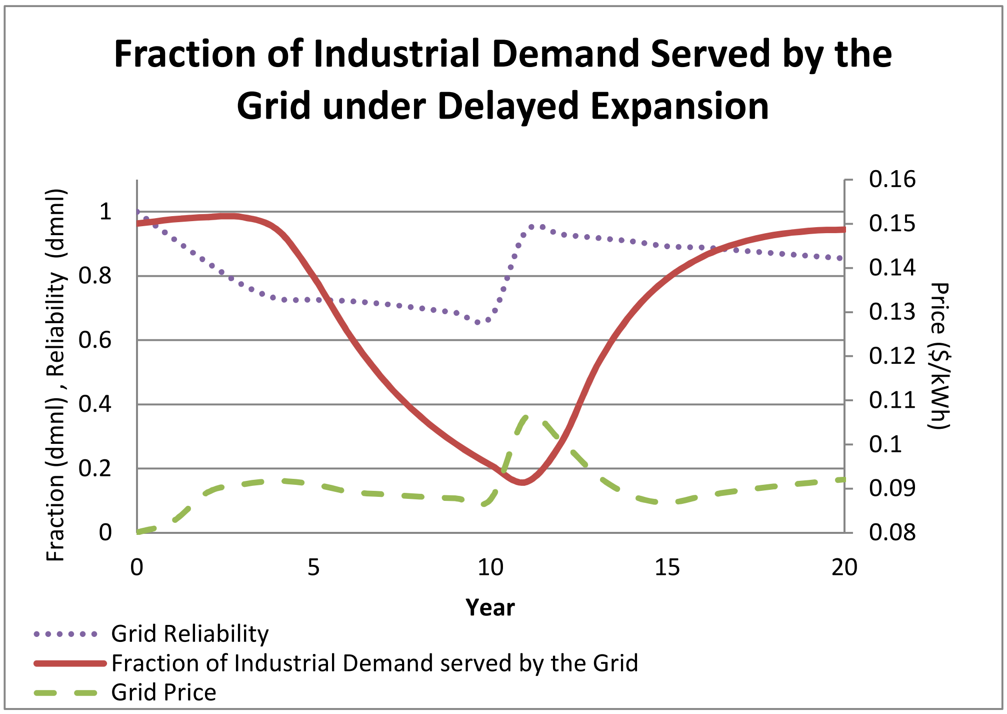


**Figure 4-7: The fraction of industrial demand served by the grid under "Delayed" expansion follows grid reliability and the inverse of grid price with delay.**

The fraction if industrial demand served by grid power follows grid reliability and the inverse of grid electricity price. For example, Figure 4-7 depicts grid reliability and electricity price along with the fraction of industrial demand served by grid power under the "Delayed" expansion strategy. Initially, prices increases and reliability declines as no new generating capacity is added to the system. The fraction of industrial demand served by the grid also declines after some delay. When new capacity is added to the system in year eleven, grid reliability increases but there is also a sharp increase in electricity price. By year twelve, grid prices begin to decline and reliability is higher than its value before the addition of new generating capacity. Accordingly, the fraction of industrial demand served by grid power begins to increase.

This interaction between grid price, grid reliability and consumer choice is demonstrated for both industrial and residential consumers under all expansion strategies. Figure 4-8 depicts the fraction of industrial demand served by the grid and Figure 4-9 depicts the fraction of residential electricity adopters requesting a grid connection. As described above for industrial consumers, a decrease in reliability or an increase in grid price causes a decrease in the fraction of adopters that choose grid power; when reliability increases or grid price decreases, the fraction of adopters requesting a grid connection increases.

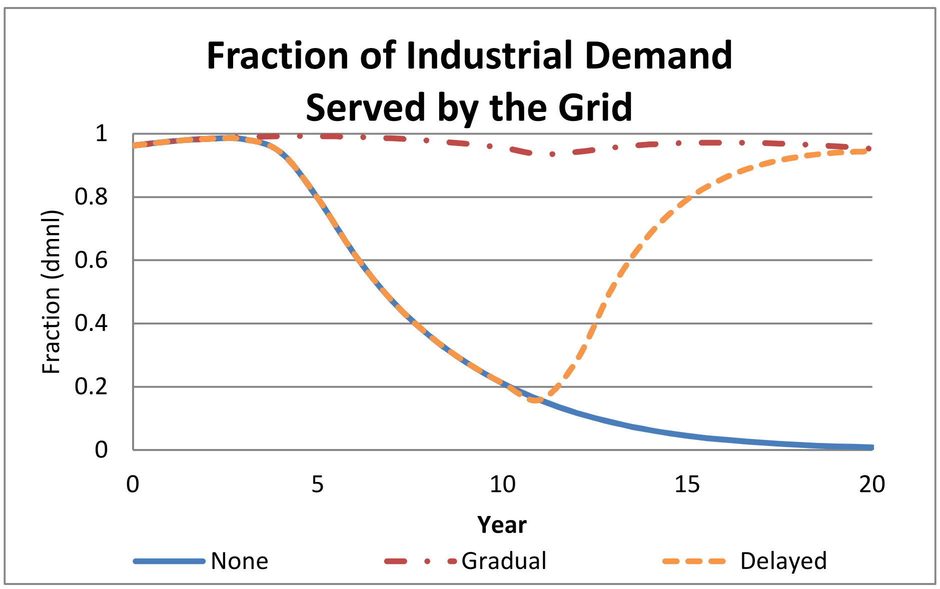


**Figure 4-8: The fraction of industrial demand served by the grid under the three expansion strategies. Consumer choice is impacted by grid reliability and grid price.**

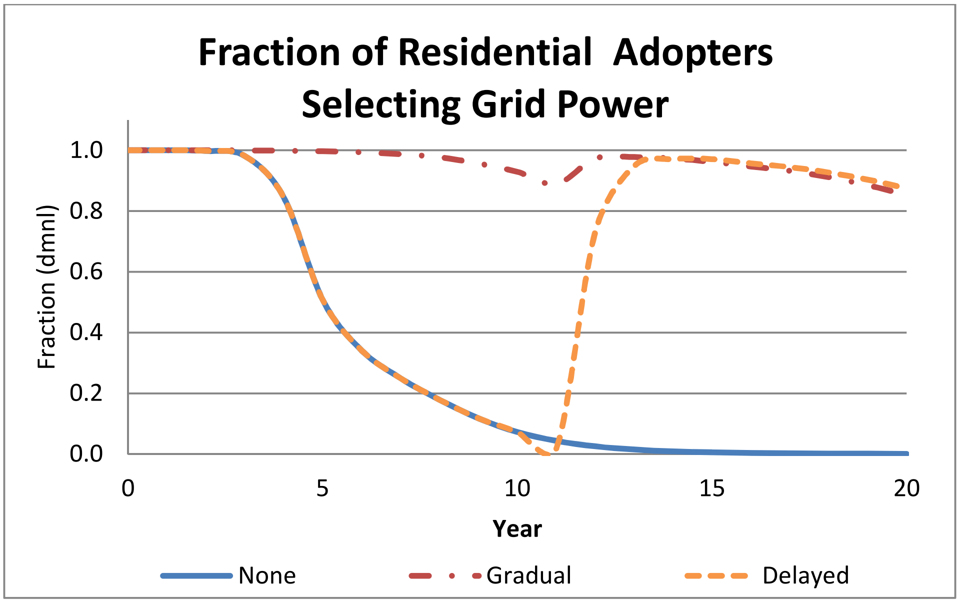


**Figure 4-9: The fraction of residential electricity adopters selecting grid power under the three expansion strategies. Consumer choice is impacted by grid reliability and grid price.**

Customer choice directly impacts total grid demand. When the fraction of industrial demand served by grid power is small, industrial consumers are powering up their diesel generators or off-grid supply options to satisfy demand. Therefore, industrial grid demand (Figure 4-10) directly follows the fraction of industrial grid demand served by grid power (depicted in Figure 4-8). Over the duration of the mode, I assume that GDP grows. As described in Chapter 3, an increase in GDP causes an increase in aggregate industrial demand. Therefore, when the fraction of industrial demand served by the grid is constant (as in the "Gradual" expansion case), industrial grid demand rises.

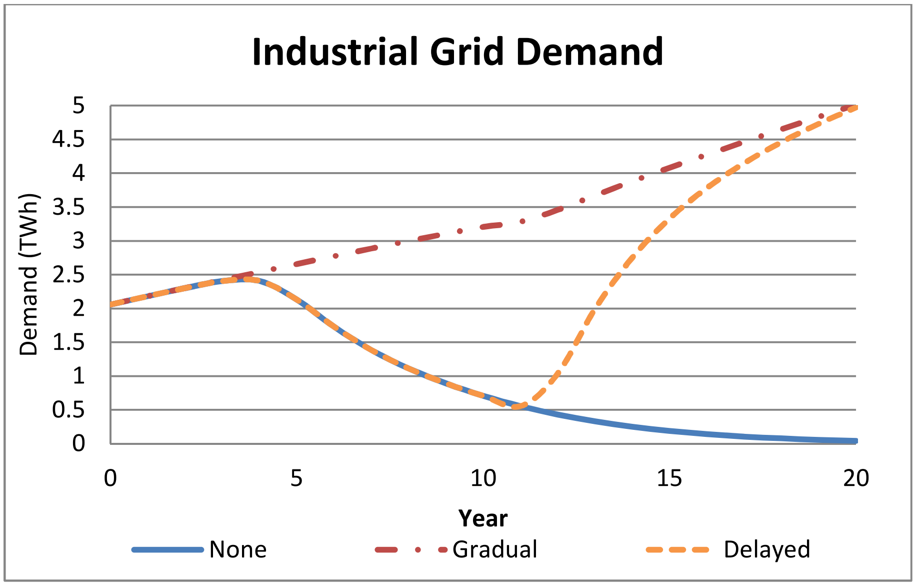


**Figure 4-10: Industrial grid demand under the three expansion strategies. Industrial grid demand is directly impacted by the fraction of industrial demand served by grid power (depicted in Figure 4-8). The increase in demand results from growing GDP.**

The fraction of electricity adopters requesting a grid connection directly impacts the number of residential grid customers and, subsequently, residential grid demand. When the fraction of electricity adopters selecting grid power is low, new electricity adopters are discouraged from requesting a grid connection and, as a result, select off-grid diesel generators or solar home systems to meet their electricity needs. Unlike industrial consumers, however, pre-existing residential grid customers remain connected to the grid and do not switch electricity supply sources. For example, when no new generating capacity is added to the grid, reliability declines and the fraction of electricity adopters requesting a grid connection falls to zero by year ten. As a result, the number of residential grid customers does not increase but remains constant from year ten through twenty. On the other hand, under "Gradual" capacity expansion, the fraction of electricity adopters choosing grid power remains close to one; therefore, the number of residential customers connected to the grid grows over the twenty-year horizon and surpasses the customer stock levels observed under no expansion. See Figure 4-11.

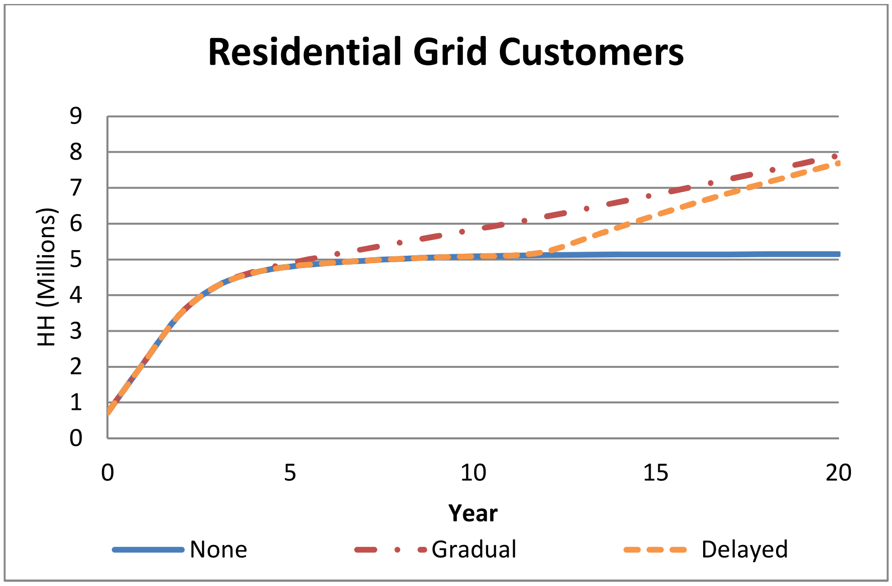


**Figure 4-11: Comparison of residential grid customers under the three expansion strategies. When no new capacity is added to the grid, residential electricity adopters are discouraged from connecting to the grid. As a result, the stock of grid customers remains constant. The number of grid customers observed under "Gradual" and "Delayed" expansion is higher than what is observed under "No" capacity expansion.**

Figure 4-12 depicts residential grid demand under the three expansion strategies. Although the stock of grid customers saturates when no new capacity is added to the system, an increase in residential demand is observed. This increase in demand results from growing GDP. Although no new residential consumers are connecting to the grid, previously existing grid customers continue to demand electricity from the grid and, as described above, an increase in GDP causes an increase in household electricity demand. Additionally, the model is formulated such that only new electricity adopters are faced with a choice of supply options. If, like industrial consumers, all residential customers were allowed to switch supply options, the variation observed between residential grid demand under the three expansion strategies would be larger.

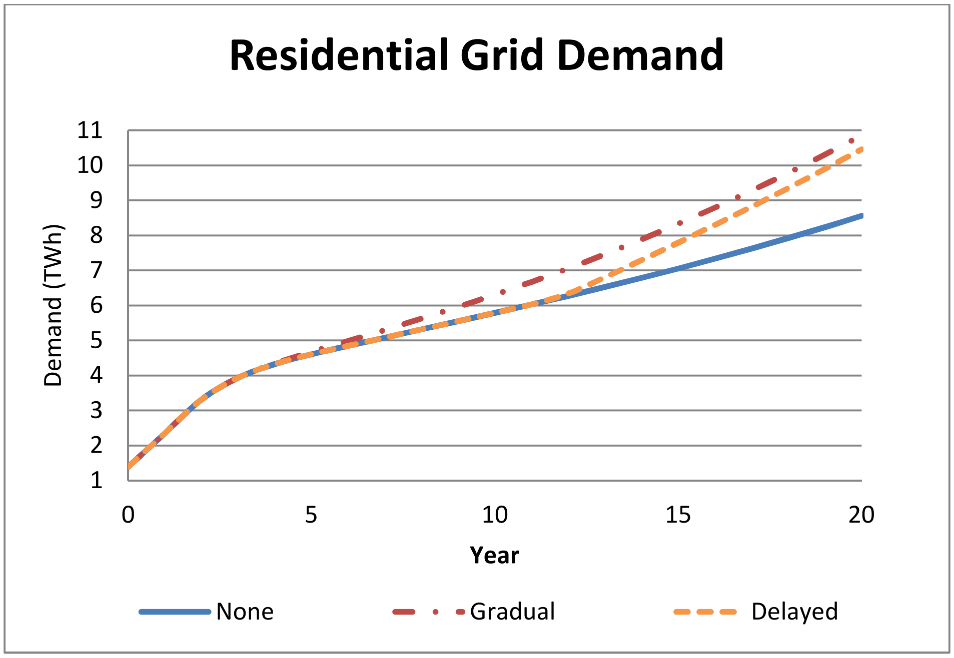


**Figure 4-12: Comparison of residential grid demand under the three expansion strategies.**

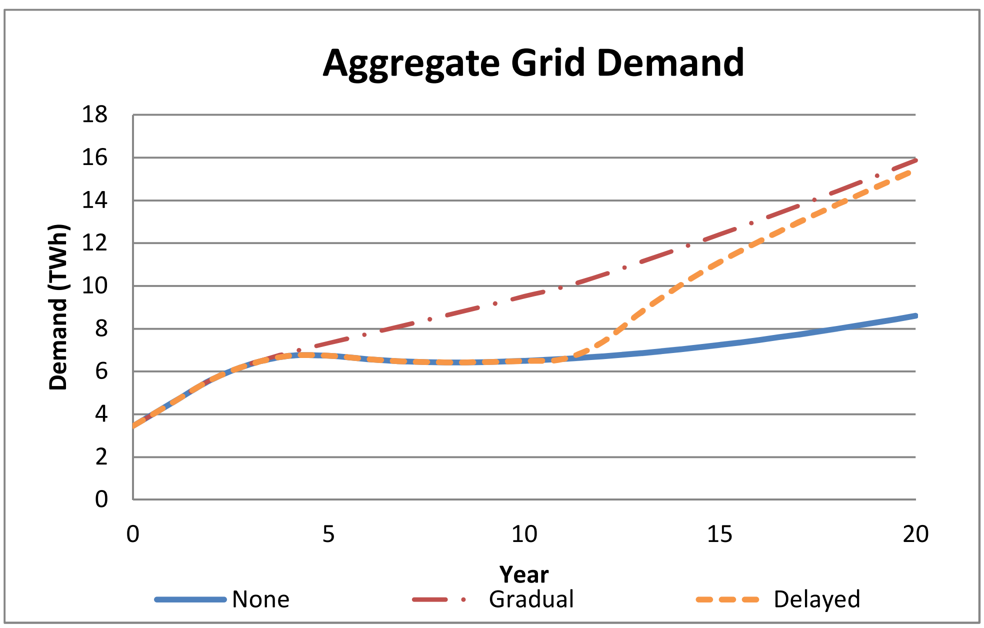


**Figure 4-13: Comparison of aggregate grid demand under the three expansion strategies. The expansion strategy largely impacts the evolution of grid demand.**

Figure 4-13 depicts aggregate grid demand under each of the expansion strategies. This figure demonstrates that the size of new generating capacity and the time in which the capacity becomes operational impacts the evolution of grid demand. More specifically, the addition of new generating capacity impacts grid reliability and electricity price, which in turn affects the evolution of grid demand through customer choice. As the aim of power planners is to meet growing demand at minimum cost, understanding and considering the endogenous evolution of grid demand is critical. Chapter 5 will demonstrate capacity expansion planning assuming endogenous demand.

#### *4.2.1.1 The Effect of Backlog on Customer Choice & Grid Demand*

In this section, I demonstrate how grid backlog impacts the behavior of residential electricity adopters. A backlog of unmet grid connections arises when the number of desired grid connections exceeds the capacity of the utility company to make the connections. This backlog lowers consumer expectations of the availability of the grid and also lowers the attractiveness of a grid connection (Steel 2008).

In order to demonstrate the effect of backlog on customer choice, I impose an external limit on the number of grid connections that can be made by the utility each year. In year one, 80,000 grid connections can be made. The connection limit increases each year such that, by year twenty, 460,000 connections can be made. I assume that grid electricity prices vary without regulatory delay. Finally, I consider the "Delayed" expansion strategy as model input. Under this expansion strategy, 600MW of hydro and 900MW of thermal capacity is added in year 11 (Table 4-2).

Figure 4-14 depicts the fraction of residential electricity adopters requesting a grid connection along with grid reliability, grid electricity price and the perceived backlog ratio (*i.e.* the backlog ratio smoothed and delayed). Table 4-3 describes the dynamics depicted in this figure. I divide the time horizon of the model into seven intervals to describe how grid reliability, grid price and the perceived grid backlog ratio vary. Further, I describe the net impact on residential customer choice.

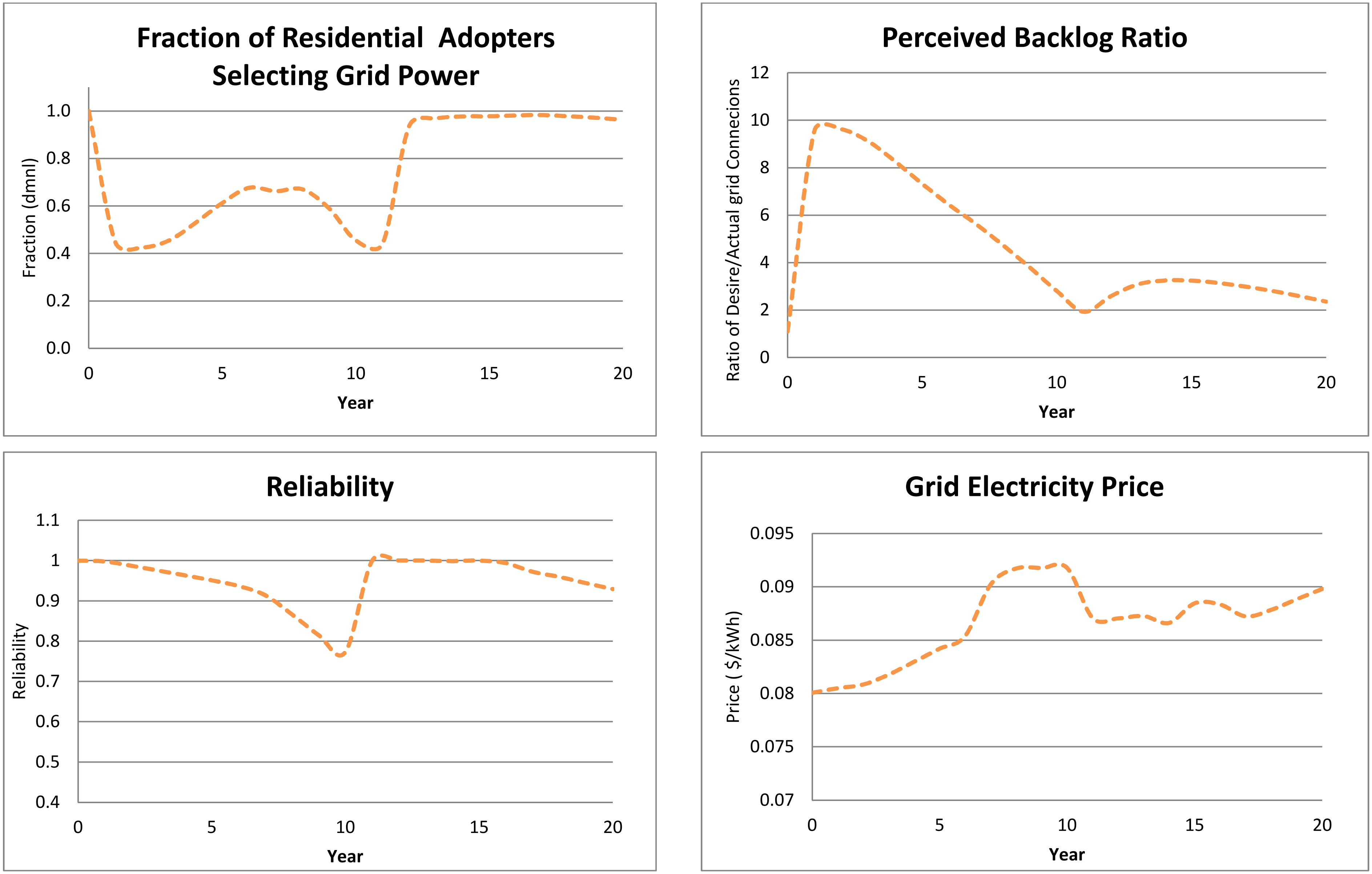


**Figure 4-14: Simulation model behavior under the "Delayed" expansion strategy. The fraction of residential adopters requesting a grid connection is impacted by the perceived backlog ratio, grid reliability, and grid electricity price.**

| Variable | Interval of 20-year Horizon | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 to 3 | 3 to 6 | 6 to 8 | 8 to 11 | 11 to 14 | 14 to 17 | 17 to 20 |
| Reliability | decrease | decrease | decrease | decrease followed by sharp increase in year 11 with the addition of new generating capacity | remains fairly constant | remains fairly constant | decrease |
| Price | increase | increase | increase | increase followed by a sharp decrease in year 11 with the addition of new generating capacity | remains fairly constant | gradual increase followed by a gradual decrease | increase |
| Perceived Backlog Ratio | sharp increase | decrease | decrease | decrease | increase | decrease | decrease |
| Fraction of Adopters Selecting the Grid | decrease | increase | constant | decrease | increase | gradual increase | gradual decrease |

**Table 4.3: Qualitative description of the trends observed in Figure 4-14. Residential choice, i.e. the fraction of electricity adopters requesting a grid connection, is largely impacted by the backlog ratio as well as grid reliability and electricity price.**

Along with reliability and grid prices, the perceived backlog ratio largely impacts customer choice. The backlog ratio, defined as the fraction of desired grid connections to actual connections made, is perceived with a small delay and weighed along with reliability, electricity price, quality and capital costs by the consumer in the residential decision model (described Section 3.1).

