Multi-objective Optimization Techniques in Electricity Generation Planning

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Abstract

The objective of this research is to develop a framework of multi-objective optimization (MOO) models that are better capable of providing decision support on future long-term electricity generation planning (EGP), in the context of insufficient electricity capacity and to apply it to the electricity system for a developing country.

The problem that motivated this study can be stated as lack of EGP models in developing countries to keep pace with the countries socio-economic and demographic dynamics. Developing countries are characterized by insufficient capital funds to develop electricity-related investments and operations. EGP problems often involve many stakeholders with different objectives, thus no single solution can be optimal on all the objectives at the same time. In addition, there is uncertainty about future electricity demand patterns and other input data.

This research focused on two approaches; mathematical programming (MP) and system dynamics (SD). The problem formulation resulted in a constrained mixed integer MOLP and EGP-SD models. The models are integrated into a EGP-DSS framework to help decision-makers think systematically about the selection of EGP scenarios based on a combination of key drivers of electricity generation capacity. The incorporation of multiple objectives to develop strategies for electricity generation capacity, the integration of MP and SD approaches into a DSS, are some of the features of this research which have not been considered simultaneously in the literature.

The EGP-DSS allows the decision-maker to simulate and investigate the alternative decision scenarios, and to significantly increase the effectiveness of decision-making. Three scenarios, including the base case scenario representing possible "future worlds" were evaluated to compare and contrast the performance of the MOLP and EGP-SD models in aiding comprehensive decision making in EGP. This research provides a new framework for understanding the long term EGP systems, in a developing country context.

Detailed model descriptions, formulations, and implementation results are presented in the thesis along with the observations and insights obtained during the course of this research.

Key words: *Electricity generation planning*, *multi-objective optimization*, *mathematical programming*, *system dynamics*, *decision support system*

Declaration

I, **Richard Tuyiragize**, hereby,

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I am now presenting the thesis for examination for the degree of Doctor of Philosophy in Statistical Sciences.

Richard Tuyiragize
February 2011

Emeritus Prof. Theodor J.Stewart
Supervisor
February 2011

Prof.Livingstone S.Luboobi
Supervisor
February 2011

Dedication

To my beloved parents
Mr.John and Mrs.Jessica Ntibarikure,

my dear wife
Mrs.Rebecca K.Tuyiragize,

and our daughter
Tisha, who was born during my study.

Acknowledgment

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A special thanks to my brother Johnson, and my parents. None of my achievements would have been possible without their enduring love and support.

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Abbreviations

AHP	Analytical Hierarchy Process
BB	Branch-and-Bound
DM	Decision Maker
DP	Dynamic Programming
DSS	Decision Support System
EA	Evolutionary Algorithm
EGP	Electricity Generation Planning
EIA	Energy Information Administration
ERA	Electricity Regulatory Authority
ERT	Energy for Rural Transformation
GA	Genetic Algorithm
GAMS	General Algebraic Modeling System
GDP	Gross Domestic Product
GIS	Geographical Information System
GoU	Government of Uganda
GP	Goal Programming
IAEA	International Atomic Energy Agency
IEA	International Energy Agency
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
KPLC	Kenya Power & Lighting Company Limited
LP	Linear Programming
MCDA	Multi-criteria Decision Analysis
MEMD	Ministry of Energy and Minerals Development
MFPED	Ministry of Finance Planning and Economic Development
MILP	Mixed Integer Linear Programming
MOLP	Multi-objective Linear Programming
MOO	Multi-objective Optimization
MP	Mathematical Programming
NEMA	National Environment Authority
O&M	Operating and Maintenance Costs
PPA	Power Planning Associates Ltd
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation

PV	Photovoltaic
REA	Rural Electrification Agency
TANESCO	Tanzania Electric Supply Company Ltd
ToE	Ton of Oil Equivalent
UBOS	Uganda Bureau of Statistics
UEB	Uganda Electricity Board
UEDCL	Uganda Electricity Distribution Company Limited
UEGCL	Uganda Electricity Generation Company Limited
UETCL	Uganda Electricity Transmission Company Limited
USDOE	US Department of Energy

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Chapter 1

Introduction

1.1 Background of the Study

In the electric utility industry, planning involves many activities like electricity generation, transmission, distribution among several others. All these activities are interdependent in the sense that they require coordinated planning in order to achieve optimal operations. The operation of electricity utilities requires careful planning due to a range of factors including: the need to strike a balance between electricity supply and demand, and generation maintenance. Electricity generation and transmission facilities are extremely capital-intensive. All costs, including capital, and operating and maintenance, must be taken into account during electricity planning.

The electricity sector in developing countries have been going through problems such as inefficient capital utilization, high electricity capacity and financial losses, demand growth far exceeding the capacity additions, unrealistic tariffs among others. A developing country is generally characterized by inadequate and limited financial resources to address them. Most developing countries need electricity for their economic development. Planning errors can cause an unmet electricity demand and can impact adversely on the country's economic growth. Reducing the risk of a mismatch between electricity demand and supply is therefore essential to optimize the use of limited budget and ensure economic development.

Planning methodologies have been developed for the three main components of an electric utility system (generation, transmission, distribution), and each one is in itself a major subject of study, [Linares and Romero, 2000, Majumdar and Chattopadhyay, 1999, Hobbs, 1995]. The main goal of electricity planning is to perform each one of the processes in the best way, when different objectives are considered. This research will focus on the electricity generation planning (EGP) process, in the developing country context.

1.2 Electricity Generation Planning

Electricity generation planning (EGP) refers to the management of existing electric utility systems as well as rationalization of investment decisions concerning new additions to generation capacity. EGP is the process of analyzing, evaluating and recommending what facilities and equipment must be put to the electricity system in order to meet changing demand for electricity. The goal of EGP is to seek an optimal generation capacity system to meet the forecast demand in the most economical manner, subject to cost and environmental constraints. There are two questions that are answered by the generation planning process, [IAEA, 1984]: *what* capacity of generating units to install (size), *when* and *where* to invest in new generating facilities (time and location). This thesis is mainly concerned with the first two dimensions, while the question of *where* or location of generation plant is not treated in any depth.

The EGP usually involves finding a generation expansion and operating policy that minimizes present worth cost while meeting the projected demands and other imposed constraints [Balachandra, 2000]. This planning exercise normally has a planning horizon of about 10 to 40 years in the future. Given forecasts of the load demand, investments costs, fuel prices, and regulation, EGP finds the least cost mix of generation plants.

The decision planner's task is to determine the best configuration, timing and type of generation technology to meet growing electricity demands. The decision making task becomes more complex with the inclusion of more generations options, greater uncertainty in demand growth, fuel markets, technological developments, government regulations and small-scale and renewable energy sources.

The development of sustainable policies for the electricity sector is a complex task that poses serious dilemmas for the economies of many developing countries. These countries are striving to increase generation capacity to keep up with the desired electricity demand. Emphasis has been placed on making electricity capacity available at as quick a pace as possible with minimal capital investment and operations cost.

The motivation of this study results from the growing amount of change in energy needs of developing countries and a worldwide shift from conventional to renewable energy resources. Depletion of conventional resources forces countries to develop effective strategies on energy mix. Developing countries are characterized by poor operational and maintenance performance and inadequate energy planning which results in inadequate investment decisions. This requires a novel normative approach in planning for and supporting research on different energy resources.

This research is also motivated by the global relevance of the issue of EGP, by the consequences that decisions of EGP may cause, and by the complexity of the decision problem in developing countries. Good energy planning coupled with good energy models offers an opportunity to keep the chance of making wrong decisions as low as possible and is thus an important development policy of a country.

1.3 Statement of the Problem

Although most developing countries have had electrification programs in place for decades, planning have not been able to keep pace with the countries socio-economic and demographic dynamics, [Steel, 2007]. The electricity planning problem in most developing countries is complicated by lack of capital investment and operating funds the electricity sector. Energy resource development is hindered by the highly capital-intensive electricity sector. Developing countries are characterized by the ever increasing population growth, urbanization, industrialization, electric-generating capacity needs, and high electricity supply costs. According to the IEA [2006], global primary energy demand is projected to increase by 53 percent between 2004 and 2030, and over 70 percent of this increase is from developing countries.

In spite of EGP problems being one of the most studied problems in Operations Research, they keep being a challenge for several reasons; like other natural resources planning problems, EGP problems often involves many different stakeholders with different priorities or (often conflicting) objectives of economic, social, political and environmental nature. The objectives might include minimization of capital and operating and maintenance costs, and minimization of environmental effects. The conflicting nature of the different stakeholder' objectives means that no solution to the planning problem can be optimal on all the objectives at the same time. To contemplate the scope of EGP problems, as experienced in many developing countries, the efforts of pursuing integrated optimal planning to achieve the sustainable uses of these natural resources becomes critical.

The complexity of the problem increases further due to the desirable inclusion of a number of objectives, some of which may be unquantifiable and/or subjectively valued, thus making energy planning decisions prone to some degree of controversy. In addition, there is uncertainty about future electricity demand patterns and other input data. Electricity demand forecasts and projections of the economy are difficult to predict even more so in frequently changing government regulations and policies for the electricity sector.

Many studies conducted for solving the decision problem in EGP have led to the development of various solutions ranging from ones based on mathematical programming, stochastic approaches, standard matrices to models that employ econometric and marginal analysis, [Windiyanto et al., 2004]. However, as the complexity of the problem increases due to the inclusion of more objectives, the extension of the model brings about more complexity in mathematical formulation, and creates a tedious computational process, which tends to reduce analysis efficiency. Karekezi and Kimani [2002] noted the lack of research in this field and the insufficient use of modeling in developing countries.

1.4 Research Questions and Objectives

This study seeks to compare and contrast the application of mathematical programming (MP)-based and system dynamics (SD)-based approaches in EGP, highlighting new significant characteristics of the approaches, and to discover new aspects of and solutions to complex EGP problems in a developing country context. This research focuses on developing mathematical models that are better capable of providing decision support on future long-term electricity generation strategies, in the context of insufficient electricity capacity and to apply it to the electricity system for a developing country like Uganda. The following research questions will be explored in this thesis;

1. How do mathematical programming (MP) and system dynamics (SD) models contribute towards explaining how EGP systems behave in the long-term, specifically for developing countries with insufficient electricity capacity?

2. To what extent can the behavior of an EGP system, operating under insufficient electricity capacity, be explained using SD methodology, as a complement to MP approach?

3. What effect does changes in various policy parameters have on the long-term behavior of an EGP system?

4. What policy options can be used to improve electricity generation capacity in

developing countries, such as Uganda?, and what are the implications of the policy options?

5. How can the integration of MP and SD models be used to identify policy combinations to aid comprehensive decision making in EGP?

It is argued that SD modeling opens up exciting new opportunities for "traditional" mathematical modelers to gain from linking these two types of modeling frameworks. The ultimate goal is to integrate the two approaches into a complete EGP decision support system, to help analysts and decision-makers think systematically about the selection of EGP scenarios, and to demonstrate the utility of this approach to research.

This general objective was achieved through the following specific aims:

1. To explore the use of multi-objective optimization techniques in EGP problems in a developing country context;;

2. To develop a model that generates alternative electricity generation capacity and allocation plans under multiple objectives;

3. To develop a SD model with the intention of examining the dynamic behavior of the electricity generation system in response to different policy decisions and a strategy of incorporating heuristic goal-seeking for EGP;

4. To integrate MP and SD models into a decision support framework.

1.5 Research Methodology

Under the methodology of this study, literature search was undertaken from secondary sources comprising of books, scientific papers and journals. Statistical data was obtained from reports from stakeholders in the Uganda energy sector. Other technical data on electricity generation technologies was obtained from international agencies like World Bank, IEA, and IAEA.

This research is based on two fundamental approaches: mathematical programming (MP) and system dynamics (SD). The mathematical formulation resulted in a constrained mixed-integer multi-objective LP optimization problem. SD modeling methodologies involve the generation and testing of the dynamic behavior of a system. The models were implemented and solved using computer programming solvers selected according to the models.

The models are designed into a complete decision aid framework for electricity generation planners. The shift from optimization to design of a DSS involved the participation of a selected number of energy experts and stakeholders in Uganda energy sector.

1.6 Contribution to Literature

The main contribution in this research lies in the added understanding of EGP models, in the context of a developing country. The research clearly demonstrates the ability of MP and SD methodologies to model EGP systems, by identifying and understanding the relationships between various factors like electricity generation technologies, capital investment cost, operation and maintenance cost, electricity demand sectors, and electricity supply levels. The comparison of the methodologies highlights their strengths, weaknesses, and differing contrasts and insights into EGP, which serves as a foundation for choosing the methodology to apply for a specific problem.

There have been efforts to explain the ability of MP and SD methodologies to model complex EGP problems. The unique aspects of this research include;

- in situations where data is scarce, use of SD modeling that is robust to data and follows a holistic system view

- considering scenarios where electricity capacity is lost due to lack of operations and maintenance expenditure
- how to allocate insufficient electricity capacity to demand sectors
- formulation as an explicit multi-objective optimization problem
- application of the integrated approach, in a developing country context

This research will develop a MP model based on electricity generation technologies and electricity demand sectors. In addition, a descriptive SD model is developed that can be used as a building block for modeling complex situations. The rationale for the SD approach is the inherent mismatch between electricity supply and demand, and loss in electricity capacity due to lack of operations and maintenance expenditure. This research is expected to establish some added understanding on structuring complex electricity planning problems, particularly in a developing country context.

In addition, this work contributes to the academic research knowledge-base by illustrating the use of MP and SD approaches in EGP. The insights obtained from this research would help in identifying the fundamental causal and feedback relationships in EGP that could be used for further research.

1.7 Structure of the Thesis

The following chapters of the thesis may be described as follows:

Chapter 2 gives a brief review of the existing MP and SD approaches, with the purpose of contributing to the understanding of how these methods can be applied to natural resources planning, and in which contexts. This chapter presents a bibliographical review, mostly based on scientific papers, with reference to previous studies on electricity planning. It describes their applications, advantages and disadvantages, and where to find more information on them. The applications are either based on individual techniques or several combined techniques.

Chapter 3 gives an overview of the entire electricity sector in Uganda including detailed analysis on the history of the electricity sector, electricity demand, supply patterns, energy resource potential, a brief note on energy policy, and discusses current electricity supply/demand challenges which the country is facing. The electricity supply/demand analysis provides critical information for further analysis and modeling.

In Chapter 4 the formulation of a mathematical multi-objective optimization model for EGP is described. The formulation involves the translation of technical requirements of electricity generation technologies into mathematical functions (constraints), and the formulation of socio-economic objectives which are also translated into mathematical functions. The formulation results in a constrained mixed-integer multi-objective optimization model. The chapter ends with a discussion of a solution framework to the problem. It describes how the Tchebycheff goal programming (reference point) approach is used to find efficient solutions to multi-objective optimization problems.

Chapter 5 presents the implementation of the mathematical multi-objective optimization model for EGP in Uganda for a 20 years planning period (2008-2028), departing from the 2008 situation. This stage of research benefited from data/information collected from government official reports and documents published by companies operating within the electricity sector. The model implementation aims at finding the optimal electricity generation configuration mix, required to minimize aggregate capital investment and operating and maintenance expenses while satisfying a number of technical and economic constraints, including satisfying future electricity demand. The GAMS computer software is used for the optimization process. The optimization results are presented and sensitivity analysis on some variables is also performed. The chapter ends with a summary of the findings.

Chapter 6 describes the development of the SD model for EGP. The construction of this model follows a first two-stage process of conceptualization and formulation, [Sterman, 2000]. The chapter starts by presenting a brief overview of the SD methodology. The model is formulated by focusing on major concepts in the electricity sector namely; electricity demand, generation and transmission, operating expenses, and electricity tariffs. Also considered is the effect of population and GDP growth on the electricity system. A stock-and-flow diagram is constructed, leading to the formulation of mathematical equations to represent interaction and interdependencies among the variables.

In Chapter 7 the implementation of the SD model is presented. This stage of the research used data/information collected from meetings and interviews with electricity experts and with managers of the electricity system in Uganda. The chapter starts with a summary of model parameters and initial conditions. Then the overall performance of the system for the base case scenario is presented. In addition, validation of the model, calibration of the parameters, sensitivity analysis are discussed. This chapter also explains how to incorporate goal-seeking methods into SD using heuristic optimization algorithms. This chapter ends with a summary of the findings.

Chapter 8 describes the decision support system that integrates MP and SD models. The system provides the DM with capabilities of inputting parameters through a graphical user interface to analyze and compare a set of results generated by both models. It helps maximize the efficiency of a decision-making process.

Based on the findings of this research, Chapter 9 of this thesis presents the summary and conclusions. In addition, the limitations of this research and recommendations for the future research are also discussed.

Finally, the bibliography is included along with a set of appendices, presenting GAMS codes, VENSIM equations, and graphical user interface for the decision support system.

Chapter 2

Literature Review

2.1 Introduction

The electricity generation planning (EGP) process involves multiple, conflicting and incommensurate objectives like minimization of new investments costs, maximization of reliability, and minimization of environmental impacts. If one would like to model the uncertainties in future electricity demand, electricity prices, etc., the planning becomes even more complex [Karaki, 2001]. As a result decision maker's need modeling tools which explicitly examine trade-offs among objectives, recognize uncertainty, and help in understanding the dynamic behaviour of the electricity generation system.

This research aims to explore the potential of applying and integrating mathematical programming (MP) and system dynamics (SD) approaches to electricity planning problems, in a developing country context. It includes a review of basic theoretical and methodological aspects as well as the application frameworks. The development of the MP and SD techniques enhances the performance of the models application especially in the fields of natural resources optimization.

The adoption of a SD modeling approach allows the quantitative assessment of system behavior at a strategic level while maintaining information flows through the system across any system boundaries. As Fowler [1999] points out, by identifying and making explicit key feedback control loops in the system, SD is especially appropriate for considerations regarding the dynamic interrelationships among individual processes and their effect on the entire system at a strategic level.

The literature reviewed in this research covers four broad areas: (1) mathematical programming, (2) system dynamics modeling, (3) energy planning models, and (4) decision support systems (DSS) in the context of electricity planning. The aim is to present the theoretical background towards a possible amalgamation of the use of MP and SD approaches to address EGP problems in a DSS framework.

2.2 Mathematical Programming (MP) Approach

Mathematical programming is a methodology for solving problems in which an optimal value is sought subject to specified constraints. It can perform as a model to represent the abstraction of the real situation in a mathematical form. As a programming tool, it can be used to resolve problems based on optimality criterion through a formalized set of instructions.

The principal components of a MP model, as defined in Taha [2003] are *alternatives*, *constraints* and an *objective function*. Generally, the alternatives of a problem are represented through various unknown *variables*. By using these variables, the restrictions and the objective criterion are constructed in appropriate mathematical functions and, as a result, *mathematical programming model* is obtained. The solution of a model gives the values of *decision variables* that optimize (i.e. maximize or minimize) the value of the objective function under all the constraints. The solution is often referred to as the *optimum feasible solution*.

A typical mathematical formulation of an optimization model is:

Maximize/Minimize:

$$f(x_1, x_2, \ldots, x_J) \tag{2.1}$$

subject to:

$$\begin{aligned} g_1(x_1, x_2, \ldots, x_J) &\leq 0 \\ g_2(x_1, x_2, \ldots, x_J) &\leq 0 \\ \vdots \qquad & \quad \vdots \\ g_k(x_1, x_2, \ldots, x_J) &\leq 0 \end{aligned}$$

where f represents the objective function, while $g_1, \ldots, g_k$ are the constraints, and $x_1, x_2, \ldots, x_J$ are the model decision variables.

The variables may be integer or continuous, and the objective and constraint functions may be linear or non-linear. The optimum solution can be obtained numerically via a set of logical and mathematical operations performed in a specific sequence called *algorithm*.

Due to a great diversity of mathematical characteristics needed to describe optimization models, a variety of programming methods have been developed. These include *linear programming (LP)*, *mixed-integer linear programming (MILP)*, *non-linear programming*, and *heuristic algorithms*.

This section presents a review of basic theoretical and methodological aspects as well as the application frameworks of some of the MP methods that have been developed for optimization in EGP. The aim is not to make an exhaustive review of all the methods and models, but rather present some examples that will give a broad overview of the planning tools mostly used. Additionally, the advantages and disadvantages of the methods and frameworks, which result in different model formulations and solutions, are also discussed.

A very rich bibliography of the mathematical programming techniques can be found in the reviews of Schrijver [2000] and Hobbs [1995].

The LP approach is used to solve the problem of minimizing or maximizing a single linear objective function subject to linear equality and/or inequality constraints. For aspects that cannot be solved by LP models, there are alternative optimization models proposed in the literature. There is MILP used to solve discrete decision variables problems, [Hobbs, 1995], in which some of the variables can be limited to integer values, or, in a special case, to binary values (0 or 1). There is also non-linear programming to solve non-linear objective functions problems, and stochastic programming to solve random parameters problems, [Taha, 2003, Winston, 2003]. In fact, the LP concept is extended to perform the models with multiple objectives, as depicted further in this thesis.

Mathematical Programming Applications

Traditionally, MP models for EGP have been formulated as least cost investment problems, utilizing the algorithmic strengths of LP to minimize total cost subject to fuel availability, electricity demand, generation and transmission capacity, and other constraints, [Diego and Nakata, 2008, Meza et al., 2007, Das et al., 2005, Antunes et al., 2004, Balachandra and Chandru, 2003]. Kagiannas et al. [2004] and Zhu and Chow [1997] provide a survey of modeling techniques developed for EGP. The authors provide a list of papers using dynamic programming approaches, decomposition techniques, stochastic optimization, fuzzy set theory, artificial neural networks, network flows, simulated annealing, etc. Applications of genetic algorithms (GA) in energy planning has been the focus of studies of Fukuyama and Chiang [1996], Jia et al. [2000], Yang and Chen [1989], Park et al. [1999], Chunga et al. [2004], and Firmo and Legey [2002].

The objective function typically includes capital, operating and maintenance costs, over the entire planning period. The constraints include forecast demand, plant availability, and other technical performance parameters. The planning period is usually split into sub-periods for modeling detail variations.

Jebaraj et al. [2008] developed a LP optimal electricity allocation model (OEAM) to determine the optimal allocation of different energy sources for the centralized and decentralized power generation in India, with special emphasis to bio-energy. The OEAM model optimizes and selects appropriate energy options for power generation on the factors such as cost, potential, demand efficiency, emissions, and carbon tax. A single objective function of the model was to minimize the cost of power generation, while the constraints included energy demand, energy efficiency, emission levels and carbon tax. Because of the incoherent data, the energy efficiency, emission levels and carbon tax, were considered fuzzy linear constraints. The authors came up with the extents of energy sources distribution for the power generation for India up to the year 2020.

Furthermore, Hashim et al. [2005] applied a multi-objective MILP to the Ontario Power Generation (OPG) fleet of power plants to reduce CO_2 emissions from the power grid. The model considered three different operating strategies: total cost reduction, CO_2 emissions reduction, and an integrated operational mode, constrained by energy balance/demand satisfaction, operational changes, and CO_2 emissions reduction target. External pollution index was used as a conversion factor from pollution to cost. The optimization problem was implemented in GAMS and results indicated that fuel balancing and fuel switching are effective ways to reduce CO_2 emissions. However, in this study, electricity generation capacity was held constant, yet in real situations, there is high variability in electricity demand. More recently, Al-Ali et al. [2010] developed a discrete MP model to give an assessment about the OPG coal-fired power plant operations in an electricity generation network.

Balachandra and Chandru [2003] describe an integrated mathematical modeling approach to minimize the social cost of dynamically matching electricity supply with demand in the context of power and capital shortages. They demonstrated an integrated LP formulation to optimally plan/schedule existing supply options, rational management of non-supply options, and introduction of new supply of electricity options, to effectively match supply and demand for electricity. A single objective function was the minimization of the total cost of achieving an effective match between supply and demand through various options. The cost components include cost of various supply and non-supply options and capital (fixed) and operating (variable) costs of new supply options. Loss in electricity generation capacity was not addressed and the electricity shortages were not categorized according to the demand sectors.

According to Kagiannas et al. [2004], mathematical optimization of long-term generation expansion planning is equivalent to finding a set of optimal decision vectors which minimizes a linear objective function under several constraints. The authors noted that the aim of traditional electricity power utility has been to provide adequate supply of electric energy at minimum cost. There are various mathematical models for generation planning developed to fulfill this function through optimization algorithms and probabilistic production costing simulation. The purpose of generation planning models is to determine the generation units to be constructed, the time to be constructed and the amount of power to be produced while the total cost (fixed and production cost) to a utility is minimized. This paper focused on EGP aiming at specifying the main advancements in optimization, simulation, and forecasting methods under a deregulated competitive market. Das et al. [2005] developed a composite long-term optimal generation and transmission system expansion model. The findings revealed that total cost of the combined generation-transmission expansion plan is minimal compared to the separate planning approaches enumerated in the literature.

A linear-integer programming algorithm was used by Khodr et al. [2002] to develop a model for the optimal selection of independent electric power generation schemes in industrial power systems. The problem was formulated as a MP problem, considering investment costs, fuels costs, O&M costs, power balance, maximum and minimum limits on the power generated of the units, along with reliability considerations, such as unavailability of the generation scheme. The authors used the BB algorithm to solve the problem, yielding the optimum number of units, as well as the corresponding size and type. Much earlier, Zahavi [1980] had described a methodology to assist in the selection of new generation additions to a power system, for given predictions of the electricity demand, focusing on cost and reliability issues. Several investment candidates are generated and then analyzed for their cost and reliability performance to find the exact characteristics of new generation modules.

The frequent use of MP means that it represents a benchmark against which it is useful to judge other proposed energy planning methodologies. One criticism that can be leveled at MP is that it is limited to deriving only one solution in a single run, whereas decision makers seem to prefer several alternatives to compare and choose from. Approximation techniques are necessary for large and complex systems, in which there are a number of non-linear relations in the objective function and constraints. Another limitation of MP is the practical effects of using a specialized model formulation. Most MP models are structured to make them compatible with the optimization method employed. This severely limits the ability of the DM to take advantage of existing simulation models, as sources of information, without a re-implementation process.

2.2.1 Multi-objective Optimization Approach

Multi-objective optimization (MOO) is the process of optimizing systematically and simultaneously a number of conflicting objective functions. As in single-objective optimization problems, the problem includes many constraints which any feasible solution (including the optimal solution) must satisfy. MOO concerns the optimum allocation of limited resources among multiple competing activities, under a set of constraints imposed by the nature of the problem being studied. These constraints could reflect socio-economical, financial, technological, marketing, organizational, or many other considerations, [Pohekar and Ramachandran, 2004]. MOO models have capability of analyzing the trade-off among several competitive objectives like cost, supply reliability, emissions, risk of plant disaster, and fuel supply vulnerability, [Majumdar and Chattopadhyay, 1999]. Most of the MOO models still retain a LP framework, while others allow nonlinearity in dealing with capital costs and economic constraints.

In order to simplify discussion, we shall assume that all the functions are expressed in minimization form. The fundamental theory concerning MOO veers from the more familiar paradigms of single-objective optimization. The general formulation of a MOO problem is as follows, [Deb, 2001];

Minimize:

$$f_1(x), f_2(x), \ldots, f_I(x) \tag{2.2}$$

subject to:

$$g_k(x) \leq 0; \qquad k = 1, 2, \ldots, K \tag{2.3}$$

where x is an n-dimensional vector of decision variables, $f_i(x)$, i=1,2,... ,I are the I objective functions, and $g_k(x)$ are the k=1,2, ..., K are K constraint functions.

In MOO models, there is generally no single, global solution, and often, it is necessary to determine a set of points that all fit a predetermined definition for an optimum. An improvement in one objective typically results in detriment to another. Consequently, the idea of a solution is less straightforward than it is with single-objective optimization. The predominant solution concept is *Pareto optimality*, introduced by Vilfredo Pareto in 1906,as cited in Deb [2001].

The formal definition of a pareto optimal point is usually in terms of the design space [Deb, 2001]. A point is pareto optimal if there is no other point that improves at least one objective function without increasing (detrimentally affecting) any other function, [Coello, 2000]. A decision x^* is said to be a non-dominated solution if and only there does not exist another $\bar{x}$ such that;

$$f_i(\bar{x}) \leq f_i(x^*) \qquad \text{for all} \qquad i = 1, 2, \ldots, I \tag{2.4}$$

with strict inequality holding for at least one i.

Typically, there are infinitely many possible optimum points in a MOO problem, and the set of all pareto optimal solutions is called the *pareto optimal set*. Arbel and Korhonen [2001] developed a mechanism of starting a MOO algorithm from any point in the criterion/objective space. The DMs task in a MOO problem is to select compromise solutions drawn from the pareto optimal set (or pareto front) using what Deb [2001] terms "higher level information", which is that knowledge that cannot be easily codified, and is based on qualitative factors such as intuition, judgment, and past experience.

The notion of pareto-optimality is only a first step towards solving a MOO problem. To select a compromise solution requires the DM to somehow articulate preferences. The choice of a suitable compromise solution depends on the subjective preferences of the DM. Therefore, it makes sense to involve the DM in the MOO process. Accordingly, depending on how the DM articulates or incorporates preferences, there are three broad classes of solution frameworks to MOO problems, [Avriel and Golany, 1996]:

A priori articulation of preferences: Here the DM specifies preferences in terms of the relative importance of the objectives or in terms of the goals, before the optimization algorithm runs. The DM quantifies opinions before actually viewing points in the criterion space. In this sense, the term *preference* is often used in relation to the importance of different objectives. Methods in this group are mainly multi-objective methods such as GP, to be discussed later.

A posteriori articulation of preferences: This involves the DM selecting a solution from a palette of possible pareto optimal solutions, after optimization algorithm runs. The DM imposes preferences directly on a set of potential mathematically equivalent solution points. Methods belonging to this group include *multi-attribute methods* and *outranking methods*, [Belton and Stewart, 2002].

Progressive articulation of preferences: Decision making and optimization are iterative and interactive, occurring at interleaved steps. In each step the optimizer poses questions to the DM, about his preferences and the DM answers. If the optimizer has sufficient knowledge regarding the DM's preferences, he makes the final recommendation, in terms of which alternatives should be chosen. Otherwise, the questioning process continues until the preferences become clearer. Methods belonging to this group include *Geoffrion-Dyer-Feinberg (GDF)* and *Zionts and Wallenius*, [Steuer, 1986].

Methods for a priori articulation of preferences have the advantage of requiring no further interaction with the DM. However, if the solution found cannot be accepted as a good compromise, new runs of the optimizer may be needed, until a suitable solution is found. These methods also have the disadvantage of requiring new runs of the optimizer every time the preferences of the DM change. Since no a priori knowledge is assumed, methods for a posteriori articulation of preferences search the whole feasible space during optimization, hence taking more computation time. Beside, when DM's preferences change, there is no opportunity for further optimization. Methods for progressive articulation of preferences require constant interaction between the DM and the optimizer. The main inconvenience with these methods, from a practical point of view, is that in case of a human DM, he might not be willing to pursue such a time and effort consuming processes, [Belton and Stewart, 2002]. Consequently, such methods are not suited to repetitive use, and are not considered in this research.

Multi-objective Optimization Applications

The decision-making process regarding the choice of alternative energy resources is multidimensional, made up of a number of aspects at different levels; economic, technical, environmental, and social. Thus, multi-objective analysis is considered the most appropriate tool to understand all the different perspectives involved and to support decision makers by creating a set of relationships between the various alternatives.

Antunes et al. [2004] has made significant contributions in EGP process. He proposed a multi-objective MILP model for power generation expansion planning. The model considered three objective functions, which quantified the total expansion cost, a measure of the environmental impact and the monetized environmental cost. The approach involves the participation of the decision maker to refine and guide the process of searching the non-dominated solutions as well as to identify a solution as a satisfactory plan. Earlier Martins et al. [1996] had developed a multi-objective LP model for power generation expansion planning, to illustrate the application of the TRIMAP method, that incorporates demand-side management alternatives in an equal footing with supply-side options. More recently, Kourempele et al. [2010] has applied MILP in energy planning of an autonomous system in Milos island in Greece, taking into account the uncertainties in future energy demand. However, this study focused more on thermoelectric power generation, and ignored exploiting other available energy.

Linares and Romero [2000] describes a methodology that combines several multiple criteria methods to determine optimal electricity planning strategies. The work aimed to present a model for electricity planning in Spain up to the year 2030, based on a MOO methodology, to combine economic and environmental criteria. Their approach integrates the decision makers preferences into the planning process. The objectives were the minimization total cost, CO_2, NO_x, SO_2 emissions, as well as the amount of radioactive waste produced. They used compromise programming (CP) to search for efficient solutions and analytic hierarchy process (AHP) was used to elicit preferential weights from the decision makers and consequently generate compromise solutions. Works like Loken [2007] or Pohekar and Ramachandran [2004] demonstrate the popularity of the various MOO methods in energy planning problems.

Ceciliano et al. [2007] developed a long-term multi-period multi-objective model for the power generation expansion planning of electric systems. Their approach was based on four multi-objective LP methods: Min-Max, Max-Min, CP, and Weighting; to generate a set of non-dominated solutions. The model optimizes simultaneously four multiple objectives (i.e., minimizes costs, environmental impact, imported fuel and fuel price risks) and decides the location of the planned generation units in a multi-period planning horizon. The AHP was used to select the "best solution" among the representative(clustered) solutions. The uncertainty associated with the combinatorial complexity of the optimization problem led Ceciliano et al. [2007] to explore the use of evolutionary algorithms (EA)[1] to solve the multi-objective problems. The time horizon consisted of 10 annual periods, and it clearly demonstrated the increasing complexity of the model for long term planning due to the rising number of variables. Becerra-Lopez and Golding [2008] argue that applying the MOO approach to find trade offs among primary competing objectives promotes useful comparisons and leads to insights that might redirect the policy for power generation planning.

Energy planning often involves large and interdisciplinary decision makers with incommensurable objectives. Decision makers are confronted with more than one objective in achieving the final goal set, while satisfying constraints dictated by the available resources, processes, and the environment. Koroneos et al. [2004] applied the MOO methodology to assist in achieving optimal use of renewable energy resources in Greece. The study has two conflicting objectives: minimization of cost and environmental effects, constrained by electricity production capacities. This study derived a series of energy solutions, providing the DM's flexibility to choose the appropriate solution.

A study by Pelet et al. [2005] designed an integrated energy system based on MOO using evolutionary algorithms. The analysis was pursued using two objective function optimization: minimization of investment and operational cost and CO_2 emissions. The method used economic and ecological parameters to compare and rank the energy system solutions. However, in this study, only the costs of capital, operation and maintenance expenses were considered and no estimation of external costs was included.

Soloveitchik et al. [2002] presented a MOO model to solve the capacity expansion problem of a long-run power generation system for Israel electricity sector. The objective functions comprised of different abatement cost scenarios and air pollutants. The authors used CAPEX computer package to optimize a weighted-sum of the objective functions. Majumdar and Chattopadhyay [1999] developed a model that incorporates investment and financial decisions into the traditional least cost planning for electricity genera-

[1] See details in Osyczka [2002] and Deb [2001]

tion expansion. The authors concluded that the investment plan in presence of binding financial constraints is significantly different compared to the plan generated by the discounted cash flow model.

With the aid of the multi-objective models, decision makers may grasp the conflicting nature and the trade-offs among different objectives in order to select satisfactory compromise solutions for the EGP problems. MOO methods are notably dependent on the weightings used, but sensitivity testing for weightings and input data accuracy may also be included to increase the reliability of the results achieved.

2.2.2 Goal Programming Approach

Goal programming (GP) was first introduced by Charnes in 1955, and gained popularity after the work by Ignizio in 1970's, as cited in Deb [2001]. GP deals with decisions involving multiple goals. The overall purpose of GP is the simultaneous satisfaction of several goals relevant to the decision making problem under consideration.

GP is a re-engineered extension of MP models with multiple and/or conflicting (trade off) objectives. Most of the methodologies used in MP problem solving can be equivalently converted to solve GP problems with minor revisions to the algorithm. One main characteristic that differentiates GP models from other MP's is that there is no decision variable in the objective function, but rather deviation variables. GP minimizes deviations from goals subject to constraints. The idea is to set a goal in objective space and try to come close to it. Coming close to a goal suggests minimizing a distance measure between an attainable objective vector and the goal vector.

Very often optimizing an EGP system could involve multiple objectives, namely, minimizing the cost, maximizing use of energy sources, maximizing employment, reducing emission of pollutants, etc. Thus, an approach or model to optimize multiple objectives for a given set of constraints is necessary. GP is a powerful and flexible modeling tool to deal with multiple objective decision-making problems in EGP and management for sustainable development of developing countries. GP provides a way of striving toward several such objectives simultaneously.

In their review of GP for decision making, Tamiz and Romero [1998] noted that the attributes of GP lies in the Simon's concept of "satisficing" of objectives. They noted that most decision makers (DMs) do not try to maximize a well defined utility function. In fact the conflicts of interest and the incompleteness of available information make it almost impossible to build a reliable mathematical representation of the DMs' preferences. On the contrary, within this kind of decision environment the DMs try and achieve a set of goals (or targets) as closely as possible subject to the constraints.

The GP optimization process involves identifying objectives, setting a target or goal for each objective, and weighting each of the targets or goals. An objective is a measurable characteristic of a problem which can be related to the decision variables. A target or goal is a desired level of achievement for any of the DMs objectives, [Tamiz and Romero, 1998, Coello, 2000].

Suppose $\mathbb{X}$ is the set of alternatives from which an element $\mathbf{x} \in \mathbb{X}$ is to be selected. If m criteria have been identified, and $f_i(\mathbf{x})$ measures the performance of alternative $\mathbf{x}$ with respect to criterion i. Suppose that the $f_i(\mathbf{x})$ are defined such that increasing values are preferred. Suppose further that some form of goal or aspiration level, say T_i can be specified for each criterion, then;

$$f_i(\mathbf{x}) + d_i \geq T_i; \qquad i \in m \tag{2.5}$$

The d_i are deviation variables, often defined on both sides of the goal level, to allow inclusion of situations in which both under- and over-achievement are undesirable.

There are four common norms to solving a GP problem, [Belton and Stewart, 2002].

Lexicographic Method

In the lexicographic (or preemptive) GP, there is a hierarchy of priority levels for the goals. Such a case arises when one or more of the goals clearly are far more important than the others. Thus the initial focus should be on achieving as closely as possible these first-priority goals. The other goals also might naturally divide further into second priority goals, third priority goals, and so on. After we find an optimal solution with respect to the first-priority goals, we break any ties for the optimal solution by considering the second-priority goals. Any ties that remain after this re-optimization can be broken by considering the third priority goals, and so on.

The disadvantage of this procedure is that, in general, when the number of goals is large, the last priority goals tend to be redundant, that is, they are not included in the solution, [Nhantumbo et al., 2001].

Archimedean Method

This method scalarizes all the goals into a single objective function by multiplying each objective with a relative weight. The relative weights are determined a priori. The task is to minimize the sum of all the unwanted deviations from the aspirations of the decision makers. The archimedean model is represented as follows;

$$\text{Minimize } \sum_{i=1}^{m} w_i d_i \tag{2.6}$$

where w_i are scale factors, to ensure that the deviations are expressed in commensurate units.

However, Stewart [2005] notes that in the archimedean method, there is a tendency to fulfill some goals fully while leaving others substantially under achieved.

Tchebycheff Approach

In the Tchebycheff approach, the goal is in principle to minimize the maximum deviation relative to the goals defined. The procedure samples the efficient set by computing the non-dominated criterion vector that is closest to an ideal criterion vector according to a randomly weighted Tchebycheff metric. The GP problem is solved by minimizing the augmented Tchebycheff metric based on each weight vector, as discussed by Stewart [2005]. The achievement function used is;

$$\psi \sum_{i=1}^{m} w_i d_i + (1 - \psi) \max_{i=1}^{m} w_i d_i \tag{2.7}$$

where $0 \leq \psi \leq 1$.

In this approach, the decision maker is trying to achieve a good balance between the achievement of the set of goals as opposed to the lexicographic approach which deliberately prioritizes some goals over others or the weighted approach which chooses the set of decision variable values which together make the achievement function lowest, sometimes at the expense of a very poor value in one or two of the goals. Some practical use of Tchebysheff GP is in Jones et al. [2002].

Reference Point Approach

The reference point approach is a generalization of the Tchebycheff method, by allowing the d_i to take on negative values as indicators of goal over-achievements. This has the advantage of extending the search for good solutions beyond the stated aspiration levels particularly when these levels are too modest, [Stewart, 2005]. The reference point approach method is an interactive multiple objective optimization technique first presented by Wierzbicki, as cited in Gal et al. [1999]. The approach uses a 'scalarizing function, which measures achievement relative to the goals, but placing the greatest weight on the least well-satisfied goal. In Ruiz et al. [2009], Wierzbicki observed that when individuals make decisions, they usually want to attain certain aspiration levels instead of by maximizing a certain value function.

An achievement function often used in this method is: (see Stewart [2005])

$$\max_{i=1}^{m} w_i d_i + \epsilon \sum_{i=1}^{m} w_i d_i \tag{2.8}$$

where ϵ is a small value and serves primarily to ensure that solutions are non-dominated in cases when the min-max solution is not unique, [Belton and Stewart, 2002].

Miettinen and Makela [2002] and Miettinen et al. [2006], presents an overview of achievement scalarizing functions.

The advantage with the reference point approach is that instead of quantifying a value function and then applying it to the alternatives, they offer the user one or several trial alternatives. The user evaluates them, and gives information that can then be used to identify additional (and hopefully more preferred) solutions. The process iterates until the user is satisfied. In this approach the user learns about the trade-offs and the implications of alternative value judgments. The only setback of interactive procedure is time to access key DMs. Hobbs [1995] pointed out that there is relatively little experience with interactive approach in a group setting, where group members have very different priorities. He further noted that there is little guidance in the literature as to how such an approach can be used with groups to promote consensus and clarification of disagreements.

Goal Programming applications

Goal programming has been applied to forest management, [Nhantumbo et al., 2001, Korhonen, 1999], energy resource allocation, [Mezher et al., 1998], land use allocation, [Aerts et al., 2003a,b], and decentralized energy planning, [Hiremath et al., 2009]. Tamiz and Romero [1998] demonstrated that GP is a pragmatic and flexible methodology especially capable of addressing complex problems where several objectives and constraints as well as many decision variables are involved. Jones et al. [2002] and Schniederjans [1995] presents a comprehensive overview of GP methodology and its applications.

Xevi and Khan [2005] developed a multi-objective framework to analyze production targets under physical, biological, economic and environmental constraints. The problem was characterized by conflicts between multiple goal requirements and the competing water demands of different sectors. The model had three objective functions: maximizing net returns, minimizing variable cost and minimizing total supplementary groundwater pumping requirements to meet crop demand from the irrigated areas. The weighted GP was used to solve the problem. However, the study does not detail the process of selecting the target values and weights for the different goals.

GP was also applied by Latinopoulos and Mylopoulos [2005] in solving water resource allocation problems with conflicts between irrigation water demand and in stream environmental flow requirements. Also Sharma et al. [2006] designed a model to illustrate how GP can be used as an aid to solving fishery management and related activities with multiple objectives. A set of goals and objectives were related to the socio-economic significance of fishery management to find the optimal solution, based on the priorities of the goals in a decision-making environment.