In years one to three, decreasing reliability, increasing electricity price and a sharply increasing backlog ratio lowers the attractiveness of the grid; as a result, the fraction of electricity adopters requesting a grid connection declines. During years three through six, declining reliability and increasing electricity price reduces grid attractiveness even further; however, the perceived backlog ratio sharply declines, improving the attractiveness of the grid. As a result, the fraction of residential adopters requesting a grid connection increases. In the period that follows (years six through eight), the perceived backlog ratio continues to decline, making the grid attractive. However, grid reliability falls below 0.9 and grid price rises above 9¢/kWh. The net impact on customer choice is that the fraction of residential adopters requesting a grid connection remains relatively constant over the three year period. These same trends in reliability, electricity price, and perceived backlog ratio persist and, from year eight through year ten, the fraction of adopters requesting grid power declines.

In year eleven, new generating capacity comes online. As a result, electricity prices decline and grid reliability sharply increases. At this point, the perceived backlog ratio has declined such that the number of desired grid connections is only twice as large (as opposed to ten times as large) as the capacity of utility to connect new customers. Therefore, the grid becomes more attractive and the fraction of electricity adopters requesting a grid connection rises dramatically between years eleven and twelve. From years twelve to fourteen, grid price remains relatively constant and so does reliability. As electricity adopters increasingly request grid connections, however, the perceived backlog ratio gradually rises. This small increase in the backlog ratio is not large enough to deter customers from requesting a grid connection. Therefore, the fraction of adopters requesting grid power increases.

Years fourteen to seventeen depict relatively constant grid reliability and a gradual increase in electricity price. During this same period, the perceived backlog ratio declines and, as a result, the fraction of electricity adopters requesting the grid gradually increases. Finally, in years seventeen through twenty, perceived backlog ratio continues to decline but the decrease in grid reliability and increase in electricity price makes the grid unattractive. Therefore, the fraction of electricity adopters that request a grid connection declines.

Overall, an increase in electricity prices, a decrease in grid reliability, or an increase in perceived backlog ratio lowers the attractiveness of the grid as an electricity supply option. Each factor (reliability, price, and backlog ratio) provides utility to a consumer, and attractiveness is the sum of the utility afforded by all factors.

Unlike residential consumers, industrial consumer choice is not impacted by the backlog ratio. As residential grid connections are limited, however, the growth in residential grid demand is also limited. The grid is less congested so reliability is higher than what is observed when there is no limit on grid connections (Figure 4-15). As a result, the fraction of industrial demand served by the grid is also higher than what was observed when there is no limit on residential grid connections (Figure 4-16).

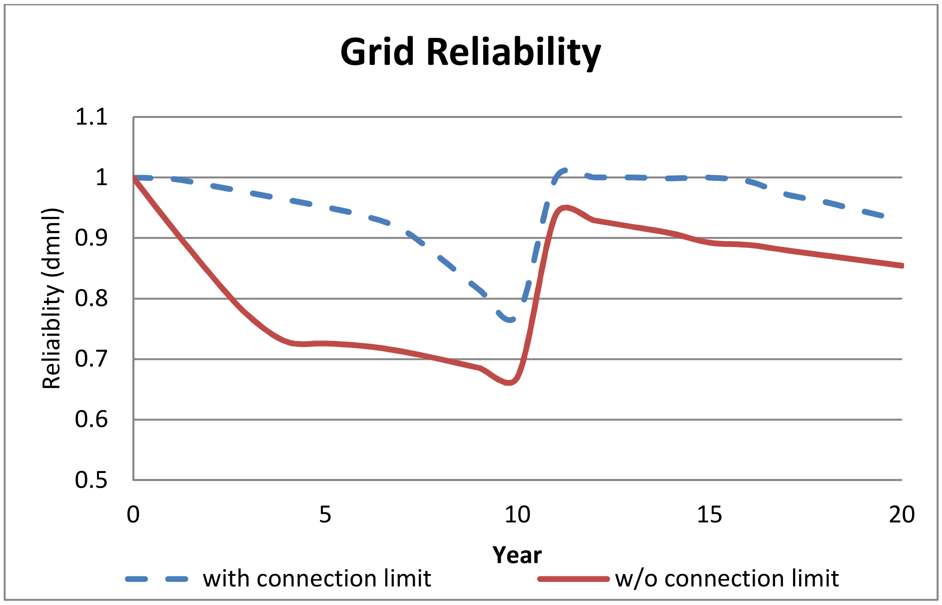


**Figure 4-15: Comparison of grid reliability with and without an external limit on the number of grid connections made per year. When there is no limit on grid connections, more electricity adopters connect to the grid, causing an increase in grid demand. As a result, reliability is lower. "Delayed" expansion is applied.**

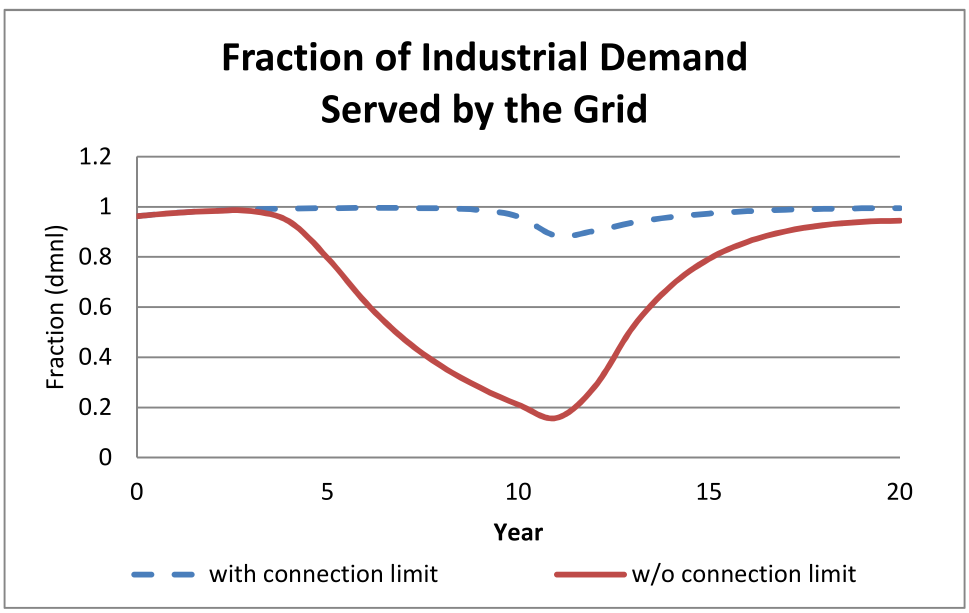


**Figure 4-16: Comparison of the fraction of industrial demand served by the grid with and without an external limit on the number of grid connections made per year. When there is a limit on residential grid connections, grid reliability is higher. This causes the grid to be more attractive to industrial customers. "Delayed" expansion is applied.**

Figure 4-17 depicts aggregate grid demand with and without a grid connection limit. The two cases show similar levels of demand when, in the case of no connection limit, reliability deteriorates such that residential electricity adopters and industrial consumers increasingly choose off-grid supply options. Overall, however, when there is a constraint on grid connections, demand is less than what is observed when there is no limit on residential connections.

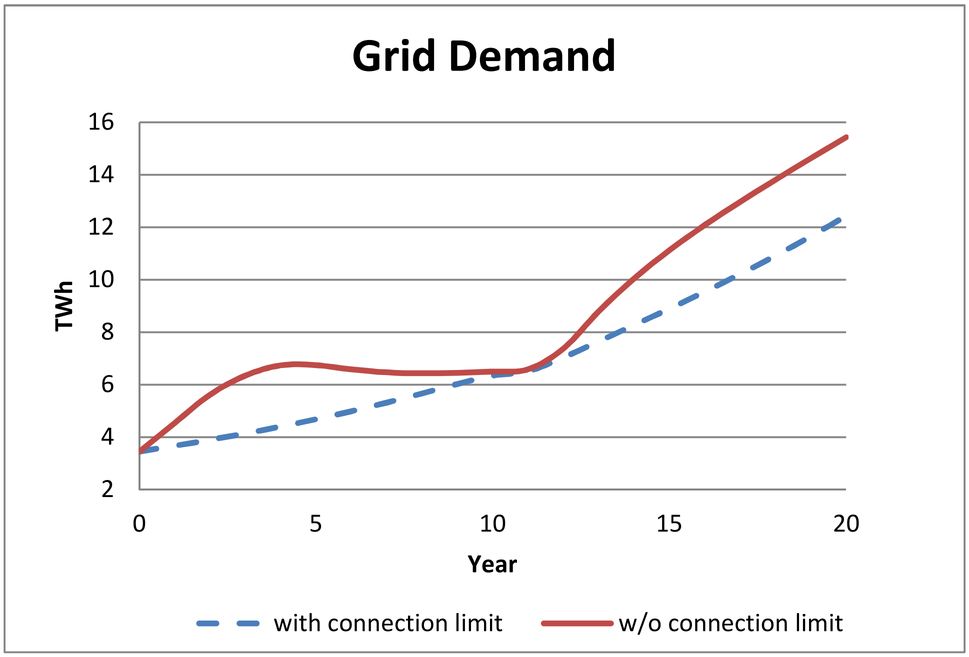


**Figure 4-17: Comparison of aggregate grid demand with and without an external limit on the number of grid connections made per year. When there is no limit on residential grid connections, grid demand grows larger than what is observed when there is a limit. "Delayed" expansion is applied.**

### 4.2.2 The Impact of Various Pricing Policies on Customer Choice

While the simulation model was developed for the capacity expansion process assuming endogenous demand (later described in Chapter 5), the simulation model is also to accept as input a single pricing policy. As described in Section 3.4, prices can: (i) vary to cover production and annualized capacity costs (ii) vary according to (i) but with a pre-specified regulatory delay or (iii) be fixed over the horizon of the model. In order to illustrate how such policies impact customer choice, the following four cases were simulated:

- Varying: prices vary without delay
- Delayed: prices vary with a 5-year regulatory delay
- Fixed Low: prices are fixed at 4¢/kWh
- Fixed High: prices are fixed at 12¢/kWh

In each case, there is no external limit on grid connections, and the following generating capacity expansion strategy is applied: in year 1, 1500MW of thermal generating capacity and 600MW of hydro capacity will become operational, and 1100MW of thermal capacity and 150MW of hydro capacity is added in year 11. This expansion strategy maintains a level of reliability that is relatively close to one over the duration of the simulation so that the impact of price on customer choice is more apparent.

The fraction of residential adopters selecting grid power, depicted in Figure 4-18, is highest when prices are fixed to a low value, and the fraction is lowest in when prices are fixed to a relatively high level. Under both the "Varying" and "Delayed" pricing policies, there is a marginal decrease in the fraction of residential adopters requesting a grid connection as a result of the increase in electricity price occurring at the start of the horizon, and the fraction decreases more significantly when electricity price increases in year eleven under the "Varying" policy and in year 16 under the "Delayed" policy. As expected, the dynamics observed under the "Delayed" policy mimic those observed when prices vary but with a five-year delay.

Figure 4-18 also depicts the fraction of industrial demand served by the grid, and it demonstrates that residential adopters are more sensitive to variation in price than industrial consumers. The fraction of industrial demand served by grid power demonstrates little variation between pricing policies because industrial consumers are more sensitive to reliability than to electricity prices. Therefore, the fraction of industrial demand served by grid power approaches one in all cases as reliability is nearly constant at one.

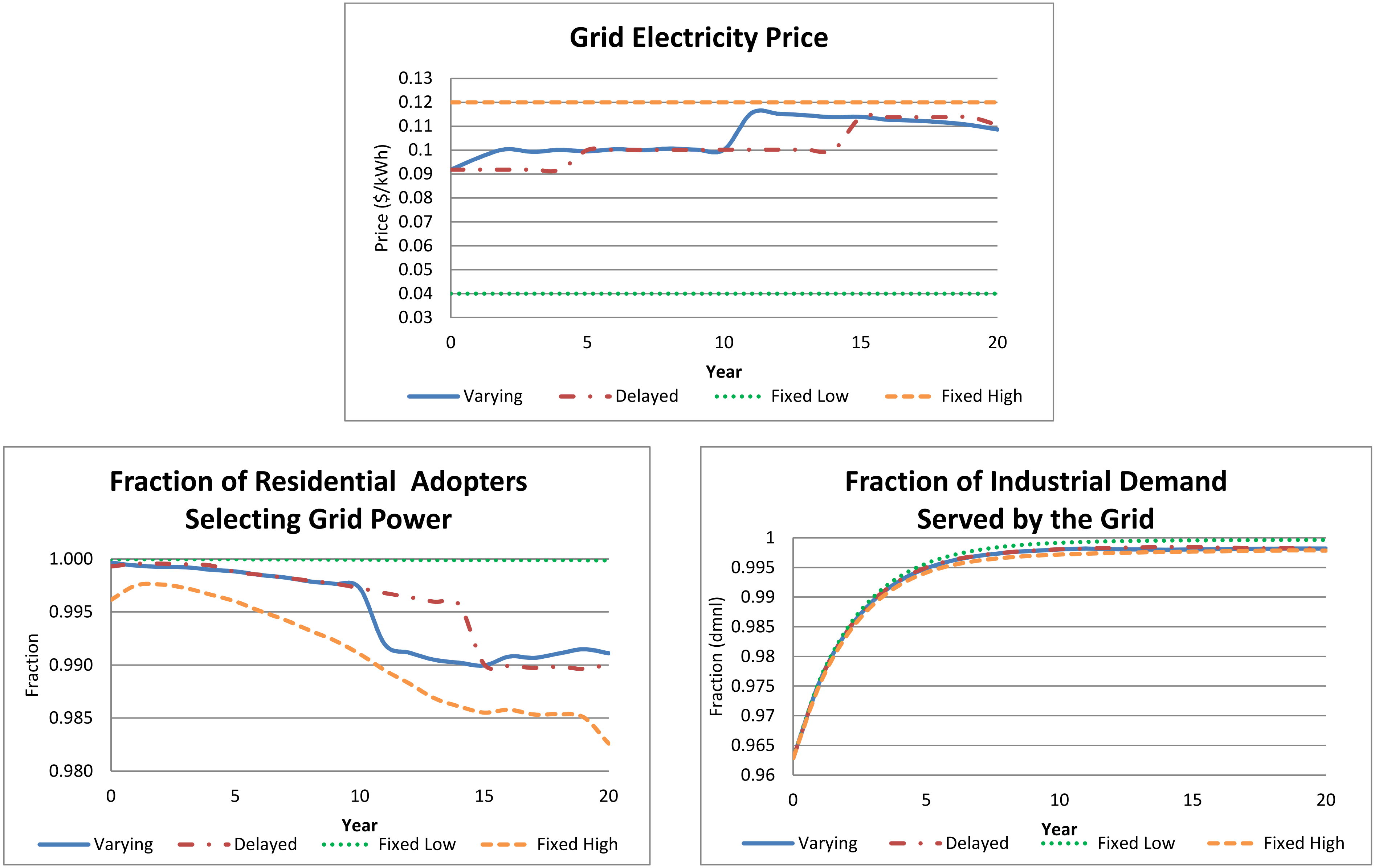


**Figure 4-18: Comparison of simulation output under four pricing policies. The impact of grid electricity price is clearly evident in the fraction of residential electricity adopters selecting grid power; however industrial consumers are less sensitive to price changes.**

## 4.3 Sensitivity Analysis: System Response to Variation in Choice Parameters

As described in Section 4.1, the values of the "choice parameters" of the multinomial logit function are estimates. These parameters dictate how consumer choice varies with reliability, electricity price, capital cost, and, in the case of residential consumers, backlog and quality of supply. I perform a one-factor-at-a-time (OFAT) analysis, varying each parameter such that it assumes three levels corresponding to low, medium and high sensitivity (see Table 4-4). Here, I present the highlights of the analysis to demonstrate how variation in these parameters impacts customer choice (*i.e.* the fraction of residential electricity adopters that select grid power and the fraction of industrial demand served by the grid).

In all cases analyzed, prices vary without regulatory delay, and new generating capacity comes online as follows: in year one, 1500MW of thermal capacity and 600MW of hydro capacity becomes operational, while 1100MW of thermal capacity and 150MW of hydro capacity comes online in year eleven. Reliability remains relatively close to one over time, and grid electricity price rises from approximately 10 to 12 ¢/kWh when new generating capacity becomes operational in year eleven.

| Parameter Varied | Low | Medium | High |
|---|---|---|---|
| Industrial Sensitivity to Reliability | 15 | **30** | 45 |
| Industrial Sensitivity to Electricity Price | **-2.5** | -5 | -10 |
| Industrial Sensitivity to Capital Cost | -2.5 | **-5** | -7.5 |
| Residential Sensitivity to Reliability | 15 | **30** | 45 |
| Residential Sensitivity to Unit Price | -15 | **-30** | -45 |
| Residential Sensitivity to Capital Cost | -1 | **-5** | -9 |
| Residential Sensitivity to Quality | 10 | **20** | 30 |
| Residential Sensitivity to Backlog | -0.5 | **-1** | -5 |

**Table 4.4: Cases explored in OFAT analysis[26]. Bold entries are Base Case Parameter Values**

[26] During the analysis of a single parameter, all other choice parameters assume Base Case Parameter Values.

### 4.3.1 Grid Reliability, Electricity Price & Backlog Ratio

As consumers become more sensitive to reliability, electricity price, or backlog ratio, consumer reaction to changes in these variables becomes more evident. For example, consider the cases in which I vary the sensitivity of consumer choice to electricity price. When consumers are relatively insensitive to grid electricity price, the fraction of electricity adopters choosing grid power and the fraction of industrial demand served by the grid remains fairly constant and close to one. As consumers become more sensitive to price, however, the fraction choosing grid power is lower and variation due to changing electricity prices becomes visible (See Figures 4-19 and 4-20).

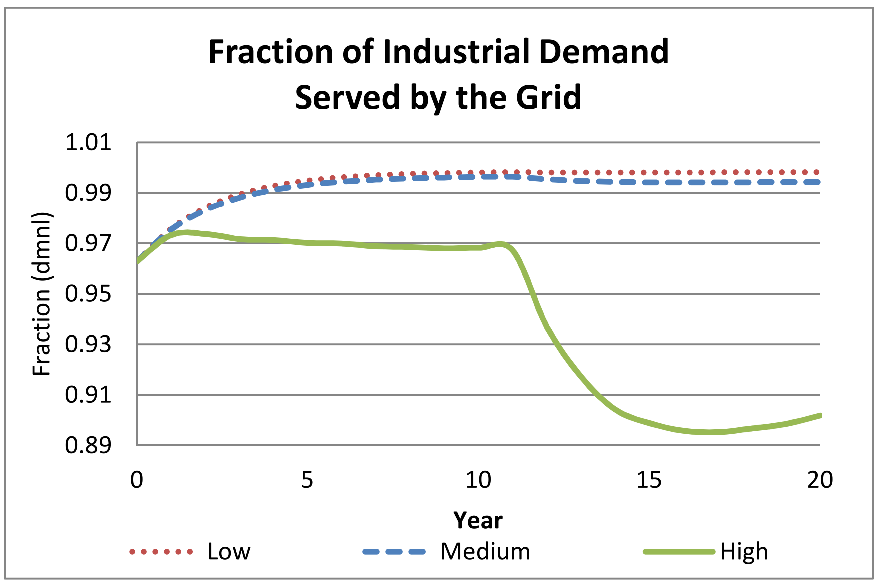


**Figure 4-19: Fraction of industrial demand served by the grid resulting from variation in industrial sensitivity to unit price.**

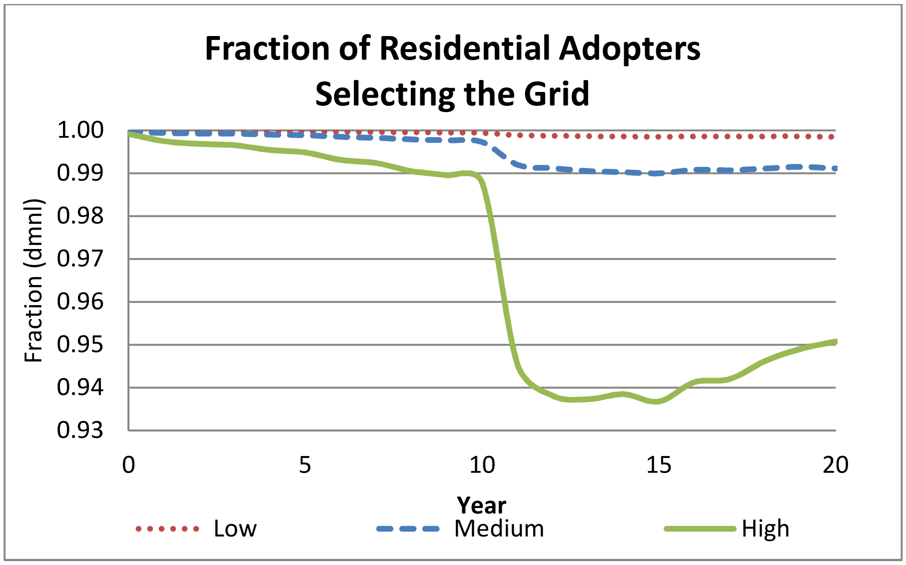


**Figure 4-20: Fraction of residential electricity adopters selecting grid power resulting from variation in residential sensitivity to unit price.**

### 4.3.2 Capital Costs

Over the horizon of the model, I assume that it is cheaper for industrial consumers to acquire a power connection from the grid than acquiring connections to off-grid supply options. As a result, when industrial consumers are most sensitive to capital costs, the grid appears most attractive. When industrial consumers are less sensitive to capital costs, the fraction of industrial demand served by the grid is lower and reaction to changes in grid electricity price is evident.