Lahdelma et al. [2005] developed a reference point approach that includes a group of decision makers in the selection of most preferred solution from a discrete set of alternatives. For each alternative, DM's are provided with a reference acceptability and central reference points. Then, the DM's can compare this information with their own preferences. This study assumes that the DM's jointly accept the achievement model to be used in the analysis. However, the involvement of many DM's in energy planning is costly and time consuming. Yang [2000] illustrates the implementation of the reference point approach and demonstrates its potential application to general multiple objective optimization problems.

Diego and Nakata [2008] presented an integrated evaluation of electricity supply systems for rural areas using renewable technologies by means of multi-objective decision making method. They describe the application of preemptive GP to obtain an optimal system configuration meeting the electricity demand, based on the location's resource availability and taking diesel generation as the alternative of reference. The authors used four performance attributes (electricity generation costs, employment, CO_2 emissions and land use) to evaluate the system, and taking the electricity to be supplied by each technology as the decision variables. However, sensitivity analysis was not conducted to provide deeper understanding of the influence which goal values may have on the configurations of renewable energy systems and their performance, since input parameters are highly dependent on decision maker's interests.

In addition to studies mentioned above, Elfkih et al. [2008] carried out research on GP techniques within Simon's bounded rationality context, where the idea of optimization is replaced by the idea of "satisficing" to deal with sustainable management of agricultural systems in a Spanish district. Selected economic and environmental criteria were used to analyze the situation from a "satisficing" perspective with the help of GP models in a normative context.

The GP approach possesses significant advantages because of the fact that the optimization problem becomes less rigid. The system goals and constraints are expressed deterministically. A constraint must be strictly satisfied, while for a goal it is desired to achieve the solution, which is as close as possible to the specified target. Because the deviations are minimized, and feasibility is guaranteed, [Elfkih et al., 2008]. GP offers a very straight forward procedure that DMs find easy to understand. In addition, many of the GP methods are suitable for being implemented directly into LP solvers, [Oliveira and Antunes, 2004].

Optimization methods must be flexible, robust and acceptably efficient in order to tackle strategic energy planning problems. The techniques implemented must also be capable of tackling problems large enough to represent real world situations. For multi-objective EGP, the goal should be to enhance the understanding of the conflicts between objectives and thus assist in making rational compromise decisions. MP methods are efficient but are significantly limited in their capacity to deal with large complex dynamic problems.

2.3 System Dynamics (SD) Approach

System dynamics (SD) was introduced by Jay Forrester around 1960 at MIT [Ford, 1997] as a policy design tool for complex dynamic problems[2]. In the terminology of SD, a *system* is defined as a collection of elements that continually interact over time to form a unified whole. *Dynamics* refers to change over time. *System dynamics* (SD) is, therefore, a methodology used to understand how systems change over time. It is based on the foundation of decision making, feedback mechanism analysis, and simulation. SD simulation provides DMs with a tool to work in virtual environment where they can view and analyze the effects of their decisions in the future, unlike in a real system.

SD has repeatedly been demonstrated to be an effective analytical tool in a wide variety of situations, both academic and practical. As Sterman [2002] pointed out, SD models are widely used in strategy and policy assessment. SD enhances the understanding of how complex systems behave over time. According to Simonovic and Fahmy [1999], SD is based on theory of system structure and a set of tools for representing complex systems and analyzing their dynamic behavior. Its main purpose is to understand and model complex and dynamic systems. Its objective is to elucidate the general behavior of a given system, based on behavior patterns among its elements and on structures determining these patterns, [Pruyt, 2007]. This way of studying a complex feedback system requires us to think the problem systematically.

A SD model is based on the reference mode and cause-effect relationships formulated from a situation under study. The modeling process starts with the development of qualitative influence diagrams and then moves into the formulation of the quantitative model. These models allow for a flexible representation of complex scenarios, and the model simulation generates patterns of behavior over time.

[2]A comprehensive and modern reference book on system dynamics is by Sterman [2000]

2.3.1 Special tools of SD

To represent complex SD model for EGP systems and analyze their dynamic behavior in an understandable manner, a specific set of special SD features have to be developed. In this section, and because they are used further throughout the thesis, a brief description of causal loop and stock-and-flow diagrams is given.

Casual Loop Diagrams

Causal loop diagrams (CLD) are used for representing the feedback structure of systems. They are used to get an overview over the causal relationships of a problem, [Spectora et al., 2001]. With the use of CLD, it is also possible to identify possible characteristic behavior of the problem. They are maps of cause-and-effect relationships between individual system variables that, when linked, form closed loops, [Eusgeld et al., 2008]. They are very helpful in conceptualizing and communicating structures.

Stock-and-Flow Diagrams

CLDs are immensely helpful in capturing the mental models. However, CLD have a limitation of inability to capture the stock-and-flow structure of systems. SD modeling has four basic building blocks: stocks, flows, connectors and converters. Stocks are accumulations[3] as a result of a difference in input and output flows to a process/component in a system.

Mathematically, equations for the stock element can be formulated as follows:

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0) \tag{2.9}$$

Thus, the value of stock at time t is the sum of the value of stock at time t_0 and the integral of difference between inflow and outflow rates from t_0 to t. In other words,

[3] The principle of accumulation states that a system's dynamic response derives from the transition of the resources accumulated in stocks and that these transitions are controlled by entry and exit flows of resources in and out of stocks, [Sterman, 2000, Page 192],[Cronin et al., 2009].

we can also state that the rate of change in stock at any point in time is equal to the difference between inflow and outflow at that point. Stocks-and-flows help describe how a system is connected by feedback loops that create the non-linearity found frequently in dynamic complex problems.

Real-world systems typically exhibit more than one stock and multiple interactions among variables is the rule, [Sterman, 2001]. Variables changing very slowly in the considered time frame are modeled as constants. Variables that can change freely and hence are not subjected to interactions due to SD are considered as exogenous variables. The derivatives of stocks in dynamic systems are, in general, non-linear functions of stocks, exogenous variables, and some constants.

2.3.2 Optimization in SD

Optimization in SD involves the manipulation of exogenous variables or constants to; (1) calibrate parameters, and (2) optimize policies, [Ventana Systems, 2007].

Parameter calibration means refining the estimate of certain exogenous variables. In other words finding the values of model constants that make the model generate behavior curves that best fit the real world data.

Policy optimization, on the other hand, refers to selecting the best among alternative policy settings. For instance consider an inventory management policy based on targets for maximum and minimum desired inventory. How should these targets be set such that over time the payoff function (e.g. profit) is maximized?

Some authors have incorporated SD optimization to substitute the traditional reliance on intuition and experience, [Prasad, 1999]. Keloharju and Wolstenholme [1989] has developed a Dynamic Simulation Model Optimizer and Developer (DYSMOD) model to determine heuristically the optimum values for any number of model parameters relative to predefined objective functions or performance measures. The search decision rule involved uses a “hill climbing” routine. The iterative method gives optimal or near optimal values of parameters. Satsangi et al. [2003] developed a simulation model with optimized simulation trajectories that are generated by applying genetic algorithms (GAs) search and optimization methods for alternative policy scenarios of input variables.

2.3.3 Implementation of SD

A number of computer programs have been developed in the recent years to aid SD modeling. These include iThink, PowerSim, VENSIM, and STELLA, [Shiflet and Shiflet, 2006]. These computer programs offer object-oriented languages, which have an advantage in simulation, because they are capable of using objects in the development of system description and modeling the system structure. In this research, the model is built using VENSIM Professional 5.10 software, with a visual graphical user interface that helps conceptualize, build and test SD models, [Ventana Systems, 2007].

SD has been demonstrated to be an effective analysis tool in EGP, [Park et al., 2000, Dyner et al., 1995]. SD has been used to analyze dynamic patterns in a range of different natural resource sectors, including the energy sector, [Toshihisa et al., 2005]. Bunn and Dyner [1996] argue that SD can serve as an important tool for the analysis of the changing conditions in the energy industry. The authors demonstrated how market forces in the UK electricity industry can be analyzed by simulating investments in new power generation capacity.

Another SD based simulation system is presented in Steel [2007]. The author used the SD modeling tools to analyze the dynamics of growth and investment in the Kenyan electric power sector. The author used ethnographic methods to understand the decision-making processes and the interaction among stakeholders. SD modeling was used to map the interactions and to understand the feedbacks in the system.

Qudrat-Ullah [2005] applied SD to investigate private participation to electricity industry in Pakistan and try to evaluate the Pakistan’s policy in contexts of electricity supply, resource import dependency and evolution of CO_2 emissions. Sufiana and Bala [2006] developed a SD computer model for analyzing electrical energy recovery from urban solid waste management. Other applications of SD modeling approach are in Olsina [2005], Liu [2001].

From the discussion, it is clear that most applications of the SD methodology to the energy sector use exogenous variables, such as economic and population growth to drive the energy sector, and they attempt to validate the models on past data. System dynamists suggest that one should concentrate on model behavior (trends, cycles, and feedback loops) rather than numerical results. Besides 'hard' quantitative data, 'soft' data and concepts should be used as well. The use of SD is complementary to traditional planning techniques.

2.4 Energy Planning Models

Models have been used to analyze complex real-world situations with large amounts of data, to help make better decisions, [Loulou et al., 2004]. Through models, various linkages and effects between different phenomena can be mathematically described and analyzed. Modeling provides an important step in quantifying the implications of energy policies identified. However, because of the complications of perfectly representing real situations, models have been rather considered as a way of gaining insight of complex situations than providing answers for decision making.

In Beeck [1999], energy planning models are built for predicting future and scenario analysis. They can also focus on issues such as energy demand and supply, impact and appraisal. Models try to answer questions of how demand or supply of energy is affected by economic, social or technical factors. The complexity of energy planning together with the negative consequences of "bad" decisions, has been the motivation to develop various energy planning models.

The classification of the energy planning models and the review of models is based primarily on IAEA [2009], Loulou et al. [2004], Makela [2000], and Beeck [1999]. The model purpose is the most commonly used parameter to characterize energy planning models.

2.4.1 Model Classifications

Jebaraj and Iniyan [2006] have discussed the different types of energy models. Energy system models can also be distinguished by their level of aggregation/detail in modeling the system and its components, as well as by their spatial and time resolution. In general, these models differ according to:

- The size of the energy system modeled (geographical coverage):
  - Models which describe an entire national energy system.
  - Models for local or regional energy systems; plus other large scale models that can be adapted for local or regional systems modeling.
- The way uncertainties are modeled:
  - Static, deterministic optimization models, which are especially suited to calculate least-cost strategies under certain boundary conditions. Static models represent the modeled system at one point in time neglecting any temporal development. A static model could be used to analyze the energy supply during maximum load in order to determine the required capacity of a new installation.
  - Dynamic, interactive models where uncertainties (e.g. future prices, energy demand, etc) can be represented stochastically through scenario simulations, etc. In a dynamic model, the objective function covers all the periods and the whole time horizon is optimized simultaneously.

- The time horizon allowed for analysis:
  - Models describing the short-term operation of the system usually describing, with sufficient details, a fixed technical system and a given socio-economic framework;
  - Long-term simulation models used in strategic planning used in the analysis of long-term technological and socio-economic developments.

2.4.2 Review of Existing Energy Planning Models

The development of energy planning models started 40-50 years ago, in response to severe energy problems, [Sungathi and Williams, 2000]. The scope for model development and application has shifted over the years to reflect the continuously changing environment for decision making. The energy planning models developed in the 1960's focused mainly on supply and demand for a single energy form or fuel, such as electricity, oil or natural gas. Then, these models became no longer useful at the beginning of the 1970's, during the first oil crisis, because they could not adequately describe inter-fuel substitutions related to changes in energy prices, technological development or environmental considerations related to energy use. Since then, integrated energy modeling was developed to solve national (even international) or regional energy problems.

MARKAL - MARKet ALlocation

MARKAL is a mathematical LP model which optimizes the supply of energy services of one or several locations that provides a technology-rich basis for estimating energy dynamics over a multi-period horizon, [Loulou et al., 2004]. The main objective function is normally to minimize the total cost of meeting the energy demand. Energy demand is represented in the model with a deterministic projection of demand for different sectors of society. The theory and mathematics underlying the model are complex, but MARKAL users can effectively work with the model without a command of the computational methods employed, [Seebregts et al., 2001]. Nguyen [2005] provides simplified forms from the detailed mathematical formulations given in the MARKAL users manual. Some modifications have been done on MARKAL and cumulated in several variants of the model such as the development of modern data handling and analysis support shells - MARKAL User Support System (MUSS); and the Windows-based ANSWER, developed by the Australia Bureau of Agricultural and Resource Economics (ABARE). Some recent applications of the MARKAL model are by Akimbami [2001], Sungathi and Williams [2000].

MESSAGE - Model for Energy Supply Systems Analysis and General Environment

The MESSAGE model is a dynamic LP model, to design long term energy supply strategies or test energy policy options by analyzing cost optimal energy mixes, investment needs and other costs for new infrastructure, energy supply security, energy resource utilization, rate of introduction of new technologies (technology learning), and environmental constraints. The model estimates detailed energy systems structures, including energy demand, supply and emissions patterns that are consistent with the evolution of primary and final energy consumption specified by a defined scenario, [Makela, 2000].

EFOM-ENV - Energy Flow and Optimization Model - ENVironment

This is an energy supply model developed by the Commission of European communities. It is a dynamic LP optimization model that covers the supply side of an energy system of a country from medium to long-term horizon.

MAED - Model for Analysis of Energy Demand

This model is developed by IAEA to compute energy demand for four end-use sectors: household, services, industry, and transport. The model is based on a set of assumptions on medium to long-term socioeconomic, technological, and demographic development in a region or country. Future energy needs are linked to the production and consumption of goods and services; technology and infrastructure innovation, mobility needs, and lifestyle changes caused by personal income. MAED provides a systematic framework for mapping trends in energy needs, particularly corresponding to alternative scenarios for socio-economic development.

LEAP - Long-range Energy Alternatives Planning model

This is a simulation model designed for total energy demand, supply, and resource analysis, and optimization, as well as environmental analysis at macroeconomic level. The model can be used for energy policy analysis ranging from local to global and from medium to long-term.

WASP[4] - Wien Automatic System Planning

The WASP model was originally developed by the Tennessee Valley Authority for the IAEA. The primary objective of WASP is to determine the optimal long-term expansion plan for a power generating system that adequately meets demand for electric power at a minimum cost while respecting constraint input by the user. Constraints may include limited fuel availability, emission restrictions, system reliability requirements and other factors.

WASP utilizes probabilistic simulation to estimate generating system production cost and LP technique to determine the optimal expansion plan by minimizing discounted total costs. WASP is used by over 100 developing countries for power system planning, [IAEA, 2009]. WASP explores all possible sequences of capacity additions that are capable of satisfying demand while also meeting system reliability requirements. It accounts for all costs associated with existing and new generation facilities, reserve capacity and un-served electricity.

FOSSIL 2

Is a system dynamics model used to forecast long term behavior of the US energy supply and demand. The model structure, which includes all energy producing and consuming sectors, simulates the market place in a series of dynamic stocks and flows; the

[4] http://www.iaea.org

stocks include energy production facilities, energy transformation facilities, and energy consuming entities, while flows include energy, prices, and information.

ENPEP - Energy and Power Evaluation Program

This is an integrated analysis tool designed by IAEA to generate energy demand forecasts based on macroeconomic analysis. It is also used to perform a detailed analysis of electric power system, and evaluate environmental implications of different energy strategies.

ENERGY 2020

This is a multi-sector energy analysis system that simulates the supply, price, and demand for all type of fuels. The energy demand is comprised of five sectors; residential, commercial, industrial, agriculture, and transport. The supply side is comprised of electric and gas utilities, and supply sectors of oil, gas, and coal. The model captures feedback dynamics between utility, demand, economy, and regulation sectors.

These models, generally use a simulation or optimization method, where the latter is usually based on linear and non-linear programming approaches. They were developed to address policy and planning concerns in the context of developed countries, but they are also useful for analyzing certain concerns of developing countries too. Developing countries are characterized by poverty, insufficient capital investment, existence of multiple social and economic barriers to growth, and growing shortages in supply of utilities including electricity. Therefore, certain aspects of policy priorities and energy system dynamics and economies unique to developing countries, need to be incorporated in the models for a comprehensive analysis.

2.4.3 Strengths and Weaknesses of Existing Models

The advantages for choosing energy system optimization models are abundant. Optimization models are normally the least expensive and easiest models to develop, [Loken, 2007]. Fundamental technical and cost relationships can be approximated accurately by linear or piecewise linear functions.

One of the most useful characteristics of optimization codes is their capability to perform sensitivity analysis on the optimal solutions obtained for the problem originally formulated. Much of the information that is used in formulating the optimization models is uncertain. Therefore, it is often significant to determine how sensitive the optimal solution is to changes in those quantities, and how the optimal solution varies when actual experience deviates from the values used in the original model. Even if the data were known with complete certainty, it is still necessary to perform sensitivity analysis on the optimal solution to find out how the recommended courses of action should be modified after some time, when changes most probably will have taken place in the original specification of the problem. In other words, instead of getting merely a static solution to the problem, it is usually desirable to obtain at least some appreciation for a dynamic situation. It may also be necessary to inquire how errors that may have been committed in the original formulation of the problem may affect the optimal solution.

However, optimization models introduce the highest degree of simplification in the model representation. Optimization models oversimplifies the solutions. The solution found is optimal from the point of view of all information available to the model, disregarding qualitative aspects which may be difficult to include in the model as constraints. They requires a lot of detailed quantitative data. The complexity of the models is a considerable drawback, along with the need to assign weights to different objectives and the difficulty of integrating qualitative criteria.

2.5 Decision Support Systems (DSS)

Decision support systems (DSS) are defined as interactive, computer-based system that helps decision makers utilize data and models to solve unstructured and ambiguous problems, [Gupta, 2006]. The key to DSS is to collect data, utilize analytical methods, such as mathematical programming algorithms, system dynamics, etc., for developing models to help decision makers formulate alternatives, analyze their impacts, and select appropriate options for implementation.

DSS primarily consist of hardware, software, and the human element. They are designed to assist decision-makers at any organizational level, depending on particular application requirements, [Keefer and Kirkwood, 2004]. A "what if" is an important feature of DSS that enables us to find what happens to certain conclusions or results if changes are being made in the assumptions or in the input information. This implies feedback between the different elements of the system, which can improve the decision-making quality and can move management toward achieving better use of limited resources.

With the widely use of computer in the management and decision making, the modem decision making systems can have five basic forms, [Power, 2007].

Model-driven DSS: These are complex systems that emphasizes access to and manipulation of optimization and/or simulation models. They use data and parameters provided by decision makers to aid decision makers in analyzing a situation. They help analyze decisions or choose between different options. These DSS can be deployed via software/hardware in stand-alone PCs, client/server systems, or the web. Versions of model-driven DSS include spreadsheet-oriented DSS

Communication-driven DSS: These use network and communication technologies to facilitate decision-relevant collaboration. The most common technology used to deploy the DSS is a web or client server. Examples: chats and instant messaging softwares, Video conferencing, and on-line collaboration.

Data-driven DSS: These DSS emphasizes access to and manipulation of time-series and/or real-time data. They contain data warehouse systems accessed by query and retrieval tools to provide most of model functionality to seek specific answers for specific purposes. It is deployed via a main frame system, client/server link, or via the web.

Document-driven DSS: They use computer storage and processing technologies to provide document retrieval and analysis. Large document data bases may include scanned or hypertext documents, images, and sounds. The purpose of such a DSS is to search web pages and find documents on a specific set of keywords or search terms.

Knowledge-driven DSS: These are person-computer systems with specialized problem-solving expertise. The "expertise" consists of knowledge about a particular domain, understanding of problems within the domain, and "skill" at solving some of these problems, [Power, 2003].

2.5.1 DSS Architecture

The DSS basically consists of three subsystems: (1) the data base subsystem; (2) the model base subsystem; and (3) the user interface subsystem. Of primary importance is the management of subsystems and the interfaces between them and the users. The following sections describe the major features and roles of each management system.

Database Management System (DBMS)

A DBMS serves as a data bank for the DSS. It stores large quantities of data that are relevant to the class of problems for which the DSS has been designed and provides logical data structures (as opposed to the physical data structures) with which the users interact. DBMS is established to pursue three major objectives: data independence, data redundancy reduction, and data resource control, [Bagui and Earp, 2003]. DBMS uses a data model to transform real world objects and activities to representations that will be used in the physical data base. A data model is a collection of data structures and operations.

Model-base Management System (MBMS)

A model is a simplified framework designed to illustrate complex processes, it can be a valuable aid to policy analysis, decision-making, and problem solving. The role of MBMS is analogous to that of a DBMS. The most important characteristic of an MBMS is that it enables the decision maker to make decisions through use of the data base with a model base of algorithmic procedures. It provides independence between specific models that are used in a DSS from the applications that use them. The purpose of an MBMS is to transform data from the DBMS into information that is useful in decision making.

Dialog generation and Management System (DGMS)

The DGMS (also called the User interface) is responsible for presentation of the information outputs of the DBMS and MBMS to the decision makers and for acquiring and transmitting their inputs to the DBMS and the MBMS. The main function of the DGMS is to produce a screen display of data and information generated by the MBMS. These outputs could be in a thematic map or in tabular formats or data files.

Technological advancements have been quickly adopted within the individual subsystems of DSS. The interoperability and content of the DBMS has been enhanced by the web-based data access and data warehousing. The DGMS interfaces use advanced visual programming environments. The MBMS, however, is considered the least developed subsystem and is the main focus of this application in DSS framework.

2.5.2 Applications of DSS in Energy Planning

This section reviews the use of DSS and describes some examples used in the field of energy planning. DSS can support the decision makers in selecting criteria, alternatives and trade-offs, thus making the energy planning simple. The applications of DSS in energy planning developed are capacity expansion, [Soloveitchik et al., 2002], transportation energy management, [Brand et al., 2002], electricity production alternatives, [Gandibleux, 1999, Ghandforoush et al., 1999], optimal capacity expansion, [Wua et al., 2005].

Another application was by Topcu and Ulengin [2004] who developed a multi-attribute DSS for evaluating energy resources to enable the selection of a suitable electricity generation alternative in Turkey. The authors used Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) approach to rank the alternatives. Using the partial ordering, wind power is ranked first followed by hydro power and photo voltaic (PV) for electricity generation.

Ramachandra et al. [2005] developed a DSS for analyzing energy consumption at the domestic level in India. The DSS differentiates between household activities like cooking, water heating, and space heating, which are the major end-use activities. It was found that the technologies and methods used to develop and deploy DSS to aid in domestic energy consumption make work easier for a DM. The possibility of quickly accessing and processing large data base over high speeds, offers tremendous improvement in decision making. Later, Ramachandra et al. [2006] developed a DSS to analyze electricity consumption through hierarchical administrative levels up to regional level.

A DSS was developed for energy planning in a district using geographical information system (GIS), [Banerjee et al., 1999]. The DSS links secondary data available in village level indicators, census with primary survey data, and regional maps. The DSS was found to effectively improve the quality of decision making and enable the analysis and understanding of energy impacts of various decisions. In addition, Hersh [1999] discussed the role of different models of DSS and their appropriateness in sustainable decision making in the areas of water resources and energy planning and management.

2.6 Summary

This literature has shown that a considerable amount of knowledge exists for EGP in a developed country's context. Although far from being exhaustive, the review illustrates the diversity of approaches used by authors when addressing issues related to energy decisions. Mathematical techniques are used to tackle the daunting task of evaluating energy capacity planning policies to meet future demand, based on MOO methodology. Currently missing from the literature is the assumption that developing countries are characterized by insufficient electricity capacity to satisfy the ever growing demand. It is clear that a study on EGP characterized by multiple conflicting technical and socio-economic characteristic of developing countries is needed. The research involves developing mathematical models that are better capable of providing decision support on future long-term electricity generation strategies, in the context of insufficient electricity generation capacity.

EGP is a complex multidimensional task that involves several steps including identification of the possible technologies, the choice of the evaluating criteria, the selection and inclusion of stakeholders influence decisions and those affected directly or indirectly by these decisions; and the generation of an evaluation tool able to incorporate all these criteria and stakeholders opinions. Accordingly, planning for energy generation systems requires a full overview of their technical and socio-economic characteristics and making trade-offs among multiple conflicting objectives.

This review of the methods of MP and SD suggests that each has its peculiar strengths and weaknesses. In fact, most of the energy planning studies reviewed did not conclude on the superiority of one method over others. On the contrary, there seems to be generalized agreement that the combination of one or more of the available techniques is frequently the best approach. Thus, with the salient features as described above, it is natural to try to integrate them in a modeling approach that would build on the capabilities of each method. An effective approach can be obtained by combining these methods into a DSS framework when solving complicated EGP problems.

Chapter 3

Electricity Sector in Uganda

3.1 Introduction

Energy is a fundamental input in the process of economic development and sustaining economic growth. Energy is considered to be a key player in the generation of wealth. Adequate and consistent availability of usable energy sources is one of the prerequisites for social and economic development of a country. In developing countries such as Uganda, the notion of providing energy, even to meet basic needs, has been a big challenge mainly because of poor infrastructure development and lack of funds for investment in the generation and management of energy resources.

Hydro electricity and biomass are two indigenous energy sources in Uganda. Biomass constitutes over 90 percent of total energy consumption, [MEMD, 2007] and is extracted beyond the sustainable supply capability of the forests. Whereas Uganda has plentiful electricity generation potential, it has one of the worlds lowest levels of electricity development, with grid access of only 5 percent for the whole country and less than 2 percent in the rural areas, [MEMD, 2007]. This chapter highlights on resource and consumption patterns in electricity sector in Uganda.

3.2 History of the Electricity Sector

The development of electricity sector in Uganda was first done in 1947, when Sir C.K.Westlake made a report to the colonial government and put forward recommendations on the development of hydro electric power in Uganda, [UEB, 1992]. The report recommended that a hydro electric power station be constructed at the Owen Falls near Jinja town and that the transmission, distribution and associated works described in the report be constructed. The dam was constructed and completed in 1954, with an installation capacity of 180 MW. The UEB [1992] report further recommended that a public corporation be set up to control the generation, transmission and distribution of electricity in the Protectorate and be given powers to acquire the East African Power and Lighting Companys electrical undertakings in Uganda. The Westlake Report was adopted and this led to the establishment of the Uganda Electricity Board (UEB) under the Uganda Electricity Ordinance, 1947. The Ordinance charged UEB with the duty to generate, transmit and distribute electricity at low cost to facilitate industrialization.

After the 1962 Uganda independence, the Electricity Act-1964 was enacted to replace the Electricity Ordinance, 1961, without altering the functions and the organizational structure of UEB as the sole institution in charge of regulation, generation, transmission and distribution of electricity in Uganda.

During the government of Idi Amin (1971 - 1979), maintenance and performance of the electricity sector declined due to the bad governance. Over time it was recognized that the commercial performance of public monopolies left much to be desired. By the mid 1980's, generation capacity had reduced tremendously due to neglect of the electricity sector. After a period of more than 40 years, electricity rate in Uganda stands at only 5 percent nationally and less than 2 percent in rural areas, [MEMD, 2007].

In 1993, work started on the Owen falls dam extension project, a second powerhouse located about 1 km from the 1954 powerhouse. A new power canal was cut to bring water from Lake Victoria to the new powerhouse. Major construction was completed in

1999 with first power from the project from two units in 2000. The extension has space for five hydroelectric turbine generators with three installed as of 2003. Each unit at the extension has a capacity of 40 MW. During official opening ceremonies in 2003, the extension was named the Kiira power station.

In 1987, the Government of Uganda (GoU) adopted a policy for the reform and divestiture of public enterprises as a means of enhancing its Economic Recovery Programme, to reduce the financial and administrative burden public enterprises placed upon Government and promote a correspondingly greater role of the private sector. The first step taken in the reform of UEB was initiated by the Board of Directors in 1995, to break the monopoly of UEB, introduce an independent regulator and allow the participation of the private sector to bring in more financial resources to expand the power sector, [MEMD, 1999].

In 1997, the MEMD formulated a comprehensive and detailed Strategic Plan for transforming the power sector into a financially viable electricity industry, in order to enable it to supply reasonably priced and reliable power, and to make its full contribution to the further economic and social development of Uganda. The new Strategic Plan 1999 placed particular emphasis on the role of competition in promoting efficiency within the power sector and on private sector participation as being a key driver to enhance the power sectors performance, [MEMD, 1999]. The reform efforts were also designed to address the need to finance large investment projects in the sector. The Power Sector policy goal is to meet the energy needs of the Ugandan population for social and economic development in an environmentally sustainable manner.

3.3 Responsibilities in the Electricity Sector

Ministry of Energy and Mineral Development (MEMD)

The overall responsibility for the power sector within government lies with the MEMD.

The MEMD provides the overall policy guidance in the development of the Energy and electricity sector in Uganda. It is mandated to establish, promote the development, strategically manage and safeguard the rational and sustainable exploitation and utilization of energy resources for social and economic development. It is responsible for creating an enabling environment in order to attract investment in the development, provision and utilization of energy resources. Finally, its supposed to inspect, regulate, monitor and evaluate activities of private companies in energy sectors so that the resources are developed, exploited and used on a rational and sustainable basis.

In 1999, the Electricity Act was enacted, providing for the liberalization of the power sector, the introduction of new private sector electricity service providers, and the privatization of existing assets. The main objective of the Act is to provide a framework for regulation of the generation, transmission, distribution, sale, export, import and distribution of electrical energy in Uganda. As a result of this, the UEB was divided into five separate companies: [MEMD, 1999]

- Uganda Electricity Generation Company, Ltd (UEGCL),
- Uganda Electricity Transmission Company, Ltd (UETCL),
- Uganda Electricity Distribution Company, Ltd (UEDCL),
- Electricity Regulatory Authority (ERA),
- Rural Electrification Agency (REA)

Uganda Electricity Generation Co Ltd (UEGCL)

Eskom Uganda Limited (Eskom Uganda) operates and maintains two hydro-electric power stations in Uganda (Nalubaale and Kiira both at Jinja), from which it supplies electricity to UETCL. Eskom Uganda receives revenue from UETCL, based on electricity supplied at tariffs regulated by the Electricity Regulatory Authority (ERA). However, UEGCL itself remains the owner of those assets and monitors compliance with terms and conditions of the concession agreements.

Uganda Electricity Transmission Co Ltd (UETCL)

The UETCL, still under Government management, owns and operates the transmission infrastructure above 33 KV. It is responsible for buying power in bulk from generators and sells it to the distribution company. UETCL is also responsible for power exports to Kenya, Rwanda and Tanzania and it serves as the Systems Operator for system coordination and dispatching generation installations.

Uganda Electricity Distribution Co Ltd (UEDCL)

The UEDCL, under the management of UMEME Ltd, owns and operates the distribution infrastructure operating at 33 KV and below. It is responsible for the retail of electricity including metering and billing of consumers in the entire country. UMEME Ltd buys bulk power from UETCL, under a regulated tariff arrangement who in turn purchases from Independent Power Producers (IPPs) - Eskom Uganda (hydro) and Aggreko (diesel generation).

Electricity Regulatory Authority (ERA)

The ERA is the body for regulating the power sector i.e. licensing of new power companies, setting/approving tariff structures, setting standards and regulations and resolving any disputes that could arise from the power sector (end-users and power companies) to ensure that the quality of power supply to the customers is acceptable and affordable.

Rural Electrification Agency (REA)

The REA was established in 2003 as a government institution to promote social and economic development in the rural areas through planning and provision of subsidies to commercial/private sector-based investments in rural electrification schemes within and out of UMEMEs designated area of supply. It was also mandated to develop and enforce rural electricity performance standards. It is in charge of the execution and coordination of projects in rural areas and regions of extreme poverty.

Other stakeholders include;

- National Environment Management Authority (NEMA) is responsible for regulating the impact of renewable investments on the environment, through instruments like environment impact assessment (EIA).
- Directorate of Water Development (DWD) is responsible for issuing permits for water extraction for hydro power schemes;
- Uganda Investment Authority (UIA) provides both foreign and local investors with licenses for investment;
- Concessionaires like-Ferdsult, WENRECo, and URECL who distribute and participate in meeting the energy needs.

3.4 Electricity Demand

In Uganda, the demand for energy is increasing at a very high rate. However, the per capita energy consumption of 2 ToE is among the lowest in the world, [Syngellakis and Arudo, 2006]. As is typical for developing countries, the energy consumption per capita is expected to increase with growing economy. Uganda is a classical example of an electricity system facing both capital and energy resource constraints resulting in electricity capacity and energy shortages. It manages with limited supply and tries to match it with the ever increasing demand. Few people have access to modern energy supplies such as electricity and petroleum products. Total modern energy consumption in Uganda is estimated at about 5 million ToE. There is over dependence on low-grade forms of energy especially traditional biomass fuels which accounts for more than 96 percent of the total energy consumption, [Syngellakis and Arudo, 2006].

Electricity demand in Uganda is classified by five end-user customer sectors: Domestic, Commercial, Medium scale industries, Large scale industries, and Street lighting, [UBOS, 2009].

- Domestic consumers; These are customers who are metered at low voltage supply single phase and supplied at 240 volts. They include residential houses, small shops and kiosks. These customers have no time-of-use tariffs.
- Commercial consumers; These are small commercial consumers. Electricity is supplied at three-phase voltage, with a load not exceeding 100 Amperes. They mainly include small industries such as maize mills, water pumps metered with connected load at low voltage.
- Medium scale Industries; These are medium scale industries that take power at low voltage (415 volts) with a maximum demand of up to 500 kVA.
- Large scale Industries; They include large-scale industries taking power at a high voltage (11,000 V or 33,000 V) with a maximum demand exceeding 500 kVA but up to 10,000 kVA.
- Street Lighting; This includes electricity supply for street lighting in cities, municipalities, towns, trading centres and community centres.

Table 3.1 shows the electricity demand by customer category for the years 2000 to 2007, where the industrial sector accounted for the largest share of 40 percent of the total energy sold, MEMD [2009]. The street lighting was left out because it had significantly very small values. The leading industry sub-sectors i.e. construction, manufacturing and services that account for biggest percentages of energy demand have grown at rates of more than 10 percent making demand for electricity to grow at rates higher than the GDP, [MFPED, 2006]. According to the ERA [2008], electricity demand varies between 360 to 390 MW during the evening peak period (1900 to 2400 hours), 260 to 280 MW during shoulder period (0600 to 1900 hours) and off peak period (2400 to 0600 hours) demand is between 180 to 250 MW. The high population growth rate and the very

Table 3.1: Electricity demand by Customer category (GWh)

Year	**Domestic**	**Commercial**	**Large industries**	**Medium industries**
2000	311.0	123.8	206.2	201.2
2001	354.4	177.1	162.6	218.6
2002	475.5	161.9	272.5	200.4
2003	418.0	155.5	263.3	220.4
2004	344.3	135.5	342.1	304.2
2005	340.6	134.2	389.9	206.9
2006	289.8	136.6	390.9	172.5
2007	289.3	150.3	482.5	210.4
2008	327.2	177.7	549.2	223.4
2009	364.4	209.0	594.0	233.1

Source: [MEMD, 2009]

high economic growth rates experienced in the last 10 years have increased the demand for energy tremendously. Over the decade, electricity demand grew at an average rate of 8.3 percent which if compared to the growth rate of 6.9 percent in generated capacity shows the ever widening gap between generation and demand. Given, current trends in population growth, industrialization, urbanization, modernization and income growth, electricity demand is expected to increase substantially in the coming decades as well.

Electricity Demand Projections

The electricity demand forecast is an important planning tool for meeting future electricity supply needs. The electricity demand in most developing countries is increasing and more investments in generation are needed every year, [IEA, 2005]. Since 1997, there has been three major electricity demand forecasts for Uganda, starting with the one presented in the Kennedy and Donkin Power Development Master Plan of November, 1997. Electricite de France (Edf) conducted its own load forecast in 2001. Another load forecast was prepared under the East African Power Master Plan by BKS Acres Limited. Table 3.2 presents recent forecasts for the period (2001 - 2025), by UETCL reflecting actual MW and GWh in generation. Its estimated that the annual growth in electricity demand to be 8 percent, [MEMD, 2007]. These projections will require substantial investment in new generation and network capacity.

Table 3.2: Electricity demand projections (MW)

Year	Peak Demand		
	Low	**Medium**	**High**
2001	270	270	270
2002	274	283	289
2003	308	308	308
2004	317	317	317
2005	279	317	345
2006	380	380	380
2010	442	498	528
2015	535	697	796
2020	647	976	1,200
2025	783	1,367	1,809
2002-25	3.88%	6.97%	8.56%

Source: Adapted from [Baanabe, 2006]

The BKS Acres forecast was part of the economic and financial evaluation study of the 250 MW Bujagali II hydro power project, [PPA, 2007]. The BKS Acres load forecast was done under the following assumptions;

- GDP growth rate of 6.5 percent per year
- Rural electrification target of 10 percent coverage by 2010 (55 percent will be connected)
- An increased observed consumption rate from -0.1 percent (2001/2003) to 11.8 percent (2003/2004)

After reviewing the load forecasts made by the PPA Consultants and based on historical load growth trends and the limitations observed in the projections by PPA and other considerations, Government prefers to use the BKS Acres demand projections (High case scenario) as the planning tool for future power development, [Baanabe, 2006].

Electricity demand will continue to increase since it is necessary to maintain modern life and is an essential input to economic growth and development. Electricity consumption in the country grossly underestimates actual demand because of suppressed demand which often results from load shedding. Load growth has been constrained by the inability of the network to accommodate new customers, power unreliability, and shortage of available capacity. With the government programme of the rural electrification scheme, domestic and small scale industrial consumption is expected to rise.

3.5 Electricity Exports/Imports

Uganda has an agreement with Kenya for export/import of non-firm electricity over the double circuit 132 KV line between Jinja and Lessos (Kenya). UETCL has export contract obligations to export 50 MW of firm power to KPLC, Kenya, and up to 80 MW non-firm, following the commissioning of Bujagali for a period of 20 years, [PPA, 2007]. However, the 50 MW to Kenya is supplied only during off-peak hours. There are also plans to increase the potential export capacity to Kenya to 360 MW, by extending the 220 KV line to Lessos via Tororo. The Kenyan government has expressed willingness to purchase more power from Uganda.

Uganda exports 9 MW to Bukoba area (Tanzania) near the Ugandan border. Bukoba is an agricultural area and is isolated from the Tanzania's TANESCO main grid. The average peak demand was 7 MW in 2006. Uganda also exports an average of 5 MW to Rwanda. It is estimated that exports to Tanzania and Rwanda increase at 5 - 6 percent annually for the next five years.

3.6 Electricity Supply

Ugandas public electricity generation started in 1954 with the commissioning of Nalubaale power station (former Owen Falls Dam) on River Nile. Until 2003, the country has been depending solely on hydro power generated from the Nalubaale power station, a generation capacity of 180 MW. The Kiira dam extension was commissioned in 2003 with an installed capacity of 120 MW bringing to a total of 300 MW the installed capacity of the 2 dams. Other hydro power producers are Kasese Cobalt and Kilembe Mines. Kakira Sugar Works Ltd has a bagasse plant with an installed capacity of 18 MW but only 12 MW is sold in energy to the national grid.

In 2006/2007, Uganda was hit by prolonged drought that affected the water levels on Lake Victoria, thus reducing the electricity generation capacity. By 2008, the combined output of Nalubale and Kiira had been reduced to 160 MW (out of a total installed capacity of 300 MW). In an attempt to reduce the countrys reliance upon hydro electricity, the Ugandan government invested in thermal power. The government contracted Aggreko (U) Ltd to operate 2 thermal plants at Lugogo and Kiira, each worth 50 MW, and Jacobsen Electro AS to operate another 50 MW thermal plant in Namanve and Mutundwe. Despite these measures Uganda continues to suffer from power supply shortages and load shedding.

The Uganda the electricity generation mix consists of hydroelectric, heavy fuel oil (HFO) and diesel thermal generators as shown in Table 3.3. In 2009, the total installed capacity of electric power plants that feed into the national grid was 492 MW with hydro electricity constituting 66.7 percent, thermal electricity 30.5 percent and bagasse electricity 2.8 percent. Power generated at the Kiira and Nalubaale dams accounts for 91 percent of the total hydro electricity generated in the country. The Lugogo thermal plant was decommissioned in 2009 because it was replaced by the heavy-fuel oil thermal plant at Namanve, which was cheaper.

In addition, to the main electricity grid, there are other mini electricity plants that do

Table 3.3: Installed electricity capacity (MW)

Plant Name	2008	2009
Hydro electricity		
Nalubaale dam	180	180
Kiira dam	120	120
Kasese Cobalt	10	10
Kilembe mines	5	5
Bugoye Tronder	-	13
Thermal electricity		
Lugogo	50	-
Kiira	50	50
Namanve	50	50
Mutundwe	50	50
Bagasse electricity		
Kakira	12	12
Kinyara	-	2
Total	527	492

Source: Adapted from UBOS [2009, 2010]

not feed into the main grid but supply power to the surrounding areas. These include Kisiizi Hospital, Kihihi generation plant for thermal power, and the West Nile Rural Electrification Company (WENRECO) among others.

The electricity supply industry currently consists of grid-connected companies which include Eskom (U) Ltd, Aggreko (U) Ltd, Kasese Cobalt Company Ltd (KCCL) and Kilembe Mines Ltd (KML). Nalubaale and Kiira power stations are managed by Eskom (U) Ltd. A breakdown of energy generated by sources is illustrated in Table 3.4. The electricity power generation in 2009 was 2,533 GWh, while in 2008, 2,176 GWh were generated, a 16.2 percent increase in power generation, [UBOS, 2010]. The increase was due to additional generation from the plants in Mutundwe and Namanve in 2009 that almost tripled the 2008 generation The future capacity required to supply the growing demand will most likely be made up of mainly hydro capacity and probably some thermal capacity operating on liquid fuel.

A number of projects have been initiated to improve Ugandas power supply and increase

Table 3.4: Amount of Energy generated (GWh)

Period	2004	2005	2006	2007	2008	2009
Hydro electricity						
Eskom	1,872.33	1,698.54	1,160.45	1,263.54	1,373.44	1,234.98
Kilembe mines	11.47	20.81	28.05	29.64	29.80	28.35
Kasese Cobalt	3.89	2.37	1.53	0.74	1.80	1.31
Bugoye Tronder	-	-	-	-	-	15.91
Thermal electricity						
Lugogo	-	140.77	319.95	272.8	141.39	-
Kiira	-	-	50.03	266.33	239.59	126.35
Mutundwe	-	-	-	-	99.52	395.14
Namanve	-	-	-	-	116.57	353.09
Bagasse						
Kinyara	-	-	-	-	-	4.47
Others	-	28.19	68.89	71.72	173.89	16.19
Back flows to UETCL	-	3.72	19.98	11.63	130.68	346.10
Electrogaz	-	1.32	2.18	1.84	2.29	2.33
KPCL(Import)	-	23.15	46.73	58.25	40.92	25.06
TOTAL	1,887.7	1,890.7	1,628.9	1,904.8	2,176.0	2,533.37

Source: Adapted from UBOS [2008, 2009, 2010]

access to electricity, MEMD [2007]. The government, with support from the Aghkan Foundation, is constructing the Bujagaali dam. The power plant is situated 1,100 meters above sea level at Bujagaali Falls, about 8 Km north of Lake Victoria, and with total installation generation capacity of 250 MW. Also plans are underway to commence the construction of Karuma hydro power plant located about 3 Km upstream from the Karuma bridge in northern Uganda, with an installation generation capacity of 200 MW.

Several companies have been licensed by ERA and these include West Nile Rural Electrification Company (WenRECO) which generates and distributes power in the districts of Arua, Nebbi and Paidha, Eco-Power for the Ishasha hydro site, China Shang Sheng International for the Kikagati Hydro Site. Other private firms like Kakira Sugar Works, Hydromaxx and Invespro have been granted licenses for the independent power producer projects, [ERA, 2006b].

3.7 Energy Resource Potential

Uganda is rich in a wide range of new and renewable energy sources including hydro electric power, wind, geothermal, bagasse[1], and solar and has abundant biomass resources, Table 3.5. Solar conditions are ideal and its radiation is currently estimated at 4-5 KWh/m^2/day while the potential of geothermal power which is evident from the hot springs found in Western Uganda with temperatures ranging from 500^o - 1000^o Celsius, has an estimated national potential of 450 MW. The wind speed in the country is estimated at 3 meters per second on average, while in flatter areas and on top of hilly areas it is as high as 6 meters per second, [MEMD, 2002a]. This is sufficient to support wind technology in the country. It is unlikely that nuclear energy will play any significant role in the foreseeable future. Considerable scope exists for accelerating electrification to meet the growing demand especially in the rural areas through off-grid electrification.

Table 3.5: Estimated energy potential (MW)

Energy resource	**Potential**
Large hydro power	2,000
Small hydro power	200
Solar PV	200
Biomass	1,650
Geothermal	450
Bagasse	800

Source: Adapted from MEMD [2007]

Hydro Power

The hydro electricity potential in Uganda is high and currently estimated at more than 2000 MW, out of which only 10 percent has been developed. There are several potential sites for hydro power generation, [MEMD, 2004].

Mini- and micro-hydro power sites exist in various locations in the country. There are more than 60 mini-hydro power sites that have been identified through different studies

[1]Bagasse is a by-product from sugar cane crushing process

in Uganda. These can be developed to supply power to isolated areas or feed into the national grid.

Biomass

Biomass encompasses diverse fuels derived from timber, agriculture and food processing wastes or from fuel crops that are specifically grown or reserved for energy generation. Biomass fuel can also include sewage sludge and animal manure. Usually biomass is used for two purposes; to produce heat, and to generate electricity.

In developing countries, especially in rural areas, 2.5 billion people rely on biomass, such as fuel wood, charcoal, agricultural waste and animal dung,to meet their energy needs for cooking, [IEA, 2006]. Biomass provides almost all the energy used to meet basic cooking and water boiling needs in rural and most urban households, institutions and commercial enterprises. It is basically the main source of energy for small and medium scale industries. The limited availability of electricity and the high prices of petroleum products are stimulating demand for biomass fuels in both industrial and other user sectors, [MEMD, 2007].

Geothermal

The potential of geothermal resources is estimated at about 450 MW in the Ugandan Rift Valley system, [Kamese, 2004]. Geothermal areas of Katwe-Kikongoro, Buranga and Kibiro in Western Uganda have geological potential with sub-surface temperatures suitable for electric power production.

Solar

Uganda is endowed with plenty of sunshine giving solar radiation of about 5 KWh/m^2/day. This level of isolation is quite favorable for all solar technology applications. However, the countrys solar potential has not been exploited yet. The solar PV systems are used for supply of basic electricity in households and rural institutions as well as areas not connected to the national grid. The total new installed solar PV capacity annually is estimated to 200 kilowatt peak (KWp) for households, institutions, and commercial use, [Kamese, 2004].

Solar technology can be used for electricity generation, but the prohibitive costs make it less favorable than other generations options. Solar panels require quite a large area for installation to achieve a good level of efficiency.

Bagasse

Uganda has opportunities for electricity generation based on renewable resources linked to its sugar industry. Electricity can be generated using bagasse, by-product of sugar production, as basic fuel for thermoelectric facilities. Bagasse generation benefits from lower and more stable cost of production than oil-based generation, as well as lower carbon emissions.

Bagasse power is being utilized on a big scale by the three sugar industries (Kakira Sugar Works (1985) Ltd., Sugar Corporation of Uganda Limited (SCOUL) and Kinyara Sugar Works) in meeting or supplementing their internal energy requirements through the generation of combined heat and power (co generation). Kakira Sugar Works Ltd has a bagasse plant with an installed capacity of 18 MW but only 12 MW is sold in energy to the national grid and 6 MW is used for own consumption, [ERA, 2007]. SCOUL generates 30 MW, while Kinyara Sugar Works generates 1.7 MW.

Wind

Wind is a renewable resource because it is inexhaustible. It is a result of the sun shining unevenly on the earth. The corresponding daily and seasonal changes in temperature consistently generate wind, producing a fuel source that can never be depleted.

The average wind speed in Uganda is about 3 meters per second in low heights (less than 10 meters), which is good enough to support wind technology applications in small scale electricity generation such as water pumping. However, the absence of a regulatory framework and of a reliable record of wind potential, together with the lack of human, financial, and technical resources, has so far hindered the exploitation of Ugandas wind power potential.

3.8 Electricity Tariffs

The 1999 Electricity Act mandates ERA to set and approve electricity tariffs in Uganda, [MEMD, 1999]. It sets the rates of charges and terms and conditions of electricity supply. ERA regulates both the levels and structures of electricity tariffs. Tariffs are set with the aim of providing consumers with fair and reasonable price structures consistent with maintenance of a financially and operationally secure electricity supply system. Tariffs are set to encourage operators to make efficient use of plants and provide reasonable return/profit to give confidence to current investors and attract new investors, [ERA, 2006a].

Electricity prices are set at three interface points in the industry: generation and transmission; transmission and distribution; and distribution and end-user consumers. UETCL is the only single buyer of electricity supplied to the transmission network in Uganda; and and the sole exporter and importer of power. The prices between Eskom (U) Limited and UETCL are negotiated between them in a form of power purchase agreement subject to approval by ERA, [ERA, 2006a]. UETCL then sells power to UMEME at a bulk power supply tariff. The bulk power supply tariff reflects the costs of power purchases from Eskom (U) limited and the costs of transmission and losses.

The end-user tariffs are time differentiated, that is, different charges are applied to usage in different time block periods (Peak, Shoulder, and Off peak). Tariff rates in each category are computed to reflect the cost of electricity supply to that category. Table 3.6 shows the average annual tariff rates (UShs/unit) at peak demand for the period 2001 - 2009, [UBOS, 2010]. Between 2005 and 2007, electricity tariffs have almost doubled mainly due to the introduction of thermal power in total energy mix, that is highly sensitive to changes in fuel prices. An increase in fuel prices has a significant upward

Table 3.6: End-user electricity tariffs at peak demand (UShs/KWh)

Year	Domestic	Commercial	Medium industries	Large industries	Street lighting
2001	189.8	189.8	171.6	104.4	176.4
2002	168.0	168.0	152.4	93.5	153.0
2003	170.1	170.1	155.1	89.4	155.0
2004	171.4	165.8	150.2	60.4	163.2
2005	217.0	208.9	183.1	74.9	205.3
2006	298.0	287.0	262.0	121.6	283.3
2007	426.1	398.8	369.7	187.2	403.0
2008	426.1	398.8	369.7	187.2	403.0
2009	426.1	398.8	369.7	187.2	403.0

Source: Own elaboration of data from [UBOS, 2009, 2010]

effect on energy purchase costs of UETCL. However, electricity tariff rates remained relatively stable in 2007, 2008 and 2009 for all the categories.

Electricity tariffs in Uganda are highly sensitive to changes in inflation, exchange rate, and fuel prices. Some of the costs that make up the revenue requirement of the companies are adjusted on a quarterly basis for changes in inflation. An increase in inflation in any given period would cause an upward movement in tariffs. A number of costs are denominated in foreign currency and therefore sensitive to exchange rate fluctuations. A depreciation of the Uganda shilling would cause tariffs to increase sharply even when other factors remain stable.

3.9 Rural Electrification Scheme

The Energy for Rural Transformation (ERT) is a government program aimed at subsidizing private investment in the rural network expansion, [MEMD, 2001]. ERT is a World bank funded project with the goal of increasing rural access to electricity from 1 percent to 10 percent over a period of 10 years. The strategy is to develop low cost mini-hydro generation further away from the grid with investments from the private sector to reach distant local markets. The project also aims at connecting customers with off grid solar power. However, the very unreliable supply of electricity and high electricity tariffs, make the rural population continue to rely on wood fuel.

3.10 Energy Policy

In Uganda, the energy sector is central in the country's quest for economic transformation and modernization process. The energy sector facilitates all the other sectors of the economy. These include among others: health, education, banking, manufacturing, agriculture, communications, and transport. It is therefore at the heart of the economy and partly determines the costs of production in all the other sectors. The energy sector also offers substantial export opportunities to neighboring countries. Thus, energy is a lifeblood of the economy of Uganda linking other sectors and has a direct bearing on the performance of other sectors.

In 2002, the GoU developed its comprehensive policy on energy, [MEMD, 2002b], to improve the quality and quantity of energy supply through appropriate sector reforms and establishment of an enabling legislation; and to promotion of efficient utilization of energy resources and execution of rural electrification programs. In expanding access to energy services, the government policy is to promote private sector participation in the development of both conventional and renewable energy resources. Another key objective is to maximize opportunities for export of power to the neighboring countries once the internal demand is adequately met. The policy seeks compatibility with the global and regional energy policies.

To combat the electricity supply problems in Uganda, several electricity policies have been developed. The broad objective of these policies is to provide adequate and reliable electricity supply to the country through increased generation capacity, demand-side management and use of alternative sources of electricity.

In 2007, renewable energy policy (REP) for Uganda was developed, [MEMD, 2007], to increase the use of modern renewable energy, so that its proportionate use increases from the current 3.8 percent to 61 percent of the total energy consumption by the year 2016. The key policy objectives include: Maintain and improve the responsiveness of the legal and institutional framework to promote renewable energy investments; establish an appropriate financing and fiscal policy framework for investments in renewable energy technologies; promote the sustainable production and utilization of biofuels; and promote the conversion of municipal and industrial waste to energy.

Under the power generation programme, the REP promotes power generation from mini-hydros, biomass, co-generation, wind, solar, geothermal and peat. There are plans to consider nuclear power generation in the power mix.

3.11 Challenges of the Electricity Sector

Electricity demand in Uganda has been growing at a very rapid rate over the last two decades. Given current trends in population growth, industrialization and income growth, electricity consumption is expected to increase substantially in the coming decades as well. The economy has doubled in the past decade, [MFPED, 2008] and is expected to grow at an average of 8.5 percent per year for the next 5 years. And the population has exploded at a rate of about 3.6 percent a year, [MFPED, 2006]. This implies enormous new financial investments will be needed to meet demand in this sector. Despite considerable growth in energy consumption, Uganda still remains one of the countries with the lowest level of conventional electricity consumption per capita in the world, [Syngellakis and Arudo, 2006].

The main challenge facing the energy sector today is the unprecedented electricity supply deficit on the national grid arising from the reduced generation capacity due to the prolonged drought and falling water levels from Lake Victoria, plus the ever increasing energy demand. Currently, the energy sector is characterized by chronic power shortages and poor power quality. With demand exceeding supply, severe peak and energy shortages continue to plague the sector.

Like most developing countries, the elementary problem being faced by the power sector is the poor financial conditions of the electricity companies. This has resulted in inadequate investment in additional generation capacity, which is likely to further exacerbate the existing gap between power supply and demand. There is limited public and private (foreign and domestic) financial resources to invest in large infrastructure power projects. Financing mechanisms to support investments in electricity sector and to address the afford-ability of consumers are inadequate.

Electricity tariffs are set with government intervention and a high degree of cross-subsidization between sectors continues to exist, with average electricity tariffs being generally below the costs of power generation and distribution. This has tended to encourage inefficient use of electricity in the subsidized sectors. The introduction of thermal electricity generation in 2006/2007, forced government to increase the electricity tariffs by 37 percent across the board with the exception of heavy industries. Whereas the tariffs have gone up, they are not adequate to meet the costs of electricity generation. Further still, they are unjustifiable and highly inequitable given that access to electricity is only 9 percent at present having increased from 5 percent in 2006, out of which only 3 percent is rural coverage, [MFPED, 2008]. The prevailing situation of increased tariff and frequent power cuts has drastically affected the industrial, commercial and the social sectors alike.

Another challenge is the escalating oil prices on the international market, which impose a heavy burden on the economy. The annual per capita consumption of petroleum products is also increasing; all petroleum products are imported. The cost of these products has become unpredictable with increases every now and then on the international market. There are more people using "self-electrification" (diesel generator-sets, car batteries, solar PV, etc) than those connected to the national grid. The annual expenditure on the import of petroleum products is very high and continues to rise. These products take a considerable percentage of Ugandas per capita income. During 2006, the total importation cost for these products was US$ 116 million, equivalent to about 15 percent of the total export earnings, [UBOS, 2008]. In addition, the high petroleum tariffs in the country have also contributed to high costs on the local market. This has meant that, the country has to spend a lot of its meager foreign exchange on these products at the expense of other development programmes.

3.12 Summary

In this chapter, the Uganda electricity system has been characterized, as an example for a developing country. The Uganda energy sector heavily relies on fuel wood (biomass) and fossil fuel imports. The main resource for electricity production is hydro power and thermal, making the system highly dependent on rain fall conditions and external fuel imports. Predictions for the next years indicate that the electricity demand will continue to rise, reaching in 2020 a value 4 times higher than in 2008. Uganda is experiencing an unprecedented electricity deficit of about 165 MW, resulting into massive load shedding, due to the prolonged drought, inadequate investment in least cost generation capacity and a relatively high load growth. This has forced the country to resort to the installation of very expensive thermal generation, while awaiting the construction and commissioning of the 250 MW Bujagali and 200 MW Karuma hydro power projects.

Considering that electrification access in Uganda is still very low, standing at approximately 9 percent nationally and 3 percent in rural areas, electrification of most parts of the country through grid extension in the near future is still a far cry. The REP sets out Governments vision, strategic goals, principles, objectives and targets for promoting and implementing renewable energy investments in Uganda. During the next two decades, the structure of power generation is expected to change significantly in favour of renewable resources.

The EGP process is a very complex task since it has to take into consideration the rapid increases in demand, the high costs, the large number and diversity of alternative investment policies, numerous choices among generation technologies, types of fuels and sources of generated power to meet customer demand at minimum cost, while still providing reliability and compliance with all environmental regulations. All these considerations are interrelated. No decision taken in isolation can be considered as complete and assumed to be inconsequential for other decisions. The issue gets further complicated because these decisions are not single period and varies from a very short to very long horizons. Moreover, the activities are performed not by single entities; Uganda's electricity is generated by UEGCL, transmitted by UETCL, distributed by UEDCL and utilized by different types of consumers, and the diverse objectives of each entity may be conflictive in nature with those of others.

An integrated EGP study, which considers adequately the role of mathematical programming techniques in identifying an optimal configuration of electricity generation technologies, is, therefore, necessary to be carried out. This is also the main goal of the present study. In the next chapters, mathematical programming models are presented and described to achieve the specified goal.

Chapter 4

Multi-Objective Linear Programming (MOLP) Model Formulation

4.1 Introduction

Electricity generation planning (EGP) has at least three important dimensions that must be evaluated. Firstly, the choice of technology and capacity size for the plant, and secondly, the timing of the investment must be evaluated, and thirdly designing a strategy of allocating available electricity capacity to demand sectors.

In developing countries, electricity generation planners are faced with the challenge of planning and operating an electricity system to meet the needs of customers at the lowest possible cost. The objective is to meet demand with the development of generation and transmission systems at a specified level of reliability and in a least-cost manner. Past attempts to modeling EGP were mainly concerned with the cost, capacity, type and number of candidate generating stations, [Park et al., 2000]. However, much of that work ignored use of multiple criteria and uncertainties that have to be taken into consideration, so that trying to identify feasible solutions has become a very difficult task, [Beltran, 2009].

EGP modeling concerns for developing countries requires an understanding of the history and current trends of energy policy regime and social-economic dynamics in those countries. Most developing countries suffer from a poor performance of the power sector for various supply-side, demand-side and economic reasons. EGP normally incorporates the information on the present electricity supply system and the potential for the future. This includes the assessment of supply resources and the evaluation of the electricity distribution and supply technologies.

This chapter deals with the socio-economic dimensions of the EGP problem in the developing country context. These dimensions can be described in terms of mathematical expressions, thus allowing for the use of mathematical programming approach to develop a mathematical multi-objective linear programming (MOLP) model to evaluate electricity generation alternatives. EGP inherently involves multiple, conflicting and incommensurate objectives. Therefore, mathematical programming is applied in order to obtain the configuration and performance of the electricity generation system. Mathematical models become more realistic if distinct evaluation aspects, such as cost, are explicitly considered.

The socio-economic dimension of the MOLP model is described by a function representing the total cost of the electricity generation configuration. The costs considered include the capital investment cost, operation and maintenance (O&M) costs. For lack of relevant information/data, this study does not consider the cost of fuel consumption and environmental impact resulting from the electricity generation systems, but these issues can be easily incorporated once reliable data are available.

4.2 Model Description

Most developing countries have abundant renewable energy resources and the policy is to diversify the energy supply sources and technologies, [MEMD, 2007]. In particular, the policy goal is to increase the use of modern renewable energy technologies and bring them into the national energy supply mix. This model addresses the question of what future available electricity technologies should be considered for the planning period assumed in the model.

The purpose of the MOLP model is to determine electricity generation options to be constructed, the generation capacity and time when to be constructed and an allocation plan for electricity under conditions of perennial shortages, so that the total electricity generation cost is minimized. The model seeks to determine the type and capacity of generation options to achieve the best compromise between different objectives and yet meet all the operating and economic restrictions that are placed on the electricity sector.

The model determines how the electric power industry will change its mix of generating capacity that provides reliable and economical supplies of electricity over the forecast planning period. In general, the problem to be addressed has several objectives to be optimized simultaneously. The general inputs to the model design at a generic level are:

- The technical and economic characteristics of the electricity generation system. The planning process starts with the existing generation mix. The mix is then modified over time, subject to not only attempting to meet the forecast demand as closely as possible but also other technical and economical constraints.
- The use of mathematical multi-objective optimization procedures that allow the integration of more than one objective.
- The economic, technical and social characteristics associated with the electricity generation technologies.

By merging this information, a MOLP model is developed, based on empirical data. The final output of the model is a set of feasible optimal electricity generation plans and supply policies integrating economic, technical and social concerns. These plans, along with a full description of their expected impacts may then be presented to the decision maker who will have the final task of choosing the best optimal plan.

4.2.1 Electricity Generation Cost

Electricity generation cost is a vital component for EGP planning. The energy systems of developing countries suffer from chronic electricity-related financial problems because of rising generating costs, accompanied by eroding revenues due to pilferage, bad debts, and supply of power at subsidized rates. The cost of generating electricity, as defined within the scope of this study, is expressed in terms of a unit cost, ($/MW), delivered up to the point of transmission, that is, at the boundary of the power plant site. The MOLP model considers two types of costs which are incurred in electricity generation;

- Capital investment costs

  These are costs associated with the capital investment in the facilities necessary to generate electricity. It is the initial level of investment required to engineer, procure the equipment and construction of the plant. Capital costs involve the construction of new generation capacity or the refurbishment of existing generation facilities. This initial capital cost is the main determinant factor in the selection of energy sources for power generation.

- Operation and Maintenance (O&M) costs

  The traditional approach considers fixed and variable costs separately. However, unlike developed countries with adequate financing, developing countries are characterized by poor sector financing with electricity tariffs below long-term marginal costs of electricity production or even average operating costs. Therefore, this model proposes to classify all O&M costs as variable because of financial deficiencies typical of energy systems in developing countries. These O&M costs are dependent on the proportion of the actual quantum of electricity capacity generated.

Combining these costs provides an estimate of the total cost of the electricity generation. This total cost is the minimum value that the electricity must be worth to society to warrant its production and provides a minimum average base price that should be charged if the full costs of generation were to be captured through the market price.

4.2.2 Electricity Generation Capacity

Electricity is generated as and when needed and can not be inventoried like manufactured physical goods. Generated capacity should desirably be sufficient to meet the instantaneous power demand from the consumers in a given period. Ideally, the total available capacity should be greater than the total demand in a given period, taking into consideration that the actual electricity capacity reaching the final consumers is less than the quantum of electricity that is generated, due to the transmission and distribution losses. Otherwise, there is a shortage in electricity capacity allocated to consumers.

Loss in electricity generation capacity may be a result of poor conditions of generation equipment, inadequate operational and maintenance performance and a high level of technical and non technical losses.

4.2.3 Electricity Transmission Capacity

Electricity transmission system links installed capacity to the ever increasing end-users to avoid a shortage. This requires the availability of adequate transmission system facilities to transport electricity to load centers. The distribution systems in turn feed transformers, carried on poles or located in underground manholes that finally reduce the voltage to the magnitude at which the consumers will use it. Therefore, its crucial to analyze the relationship between electricity generation, demand or load, and transmission capacity.

Transmission capacity losses occur in the process of delivering electricity from the point of generation to the end-users. In the context of developing countries, where there are poor infrastructural development, accompanied by inadequate operational and maintenance performance, there are high losses of transmission capacity. Transmission capacity losses cannot be eliminated fully, but can be minimized by strengthening of electrical facilities, [Ramachandra et al., 2006]. This research evaluates and analyzes the loss of transmission capacity as a function of maintenance expenditure on the electricity transmission system.

4.2.4 Electricity Shortage

The basic function of an electricity utility is to provide adequate supply of electricity to its customers when they demand it, as economically as possible, and with reasonable level of reliability. Unlike other commodities, the electricity demand is met instantaneously. There is no time lag between the customer requirement for electricity and the time he actually gets it. Since the demand for electricity varies continuously, it is possible to have situations where there is no electricity when the customer needs it and conversely its available when there is no need for it.

Electricity shortage denotes electricity interruptions or power outages when the utility does not supply electricity to the customer when required. It is when the available capacity is insufficient relative to the current demand, [Balachandra, 2000]. In other words, electricity shortage occurs when the available generation capacity at a given instant is not sufficient to satisfy the users' demand for power at that particular instant.

In developing countries, electricity shortages are a result of failures in the generation system, ineffective management of electricity installations or simply because there is insufficient installed capacity. Balachandra [2000] notes that if the total installed capacity is insufficient to generate sufficient electricity to meet the demand then the shortage in supply occurs. Non-availability of funds and delays in project implementation slow down the addition of new installed capacity. Electricity utility systems in developing countries are characterized by frequent breakdowns in electrical installations and badly planned maintenance schedules, which substantially lowers the available capacity.

Sectoral differences in consumption patterns have significant influence on the electricity shortage costs, [Wang and Min, 2000]. In the case of domestic sector, electricity shortage cost is the cost to the consumer in terms of lost leisure, inconvenience, cost of stand-by generator, etc. For the industries, the costs are related to idle labour, capital, raw materials, equipment damage and costs related to human safety. Unlike in the domestic sector, shortage costs for industrial sector are directly measurable in terms of monetary losses associated with the cost of idle resources and loss of production, [Bose et al., 2006]. Balachandra [2000] reports that the expected cost of any system plan can be assessed as the sum of its capital costs, expected operating costs and expected customer cost of electricity shortage.

Electricity utility systems with inadequate generation capacity find it very difficult to satisfy electricity customer demand requirements, [Balachandra, 2000]. In these systems, the supply-demand matching is achieved by controlling both supply and demand as the situation demands. Some of the commonly employed methods include imposition of power-cuts on identified customers and load-shedding during a given period for a given geographical area.

This study "lumps" shortages into degree of shortage allocated to various demand sectors. The real world implementation, where a prescribed proportion or percentage of demand is supplied in a given planning period, that is, load shedding, is not explicitly part of this model.

4.3 Model Formulation

A mathematical MOLP model for EGP is developed, evaluating the electricity generation options' capital investment cost by its effect on the entire systems O&M and fuel costs. The generation options are evaluated considering technical, economic and social attributes simultaneously. The optimization is subject to a number of constraints ensuring the reliability of the electricity system and its technical and economic requirements.

There are two types of decision variables in the model: the structural and the operational. The structural variables represent new capacity added to the existing electricity generation system and are associated with capital investment costs. The operational variables represent the level of utilization of the capacity of various electricity generation options. The model expresses the electricity demand of the demand-sectors, which should be met by the electricity generation options in the system. Thus, in each planning period, the demand-sectors are linked to the electricity supply systems.

The MOLP model considers planning decisions involving changes in capital stock that occur over several years and require a substantial capital investment. It projects how the electricity power industry will change its generating capability in response to changes in capital investment costs, insufficient generation capacity, and variations in sectoral electricity demand.

This section describes the mathematical formulation of the MOLP model. Due to the complexity of the model, this section starts with some of the assumptions used. The set of constraints are then described, followed by the objective functions used in the model.

4.3.1 Model Assumptions

All models are wrong, [Sterman, 2002], but can be useful, [Pidd, 2002]. Models are simplified representations of the real world. Models are only valid under certain assumptions. For the sake of simplicity and tractability, several assumptions are adopted for this particular model. The following assumptions are made:

- For new installations, the capital investment cost is assumed to be known and linearly related to the installed capacity,
- The ideal operation and maintenance (O&M) costs are linearly related to the amount of electricity generated,
- The planning period is known, but conditions at the end point are constrained to avoid unboundedness
- The demand from the various consumer sectors is given as an aggregated peak demand in MW for each time period and total demand in MWh is linearly related to peak demand.

The above assumptions are quite strong, but are aimed at a realistic view of a developing country's context.

4.3.2 Model Constraints

These constraints describe mathematically conditions imposed by the optimization problem. The restrictions must be satisfied in order to accept the solution(s) as feasible. This model includes both equality and inequality constraints. All the constraints combined describe the feasible space or region for the problem.

Generation capacity

The generation capacity (MW) at a given moment is the maximum capacity at which a power plant can be or is authorized to be operated at a continuous rating under the prevailing conditions assuming unlimited transmission facilities. For each technology and period, the capacity balance limits production of electricity by the available generation capability.

The generation capacity of technology k, (for k=1,2, . . . , K) options and in t, (for t=1,2, . . . , T) planning periods, denoted by ICI_{kt}, is expected to increase during the planning period. For $t > 1$,

$$ICI_{k,t+1} = ICI_{kt} + INC_{kt} - SRC_{kt} \tag{4.1}$$

where INC_{kt} is the new installed capacity (MW) and SRC_{kt} is loss in generation capacity (MW) of technology k in period t.

To avoid unboundedness of the model, for the final planning period, T, the generated capacity is constrained by small capacity growth rate, r, such that;

$$ICI_{kT} + INC_{kT} - SRC_{kT} \geq r * ICI_{k,T-1} \tag{4.2}$$

In an electricity generation system, loss in generation capacity is due to insufficient generation maintenance expenditure and unforeseen breakdowns. Developing countries are characterized by insufficient capital funds such that they cannot achieve the ideal generation maintenance expenditure for full retention of generation capacity. Even the minimum generation maintenance expenditure leads to some significant loss in generation capacity.

In fact, lack of funds for generation maintenance has two effects (1) permanent loss in generation capacity, and (2) reduction in generation technology availability in a particular planning period. The modeling approach here is to consider the loss in generation capacity as a function of generation capacity and funds allocated to generation maintenance.

Loss in generation capacity

For each technology k in period t, there exists a standard level of maintenance expenditure, say μ_k (\$/MW). Thus, if the installed capacity (MW) in period t is ICI_{kt}, the associated maintenance expenditure is $\mu_k ICI_{kt}$. In practice, in most developing countries, funds are not available to meet this requirement, and it is this shortfall that leads to loss in generation capacity.

In order to model permanent losses in generation capacity for this reason, we start with two further assumptions;

- There is a minimum cost of $\xi_k(\leq \mu_k)$ per MW that can not be avoided.
- At this minimum level their would be a proportional loss in generation capacity of τ_k . In other-words, an amount of $\tau_k ICI_{kt}$ of installed capacity would then be lost in period t.

In our context, we assume that a decision will be made to allocate an amount CXP_{kt} to technology k in period t for maintenance, where

$$\xi_k ICI_{kt} \leq CXP_{kt} \leq \mu_k ICI_{kt}$$

The permanent loss in capacity of technology k in period t, which we call SRC_{kt} is related to CXP_{kt};

$$SRC_{kt} = \begin{cases} \tau_k ICI_{kt}; & \text{when} \quad CXP_{kt} = \xi_k ICI_{kt} \\ 0; & \text{when} \quad CXP_{kt} = \mu_k ICI_{kt} \end{cases}$$

We approximate the value of SRC_{kt} for other values of CXP_{kt} by linear interpolation (see Figure 4.1);

$$SRC_{kt} = \tau_k ICI_{kt} - \frac{\tau_k}{\mu_k - \xi_k}\Bigg(CXP_{kt} - \xi_k ICI_{kt}\Bigg) \tag{4.3}$$

where;

$$\xi_k ICI_{kt} \leq CXP_{kt} \leq \mu_k ICI_{kt}$$

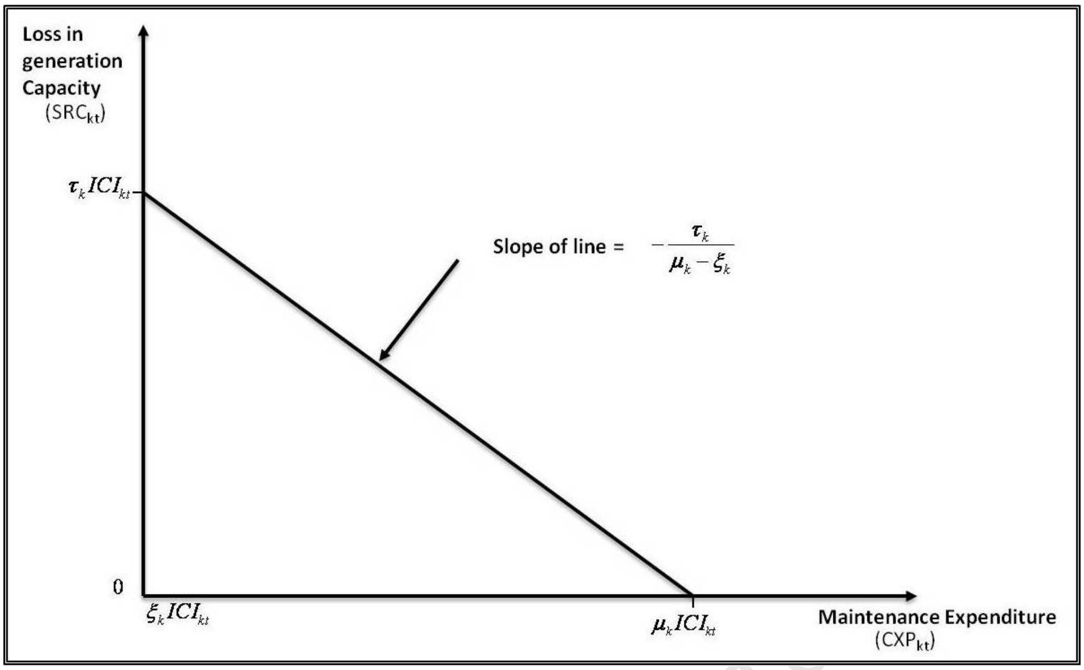


Figure 4.1: Loss in generation capacity function

Available generation capacity

Here, we also model available generation capacity in relation to generation maintenance expenditure and the availability factor, by linear interpolation. In each planning period, the available generation capacity (MW) of each generation option may not exceed its installed capacity multiplied by its availability factor. The availability factor is computed as the ratio between the average available generation capacity in the planning period and the installed capacity for each generating technology option. Evaluating the generation maintenance expenditure at various levels of availability factors provide insight into the optimum operating levels for the technologies.

If σ_k is the availability factor of technology k at desired generation maintenance expenditure, and ϵ_k as the availability factor of technology k with minimum maintenance expenditure, such that $\sigma_k \geq \epsilon_k$.

If AVL_{kt} is the availability of technology k in period t, then;

$$AVL_{kt} = \sigma_k ICI_{kt} \quad \text{when expenditure} = \mu_k CXP_{kt}$$

and

$$AVL_{kt} = \epsilon_k ICI_{kt} \quad \text{when expenditure} = 0$$

Thus, since $\sigma_k \geq \epsilon_k$, then

$$AVL_{kt} = \sigma_k * ICI_{kt} - \left(\frac{\sigma_k - \epsilon_k}{\mu_k}\right) CXP_{kt} \tag{4.4}$$

Allocation of available generation capacity

If CAL_{kt} is the available capacity for allocation from technology k in period t, then electricity generation capacity allocated can not exceed what is available.

$$CAL_{kt} \leq AVL_{kt} \tag{4.5}$$

Let PCS_{st}, measured in MW, be the electricity supply allocated to the demand sector, s, (for $s = 1, 2, \ldots, S$) in period t. Then what is allocated to all demand sectors does not exceed total allocation, corrected by the corresponding power reserve margin[1], Λ. This is considered as the supply decision variable.

$$\left(1 + \Lambda\right) \sum_{s}^{S} PCS_{st} \leq \sum_{k}^{K} CAL_{kt} \tag{4.6}$$

Available transmission capacity

Coordinated generation planning involves power transmission requirements from gener-

[1]Reserve margin is a measure of the generating capacity that is available over and above the amount required to meet the exceptional demand variation and unplanned outages of generation plants, [IAEA, 1984].

ation sites to end-users at distant places. Thus, transmission capacity modeling is an associated issue, which needs to be addressed with the framework of EGP. The transmission capacity, ITC_t, measured in MW, is expected to increase during the planning period t. For $t > 1$,

$$ITC_{t+1} = ITC_t + NTC_t - STC_t \tag{4.7}$$

where NTC_t is the new transmission capacity added and STC_t is the transmission capacity loss in period t.

For the final planning period, T, the transmission capacity is constrained by a small capacity growth rate, r, such that;

$$ITC_T + NTC_T - STC_T \geq r * ITC_{T-1} \tag{4.8}$$

Loss in transmission capacity

Transmission of power over wires encounters resistance, and resistance creates losses in capacity. In most cases, inadequate maintenance increases the resistance of the wires thus contributing to loss in electricity transmission capacity. In the same way as for loss in generation capacity, loss in transmission capacity is modeled as a function of available transmission capacity and funds allocated to transmission maintenance.

For period t, if Ω is the cost for full retention of transmission capacity (\$/MW) and Ψ is the proportion of capacity lost if minimum transmission maintenance is done. Then the required expenditure for full retention of transmission capacity is ΩITC_t, and loss if there is minimum expenditure on transmission maintenance is given by ΨITC_t. We shall relate loss in transmission capacity to expenditure on transmission maintenance, TXP_t, by linear interpolation, and estimate the transmission capacity lost, STC_t, in period t from the following expression;

$$STC_t = \Psi ITC_t - \left(\frac{\Psi}{\Omega}\right) TXP_t \tag{4.9}$$

where;

$$0 \leq TXP_t \leq \Omega ITC_t \tag{4.10}$$

The transmission capacity lost in period t is permanently lost. This loss affects the transmission capacity for the period $t+1$.

Allocation of transmission capacity

The total capacity allocated to the various demand sectors s in period t does not exceed that available transmission capacity corrected by the reserve electricity transmission capacity, Φ. The importance of considering the transmission capacity is to basically find an electricity generation configuration system which can optimize the electricity supply.

$$\left(1+\Phi\right)\sum_{s}^{S} PCS_{st} \leq ITC_t \tag{4.11}$$

Electricity supply levels

The proportion of electricity demand satisfied depends entirely on the share of power supplied from the electricity generation technologies. There is need for the utility systems to devise strategies to allocate the inadequate electricity capacity to various consumers in order to control the demand. This can be done by controlling the electricity supply levels allocated to the consumers. In this model, electricity demand is measured as peak load because this is what primarily is affected by the insufficient capacity. Besides, power rationing and outages are based on peak load.

Suppose that for each demand sector s, in period t, there is a value relation between electricity supply benefits attained, ν_{st}, and the electricity supply made, for example, $\nu_{st}(PCS_{st})$, which is in general a monotonic increasing but non-linear function. For purposes of representation in an LP model, we shall approximate the benefit function in piecewise linear form, using four linear segments, d, for $d = 1, 2, 3, 4$.

Also, suppose Δ_{st} is the desired demand (MW) of sector s in period t. Then the fractional supply is firstly represented by;

$$\frac{PCS_{st}}{\Delta_{st}} = \sum_{d=1}^{4} PPSS_{sdt} \tag{4.12}$$

where $PPSS_{sdt}$ can be received as the proportion of the satisfied supply attributed to segment d. We shall assume equal length segments and that $0 \leq PPSS_{dt} \leq \frac{1}{4}$ for each d. Naturally, $PPSS_{sdt}$ must reach $\frac{1}{4}$ before $PPSS_{s,d+1,t}$ can be greater than 0. This is achieved by introducing binary variables, b_{sdt};

$$b_{sdt} = \begin{cases} 1 & \text{if segment } d \text{ is fully supplied} \\ 0 & \text{otherwise} \end{cases}$$

with associated constraints,

$$\frac{1}{4} b_{s1t} \leq PPSS_{s1t} \leq \frac{1}{4} \tag{4.13}$$

$$\frac{1}{4} b_{s2t} \leq PPSS_{s2t} \leq \frac{1}{4} b_{s1t} \tag{4.14}$$

$$\frac{1}{4} b_{s3t} \leq PPSS_{s3t} \leq \frac{1}{4} b_{s2t} \tag{4.15}$$

$$0 \leq PPSS_{s4t} \leq \frac{1}{4} b_{s3t} \tag{4.16}$$

Now, let λ_{sd} be the proportional value increment from electricity supply allocation in segment d, as illustrated in Figure 4.2, such that;

$$\sum_{d=1}^{4} \lambda_{sd} = 1 \tag{4.17}$$

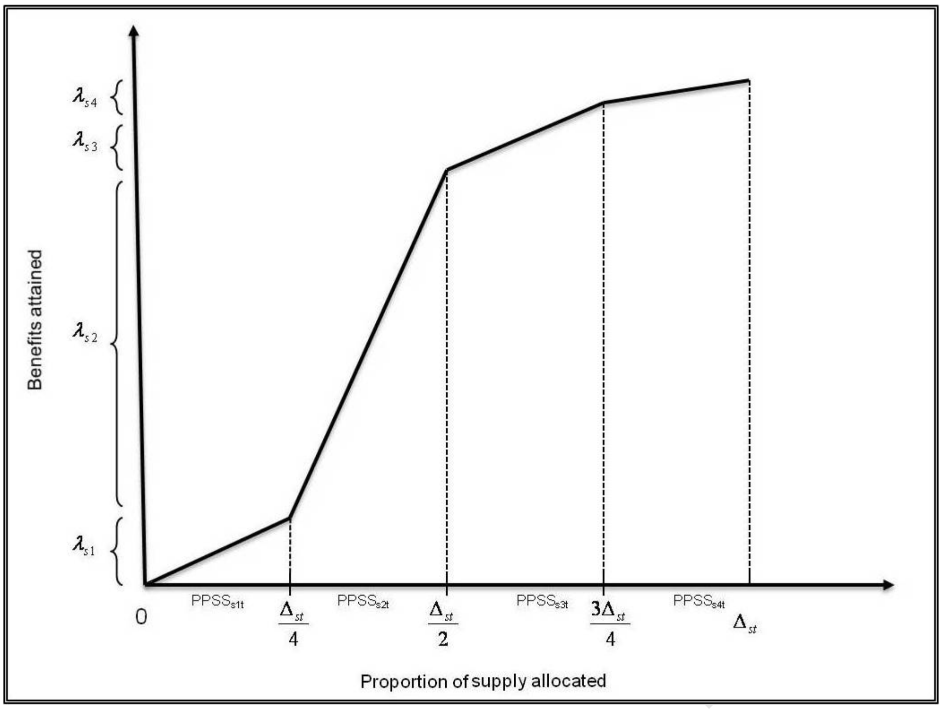


Figure 4.2: Electricity supply level

In other words,

$$\begin{aligned}
\nu_{st}(\frac{\Delta_{st}}{4}) &= \lambda_{s1} \\
\nu_{st}(\frac{\Delta_{st}}{2}) - \nu_{st}(\frac{\Delta_{st}}{4}) &= \lambda_{s2} \\
\nu_{st}(\frac{3\Delta_{st}}{4}) - \nu_{st}(\frac{\Delta_{st}}{2}) &= \lambda_{s3} \\
\nu_{st}(\Delta_{st}) - \nu_{st}(\frac{3\Delta_{st}}{4}) &= \lambda_{s4}
\end{aligned}$$

By definition, $\nu_{st}(\Delta_{st}) = 1$

Finally, then, the overall benefit attained in demand sector s in period t can be estimated as;

$$\nu_{st}(PCS_{st}) = 4\sum_{d=1}^{4} \lambda_{sd} PPSS_{sdt} \tag{4.18}$$

where $PCS_{st} = \Delta_{st} * \sum_{d=1}^{4} PPSS_{sdt}$

Note, therefore, that although the supply decisions are generally defined by PCS_{st}, these variables are constituted by the more fundamental model decision variables, $PPSS_{sdt}$, that is, proportion of the demand satisfied, as discussed in Equation 4.12.

Non-negativity constraint

No negative values are permitted for the decision variables in the model.

4.3.3 Model Objective Functions

The objective functions represent the criteria used to evaluate the alternatives. They describe mathematically the relationship between the decision variables. In this model the objectives considered are minimization of capital investment costs, and O&M costs, for the whole electricity generation system, and maximization of the electricity supply levels to the demand sectors, as a proxy of mitigating electricity shortages that may result out of insufficient electricity generation capacity.

The objective of maximizing the relative electricity supply levels to the demand sectors, as a proxy of minimizing the electricity shortages have not been explicitly considered in the literature when determining optimal electricity generation plans with the use of mathematical programming methods.

A detailed description of the objective functions for this model is presented below;

- Capital investment costs ($/MW)

  The main factor affecting the choice of electricity generation technology is generally capital investment cost-effectiveness. The term "capital generation investment cost" refers to the actual cost of installing the electricity generation unit to produce electricity for end-use. This objective implies the minimization of the cost of electricity for the planning period considered, which is a certain period in which all the feasible (existing and new) generation options are assumed to be already installed. These costs include the total present value of the capital investment costs associated with capital stock, for that planning period incurred by the existence of the new installed generation plants (represented by the installed power).

The capital generation investment costs and new transmission capacity costs are assumed to be linear functions of the total installed power of each generation option and new transmission capacity, respectively. Therefore, the capital investment cost values, χ_k, must be multiplied by the total installed capacity of each generation option, and the transmission costs, π, multiplied by the new transmission capacity in planning period t. Thus, the MOLP model considers minimization of capital investment cost function, Z_{1t}, expressed as;

$$Z_{1t} = \sum_{k}^{K} \chi_k INC_{kt} + \pi NTC_t \quad \text{for} \quad t \in T \tag{4.19}$$

- Operation and Maintenance (O&M) costs ($/MW)

These refers to all non-fuel costs such as the direct and indirect costs of labor and supervisory personnel, consumable supplies and equipment, outside support services. O&M costs are made up of two components: fixed costs (those that are invariant with the electrical output of the plant) and variable costs (those non-fuel costs that are incurred as a consequence of plant operation, e.g. waste disposal costs). This objective represents the sum of the capacity maintenance costs (both generation and transmission), excluding fuel costs, expected for the operation of technology k in period t.

$$Z_{2t} = \sum_{k}^{K} CXP_{kt} + TXP_t \quad \text{for} \quad t \in T \tag{4.20}$$

It is desirable to minimize the (O&M) costs, Z_{2t}.