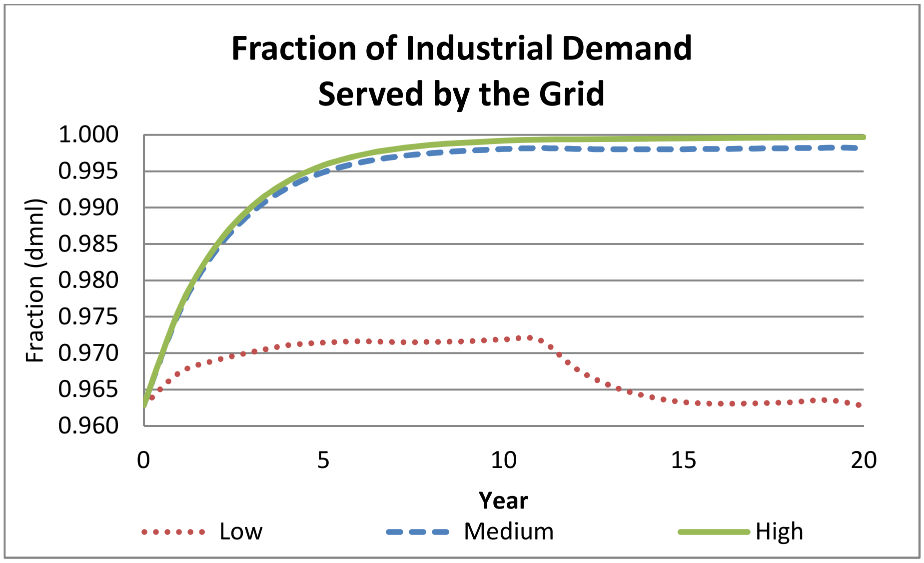


**Figure 4-21: Fraction of industrial demand served by the grid resulting from variation in industrial sensitivity to capital costs.**

On the other hand, when residential consumers become increasingly more sensitive to capital costs, the new electricity adopters will increasingly select off-grid supply options as I assume that it is more expensive for these customers to connect to the national grid. If residential consumers are less sensitive to capital costs, the fraction of electricity adopters selecting grid power remains closer to one.

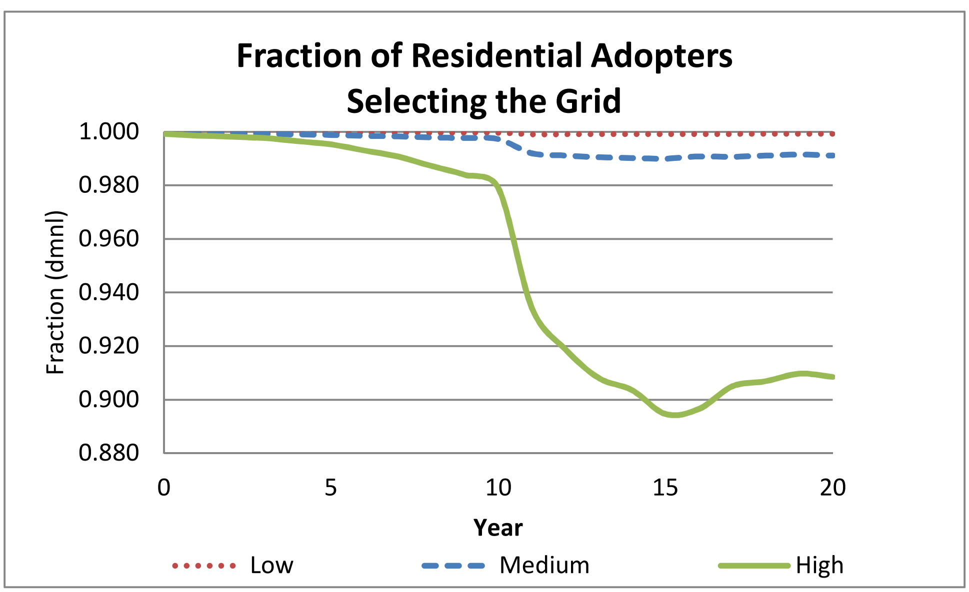


**Figure 4-22: Fraction of residential electricity adopters selecting grid power resulting from variation in residential sensitivity to capital costs.**

### 4.3.3 Quality

As found in the ethnographic work of Steel (2008), the quality of electricity supply impacts residential choice. Steel found that residents perceived the quality of grid power to be superior to that of off-grid supply options, even if the grid was unreliable. The idea of "quality" reflects the preference for grid-based power as the "modern" electricity source (Steel 2008). Accordingly, the grid is assumed to have the highest quality over the horizon of the model.

Figure 4-23 depicts the fraction of residential adopters requesting a grid connection. When residents are moderately sensitive to quality, the fraction of adopters selecting grid power is close to one, slightly declining in year 11 when the price of grid power increases. When electricity adopters are less sensitive to quality, the share of residential electricity adopters selecting the grid is significantly lower, dropping dramatically when the price of grid power increases. When adopters are more sensitive to quality, however, the fraction selecting the grid remains constant at one.

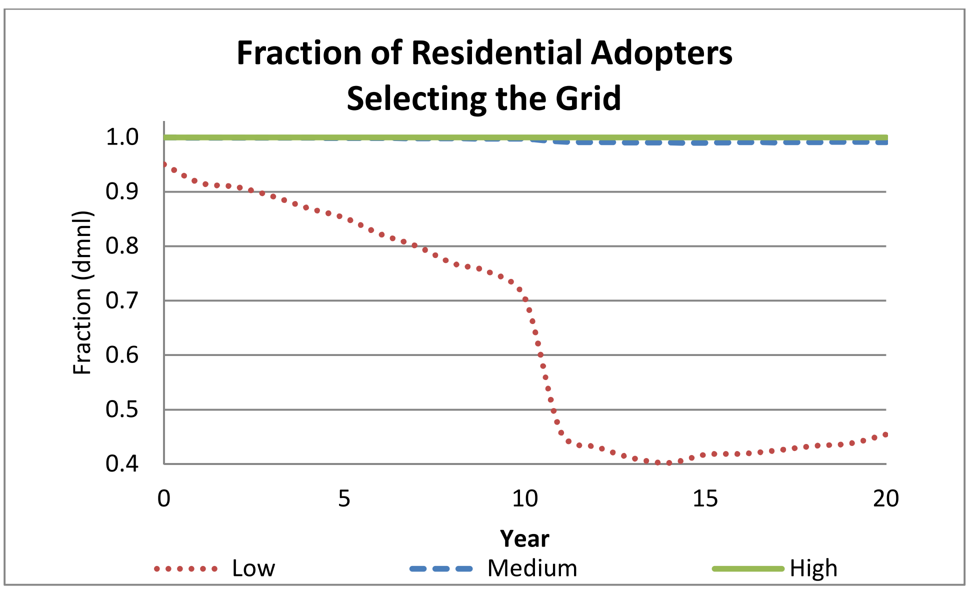


**Figure 4-23: Fraction of residential electricity adopters selecting grid power resulting from variation in residential sensitivity to quality.**

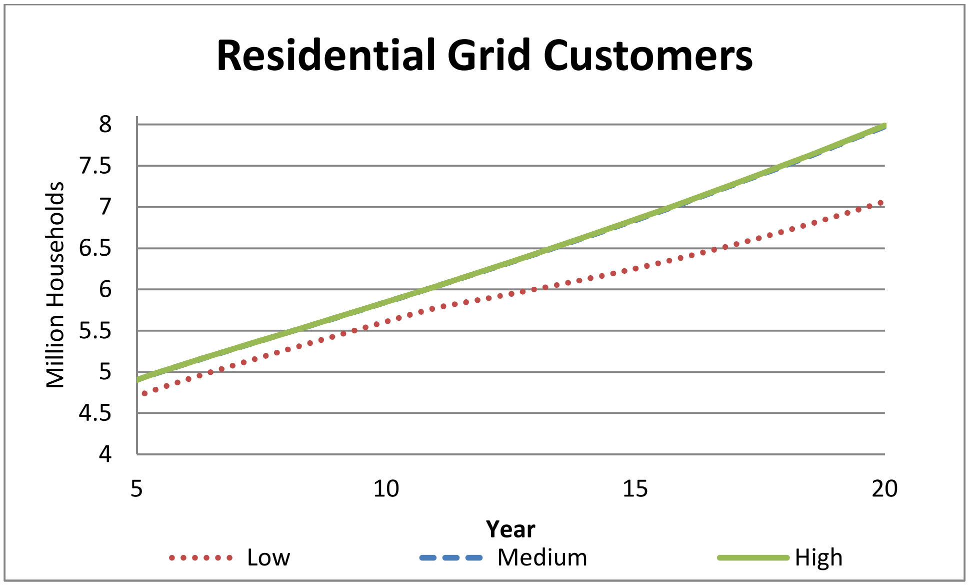


**Figure 4-24: Residential grid customers under variation in residential sensitivity to quality.**

Relaxing the assumption that the grid provides the best quality would result in a power system with significantly fewer residential consumers connected to the national grid (see Figure 4-24).

## 4.4 Simulation Model Limitations & Future Expansions

Varying the capacity expansion strategies and pricing policies as well as performing a sensitivity analysis on uncertain model parameters illustrate the major power system feedbacks present in the simulation model. Residential demand is a function of the number of grid customers, and the change in the number of grid customers is a function of electricity price, capital costs, the backlog of customers awaiting connection, the quality of supply, and the reliability of supply. Similarly for industrial consumers, the fraction of industrial demand that is supplied by the national grid is a function of electricity prices, capital costs and reliability. As a result, the addition of new generating capacity largely impacts grid demand over time. Ultimately, grid demand is endogenous to the model, evolving over time based on the relationship between customer choice and power grid performance.

While the simulation model is effective at capturing detailed grid operation and endogenous demand, a number of simplifications have been made. As in Steel (2008), the quality of all electricity supply options is assumed to remain constant over the time horizon of the model (*i.e.* residential consumers will always perceive the grid to be the supply option with the best quality); a grid connection is assumed to be cheaper than off-grid supply connections for industrial consumers; and, for residential consumers, a grid connection is assumed to more expensive than off-grid supply options. Finally, economic development and GDP growth are exogenous to the model, and the percent increase in electricity demand resulting from a percent increase in GDP is also assumed constant.

Additional simplifications were made to keep the model manageable. These simplifications, however, may limit the accuracy of power system representation. For example, the simulation model neglects the location of demand, urbanization and hydro resource depletion. These are important features as the depletion of hydro resources will drive up the costs of hydro power, the changing location of demand throughout the network (resulting from urbanization) will impact required generating capacity. The model also assumes that residential customers do not switch from grid to off-grid once connected but, in the recent power crisis in Tanzania, this was found to be a false assumption. Finally, an abundance of off-grid supply options is assumed; however, the supply of affordable solar home systems, for example, may be limited[27] in this context. Adding such features to the simulation model would better capture the realities of the local context.

Finally, several assumptions and modeling choices should be further explored in the future. First, uncertainty in numerous parameters is not captured. These include the volatility of foreign exchange rates and fuel prices (impacting both on-grid and off-grid production costs), the variability in hydro production each year, and the variability in demand between individual households. Second, there is no link between power company cash flow and their ability to connect new grid customers. In power systems in which electricity prices are not set to cover capacity and production costs, debt accumulates and impacts the ability of the utility to connect new customers. Adding this feedback would limit the increase in demand resulting from residential customers connecting to the grid.

[27] During field research in Tanzania in 2010, one energy service provider comments on solar suppliers, asserting that "There aren't that many companies involved in installation or distribution... [and] it's hard to find reliable technicians."

A third assumption to be analyzed in the future is that residential and industrial consumers act as homogenous groups. Residential consumers are indeed represented separately and distinctly from industrial consumers; however, within each group there is a single decision-maker. Literature suggests that demand be further disaggregated based on location and income. A resident's location to the grid indicates the price of a grid connection in Tanzania and many other developing countries, and, as demonstrated in Parshall et al (2009), recent research efforts have been aimed at incorporating GPS data into analyses for power planning. Utilizing this information in an agent-based expansion of the simulation model is a logical next step in future research. Finally, as described in Sections 4.1 and 4.3, many model parameters are estimates. Of great importance are the consumer choice parameters. An extensive survey to assess consumer utility and sensitivity to various factors would be a huge contribution to capacity expansion planning, electrification planning and more broadly energy use in developing countries.

The aim of this research is to determine if, how and why incorporating endogenous demand into capacity expansion planning identifies a strategy that differs from the strategy suggested by a more conventional approach. While the limitations presented above indeed constrain the scope and detail of the model, the purpose of the simulation model is to capture endogenous demand and be a descriptive model of a power system similar to that of Tanzania. The simulation model indeed incorporates the feedbacks between the technical grid and consumers, and endogenously determines the evolution of grid demand. In the next chapter, this simulation model will be used to inform capacity expansion planning.

# Chapter 5 Comparing Capacity Expansion Approaches: Endogenous versus Exogenous Demand

Power systems in developing countries are frequently characterized by high costs and low reliability. The majority of residents in this context lack access to modern energy sources, and technology adoption is a critical component of electricity demand growth over time. The growing demand of customers already connected to the grid must be met along with the demand generated by new connections. However, the number of new grid connections realized is determined by the performance of the system, which impacts consumers through price and reliability. Traditional generation expansion models do not represent demand endogenously. They do not capture the relationship between the growing number of grid customers and electricity demand and may provide misleading results when used to inform planning. In this chapter, I address the first research question posed at the start of the thesis:

> ***Does it Matter?*** *Does incorporating endogenous demand into planning result in a different optimal capacity expansion strategy?*

To answer this research question, I compare two alternative capacity expansion planning approaches: the first approach assumes endogenous demand and the second approach assumes exogenous demand. I begin by explicitly defining the capacity expansion decision problem, and move on to describe the first planning approach. More specifically, I describe how the simulation model (described in Chapters 3 and 4) is used to inform expansion planning. Next, I describe the traditional formulation, assuming exogenous demand, and then compare the strategic plans resulting from the two approaches.

We compare the strategies in two ways. First, as the goal of the central planner in this context is to meet growing demand at minimum costs, we compare the total costs of supply and total generating capacity added to the system under each expansion plan. Next, we compare how the strategies impact demand for grid connections and the level of grid demand not served. In order to do so, I impose the two expansion strategies on the simulation model described in Chapter 3, and describe the evolution of grid reliability, electricity price, non-served grid demand, and discounted operational and capacity costs. Analysis of the system response will clarify the differences in expansion strategies that arise between the two methods.

I present an overview of the major differences arising in the power system under the two expansion strategies and conclude with a discussion on the fundamental differences between generation planning assuming endogenous demand and planning that assumes exogenous demand.

## 5.1 The Decision Problem: Generation Expansion

In this thesis, the role of the centralized planner is to answer the question:

> *When and how much new generating capacity should come on line over the next twenty years to meet the growing demand for grid power?*

The power system consists of both hydro and thermal based generation. The 2009 Power System Mater Plan presents an extensive list of candidate hydro and thermal generators to be built to meet growing demand. However, a subset of the PSMP's list of options will be considered in this thesis. Table 5-1 presents the existing and candidate generation options assumed here.

More specifically, in this simplified example the planner must decide how many coal and gas units will come online in years one (2009) and eleven (2019) of the planning horizon. Assuming a growth in grid demand of 7%[28] per annum, the objective of the planner is to select an expansion strategy that minimizes the total discounted[29] costs of supply, including variable production costs, the annualized costs of generating capacity and penalties for non-served grid demand. For this **two-stage deterministic planning problem**, up to four units of each plant type can become operational over the twenty-year horizon. This equates to 225 possible expansion strategies.

In all cases presented in this chapter, it is assumed that the three hydro units have been previously approved for installation; Ruhudji and Ikondo will come online in year one, while

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[28] Historical data used during parameter estimation along with Mwasumbi and Tzoneva (2007) indicate 7% growth in grid demand each year.
[29] A 10% discount rate is assumed in the analyses of this chapter.

Kihansi_2 will become operational in year eleven. Additionally, there are no limits to the ability of the electric utility to connect new grid customers.

| Plant Name | Plant Type | Units | Size/Unit [MW] |
|---|---|---|---|
| Songas | Gas | 1 | 185 |
| Diesel | Oil | 1 | 5 |
| Ubungo | Gas | 1 | 70 |
| Kihansi | Hydro | 1 | 75 |
| Kidatu | Hydro | 1 | 180 |
| Hale | Hydro | 1 | 5 |
| Nyumba na Mungu | Hydro | 1 | 3.5 |
| Mtera | Hydro | 1 | 66 |
| Pangani Falls | Hydro | 1 | 20 |
| *Coal* | *Coal* | *n* | *200* |
| *CCGT* | *CCGT* | *n* | *300* |
| *Kihansi_2* | *Hydro* | *1* | *150* |
| *Ruhudji* | *Hydro* | *1* | *300* |
| *Ikondo* | *Hydro* | *1* | *300* |

**Table 5.1: Existing and candidate (italicized) generators in the power system. Information adapted from (Tanesco 2009). Please see APPENDIX for characteristics of each plant.**

## 5.2 Capacity Expansion with Endogenous Demand

As demonstrated in Chapter 4, the simulation model described in Chapter 3 takes as input a capacity expansion strategy and calculates the total discounted costs of supply over the twenty year time horizon. The expansion strategy indicates when and how many units of each plant type will become operational. In order to use this simulation model to inform planning, I use an exhaustive search optimization method, systematically enumerating all possible candidate strategies. This method then identifies the expansion strategy that minimizes the total costs of supply as the optimal solution.

For the decision problem described in Section 5.1, a single expansion strategy identifies the number of coal and gas units that will come online in years one and eleven of the planning horizon. Given a single expansion strategy, the simulation model[30] generates the following time-series data:

| | |
|---|---|
| $vProdC_y$ | Production costs |
| $vCommitC_y$ | Commitment costs |
| $vNSEC_y$ | Penalties for non-served energy |
| $vACC_y$ | Annualized capacity costs |

where *y* ranges from year 1 to 20 and each of the above variables is defined as described in Chapter 3 for a single year.

The **objective** of this model is to minimize the total costs of supply, *TCS*. As described in Section 5.1, total cost of supply includes annualized capacity costs, variable electricity production costs, and the penalties incurred for non-served grid demand (also called "non-served energy").

$$Min\,\{TCS\} \qquad --[23]$$

where

$$TCS = \sum_{y=1}^{20} pDiscount_y \times \{vProdC_y + vNSEC_y + vCommitC_y + vACC_y\} \qquad --[24]$$

and

$$pDiscount_y = \frac{1}{(1+dr)^y} \qquad --[25]$$

The components of *TCS*, the total cost of supply, are defined for each year by equations [12] to [15] in Chapter 3, but are repeated here for ease of understanding:

$$vProdC_y = \sum_{p,s,n,g} pDuration_{p,s,n} \cdot pVarCost_g \cdot vProduct_{y,s,n,g} \qquad --[26]$$

[30] The parameter values assumed for the simulation model are set to those determined in Section 4.1

$$vNSEC_y = \sum_{p,s} pPNSCost \cdot vPNS_{y,p,s} + \sum_{p,s,n} pDuration_{p,s,n} \cdot pENSCost \cdot vENS_{y,p,s,n} \qquad --[27]$$

$$vCommitC_y = \sum_{p,s,n,t} pDuration_{p,s,n} \cdot pNoLoadCost_t \cdot vCommit_{y,p,s,t} \qquad --[28]$$

$$ACC_y = \sum_{g} (pAnCap_g + pFixedOM) \cdot pInstalled_{y,g} \qquad --[29]$$

See APPENDIX for pseudo code of planning algorithm.

## 5.3 Capacity Expansion with Exogenous Demand

In order to compare capacity expansion assuming exogenous demand to the planning procedure (described in Section 5.2) that assumes endogenous demand, I develop a traditional deterministic capacity expansion model. The medium-term operations model described in Chapter 3 is the basis of this capacity expansion formulation. The model minimizes total discounted costs of supply (equations [23] to [29]) while satisfying demand balance and production constraints each year of the model horizon. It takes as input the grid demand profile of both residential and industrial consumers at the start of the planning horizon, and it also takes as input the forecasted increment in demand each year[31]. The model then determines when and how much new generating capacity should become operational as well as unit commitment and the production of each generator during every period, day type, and load level of each year.

While block-wise unit commitment is typically not incorporated in long-term capacity expansion models, it was imperative to capture this feature in this capacity expansion model. Unit commitment is included in the medium-term operations model (described in Section 3.3) and in generation expansion with endogenous demand. Literature suggests that including commitment (*i.e.,* minimum operating constraints for thermal units) in planning can lead to an optimal expansion strategy that differs from the strategy identified when unit commitment is not included (Rosekrans et al 1999). Therefore, this exogenous capacity expansion model is formulated to

[31] The traditional planning approach mimics the process by which strategic planning is performed; however, a long-term power system planner would, in reality, revise demand predictions and revise the expansion plan after five or ten years have passed and true demand growth is observed. This "learning" is not incorporated into the traditional approach. Therefore, the approach assumes a single demand projection for a complete twenty years.

include unit commitment (just as the approach assuming endogenous demand) to ensure a common basis for comparison. See APPENDIX for the detailed formulation of the capacity expansion model that assumes exogenous demand.

## 5.4 Comparing Expansion Strategies

### 5.4.1 Total Costs of Supply & Generation Capacity Added to the Grid

The total cost of supply (TCS), the objective value to be minimized in both planning approaches, is a metric defined as the sum of annualized capacity costs, variable production costs, and penalties imposed for non-served grid demand. With a total cost of 1064.003 million USD, the strategy identified when using the conventional planning approach (the **"exogenous strategy"**) suggests adding a total of 800MW of generating capacity to the grid, in addition to the hydro capacity (750MW) scheduled to come on line. On the other hand, the strategy identified using the planning approach developed in this thesis (the **"endogenous strategy"**) suggests adding 2000MW to the grid in addition to the hydro capacity (750MW) scheduled to come on line. This results in a total cost of 3928.772 million USD.

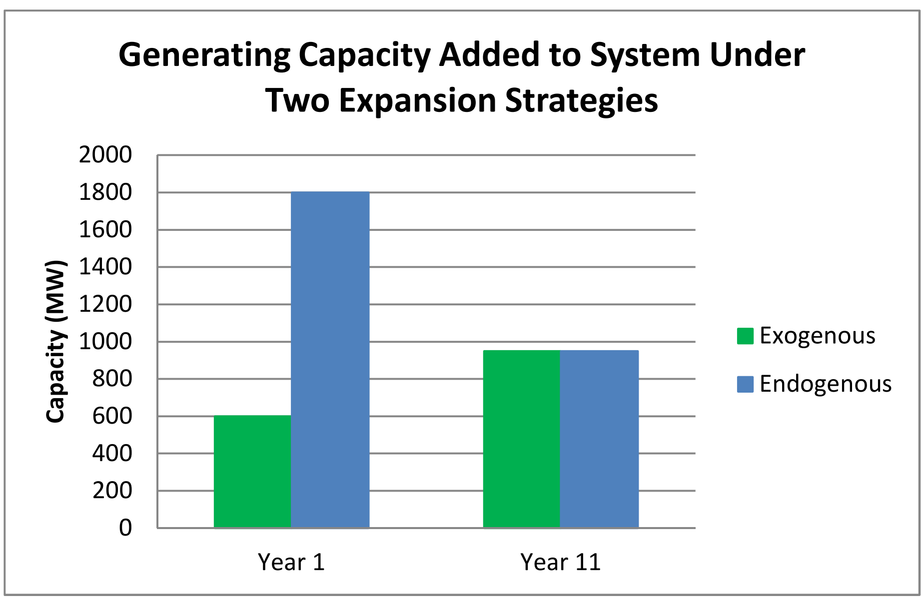


**Figure 5-1: Total generating capacity added to the grid under the two expansion strategies.**

More specifically, the exogenous strategy adds no new thermal capacity in year one and schedules 200MW of coal and 600MW of CCGT capacity to become operational in year eleven, while the endogenous strategy schedules 1200MW of CCGT to come on line in year one and 800MW of coal to come online in year eleven. Under both strategies, Ruhudji and Ikondo hydro plants (totaling 600MW) become operational in year one and Kihansi_2 (150MW) becomes operational in year eleven. There is a significant difference in the total generating capacity added to the system under the two strategies (see Figure 5-1). Understanding why this difference arises requires a detailed review of the evolution of the power system under both strategies.

### 5.4.2 Power System Development under the "Endogenous" & "Exogenous" Expansion Strategies

The model described in Chapter 3 simulates twenty years of electric power system operation given a single capacity expansion strategy. Because the model captures customer choice and detailed power grid operations, it is assumed that this model provides a more realistic description of power system operation. Therefore, the two expansion strategies are imposed on the simulation model in order to compare how the two proposed expansion strategies impact power system development (*i.e.* the evolution of grid reliability, grid price, non-served grid demand and the total costs of supply).

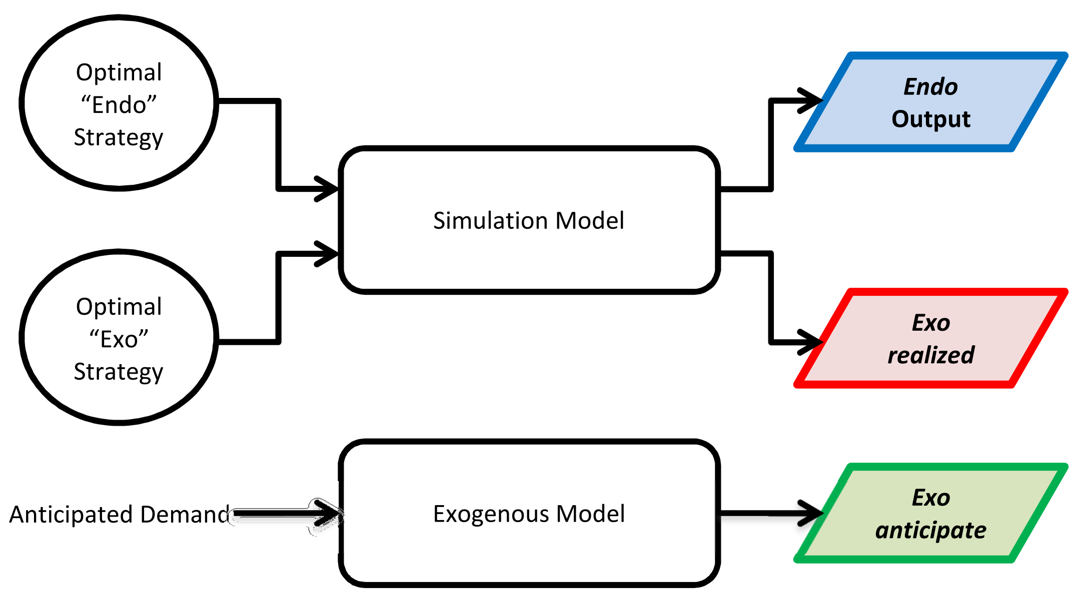


**Figure 5-2: Output assessed to compare the two planning approaches**

"Endo" refers to results from the planning process that assumes endogenous demand[32]. When the strategy identified by the traditional capacity expansion model is imposed on (*i.e.*, used as input to) the simulation model, we obtain the output labeled "exo realized". In this case, new capacity comes online as prescribed by the exogenous strategy but demand endogenously evolves. The figure also depicts "exo anticipated" and refers to the output of the traditional capacity expansion model, which assumes that demand behaves exactly as anticipated for the twenty year horizon.

Figure 5-3 compares simulation results. For this particular case, electricity prices are highest under the endogenous strategy because more generating capacity becomes operational and higher capital costs are incurred. Under the exogenous strategy, grid reliability is much lower than expected based on the output of the traditional capacity expansion model (which assumes exogenous demand). Similarly, non-served grid demand is much larger than anticipated. Such levels of non-served energy accrue penalties that result in a much larger cost of supply. Under the exogenous strategy, the actual total costs of supply (over the twenty year horizon) sum to 9275 million USD (versus the anticipated value of 1064 million USD).

Why is there such a significant difference in the output of the conventional model versus what is observed when the exogenous strategy is imposed on the simulation model? **The conventional model assumes that demand growth will be 7% per annum, but in fact demand is realized to be an average of 8.15% per annum** when the exogenous strategy is imposed on the simulation model. Figure 5-4 depicts the demand realized along with the anticipated grid demand.

[32] As the planning algorithm developed in this thesis uses the simulation model to identify the optimal expansion plan, the values realized when imposing the endogenous strategy on the model simulation are equal to what is expected based on the output of this new planning algorithm.

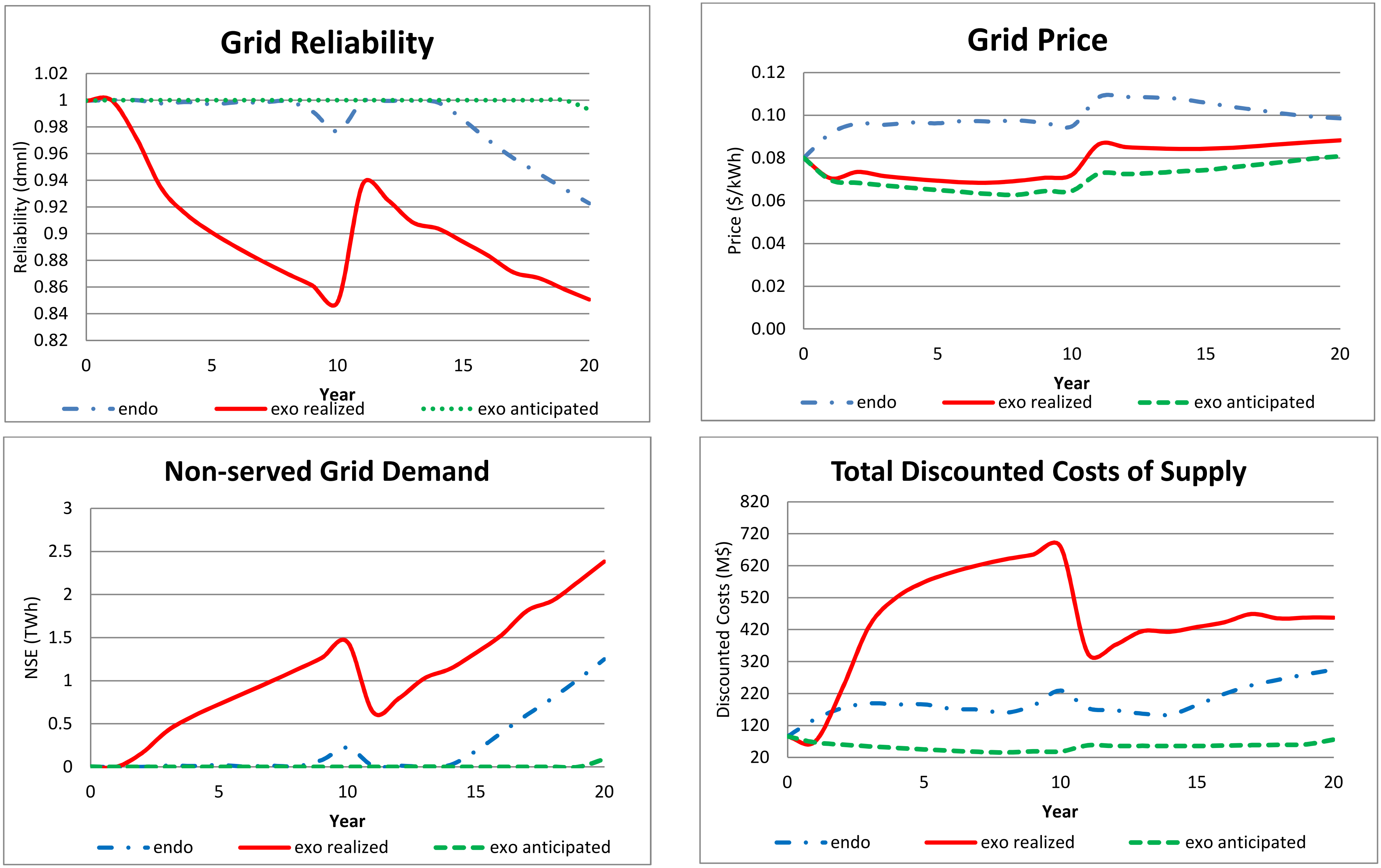


**Figure 5-3: Comparison of output under strategies identified by two planning approaches. (i) Grid Reliability (ii) Per unit price of grid power (iii) Non-served grid demand and (iv) Total discounted costs of supply.** Under the exogenous strategy, realized values are different than anticipated. The exogenous strategy also results in significantly more non-served grid demand. As a result the total discounted costs of supply are much higher than that of the endogenous strategy.

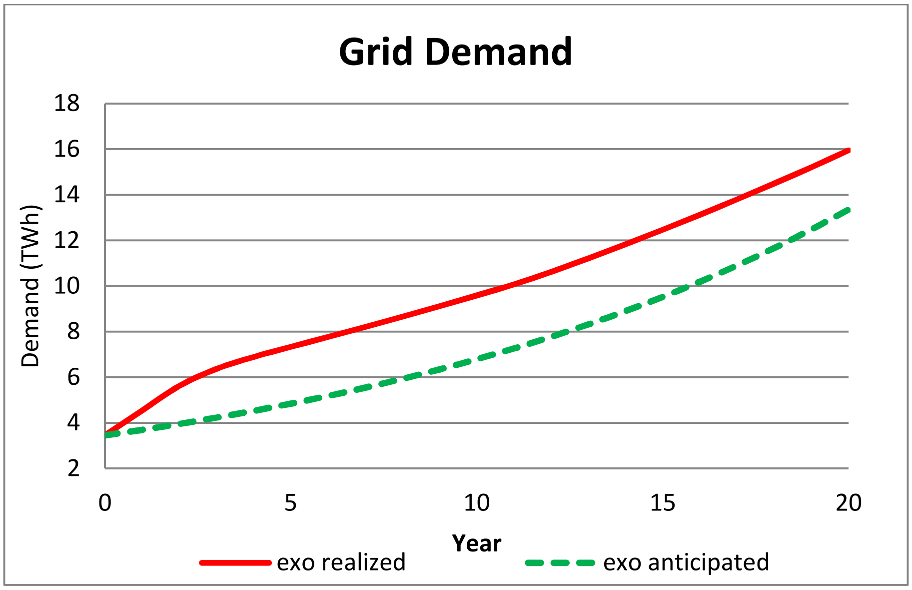


**Figure 5-4: Actual versus assumed demand. The actual demand realized is different than what was assumed using the conventional expansion model.**

Why the unexpected increase in demand under the exogenous strategy? As depicted in Figure 5-3 (i), a relatively high level of grid reliability (> 92%) in the first four years encourages residential electricity adopters to request a grid connection. The grid provides the best quality of power, and electricity price does not increase during this period. In fact, the introduction of new hydro units in year one results in a decrease in grid electricity prices (see Figure 5-3 (ii)). Additionally, residential demand is no longer limited by the ability of the electric utility to connect[33] new grid customers. Over the planning horizon, I assume that there is no limit on the number of grid connections made each year and, therefore, there is no backlog of customers awaiting a connection. As a result, many new customers connect to the grid at the start of the horizon.

The fraction of residential adopters selecting grid power is depicted in Figure 5-5. As demand begins to outgrow installed generating capacity, grid reliability declines. By year 5, reliability declines below 90% and, through year ten, residential electricity adopters increasingly select off-grid supply options. With the addition of new generating capacity in year eleven, electricity prices increase and a sharp decrease in the fraction of residential adopters selecting grid power is

[33] In the years leading up to the start of the panning horizon, I assume that the number of grid connections were limited. For example, in 2007 and 2008, Tanesco was only able to make 40,000 and 60,000 grid connections, respectively. This data was incorporated during the definition of simulation model parameters (Section 4.1).

observed. By year twelve, however, electricity price gradually decreases and reliability has improved significantly. As a result, there is an increase in the fraction of adopters requesting a grid connection. Beyond year twelve, there is a gradual decrease in this fraction as reliability deteriorates further. Overall, however, at least 80% of new residential electricity adopters connect to the grid each year of the planning horizon. Similarly, at least 96% of industrial grid demand is served by the grid (Figure 5-6). **Although demand eventually outgrows the installed generating capacity, the exogenous strategy adds just enough capacity so that the grid remains relatively attractive.** As a result, many electricity adopters select grid power (7.2 million homes are connected) and demand exceeds the level of demand that was assumed in the conventional planning model and expected based on historical data.

Unlike the exogenous strategy, the endogenous strategy introduces additional generating capacity early in the planning horizon to meet growing demand. Although the additional generating capacity added to the grid leads to larger capacity costs (and higher electricity prices to consumers), this strategy avoids large penalties resulting from non-served energy. Therefore, when the two strategies are imposed on the simulation model, the endogenous strategy outperforms the exogenous strategy in minimizing the total costs of supply (see Figure 5-3 (iv)).

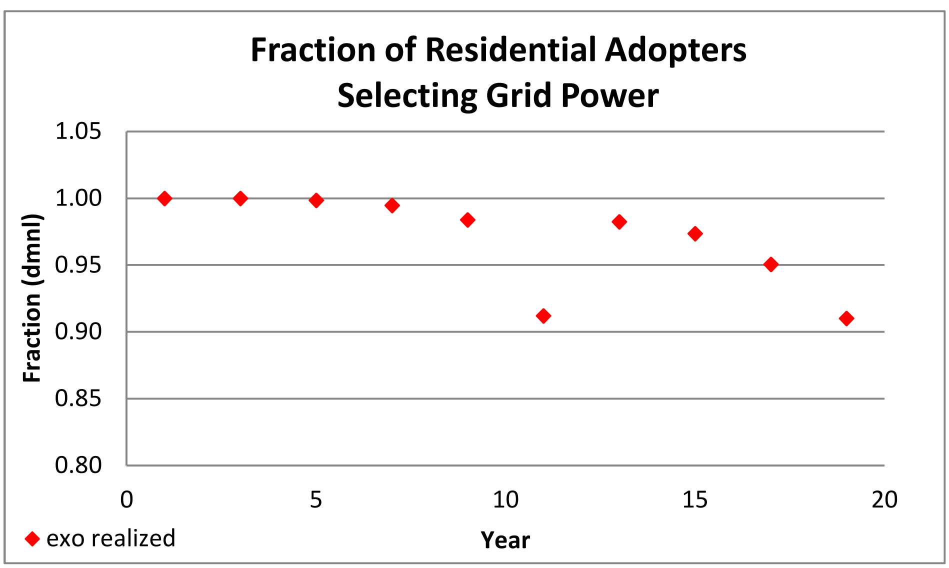


**Figure 5-5: Fraction of residential adopters selecting grid power under the "exogenous" expansion strategy. The decreases result from deteriorating grid reliability and an increase in grid price in year eleven. The increase in year twelve results from the introduction of new generating capacity**

**and the corresponding perceived increase in grid reliability. Overall, the grid remains attractive to customers.**

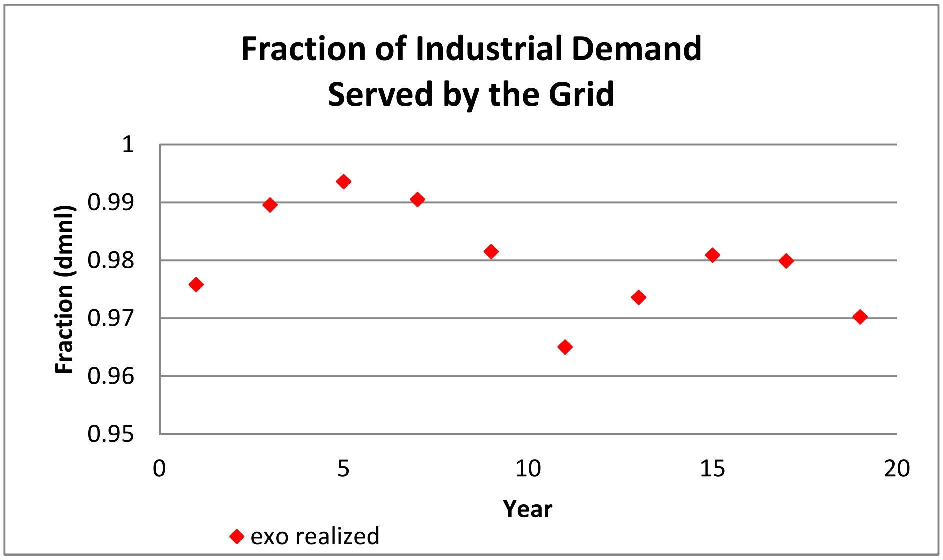


**Figure 5-6: Fraction of industrial grid demand served by the grid under the "exogenous" expansion strategy. The decreases result from deteriorating grid reliability. When this occurs, industrial consumers fire up their diesel generators or other off-grid supply options for reliable electricity supply. The increase in year twelve results from the introduction of new generating capacity and the corresponding increase in grid reliability. Overall, the grid remains attractive to industrial consumers.**

### 5.4.3 Summary: Exogenous Strategy versus Endogenous Strategy

Table 5-2 compares the exogenous strategy against the endogenous strategy. The output of the conventional planning model would suggest that the exogenous strategy outperforms the endogenous strategy in terms of costs and reliability. However, when the strategies are imposed on the more realistic power system simulation model, we find that the power system, under the endogenous strategy, meets a larger fraction of grid demand relative to what is realized under the exogenous strategy.

| | New Capacity Installed (MW) | Total Installed Capacity (MW) | Capital Costs (M$) | Annual Demand Growth (%/year) | Variable Production Costs (M$) | Average Grid Reliability | Total Costs of Supply (M$) |
|---|---|---|---|---|---|---|---|
| Exogenous (Anticipated) | 1550 | 2159.5 | 805 | 7 | 237 | 1.0 | 1064 |
| Exogenous (Realized) | 1550 | 2159.5 | 805 | 8.15 | 604 | 0.90 | 9275 |
| Endogenous (Realized) | 2750 | 3359.5 | 1623 | 8.22 | 1267 | 0.98 | 3929 |

**Table 5.2: Summary of power system operation under the two expansion strategies. All costs are discounted using a discount rate of 10%. The Total Costs of Supply, the objective value to be minimized during planning, includes capacity and production costs as well as penalties resulting from non-served grid demand.**

The differences in the expansion strategies arise, in this case, due to the fact that the conventional model assumes a level of demand growth that is much less than what is truly realized. As a result, the conventional approach adds less generating capacity to the power system.

## 5.5 Discussion

This chapter set out to address the following research question posed at the beginning of the thesis:

> ***Does it Matter?*** *Are the strategies generated when assuming endogenous demand growth different than those generated using a more traditional approach, which assumes exogenous demand? If so, how and why?*

Accordingly, this chapter compared the strategy identified using the new planning approach that assumes endogenous demand to the capacity expansion strategy identified by the conventional approach. I find that the strategies differ dramatically, with the new approach recommending significantly more generating capacity to come on line (and earlier in the planning horizon) to meet growing demand.

The planning approach assuming endogenous demand is more holistic, representing consumer choice and the evolution of grid customers as well as the detailed operation of the power grid. Unlike the conventional method, this approach does not assume a single trajectory for demand based on historical data; it instead assumes *how* consumers react to the performance of the power system, signaled to them via electricity prices and grid reliability. Additionally, this approach captures changes in non-technical aspects of the system. For example, the external limit placed on the number of grid connections made per year has a tremendous impact on the number of residential electricity adopters that are connected to the grid. As this limit is relaxed, more customers are encouraged and able to connect. Therefore, when the historical growth in demand is not a good indicator of how demand will evolve in the future, as demonstrated in the case presented in this chapter, the planning approach assuming endogenous demand is able to identify an expansion strategy that truly meets the specified objective.

The comparison presented in Section 5.4 demonstrates that, for this particular case, grid demand may evolve drastically different than expected, resulting in the selection of sub-optimal expansion strategies when employing the conventional planning approach. In Chapter 6, I will explore additional cases, repeating the exercise presented in Sections 5.3 and 5.4 to determine whether or not the capacity expansion strategy identified by the approach assuming endogenous demand again differs from that of the conventional approach.

# Chapter 6 A Review of Cases in which Incorporating Endogenous Demand is Necessary for Planning

Chapter 5 demonstrated that, for a stylized case inspired by Tanzania, incorporating the endogenous demand dynamics commonly present in developing countries is critical to identifying optimal generation expansion strategies. In this chapter, I address the second research question posed at the start of this thesis:

> ***When Does it Matter?*** *When or in what cases are the strategies generated when assuming endogenous demand growth different than those generated using a more traditional approach?*

For the case presented in Chapter 5, the approach assuming exogenous demand underestimates demand growth. As a result, the exogenous strategy adds less generating capacity and adds it later in the planning horizon. This is because the traditional planning approach assumes a trajectory of grid demand a priori. The endogenous model, on the other hand, assumes that customers and potential customers respond to changes in the performance of the power system.

In this chapter, I perform sensitivity testing on two critical factors, the installed base of grid customers at the start of the planning horizon and the improvement in reliability afforded through capacity expansion, to determine when the endogenous demand approach generates an expansion strategy similar to that of the exogenous demand approach. I conclude the chapter with a broader discussion on the factors that unlock or suppress grid demand in the context of developing countries, and the cases in which assuming endogenous demand during capacity expansion planning is necessary.

## 6.1 Comparing Capacity Expansion Approaches: the Convergence of Strategies?

In the case described in Chapter 5, the fraction of residential consumers connected to the grid at the start of the planning horizon was 16%[34]. Grid demand increased dramatically as new

[34] Countrywide residential grid access was 10%; however, only 65% of the population is assumed to afford electricity.

generating capacity became operational and as the annual limit on residential grid connections was relaxed.

In this section, I repeat the exercise presented in Chapter 5 in which I compare the expansion strategy generated by the endogenous demand approach to that of the exogenous demand approach. In this hypothetical case, however, the planning horizon is ten years and new generating capacity becomes operational only in year one; more importantly, I assume that the fraction of residential consumers connected to the grid at the start of the planning horizon is 55%.

### 6.1.1 Case Setup

For this case, I consider a hypothetical East African country that is similar to Tanzania in size and population[35]. I assume an external limit on the number of residential grid connections made per year, starting at 60,000 in year one and gradually increasing over time. I simulate the operation of the power system, where reliability is relatively constant at one (with the addition of new generating capacity) and grid electricity price varies according to [20]. When the fraction of households with a grid connection reaches 55%, I stop the simulation, recording all customer and demand stocks as well as grid reliability, electricity price and the backlog ratio. The level of grid demand is 6.7 TWh and the average growth in demand for both residential and industrial consumers is 11%/annum and 5%/annum, respectively. I use this information as the starting condition of the capacity expansion exercise.