- Electricity supply benefits

Sectoral differences in consumption patterns have significant influence on the estimation of electricity supply levels, [Balachandra and Chandru, 2003]. If the deficit between demand and supply is large and occurs over a long period of time, some strategies of load reduction have to be implemented which may result in severe consequences for the consumers. Power outages cause different types of economic losses to the different demand sectors.

The MOLP model aims at maximizing the electricity supply benefits attained, Z_{st}, for the electricity supply made to the demand sector s, in period t, expressed as follows;

$$Z_{st} = \quad 4\sum_{d=1}^{4} \lambda_{sd} PPSS_{sdt} \qquad \text{for} \qquad s \in S; \quad t \in T \tag{4.21}$$

4.3.4 Summary of Model

The MOLP model is summarized as follows;

$$\text{Min } Z_{1t} = \quad \textstyle\sum_k^K \chi_k INC_{kt} + \pi NTC_t \quad \forall \quad t \in T \qquad \ldots \text{Capital investment costs}$$

$$\text{Min } Z_{2t} = \quad \textstyle\sum_k^K CXP_{kt} + TXP_t \quad \forall \quad t \in T \qquad \ldots \text{Maintenance costs}$$

$$\text{Max } Z_{st} = \quad 4\textstyle\sum_{d=1}^4 \lambda_{sd} PPSS_{sdt} \quad \forall \quad s \in S;\ t \in T \qquad \ldots \text{Electricity supply benefits}$$

subject to

$$
\begin{aligned}
ICI_{kt} + INC_{kt} - SRC_{kt} &= ICI_{k,t+1} \\
ICI_{kT} + INC_{kT} - SRC_{kT} &\geq r * ICI_{k,T-1} \\
\tau_k ICI_{kt} - \frac{\tau_k}{\mu_k - \xi_k}\left(CXP_{kt} - \xi_k ICI_{kt}\right) &= SRC_{kt} \\
\xi_k ICI_{kt} \leq CXP_{kt} &\leq \mu_k ICI_{kt} \\
\epsilon_k ICI_{kt} + \left(\frac{\sigma_k - \epsilon_k}{\mu_k}\right) CXP_{kt} &= AVL_{kt} \\
\left(1 + \Lambda\right) \sum_{s}^{S} PCS_{st} &\leq \sum_{k}^{K} CAL_{kt} \\
CAL_{kt} &\leq AVL_{kt} \\
ITC_t + NTC_t - STC_t &= ITC_{t+1} \\
ITC_T + NTC_T - STC_T &\geq r * ITC_{T-1} \\
\Psi ITC_t - \left(\frac{\Psi}{\Omega}\right) TXP_t &= STC_t \\
TXP_t &\leq \Omega ITC_t \\
\left(1 + \Phi\right) \sum_{s}^{S} PCS_{st} &\leq ITC_t \\
\Delta_{st} \sum_{d=1}^{4} PPSS_{sdt} &= PCS_{st} \\
\frac{1}{4} b_{s1t} \leq PPSS_{s1t} &\leq \frac{1}{4} \\
\frac{1}{4} b_{s2t} \leq PPSS_{s2t} &\leq \frac{1}{4} b_{s1t} \\
\frac{1}{4} b_{s3t} \leq PPSS_{s3t} &\leq \frac{1}{4} b_{s2t} \\
0 \leq PPSS_{s4t} &\leq \frac{1}{4} b_{s3t} \\
\nu_{st}\left(\frac{\Delta_{st}}{4}\right) &= \lambda_{s1} \\
\nu_{st}\left(\frac{\Delta_{st}}{2}\right) - \nu_{st}\left(\frac{\Delta_{st}}{4}\right) &= \lambda_{s2} \\
\nu_{st}\left(\frac{3\Delta_{st}}{4}\right) - \nu_{st}\left(\frac{\Delta_{st}}{2}\right) &= \lambda_{s3} \\
\nu_{st}(\Delta_{st}) - \nu_{st}\left(\frac{3\Delta_{st}}{4}\right) &= \lambda_{s4} \\
INC_{kt} \geq 0; \quad PPSS_{sdt} \geq 0; \quad NTC_t \geq 0; & \\
\nu_{st} \geq 0; \quad CXP_{kt} \geq 0; \quad TXP_t \geq 0 &
\end{aligned}
$$

4.4 Model Solution Framework

The MOLP model formulated above is clearly a constrained mixed-integer LP problem. It is a multiple objective problem, where the objectives have to be traded off against each other, in order to get an efficient solution.

4.4.1 Solution Procedure

Solving this MOLP model, may lead to two problems. Firstly, the precise generation of the efficient solution set for the problem of this size is a difficult task, [Steuer, 1986]. Secondly, even if only the set of extreme efficient points is approximated, its size will be too huge, which is obviously useless to any DM. Due to these reasons and the multiple conflicting objectives, the model must be analyzed with methods that provide values for trade-off among objectives.

The approach to solve the MOLP model involves the following stages;

- Optimize each objective function over all the constraints
- Generate a payoff table to determine the ideal and anti-ideal solutions to be used as lower and upper bounds (i.e feasible range of variation) for each objective
- Specify the feasible goals or aspiration levels to achieve for each objective
- Construct the set of optimal solutions using the GP - Tchebycheff approach. This approach seeks the solution that minimizes the worst unwanted deviation from a goal (see details in Section 2.2.2).

The optimization process starts with optimizing each objective separately over the feasible set defined by all the constraints to get the ideal or optimum value for each objective. The values for the other objectives corresponding to the ideal value are substituted into those objectives to get the anti-ideal values. The results, i.e. levels of performance for all objectives when optimizing for each objective in turn, are summarized in a "pay-off" table. This is performed to identify the boundaries (i.e. extreme solutions) for the admissible values for the objectives.

The elements of the main diagonal represent the ideal value for each objective, while the largest value of each column indicates the corresponding anti-ideal value. The difference between the ideal and the anti-ideal values is the feasible range of variation for each objective. This also gives an indication of the feasible "goal" or aspiration level for each objective.

4.4.2 Tchebycheff GP Model

In a situation where DMs know their goals but have difficulties with valuing or weighting the relevant attributes in multi-objective optimization, GP is a commonly known technique to aid DMs with their task. In this research, a Tchebycheff GP approach, related to the Wierzbicki reference point approach, [Ogryczak, 2001] is chosen to obtain efficient solutions to the MOLP problem. This approach seeks to minimize the maximum unwanted deviation, rather than the sum of deviations from the goals. This balances the deviation of different objective functions. Tchebycheff GP has the potential to give the most appropriate solution where a balance between the levels of satisfaction of the goals is needed.

For each objective j, for $j = 1, 2, \ldots, 7$, some goal or reference point is defined, say T_j, indicating some desirable level of performance, currently viewed as a good starting point for further exploration of the decision space. By introducing the deviation variables, say δ_j^+ and δ_j^-, we get the following goals and constraints;

Goals:

$$\begin{array}{rrcll}
\text{Capital investment cost} & Z_{1t} + \boldsymbol{\delta_{1t}^{+}} - \delta_{1t}^{-} & = & T_{1t} & \forall t \\
\text{Maintenance cost} & Z_{2t} + \boldsymbol{\delta_{2t}^{+}} - \delta_{2t}^{-} & = & T_{2t} & \forall t \\
\text{Domestic supply} & Z_{3t} + \delta_{3t}^{+} - \boldsymbol{\delta_{3t}^{-}} & = & T_{3t} & \forall t \\
\text{Commercial supply} & Z_{4t} + \delta_{4t}^{+} - \boldsymbol{\delta_{4t}^{-}} & = & T_{4t} & \forall t \\
\text{Medium industry supply} & Z_{5t} + \delta_{5t}^{+} - \boldsymbol{\delta_{5t}^{-}} & = & T_{5t} & \forall t \\
\text{Large industry supply} & Z_{6t} + \delta_{6t}^{+} - \boldsymbol{\delta_{6t}^{-}} & = & T_{6t} & \forall t \\
\text{Street light supply} & Z_{7t} + \delta_{7t}^{+} - \boldsymbol{\delta_{7t}^{-}} & = & T_{7t} & \forall t
\end{array}$$

Logical requirements:

$$\delta_{1t}^{-} \geq 0,\ \delta_{2t}^{-} \geq 0,\ \delta_{3t}^{+} \geq 0,\ \delta_{4t}^{+} \geq 0,\ \delta_{5t}^{+} \geq 0,\ \delta_{6t}^{+} \geq 0,\ \delta_{7t}^{+} \geq 0 \qquad (4.22)$$

The negative and positive deviation variables appearing in the goals defined above measure under-achievement and over-achievement with respect to target values. The unwanted deviation variables, that is, the negative ones for "supply-type" goals and the positive ones for target capital investment and maintenance costs are printed in bold face. In fact, goals Z_{1t} and Z_{2t} derive from "less is better" criteria. Therefore, over-achievement is unwanted, while goals Z_{3t} to Z_{7t} derive from "more is better" criteria. Therefore, under-achievements are unwanted. The GP approach calls for the minimization of the relevant deviation variables. A solution that satisfies all goals, corresponds to one in which all relevant deviation variables have a value 0. Such a situation rarely occurs, so that we need, in general, to find a solution which minimizes the relevant deviation variables in some aggregate sense.

As cited in Stewart [2005], Wierzbicki uses a scalarizing or achievement function which measures under-achievement relative to the goals, by placing the greatest weight on the least well satisfied goal. Achievement functions are derived on the basis of reference points to project an arbitrary reference point to the efficient set of solutions. The achievement function is constructed in such a way that if the reference point is dominated, the optimization will advance past the reference point to a non-dominated solution.

The Tchebycheff GP approach is applied to construct an achievement function, which represents the overall achievement of all the objectives. The goal is to minimize the maximum weighted deviations relative to the goals defined, [Miettinen and Makela, 2002, Ogryczak, 2001]. The achievement function is expressed as follows;

$$\text{Minimize} \qquad D + 0.02\left[\sum_{j=1,2}(Z_{jt} - T_{jt})w_j + \sum_{j=3,4,5,6,7}(T_{jt} - Z_{jt})w_j\right] \tag{4.23}$$

where,

$$\mathrm{D} = \mathrm{Max}\left[\mathrm{Max}\left[(Z_{jt} - T_{jt})w_j; (T_{jt} - Z_{jt})w_j\right]\right]$$

which can be represented by the constraints:

$$D \geq (T_{jt} - Z_{jt})w_j$$

$$D \geq (Z_{jt} - T_{jt})w_j$$

$$\text{for} \quad t \in T \quad \text{and} \quad j = 1, \ldots, 7$$

The $w_j = \frac{P_j}{R_j}$ are the weights attached to each objective j. The P_j are importance factors and are considered as a measure of the significance of each objective j in the optimization process. In MOO, decision makers may view different objectives as having different levels of importance. Therefore, we need to assess the relative importance, of the worst-to-best swing for each objective on a scale of 0 for "least" and 100 for "best". These assigned values are often referred to as *Swing values*, [Belton and Stewart, 2002].

The R_j is the difference between ideal and anti-ideal solutions of objective j. The R_j serve primarily to ensure a comparable scaling for all objectives (e.g. to normalize all deviations to the [0,1] interval). Since the objectives are measured on very different scales, the performance measures may differ by many orders of magnitude. The normalization is done by dividing the coefficients of each objective function by the difference, R_j. This weighting scales all performance measures to have a range of 1 unit, and in effect places equal importance on achieving a best outcome for each objective.

Therefore, minimizing the achievement function corresponds to finding the solution that minimizes the overall distance to the targets. A solution is thus sought that best satisfies the goals simultaneously, so that the individual objectives are all as close to their target value as they can possibly be at the same time. The implementation of the MOLP model is presented in the next chapter.

4.4.3 GAMS Computer Software

The optimization of the model is done using the General Algebraic Modeling System (GAMS) computer software. GAMS is a high-level modeling system for solving large complex linear and nonlinear mixed integer optimization problems. It consists of a language compiler and a number of integrated high-performance solvers. GAMS provides a common language that makes use of a variety of solvers depending on the specific characteristics of the problem. A detailed description of the GAMS programming language can be found in the website, `http://www.GAMS.com` and Users' Manuals; Rosenthal [2007] and Chattopadhyay [1999]. For this model, the GAMS/COINGLPK solver from the GNU open software foundation is used, `http://www.gnu.org`. The GAMS code for solving this model is in the Appendix.

4.5 Summary

This chapter has presented the formulation of the MOLP model for EGP based on mathematical programming methodology. The MOLP model aims at determining the electricity generation options to be constructed, the time when to be constructed and the amount of power to be produced so that the total electricity generation cost is minimized, in a given planning period. The model seeks to determine the type and capacity of generation options to achieve the best compromise between different objectives and yet meet all the operating and economic restrictions that are placed on the electricity generation system.

The MOLP model considers some aspects that the previous models have not included. The incorporation of the objective of maximizing relative electricity supply benefits to the demand sectors, in circumstances of insufficient generation capacity, to determine feasible electricity generation plans using MOO techniques, have not been considered in the literature.

The main variables of interest are described: electricity generation cost, electricity generation capacity, transmission capacity, and electricity supply benefits attained. This is followed by a mathematical formulation of the model based on mathematical LP approach; including the objectives and constraints.

The Tchebycheff GP approach (or reference point approach) is proposed to solve the MOLP model and find efficient solutions to the problem. The model is optimized using the GAMS computer software.

4.6 Model addendum

Dimensions

t: $1, 2, \ldots, t, \ldots, T$; Planning periods;

k: $1, 2, \ldots, k, \ldots, K$; Electricity generation options ;

s: $1, 2, \ldots, s, \ldots, S$; Electricity demand sectors ;

d: $1, 2, 3, 4$; Electricity supply segments;

j: $1, 2, \ldots, j, \ldots, J$; Index of objective functions;

Decision Variables

INC_{kt} = New installed capacity of technology k in period t (MW)

$PPSS_{sdt}$ = Proportion of supply level to sector s over segment d in period t

NTC_t = New transmission capacity added in period t (MW)

CXP_{kt} = Variable generation O&M expenditure on technology k in period t($)

TXP_t = Expenditure on transmission maintenance in period t ($)

Supplementary Variables

ICI_{kt} = Generation capacity for technology k in period t (MW)

CAL_{kt} = Generation capacity for allocation from technology k in period t (MW)

$AVL_{k,t}$ = Available capacity of technology k in period t (MW)

SRC_{kt} = Loss in generation capacity of technology k in period t (MW)

PCS_{st} = Electricity supply level for demand sector s in period t (MW)

ITC_t = Available transmission capacity in period t (MW)

STC_t = Loss in transmission capacity in period t (MW)

Parameters of the Model

$\Lambda =$	Reserve margin
$\chi_k =$	Capital investment costs in new technology k (\$/MW)
$\mu_k =$	Maintenance cost for full retention of generation capacity of technology k(\$/MW)
$\tau_k =$	Proportion of capacity lost if minimum generation maintenance is done in technology k
$\xi_k =$	Minimum generation maintenance cost on technology k (\$/MW)
$\epsilon_k =$	Availability factor of technology k with minimum maintenance expenditure
$\sigma_k =$	Availability factor of technology k at ideal maintenance expenditure
$\Phi =$	Reserve transmission capacity (MW)
$\Omega =$	Cost for full retention of transmission capacity (\$/MW)
$\Psi =$	Proportion of capacity lost if minimum transmission maintenance is done
$\pi =$	Cost for new transmission (\$/MW)
$\Delta_{st} =$	Peak demand from sector s in each period t (MW)
$\lambda_{sd} =$	Proportionate addition of supply level to sector s in segment d
$\nu_{st} =$	Benefit attained from electricity supply made to demand sector s in period t

Chapter 5

MOLP Model Implementation

5.1 Introduction

This chapter presents the implementation details of the MOLP model. This involves the use of MP techniques (i.e. goal programming) to solve multi-objective optimization problems. The MOLP model is illustrated using data from the Uganda energy sector, as an example for a developing country. The Uganda electricity generation system is modeled taking into account the existing and potential technologies currently available namely: small hydro power, large hydro power, thermal, geothermal, biomass, solar PV, and bagasse.

The output of the model implementation process is the electricity generation schedule, for the next 20 years, in 5-year intervals, detailing capital investment plans for the Uganda electricity sector, identifying the optimal timing and size of new generation capacity, and allocation plans for the available electricity capacity to the various demand sectors during the planning period. First, a description and motivation of some assumptions and data used for model implementation are presented. Second, base run numerical results are presented and later on sensitivity analysis is conducted to ascertain the impact of changes in the input data to the model solution.

5.2 Data for Model Implementation

This section presents the assumptions and data used for model implementation, validation and testing, to provide decision support for selecting a satisfactory electricity generation mix in Uganda based on the mathematical programming approach. Most of the data were obtained from various sources related to the energy sector in Uganda, such as MEMD, UMEME, Eskom, ERA, UETCL plus several other secondary sources, both in published and public domains. The input data describes the technical and economic characteristics of the electricity generation technologies and the expected demand pattern between 2008 and 2028.

The model implementation phase includes the following data modules:

- Information on all generation technologies in the system i.e. capacity at the start of the study, capital generation investment costs, availability factor, and generation maintenance costs.
- Information on peak demand for the planning period.
- Information on transmission capacity, transmission investment costs and estimates of transmission maintenance costs.
- Other user-defined parameters, based on judgment for illustration of the model.

The model does not deal with individual power plants but with technologies.

5.2.1 Planning Period

The planning period depends on the availability of relevant data and on the assumptions of the model. Hobbs [1995] indicates that the resource planning for electricity generation is usually made for a 10-40 years period. Antunes et al. [2004] used a 30 years planning period divided into six-months intervals. Ceciliano et al. [2007] used 2005-2014 planning period consisting of 10 annual sub-periods.

For this study, the planning period is 20 years (between 2008-2028). This is in benefit of the accuracy of the data. Also, during this time, it is possible to obtain relevant information on electricity demand forecasts and other parameters for Uganda from the Power Sector Investment Plan (PSIP), [MEMD, 2009] and other stakeholders. This planning period contributes to the practical computation of the model, as the planning period is divided into 5-years periods, thus increasing the number of variables.

5.2.2 Electricity Generation Technologies

According to MEMD [2007], future electric power generation will be in favor of renewable technologies, that is, solar PV, hydro power, biomass, wind, and geothermal, as well as organic wastes, see Section 3.7. This is of strategic importance because it promotes energy security and independence.

The large-scale hydro power potential along River Nile, is estimated at about 2,000 MW. However, the decision to invest in hydro power plants is a complex and long procedure involving many social, economic and environmental criteria. With the discovery and exploration of oil deposits in Western Uganda, thermal power is expected to maintain its composition in Uganda's energy generation mix. In order to reduce the complexity of the model, the parameters for Solar, Wind, Biomass, and Geothermal will be based on their future expected values.

Table 5.1 summarizes the technical and economic characteristics of the electricity generation options. This information was drawn from various sources; World Bank [2006], Tarjanne and Kivist [2008], IEA [2005], Athanassopoulos [1995] and from The Royal Academy of Engineering [2004]. The capital investment costs were real values of 2006 for new installations.

The total installed generation capacity in Uganda in 2008 was 527 MW, [UBOS, 2009], as detailed in Section 3.6. The EGP-SD requires this initial installed capacity for each generation technology as showed in Table 5.1.

The average values for the availability factor are considered for each technology based on the average operating conditions and expected performance of future power plants. Data on availability factor at ideal maintenance expenditure was got from World Bank [2006].

The data for minimum generation maintenance expenditure ($/MW), availability factor at minimum maintenance expenditure (%), and the proportion of generation capacity lost (%) if there is minimum generation maintenance is based on judgment estimates for illustration of the model. In real-run, it would be judgment of experts.

The generation maintenance costs comprise of all non-fuel costs such as the direct and indirect costs of labour and supervisory personnel, consumable supplies and equipment.

Table 5.1: Data estimates on Electricity Generation Technologies

Electricity generation technology	**Current installed capacity** (MW)	**Capital investment cost** ($m/MW)	**Cost for full retention of generation capacity** ($m/MW)	**Proportion of capacity lost if minimum maintenance** (%)	**Minimum generation maintenance cost** ($m/MW)	**Availability factor at ideal maintenance expenditure** (%)	**Availability factor at minimum maintenance** (%)
Biomass	0.00	2.50	0.023	8	0.019	70	50
Geothermal	0.00	3.01	0.037	3	0.023	80	60
Wind	0.00	2.90	0.020	7	0.016	60	40
Solar PV	0.00	3.60	0.021	2	0.012	50	30
Thermal	200.0	4.00	0.035	9	0.026	80	60
Bagasse	12.0	2.85	0.029	4	0.014	70	50
Small hydro	15.0	2.70	0.025	7	0.019	80	60
Large hydro	300.0	2.10	0.031	9	0.023	90	70

5.2.3 Electricity Transmission Capacity

Electricity in Uganda is transmitted using 66 KV and 132 KV high voltage transmission lines. According to UETCL [2005], by 2005, Uganda had a total of 1,366.5 Km of 132 KV transmission network, Table 5.2. There is only one 66 KV transmission line from Nalubaale to Lugazi, covering a distance of 38 Km, giving a total of 1,404.5 Km of transmission network, with a total transmission capacity of 1,647 MW.

UETCL [2005] reports that the cost of a new transmission is $70,000 and $110,000 per Km for 66 KV and 132 KV respectively. Since the 132 KV transmission lines form about 97 percent of the whole transmission network in Uganda, this study shall use the $110,000 per Km as the cost of a new transmission line.

Table 5.2: UETCL Transmission Lines

Number	**Transmission Line**	**Network**	**Distance** (Km)	**Capacity** (MW)
1	Nalubaale - Lugogo	Double	140.4	362
2	Nalubbale - Kampala North	Bundled	68.9	147
3	Nalubaale - Tororo	Double	233.6	140
4	Tororo - Kenya border	Double	54	140
5	Tororo - Opuyo	Single	119.5	57
6	Opuyo - Lira	Single	141.2	57
7	Lugogo - Kampala North	Double	11.4	132
8	Lugogo - Mutundwe	Single	10.2	162
9	Kampala North - Mutundwe	Single	10.2	71
10	Mutundwe - Kabulasoke	Single	84.7	57
11	Kabulasoke - Konge	Single	78.5	57
12	Kabulasoke - Masaka West	Single	60	57
13	Konge - Nkenda	Single	138.9	57
14	Masaka West - Mbarara North	Single	130.5	136
15	Masaka West - Tanzania Border	Single	84.5	66
TOTAL			1336.5	1647
1	Nalubaale - Lugazi	Single - 66Kv	38	21

Source: [UETCL, 2005]

Thus,

$$\begin{array}{c}\textit{Cost of new} \\ \textit{transmission capacity}\end{array} = \left(\frac{\begin{array}{l}\textit{Average transmission} \\ \textit{line (Km)}\end{array}}{\begin{array}{c}\textit{Average capacity} \\ \textit{per line (MW)}\end{array}} \right) * \begin{array}{l}\textit{Cost per line} \\ \textit{(\$/Km)}\end{array}$$

$$= \frac{\frac{1366.5}{19}}{\frac{1647}{19}} * 110,000 = \$91,282 \text{ per MW} \tag{5.1}$$

5.2.4 Electricity Demand Estimates

The future capacity requirements of an electricity system derive directly from the expected future sectoral peak demand. Electricity demand forecasts are therefore a key aspect of the planning process.

According to ERA [2007], the share in electricity demand by end-users in 2007 was distributed as Domestic (26.0 percent), Commercial (13.6 percent), Medium industries (18.8 percent), Large industries (41.5 percent), and Street light (0.1 percent), see Table 3.1, in Section 3.4. Uganda's electricity peak demand varies between 360 - 390 MW during the evening period 19:00 - 24:00 hours, [ERA, 2007].

The MEMD [2007] report indicates that BKS Acres Ltd estimated an annual growth rate in electricity demand to be 8 percent, see Section 3.4. Therefore, the estimated electricity demand by the sectors was taken to be the proportional share of the peak demand. It should be noted that, in predicting the future electricity demand estimates, the annual growth rate is assumed to persist in the future. Thus, a simple geometric growth formula was used to make predictions for the subsequent periods, as follows;

$$DEM_{st} = DEM_{s1}(1+g)^t \tag{5.2}$$

where;

DEM_{st} = the forecast demand (MW) for demand sector s, in planning period t

DEM_{s1} = the base period load for demand sector s, at t=1 (the base period) and

g = the sectoral demand growth rate.

Taking this into consideration, Table 5.3 shows the electricity demand estimates, using a demand growth rate of 8 percent per annum, for the five 5-year planning periods, used in this study.

Table 5.3: Electricity demand estimates (MW) by sector

Demand Sector	**Peak demand % share**	**Planning periods**				
		2008	2013	2018	2023	2028
Domestic	26.0	101	142	199	278	390
Commercial	13.6	53	74	104	146	204
Medium industry	18.8	73	103	144	201	282
Large industry	41.5	162	227	317	444	622
Street light	0.1	2	3	4	5	8
Total	100	391	549	768	1074	1506

5.2.5 Electricity Supply Benefits

The concept of value function is used to reflect the electricity supply benefits attained at different levels of electricity supply. The benefits of certain electricity supply allocations are preferred to others, as explained in Section 4.3.2. Electricity supply benefit values below a certain proportion of the desired demand may all be considered to be highly unsatisfactory, while values above a higher proportion may offer relatively low further marginal value. The value function is a monotonically increasing S-shaped piecewise linear function.

Let the electricity supply benefit value function be approximated in a piecewise linear form, using 4 segments. The proportional value increments from supply allocation are defined by values at each "breakpoint", that is, $\frac{1}{4}$, $\frac{1}{2}$, and $\frac{3}{4}$, of the desired demand of sector s in period t.

In such a situation, benefits attained below $\frac{1}{4}$ of the desired demand may be considered to be highly unsatisfactory, while benefits attained above $\frac{3}{4}$ may offer relatively low further marginal benefit. The benefit value function will thus vary most rapidly between $\frac{1}{4}$ and $\frac{3}{4}$ of the desired demand.

Table 5.4 shows assumed proportional benefit value increments from electricity supply allocations to demand sectors in each segment.

Table 5.4: Proportional benefit value increments from electricity supply allocation

Demand sectors	**Segments**			
	1	2	3	4
Domestic	0.13	0.54	0.24	0.09
Commercial	0.12	0.52	0.23	0.13
Medium industry	0.10	0.55	0.55	0.10
Large industry	0.15	0.50	0.20	0.15
Street light	0.12	0.58	0.21	0.09

5.2.6 User Defined Parameters

The following is a summary all the user defined parameters, based on judgment for illustration of the model.

- Reserve generation capacity margin per annum, R = 5 percent, which is equal to 25 percent for 5 years period.
- The capacity growth rate for the last period (i.e. t=5) is assumed to have a small rate, r = 5 percent; see details in section 4.3.2 on *Generated capacity* constraint
- Reserve transmission capacity margin per annum, Φ = 2 percent

5.3 Numerical Results

5.3.1 The Pay-off Table

The pay-off table, shown in Table 5.5, was determined using the objective functions given by equations (4.19), (4.20), (4.21) and constraint equations (4.1) - (4.16), as described in Section 4.3.2. The elements of the pay-off matrix were obtained by minimizing each of the objectives (4.19), (4.20), and maximizing (4.21) individually. The process involved maximizing/minimizing an objective function, then fixing its optimal values, followed by maximizing/minimizing the rest of the objectives. The aim is to obtain the extreme solutions for each objective, described by the least electricity generation cost and capacity supply plans. The pay-off table was summarized by taking an average value for the 5 planning periods.

Table 5.5: Payoff Table

Objectives	Investment	Maintenance	Domestic	Commercial	Medium Ind.	Large Ind.	Street
Investment	**29.25**	13.72	53.32	85.82	62.86	79.12	92.32
Maintenance	53.20	**10.50**	96.40	100	96.00	94.02	97.67
Domestic	157.56	20.36	**100**	100	96.00	87.26	100
Commercial	35.06	18.34	96.40	**100**	96.00	94.02	100
Medium Ind.	74.66	18.92	96.40	100	**100**	89.12	100
Large Ind.	346.94	24.82	85.02	94.80	90.78	**100**	100
Streetlight	35.06	18.36	96.40	100	96.00	95.62	**100**
Ideal	29.25	10.50	100	100	100	100	100
Anti-ideal	346.94	24.82	53.32	85.82	62.86	79.12	92.32
Range	316.69	14.32	46.68	14.18	37.14	20.88	7.68

The elements of the main diagonal, in bold face, represent the ideal or optimum value for each objective. The maximum values for the 'costs' objectives in the columns represent the anti-ideal or worst possible values, while for the "demand sectors" objectives, the minimum elements in the columns represent the anti-ideal or worst possible values. The difference between the ideal and the anti-ideal values is the feasible range of variation for each objective.

For example, the first row of Table 5.5 shows results from minimizing the 'Investment cost' objective. When the investment cost is minimized, its average optimum value is 29.25 \$m/MW, and the associated maintenance cost are 13.72 \$m/MW, while the electricity supply benefits goals for each of the demand sectors are as shown.

The third row shows the results from maximizing electricity supply benefits for the domestic sector. When the 'domestic sector' objective is maximized, its optimum supply benefits goal is 100 percent, in bold face, and the associated investment cost and maintenance costs are 157.56 \$m/MW and 20.36 \$m/MW respectively, including the electricity supply benefits goals for the rest of the demand sectors.

Analysis of the pay-off table leads to the following conclusions;

- There is a strong conflict between the "costs" objectives and the "demand sectors" objectives. Minimization of "investment" and "maintenance" cost objectives, implies achieving minimal goals to the "demand sectors' objectives.
- Pairwise comparison between rows of the pay-off table shows a significant degree of conflict between the corresponding objectives. This level of conflict is even stronger when the "investment cost" objective is compared with "domestic" and "large industry" sectors objectives.
- There is a relatively weak conflict between the "costs" objectives. The minimum investment cost corresponds to a minimum maintenance cost.
- There is a conflict between the "demand sectors" objectives. By maximizing one "demand sector" objective, it results in having the minimum value for the rest of the "demand sectors" objectives, except for the "commercial' and "Street light" sector objectives, which are relatively very small.
- There is no solution generated by the single optimization of the objectives that is acceptable. Solutions corresponding to "costs" objectives are not financially

feasible while solutions corresponding to "demand sectors" objectives are not sustainable.

Therefore, we conclude that it is necessary to look for "satisficing" or compromise solutions among the objectives considered. This task is undertaken in the next section by solving the Tchebycheff GP model formulated in Section 4.4.2. But beforehand, there is need to set targets or goals for each of the 7 objectives and their corresponding weights.

5.3.2 Setting Weights and Goals

Taking into account the information contained in the pay-off table, that is, ideal and anti-ideal values as well as the ranges of each of the 7 objectives, the base weights for the objectives are as indicated in Table 5.6, with variations considered later, during sensitivity analysis. As described in Section 4.4.2, the objectives are assigned importance levels. To illustrate this model, the relative objective importance levels are based on judgment on a 0 to 100 scale; in a real model analysis, it would be judgment of experts or decision makers.

Table 5.6: Relative objective importance levels and Weights

Objectives	**Importance level**	**Range**	**Weight**
Investment cost	41	316.69	$41/316.69 = 0.130$
Maintenance cost	34	14.32	$34/14.32 = 2.348$
Domestic	65	46.68	$65/46.68 = 1.390$
Commercial	13	14.18	$13/14.18 = 0.90$
Medium industry	59	37.14	$59/37.14 = 1.60$
Large industry	29	20.88	$29/20.88 = 1.40$
Street light	5	7.68	$5/7.68 = 0.60$

The "costs" objectives derive from "less is better" criteria, while the "demand sectors" objectives derive from "more is better" criteria. Hence, as a starting point of analysis, the ideal or base targets/goals for the minimization "costs" objectives were set to 0, while for the maximization "demand sectors" objectives, the 100 percent goal was considered.

By experimenting with the weights and goal levels set, it is easy to generate a range of potentially good and balanced solutions to the multi-objective optimization problem.

5.3.3 Base case Results

Optimal solution

Tables 5.7 presents the base case results after optimizing the multi-objective problem, whereby the "costs" objectives are minimized while the "demand sectors" objectives are maximized to achieve their respective ideal goals of 0 and 100 percent respectively. The elements in the first and second rows represent the optimal cost solution. This includes the investment cost ($m/MW) and the maintenance cost ($m/MW).

The third row up to seventh row represents the optimal electricity supply benefits goals to the demand sectors.

Table 5.7: Base run Solution

Objectives	**Planning periods**				
	2008	2013	2018	2023	2028
Investment cost	0.0	468.2	468.2	468.2	145.1
Maintenance cost	15.0	21.5	25.9	23.4	25.9
Domestic	91.0	91.0	91.0	67.0	56.2
Commercial	100.0	100.0	89.0	87.6	32.4
Medium Industry	100.0	100.0	96.8	90.0	62.0
Large Industry	65.2	65.2	65.2	56.5	56.5
Street light	100.0	100.0	100.0	100.0	91.0

Table 5.7 further shows that not all the electricity supply benefits goals are currently achievable and it gets worse with time. This is due to the model objective of minimizing capital investment costs foe each planning period that eventually leads to a reduced electricity generation capacity. Its only the commercial and street light sectors that are satisfied because they use less electricity capacity compared to the other sectors.

Generation capacity

The electricity generation configuration plan is presented in Table 5.8. The type of technologies proposed include thermal, bagasse, small hydro and large hydro power. This diversity is similar to the current Uganda government's electricity generation configuration mix, [MEMD, 2009]. The Uganda government electricity generation plan was obtained using different methods and input data, a comparison with it is not possible.

Table 5.8: Generation capacity(MW)

Generation technologies	**Planning periods**				
	2008	2013	2018	2023	2028
Thermal	200.0	182.0	165.6	150.7	137.2
Bagasse	12.0	11.5	11.1	149.4	164.1
Small hydro	15.0	15.0	15.0	14.0	15.8
Large hydro	300.0	523.0	739.2	744.6	859.2
Total	527.0	731.5	930.9	1058.7	1176.1

This study reveals that under a least-cost optimization of Ugandas electricity sector, thermal and hydro electric power generation are the preferred technologies. This finding is in line with Uganda's medium and longterm strategies of developing thermal and hydro power sites to supply adequate and reliable electricity. However, the finding on bagasse is not feasible given the small scale operations of bagasse technology in Uganda. Biomass, Geothermal, wind, and solar power, were not included in the solution. They are not preferred mainly because of their relatively high initial capital investment costs.

Electricity allocation plan

Table 5.9 presents the electricity supply plan for the optimal solution. Over the planning periods, the generated capacity from large hydro power increases as the investments into the electricity sector increases. By considering the reserve margin and lost electricity capacity, the available capacity is allocated to the demand sectors based on proportional share of total demand. The largest electricity consumers are allocated the biggest share of available electricity capacity. However, the desired demand does not seem attainable.

Table 5.9: Electricity capacity (MW) supplied to demand sectors

Demand sectors	**Planning periods**				
	2008	2013	2018	2023	2028
Domestic	75.8	106.5	149.3	139.0	175.5
Commercial	53.0	74.0	78.0	107.7	72.2
Medium Industry	73.0	103.0	132.6	150.8	137.1
Large Industry	81.5	114.0	158.5	203.2	284.6
Street light	2.0	3.0	4.0	5.0	6.0
Total Supply	285.2	400.5	522.4	605.6	675.5

5.4 Sensitivity Analysis

The input data always contain to some extent uncertain or approximate values. Furthermore, the future involves own uncertainty factors. Sensitivity analysis basically ascertains whether or not minor shifts in the model parameters can cause shift in the behavior of the model, [Ozdemir and Saaty, 2006]. There are two main methods of conducting sensitivity analysis, [Latinopoulos and Mylopoulos, 2005]. The first involves varying one parameter at a time while keeping all other parameters at their mean or best estimate value. The second method is to vary two or more parameters together at the same time. Judgment is required to identify a suite of sensitivity combinations that will provide reasonable insight into the significance of various combinations of parameters.

Sensitivity analysis is a key feature in EGP because it helps to present to the decision-maker a wide range of options to select from depending on the socio-economic climate that is perceived. Sensitivity analysis also serves to provide further insight into the relationships between the parameters of the model, thus playing an important role in fine-tuning decisions and focusing on the exact characteristics of the electricity generating units to be installed in the system.

The increasing uncertainty surrounding the electricity generating sector makes the sensitivity analysis an essential tool to long term planning, [Chatzimouratidis and Pilavachi, 2009]. The capital investment cost fluctuations and electricity demand variations, probably represent the major sources of uncertainty, since the economic interest of electricity generation largely depends on these factors.

The sensitivity analysis will focus on the effects of variations in objective function weights and model parameters on electricity supply goals.

5.4.1 Weight Sensitivity Analysis

Table 5.10 indicates the sensitivities conducted in this analysis. All the other assumptions remain the same, here called the *base case*. The weights of capital investment cost, maintenance cost, and electricity supply benefits goals, were varied to both a high (100 percent increase) and higher (200 percent increase) value.

Table 5.10: Weight sensitivity analysis values

Objectives	**Weight variations**		
	Base	**High (100%)**	**Higher (200%)**
Investment cost	0.130	0.260	0.390
Maintenance cost	2.348	4.696	7.044
Domestic	1.400	2.800	4.200
Commercial	0.900	1.800	2.700
Medium industry	1.600	3.200	4.800
Large industry	1.400	2.800	4.200
Street light	0.600	1.200	1.800

5.4.1.1 Electricity Costs

Investment cost

The impact of weight on investment costs is illustrated in Figure 5.1. On the horizontal axis are the variations in weight on investment costs. The vertical axis contains information on the electricity supply benefits goals and how they are affected by the varying weights on investment cost. The varying electricity supply benefits goals of each demand sector is represented with a corresponding piecewise equation.

If the weight on investment costs would increase from 0.130 to 0.260, the investments would reduce by 50 percent. The impact of reducing investments would considerably reduce the electricity supply benefits goals to all the demand sectors, except commercial and street lighting, as showed in Figure 5.1. Increased weight on investment costs has a negative interaction with the level of spending on capital investments in the electricity sector.

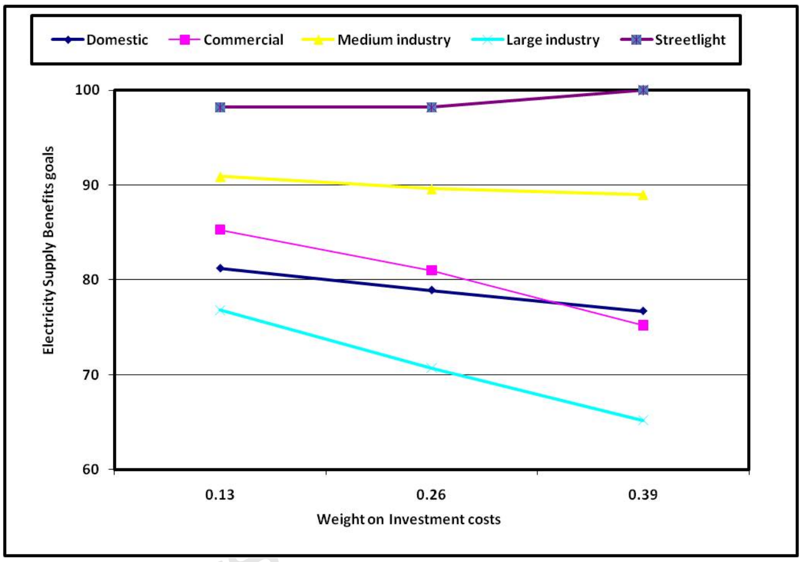


Figure 5.1: Impact of weight on Capital investment costs

Figure 5.1 indicates that a further increase in the weight on investment costs leads to meeting the goal for the less important sector (i.e. street light), while the goal achievement for the important goals is drifting away.

With less investments, there is less electricity capacity to supply to the demand sectors and hence a 29 percent and 45 percent reduction in the benefits goal achievement for domestic and large industry supply benefits goals, respectively. This is because of a significant decrease in the generated capacity for particularly, large hydro power plants. Overall, achieving electricity supply benefits goals is very robust to imprecision or differences of opinion about the relative weight on investment costs.

Maintenance cost

The application of regular and improved maintenance techniques leads to more efficient and reliable electricity generation plants. The direct result of this evolution is as remarkable decrease of the maintenance costs.

A 100 percent increase in the weight on maintenance costs leads to a reduction in the electricity capacity supplied to all sectors, except for street light, hence reducing chances of achieving their benefits goals.

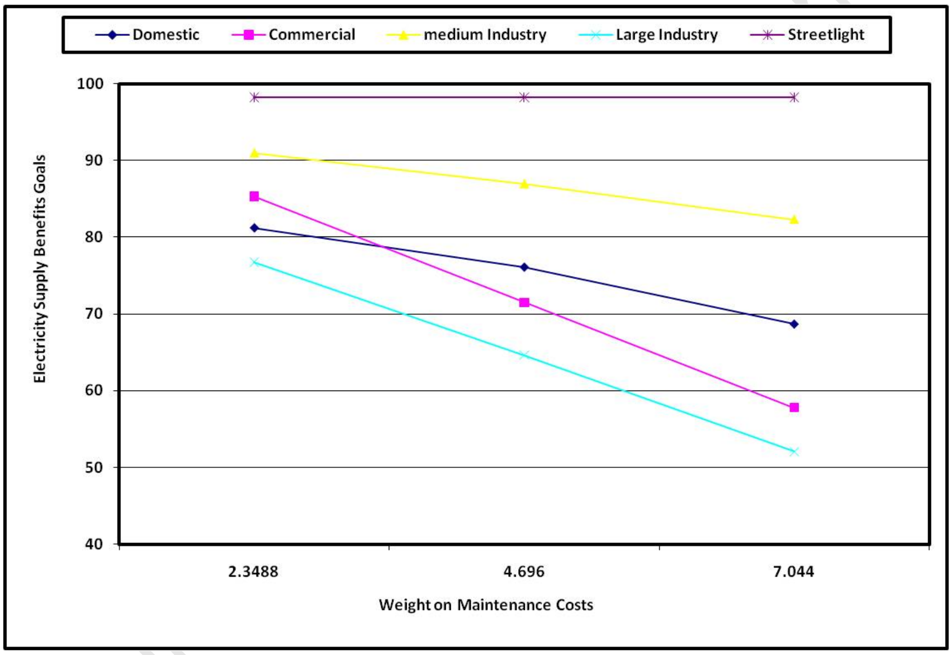


Figure 5.2: Impact of weight on Maintenance costs

The impact of weight on maintenance costs on electricity capacity supplied is illustrated in the Figure 5.2. Its shows that as the weight on maintenance costs increases, the available generation capacity reduces. Therefore, to increase available generation capacity, weight on generation costs must be reduced.

5.4.1.2 Electricity Supply Benefits Goals

Domestic supply

A 100 percent increase in the weight on domestic supply requires an increase in both capital investment costs (16.%) and maintenance costs (5%). The increase in new generation capacity is more reflected in the thermal and large hydro power plants than in any other technology option, Table 5.11.

As the weight on domestic supply increases, it gets closer and closer to achieving the domestic supply benefits goals compared to other supply sectors. For the less important supply sector (i.e. street light), the increase in the weight on domestic supply, does not have any essential impact on the supply benefits goals, as shown in the table below.