As described in Chapter 5, the central planner must decide how much generating capacity should be added to the system to meet growing demand, and it is assumed that there are no limits to the ability of the electric utility to connect new grid customers over the planning horizon. In this case, only gas units (400MW each) are considered and new generating capacity can come online in year one of the ten year horizon. Both the traditional and the new approach developed in this thesis are employed to identify optimal expansion plans.

[35] Choice parameters assume Base Case Parameter Values presented in the APPENDIX.

### 6.1.2 Exogenous versus Endogenous Expansion Strategies

The total cost of supply (TCS), the objective value to be minimized in both planning approaches, is a metric defined as the sum of the annualized capacity costs, variable production costs, and penalties imposed for non-served grid demand. With an objective value of 3244 million USD, the strategy identified when using the conventional planning approach (the **"exogenous strategy"**) suggests adding a total of 2400MW of new generation to the grid. On the other hand, the strategy identified using the endogenous demand approach (the **"endogenous strategy"**) suggests adding 1600MW of new generation to the grid for an objective value of 2730 million USD. The difference between the two strategies in the total generating capacity added to the system is 800MW (see Figure 6-1) and the total costs of supply differ by 514 million USD (16% of maximum costs).

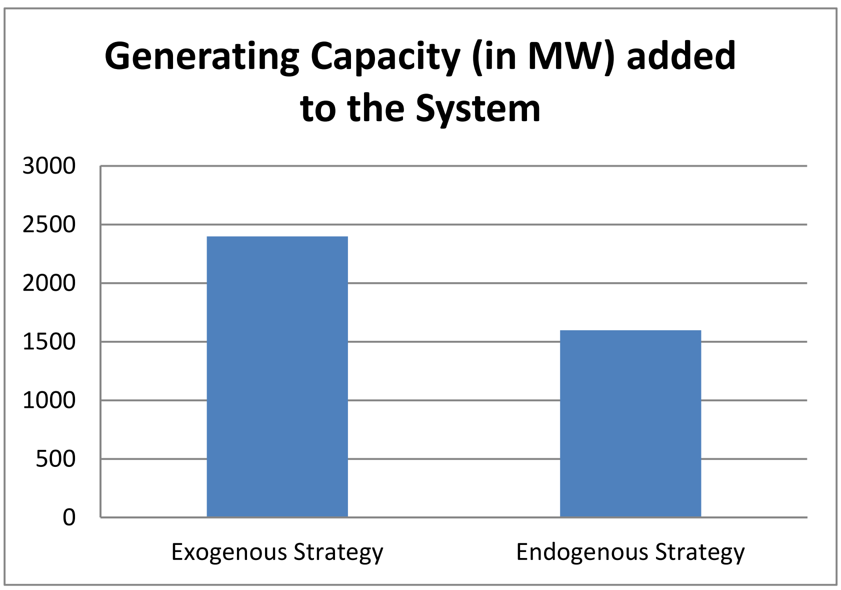


**Figure 6-1: Total generating capacity added to the grid under the (a) "exogenous" and (b) "endogenous" strategies. Initial electrification rate is 55%.**

Table 6-1 compares the exogenous strategy against the endogenous strategy. In this case, the endogenous strategy appears to outperform the exogenous strategy in terms of costs while meeting the same fraction of grid demand. The conventional model assumes that aggregate demand grows at 9.5% per year; however, when the exogenous strategy is imposed on the simulation model, growth in grid demand is realized to be only 7.2%. Unlike the case described in Chapter 5, demand grows less than expected and the exogenous strategy adds excess generating capacity to the system. The endogenous strategy incurs fewer costs as it adds less generating capacity. If the central planner is more concerned with meeting growing demand, the conventional approach would suffice in this case. If the central planner is more concerned with keeping costs low, the approach assuming endogenous demand would be required to identify to optimal expansion strategy.

| | New Capacity Installed (MW) | Total Installed Capacity (MW) | Capital Costs (M$) | Annual Demand Growth (%/year) | Variable Production Costs (M$) | Average Grid Reliability | Total Costs of Supply (M$) |
|---|---|---|---|---|---|---|---|
| Exogenous (Anticipated) | 2400 | 4209.5 | 1635 | 9.54 | 1433 | 0.998 | 3244 |
| Exogenous (Realized) | 2400 | 4209.5 | 1635 | 7.23 | 1294 | 0.999 | 3004 |
| Endogenous (Realized) | 1600 | 3409.5 | 1318 | 7.23 | 1287 | 0.998 | 2730 |

**Table 6.1: Summary of power system operation under the two expansion strategies. All costs are discounted using a discount rate of 10%. The Total Costs of Supply, the objective value to be minimized during planning, includes capacity and production costs as well as penalties resulting from non-served grid demand.**

In the case inspired by Tanzania (presented in Chapter 5), the difference in generating capacity added to the system was 1200MW and the capacity installed under the exogenous strategy did not meet growing demand. In this case, however, the difference in generating capacity added to the system is 800MW and the exogenous strategy adds excess generating capacity to the system. Additionally, the optimal costs identified by the two approaches differed by 73% for the case presented in Chapter 5 but differ by only 16% in this scenario. In the former case, the households with electricity access at the start of the planning horizon is 16% while, in this case, 55% of homes are connected to the grid. With a larger installed base of grid customers, do the two expansion strategies converge? In the next section, I will explore a range of initial electrification rates to assess how the difference in capacity expansion strategies varies with the initial fraction of the population connected to the grid.

## 6.2 Sensitivity on Initial Electrification Rate

In order to further explore the impact of the installed customer base on the difference in expansion strategies, I repeat the procedure described in Section 6.1 for three additional cases: in the first case, the fraction of households with electricity (at the start of the planning horizon) is 33%; in the second case this value is 76% and, in the third case it is 96%. As a reminder, I identify the cases by simulating the operation of the power system, where reliability is relatively constant at one (with the addition of new generating capacity) and grid electricity price varies according to [20]. When the fraction of households connected to the grid is 33%, 76% and 96%, I record all customer and demand stocks as well as grid reliability, electricity price and the backlog ratio, using this information as the starting point of the planning exercise. Figure 6-2 depicts the households connected to the grid over time during initial simulation; the initial installed customer base of each case is indicated by a maroon square. Additionally, Table 6.2 provides the initial planning conditions for each case.

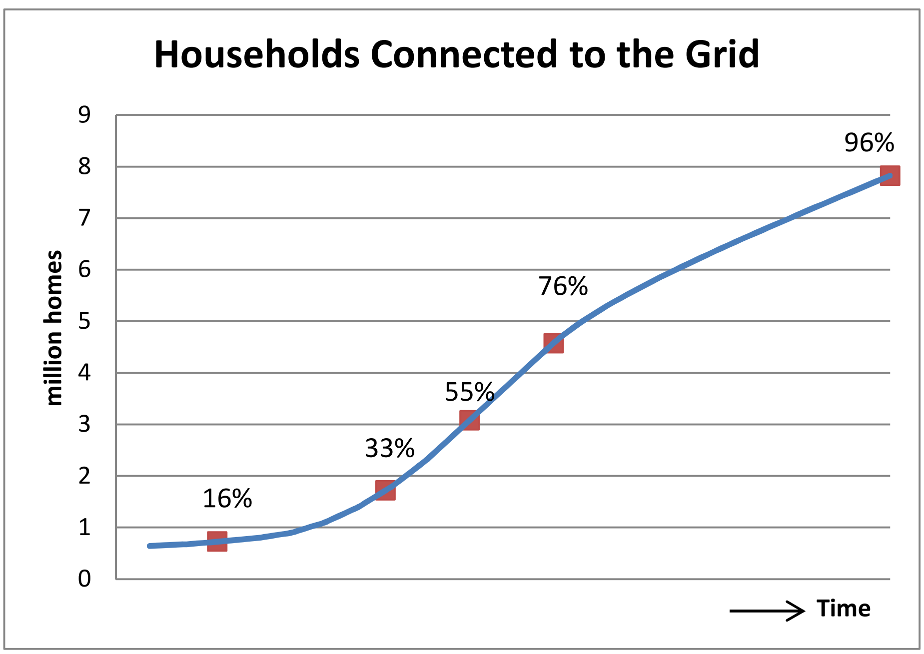


**Figure 6-2: Households connected to the grid over time observed during the initial simulation (used to identify cases of sensitivity analysis).**

| Initial Electrification Rate (%) | Residential Grid Demand (TWh) | Industrial Grid Demand (TWh) | Residential Demand Growth (%/year) | Industrial Demand Growth (%/year) | Residential Grid Customers (million households) | Off-grid Industrial Demand (TWh) |
|---|---|---|---|---|---|---|
| 16 | 1.39 | 2.06 | 7 | 7 | 0.72 | 0.079 |
| 33 | 2.35 | 2.66 | 9.51 | 5.47 | 1.72 | 0.013 |
| 55 | 3.49 | 2.99 | 12.22 | 5.19 | 3.08 | 0.007 |
| 75 | 4.83 | 3.35 | 13.29 | 4.99 | 4.57 | 0.005 |
| 96 | 9.64 | 5.25 | 7.17 | 4.6 | 7.82 | 0.011 |

**Table 6.2: Initial levels used as input to capacity expansion planning exercise, Section 6.2**

I then employ both the traditional ("exogenous") and new ("endogenous") planning approaches. I quantify the difference in capacity expansion strategies generated by the exogenous and endogenous approaches using the following metric:

$$\Delta S = \frac{b - a}{Max(a, b)} \qquad --[30]$$

where *a* is the total capacity installed under the exogenous strategy and *b* is the total capacity installed under the endogenous strategy. I also quantify the difference between expected and realized grid demand ΔD for each of the five cases by (1) using the mean grid demand growth values presented in Table 6.2 and projecting forward ten years to determine expected demand over the planning horizon and (2) using the demand realized under the endogenous strategy to calculate the mean squared percent error between the anticipated grid demand $D_A$ and realized grid demand $D_R$ as:

$$\Delta D = \frac{1}{10}\sum_{y=1}^{10}\left[\frac{D_{A,y} - D_{R,y}}{D_{R,y}}\right]^2 \qquad --[31]$$

Figure 6-3 summarizes the results and demonstrates how the difference in capacity expansion strategies, ΔS, varies with the fraction of residential households connected to the grid at the start of the planning horizon. ΔS is positive when the endogenous strategy adds more generating capacity, and negative when the exogenous strategy builds more generating capacity. The results demonstrate that the approach assuming exogenous demand can under or overestimate grid demand growth over the course of the development of a country. For the cases analyzed here, the exogenous strategy builds less generating capacity than the endogenous strategy until the electrification rate at the start of the planning horizon reaches and exceeds 55%. Additionally, the magnitude of ΔS decreases as the fraction of households connected to the grid at the start of the planning horizon increases. Similarly, as demonstrated in Figure 6-4, the difference between anticipated and realized grid demand under the endogenous strategy, ΔD, decreases as the fraction of the population connected to the grid at the start of the planning horizon increases.

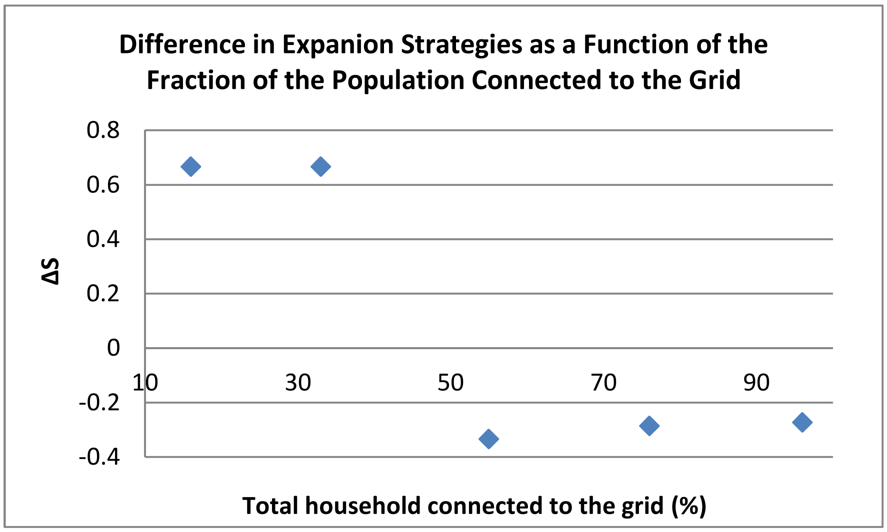


**Figure 6-3: The difference in the two expansion strategies as a function of the percent of the population connected to the grid at the start of the ten-year planning horizon.**

Although there is a noticeable difference between the strategies for all cases presented in this sensitivity, the difference in anticipated and realized demand indeed converges to zero as the percent of the population connected to the grid increases. As shown in Figure 6-5, the ratio of demand resulting from new grid connections made during the planning horizon to total grid demand, $D_{NC}:D_T$, decreases as the electrification rate at the start of the planning horizon increases. Therefore, as the electrification rate increases, the less demand is a function of new electricity adopters and the more it is a function of previously existing demand and its response to price, reliability and GDP growth. This is largely intuitive; however, this reality is often neglected when planning for developing countries with low electrification rates. In such cases, not only does the planner have to consider the sensitivity of existing grid demand to price and reliability; they must also consider the change in demand resulting from the large fraction of the population that does not initially have electricity but who may adopt the new technology and connect to the grid.

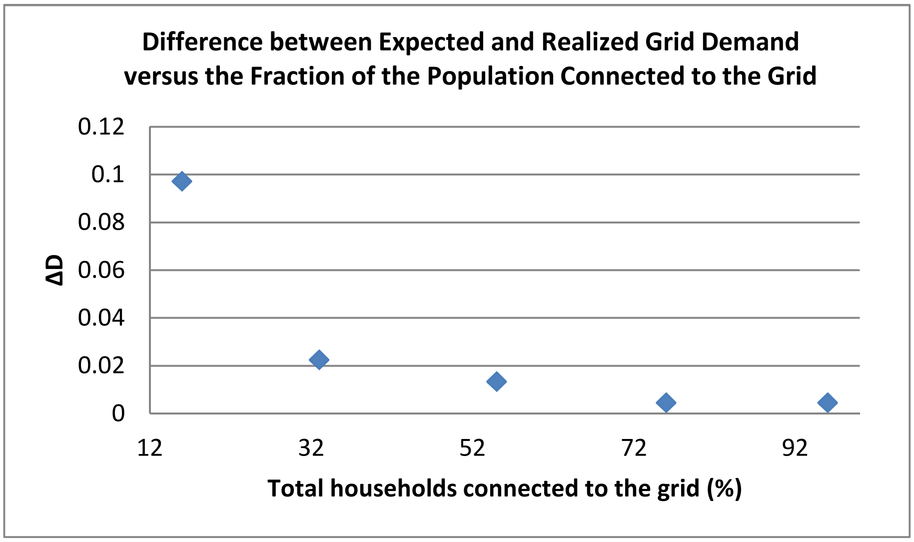


**Figure 6-4: The difference between anticipated and realized demand [31] as a function of the fraction of the population connected to the grid at the start of the planning horizon.**

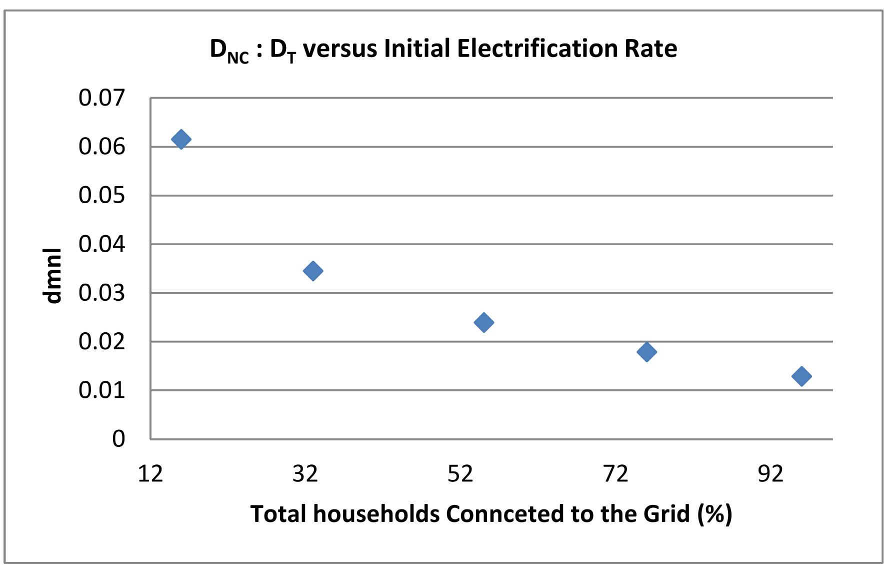


**Figure 6-5: $D_{NC}$:$D_T$ as a function of the fraction of the population connected to the grid at the start of the planning horizon.**

## 6.3 Sensitivity on Historical Grid Reliability

As demonstrated in the testing of the simulation model (described in Chapter 4), the fraction of served to total grid demand, grid electricity price, or grid backlog ratio can unlock or suppress industrial demand, and can encourage or discourage residential electricity adopters from requesting a grid connection. Therefore, if demand is observed during a period of low reliability, then power planners may incorrectly forecast demand, under-estimating the demand realized once new generating capacity becomes operational. In this section, I demonstrate that, as the improvement in reliability achieved through capacity expansion increases (*i.e.* as historical reliability decreases), the difference between expected and realized grid demand increases.

### 6.3.1 Case Setup

In this analysis, I again consider a hypothetical East African country that is similar to Tanzania in size and population. I assume an external limit on the number of residential grid connections made per year, starting at 60,000 in year one and gradually increasing over time. 16% of residential household are initially connected to the grid. I simulate the evolution of grid demand, fixing reliability to five levels: 0.75, 0.8, 0.85, 0.9 and 0.95. I stop the simulation when 46% of the population has access to the grid. Average demand growth (observed in the final ten years of the simulation period) and the final level of grid demand are listed in Table 6.3 for each case.

| Historical Reliability "$Rel_B$" (dmnl) | Residential Grid Demand (TWh) | Industrial Grid Demand (TWh) | Residential Demand Growth (%/year) | Industrial Demand Growth (%/year) | Residential Grid Customers (million households) | Off-grid Industrial Demand (TWh) |
|---|---|---|---|---|---|---|
| 0.75 | 4.04 | 1.45 | 8.95 | 0.34 | 3.00 | 2.39 |
| 0.8 | 4.05 | 2.80 | 8.98 | 3.33 | 3.02 | 1.04 |
| 0.85 | 4.05 | 3.55 | 8.98 | 4.36 | 3.02 | 0.29 |
| 0.9 | 4.05 | 3.77 | 8.98 | 4.63 | 3.02 | 0.07 |
| 0.95 | 4.05 | 3.82 | 8.98 | 4.69 | 3.02 | 0.02 |

**Table 6.3: Initial levels used as input to capacity expansion planning exercise, Section 6.3**

Next, I determine how much generating capacity should be added to the system to meet growing demand over the next ten years by employing the endogenous planning approach. Coal and gas units are considered in the planning process and can come online in year one of the planning horizon; the candidate hydro units presented in Table 5.1 come online in year one as well.

### 6.3.2 Anticipated versus Realized Grid Demand

I quantify the difference between expected and realized grid demand ΔD for each of the five cases by (1) using the mean grid demand growth values presented in Table 6.3 and projecting forward ten years to determine expected demand over the planning horizon and (2) using the demand realized under the endogenous strategy to calculate the mean squared percent error between the anticipated grid demand $D_A$ and realized grid demand $D_R$ according to [31]. I also quantify the improvement in reliability achieved by capacity expansion as:

$$\Delta R = Rel_A - Rel_B \qquad --[32]$$

where $Rel_A$ is the average reliability over the ten year planning horizon[36] and $Rel_B$ is the historical reliability (listed in Table 6.3).

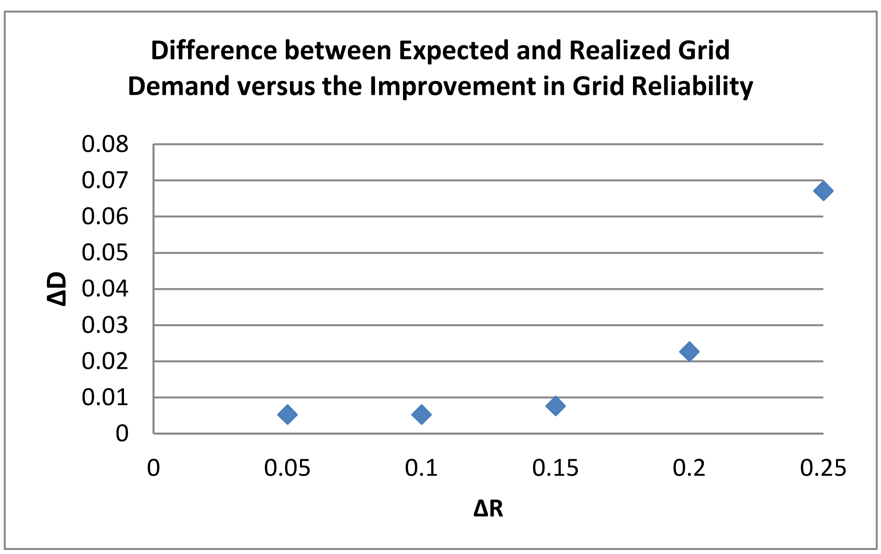


**Figure 6-6: The difference between anticipated and realized demand [31] as a function of the improvement in reliability afforded by capacity expansion [32].**

[36] In all cases, the fraction of served to total grid demand over the planning horizon is approximately 1.0.

Figure 6-6 depicts the results of the analysis. ΔD is shown to increase as the improvement in reliability achieved by capacity expansion increases. An improvement in reliability makes the grid attractive to potential electricity adopters and to those industrial consumers who had previously switched to off-grid supply during the period of low reliability. Therefore, when new capacity comes online to improve reliability, demand in fact grows larger than expected.

The fraction of industrial demand served by the grid over the planning horizon is depicted in Figure 6-7 for each case. In year one, new capacity comes online, increasing grid reliability to approximately one. As expected, the case in which historical reliability ("$Rel_B$") was 0.75 shows a significant increase in the fraction of industrial demand served by grid over time, indicating that industrial consumers are responding to the improvement in reliability by powering down their off-grid supply sources.

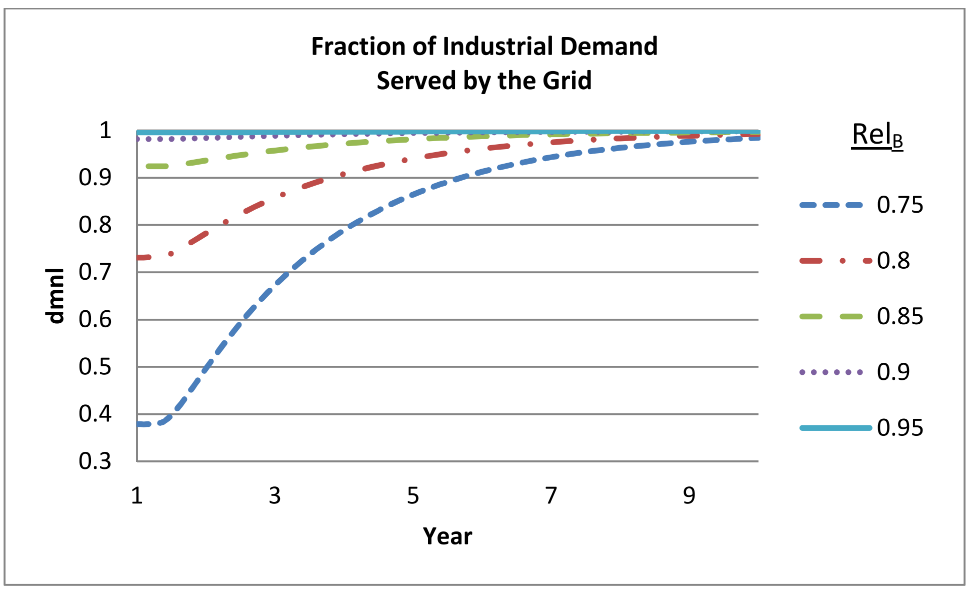


**Figure 6-7: Fraction of industrial demand served by the grid over the planning horizon for each case (indicated by "$Rel_B$" column of Table 6.3)**

## 6.4 Discussion

As demonstrated in Chapter 4 and throughout the existing literature, numerous factors impact the evolution of grid demand within the context of developing countries. If these factors are not considered when planning the expansion of generating capacity, the use of conventional planning models that assume exogenous demand can result in the implementation of sub-optimal expansion strategies.

The analyses presented in this chapter focus on the difference between the strategy identified using the endogenous demand approach developed in this thesis and the exogenous demand approach, and explore how this difference varies with the fraction of the population connected to the grid at the start of the planning horizon and the improvement in grid reliability resulting from capacity expansion.

The results presented in this chapter do not exhaustively identify all cases in which incorporating endogenous demand dynamics into capacity expansion exercises is required. Additionally, the cases analyzes are hypothetical. Nevertheless, the results suggest that the difference in expansion strategies increases as the fraction of the population connected to the grid decreases and as the improvement in reliability resulting from capacity expansion increases. Intuitively, these findings are logical. As the stock of potential residential grid customers decreases, demand will increasingly become a function of population and GDP growth. When all residential homes are connected to the grid, the impact of electricity adoption is minimal as only the new homes resulting from population growth will be adopting electricity and selecting supply options.

Similarly, historical grid reliability should be considered when performing capacity expansion. If the growth in demand is observed in a system in which the fraction of served to total grid demand was 0.6, the growth in grid demand may very well be larger than what is suggested by history when a significant amount of generating capacity is added to the system. The new generating capacity improves grid reliability and makes the grid very attractive to residential electricity adopters and industrial consumers who had most-likely switched to off-grid power supply during the period of low reliability.

The simulation model testing presented in Chapter 4 also suggests that the pricing policy and the ability of the utility to connect new grid customers will impact the difference observed between planning approaches. For instance, in many developing countries, grid electricity tariffs are subsidized so that it is more affordable for impoverished consumers to connect to the grid. If this subsidy is lifted and consumers are forced to pay the true price of electricity, there may be a decrease in industrial grid demand and residential electricity adopters will be discouraged from requesting a grid connection. The stock of grid customers may stop growing. Similarly, the ability of the power company to connect new grid customers will impact the growth in residential grid demand over time. The number of residential grid customers directly impacts the load experienced on the grid, and the perception of a backlog of grid customers awaiting a grid connection also discourages new electricity adopters from requesting a grid connection. If grid demand is observed during a period in which the backlog ratio is high, then planners may under-estimate the growth in demand when the utility increases the number of grid connections it can complete each year.

In short, when the past is not likely to be a good predictor of the future, incorporating endogenous demand dynamics into the generation planning process will be critical. This is particularly true of developing countries where changes in infrastructure (in terms of price and performance) can unlock a large potential demand for grid power stored in off-grid industrial consumers and the large fraction of potential residential electricity adopters.

# Chapter 7 Conclusions and Future Research

## 7.1 Summary of Key Findings

In developing countries around the world, billions of people lack access to electricity. Extensive efforts are aimed increasing access to power but also at expanding infrastructure and generating capacity to meet growing power demand. The research presented in the previous six chapters contributes to the existing literature on generation expansion planning in the context of developing countries. Specifically, I have developed a novel approach to generation capacity expansion that endogenously represents the evolution of grid demand as a function of customer choice, which is influenced by reliability and electricity price as well as connection costs, the quality of supply and the backlog of customers awaiting connection.

In Chapter 5, I demonstrated that the strategy generated from an endogenous demand approach indeed differs from the strategy generated from a traditional exogenous demand approach. For this particular case, the endogenous strategy adds more generating capacity and adds it earlier than the exogenous strategy because the traditional approach underestimates growth in grid demand. In Chapter 6, I demonstrated that the difference in expansion strategies decreases as the fraction of the population connected to the grid at the start of the planning horizon increases. The difference in expansion strategies was also found to decrease as the improvement in reliability (afforded by the addition of new generating capacity) decreased. This confirms that assuming endogenous demand during planning is important in countries with low grid access and poor grid reliability; this work also suggests that it would be reasonable to assume exogenous demand when planning in more developed countries, with higher rates of electrification and higher levels of reliability in the current system as long as there are no huge changes in GDP growth and the price of power. Of course, this research presents a proof of concept and each case should be examined thoroughly to understand the contextual factors that impact the growth in power demand.

The strategies generated when assuming endogenous demand growth differ from those generated when using a more traditional expansion planning approach due to the fact that the traditional approach assumes grid demand a priori while the new planning approach assumes *how* consumers select electricity supply options and react to changes in the power system. While the price elasticity of demand has indeed been incorporated into capacity expansion models in the past (Rutz et al 1985), the approached developed in this thesis also captures the impacts of changing reliability and supply switching on grid demand, and explicitly represents the adoption of electricity and selection of supply options by the large stock of residential households without power. In the context of developing countries, such consumer behavior and customer choice have larger implications on aggregate grid demand than the marginal demand changes resulting from price elasticity.

## 7.2 Research Contributions

This research has both academic and applied contributions. Building off of the work of Steel (2008) and the extensive literature on generation capacity expansion presented in Chapter 2, I built an integrated platform that simulates the detailed operation of the electric power grid as well as endogenous demand dynamics (resulting from social process of electricity adoption and customer choice) commonly found in developing countries. Then, using the simulation model to inform planning, I demonstrated a novel approach to generation capacity expansion.

This work extends existing capacity expansion literature by employing a holistic approach to planning that incorporates not only the impact of electricity prices on grid demand (which is commonly found in generation expansion models) but also incorporates: electricity adoption among residential consumers, the impact of grid reliability and connection costs on industrial grid demand, and the impact of reliability, customer backlog, connection costs, and supply quality on the change in residential grid demand. As suggested by Meier and Chatterjee (1987), residential grid demand is formulated to depend on the number of households connected to the grid. Additionally, this work contributes to existing engineering systems literature on decision-making within large-scale socio-technical systems.

While the planning approach developed in this thesis was demonstrated on a system inspired by the case of Tanzania, it was developed with the flexibility to be applied to other developing countries. A country with a centralized power system and similar electricity adoption and customer choice dynamics can be represented using the modeling platform developed in this thesis. For example, the annual power system module can be replaced with the operational power system model of another country, and the supply options can be modified to mimic the supply mix of the country of interest.

Additionally, this research developed a modular power system modeling framework that integrates the social and technical aspects of the system, and can be used to represent power systems around the world. For example, while 100% of the population in Spain has access to the national grid, consumers are now faced with a different set of decisions. Should they use gas or electric heating? Should they purchase gasoline or electric vehicles? In this context, customer choice will also have a large impact on grid demand. One can imagine replacing the existing "Electricity Adoption & Customer Choice" module of the simulation model with another model capturing the decisions specific to this context.

Finally, this work demonstrates that incorporating such endogenous demand dynamics into the planning process generates expansion strategies that differ from those identified using more traditional planning approaches; and, more importantly, it demonstrates a case in which the traditional model essentially failed at meeting growing grid demand at minimum costs. The key findings of this research suggest that consumer behavior should be studied in greater detail and incorporated into the expansion planning process to avoid the implementation of sub-optimal strategies.

There are two main policy implications of this research. The first and most obvious implication is that this work informs the process by which policy should be shaped in developing countries. This research shows that the use of historical data and trends to inform policy decisions creates false expectations of how systems such as the electric power system will develop in the future. Even if more complex extrapolation methods are employed to create forecasts, the approach assumes that the future is conditioned by the same factors that operated in the past (IEHIAS 2012); this may not be true and, if it is true, the state or level of the factors moving forward may certainly change from past values. This idea was demonstrated in Chapter 6, as the exogenous strategy at times over and underestimated growth in grid demand, and it was also demonstrated in what has been termed the "NERC fan" (Figure 7-1). It is a figure depicting the North American Electricity Reliability Council's ten-year forecasts of total US electricity demand. The forecasts, simulated by Nelson and Peck (1985) using exponential extrapolation, were grossly overoptimistic for over a decade, from 1975 to 1990 (Sterman 2000). Nelson and Peck found that formulating demand as a function of income and electricity price produced less optimistic forecasts. Thus, in order to avoid making misinformed decisions, policy-makers must incorporate into planning those factors that impact demand. It is, therefore, imperative for decision-makers to invest in studies that characterize technology adoption and customer choice; otherwise, resources will be misallocated, resulting in inadequate infrastructure development.

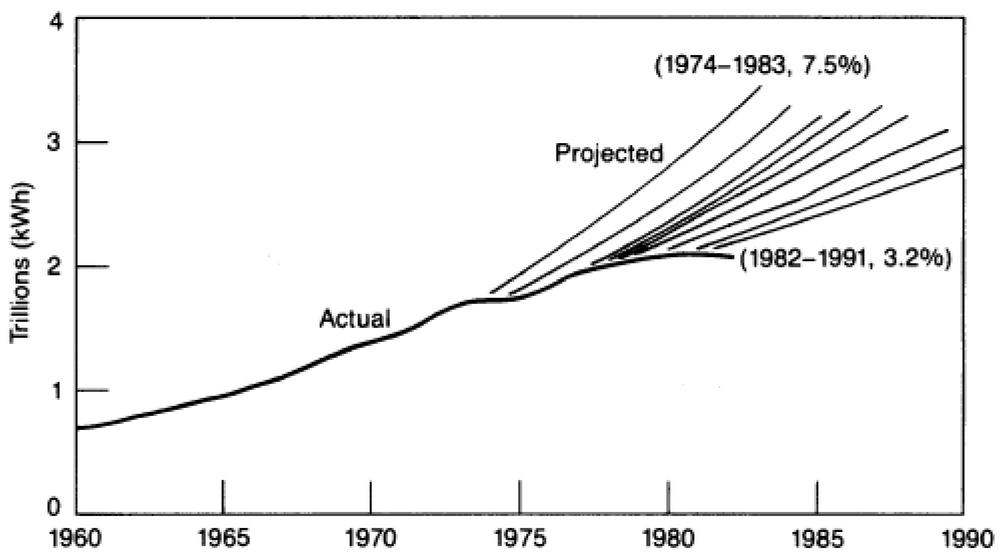


**Figure 7-1: Actual (1960-1982) and Projected (1874-1990) Total Sales of Electricity and Growth Rates. Source: Nelson and Peck 1985**

This work also demonstrates that policy-makers in developing countries have tremendous opportunity to shape the development of electric power systems. Steel (2008) writes: "Africa has a nascent electric power system. Instead of thinking of it as a backward or simplistic version of an industrialized grid, we need to think of it as a complex system where the architecture is not already determined…. Instead of determining what should have been done, or what needs to be done now that problems have arisen, we are able to look at the possibility of what can be done." The results of the analysis presented in Chapter 5 suggest that power planners in places like Tanzania should build significantly more generating capacity and they should build it sooner to meet growing demand. Most developing countries are budget-constrained and adding large amounts of new generating capacity may not be feasible. However, this research also highlights the opportunity for decentralized and distributed power generation. As demonstrated in Chapter

4, numerous factors, including reliability, electricity price, connection costs, and the backlog of customers awaiting a connection, impact consumer choice. Instead of thinking that the power system must evolve centrally, a government concerned about increasing access to electricity as well as having an efficiently operating power system may implement a strategy that provides support to and partners with suppliers of decentralized power options so that they can innovate and distribute their products, thereby improving the social welfare of those without access to the grid. As was the case with the mobile phone industry, developing countries can do things differently; they can diverge from the path taken by more industrialized countries and begin to generate solutions and systems that best fit the needs of their countries.

## 7.3 Future Work

This research has developed a generation expansion approach that incorporates endogenous demand. Four areas of further research have been identified. The first extends the analyses presented in this thesis to identify when incorporating endogenous demand is critical for capacity expansion planning. Chapter 6 explored hypothetical scenarios of countries with varying levels of grid access and grid reliability. However, insight may be gained from repeating the exercises on real cases.

A second area for future research would improve the simulation model that lies at the heart of the planning approach. The simulation model limitations, presented at the end of Chapter 4, indicate the additional features that could be added to the model in the future to better reflect reality. These features include: uncertainty (in foreign exchange rates, GDP growth, fuel prices, hydro production each year, the demand of individual consumers and demand growth), hydro resource depletion, shifting demographics of urbanization, residential supply-switching, and off-grid supply constraints. Each of these factors will have an impact on grid demand or power supply and should therefore be incorporated into the planning approaches developed in this thesis. Similarly, an agent-based extension of the simulation model presented in Chapter 3 would allow further disaggregation of electricity demand by location and customer type. It would also enable a more detailed formulation of urbanization.

The third area of future work improves upon the existing planning approach. I implemented this expansion planning approach using a brute force optimization method (described in Chapter 5) that takes a minimum of three hours to execute a deterministic, two-stage decision problem with seven hundred possible expansion strategies. If additional features, such as uncertainty and the transmission network, are indeed incorporated into the simulation model, the execution time of the planning algorithm will increase dramatically (see APPENDIX G). A model that requires such extensive computation time is not practical and most likely would not be regularly used in developing countries. Therefore, future work to improve the speed of the optimization algorithm is a logical next step in research. Heuristic algorithms, such as approximate dynamic programming or evolutionary genetic algorithms are promising options to explore.

The final area for future work involves social science research that also enhances the simulation model. As demonstrated in Chapter 5, considering how consumer decisions impact grid demand is a critical component of generation expansion planning in developing countries. A series of ethnographic studies that categorize developing countries based on the factors that impact residential and industrial choice of electricity supply options will be useful to make the model more generalizable.

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## Appendix A – Daily Electricity Demand of Residential Consumers in Peru

Mr. Julio Eisman Valdés, Managing Director at Fundación ACCIONA Microenergía, provided information on the daily electricity demand of 3335 newly electrified residential customers in Peru. Figure A-1 depicts the information. A similar load profile is assumed for newly connected residential consumers in Chapters 5 and 6.

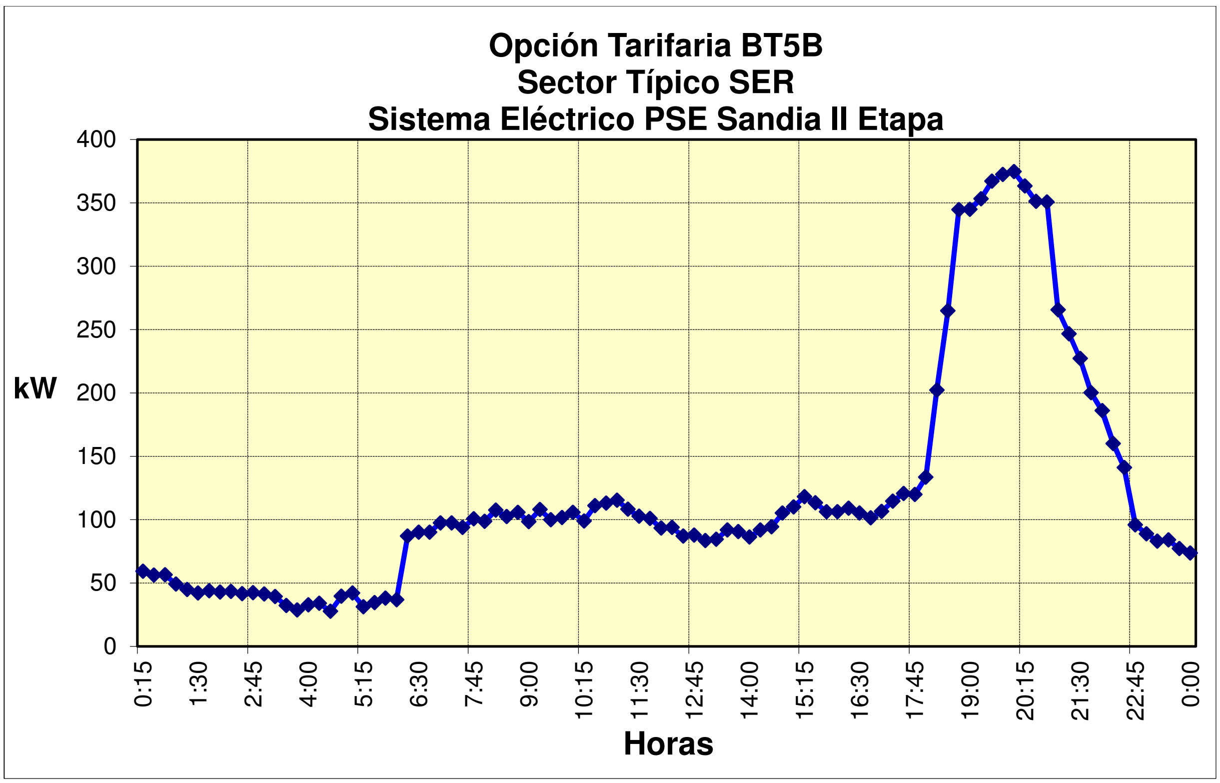


**Figure A-1: Daily electricity demand of newly electrified residential customers in Peru.**

## Appendix B - Regions of Tanzania

The following map depicts the major regions of Tanzania (excluding Geita, Katavi, Njombe, and Simiyu created in March 2010[37]).

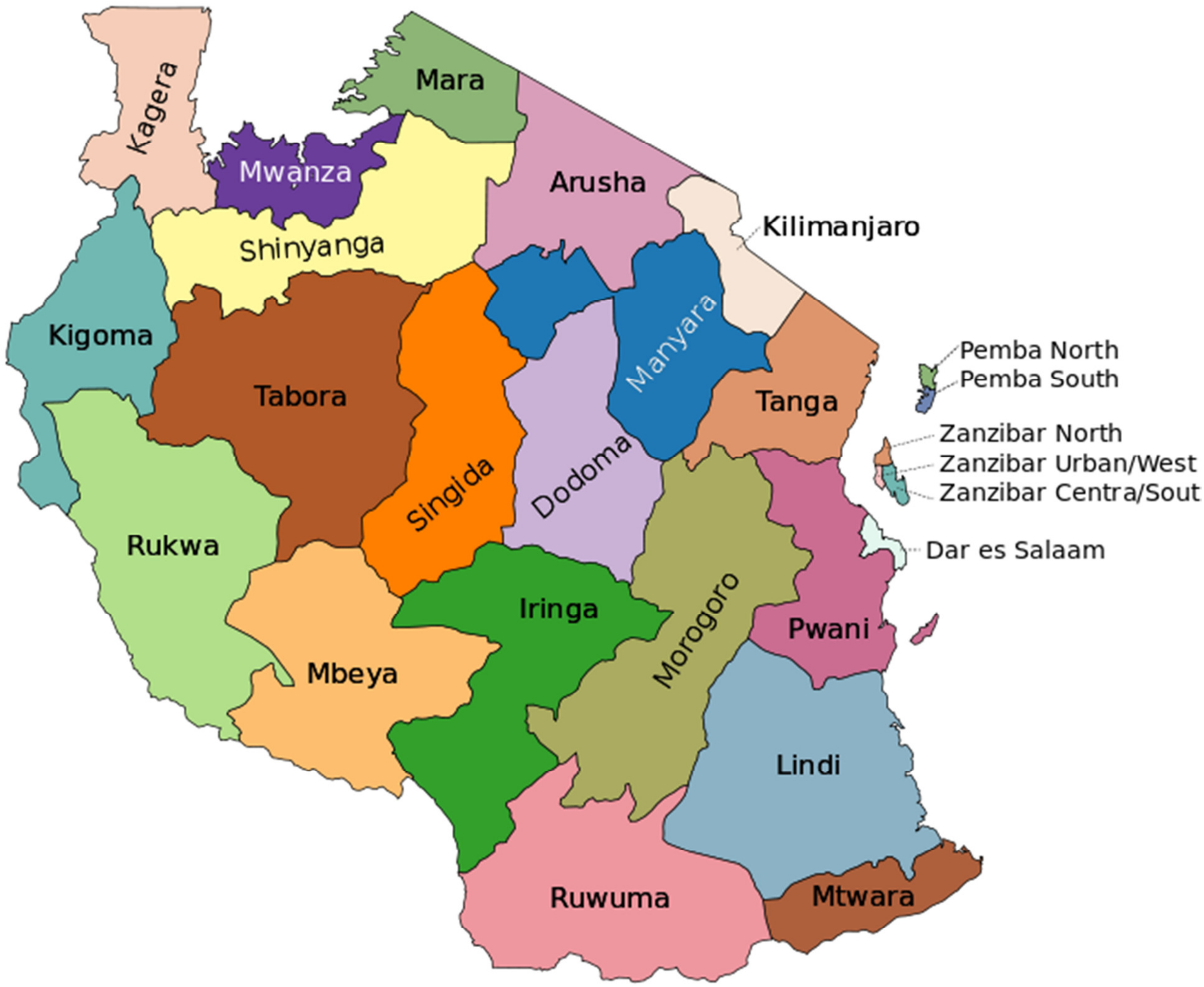


**Figure B-1: Map of Tanzania[38]**

Tanzania is divided into 26 regions. The following table indicates whether or not a region is connected to the national grid.