Table 5.11: Impact of weight on Domestic supply

Impact on	**Weight on domestic supply**		
	1.40(Base)	2.80	4.20
Costs ($m)			
Investment costs	387.4	445.5	453.4
Maintenance costs	22.3	23.9	24.6
Supply goals(%)			
Domestic	81.2	93.9	95.4
Commercial	85.3	84.5	84.1
Medium industry	90.1	90.5	90.3
Large industry	76.8	70.5	72.9
Street light	98.2	98.2	98.2

Commercial supply

If the weight on commercial supply would increase by 100 percent, commercial supply benefits would increase by over 15 percent. However, as the weight on commercial supply increases, the investment and maintenance costs increases. The chances of achieving the electricity supply benefits goals of domestic, large and medium industries reduces as the commercial sector supply weight increases. This is explained by the larger quantities of electricity required by these sectors. The least important sector is not affected by the increase in the weight on the commercial supply, Figure 5.3. Therefore, increasing weight on commercial sector only does not help in achieving goals of the main sectors on domestic, large and medium industries.

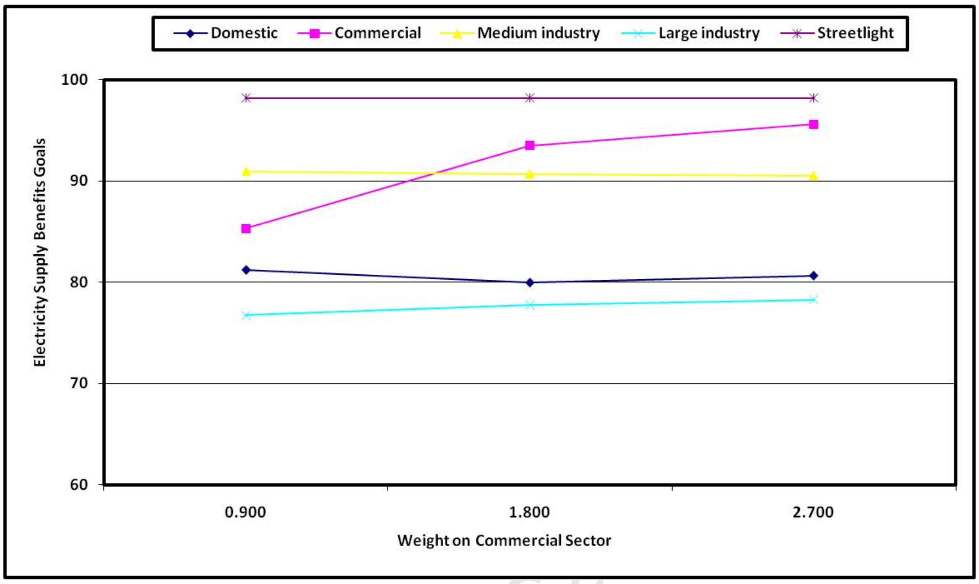


Figure 5.3: Impact of weight on Commercial supply

Large and Medium industry supply

The investment and maintenance costs increases with an increase in the weight on medium industry, particularly in thermal and large hydro power plants. A 100 percent increase in the weight on medium industry leads to closely achieving its benefits goals, while the achievement in other sectors is reduced.

Similarly, Table 5.12 shows that a 100 percent increase in the weight on large industry leads to closely achieving its benefits goals, while the achievement in other sectors is reduced. This means that increasing weight on large and medium industry sectors requires more capital investment and maintenance costs.

Table 5.12: Impact of weight on Large industry supply

Impact on	**Weight on large industry supply**		
	1.40(Base)	2.80	4.20
Costs ($m)			
Investment costs	387.4	442.7	472.7
Maintenance costs	22.3	24.1	25.5
Supply goals(%)			
Domestic	81.2	79.3	79.2
Commercial	85.3	80.9	79.7
Medium industry	90.9	88.0	89.0
Large industry	76.8	91.9	94.4
Street light	98.2	98.2	98.2

5.4.2 Parametric Sensitivity Analysis

All model approaches are subject to simplifications, assumptions and mathematical restrictions. Further, empirical analyses are affected by missing information and possible data errors. In the EGP model, estimation of the electricity generation costs and supply levels involves various assumptions and expectations concerning the accuracy of the input parameters which has been used and how the future will unfold in terms of technical and economic forces.

In order to understand and to quantify the impact of uncertainty on data inputs on the results, we performed a systematic and detailed examination of the influence of these assumptions on the key parameters for the different scenarios. This examination involves using parameter sensitivity analysis. Parameter sensitivity is usually performed as a series of tests in which the modeler sets different parameter values to see how a change in the parameter causes a change in the dynamic behavior of the model. By showing how the model behavior responds to changes in parameter values, sensitivity analysis is a useful tool in model building as well as in model evaluation.

This sensitivity analysis expresses the degree of uncertainty associated with the input parameters as well as the testing the robustness of the resulting cost and supply level estimates. Table 5.13 indicates the selected sensitivities included in this analysis. All the other assumptions remain the same, here referred to the base case.

Table 5.13: Parametric sensitivity analysis values

Parameters		**Base**	**Low**	**High**
Generation reserve margin		5%	2%	8%
Availability factor at minimum maintenance expenditure	Thermal	50%	-	80%
	Bagasse	40%	-	70%
	Small hydro	50%	-	80%
	Large hydro	60%	-	90%
Electricity demand estimates		8%	4%	12%

The impact of plant availability factor at minimum maintenance expenditure is conducted for thermal, bagasse, small hydro and large hydro power plants.

Generation reserve margin

For base case, an annual 5 percent reserve margin was used, $R = 0.05$. Sensitivity analysis addresses the impact of having a moderate reserve margin of 2 percent per annum compared to a higher reserve margin of 8 percent per annum. Table 5.14 summarizes the main results of this sensitivity run for the model.

Table 5.14: Impact of variations on reserve margin

Impact on	**Variations on reserve margin**		
	2.00%	5.00%(Base)	8.00%
Costs ($m)			
Investment costs	344.8	387.4	413.1
Maintenance costs	19.8	22.3	23.6
Supply goals(%)			
Domestic	84.8	83.3	82.2
Commercial	87.8	77.8	69.2
Medium industry	93.6	92.3	91.2
Large industry	82.3	80.5	78.2
Street light	98.0	98.0	98.0

A 3 percent reduction in the reserve margin from 5 percent to 2 percent per annum reduces both the investment and maintenance costs. As indicated in Table 5.14, the reduction leads to an increase in the generated capacity and available capacity for allocation to demand sectors.

These sensitivity results suggest that in order to achieve electricity supply benefits goals, the reserve margin should be kept low. Whereas a reduction in the reserve margin leads to closely meeting the electricity supply benefits goals, an increase in reserve margin increases the investment costs (12%) and maintenance costs (4%)) while at the same time not getting closer to meeting the supply benefits goals, Figure 5.4.

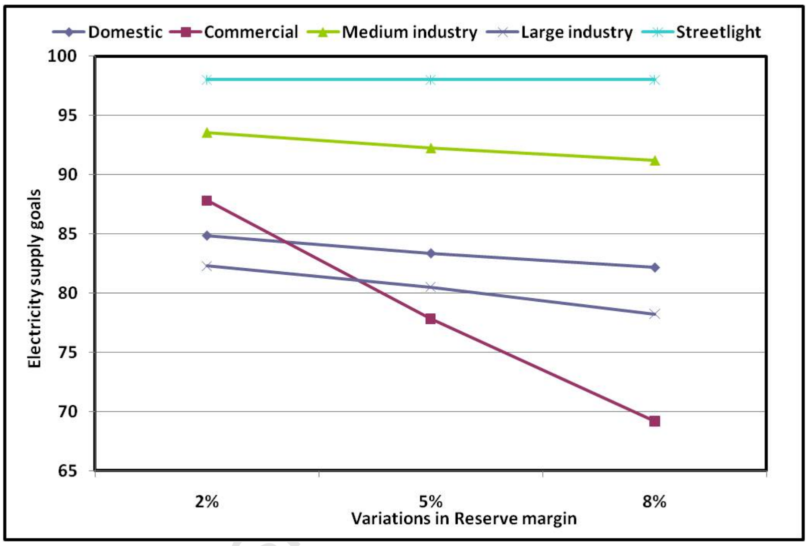


Figure 5.4: Impact of variation in reserve margin

Plant availability factor

The availability factor, measured as a percentage, of a plant defines the total time of plant in operation during a specified period. The availability of a power plant varies greatly depending on how the plant is operated. The difference is due to planned maintenance and outages. Consequently, plant availability factors are a function of the underlying technology and operational and management practices. Everything else being equal, plants that are run less frequently have higher availability factors because they require less maintenance.

The unavailability of the plant (planned or forced outage) may be as a result of minimum generation maintenance expenditure. Generation maintenance expenditure is meant for the upkeep of the electricity generation system. In addition to the base case assumption of availability factors, we also consider how the technologies compare under assumed plant availability factors as a function of maintenance expenditure.

For the base case, a 80 percent thermal plant availability factor was used, [World Bank, 2006]. A reduction in maintenance expenditure will reduce the plant reliability and output capacity, implying that the plant availability factor is much less than the ideal. Based on this judgment, the model considered 50 percent as the thermal plant availability factor at minimum maintenance expenditure. Sensitivity analysis addresses the impact of the variation in thermal plant availability at minimum maintenance expenditure on generated capacity.

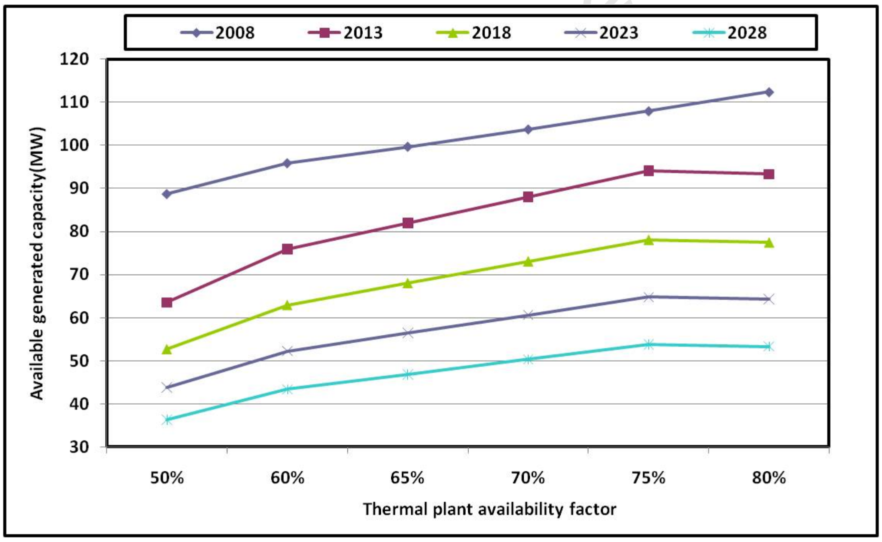


Figure 5.5: Impact of Thermal plant availability factor at minimum maintenance expenditure

Figure 5.5 illustrates the impact of the variation in thermal plant availability factor at minimum maintenance expenditure on generated capacity. An increase in the thermal plant availability factor at minimum maintenance expenditure causes a steady increase in the thermal power generated capacity. Thus, as the availability factor increases more electricity is produced.

Bagasse power plants depend entirely on the availability of sugarcane. For the base case, a 70 percent availability factor for bagasse at ideal maintenance expenditure was used. At minimum maintenance expenditure, a 40 percent availability factor was considered.

Sensitivity analysis considered varying the availability factor from 40 percent to 70 percent. An increase in availability factor for bagasse plant would lead to a commensurate increase in generated capacity. According to the results, increasing the generation maintenance expenditure improves the plant reliability and output, and hence increased availability factor.

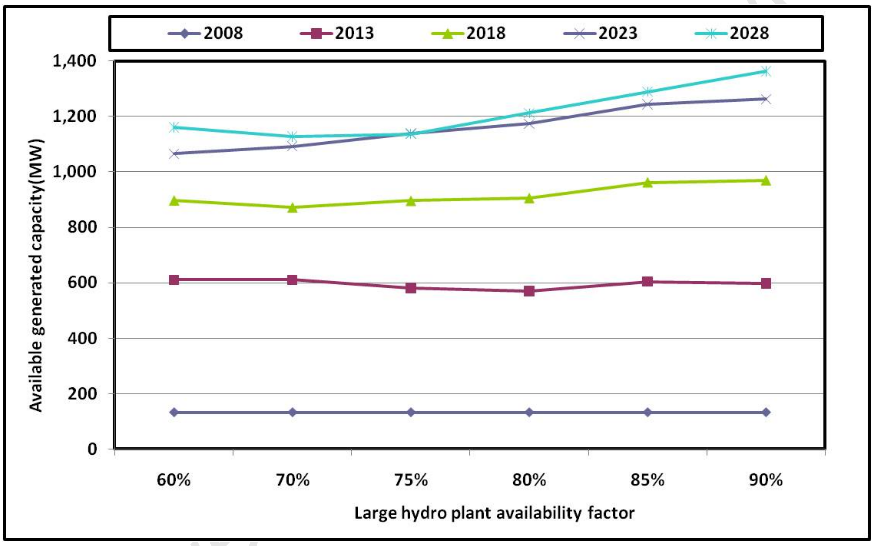


Figure 5.6: Impact of large hydro power plant availability factor at minimum maintenance expenditure

As may be observed in Figure 5.6, there is an almost positive linear relation between availability factor values of large hydro power plants and the electricity generated capacity. The availability factor value of a hydro power plant depends on the water potential of installation site.

Electricity demand estimates

The sensitivity of the electricity supply benefits goals to changes in demand growth is demonstrated in the Figure 5.7 below. Sensitivity analysis shows the variations in electricity supply goals under different demand growth rates. As mentioned earlier, sectoral differences in consumption patterns have significant influence on the electricity supply benefits goals.

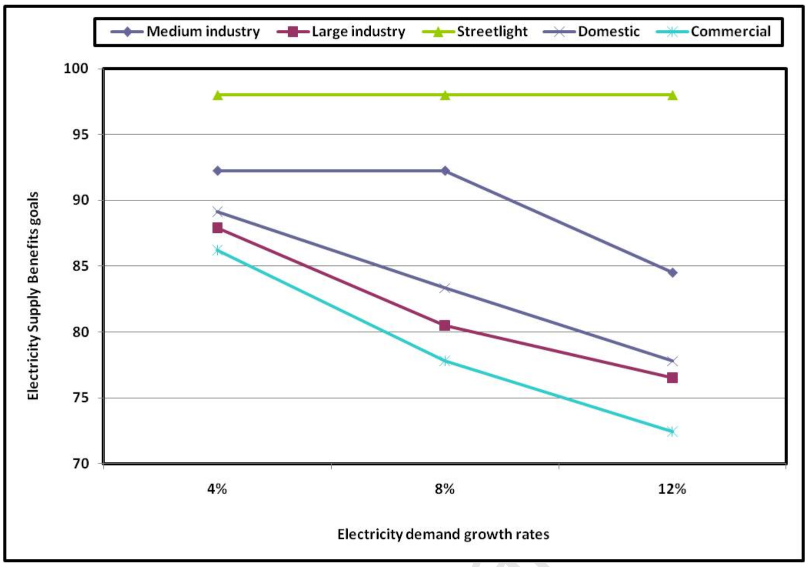


Figure 5.7: Impact of electricity demand growth

A reduction of growth rate from 8 percent to 4 percent makes noticeable improvement towards achieving the supply benefits goals in the domestic, commercial, and medium industry sectors. However, variations in demand growth rate does not affect the electricity supply benefits goals for the streetlight sector, since its electricity requirements are relatively small.

5.5 Summary

This chapter has explained in detail the development of a MP approach appropriate for EGP, in the case of insufficient electricity capacity to satisfy future demand. The model implementation takes a list of electricity generation technologies and determines which ones to construct and in which planning period to construct them. The results showed an optimal mix of generation options and unit generation cost of supply. The analysis also showed a corresponding electricity capacity supply strategy to the demand sectors. Further, using sensitivity analysis, indicates how the results depend on some of the uncertain parameters of the generation system.

The results of the MOLP model implementation indicate that an important degree of conflict exists between the cost and supply objectives. Increasing the weights on costs leads to a reduction in investments, thus negatively impacting on the electricity supply benefits goals. On the other hand, increasing weights on supply goals, especially the big electricity consumers (Industry and domestic sectors) calls for increasing financial effort for the assumed demand and operating activities. Although the results obtained can be considered as approximations to the real EGP problem, they look reasonable.

The MOLP model formulation and implementation results assume linear relationships among variables. Capital investments costs and O&M costs are assumed to be linearly related to installed capacity and amount of electricity generated respectively. However, this is a simplification of the reality frequently used in MP models, that allows the reduction of computational effort by working with linear functions.

The next chapter presents a SD model to explain the dynamic behavior of the electricity generation system over the planning period. This approach helps understand the inter-relationships and feedback behavior of some key elements in the electricity generation system.

Chapter 6

System Dynamics Model Formulation

6.1 Introduction

Electricity generation planning (EGP) is a complex task which requires the use of various planning methods and decision support models. Difficulties increase further when social, economic, and environmental perspectives are integrated with realities of physical processes. The dynamic character of input variables and how they affect electricity generation in the future is not captured through traditional modeling approaches. Steel [2007] notes that focusing on technical problems alone ignores many of the key roadblocks in improving access to electricity in developing countries. It is only by addressing the policy driven issues in electrification that planning can move forward.

There is need to explore tools to represent the complex relationships found in EGP systems. One promising option is system dynamics (SD), a feedback-based, object-oriented approach. Whereas, mathematical programming (MP) find an optimum decision meeting all system constraints while maximizing or minimizing some objective(s), on the other hand SD provides the response of the system for certain inputs, which include decision rules, so that it enables the DM to examine the consequences of various scenarios of a system. SD models are unable to directly generate an optimal solution to a decision problem, but DMs can obtain optimal or near optimal solutions by making numerous runs of a SD model with alternative decision operation policies.

SD is used to complement the MP techniques previously used, in understanding the dynamic behaviour and offering a global view point of EGP systems. Additionally, it is used as a simulation tool allowing a clear observation of feedback interactions on the system, which help to analyze possible policy changes, as well as variations on parameters and exogenous variables.

The main purpose of this chapter is to develop a SD-based model, denoted as EGP-SD, that explores the internal mechanism of the electricity generation system in a developing country context, and to see how to support electricity generation decision-making, in the case of a strategy to obtain the optimal electricity generation configuration meeting future electricity demand. The EGP-SD model will shed light on understanding the dynamic and complex interactions found in electricity generation systems.

6.2 Overview of System Dynamics Methodology

This research has adopted the SD methodology to add more understanding on the structure of the EGP problem and to develop a model for evaluating the impact of different operating policies on the problem. SD modeling is especially appropriate to address issues pertaining to dynamic complexity at an aggregate level since informational and physical feedbacks, non-linearities and stock-and-flow structures can be easily modeled.

In general the SD methodology is based on identifying the structure and the logic of the interrelationships among the different system components to derive its dynamical response. As a modeling formalism, it consists of a set of tools to describe the structure of systems, as described in Section 2.3.

The purpose of developing a SD model is usually to gain better insight into a real world system. Simulation models based on SD are therefore a valuable tool for descriptive analyses, which in turn can result in increased knowledge and thereby improved decision making. The process of developing a EGP-SD model follows the steps and guidelines presented by Sterman [2000, Page 86-104], as briefly described below.

Step 1: *Model description:* Initial step of this methodology is to define the problem. This step provides a qualitative description of the SD model. The key components of the description include an illustration of the reference mode, model assumptions, and mapping structure. All key variables in the problem are described. An appropriate time horizon for the model is also chosen.

Step 2: *Model formulation:* This section involves using the stock-and-flow diagrams to develop a formal model complete with differential equations, parameters and initial conditions that represent the system. The stock-and-flow structure helps quantify the dynamic interactions between variables and concepts manifested in the problem.

Step 3: *Model implementation:* The qualitative model is used to develop a quantitative simulation model using VENSIM® software, [Ventana Systems, 2007].

Step 4: *Model testing and analysis:* Once the simulation model is built sensitivity analysis will be performed to understand the dynamics of the systems. During sensitivity analysis the numerical values of variables that affect the model are changed to gain understanding of how the model is affected by these variables.

Step 5: *Policy formulation and evaluation:* This involves specifying new decision rules, strategies, and structures that might be tried in the real world and how they can be represented in the model. It also involves establishing the effects of policies, and how robust are the policy recommendations under different scenarios and given uncertainties.

This chapter presents Step 1: Model description and Step 2: Model formulation, of the EGP-SD modeling process. It includes problem definition, reference mode, time horizon, and mapping structure. The stock-and-flow diagram is developed to explain the dynamic interactions between variables in the electricity generation system.

Steps 3, 4, and 5, of EGP-SD model implementation, testing and analysis, and policy formulation and evaluation are presented in the next chapter.

6.3 EGP-SD Model Description

6.3.1 Problem Definition

The background and challenges to the electricity sector in Uganda is discussed in Chapter 3. Electricity generation capacity in Uganda is low in spite of the numerous available electricity generation options. Electricity shortages are mainly due to insufficient generation capacity to meet the electricity demand, caused primarily by lack of capital investment funds; and failures in the generation and transmission systems as a result of insufficient system maintenance and operating funds.

Electricity system planning is a complex task with the advent of multiple conflicting objectives to achieve, rapid increases in demand, high operating costs, and a large number of potential generations options. Identifying the factors that contribute to this complexity and analyzing the interactions among them can possibly help us make better decisions in a developing country's context. This calls for a clear understanding of the dynamics of the electricity generation system and how they affect the system's performance. The EGP-SD model attempts to analyse the interactions between the variables and/or parameters that create dynamics in the electricity generation system.

The key variables of the EGP-SD model are;

- *Electricity capacity:* This variable refers to the peak load in MW that generating technologies can supply.

- *Capital investment cost:* This is the total investment of generating and transmission of electricity up to the point of usage, measured in \$/MW.

- *Operating and Maintenance cost:* These are costs associated with the preventive and corrective operations on the generation and transmission facilities, measured in \$/MW.

- *Sectoral electricity demand:* This refers to the end-users total peak electricity demand, measured in MW.

- *Electricity allocations:* This is the amount of electricity capacity (MW) allocated to the demand sectors.

Unlike in the MOLP model, the EGP-SD model aggregates the electricity generation technologies for simplicity purposes. The sectoral electricity demand in EGP-SD model is also simplified by a broad grouping into industrial sector demand and non-industrial sector demand. The industrial sector includes medium and large industry whereas non-industrial sector comprises domestic, commercial, and street lighting. The electricity demand behavior of these two aggregate sectors is modeled as separate demand variables. The electricity demand behavior of the industrial sector is related to external forces like economic growth (GDP), and the non-industrial sector is related to population growth, and to non-industrial policy decisions.

6.3.2 Reference Mode

A reference mode is a pattern of behavior, which can characterize the problem dynamically, unfolding over time, showing how the problem arose and how it might evolve in the future. It describes the problem through a set of graphs and other descriptive data showing how it develops over time, [Sterman, 2000, Page 90]. To do so, we consider the time horizon and some key variables that are viewed to be important for understanding the problem are defined. Graphing important variables, and inherent graphs of other significantly related variables, produces the problem focus for a EGP-SD study.

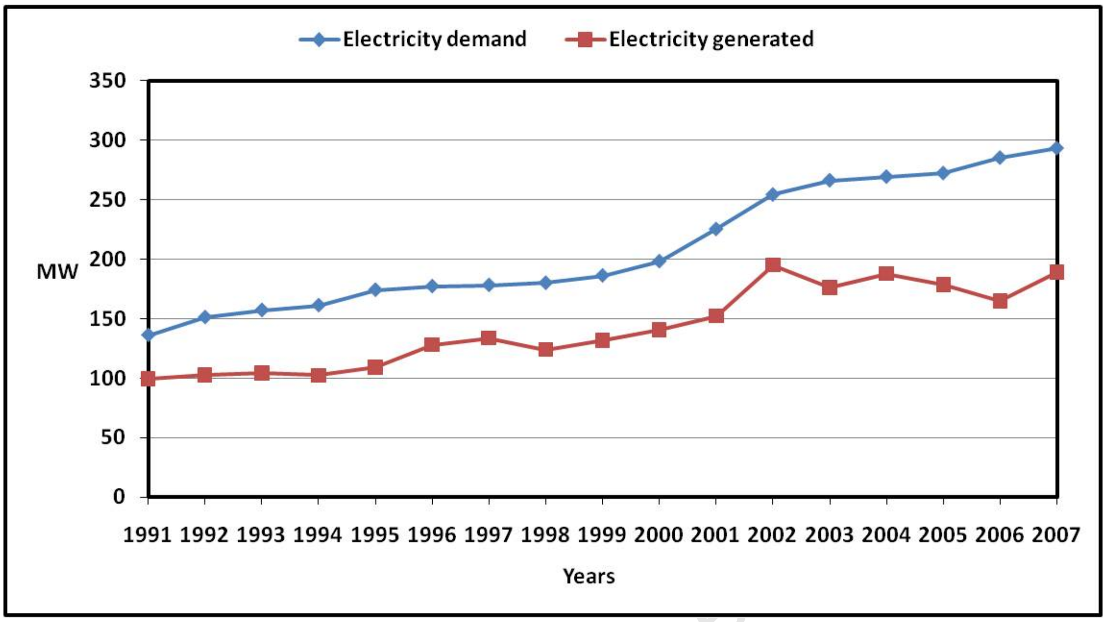


Figure 6.1: Electricity reference mode, [MEMD, 2009]

Figure 6.1 shows two main variables of interest and the pattern of behavior over the recent historical period, [MEMD, 2009]. The sectoral electricity demand increases significantly with time. Although the electricity generated increases as well, but it is slower than the rising trend in electricity demand. This suggests that there is always electricity shortage and this trend is likely to continue. This phenomenon is explained by the continued increase in GDP and population growth rates compared to the slower rate of expanding electricity generation capacity.

The data collected also indicates a sudden jump in electricity generation capacity between the years 2001 and 2002. This sudden increase in electricity generated capacity appears to be a result of the commissioning of additional units at Kiira hydro power station.

This chapter examines the persistent gap between electricity demand and generated capacity of Ugandas electricity industry. Then a SD model is developed and used to discover the structure which might be responsible for the problematic behavior. Some policy options are also developed.

6.3.3 Time Horizon

The time horizon, or time frame, is the period of time over which the problem plays itself out. It is the length of simulated time over which one will eventually run a dynamic model. The time frame of the EGP-SD study was chosen as 30 years, between 2000-2030. This time period coincides with the Power Sector Investment Plan (PSIP) for Uganda, [MEMD, 2009]. In addition, tracing back to 2000 can show how the problem emerges and what its symptoms are.

6.3.4 Model Assumptions

The following assumptions are made;

- An increase in generation and transmission operating expenditure increases the available capacity by reducing the generation and transmission capacity losses in the relevant time period.
- Non-industrial electricity demand is closely related to population growth.
- An increase in generation and transmission investment and operating funds leads to an increase in available electricity capacity at least in the short term.
- GDP is a key determinant of electricity demand. Although there is not a one-to-one relationship between GDP growth rates and electricity demand growth rates, there is a strong positive correlation. This means that electricity demand typically increases with increasing GDP growth.

- Electricity operating expenditure is a function of GDP growth.
- Electricity generation technologies are not explicit in this SD model.

6.3.5 Mapping Structure

A model boundary chart is used to help us communicate the boundary of the EGP-SD model and represent its causal structure. It summarizes the scope of the model by listing and classifying key variables into three categories; endogenous, exogenous, and excluded variables. The excluded variables are not taken into consideration. The exogenous variables refer to outside variables that affects the model but are not affected by the behavior of the model. In this particular model, the electricity prices, GDP growth and population growth rates are assumed to be exogenous. They have a positive correlation with electricity demand and supply. The exogenous plus excluded variables define the model boundary. The selection of what variables to be included in the model is determined by the overall modeling objectives. The endogenous variables create the dynamics of the model. The key variables defining the boundary of the model are summarized in Figure 6.2.

As mentioned in Section 6.3.1, sectoral electricity demand is grouped into industrial and non-industrial demand. The non-industrial demand is assumed to depend on population size, household income, electricity tariffs, and end-use efficiencies of electrical appliances. The industrial demand is assumed to be affected by the economic changes that faces the country like GDP growth and other government policy decisions.

6.4 EGP-SD Model Formulation

This section presents a stock-and-flow diagram of the EGP-SD model as shown in Figure 6.3. The level variables are shown as rectangular boxes which represent accumulated

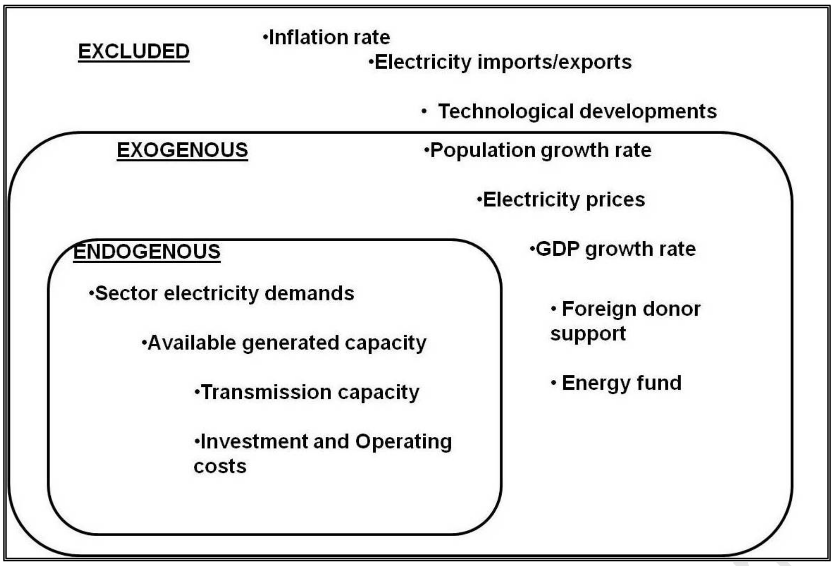


Figure 6.2: System boundary structure

flows to that level. A double arrow represents the physical flows, and the flow is controlled by a flow rate. A single line is for showing information flow. Source and sink of the structure are represented by a cloud. The cloud symbol marks the boundary of the EGP-SD model.

For simplicity, the EGP-SD model is divided into a number of sub models interacting with one another. Each sub model is described individually in the following sections, with the aim of formulating the long term dynamic system equations in a simplified manner so that their mathematical nature can be easily identified and some important implications can be derived.

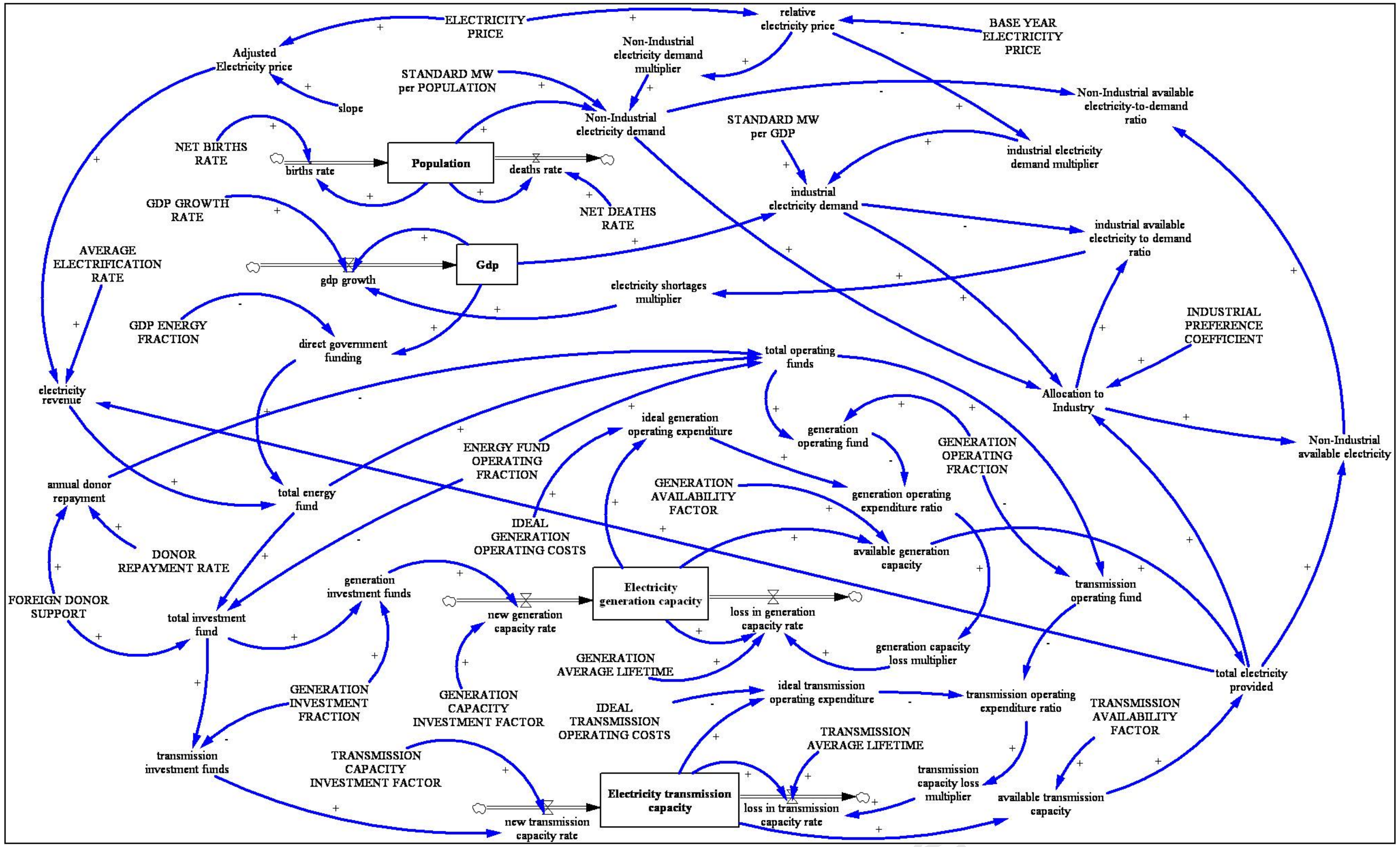


Figure 6.3: Stock-and-Flow diagram

6.4.1 Industrial Electricity Demand sub model

The underlying assumption in this sub model is that industrial electricity demand (MW) is driven by GDP ($) and electricity price ($/MWh), as showed in Figure 6.4. GDP is favoured as the main driver of the industrial demand sector, as GDP and industrial production are closely linked.

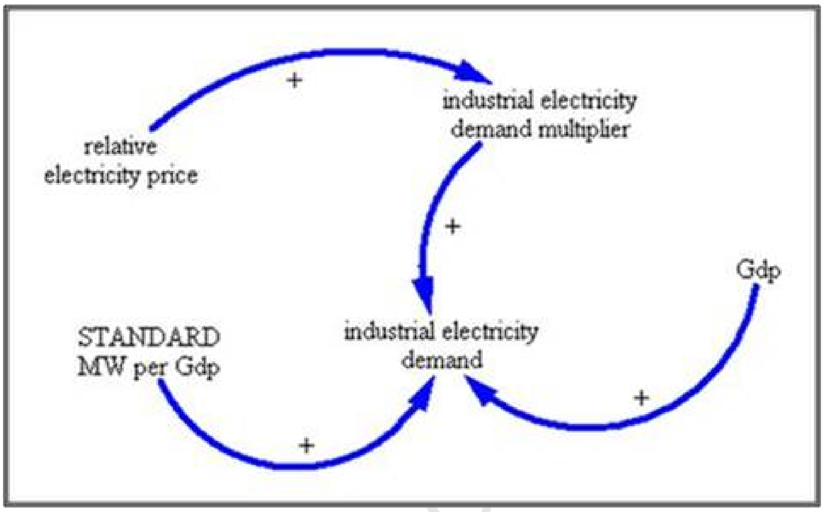


Figure 6.4: Industrial electricity demand sub model

The industrial electricity demand is modeled in principle as;

$$\begin{matrix}\textit{Industrial} \\ \textit{electricity demand (t)} \\ \textit{[MW]}\end{matrix} = \begin{matrix}\textit{Standard} \\ \textit{MW per GDP} \\ \textit{[MW/\$]}\end{matrix} * \begin{matrix}\textit{GDP (t)} \\ \textit{[\$]}\end{matrix} * \left(\begin{matrix}\textit{Industrial electricity} \\ \textit{demand multiplier} \\ \textit{[dimensionless]}\end{matrix}\right)$$

The industrial electricity demand is also assumed to be influenced by electricity price; modeled by means of the ‘industrial electricity demand multiplier’. The multiplier then modifies the GDP relationship as a function of the relative electricity price, defined as a ratio of current price to base year price (in real terms).

The ‘standard MW per GDP’ is defined by;

$$Standard\ MW\ per\ GDP \ = \frac{Base\ year\ industrial\ demand\ [MW]}{Base\ year\ GDP\ [\$]}$$

thus, also defining the multiplier to be equal to 1 in the base year or whenever the relative electricity price is equal to 1.

A decrease in relative electricity price implies that the current electricity price is less than the base year price and hence more affordable, leading to an increase in industrial electricity demand multiplier (multiplier > 1). Conversely, when the relative electricity price increases, industrial demand falls. Industrial electricity demand is elastic and as such any rise in electricity price is likely to be followed by a fall in demand (multiplier < 1). Hence, it is expected that the higher the relative electricity price, the lower the industrial electricity demand multiplier.

By definition, the multiplier has value of 1 when relative electricity price is equal to 1. It is assumed that relative electricity price will not exceed 6, at which point the industrial electricity demand will be crippled, represented in Figure 6.5 by demand multiplier equal to 0.2.

On the other hand, other infrastructural constraints would limit expansion of demand and an upper limit of 20 percent is illustrated here. These values are for illustration of the model, users need to use their own judgment to experiment with different values to analyze the impact of relative electricity price on industrial electricity demand. The illustration of the multiplier function is shown in Figure 6.5, where the numerical values are as follows;

Relative electricity price	0.00	0.70	1.00	1.20	1.65	1.80	2.30	3.40	5.00	6.00
Industrial demand multiplier	1.20	1.11	1.00	0.90	0.70	0.64	0.50	0.30	0.23	0.20

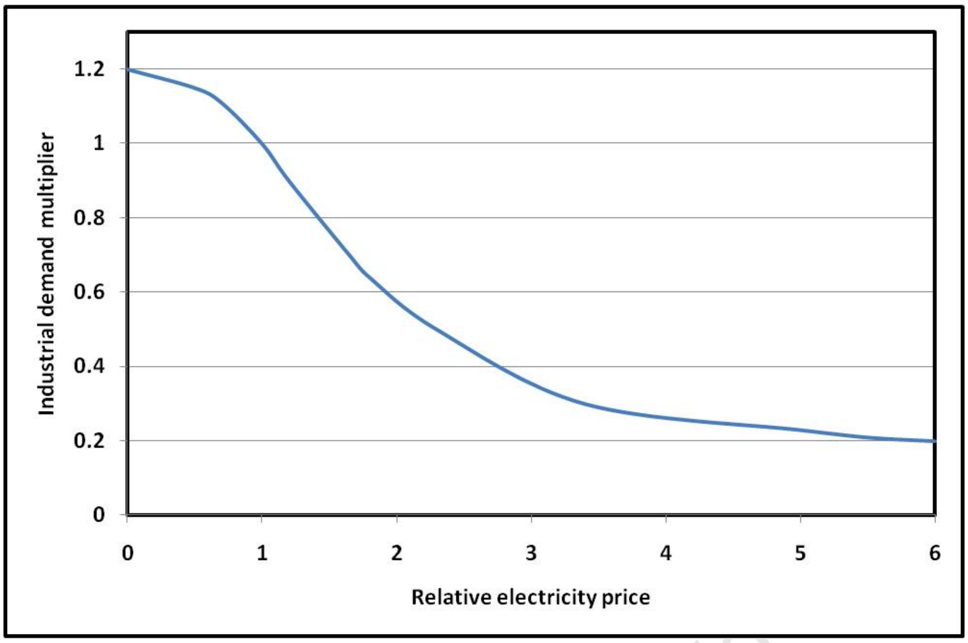


Figure 6.5: Effect of relative electricity price on Industrial electricity demand

6.4.2 Non-industrial Electricity Demand sub model

This sub model analyses the changes in non-industrial electricity demand (MW) due to changes in population (people) and electricity price (\$/MWh). The non-industrial electricity demand is driven exogenously by the population and electricity price, as shown in Figure 6.6.

The non-industrial electricity demand is modeled in principle by;

$$\begin{array}{l} \textit{non-industrial} \\ \textit{electricity} \\ \textit{demand (t)} \\ \textit{[MW]} \end{array} = \begin{array}{c} \textit{Standard MW} \\ \textit{per Population} \\ \textit{[MW/People]} \end{array} * \begin{array}{c} \textit{Population (t)} \\ \textit{[People]} \end{array} * \left(\begin{array}{c} \textit{Demand level multiplier} \\ \textit{for electricity price} \\ \textit{[dimensionless]} \end{array} \right)$$

The 'non-industrial electricity demand' is also assumed to be influenced by electricity price, modeled by means of the 'non-industrial electricity demand multiplier' in the same case as for industrial demand. The non-industrial electricity demand multiplier modifies the Population relationship as a function of relative electricity price.