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[37] Information source: http://allafrica.com/stories/201203090225.html Tanzania Daily News March 2, 2012.
[38] Image source: http://upload.wikimedia.org/wikipedia/commons/thumb/1/18/Tanzania_regions.svg/712px-Tanzania_regions.svg.png by Greor Aisch January 16, 2012

| Region | Connected to the Grid? |
|---|---|
| Arusha | Yes |
| Dar es Salaam | Yes |
| Dodoma | Yes |
| Iringa | Yes |
| Kagera | No |
| Kigoma | No |
| Kilimanjaro (K’jaro) | Yes |
| Lindi | No |
| Manyara | Yes |
| Mara | Yes |
| Mbeya | Yes |
| Morogoro | Yes |
| Mtwara | No |
| Mwanza | Yes |
| Pwani | Yes |
| Rukwa | No |
| Ruvuma | No |
| Singida | Yes |
| Shinyanga | Yes |
| Tabora | Yes |
| Tanga | Yes |
| Pemba (North, South) | No |
| Zanzibar (North, Urban/West, Central/South) | Yes |

**Table B.1 List of Tanzania Regions connected to the national grid.**

# Appendix C – Base Case Parameter Values & Model Input

Section 4.1 described the process by which parameter values were defined to generate simulation model output that matches historical Tanzania data. The final results of the procedure are depicted in Table C.1.

| **Parameter** | **Estimated Value** |
|---|---|
| Contact Frequency | 20 |
| Adoption Fraction | 0.1 |
| Demand Profile Scale Factor for Residential Consumers | 1.0683 |
| Demand Profile Scale Factor for Industrial Consumers | 1.2 |
| Sensitivity to Capital Costs of Connection (Residential Consumers) | -5 |
| Sensitivity to Reliability (Residential Consumers) | 30 |
| Sensitivity to Electricity Price (Residential Consumers) | -30 |
| Sensitivity to Quality (Residential Consumers) | 20 |
| Sensitivity to Backlog (Residential Consumers) | -1 |
| Sensitivity to Capital Costs of Connection (Industrial Consumers) | -5 |
| Sensitivity to Reliability (Industrial Consumers) | 30 |
| Sensitivity to Electricity Price (Industrial Consumers) | -2.5081 |

**Table C.1: Base case parameter values.**

Chapter 5 presents generation capacity expansion for a system inspired by the case of Tanzania. The information provided below presents the input assumptions for this case.

| Variable | Description | Value | Units |
| --- | --- | --- | --- |
| above_poverty | Fraction of the Population Above Poverty | 0.65 | dmnl |
| grid_unit_price | Initial price of electricity | 0.0918 | USD/kWh |
| Tariff factor | is a value greater than 1, that indicates the increase (above true price) in tariff paid by residential consumers | 1 | dmnl |
| grid_connex_fee | the average cost for a residential consumer to connect to the grid | 800 | USD/HH |
| $tax_{gov}$ | taxes paid by the utility for each unit of energy supplied; this tax is passed directly to the customers | 0.02 | dmnl |
| $tax_{corruption}$ | an estimate of the percentage of cash flow that is lost to corruption. | 0 | dmnl |
| $tax_{REA}$ | additional tz paid to the Rural Energy Agency for all unit sales | 0.03 | dmnl |
| %meters_read | the fraction of total meters read by the utility | 1 | dmnl |
| %bills_col | the fraction of bills collected by the utility | 1 | dmnl |
| $\gamma_{res}$ | the fractional increase in residential demand per a unit increase in GDP | 0.614 | dmnl |
| $\Delta$gdp | the average assumed increase in GDP per year | 0.064 | dmnl |
| ini_ind_demand_grid | countrywide industrial demand for 2008 | 1.71E+09 | kWh |
| ini_ind_demand_diesel | initial industrial demand served by off-grid diesel units | 59610976 | kWh |
| ini_ind_demand_hydro | initial industrial demand served by off-grid hydro units | 19870325 | kWh |
| ini_ind_demand_pv | initial industrial demand served by off-grid pv systems | 0 | kWh |
| %shift | Fraction of Industrial Demand that will switch supply sources each year | 0.4 | Dmnl |
| $\gamma_{ind}$ | the fractional increase in industrial demand per a unit increase in GDP | 0.7043 | Dmnl |
| ini_perc_rel_grid | initial reliability level perceived by customers | 0.98 | Dmnl |
| pv_cap_res | this is the average pv capacity of a unit in a residential home | 0.25 | kW/HH |
| reference_capex | this reference cost normalizes the residential capital cost and makes the units dimensionless for calculating the attractiveness and indicated market share | 800 | USD/HH |
| reference_up | this reference cost normalizes the residential electricity price and makes the units dimensionless for calculating the attractiveness and indicated market share | 0.5 | USD/kWh |
| res_perc_delay_capex | This is the delay in perception of a price change in capital costs | 1 | Year |
| res_perc_delay_price | This is the delay in perception of a change in electricity prices | 1 | Year |
| res_perc_delay_backlog | This is the delay in perception of a change in backlog | 1 | Year |

| | | | |
|---|---|---|---|
| res_perc_delay_rel | This is the delay in perception of a change in reliability | 1 | Year |
| capex_PV | The assumed cost for a solar home system | 200 | USD/HH |
| per_qual_grid | This variable estimates the perceived quality of the connection to grid; a highly subjective estimate | 1 | Dmnl |
| per_qual_diesel | This variable estimates the perceived quality of the connection to a diesel generator in the home; highly subjective estimate | 0.5 | Dmnl |
| per_qual_pv | This variable estimates the perceived quality of the connection to a pv system in the home; highly subjective estimate | 0.5 | Dmnl |
| unit_price_pv | estimated cost per unit of electricity for small pv system | 0.05 | USD/kWh |
| unit_price_diesel | Assumed price of electricity | 0.2 | USD/kWh |
| backlog_ratio_pv | Fraction of requested/desired pv system to total installed units | 1.1 | Dmnl |
| backlog_ratio_diesel | Fraction of requested/desired diesel generators to total installed units | 1.1 | Dmnl |
| pop_08 | population of grid-connected regions in 2008 | 30853 | x1000 people |
| average_hh_size | the average number of people that live in a singel household | 4.5 | people/HH |
| pop_growth | average growth in population per year | 0.0304 | Dmnl |
| con_success | percentage of intended connections successfully made by power company | 1 | Dmnl |
| des_grid_dies | Fraction of diesel customers that will consider requesting a grid connection | 0.2 | Dmnl |
| des_grid_pv | Fraction of PV customers that will consider requesting a grid connection | 0.2 | Dmnl |
| max_connections | maximum number of residential households the power company can make in a single year | 11000000 | HH |
| inigrid | Initial grid customers | 723873 | HH |
| inipv | Initial pv customers | 185124 | HH |
| inidiesel | Initial diesel customers | 185124 | HH |
| ini_noelec | Initial households without electricity | 4086296 | HH |
| ind_pv_surcharge | Surcharge for pv systems | 5 | USD/W |
| ind_pv_comp | Cost for pv components | 15 | USD/kW |
| avg_cap_ind | The average capacity of industrial systems | 1000 | kW/system |
| ind_ref_capex | this reference cost normalizes the industrial capital costs and makes the units dimensionless for calculating the attractiveness and indicated market share | 1000000 | USD/system |
| ind_ref_up | this reference cost normalizes the industrial electricity price and makes the units dimensionless for calculating the attractiveness and indicated market share | 0.1115 | USD/kWh |
| ind_diesel_om | Estimate O&M costs for industrial diesel units | 0.035 | USD/kWh |
| diesel_density | density of diesel oil | 0.832 | kg/L |
| ind_fuel_cons | Fuel consumption of industrial consumers using off-grid diesel units | 0.27 | kg/kWh |
| ind_grid_capex | Estimated cost to the connect to the grid for industrial consumers | 50000 | USD/connection |

| | | | |
|---|---|---|---|
| ind_perc_delay_rel | This is the delay in perception of a change in reliability | 1 | Year |
| ind_perc_delay_price | This is the delay in perception of a change in electricity price | 1 | Year |
| ind_capex_diesel | Estimated cost of off-grid diesel systems for industrial consumers | 620 | USD/kW |
| ind_capex_hydro | Estimated cost of off-grid hydro systems for industrial consumers | 1800 | USD/kW |
| ind_unit_price_pv | Estimated price of electricity supplied by off-grid pv systems | 0.07 | USD/kWh |
| ind_unit_price_hydro | Estimated price of electricity supplied by off-grid hydro systems | 0.05 | USD/kWh |
| per_rel_diesel | This is the perceived reliability of off-grid diesel systems (residential consumers) | 0.95 | Dmnl |
| per_rel_pv | This is the perceived reliability of off-grid pv systems (residential consumers) | 0.95 | Dmnl |
| ind_per_rel_pv | This is the perceived reliability of off-grid pv systems (industrial consumers) | 0.95 | Dmnl |
| ind_per_rel_hydro | This is the perceived reliability of off-grid hydro systems(industrial consumers) | 0.95 | Dmnl |
| ind_per_rel_diesel | This is the perceived reliability of off-grid diesel systems (industrial consumers) | 0.95 | Dmnl |
| maturity | this is the time the power co has to repay loans | 20 | Years |
| debt_bailout | this is the percentage of debt bailout by the government | 0.1 | Dmnl |
| debt_interest | this is the interest on debt paid by the power co | 0.15 | Dmnl |
| cash_interest | this is the interest earned on cash | 0.03 | Dmnl |
| max_borrowing_limit | indicates the maximum level of debt possible | 20000 | million USD |

**Table C.2: Input Assumptions for Simplified Case of Tanzania (Chapter 5)**

| Year | Simulation Year | Variable | |
|---|---|---|---|
| | | pv_price [USD/W] | oil_price [USD/barrel] |
| 0 | 2008 | 2.53 | 64.1 |
| 1 | 2009 | 2.38 | 60.9 |
| 2 | 2010 | 2.25 | 57.5 |
| 3 | 2011 | 2.12 | 54.3 |
| 4 | 2012 | 2 | 51.7 |
| 5 | 2013 | 1.89 | 50 |
| 6 | 2014 | 1.78 | 49.6 |
| 7 | 2015 | 1.68 | 49.9 |
| 8 | 2016 | 1.58 | 49.7 |
| 9 | 2017 | 1.49 | 50.8 |
| 10 | 2018 | 1.41 | 51.3 |
| 11 | 2019 | 1.33 | 52 |
| 12 | 2020 | 1.25 | 52 |
| 13 | 2021 | 1.25 | 52.7 |
| 14 | 2022 | 1.25 | 53.4 |
| 15 | 2023 | 1.25 | 54.9 |
| 16 | 2024 | 1.25 | 55.6 |
| 17 | 2025 | 1.25 | 56.4 |
| 18 | 2026 | 1.25 | 57.1 |
| 19 | 2027 | 1.25 | 57.6 |
| 20 | 2028 | 1.25 | 58.1 |

**Table C.3: The assumed cost of PV and price of oil over the planning horizon**

| [kW] | WeekDays | | | WeekEnds | | |
|---|---|---|---|---|---|---|
| Period | Peak | Shoulder | Base | Peak | Shoulder | Base |
| 1 | 0.724449 | 0.195228 | 0.0957 | 0.1341368 | 0.094325 | 0.094325 |
| 2 | 0.71881269 | 0.1937091 | 0.094955441 | 0.1325067 | 0.093179 | 0.093179 |
| 3 | 0.70172246 | 0.18910354 | 0.092697815 | 0.1355548 | 0.095323 | 0.095323 |
| 4 | 0.72776752 | 0.19612229 | 0.096138378 | 0.1333385 | 0.093764 | 0.093764 |
| 5 | 0.74195188 | 0.19994476 | 0.098012137 | 0.1363851 | 0.095907 | 0.095907 |

**Table C.4: Residential demand profile per household connected at start of model horizon (estimated).**

The demand profile of newly connected residential grid customers can be found in Section 3.2. Similarly, the duration (in hours) of each load block is presented in Section 3.2 as well.

# Appendix D – Generation Plant Characteristics

The following table lists the production and cost assumptions for each generation plant/unit considered in the capacity expansion exercise presented in Chapter 5.

| Plant | EFOR [p.u.] | MaxProd [MW] | MinProd [MW] | VarCost [$ per MWh] | NoLoadCost [$ per h] | MaxPlantFactor [dmnl] | AnCap [k$] |
|---|---|---|---|---|---|---|---|
| Songas | 0.05 | 185.3 | 60 | 48.6 | 502.1 | 0.8 | 13029 |
| Diesel | 0.05 | 5.3 | 0 | 145.1 | 1876.5 | 0.75 | 366 |
| UbungoGas | 0.05 | 70.00 | 0 | 27.3 | 502.1 | 0.8 | 5406 |
| Kihansi | 0 | 75 | 75 | 0 | 0 | 1 | 8100 |
| Kidatu | 0 | 180 | 180 | 0 | 0 | 1 | 9180 |
| Hale | 0 | 5 | 5 | 0 | 0 | 1 | 945 |
| Nyumba | 0 | 3.5 | 3.5 | 0 | 0 | 1 | 360 |
| Mtera | 0 | 66 | 66 | 0 | 0 | 1 | 3600 |
| Pangani | 0 | 20 | 20 | 0 | 0 | 1 | 3060 |
| *Coal* | *0.08* | *200* | *100* | *22* | *223.8* | *0.8* | *35200* |
| *CCGT* | *0.04* | *300* | *100* | *47.1* | *400* | *0.8* | *19350* |
| *Kihansi_2* | *0* | *150* | *100* | *0* | *0* | *1* | *4961* |
| *Ruhudji* | *0* | *300* | *250* | *0* | *0* | *1* | *12785* |
| *Ikondo* | *0* | *300* | *250* | *0* | *0* | *1* | *15810* |
| *CCGT_2*[39] | *0.04* | *400* | *133* | *47.1* | *500* | *0.8* | *25800* |

**Table D.1: Characteristics of existing and candidate (italicized) generators**

[39] For the analyses presented in Sections 6.1 and 6.2 only.

# Appendix E – Pseudo Code for Capacity Expansion Planning Algorithm that Assumes Endogenous Demand

**Input:** expansion matrix D, where each column i indicates a single generation expansion strategy ($D_i$); n is the number of strategies considered

**Initialize:** optimal expansion strategy $B_D = 0$ (a column vector of zeros) and optimal cost V = 99999 million USD.

**Loop** over i from 1 to n.

For each i, **execute** the simulation model and **calculate** the total cost of supply for the planning horizon as

$$C(D_i) = \sum_{y=1}^{20} pDiscount_y \times \{vProdC_y + vNSEC_y + vCommitC_y + vACC_y\}$$

where

$$pDiscount_y = \frac{1}{(1+dr)^y}$$

and the components of $C(D_i)$, the total cost of supply, are defined as:

$$vProdC_y = \sum_{p,s,n,g} pDuration_{p,s,n} \cdot pVarCost_g \cdot vProduct_{y,s,n,g}$$

$$vNSEC_y = \sum_{p,s} pPNSCost \cdot vPNS_{y,p,s} + \sum_{p,s,n} pDuration_{p,s,n} \cdot pENSCost \cdot vENS_{y,p,s,n}$$

$$vCommitC_y = \sum_{p,s,n,t} pDuration_{p,s,n} \cdot pNoLoadCost_t \cdot vCommit_{y,p,s,t}$$

$$ACC_y = \sum_{g} (pAnCap_g + pFixedOM) \cdot pInstalled_{y,g}$$

**Check** if this expansion strategy minimizes costs.

If $C(D_i) < V$, set $B_D = D_i$ and set $V = C(D_i)$.

Otherwise do nothing.

**End** loop.

**Output:** Optimal expansion strategy $B_D$ and optimal value V.

# Appendix F – Model of Capacity Expansion Assuming Exogenous Demand

The **objective function** is defined as:

$$Min\ \{TCS\}$$

where

$$TCS = \sum_{y=1}^{20} pDiscount_y \times \{vProdC_y + vNSEC_y + vCommitC_y + vACC_y\}$$

and

$$pDiscount_y = \frac{1}{(1+dr)^y}$$

$$vProdC_y = \sum_{p,s,n,g} pDuration_{p,s,n} \cdot pVarCost_g \cdot vProduct_{y,s,n,g}$$

$$vNSEC_y = \sum_{p,s} pPNSCost \cdot vPNS_{y,p,s} + \sum_{p,s,n} pDuration_{p,s,n} \cdot pENSCost \cdot vENS_{y,p,s,n}$$

$$vCommitC_y = \sum_{p,s,n,t} pDuration_{p,s,n} \cdot pNoLoadCost_t \cdot vCommit_{y,p,s,t}$$

$$ACC_y = \sum_g (pAnCap_g + pFixedOM) \cdot pInstalled_{y,g}$$

Model **input parameters** are:

| | | |
|---|---|---|
| $pDRes_{p,s,n}$ | residential demand in 2008 | [MW] |
| $pDInd_{p,s,n}$ | industrial demand in 2008 | [MW] |
| $pDemIncrInd_y$ | yearly demand increment | |
| $pDemIncrRes_y$ | yearly demand increment | |

and **decision variables** of this model are defined below:

| | | |
|---|---|---|
| $vBuilt_{y,g}$ | additional units operating in year y | [positive integer] |
| $vInstalled_{y,g}$ | number of total units operating in year y | [positive integer] |
| $vCommit_{y,p,s,t}$ | commitment of thermal unit | [positive integer] |
| $vProduct_{y,p,s,n,g}$ | production of the plant | [MW] |
| $vENS_{y,p,s,n}$ | power non served | [MW] |
| $vPNS_{y,p,s}$ | total power non served | [MW] |

The objective must be minimized subject to numerous constraints. The **constraints** for each year are described in Sections 3.3.2 to 3.3.6. They are formulated below for clarity.

**Demand Balance Constraint**

The sum of electricity generated and non-served energy must equal the demand for all *y*, *p*, *s* and *n*.

$$\left[\sum_{g,nd} vProduct_{y,p,s,n,g}\right] + vENS_{y,p,s,n} = \quad pDemand_{y,p,s,n} \qquad \forall\, y,p,s,n \qquad --[33]$$

where

$$pDemand_{y,p,s,n} \;= \left[pDInd_{p,s,n} \times pCumIncrInd_{y}\right] + \;\left[pDRes_{p,s,n} \times pCumIncrRes_{y}\right] \qquad --[34]$$

and

$$pCumIncrInd(y) = \prod_{z=1}^{y} 1 + pDemIncrInd(y) \qquad \forall\, y \qquad --[35]$$

$$pCumIncrRes(y) = \prod_{z=1}^{y} 1 + pDemIncrRes(y) \qquad \forall\, y \qquad --[36]$$

**Reserve Margin Constraint**

The reserve margin is the generating capacity available in excess of what is required to meet peak demand levels. The constraint is formulated as:

$$vPNS_{y,p,s} + \textstyle\sum_h pMaxProd_h \cdot vInstalled_{y,h} \; + \textstyle\sum_t pMaxProd_t \cdot vCommit_{y,p,s,t} \;\; \geq$$

$$\left[pDemand_{y,p,s,n}\right] \times (1 + pOpReserve)) \qquad \forall\, y,p,s,n1 \qquad --[37]$$

and $pMaxProd_g$ is the maximum production (in MW) of each generating unit and $n1$ is the peak demand level. Here, the reserve margin is assumed to be negligible.

### Production & Commitment Constraints

The power generated must not exceed the rated capacity of the unit or, for thermal units, fall below the minimum production capacity specified. Electricity production in the peak load blocks must be greater than that of the shoulder load blocks, and the production in the shoulder load blocks must be greater than that of the base load blocks. Finally, once built and installed, thermal units can be committed as follows:

$$vCommit_{y,p,s,t} \leq vInstalled_{y,t} \qquad \forall\, y,p,s,t$$

$$vProduct_{y,p,s,n,t} \leq pMaxProd_t \times vCommit_{y,p,s,t} \qquad \forall\, y,p,s,n,t$$

$$vProduct_{y,p,s,n,t} \geq pMinProd_t \times vCommit_{y,p,s,t} \qquad \forall\, y,p,s,n,t$$

$$vProduct_{y,p,s,n,h} \leq pMaxProd_h \qquad \forall\, y,p,s,n,h$$

$$vProduct_{y,p,s,n+1,g} \leq vProduct_{y,p,s,n,g} \qquad \forall\, y,p,s,n,g$$

$$pMaxProd_g = pRatedMaxP_g \times \left[1 - pEFOR_g\right] \qquad \forall g$$

$$\textstyle\sum_{p,s,n} vProduct_{y,p,s,n,t} \leq 8760 \times pMaxPlantFac_g \times pMaxProd_t \times vInstalled_{y,t} \qquad \forall\, y,t$$

$$\sum_{s,n} vProduct_{y,p,s,n,h} \cdot pDuration_{p,s,n} \leq pAPProdhmax_{h,p} \qquad \forall y,h,p$$

$$\sum_{s,n} vProduct_{y,p,s,n,h} \cdot pDuration_{p,s,n} \geq pAPProdhmin_{h,p} \qquad \forall y,h,p$$

where $pRatedMaxP_g$ is the rated capacity of the generating unit, $pEFOR_g$ is the equivalent forced outage rate of each unit, $pMaxPlantFac_g$ is the fraction indicating the maximum generation that is feasible in a single year for each thermal unit, $pMinProd_g$ is the minimum production of a committed thermal unit, and $pAPProdhmax_{h,p}$ and $pAPProdhmin_{h,p}$ are the maximum and minimum production of each hydro unit in a single period, respectively.

### Capacity Expansion Constraints

Additional capacity expansion constraints are considered in this capacity expansion formulation to represent the decision problem described in Section 5.1.

$$\sum_{y} vBuilt_{y,t_n} \leq pMaxUnits \qquad --[38]$$

$$\sum_{y} vBuilt_{y,h_n} \leq 1 \qquad --[39]$$

$$vInstalled_{y,g} = \sum_{z=1}^{y} vBuilt_{y,g} \qquad --[40]$$

Where $t_n$ indicates candidate thermal plants, and $h_n$ indicates candidate hydro units. Based on the description of the decision problem presented in Section 5.1, a number of variables were fixed. For all pre-existing thermal and hydro units $vBuilt_{1,g}$ is set equal to 1. To simulate the operation of the new hydro units coming line, $vBuilt_{1,Ruhudji}$, $vBuilt_{1,Ikondo}$ and $vBuilt_{11,Kihansi\_2}$ are set to 1 as well. Finally, it should be noted that $vBuilt_{y,g}$ is set equal to 0 for all years except years 1 and 11 to implement the two-stage decision problem.

# Appendix G – Annual Power Grid Operation with Transmission Constraints

The Annual Power Grid Operation Module presented in Section 3.3 does not represent the transmission network. The network and its constraints, however, may have a large impact on when, how much and where new generating capacity should be added to the system. Therefore, the model was extended to include the transmission network; it is formulated below.

## Transmission Network Representation

This model captures high and medium voltage transmission lines. Due to the discrepancy in data provided by Tanesco employees and in the 2009 Power System Master Plan (Tanesco 2009), the network depicted in Figure G-1 is assumed in this model. It consists of 16 nodes and 22 transmission lines.