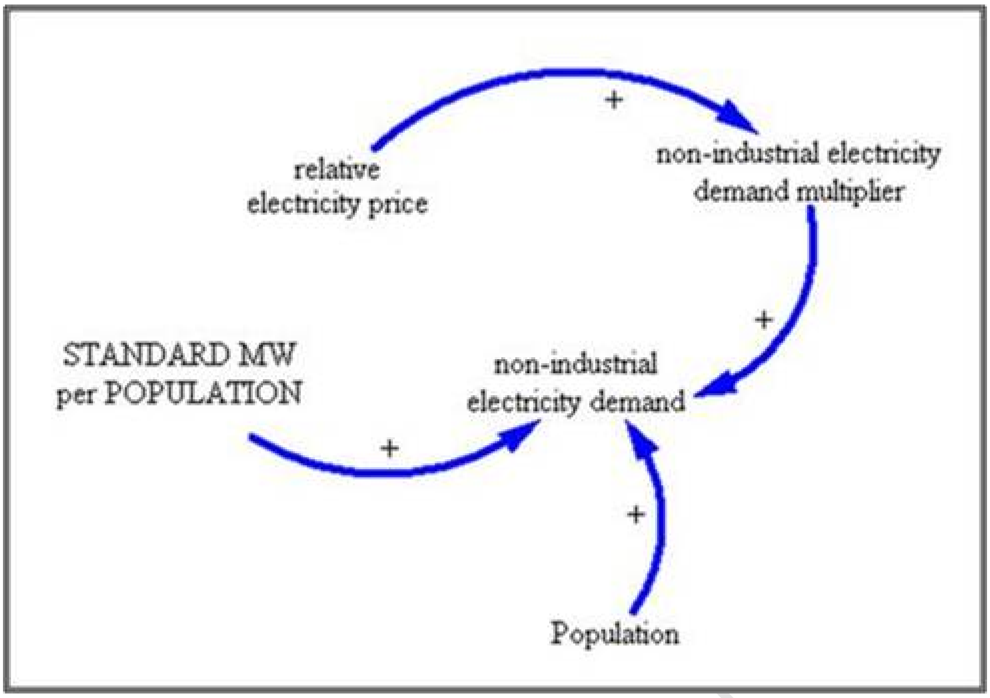


Figure 6.6: Non-industrial electricity demand sub model

The ‘standard MW per population’ is defined by;

$$\textit{Standard MW per Population} = \frac{\textit{Base year non-industrial demand [MW]}}{\textit{Base year population [People]}}$$

Once again, by definition, the multiplier is equal to 1 in the base year or whenever the relative electricity price is equal to 1. As for industrial demand, high price increase will destroy demand (perhaps more so than for industrial demand), while increased demand may have slightly more scope. This is illustrated in Figure 6.7, from which the numerical values are as follows;

Relative electricity price	0.00	0.50	1.00	1.14	1.46	1.83	2.50	3.48	4.32	6.00
Non-industrial demand multiplier	1.25	1.18	1.00	0.86	0.65	0.46	0.30	0.18	0.14	0.10

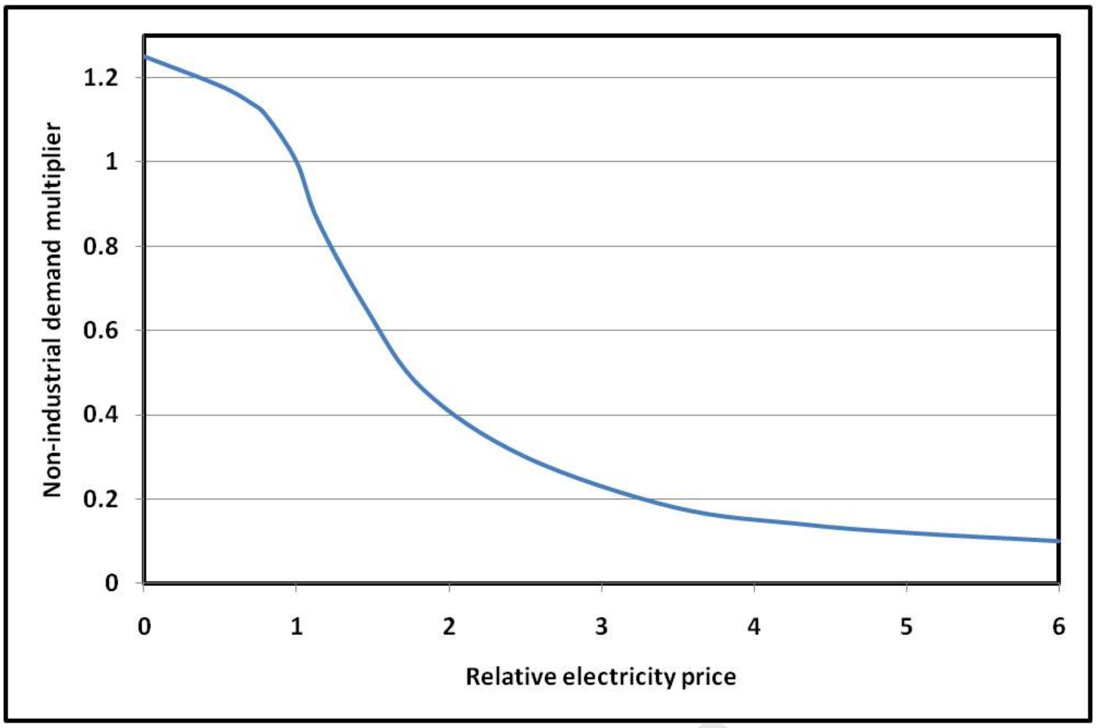


Figure 6.7: Effect of relative electricity price on non-industrial electricity demand

6.4.3 Population Growth rate sub model

Population is considered to play an important role in the dynamics of electricity demand. The variations in electricity demand are obviously affected by changes in population growth rate. In this model, population is considered as an exogenous variable. The idea underlying this sub model is that births and deaths are proportional to population, and population is a stock that accumulates population growth i.e. births less deaths, with an initial population predefined, as showed in Figure 6.8.

By differentiation, the population at any time t can be determined. The equations estimating the population growth rate are shown as follows:

$$\frac{d}{dt}\left(\begin{array}{l} \textit{Population(t)} \\ \textit{[People]} \end{array}\right) = \left(\begin{array}{lcl} \textit{births} & & \textit{deaths} \\ \textit{rate (t)} & - & \textit{rate(t)} \\ \textit{[1/year]} & & \textit{[1/year]} \end{array}\right) * \begin{array}{l} \textit{Population} \\ \textit{[People]} \end{array}$$

In this particular model, the births and deaths rates are assumed to be constant because

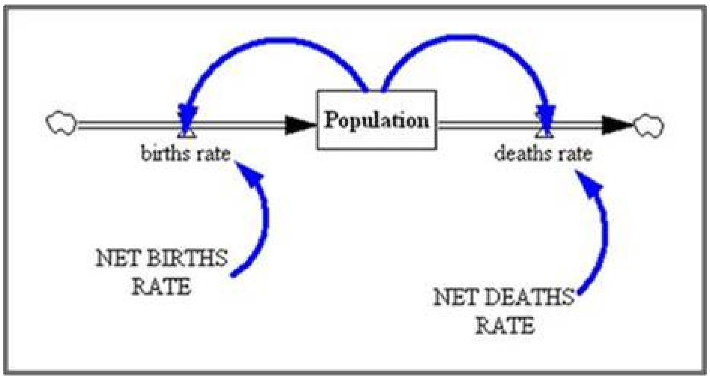


Figure 6.8: Population growth sub model

they are affected by other factors that are beyond the scope of this research.

6.4.4 GDP Growth rate sub model

GDP refers to the total value of goods and services produced in the country during one year. GDP ($) is a stock that accumulates GDP growth, with an initial GDP predefined. GDP growth rate ($/year) is a basic measure of economic performance within in a stipulated period of time (usually a year). GDP growth indicates increased economic activity and available income, both of which are correlated positively with electricity demand. For example, increased industrial output contributes to GDP growth and is the key income driver in the industrial sector. Electricity shortages, where disruptions in the supply of electricity compromise economic activities, hold back the potential of economic growth. This is a key developing country issue.

This sub model introduces the aspect on how electricity shortages affect GDP growth. Specifically, GDP is modeled as a function of GDP, GDP growth rate and the 'electricity shortages multiplier' on GDP, as illustrated in Figure 6.9.

The equations estimating the GDP growth are shown as follows:

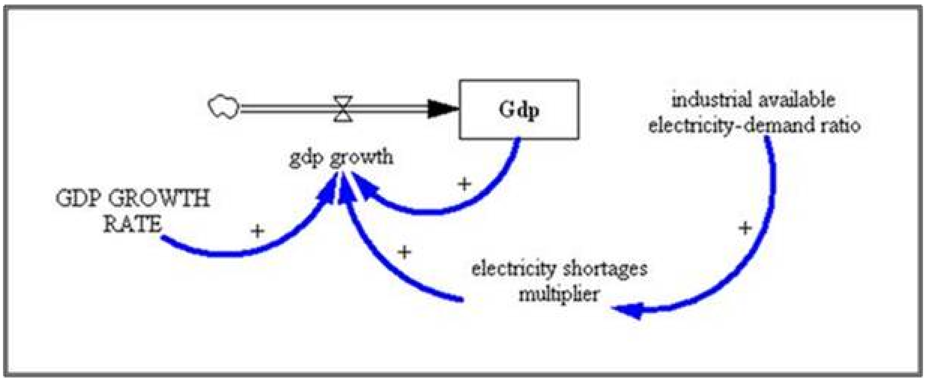


Figure 6.9: GDP growth rate sub model

$$\begin{array}{c} \textit{GDP growth (t)} \\ \text{[\$/year]} \end{array} = \left(\begin{array}{l} \textit{GDP growth} \\ \textit{rate (t)} \\ \textit{[1/year]} \end{array} * \begin{array}{c} \textit{GDP(t)} \\ \textit{[\$]} \end{array} \right) * \begin{array}{c} \textit{Electricity} \\ \textit{shortages multiplier} \\ \textit{[dimensionless]} \end{array}$$

The aspect of 'electricity shortage multiplier' is modeled as a function of the ratio of industrial available electricity to industrial electricity demand, which by definition will not exceed 1. The multiplier has a unit value when the industrial available electricity-to-industrial electricity demand ratio is equal to 1. This implies that there is just enough industrial available electricity to satisfy the industrial electricity demand. With less than full satisfaction of demand, the multiplier will then be < 1. The lack of reliable and available power supply has an adverse effect on the economy. The power shortage and resultant load-shedding results in an uncomfortable business environment that negatively affects the economy.

The multiplier curve will largely be defined by two key features namely (1) the point at which GDP growth is equal to 0 (in the illustrative Figure 6.10 this occurs at a supply-demand ratio equal to 0.54); and (2) the asymptotic growth rate (necessarily negative) in the demand as supply collapses (shown as -0.32 in Figure 6.10).

An illustration function form is shown in Figure 6.10, where the values are as in the following table. Once again, users would need to input their own judgments and to experiment with different values.

Industrial electricity -to-demand ratio	0.00	0.15	0.35	0.54	0.75	1.00	1.34	1.54	1.84
GDP growth	-0.32	-0.28	-0.18	0.00	0.60	1.00	1.20	1.24	1.30

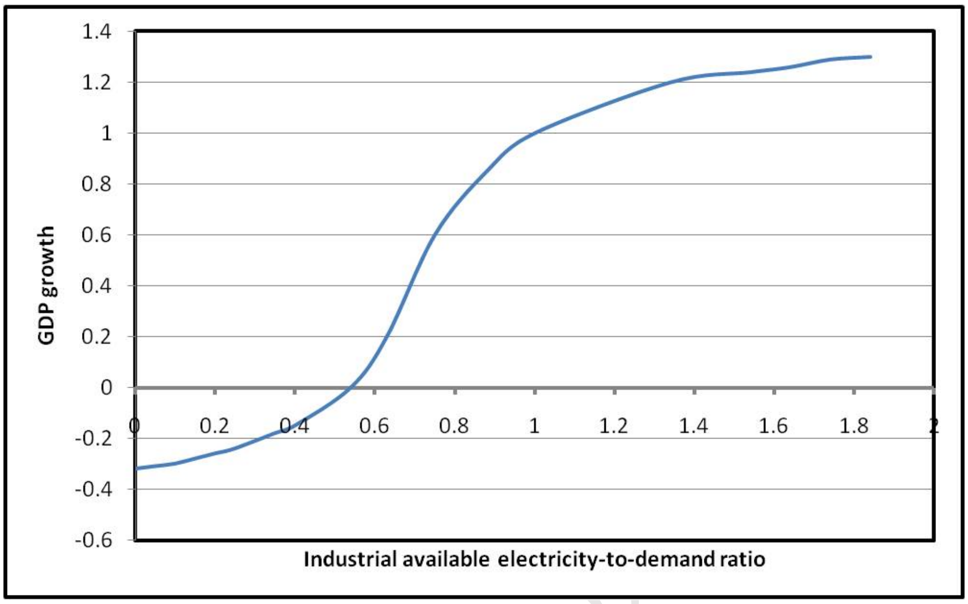


Figure 6.10: Effect of electricity shortage on GDP growth

6.4.5 Electricity Operating Expenditure sub model

Electricity generation and transmission involves operating costs/expenses. In situations of deteriorating financial performance and inefficient operations and management, the required operating expenditure is not met. Developing countries are financially constrained that electricity operating expenditure is always below what is required. This sub model considers the concept of ideal electricity operating expenditure for generation and transmission.

The electricity operating expenditure is modeled separately for generation and transmission; ideal generation operating expenditure ($/year) as a function of ideal generation operating costs ($/MW/year) and generation capacity (MW), as shown in Figure 6.11, and ideal transmission operating expenditure ($/year) as a function of ideal transmission operating costs ($/MW/year) and transmission capacity (MW), as shown in Figure

6.12.

The equations estimating the ideal generation and transmission operating expenditure are shown as follows:

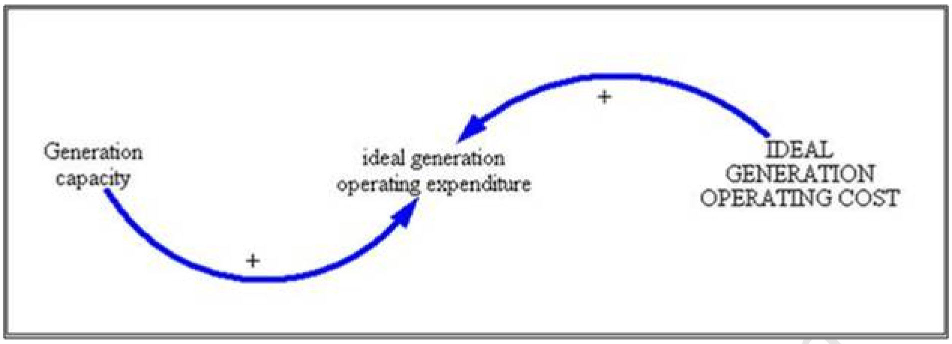


Figure 6.11: Ideal generation operating expenditure sub model

$$\begin{array}{lll} \textit{Ideal generation} & \textit{Ideal generation} & \\ \textit{operating expenditure } (t) = & \textit{operating costs } (t) \; * & \textit{Generation capacity } (t) \\ \textit{[\$/year]} & \textit{[\$/MW/year]} & \textit{[MW]} \end{array}$$

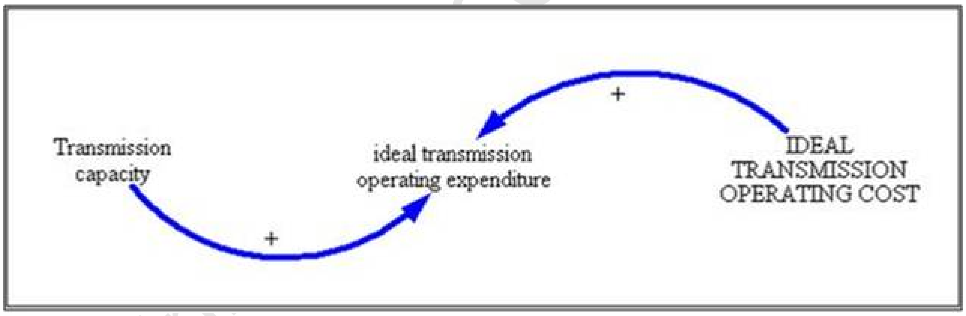


Figure 6.12: Ideal transmission operating expenditure sub model

$$\begin{array}{lll} \textit{Ideal transmission} & \textit{Ideal transmission} & \textit{Transmission} \\ \textit{operating expenditure } (t) = & \textit{operating costs } (t) \; * & \textit{capacity } (t) \\ \textit{[\$/year]} & \textit{[\$/MW/year]} & \textit{[MW]} \end{array}$$

6.4.6 Generation Capacity sub model

The generation capacity sub model simulates how the system reacts to changes in generation investment and operating funds. Reductions in operating funds has a direct impact on the loss in generation capacity. The inputs for the sub model are the available generation investment and operating funds and the ideal generation operating costs. The model output is the generation capacity at any time t.

Figure 6.13 shows that electricity generation capacity (MW) is a stock that accumulates new generation capacity rate. Therefore, generation capacity at any time t can be expressed as a differential equation of new generation capacity rate (MW/year) and loss in generation capacity rate (MW/year), with an initial capacity predefined.

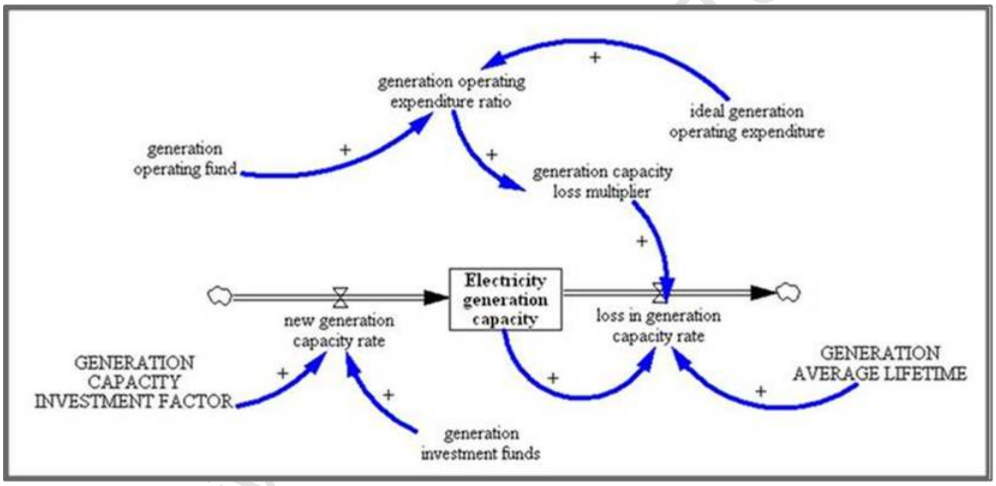


Figure 6.13: Generation capacity sub model

New generation capacity rate (MW/year) depends on the generation investment funds (\$/year) and a factor for generation capacity investment (MW/\$). An increase (decrease) in the generation investment funds leads to an increase (decrease) in new generation capacity rate. Therefore, it can be modeled as a function of generation investment funds available, as follows;

$$\begin{array}{lll} \textit{New generation} & \textit{Generation} & \textit{Generation capacity} \\ \textit{capacity rate (t)} = & \textit{investment funds (t)} \; * & \textit{investment factor} \\ \textit{[MW/year]} & \textit{[\$/year]} & \textit{[MW/\$]} \end{array}$$

In this sub model, loss in generation capacity rate (MW/year) is considered to be driven by generation average lifetime (years), generation capacity (MW) and a generation capacity loss multiplier discussed below, as shown in Figure 6.13. Specifically, it is modeled as a function of the ratio of generation capacity to generation average lifetime and 'generation capacity loss multiplier'.

Mathematically, loss in generation capacity rate is modeled as follows;

$$\begin{array}{l} \textit{Loss in} \\ \textit{generation} \\ \textit{capacity rate (t)} \\ \textit{[MW/year]} \end{array} = \underset{\textit{[MW/year]}}{\left(\frac{\textit{Generation capacity (t)}}{\textit{Generation average lifetime}} \right)} * \begin{array}{l} \textit{Generation capacity} \\ \textit{loss multiplier} \\ \textit{[dimensionless]} \end{array}$$

The 'generation capacity loss multiplier' depends ultimately on the generation operating expenditure ratio (i.e. ratio of generation operating fund to the ideal generation operating expenditure). The multiplier has value equal to 1 when there is just enough generation operating fund to cater for the ideal generation operating expenditure. In a situation of inadequate resources, the generation operating fund is expected to be less than the ideal generation operating expenditure.

This relationship is illustrated in Figure 6.14, where an asymptotic loss multiplier of 2.5 is shown in the absence of expenditure on maintenance. Deteriorating financial performance and declining efficiency of operations and management in the electricity sector are the major reasons for the continued loss in generation capacity.

Generation operating expenditure ratio	0.00	0.30	0.50	0.70	1.00
Generation capacity loss multiplier	2.50	2.40	2.25	1.90	1.00

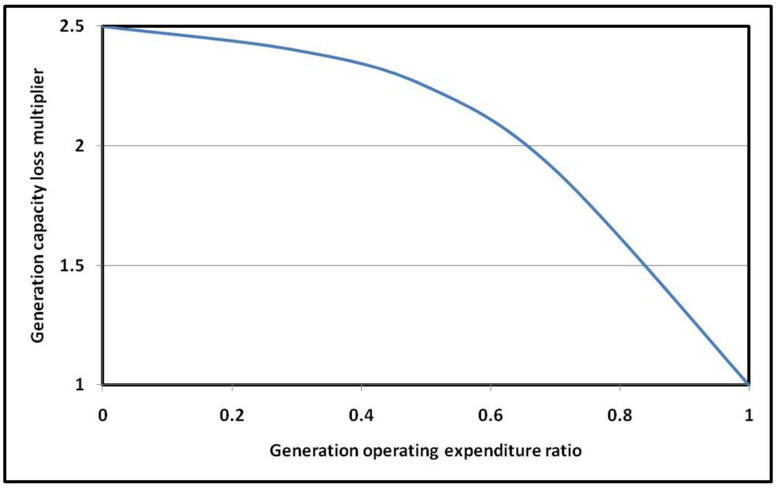


Figure 6.14: Effect of generation operating expenditure ratio on generation capacity loss

6.4.7 Transmission Capacity sub model

The transmission capacity sub model analyses changes in the transmission capacity due to changes in transmission investment and operating funds. Like for generation capacity, reductions in operating funds has a direct impact on the loss in transmission capacity. Figure 6.15 shows formulation of the transmission capacity model.

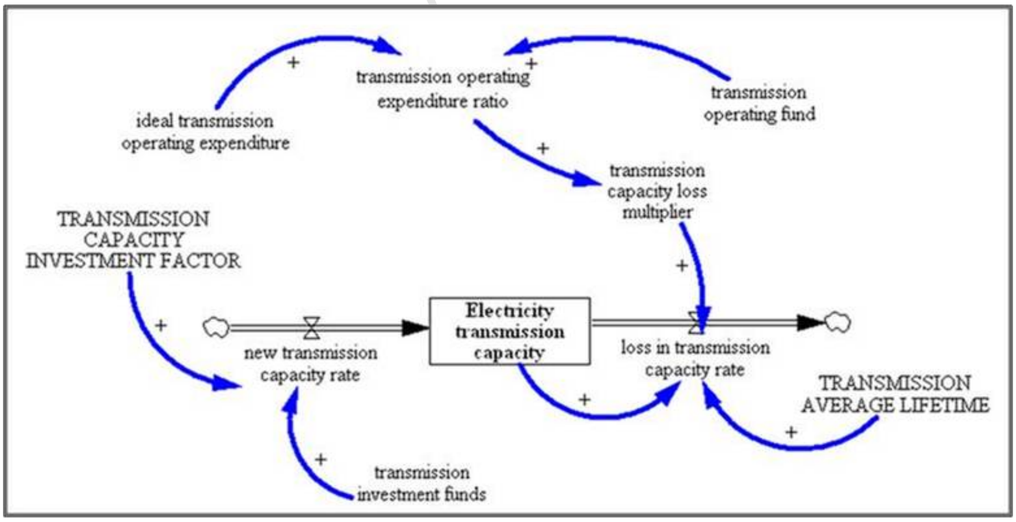


Figure 6.15: Transmission capacity sub model

In the same sense, as for generation capacity loss multiplier, lack of transmission operating expenditure results in a transmission capacity loss multiplier of up to 2.00, as depicted in Figure 6.16, where the values are as in the following table;

Transmission operating expenditure ratio	0.00	0.30	0.50	0.70	1.00
Transmission capacity loss multiplier	2.00	1.95	1.85	1.60	1.00

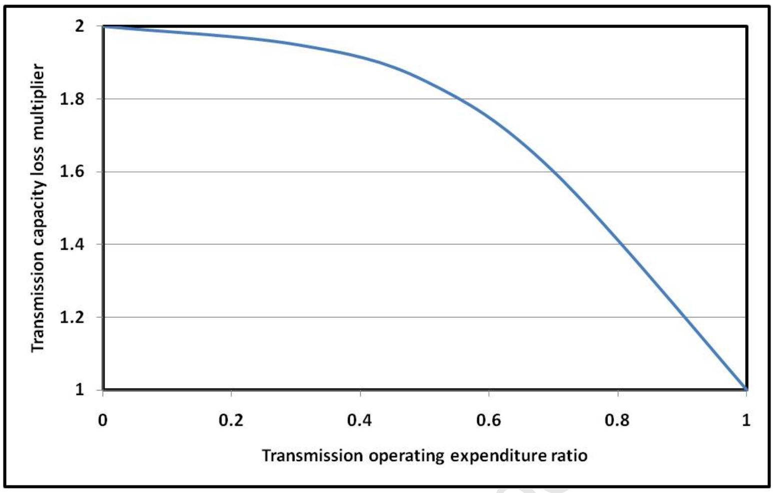


Figure 6.16: Effect of transmission operating expenditure ratio on transmission capacity loss

6.4.8 Available Electricity sub model

The available electricity sub model analyses the changes in available electricity to the industrial and non-industrial demand sectors due to changes in the generation and transmission availability factors. The model input is the generation and transmission capacity plus their corresponding availability factors. The sub model output is the total electricity available to be allocated to industrial sector and non-industrial sector.

The available generation and transmission capacity (MW) are derived as functions of the generation and transmission availability factor, respectively, measured as a percentage.

$$\begin{array}{l} \textit{Available generation} \\ \textit{capacity (t)} \\ \textit{[MW]} \end{array} = \begin{array}{l} \textit{Generation} \\ \textit{availability factor} \\ \textit{[dimensionless]} \end{array} * \begin{array}{l} \textit{Generation capacity (t)} \\ \textit{[MW]} \end{array}$$

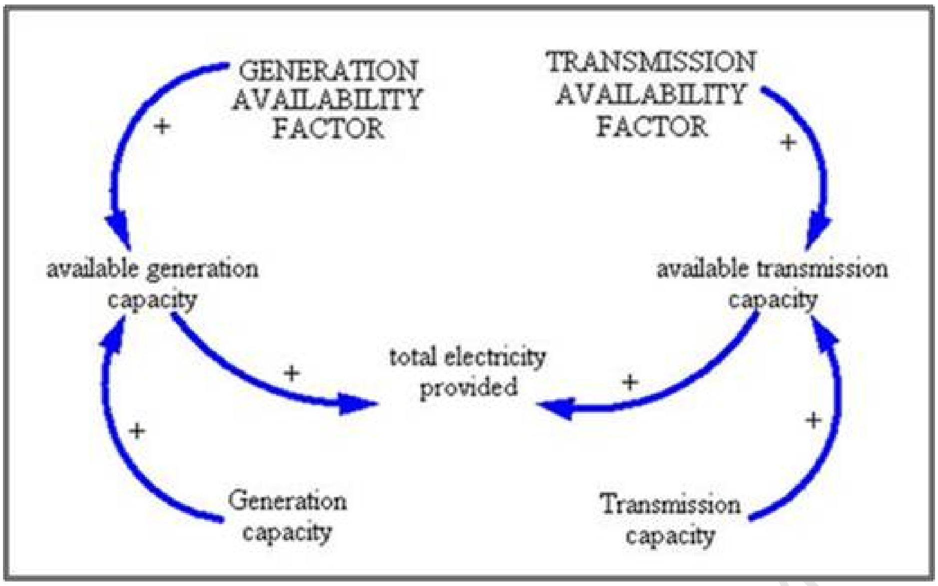


Figure 6.17: Available electricity sub model

$$\begin{array}{l} \textit{Available transmission} \\ \textit{capacity (t)} \\ \textit{[MW]} \end{array} = \begin{array}{l} \textit{Transmission} \\ \textit{availability factor} \\ \textit{[dimensionless]} \end{array} * \begin{array}{l} \textit{Transmission capacity (t)} \\ \textit{[MW]} \end{array}$$

The total electricity available is obtained as the minimum of the available generation capacity and available transmission capacity.

$$\begin{array}{l} \textit{Total electricity} \\ \textit{available(t)} \\ \textit{[MW]} \end{array} = MIN \left(\begin{array}{c} \textit{Available generation} \\ \textit{capacity(t)} \\ \textit{[MW]} \end{array} ; \begin{array}{c} \textit{Available transmission} \\ \textit{capacity(t)} \\ \textit{[MW]} \end{array} \right)$$

6.4.9 Electricity Allocation sub model

The underlying hypothesis in this sub model is that electricity allocations are driven by the proportion of total available to desired demand and a policy preference coefficient, as shown in Figure 6.18. This sub model examines the changes in electricity supply allocations due to changes in sectoral proportion of total desired demands, total electricity available, and policy preference coefficient.

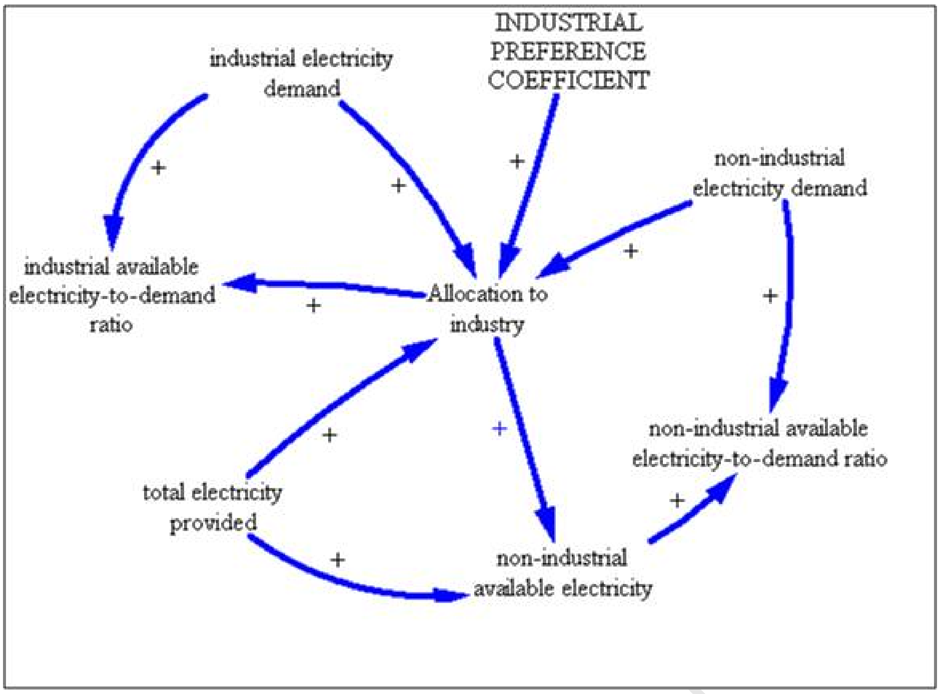


Figure 6.18: Electricity allocation sub model

Under full electricity supply, the proportion of supply allocated will be equal to the proportion of desired demand. If total electricity available is greater than the sum of industrial and non-industrial desired electricity demand, then both sectors will get full electricity supply.

This sub model considers a situation of electricity shortage, whereby the total available electricity-to-demand ratio is less than 1.

In such a situation, the electricity capacity (MW) allocated to industry sector, for example, will be a function the total available electricity-to-demand ratio and industrial electricity demand. We suggest a policy preference coefficient such that if industry sector gets preference, then the electricity capacity allocated to industry is given by;

$$\begin{array}{l}\textit{Electricity capacity}\\ \textit{allocated to industry(t)}\\ \textit{[MW]}\end{array} = \left(\frac{\textit{Total available electricity(t)}}{\textit{Total demand(t)}}\right)^{\alpha} * \begin{array}{l}\textit{Industrial electricity}\\ \textit{demand (t)}\\ \textit{[MW]}\end{array}$$

where;

α= Industrial preference coefficient, $0 < \alpha < 1$

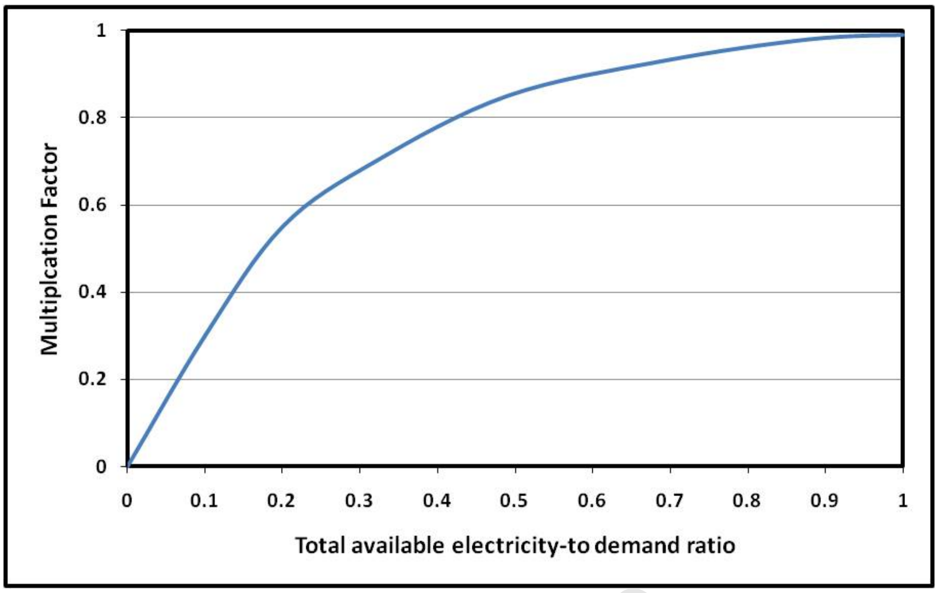


Figure 6.19: Effect of Industrial preference coefficient on industrial proportional allocation

When the total available electricity-to-demand ratio equal to 1, then all the desired industrial demand will be satisfied. However, during electricity shortages, the total available electricity-to-demand ratio will be less than 1 (e.g. 0.7). This means that, with an industrial preference coefficient of say, $\alpha = 0.6$, the proportion of electricity allocated to industry will be $(0.7)^{0.6}$. Variations in the preference coefficient leads to the amount allocated varying logarithmically with the total available electricity-to demand ratio, as shown in the Figure 6.19. The industrial preference coefficient defines the degree to which the amount of electricity allocated to industry reacts to a change in the total available electricity-to demand ratio, that is, curve's elasticity.

$$\begin{array}{lcl} \textit{Electricity capacity allocated} & & \textit{Total electricity} & & \textit{Electricity capacity} \\ \textit{to Non-industrial sector(t)} & = & \textit{provided(t)} & - & \textit{allocated to industry(t)} \\ \textit{[MW]} & & \textit{[MW]} & & \textit{[MW]} \end{array}$$

6.4.10 Electricity Revenue sub model

Electricity revenue is computed to reflect the cost of total electricity supplied. It is derived as a function of total electricity provided (MW), electricity price ($/MWh), and average electrification rate (Hours).

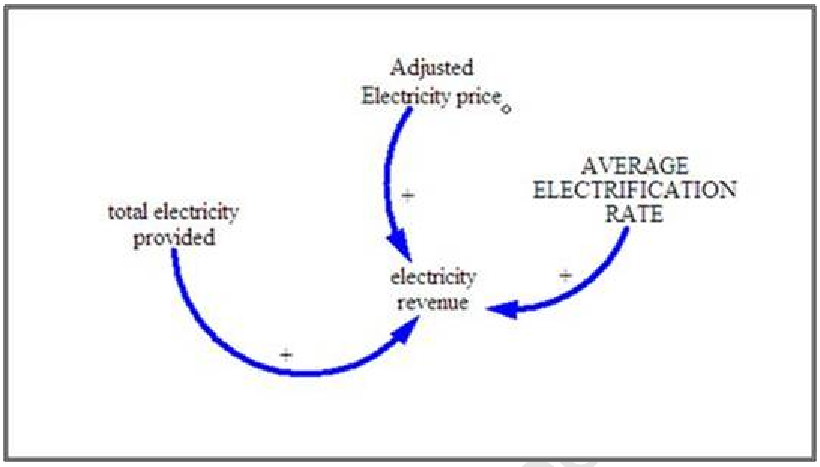


Figure 6.20: Electricity revenue sub model

Mathematically, electricity revenue is computed as;

$$\begin{array}{lllllll} \textit{Electricity} & & \textit{total electricity} & & \textit{Electricity} & & \textit{Average} \\ \textit{revenue } (t) & = & \textit{provided } (t) & * & \textit{price } (t) & * & \textit{electrification rate } (t) \\ \textit{[\$/year]} & & \textit{[MW]} & & \textit{[\$/MW]} & & \textit{[hours/year]} \end{array}$$

The average electrification rate is estimated as an annual fraction of the electrification time provided, by considering a 24-hours load pattern of peak (18.00 - 24.00), shoulder (6.00 - 18.00) and off-peak (24.00 - 6.00), for 365 days.

6.4.11 Electricity Price sub model

This sub model deals with the formulation of electricity price; it is one of the drivers of electricity demand. In addition, it influences investments and operations in form of electricity revenue. Electricity price is measured in US dollars per MWh. The structure of this sub model is shown in Figure 6.21;

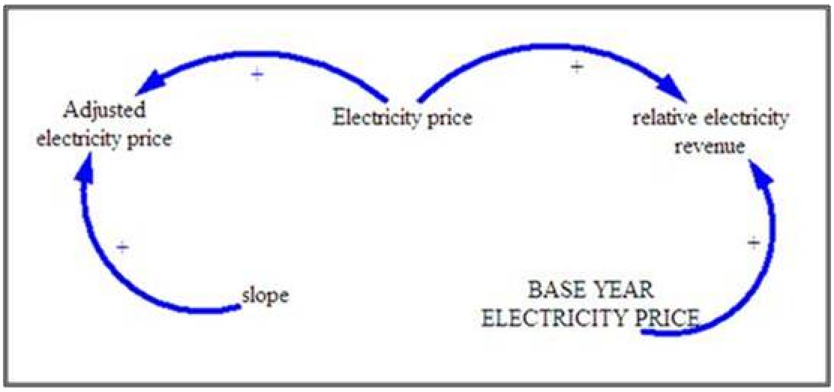


Figure 6.21: Electricity price sub model

The electricity price change between the base period and the current period is expressed by the relative electricity price.

$$\textit{Relative Electricity price(t) [dimensionless]} = \frac{\textit{Electricity price(t)[\$/MWh]}}{\textit{Base year electricity price[\$/MWh]}}$$

The electricity price for the historical period is introduced directly using an electricity price table function. From the current period, we use a RAMP function as an exogenous input to predict the adjusted electricity price, computed as follows;

$$\textit{Adjusted Electricity price (t)} = \textit{Electricity price table (time)} * \left(1 + RAMP(slope, current, final) \right)$$

A RAMP function means that from the current to the final period, electricity price will increase at a certain 'slope'. The 'slope', that is, the magnitude of the price increase, of the RAMP function is subjected to sensitivity tests (done later).

6.4.12 Total Investment Fund sub model

The total investment fund sub model attempts to analyze the dynamics between government funding, foreign donor support, and electricity sales and to identify policy levers that can be used to affect the generation and transmission investments. The total energy fund is assumed proportional to GDP. The more GDP generated, the bigger the total energy funding pie. Therefore, total energy fund is first derived as the product of GDP and the fraction of GDP dedicated to energy resources, in other words a fixed fractional GDP allocation.

The total investment fund is obtained as a function of foreign donor support and a fraction of total energy fund as illustrated in Figure 6.22. For a given level of allocation to investment, the energy policy is modeled in terms of proportion of funds allocated to generation investment and to transmission investment.

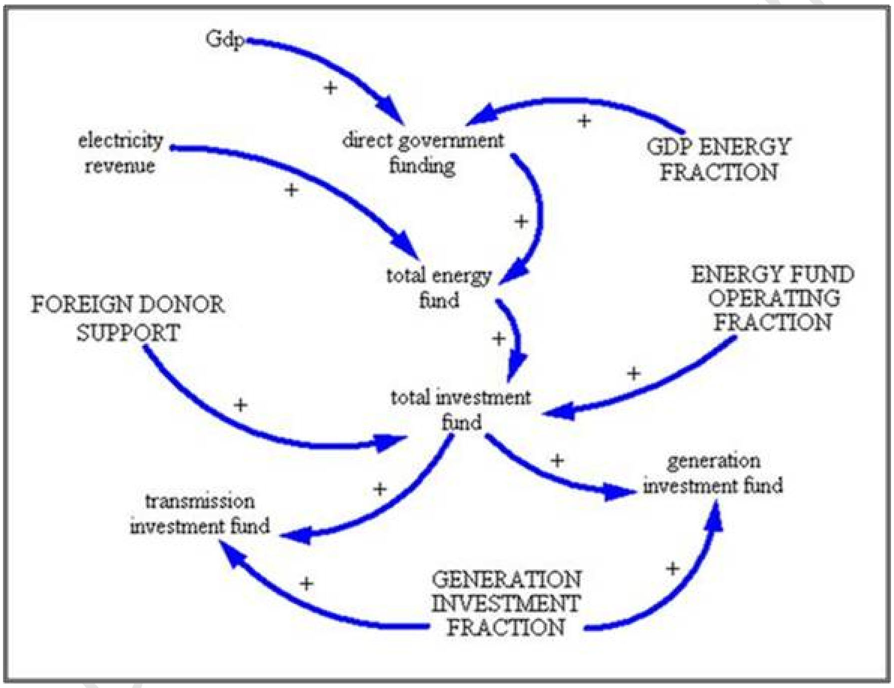


Figure 6.22: Total investment fund sub model

$$\begin{array}{l}\textit{Total energy fund}(t)\\ \textit{[\$/year]}\end{array} = \begin{array}{l}\textit{GDP}(t)\\ \textit{[\$]}\end{array} * \begin{array}{l}\textit{Energy policy fraction}\\ \textit{[1/year]}\end{array}$$

$$\begin{array}{l}\textit{Total}\\ \textit{investment}\\ \textit{fund}(t)\\ \textit{[\$/year]}\end{array} = \begin{array}{l}\textit{Foreign}\\ \textit{donor}\\ \textit{support}(t)\\ \textit{[\$/year]}\end{array} + \begin{array}{l}\textit{Total}\\ \textit{energy}\\ \textit{fund}(t)\\ \textit{[\$/year]}\end{array} * \left(1 - \begin{array}{l}\textit{Energy fund}\\ \textit{operating fraction}\\ \textit{[dimensionless]}\end{array}\right)$$

The generation investment fund is obtained as a fraction of the total investment fund, while the remaining fraction, $(= 1 - \textit{Generation investment fraction})$, is allocated to the transmission investment fund. Thus, generation and transmission investment fund at any time t are mathematically derived as follows;

$$\begin{array}{l} \textit{Generation} \\ \textit{investment fund(t)} \\ \textit{[\$/year]} \end{array} = \begin{array}{l} \textit{Total} \\ \textit{investment fund(t)} \\ \textit{[\$/year]} \end{array} * \begin{array}{l} \textit{Generation} \\ \textit{investment fraction} \\ \textit{[dimensionless]} \end{array}$$

$$\begin{array}{l} \textit{Transmission} \\ \textit{investment fund(t)} \\ \textit{[\$/year]} \end{array} = \begin{array}{l} \textit{Total} \\ \textit{investment fund(t)} \\ \textit{[\$/year]} \end{array} * \left(1 - \begin{array}{l} \textit{Generation} \\ \textit{investment fraction} \\ \textit{[dimensionless]} \end{array} \right)$$

6.4.13 Total Operating Fund sub model

The total operating fund sub model seeks to determine the generation and transmission operating fund. Figure 6.23 shows that total operating fund is obtained as a fraction of total energy fund. Additionally, most developing countries depend on foreign donor funds to manage the electricity generation systems. These donor funds are repaid, using the total energy operating fund, at an agreed repayment rate over a specified period of time.