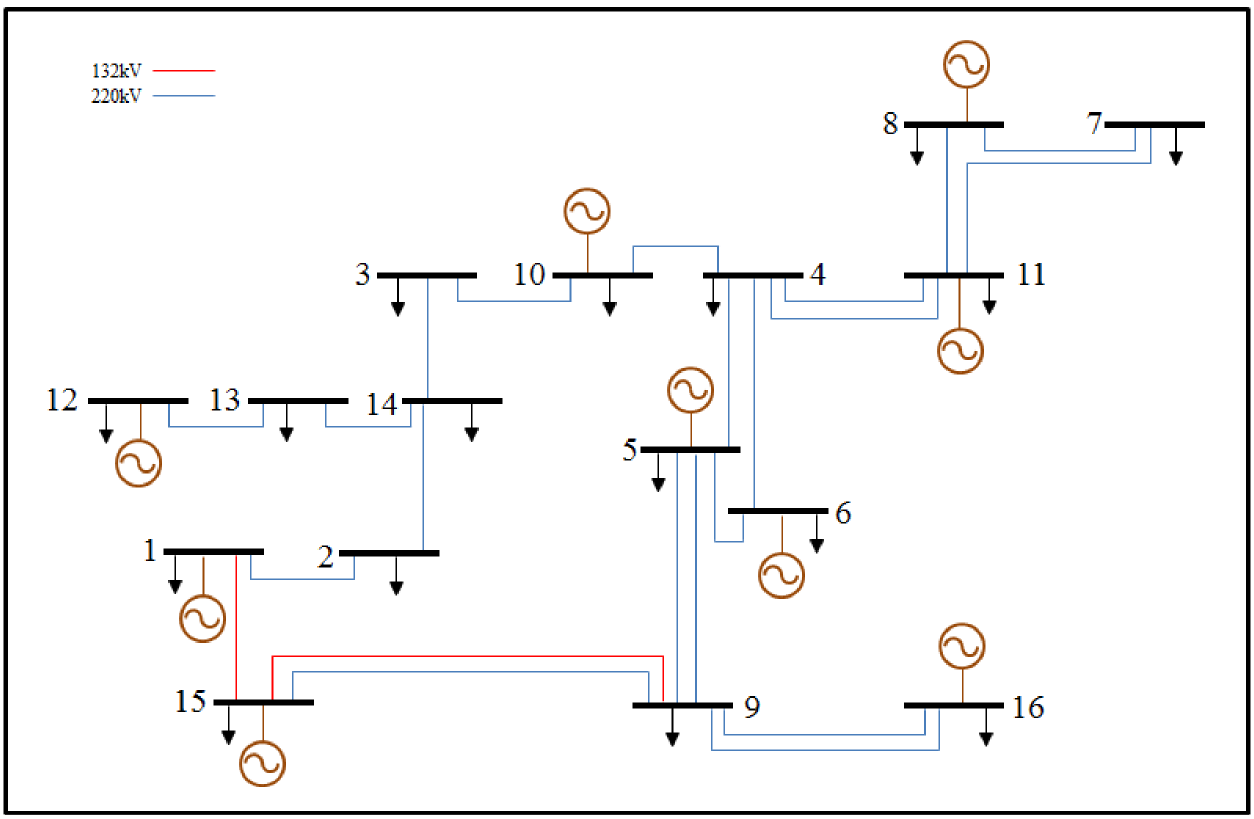


**Figure G-1: Single line diagram of simplified transmission network**

All existing transmission lines (shown in Figure G-1) can be reinforced by adding additional circuits (of 220kV), referred to below as "candidate lines".

## Location of Demand throughout the Network

The country of Tanzania is divided into 23 formal regions, of which only 16 are connected to the national grid[40]. Based on data provided in Tanzania's PSMP (Tanesco 2009) and neglecting urbanization, the demand experienced at each node in the network is comprised of the grid demanded in various regions as shown in Table G.1.

| Node Name | Node # | Demand (as % of demand in specified region) | Share of Annual Demand |
|---|---|---|---|
| Arusha | 1 | 0.8 (Arusha) + 1(K'jaro) | 0.110 |
| Babati | 2 | 0.2(Arusha) + 0.2(Dodoma) | 0.022 |
| Dodoma | 3 | 0.8(Dodoma) | 0.026 |
| Iringa | 4 | 0.2(Iringa) | 0.005 |
| Kidatu | 5 | 0.2 (Morogoro) | 0.008 |
| Kihansi | 6 | 0 | 0.000 |
| Makambako | 7 | 0.3 (Iringa) | 0.008 |
| Mbeya | 8 | 1(Mbeya) | 0.042 |
| Morogoro | 9 | 0.8(Morogoro) | 0.033 |
| Mtera | 10 | 0 | 0.000 |
| Mufindi | 11 | 0.5 (Iringa) | 0.013 |
| Mwanza | 12 | 1(Mara) + 1(Mwanza) | 0.066 |
| Shinyanga | 13 | 1(Tabora) + 1(Shinyanga) | 0.039 |
| Singida | 14 | 1(Singida) | 0.010 |
| Tanga | 15 | 1(Tanga) | 0.037 |
| Ubungo | 16 | 1(Dar) + 1(Zanzibar) | 0.581 |

**Table G.1: Assumed share of annual demand in each node of the grid network**

For example, the demand realized at Node 1 is the sum of 80% of total demand in Arusha and 100% of demand in Kilimanjaro. Using 2008 data on the annual demand of each of the grid-connected regions, the fraction of demand at each node in the network is assumed to be fixed as shown in column 4 of Table G.1.

[40] For simplicity, regions that were not connected to the national grid as of 2009 are excluded from the model. See APPENDIX B for map of Tanzania and list of grid connected regions.

## Model Formulation

The "Annual Power Grid Operation" module is a medium term power system model. Mixed-integer programming is employed to formulate this deterministic DC optimal power flow[41] model with crude hydro-thermal coordination and block-wise unit commitment. The model minimizes total variable costs while satisfying demand balance constraints and meeting production and flow constraints. It takes as input the newly installed generation *and transmission* capacity and the grid demand profile of both residential and industrial consumers to determine the power flow in each line of the transmission network as well as the production of each generator during every period, day type, and load level of the year. This model also determines total annual operational costs, network losses, annual electricity production and consumption, and total non-served energy.

### Model Objective

The **objective** of the problem is to minimize costs, defined as:

$$Min\,\{vProdC + vNSEC + vCommitC + vLossC\} \qquad --[41]$$

*vProdC* represents the variable costs of production, *vNSEC* indicates the penalty resulting from non-served energy and power, *vCommitC* represents the cost of operating thermal units and *vLossC* is the penalty incurred from transmission losses. They are defined as:

$$vProdC = \sum_{p,s,n,g} pDuration_{p,s,n} \cdot pVarCost_g \cdot vProduct_{p,s,n,g} \qquad --[42]$$

$$vNSEC = \sum_{p,s} pPNSCost \cdot vPNS_{p,s} + \sum_{p,s,n,nd} pDuration_{p,s,n} \cdot pENSCost \cdot vENS_{p,s,n,nd} \qquad --[43]$$

$$vCommitC = \sum_{p,s,n,t} pDuration_{p,s,n} \cdot pNoLoadCost_t \cdot vCommit_{p,s,t} \qquad --[44]$$

$$vLossC = \; pLossCost \; \times \sum_{p,s,n,ll(ni,nf,ckt)} pDuration_{p,s,n} \cdot vLoss_{p,s,n,ll_{ni,nf,ckt}}) \qquad --[45]$$

---

[41] The simplifying assumptions of DC optimal power flow models are: (1) all node voltages have similar magnitudes (2) the inductive components of transmission lines is bigger than the resistive component (3) the difference in the phase angle of node voltages is small (García-González 2010).

where

| | |
|---|---|
| $y$ | year (ranging from 1 to 20) |
| $p$ | period (ranging from 1 to 5) |
| $s$ | day-type (weekday or weekend) |
| $n$ | load level (peak, shoulder, base) |
| $g$ | generating unit |
| $t$ | thermal generating unit |
| $h$ | hydro generating unit |
| $nd/ni/nf$ | node in grid network |
| $ckt$ | circuit |
| $ll_{nd,nd,ckt}$ | transmission line |
| $le_{nd,nd,ckt}$ | transmission line existing prior to simulation |
| $lc_{nd,nd,ckt}$ | candidate transmission line |

and

| | | |
|---|---|---|
| $pDuration_{p,s,n}$ | duration | [hours] |
| $pVarCost_g$ | variable costs | [M$ per MWh] |
| $pNoLoadCost_t$ | no load costs | [M$ per h] |
| $pPNSCost$ | cost of power non-served | [M$ per MW] |
| $pENSCost$ | cost of energy non-served | [M$ per MWh] |
| $pLossCost$ | cost of transmission losses | [M$ per MWh] |
| $pAnCap_g$ | annualized capacity costs of generator | [M$] |
| $pFC_{ni,nf,ckt}$ | fixed cost per year for new line | [M$] |

Model **input parameters** are:

| | | |
|---|---|---|
| $pDemShare_{nd}$ | fraction of demand at node | |
| $pDRes_{p,s,n}$ | residential demand | [MW] |
| $pDInd_{p,s,n}$ | industrial demand | [MW] |
| $pInstalled_g$ | number of generating units installed of type g | |
| $pInstCap_{ni,nf,ckt}$ | binary variable indicating whether candidate line is installed | |

and **decision variables** of this model are defined below:

| | | |
|---|---|---|
| $vProduct_{p,s,n,g}$ | production of the unit | [MW] |
| $vCommit_{p,s,t}$ | commitment of thermal unit | [positive integer] |
| $vENS_{p,s,n,nd}$ | power non served at node | [MW] |
| $vPNS_{p,s}$ | total power non served | [MW] |
| $vFlow_{p,s,n,nd,nd,ckt}$ | flow in line | [MW] |
| $vLoss_{p,s,n,nd,nd,ckt}$ | losses in the transmission line | [MW] |
| $vTheta_{p,s,n,nd}$ | voltage angle | [rad] |
| $vAuxBin_{p,s,n,nd}$ | auxiliary binary variable indicating whether or not the voltage angle difference between two nodes is positive or negative | |

The objective must be minimized subject to numerous network and production constraints. The **constraints** are described in the following subsections.

**Demand Balance Constraint**

The sum of electricity generated and non-served energy less network losses and flow out of the node must equal the demand plus flow into the node for all *p*, *s*, *n* and *nd*.

$$\left[\sum_{g,nd} vProduct_{p,s,n,g}\right] + vENS_{p,s,n,nd} - \left[\sum_{ll_{ni,nd,ckt}} \frac{vLoss_{p,s,n,ni,nd,ckt}}{2}\right] - \left[\sum_{ll_{nd,nf,ckt}} \frac{vLoss_{p,s,n,nd,nf,ckt}}{2}\right]$$
$$= \quad pDemand_{p,s,n,nd} + \left[\sum_{ll_{nd,nf,ckt}} vFlow_{p,s,n,nd,nf,ckt}\right] - \left[\sum_{ll_{ni,nd,ckt}} vFlow_{p,s,n,ni,nd,ckt}\right]$$

and

$$pDemand_{p,s,n,nd} = pDemShare_{nd}\left[pDInd_{p,s,n} + \ pDRes_{p,s,n}\right]$$

$$\forall p, s, n, nd$$

**Reserve Margin Constraint**

The reserve margin is the generating capacity available in excess of what is required to meet peak demand levels. In most systems, regulators require reserve margins to be approximately 10% to 20% in order to ensure that, during times of generator breakdowns or sudden increases in demand, the power grid is still operational.

$$vPNS_{p,s} + \sum_{h} pMaxProd_h \cdot pInstalled_h \ + \sum_{t} pMaxProd_t \cdot vCommit_t$$

$$\geq \left[pDInd_{p,s,n} + \ pDRes_{p,s,n} + \textstyle\sum_{ll_{ni,nf,ckt}} vLoss_{p,s,n,ni,nf,ckt}\right] \times (1 + pOpReserve)) \qquad \forall p, s, n1$$

where $pMaxProd_g$ is the maximum production (in MW) of each generating unit and $n1$ is the peak demand level. According to EWURA, the reserve margin is negligible in the Tanzanian power system. Accordingly, *pOpReserve* is equal to zero.

**Network Flow Constraints**

The flow on a transmission line cannot exceed the capacity of the line and is proportional to the phase difference of node voltages.

For existing lines:

$$vFlow_{p,s,n,ni,nf,ckt} = \left[vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}\right] \cdot \frac{pSbase}{pX_{ni,nf}}$$

$$vFlow_{p,s,n,ni,nf,ckt} \geq -pMaxFlow_{ni,nf,ckt}$$

$$vFlow_{p,s,n,ni,nf,ckt} \leq pMaxFlow_{ni,nf,ckt}$$

$$\forall p, s, n, le_{ni,nf,ckt}$$

and for candidate lines:

$$\frac{vFlow_{p,s,n,ni,nf,ckt}}{pMaxFlow_{ni,nf,ckt}} \geq \frac{\left[vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}\right] \cdot pSbase}{pX_{ni,nf,ckt} \cdot pMaxFlow_{ni,nf,ckt}} - 1 + pInstCap_{ni,nf,ckt}$$

$$\frac{vFlow_{p,s,n,ni,nf,ckt}}{pMaxFlow_{ni,nf,ckt}} \leq \frac{\left[vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}\right] \cdot pSbase}{pX_{ni,nf,ckt} \cdot pMaxFlow_{ni,nf,ckt}} + 1 - pInstCap_{ni,nf,ckt}$$

$$vFlow_{p,s,n,ni,nf,ckt} \geq -pMaxFlow_{ni,nf,ckt} \cdot pInstCap_{ni,nf,ckt}$$

$$vFlow_{p,s,n,ni,nf,ckt} \leq pMaxFlow_{ni,nf,ckt} \cdot pInstCap_{ni,nf,ckt}$$

$$\forall p, s, n, lc_{ni,nf,ckt}$$

where $pSbase$ is the base power (in MW) of the system, $pX_{ni,nf,ckt}$ and $pR_{ni,nf,ckt}$ are the inductance and resistance of each transmission line, respectively, and $pMaxFlow_{ni,nf,ckt}$ is the maximum flow on each transmission line.

**Transmission Losses**

Transmission losses in a single line are proportional to the square of the line drop voltage (the difference in voltages of the two nodes connecting the transmission line). In a DCOPF model using per unit quantities (*i.e.* normalizing by the base power), this simplifies to:

$$vLoss_{p,s,n,ni,nf,ckt} = \alpha \times \left\{1 - \cos\left(vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}\right)\right\} \qquad \forall p, s, n, ll_{ni,nf,ckt}$$

where

$$\alpha = pSbase \times \frac{2 \cdot pR_{ni,nf}}{pR^2_{ni,nf,ckt} + pX^2_{ni,nf,ckt}}$$

The loss equation above is nonlinear; therefore, it has been approximated as:

$$vLoss_{p,s,n,ni,nf,ckt} \geq \alpha \times \{m_{seg}(vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}) + ne_{seg}\}$$

$$\forall p, s, n, le_{ni,nf,ckt}, seg$$

$$vLoss_{p,s,n,ni,nf,ckt} \geq \alpha \times \{m_{seg}(vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}) + ne_{seg}\} - 10^4(1 - pInstCap_{ni,nf,ckt})$$

$$\forall p, s, n, lc_{ni,nf,ckt}, seg$$

where the set of lines (*seg* = 1 to 30) make up the linear approximation of the cosine function (see Figure G-2), and $m_{seg}$ and $ne_{seg}$ are the slope and intercept, respectively, of line *seg*.

The losses formulation above often results in excess network losses. As the system attempts to decrease costs, hydro production is increased to reduce the more expensive thermal production. Since the formulation above only sets a lower bound on losses, excess losses arise. In order to correct this, a small penalty on transmission losses is assumed (as shown in the objective function in equation [41]) and an upper bound is placed on line losses. Figure G-2 depicts the upper bound in red and the equations follow.

$$vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf} \geq -vAuxBin_{p,s,n,ni,nf} \times 2$$

$$vTheta_{p,s,n,nf} - vTheta_{p,s,n,ni} \geq -\{1 - vAuxBin_{p,s,n,ni,nf}\} \times 2$$

$$\forall p, s, n, ll_{ni,nf,ckt}$$

$$vLosses \leq \alpha \times \{\beta[vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}] + [6 \times vAuxBin_{p,s,n,ni,nf}]\}$$

$$vLosses \leq \alpha \times \{\beta[vTheta_{p,s,n,nf} - vTheta_{p,s,n,ni}] + [6 \times (1 - vAuxBin_{p,s,n,ni,nf}))]\}$$

$$\forall p, s, n, le_{ni,nf,ckt}$$

$$vLosses \leq pInstCap_{ni,nf,ckt} \times \alpha \times \{\beta[vTheta_{p,s,n,ni} - vTheta_{p,s,n,nf}] + [6 \times vAuxBin_{p,s,n,ni,nf}]\}$$

$$vLosses \leq pInstCap_{ni,nf,ckt} \times \alpha \times \{ \beta[vTheta_{p,s,n,nf} - vTheta_{p,s,n,ni}] + [6 \times (1 - vAuxBin_{p,s,n,ni,nf})]\}$$

$$\forall p, s, n, lc_{ni,nf,ckt}$$

where $vAuxBin_{p,s,n,ni,nf}$ is an auxiliary binary variable indicating whether or not the voltage angle difference between two nodes is positive or negative, and $\beta$ is $\frac{0.929}{1.5\ radians}$.

Due to the gap between the solid black line and dashed red line depicted in Figure G-2, there is still the possibility that losses are over-estimated.

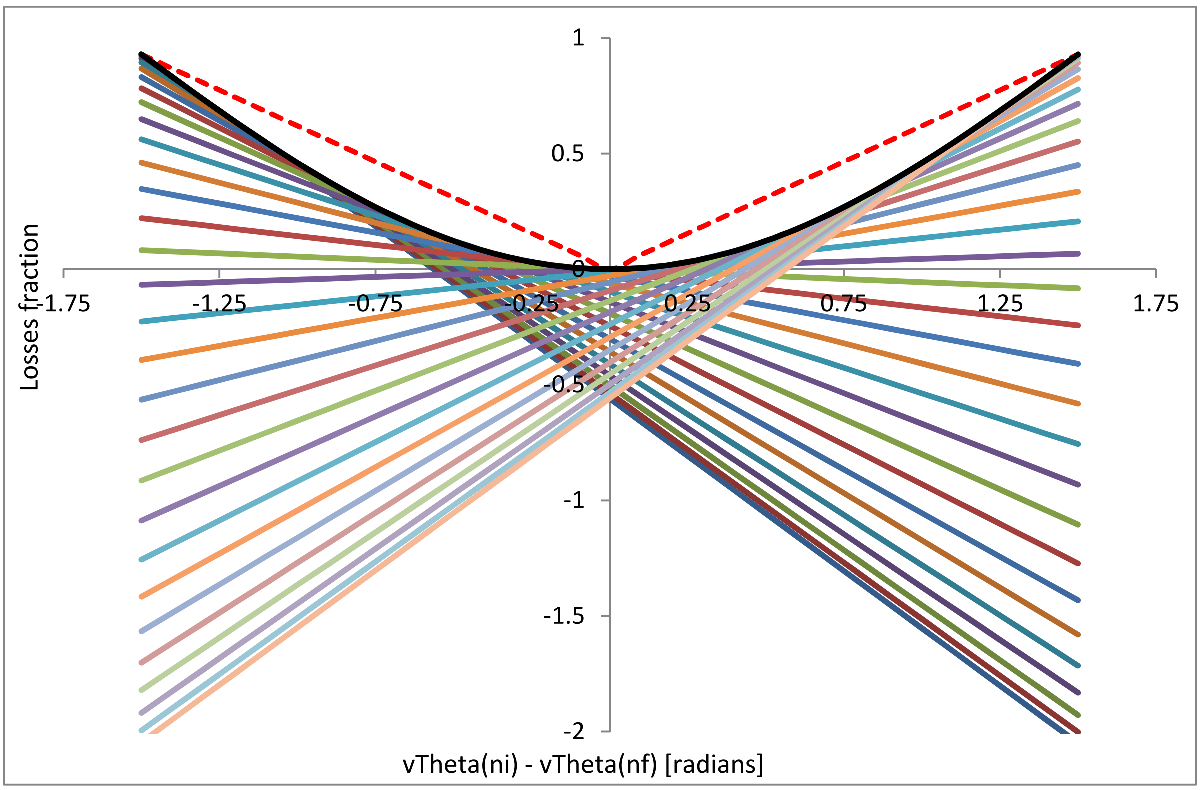


**Figure G-2: Non-linear losses (shown by the black solid line) are approximated as the maximum of the 30 colored solid lines. The upper bound on losses is shown by the dashed red line.**

### Production & Commitment Constraints

The power generated must not exceed the rated capacity of the unit or, for thermal units, fall below the minimum production capacity specified. Electricity production in the peak load blocks must be greater than that of the shoulder load blocks, and the production in the shoulder load blocks must be greater than that of the base load blocks. Data for each thermal unit was used to determine the maximum annual energy production of the units, and historical hydro production data was used to determine the average maximum and minimum energy production of each hydro unit in a single period.  Additionally, the variable production costs of hydro power are assumed to be zero.

$$vProduct_{p,s,n,t} \leq pMaxProd_t \times vCommit_{p,s,t} \qquad \forall p,s,n,t$$

$$vProduct_{p,s,n,t} \geq pMinProd_t \times vCommit_{p,s,t} \qquad \forall p,s,n,t$$

$$vProduct_{p,s,n,h} \leq pMaxProd_h \qquad \forall p,s,n,h$$

$$vProduct_{p,s,n+1,g} \leq vProduct_{p,s,n,g} \qquad \forall p,s,n,g$$

$$pMaxProd_g = pRatedMaxP_g \times \left[1 - pEFOR_g\right] \times pInstalled_g \qquad \forall g$$

$$vProduct_{p,s,n,t} \leq 8760 \times pMaxPlantFac_g \times pMaxProd_t \qquad \forall t$$

$$\sum_{s,n} vProduct_{p,s,n,h} \cdot pDuration_{p,s,n} \leq pAPProdhmax_{h,p} \qquad \forall h,p$$

$$vProduct_{p,s,n,h} \cdot pDuration_{p,s,n} \geq pAPProdhmin_{h,p} \qquad \forall h,p$$

where $pRatedMaxP_g$ is the rated capacity of the generating unit, $pEFOR_g$ is the equivalent forced outage rate of each unit, $pMaxPlantFac_g$ is the fraction indicating the maximum generation that is feasible in a single year for each thermal unit, $pMinProd_g$ is the minimum production of a committed thermal unit, and $pAPProdhmax_{h,p}$ and $pAPProdhmin_{h,p}$ are the maximum and minimum production of each hydro unit in a single period, respectively.  Finally, once built and installed, thermal units can be committed as follows:

$$vCommit_{p,s,t} \leq pInstalled_t \qquad \forall p,s,t$$

### Additional Model Outputs

The "Annual Power Grid Operation" module determines the following values, which it passes to the "Power Company Cash Flow and Electricity Prices" module:

$$ACC = \sum_{g} pAnCap_g \cdot pInstalled_g + \sum_{lc_{ni,nf,ckt}} pFC_{ni,nf,ckt} \cdot pInstCap_{ni,nf,ckt} \quad --[46]$$

$$NSE = \sum_{p,s,n,nd} pDuration_{p,s,n} \cdot vENS_{p,s,n,nd} \quad --[47]$$

$$TD = \sum_{p,s,n,nd} pDuration_{p,s,n} \cdot pDemand_{p,s,n,nd} \quad --[48]$$

$$Cons = TD - NSE \quad --[49]$$

$$TLoss = \sum_{p,s,n,ll_{ni,nf,ckt}} pDuration_{p,s,n} \cdot vLoss_{p,s,n,ni,nf,ckt} \quad --[50]$$

$$FSTD = 1 - \frac{NSE}{Cons} \quad --[51]$$

where *ACC* is the annualized capacity costs of installed generating units, *NSE* is annual non-served grid demand, *TD* is the total energy demanded over the year, *TLoss* is annual network losses, and *FSTD* is the fraction of served to total grid demand. The module also passes along *vNSEC* and *vProdC*, the annual costs of non-served energy and the annual variables costs of electricity production, respectively.

## Impact on Execution Time

The execution time of the endogenous planning algorithm increases dramatically when the simulation model includes the transmission network. It takes approximately twelve hours to explore three hundred expansion plans; without transmission, it only takes three hours to explore seven-hundred and eighty possible plans.