For a given level of allocation to energy operating fund, the energy policy is modeled in terms of proportion of funds allocated to generation operating fund, transmission operating fund, and to annual donor repayment.

$$\begin{array}{l} \textit{Total} \\ \textit{operating} \\ \textit{fund(t)} \\ \textit{[\$/Year]} \end{array} = \begin{array}{l} \textit{Total} \\ \textit{energy} \\ \textit{fund(t)} \\ \textit{[\$/Year]} \end{array} * \begin{array}{l} \textit{Energy fund} \\ \textit{operating} \\ \textit{fraction} \\ \textit{[dimensionless]} \end{array} - \begin{array}{l} \textit{Annual} \\ \textit{donor} \\ \textit{repayment} \\ \textit{[\$/Year]} \end{array}$$

$$\begin{array}{l} \textit{Annual donor} \\ \textit{repayment(t)} \\ \textit{[\$/Year]} \end{array} = \begin{array}{l} \textit{Foreign donor} \\ \textit{support(t)} \\ \textit{[\$/Year]} \end{array} * \begin{array}{l} \textit{Donor} \\ \textit{repayment rate} \\ \textit{[dimensionless]} \end{array}$$

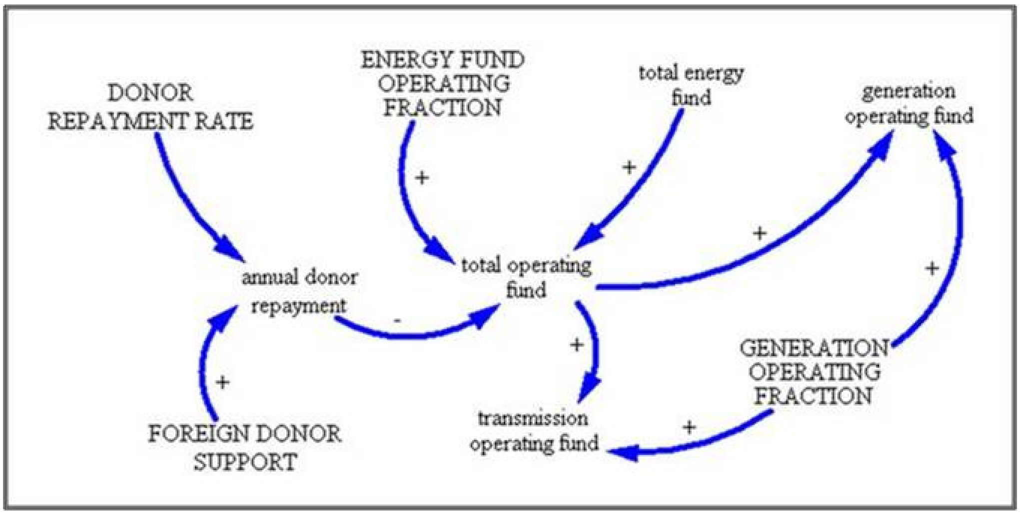


Figure 6.23: Total energy operating fund sub model

The generation operating fund is obtained as a fraction of the total operating fund, while the remaining fraction, ($= 1 - \textit{Generation operating fraction}$), is allocated to the transmission operating fund. Thus, generation and transmission operating fund at any time t are derived as follows;

$$\begin{array}{l} \textit{Generation} \\ \textit{operating fund(t)} \\ \textit{[\$/year]} \end{array} = \begin{array}{l} \textit{Total} \\ \textit{operating fund(t)} \\ \textit{[\$/year]} \end{array} * \begin{array}{c} \textit{Generation} \\ \textit{operating fraction} \\ \textit{[dimensionless]} \end{array}$$

$$\begin{array}{l} \textit{Transmission} \\ \textit{operating fund(t)} \\ \textit{[\$/year]} \end{array} = \begin{array}{l} \textit{Total} \\ \textit{operating fund(t)} \\ \textit{[\$/year]} \end{array} * \left(1 - \begin{array}{c} \textit{Generation} \\ \textit{operating fraction} \\ \textit{[dimensionless]} \end{array}\right)$$

6.5 Summary and Discussion

This chapter has presented a EGP-SD model for long-term planning of electricity generation in a developing country context. The SD simulation model is a tool for improving on the qualitative understanding complex inter-relationships between elements within the system. Increased insight will, in turn, result in better decision making.

The developed model allows the comprehensive description and analysis of EGP system operations taking into account electricity generation and transmission capacity, capital investments, operating expenses, capacity loss due to insufficient operating expenditure, available electricity capacity allocations to demand sectors, and the effects of GDP growth rate and population growth rate on the system. The EGP-SD model includes causal relationships and feedback interactions that give rise to the electricity generation and capacity allocation dynamics in the system.

The available electricity capacity allocation to demand sectors is modeled as function of sectoral electricity demand and the planner's preference coefficient. Variations in the preference coefficient leads to the electricity capacity proportional allocation varying logarithmically with the total available electricity-to demand ratio.

The EGP-SD model is meant to simulate how the system reacts to changes in investment and operating funds. The structure of the model captures the electricity generation and transmission process and the relationship between the operating expenditure and loss in electricity capacity. Available electricity is driven by the generation and transmission availability factors. Electricity shortage is derived by the ratio of available electricity to demand.

The model explores the effect of some factors, like population growth rate, GDP growth rate, and electricity price on available electricity capacity. The model attempts to analyze the dynamics between government funding, foreign donor support, and electricity sales and to identify policy levers that can be used to affect the electricity investments and operations. The total energy fund is assumed to be proportional to GDP, such that, the more GDP generated, the bigger the total energy pie.

The next chapter presents the implementation of the EGP-SD model, including developing and testing of a strategy for incorporating goal-seeking methods into SD modeling.

Chapter 7

EGP-SD Model Implementation

7.1 Introduction

This chapter implements the EGP-SD model, by examining the dynamic behavior of the electricity generation system in response to different policy decisions. Computational simulation results of applying this model to the electricity sector in Uganda are presented. The understanding of the long term behavior of EGP is improved by means of a sensitivity analysis on some key parameters. Analysis of different policies is done by varying controllable parameters to study the system's impacts. An investigation by means of Monte Carlo simulations are conducted to assess the ability of the developed model to capture the uncertainty of the long term dynamics of the system.

The chapter also discusses the development and implementation of a strategy for incorporating goal-seeking into the EGP-SD model. The strategy uses a heuristic optimization approach aimed at identifying a combination of parameter values that produces the ideal model behavior over the entire simulation time. The resulting, validated and verified, model will provide important insights into the EGP system behavior and its causes. This chapter concludes with a summary of findings and some suggestions for policy implementation.

The VENSIM® Professional 5.10 has been chosen to be used for the implementation of the EGP-SD model, [Ventana Systems, 2007].

7.2 EGP-SD Model Parameters

Generally, a SD model can be represented by two characteristics: variables and parameters. A variable is a quantity whose values change dynamically in the model, whereas parameter values are fixed for the duration of the model run. Typically, parameters may represent external conditions under which policies are to be evaluated. The EGP-SD model parameters were derived from analysis of energy data and through meetings with energy experts. A summary of basic values for model parameters is presented in Table 7.1. To some extent these are illustrative and mainly for purposes of sensitivity analysis, and users may later implement other values.

The initial conditions correspond to the initial values of the variables in the model. The initial period for the EGP-SD model is the year 2000. The initial conditions establish the state of the system at the beginning of the simulation. They are set in such a way as to attempt to start the simulation in a balanced equilibrium. A summary of initial conditions is presented in Table 7.2.

7.3 EGP-SD Simulation Results: Base Case scenario

This section presents the simulation results with base case values. The model is simulated to see the behavior with the normal values for the model's parameters. The simulation results are analyzed in terms of the underlying causes of the simulated behavior.

Table 7.1: EGP-SD model parameters

Parameters	**Value [Units]**
External parameters	
Time Step	0.0625[Years]
GDP growth rate	6.5%[1/year]
Ideal generation operating cost	90,000 [$/MW]
Ideal transmission operating cost	99,000 [$/MW]
Generation average lifetime	50 [Years]
Transmission average lifetime	35 [Years]
Generation capacity investment factor	3.1e-007 [MW/$]
Transmission capacity investment factor	2.05e-007 [MW/$]
Generation availability factor	0.95 [Dimensionless]
Transmission availability factor	0.90 [Dimensionless]
Foreign donor support	1.1e+008 [$/year]
Donor repayment rate	4.5% [1/Year]
Net birth rate	4.65% [1/Year]
Net death rate	1.47% [1/Year]
Policy parameters	
Generation operating fraction	0.55 [Dimensionless]
Generation investment fraction	0.45 [Dimensionless]
Energy fund operating fraction	0.235 [Dimensionless]
GDP energy fraction	0.0025 [1/Year]
Industrial preference coefficient	0.75 [Dimensionless]
Average electrification rate	2920 [Hours/Year]

Table 7.2: EGP-SD model initial values

Parameters	**Initial value[Units]**
Base year	2000
GDP	5.734 [Billion $]
Population	22.5754 [Million People]
Industrial demand	180 [MW]
Non-industrial demand	100 [MW]
Electricity price	92 [$/MWh]
Electricity generation capacity	200 [MW]
Electricity transmission capacity	230 [MW]
Standard MW per GDP[a]	3.13917e-08 [MW/$]
Standard MW per Population[b]	4.4296e-06 [MW/People]

[a] $= \frac{Base year industrial demand}{Base year GDP}$
[b] $= \frac{Base year Non-industrial demand}{Base year Population}$

7.3.1 Electricity Price

In Uganda, like any developing country, electricity prices are set to foster economic development. As a matter of policy, electricity prices are set below real costs of producing and transmitting electricity. In the process, government subsidizes electricity capital investments and operations. In this study, electricity price is an exogenous variable that is introduced directly from data series from 2000 to 2009; [UBOS, 2009],[UBOS, 2010]. For the base case scenario, its is assumed to keep at that level of 2009 until 2030. In fact, electricity price is a primary driver of electricity generation and transmission capacity.

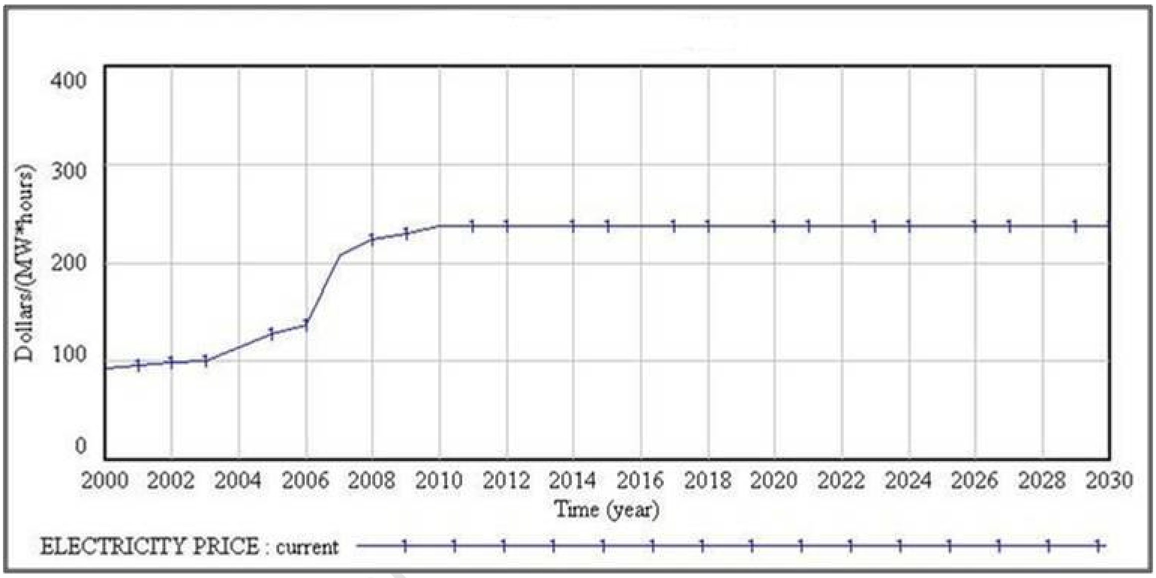


Figure 7.1: Electricity price for base case scenario

Figure 7.1 shows the electricity price keeps at \$237.19 per MWh until 2030. For the time after 2009, we use some exogenous input to predict the electricity price trend (done later).

7.3.2 Electricity Generation Capacity

Figure 7.2 shows the base case simulation results for electricity generation capacity. The inputs for the electricity generation capacity model are generation investment funds and generation operating funds. The model predicts that generation capacity will keep increasing over time. The trend in the 2000 - 2008 period matches the historical data presented in the reference mode, see Section 6.3.2.

The results of the simulation demonstrate that the increasing trend in generation capacity will continue into the future. This may be explained by GDP growth as the primary driver of electricity generation capacity. This results in more investments into new generation capacity and reduction in loss in generation capacity. In spite of natural loss in generation capacity due to aging of the generation plants, an increase in the generation operating fund reduces the loss in generation capacity. However, actual available generation capacity is guided by the generation availability factor.

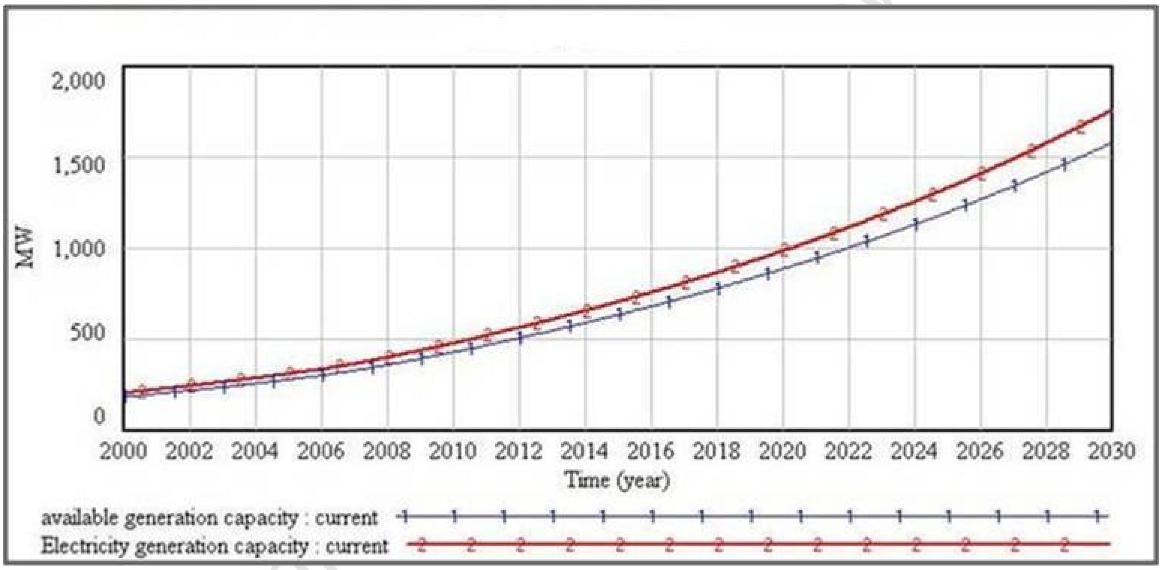


Figure 7.2: Electricity generation capacity for base case scenario

This finding is consistent with the World Energy Outlook[2006] that projects an increase in world total electricity generation capacity from 2 percent to 7 percent between 2005 and 2030. This increase occurs largely in developing countries that are adopting policies to increase use of renewable sources of energy. This model can be used to analyze the relationships between new and lost generation capacity, and the actual available electricity capacity that is transmitted to the consumers.

An electricity generation system aiming at avoiding a shortage of electricity, requires the availability of adequate transmission capacity to transport electricity to the end-consumers. As seen in Figure 7.3, for the base case scenario, electricity transmission capacity will keep increasing for a period of time. The transmission of electrical energy is a very important consideration, particularly in developing countries with widely separated population centers.

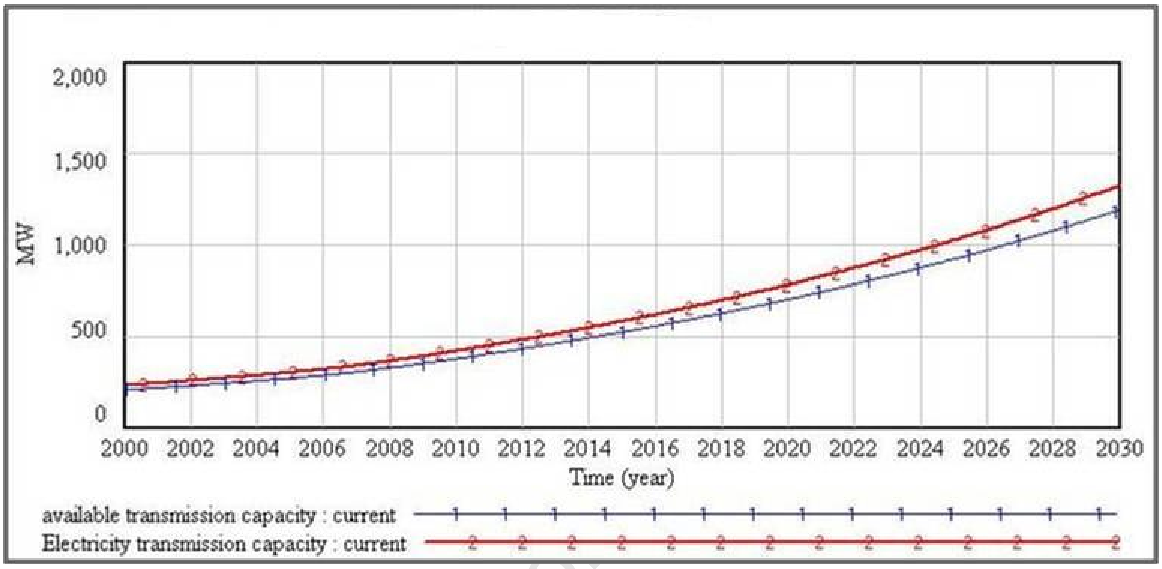


Figure 7.3: Electricity transmission capacity for base case scenario

These models developed can simulate the electricity generation and transmission system to determine the actual electricity provided to the consumers. The models predicts that, as long as there is GDP growth to stimulate new investments in generation and transmission capacity, the increasing trend in actual electricity provided to consumers will continue in the future.

7.3.3 Electricity Demand

The electricity peak demand is grouped into industrial and non-industrial electricity demand sectors. Total electricity demand is the sum of industrial and non-industrial electricity demand. GDP and relative electricity price are the primary drivers of the industrial electricity demand, while population growth is a driver to non-industrial electricity demand. The initial conditions for the base year (2000) indicate that industrial electricity demand in Uganda was 1.8 times more than the non-industrial demand.

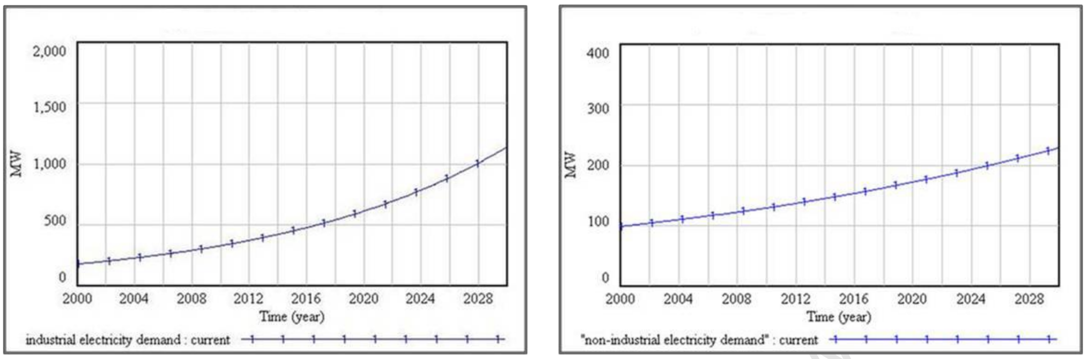


Figure 7.4: Electricity demand for base case scenario

Figure 7.4 indicates an increasing trend in industrial and non-industrial electricity demand. Improvements in GDP and general economic growth are responsible for an increase in electricity consumption. This finding is consistent with IEA [2006] that projects global electricity demand to increase at an average rate of 2.6 percent up to 2030. The fastest growth in electricity demand will be in developing countries, at an average rate of 4.6 percent. A growing economy, combined with innovation to develop new electronic devices and therefore new ways to use electricity, leads to a considerable upward pressure on industrial electricity demand.

In absolute terms, industrial electricity demand grows more rapidly than the non-industrial demand. This is explained by the slower rate at which population grows compared to GDP, as shown in Figure 7.5. An increase in GDP leads to a corresponding increase in industrial electricity demand, while an increase in population leads to an increase in non-industrial electricity demand.

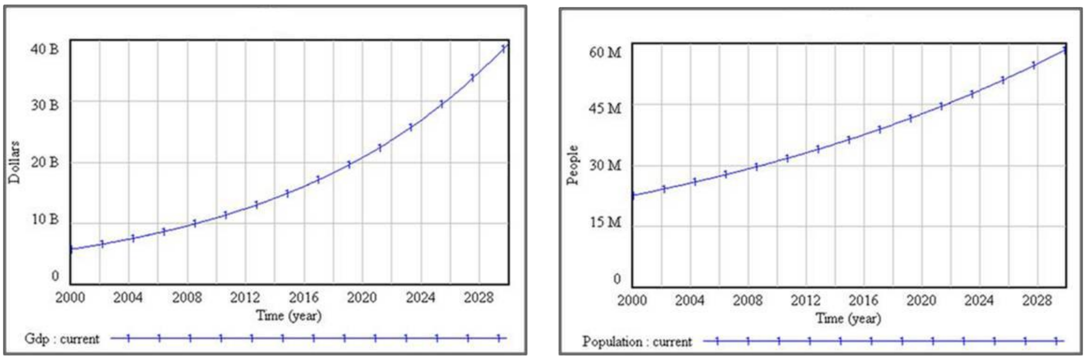


Figure 7.5: GDP and Population growth

7.3.4 Electricity Allocation

Electricity capacity allocation to demand sectors is determined by the proportion of total available electricity to demand and the sectoral preference coefficient. The available electricity-to-demand ratio measures the degree of electricity supply satisfaction to the demand sectors. For example, if the industrial available electricity-to-demand ratio is less than one, it implies that there is an electricity shortage in the industrial sector.

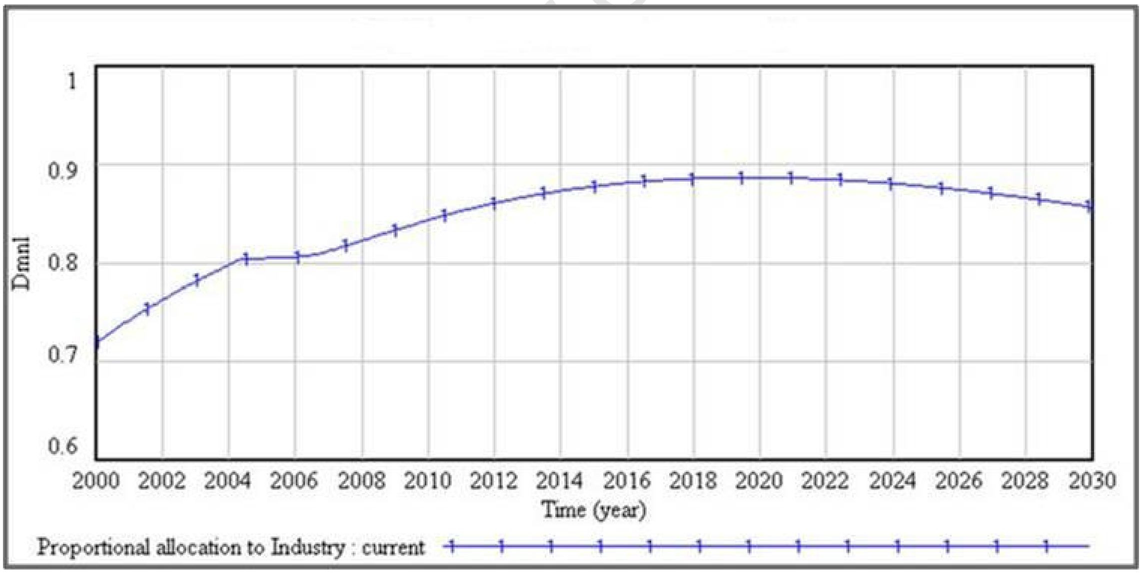
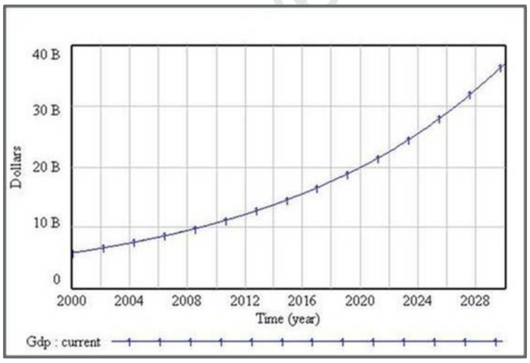


Figure 7.6: Allocation to Industry for base case scenario

Figure 7.6 shows the proportional allocation of electricity capacity to industry sector for the base case scenario. As seen in the figure, for the historical period 2000 - 2008, allocation is influenced by variations in industrial electricity demand, induced by the historical electricity prices. After 2008, there is an increasing trend in allocation to industry sector mainly because of the increase in industrial available electricity, that is driven by GDP growth. However, the trend eventually settles to less than 1.0 as a result of electricity shortages. This is because industrial available electricity cannot exceed the industrial electricity demand. There can not be electricity allocation of more than what is demanded.

7.3.5 Electricity Fund

Electricity planning in many developing countries is constrained by lack of finances for electricity-related investments. The capital and operating funds required to develop and run the electric power sector, of course, compete with those same requirements in other sectors of the economy. In this study, total electricity fund is generated from electricity revenue and direct government funding. It is assumed that a fraction of GDP is allocated to the energy fund, and for the base case scenario, the GDP fraction is assumed to be 0.0025, and will keep at this level until 2030. Figure 7.7 shows that the energy fund grows in response to increases in GDP, since GDP growth is considered as the primary driver.



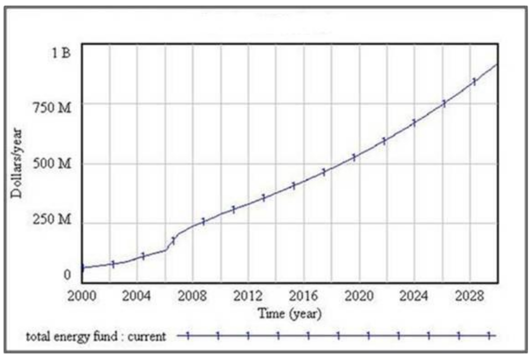


Figure 7.7: GDP and Total energy fund for base case scenario

The total energy fund is allocated to investment and operations fund by an operations fraction, assumed as 0.45, for the base case scenario. Investment and operations fund increase as a response to the increase in the total energy fund. The investment fund is also boosted by the foreign donor support, that is eventually repaid from the operating fund at some predefined donor repayment rate. Investments in new generation and transmission capacity are based upon the adequacy of the generation and transmission investment fund, respectively. These funds are derived from the total investment fund using a generation investment fraction of 0.45, while the balance of 0.55 goes to the transmission investment fund. These values are for illustration of the model, users may implement with other values.

The total operating fund is used to facilitate generation and transmission operations expenses. The ratio of actual and ideal generation or transmission operating expenditure is the main determinant of loss in generation or transmission capacity. If the generation or transmission operating expenditure ratio is less than 1, it implies that ideal operating expenditure is more than the actual operating expenditure indicating a loss in generation or transmission capacity.

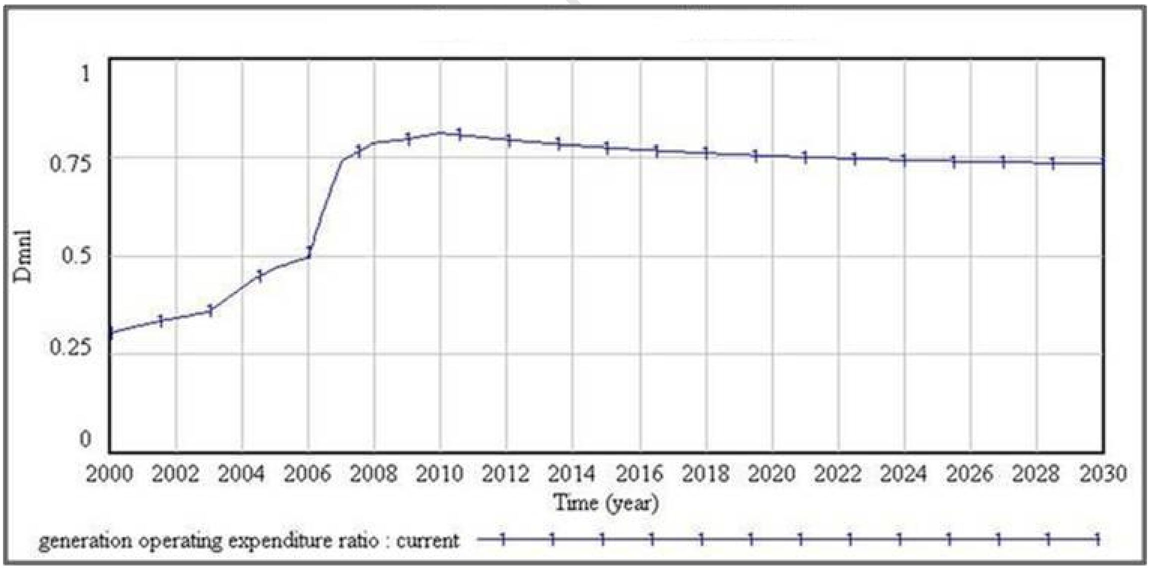


Figure 7.8: Generation operating expenditure ratio for base case scenario

As illustrated in Figure 7.8, the generation operating expenditure ratio first increases before attaining equilibrium. This is influenced by the behaviour of historical electricity price that is the primary driver of electricity revenue. After the year 2008, electricity price is assumed to be constant for the rest of the planning period, thus stabilizing the generation operating expenditure ratio.

7.4 EGP-SD Model Calibration

Model calibration is the process of estimating the model parameters to match available "real world" data of the system. The objective of model calibration is to find values of model parameters that make the model generate behavior curves that best fit the "real world" data. The values of the parameters constituting the model are estimated by investigating the relationships among the observed data gained from the real world. Model calibration can either be done by iteratively varying one parameter at a time or automated, [Oliva, 2003]. The model calibration continues until the gap between the observations and the estimates falls within a specified level of confidence. However, comparisons between the estimated and the observed data always show the range of unavoidable uncertainty that is inherent in the observed data, [Kim, 1998].

VENSIM® has a built-in optimizer functionality which can be used for model calibration. The VENSIM® optimizer is based on the Powell algorithm, [Elmahdi, 2006], which numerically maximizes or minimizes an arbitrary objective function; in VENSIM® terminology the objective function is called "payoff".

The payoff is automatically specified by the software as the sum of the squared deviations between the observed values and the model output for one or more user-specified variables; a weight can be attached to each of the variables. Parameter values are then chosen in an iterative process to minimize payoff. The optimizer searches through all the values for the parameter to find the best fit of the model data with the "real world" data.

First, data on total electricity demand (MW) and GDP ($) were collected from various sources, in order to calibrate the EGP-SD model.

Next, a payoff function must be defined for the optimization process. For this particular simulation, the payoff function includes the four variables for which data was obtained: total electricity demand, population, and GDP. The payoff weights for the variables are set equal to one. The payoff function is defined as the difference between the data and the model estimates multiplied by the specified weight (in this case one). This product is then squared. This number summed for all the data points is equivalent to $\sum(Y_i - \hat{Y})^2$ which is the residual sum of squares. Finally, the payoff function, or residual sum of squares, is minimized via Powells method. The end result of these stages is a set of parameter estimates derived through a nonlinear minimization of the residual sum of squares.

In order to indicate the reliability of the calibrated parameter estimates, a statistical indicator called the *confidence interval* (CI) is computed for each parameter, [Keller and Warrack, 2003]. The more likely it is for the interval to contain the parameter value, the wider the interval is. A result with a smaller CI is more reliable than a result with a large CI. Without the CI test, it is difficult to determine whether the parameter values can be significantly different from the estimated values, and therefore also difficult to assess the reliability of the estimates.

Table 7.3: EGP-SD model calibration parameters

Parameter name	**Assumed value**	**Calibrated value**	**Confidence interval**
Generation operating fraction	0.55	0.408	0.283 - 0.831
Generation investment fraction	0.45	0.592	0.169 - 0.717
Energy fund operating fraction	0.235	0.240	0.166 - 0.379
Industrial preference coefficient	0.75	0.767	0.493 - 1.000
GDP energy fraction	0.0025	0.003	0.00089 - 0.0072

Table 7.3 presents a list of internally specified parameters used to obtain a match between

observed and simulated EGP-SD model behavior. Also indicated is the 95 percent confidence intervals for the calibrated parameter estimates.

The calibrated parameter values are generally in line with original assumptions and hence increasing their numerical accuracy. And the confidence interval gives an estimated range of values which is likely to include the parameter values.

7.5 EGP-SD Model Validation

Confidence in the EGP-SD model is established through its testing and validation on the basis of the data utilized. In order to draw inferences about the future behavior of the system from results obtained from the simulation, the model should be a reasonably valid representation of the real system. Sterman [2000] outlines model testing as an iterative process that starts at the beginning of the modeling process. This step involves the testing of the model as to whether it replicates the behavior of the real-world system.

Validation requires comparing model predictions with information other than that used in estimating the model. A wide range of tests helps the modeler understand the robustness and limitations of the SD model. And to verify whether the variables and parameters of the model have a meaningful concept in the real world, [Dimitrovski et al., 2007].

If the model output is reasonable and consistent with whatever supporting data might exist, then the model can be considered validated. The validation is carried out under three categories, viz. historical validation of the data, a structural verification test and a dimensional consistency test, [Shreckengost, 1985].

7.5.1 Historical Data Validation

This involves comparing model behavior to the historical data collected in the "real world". The validation of the model is performed by comparing estimates of the key variables with the observed data for each of the variables. In order to establish how close the estimates are to the "real data", a correlation coefficient analysis is applied. Ford and Flynn [2005] calls this process "statistical screening".

The major challenge in validating models specific to developing countries is lack of reliable historical data. In fact, it was not possible to get complete data on electricity supply for the period 2000 - 2009. For this study, the selected key variables for validation of the EGP-SD model are total electricity demand (MW) and GDP ($).

Table 7.4: Model validation using Historical data

Year	Total electricity demand (MW)		GDP (Billion $)	
	Real	Estimated	Real	Estimated.
2000	280.0	268.20	5.734	5.734
2001	295.3	281.95	6.177	6.109
2002	310.1	296.70	6.320	6.508
2003	325.5	312.31	6.598	6.934
2004	332.5	327.68	6.822	7.387
2005	339.4	344.01	8.712	7.870
2006	348.4	362.04	9.322	8.385
2007	360.2	378.30	12.436	8.933
2008	372.8	397.64	13.529	9.517
2009	381.2	411.05	14.287	11.014
	$R^2 = 0.9645$		$R^2 = 0.9888$	

Table 7.4 shows the actual and estimated values, plus the corresponding correlation coefficients, R^2. The estimates generated by the EGP-SD model demonstrate an excellent correlation between the "real world" data and the model estimated data. The correlation analysis was conducted by importing the sensitivity data from VENSIM® to the STATA[1] computer program version 10.0

[1]http://www.stata.com

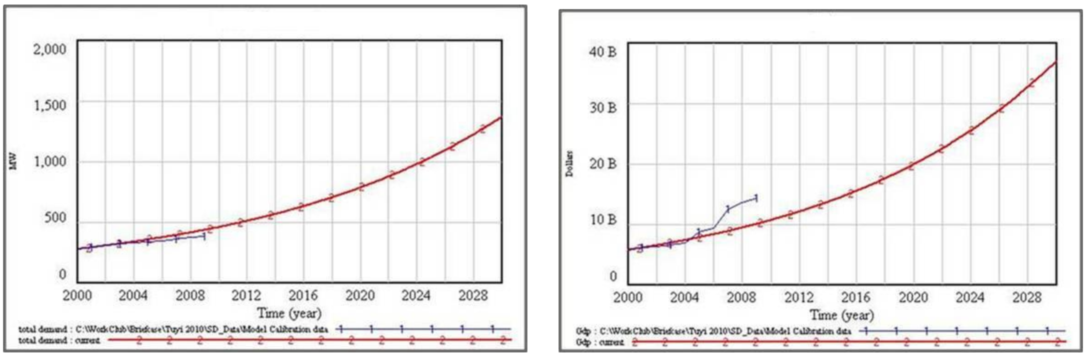


Figure 7.9: Total demand and GDP validation

Figure 7.9 shows the comparison between “real world” and model estimated data. Points representing the real and model estimated values show an overall increasing trend. From 2006, Uganda recorded tremendous increase in GDP, due in part to increased foreign direct investment, improved incentives for production and exports, and reduced inflation. It can be observed that there is a reasonably good match between the real and the corresponding EGP-SD model generated behavior patterns. Thus, it can be concluded that the model is behaviorally acceptable.

Besides, an exact matching between real data and model data points is not required for model validity, because a SD model is not designed to include the internal and external details and random factors that are needed in short term forecasting, [Barlas, 1989, 1996]. The purpose of a SD model is to generate the major dynamic behavior patterns of the system, in the long term. Thus, what is required is the matching of the major patterns of behavior of the model and the real system, rather than individual data points.

7.5.2 Structural Assessments Tests

Structural assessment tests ask whether the model is consistent with knowledge of the real system relevant to the purpose. For a SD model to be structurally valid, causal relationships in the model have to be valid and the assumptions and simplifications that are made in the modeling process are justified, [Barlas, 1996]. The validity of the dynamic hypotheses must thus be analyzed. Barlas [1996] notes that, if the structure of the model is not correct, there is a risk that the model might replicate historical behavior for the wrong reasons.

The structure of the EGP-SD model was validated through interviews with energy experts from MEMD, ERA, UMEME, UETCL, and UEDCL. The experts interviewed agreed with the overall structure of the model. For example, they concur that industrial electricity demand would increase as GDP increases. The experts also agreed with how non-industrial electricity demand is influenced by population growth and electricity price. However, there were some debate on the GDP energy fraction, total investment and operating fraction, and generation investment and operating fraction. They noted that electricity capacity would change significantly if these parameters were changed. Overall, the experts agreed that the parameters were indicative of the same values in a real system. These types of disagreements are normal within SD methodology.

The overall purpose of the EGP-SD model is to simulate the dynamic behaviour of the electricity generation system, and debate over structure and parameters helps to clarify the system under study. With any simulation, there will be areas of the system that are not explored or are oversimplified because of the difficulty in expressing them clearly. This is true particularly with a SD approach.

7.5.3 Dimensional Consistency

Dimensional consistency tests seek to verify that each model equation is dimensionally consistent. Dimensional consistency test entails checking the right-hand side and left-hand side of each equation for dimensional consistency. These tests are carried out by direct inspection of the equations and the actual simulation of the model, [Sterman, 2000, page 866]. The dimension of each variable is specified when the model is being built. The consistency test for dimension may reflect nothing more than unit error or missing units.

The EGP-SD model was simulated using VENSIM® 5.10 software and the simulation did not generate any dimensional consistency errors. Results were obtained and have been presented in earlier sections of this chapter. Furthermore, by inspecting all the equations and automated dimensional analysis by the simulation software, the model is dimensionally consistent.

7.6 EGP-SD Sensitivity Analysis

Sensitivity tests basically ascertain whether or not minor shifts in the model parameters can cause shift in the behavior of the model. Sensitivity analysis is conducted, using the sensitivity tool in VENSIM®, to ensure parameter estimation errors do not have large impacts on the model results. It helps modelers decide the accuracy required when estimating the model parameters. The higher the accuracy of the estimations of the model outputs desired, the higher would be the resources required.

7.6.1 Parametric Sensitivity Analysis

The conventional approach of SD is to vary these parameters either one at a time or in combination to establish their effect. Once the robustness of the model is ensured, the model can be used for policy making, [Anand et al., 2006]. Ideally, one would identify the parameters which contribute most to variation in the optimal performance over the full parameter space of the model. However, this is computationally infeasible.

Another approach is to evaluate the relative sensitivity of the key model variables to variation in individual policy parameters. If the model output is linear in all the parameters, this approach would provide a full understanding, but this is very unlikely.

The best that this method can provide is a sense of the model's response to each parameter. In principle, they are manageable, and it is hoped that by changing them, the behavior of the model will be different; i.e., it is possible to improve the models behavior.

Impact of GDP growth rate

The assumption of no GDP growth rate in the base case scenario is relaxed, while keeping other parameters just as they behave in the base case scenario. In the last decade, Uganda's GDP growth rate has average 6.5%. Sensitivity analysis on GDP growth rate considers two scenarios; High growth (9%) and low growth (4%). The behavior of GDP growth is showed in Figure 7.10. It can be noted that the GDP in both scenarios grows exponentially.

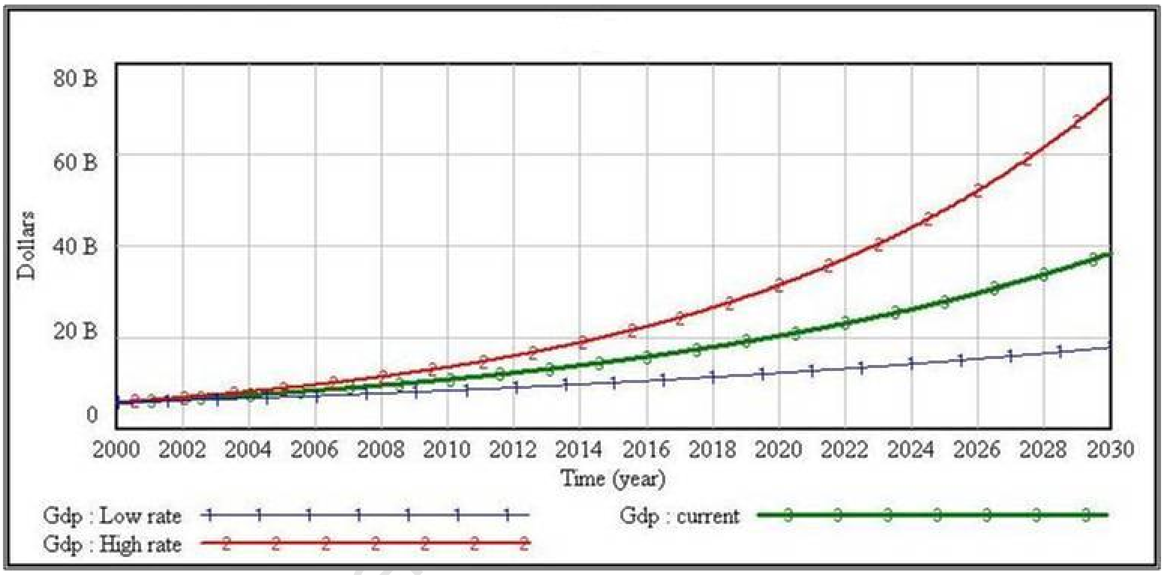


Figure 7.10: GDP sensitivity

The industrial electricity demand is closely related to GDP growth, this situation can happen if the economic growth experiences an increase. An increase in GDP does contribute to the increased industrial electricity demand, Figure 7.11. In such a situation, any shocks to electricity generation will adversely affect industrial output and thereby reducing real GDP growth.

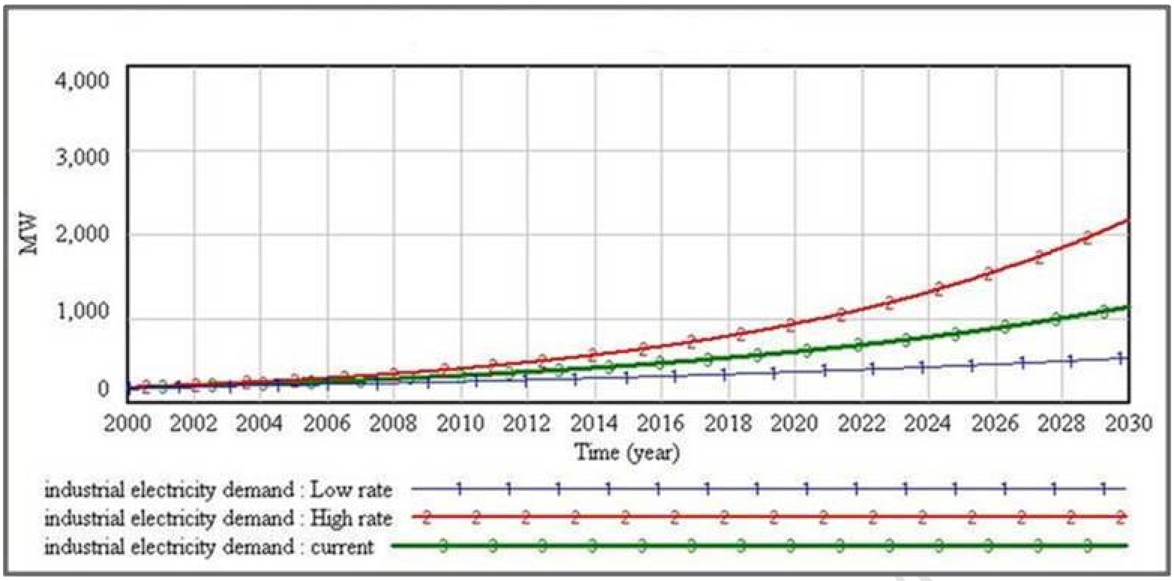


Figure 7.11: Industrial electricity demand under GDP sensitivity

Impact of GDP energy fraction

A feasible variable that can be politically influenced is the fraction of GDP to allocate to the energy fund. This could be influenced by the country's economic development. This value works as the budget cap for all the energy activities. For this reason, the numerical value of GDP energy fraction must be carefully selected as it has a decisive influence on the long-term electricity generation dynamics. Figure 7.12 shows the total electricity provided under different assumptions for the GDP energy fraction, that is, low fraction (0.001) and high fraction (0.006).

Impact of generation investment fraction

Further simulations were carried out with generation investment fractions of 2.5% in both directions, in order to determine the consistency of results and gain more insights into the behavior of the system. Such deviations can occur as a consequence of changes in both total investment fund and the perceived policy of investing in electricity generation at a certain time. Another influencing factor could be the energy sector financing structures.

The results indicate that increasing generation investment fraction results into increased

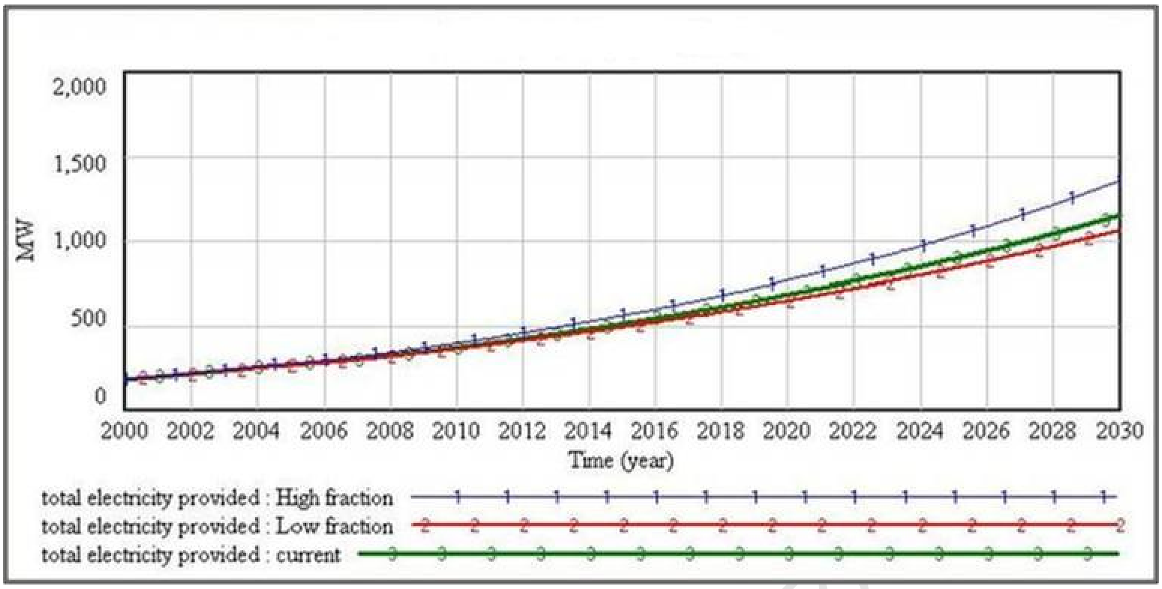


Figure 7.12: Total electricity provided under GDP energy fraction sensitivity

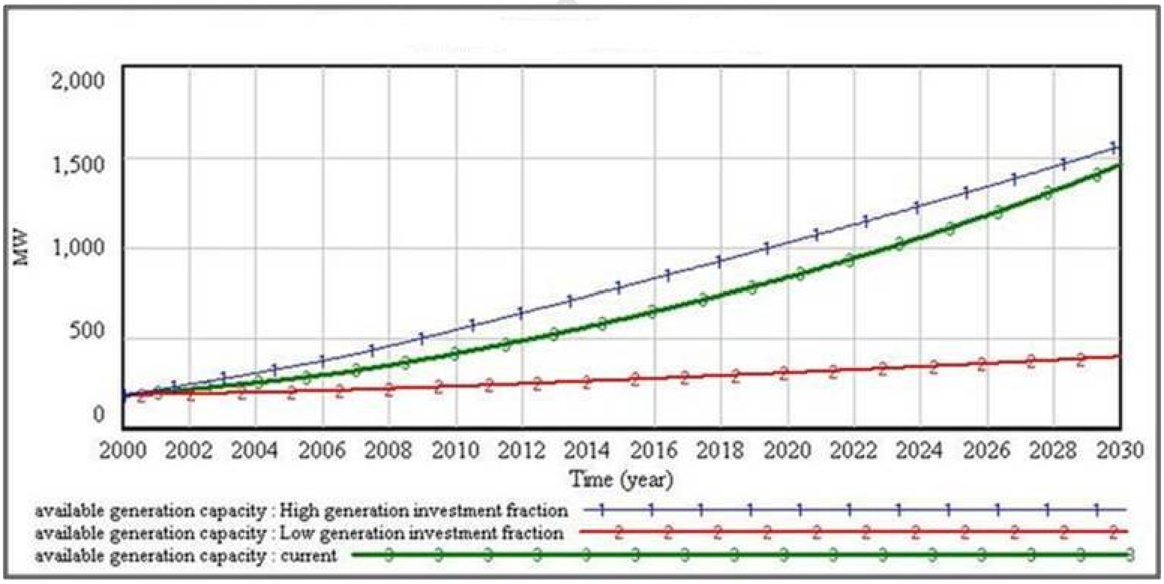


Figure 7.13: Available generation capacity under generation investment fraction sensitivity

available generation capacity. Thus the results of this model overturn the traditional mental models that we possess and encourage us to investigate system structure in more detail.

Parametric sensitivity analysis is unsatisfying for two reasons: First, the model behavior is highly nonlinear, and univariate sensitivity analysis neglects potentially critical interactions among variables. Second, the analysis makes no use of subjective information about the relative uncertainty of the various parameters; it merely identifies parameters which, if they were uncertain, might have a substantial impact.

7.6.2 Multivariate Sensitivity Analysis

In the EGP-SD model, there are some parameters that are subject to significant uncertainty, so it is important to assess their impact. This section presents a multivariate sensitivity analysis (also called Monte Carlo simulation analysis) to determine the effects of variation in the model parameters on the model outputs in a stochastic manner.

A random noise input is used to drive parameter variations. Next, 200 simulations are conducted with varying noise seeds to ensure the random variations are unique, by using Latin hypercube sampling. A sensitivity graph is drawn with percentage delimitations showing the confidence bounds, to show how much changes in the input parameters affect the output of the model. The graph illustrates the amount of uncertainty associated with each parameter. In addition, the mean value is plotted for purposes of comparison.

Electricity price

Based on the baseline scenario, the constant electricity price assumption is relaxed and then simulate the EGP-SD model with a RAMP increase in electricity price.

From the historical trend and literatures, there has been a rapidly increasing rate on electricity price before 2009, more than 2 times the price level in 2000. No body knows how it will behave in the future, but there are high possibilities that electricity price will keep increasing after 2009. A RAMP function is used to assume some variations in electricity price, as follows;

$$\textit{Adjusted Electricity price} \quad = \quad \textit{Electricity price(time)} * (1 + RAMP(slope, 2009, 2030))$$

The RAMP function above means, from 2009, the electricity price will increase at a certain *slope*. A sensitivity test on the slope of RAMP function is carried, varied between 0.00 and 0.010 and the model will be simulated for 200 times.

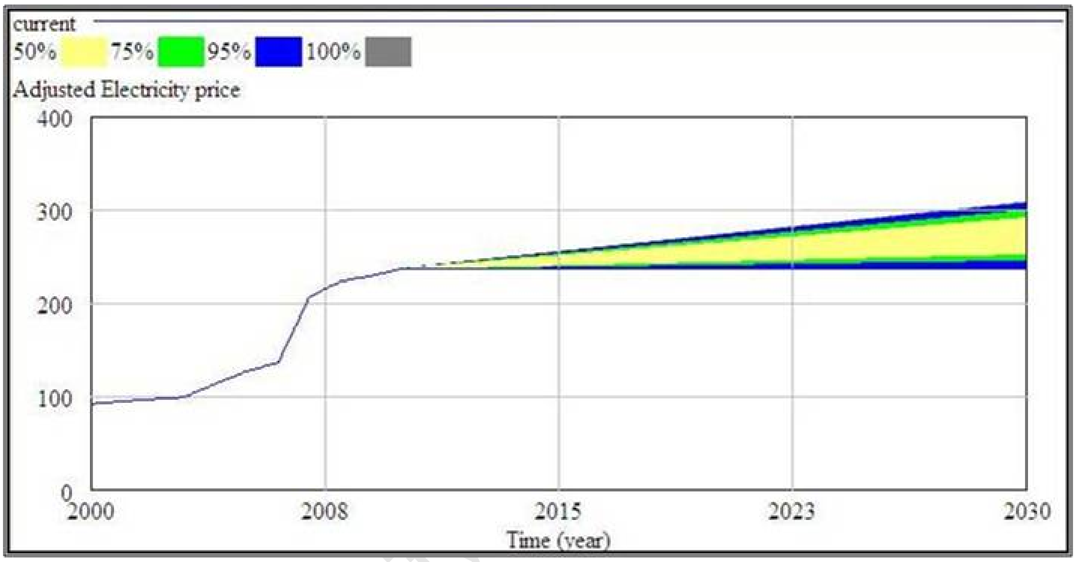


Figure 7.14: Electricity price sensitivity

Figure 7.14 shows the variations in electricity price. The line in bottom area is the behavior of baseline scenario. The simulation results in the graph are displayed as confidence bounds. These are computed at each point in time by ordering and sampling all the simulation runs. For a confidence bound shown as 50 percent, there is a 50 percent probability that the variable will have a value between the boundaries that delimit that percentage. A 50 percent means half of the 200 simulations will concentrate in this area with specified color. A 75 percent means a quarter of the 200 simulations will concentrate in the area with specified color.

When the electricity price varies like Figure 7.14 shows, the available electricity-to-demand ratio will increase correspondingly as a result of RAMP input, the bigger the RAMP slope, the bigger the variation is. The results of the available electricity-to-demand ratio caused by the change of the RAMP slope are depicted Figure 7.15. It shows that there is a 50 percent chance that available electricity-to-demand ratio will vary between approximately 0.88 and 0.95 as a result of variation of electricity price in a stochastic manner.

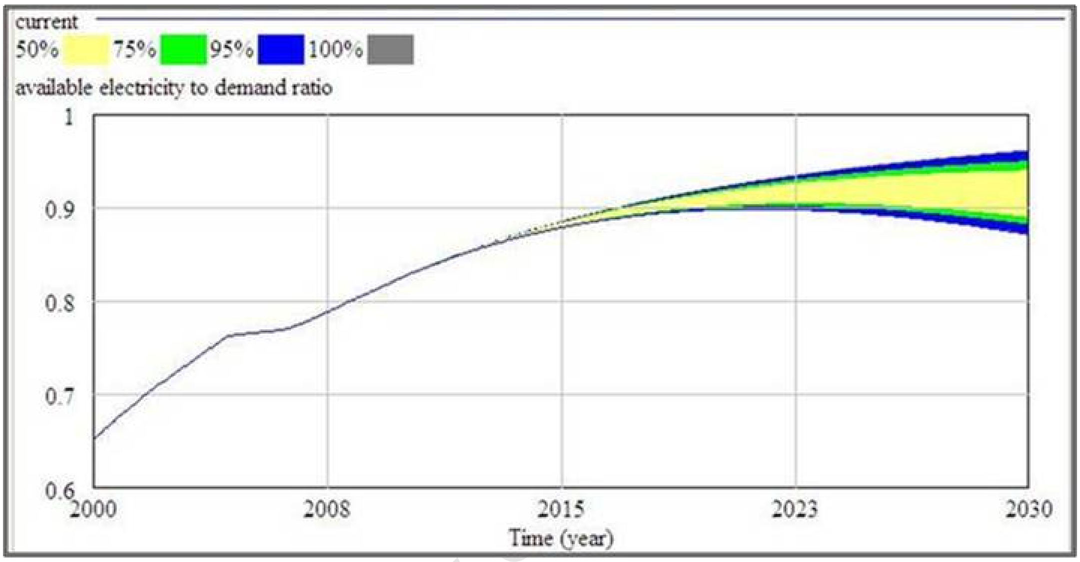


Figure 7.15: Available electricity-to-demand ratio under electricity price sensitivity

GDP growth rate

In developing countries, GDP varies a lot in historical data, and its difficult to predict its future with absolute certainty. As depicted in the parametric sensitivity analysis, and its recent years' trend, the GDP growth rate maintains an average of 6.5 percent. Assume that GDP growth rate varies from its base case scenario of 6.5 percent and varies between 4.5 percent and 8.0 percent.

As evidenced by Figure 7.16, the industrial electricity demand increases with stochastic variation in GDP growth rate. It shows that there is 50 percent chance that the industrial electricity demand will be between 650 MW and 1400 MW, the mean industrial

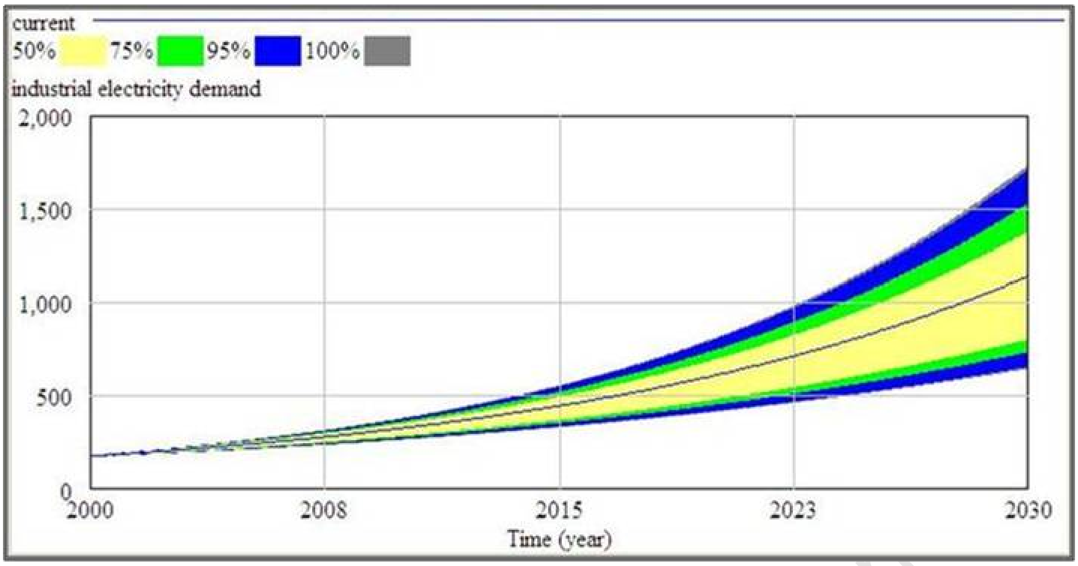


Figure 7.16: Industrial electricity demand under GDP growth rate sensitivity

electricity demand in 2030 is 1200 MW. These intervals are wider and also the mean is considerably higher than in the base case scenario. This is attributable almost entirely to increases in GDP growth that significantly increases the industrial electricity demand.

7.7 Policy Development

This section attempts to develop and better understand policy scenarios aimed at improving electricity generation capacity by means of simulation. The analysis of the results is based on the assumption that the main goal of electricity planners is to increase electricity capacity to meet the energy needs of consumers for social and economic development. The key variable for policy analysis is total electricity provided. The total electricity provided is an indicator of how much electricity capacity has been generated. Effective and sustainable EGP policies are needed to stimulate investment in the electricity generation sector to increase electricity capacity provided.

The key questions to be answered in this analysis are the two research questions (from Section 1.4; What policy scenarios can be used to improve electricity generation capacity in developing countries, like Uganda?, and what are the implications of the policy options?

Three policy scenarios were identified. There is the base case scenario (or Without Policy Scenario 1) and two scenarios are compared to the base case scenario to explore and predict their impacts on the model outcomes.

***Without Policy Scenario 1:* Base case**

The base case scenario is assumed to be in equilibrium, with no changes in parameters and maintains a stable simulation. The base case scenario reflects the current conditions of the model. The results from the simulation are used as a baseline to be compared to those for other policy scenarios.

***Policy Scenario 2:* Expansionary Energy Fund**

This policy scenario builds on the base case scenario except that it simulates expansionary energy fund due to increases in GDP growth rate. This policy aims at raising the total energy fund in order to stimulate investment into the electricity sector. The approach is to increase the GDP energy fraction, which will eventually increase the available electricity capacity. To test this policy, GDP growth rate is set to 7.5% and GDP energy fraction increased to 0.0045.

The simulations show that total electricity provided can significantly be increased by setting GDP energy fraction at higher values. Nevertheless, a mistake in setting the GDP energy fraction too low can induce undesired effects. In fact, total electricity provided is significantly reduced when the GDP energy fraction is set too low. In the long-run, there will be electricity shortages. This direction of causation sheds light on future electricity policies regarding electricity generation and transmission capacity.

***Policy Scenario 3:* Electricity Investment policy**

This scenario is similar to scenario 2 (Expansionary Energy Fund), except that an additional policy structure that emphasizes investments in electricity sector is added. This

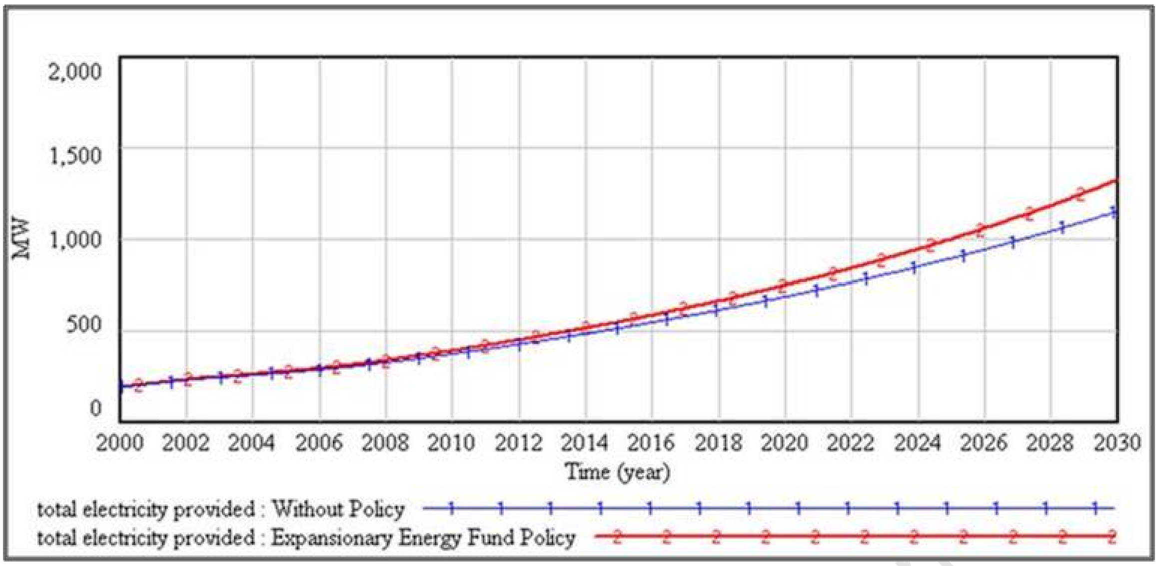


Figure 7.17: Total electricity provided under Expansionary energy policy

policy aims at increasing proportion of funds allocated to generation investment and to transmission investment, that eventually leads to increased electricity capacity provided. In this particular model, the total energy fund is divided into total operating and total investment fund by an energy operating fraction. Therefore, in order to increase the proportion for total investments, the energy operating fraction has to be reduced. This policy is tested by setting GDP growth rate = 7.5% and GDP energy fraction = 0.0045, energy operating fraction reduced to 0.135.

Based on the results and testing done on the SD model, certain policy suggestions to improve electricity generation capacity can be made. GDP energy fraction was observed to have a substantial impact on available electricity generation capacity. It would make sense as a policy shift to devote more resources to the energy sector development projects. This issue gains more importance in the context of increased economic growth. The thrust of expansionary energy fund implementations should be towards spending more funds and effort on investment in electricity generation and transmission facilities. It can be conjectured that more investment funds would significantly increase the total available electricity capacity.

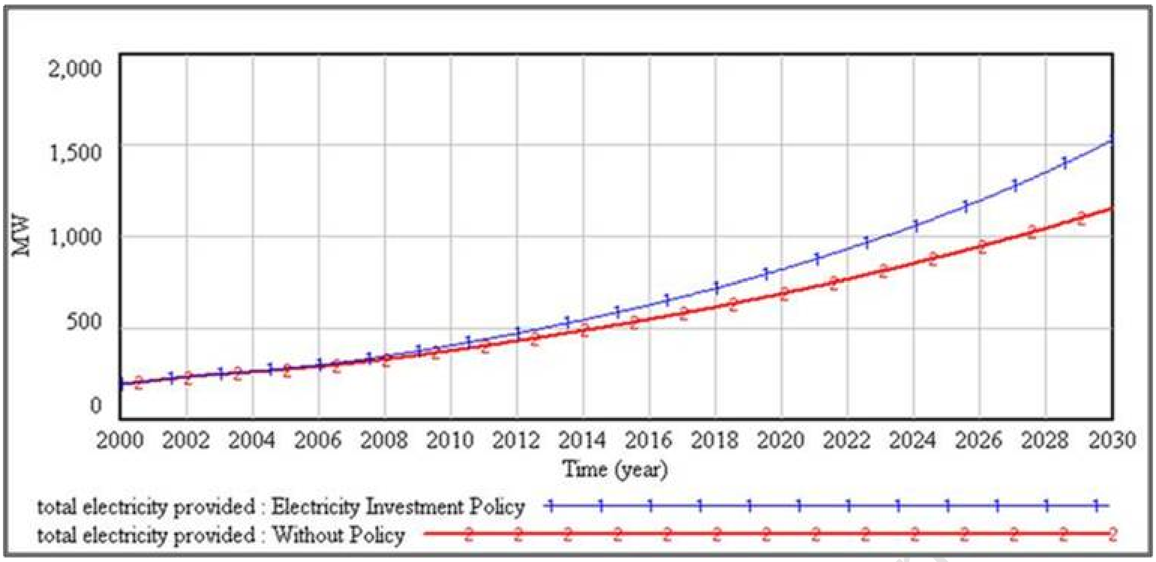


Figure 7.18: Total electricity provided under Electricity Investment policy

7.8 System Dynamics Optimization

SD modeling allows the user to run repeated simulations by altering the parameter values, and observe the system performance immediately. In this way, the user gets a good intuition of how the system behaves, and the impact different parameters have on system performance. By observing the impact, the user can achieve a greater awareness and understanding about the system, and how sensitive it is to even small changes in parameter values. However, when a user has a good understanding of the overall system structure, and has gained a good insight into the choice of parameters, the user will want an answer to the question: *"What combination of parameters will optimize the problem?"*. The answer to this question is not repeated experimentation. This computation is best solved by a SD optimization algorithm, whose primary motivation is to search for an acceptable model by using some objective function as the measure of performance, [Keloharju, 1988]. The search process, based on heuristic optimization, occurs in the model parameter space.

The SD optimization is based on the idea that some combination of parameter values produces the ideal model behavior over the entire simulation time. The maximization (or minimization) of the objective function, that is, an average performance measure, is the goal of the optimization process. Given a target output value (also called a 'goal') of the performance, one must find an input value for the parameter, which generates such an output, that is, *goal seeking*.

To perform SD optimization using VENSIM®, three fundamental steps are required, [Vaneman, 2002]:

1. An objective function (or 'payoff') must be defined that represents the desired model behavior;
2. Parameters, which represent constraints within the model, with their feasible range of values, must be defined;
3. The number of iterations which the model must complete must be defined

A 'payoff' is a single number that collapses the whole model over the entire time it is simulated. It measures the accuracy of a simulation. The optimization is controlled by an optimization control that defines the maximum and minimum bounds for each parameter.

The constraints in the model are parameters that have some special significance to the system. These parameters are to be searched over to optimize the objective function. The range of feasible values for each constraint must be carefully considered because an unrealistic constraint could provide an erroneous solution to the objective function, [Vaneman, 2002].

SD optimization is achieved through a hill-climbing algorithm, [Elmahdi, 2006]. The fundamental idea of the hill-climbing search algorithm is to systematically vary the variables of the objective function in order to find its minimum or maximum value. It starts with a random (potentially poor) solution, and iteratively makes small changes to the solution, each time improving it a little. When the algorithm cannot see any improvement anymore, it terminates. Ideally, at that point the current solution is close to optimal, but it is not guaranteed that hill climbing will ever come close to the optimal solution, [Elmahdi, 2006]. The heuristic operates in the sense that if a move from one point to another point in an n-dimensional space moves in the desired direction of the objective function, then the next move should be in that same direction.

7.8.1 EGP-SD Optimization Formulation

The EGP-SD optimization model considers four fundamental objectives and their corresponding performance measures are as follows;

- Provide affordable electricity to consumers (Average electricity price);
- Stimulate economic development through the electricity sector (Average GDP);
- Provide reliable electricity to the industrial sector (Average industrial available electricity-to-demand ratio);
- Provide reliable electricity to the Non-industrial sector (Average Non-industrial available electricity-to-demand ratio);

Mathematical equations for the performance measures can be formulated as follows;

$$\text{Average electricity price rate}(t) = \frac{\text{Electricity price}(t)}{\text{Time horizon}}$$

$$\text{Average GDP rate}(t) = \frac{\text{GDP}(t)}{\text{Time horizon}}$$

$$\begin{array}{l}\text{Average industrial available}\\ \text{electricity-to-demand ratio}(t)\end{array} = \frac{\text{industrial available electricity-to-demand ratio}(t)}{\text{Time horizon}}$$

$$\begin{array}{l}\textit{Average non-industrial available} \\ \textit{electricity-to-demand ratio(t)}\end{array} = \frac{\textit{non-industrial available electricity-to-demand ratio(t)}}{\textit{Time horizon}}$$

Using Simon's concept of "satificing", [Belton and Stewart, 2002], the emphasis to optimizing such a model, is placed on achieving satisfactory levels of achievement on each objective, with attention shifting to other objectives once one is achieved. The performance variables have to compete for the resources input to the system, thus, the problem is clearly a multi-objective problem, with some parameters to be traded off. Alborzi [2008] explored the idea of SD optimization of several objectives.

Figure 7.19 presents the details of the EGP-SD optimization model. The shadow variables (ELECTRICITY PRICE, Gdp, industrial available electricity-to-demand ratio, non-industrial available electricity-to-demand ratio, and Time horizon) indicates that they are linked from the main EGP-SD model in Figure 6.3.

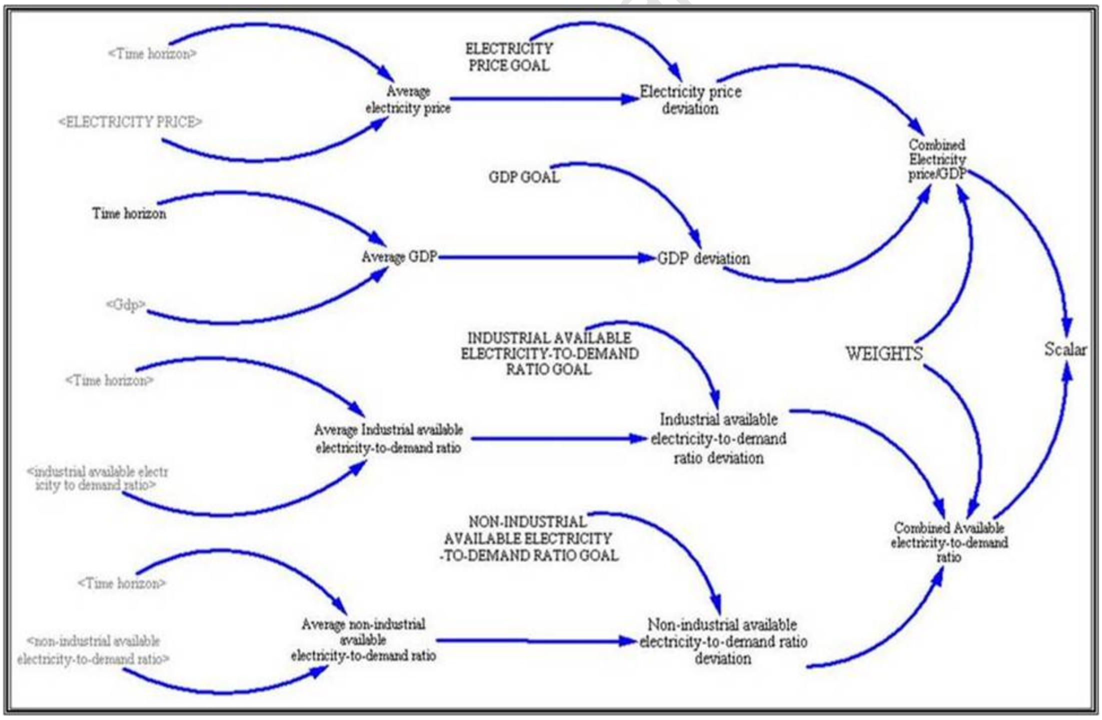


Figure 7.19: EGP-SD optimization Model

For each of the four objectives, Z_i, for all $i = 1, 2, 3, 4$, a goal or aspiration level, g_i, is defined in terms of desirable levels of performance, which the decision maker wishes to achieve as closely as possible. These goals are interpreted as a desire to find a feasible solution such that the performance level is greater than or equal to the goal, [Ogryczak, 2001]. For realistically defined goals, there is probably no feasible solution satisfying this requirement, and for this reason a non-negative deviation variable, δ_i, is introduced, which measures the degree to which the achieved performance measure falls short of the goal. They represent the amount by which each goal deviates from its target value. Therefore,

$$\text{Deviations, } \delta_i = \begin{cases} g_i - Z_i\ ; & \text{Maximizing objective} \\ Z_i - g_i\ ; & \text{Minimizing objective} \end{cases}$$

The $d_i = g_i - Z_i$ represents the amount by which the goal is underachieved and $d_i = Z_i - g_i$ represents the amount by which each goal's target is overachieved. The diagrammatic representation of the deviation variables for the EGP-SD model is showed in Figure 7.19, and the mathematical expressions are as follows;

$$\begin{array}{l} \textit{Electricity price} \\ \textit{deviation(t)} \end{array} = \begin{array}{l} \textit{Average} \\ \textit{electricity price(t)} \end{array} - \begin{array}{l} \textit{electricity} \\ \textit{price goal(t)} \end{array}$$

$$\textit{GDP deviation(t)} = \textit{GDP goal(t)} - \textit{Average GDP(t)}$$

$$\begin{array}{l} \textit{Industrial available} \\ \textit{electricity-to-demand} \\ \textit{ratio deviation(t)} \end{array} = \begin{array}{l} \textit{Industrial} \\ \textit{available electricity} \\ \textit{-to-demand ratio goal(t)} \end{array} - \begin{array}{c} \textit{average industrial} \\ \textit{available electricity} \\ \textit{-to-demand ratio(t)} \end{array}$$

$$\begin{array}{l} \textit{Non-industrial available} \\ \textit{electricity-to-demand} \\ \textit{ratio deviation(t)} \end{array} = \begin{array}{l} \textit{Non-industrial} \\ \textit{available electricity} \\ \textit{-to-demand ratio goal(t)} \end{array} - \begin{array}{c} \textit{average non-industrial} \\ \textit{available electricity} \\ \textit{-to-demand ratio(t)} \end{array}$$

Since the deviation variables measure entirely different attributes, we introduce the normalization techniques to overcome incommensurability. The deviation variables are normalized so that they measure the percentage deviations from the various goals, by dividing the deviations by the target value for the goals, [Tamiz and Romero, 1998]. The general expression is given by;

$$d_i = \left(\frac{Z_i - g_i}{t_i}\right) * 100 \tag{7.1}$$

where t_i represents the target value for goal i.

For the decision maker to objectively evaluate the deviations, s/he must assign weights, w_i, to deviation variables to better reflect the importance and desirability of deviations from the various goals. A variable that represents a highly undesirable deviation from a particular goal is assigned a relatively large weight - making it highly undesirable for that variable to assume a value larger than 0. A variable that represents a neutral or desirable deviation from a particular goal is assigned a weight of 0 or some value lower than 0 to reflect that it is acceptable or even desirable for the variable to assume a value greater than 0.

Weights within a GP context are introduced to normalize the standardized deviations from goals. Unfortunately, there is no available standard procedure for assigning values to the weights, in a way that guarantees the most desirable solution to a GP problem, [Ragsdale, 2001]. Rather, an iterative procedure is followed, in which a particular set of weights is tried to solve the problem, analyze the solution, and then refine the weights and solve the problem again. This process is repeated many times to find a solution that is most desirable to the decision maker.

As the goals may or may not be simultaneously achievable, the approach is to adopt some form of generalized goal programming using the reference point approach, as described in Chapter 2. The reference point approach uses a 'scalarizing' function which measures the degree of under-achievement of the goals, given by;

$$\text{Scalarizing function:} \qquad \max_{i}^{4} \ w_i\delta_i + \epsilon \sum_{i}^{4} w_i\delta_i \qquad \text{for all } i = 1, 2, 3, 4 \tag{7.2}$$

where w_i are weights on the standardized deviations and ϵ is a small positive value. Since a percentage normalization has been used, this 'scalarization' function measures the total percentage sum of deviations from goals.

The fundamental aim in such a problem is to determine a solution that achieves all the goals as closely as possible. The ideal solution is one in which each goal is achieved exactly at the level specified by its target value. Therefore, we optimize the EGP-SD model using the "scalarizing" function in equation (7.2) as the objective function, for a given set of goal levels, subject to the controllable optimization parameters, that is, parameters under the jurisdiction of the model user, within allowable ranges.

To illustrate the optimization model, the goals and weights corresponding to the objective functions are assumed as shown in Table 7.5 below;

Table 7.5: EGP-SD model Performance measure

Performance Measure	**Min**	**Max**	**Mean**	**Goal**	**Weight**
Electricity price	92.40	237.19	206.64	180	0.1
GDP (Billions $)	5.73	3.83	1.71	2.10	0.4
Industrial available electricity-to-demand ratio	0.7061	0.8672	0.7596	0.8	0.3
Non-industrial available electricity-to-demand ratio	0.5318	0.7873	0.5636	0.6	0.2

7.8.2 Optimization Results

To ensure that feasible and important effects are captured by the optimization model, the goals are selected by considering the statistics data of the performance measures over the entire simulation period. The aim is to search through a large space of policy parameter values looking for optimal solutions that minimize the total percentage sum of deviations from goals.

The combination of optimal policy parameter values best achieving the goals for each of the objectives is shown in Table 7.6 below.

Table 7.6: EGP-SD model Optimized parameters

Parameter name	**Optimal Value**
Generation operating fraction	0.6452
Generation investment fraction	0.3548
Energy fund operating fraction	0.1928
Industrial preference coefficient	0.7672
GDP energy fraction	0.00389

Results indicate that in order to achieve the goal of increasing the proportion of electricity allocated to industry sector to 0.8, the GDP energy fraction should be 0.00389 and industrial preference coefficient of 0.7672. It is also that with a GDP of $ 21.0 billions, the electricity price would be reduced to $ 180 per MWh. The goal of supplying 60 percent of electricity capacity to non-industrial sector will also be achieved. By experimenting with the goal values and weights set, it is also easy to generate a range of potentially good combination of parameter values.

7.9 Summary

An EGP-SD simulation model has been implemented to analyze electricity generation strategies. It is designed to assist electricity planners analyze the system's behaviour under various policy scenarios, as well as understand the sensitivity of individual parameters.

The model was calibrated and validated using historical data. The total demand (MW) and GDP ($) were used for calibration and validation. Structural tests were carried out and the model was dimensionally consistent. The model was used to simulate the base case scenario and to conduct some parametric and multivariate sensitivity analysis.

The base model can be summarized as a growth model where electricity generation capacity tries to keep pace with the growing electricity demand. Policies aimed at improving electricity generation capacity have been proposed. While not all of them have realistic sense, some of them can achieve good results but with high expenditure. Raising the proportion of GDP allocated to energy fund is a policy that can achieve good results in the long run. It is simply because of the incentives of capital investment in generation and transmission capacity.

The EGP-SD model implementation tests policies and scenarios instead of a way of forecasting or predicting the future. Policies here provide new ways of thinking in a "what if" manner for the policy makers to improve on the electricity generation system. However, single policies may not achieve significant results in a cost-effective manner with easy implementation, policy makers need to seek a combination of different policies, for example, increasing GDP energy fraction and emphasizing investment in the electricity generation capacity.

The present behavior of the EGP-SD model are caused by the changes of various factors. This counter-intuitive behavior intrinsically existing in SD models make it difficult for simulation tools to find the solution. There is no direct optimization but rather to experiment with different values. The characteristics of SD models are that it contains complicated nonlinear feedback loops and a lot of variables and parameters. Under the influence of nonlinear characteristics, systems are insensitive to changes in many system parameters.

Chapter 8

EGP-Decision Support System

8.1 Introduction

In multi-objective optimization, the concept of "optimal solution" does not have meaning. In most cases there will be several "optimal solutions" and the decision maker will have to look to the values of the objective functions corresponding to solutions in order to decide which value seems the most appropriate. This process in which the 'best' solution is chosen is called the *decision making process*. Decision analysis aims to improve decision making through better understanding of the problem leading to a more informed evaluation and choice of scenario options. It is for this reason that there has to be interaction during which the DM provides feedback on the solutions generated by the model. This feedback mechanism enables improvement of the decision-making quality towards achieving better solutions.

Electricity planning and management involves different types and levels of decisions. Kim [1998] classifies decisions according to the hierarchical flow of information as:

- Strategic planning decisions: these are decisions related to choosing the highest-level policies and objectives - decisions with a reasonably low frequency and high potential consequences;

- Management control decisions: decisions made for the purpose of assuring effectiveness in the acquisition and use of resources;
- Operational control decisions: decisions made for the purpose of assuring effectiveness in the performance of operations; and
- Operational performance decisions: day-to-day decisions made while performing operations.

The EGP process involves making frequent strategic and managerial decisions regarding electricity generation and operating policies to find the 'best' solution. Predicting how the system will react to changes in policy decisions is often difficult. There are many system variables and complex interactions making predicting the outcome a daunting task. Hence, in order to carry out the planning process effectively, some type of decision support is essential. The purpose of a DSS is to create tools that help maximize the efficiency of a decision-making process through the application of relevant knowledge, [Churchill and Baetz, 1999]. DSS also provide the tools for making better decisions.

The need for decision support in EGP varies with the decision level and the number of participants involved in the decision process. Integrated system models that can centralize large amounts of information regarding the electricity demand and electricity availability are usually used for decision support in both strategic and operative planning. Based on the theoretical discussion and implementation of the MP and SD models in the previous chapters, an electricity generation planning decision support system, denoted EGP-DSS, that integrates both models is developed.

This chapter describes the methodology used to develop the EGP-DSS. It includes a summary of the general layout and flow of the system modules, starting from when the user first opens the program up to the end result of evaluating the results and making a decision. The EGP-DSS is not designed to replace human decision making but to improve on the quality of their decisions.

8.2 EGP-DSS Methodology

The EGP-DSS is developed primarily with the profile of a typical strategic energy planner in mind. Generally, these are planners with basic knowledge about computer information systems. To support these users, the EGP-DSS is designed logically and clearly. The emphasis is put on ensuring that the system has obvious logical flow to support users in supplying information, running the models, and interpreting the results. These planners need to have the desire to clearly understand the effect of the parameters being supplied on the results generated by the DSS. Thus, the overall objective of this DSS is to develop a set of tools aimed at transforming data into information and aid decision making for electricity planning.

The main objective is to design and implement an EGP-DSS, which is capable of generating understanding of the EGP by integrating MP and SD approaches. It is expected that the EGP-DSS should provide inputs to construct future electricity generation development scenarios, and to compare and contrast between the two model outputs and study impacts of key parameter variations.

The model base integrates a MOLP model that generates feasible electricity generation configuration mix of technologies and determines a corresponding electricity supply strategy for a combination of parameter values, and a SD model that produces behaviour patterns of the system components over the entire simulation time, under different policy decisions.

The EGP-DSS aids in the process of identifying key issues in selecting feasible electricity generation options and systematically guides the user to quantify potential energy sources and assess critical parameters. An analysis of the data would help to identify the key indicators or variables affecting electricity generation and demand. These key variables are the drivers which will be used to obtain future electricity generation scenarios and supply strategies.

8.3 Model Parameter inputs

The effectiveness of the EGP-DSS results depends on the quality of information provided by the user. As such, each parameter should be carefully developed to represent the true conditions of the energy sector and viewpoints of the decision makers. However, in a developing country's context, these parameters are generally unknown and are estimated. To consider such uncertainties, the EGP-DSS provides an avenue for conducting various "what-if" scenarios to identify plausible estimates. The input parameters entered in the DSS are saved and results are displayed in tabular form, and the result data sheet can be accessed for further analysis.

The following list of parameters has been identified for the EGP-DSS implementation. These parameters have been identified as key drivers of the model outputs. They are used to define scenarios for comparison of the model performance. Some of the parameters are relevant to the MOLP model and others to the EGP-SD model, Table 8.1.

Table 8.1: List of EGP-DSS parameters

EGP-DSS parameters	**Relevant to**	
	MOLP	**EGP-SD**
Generation investment factor (MW/$)		✓
Generation availability factor (%)		✓
Minimum generation operating cost ($/MW)		✓
Transmission investment cost ($/MW)		✓
Transmission investment factor (MW/$)		✓
Transmission availability factor (%)		✓
Minimum transmission operating cost ($/MW)		✓
Capital investment cost ($/MW)	✓	
Availability factor (%)	✓	
Cost for full retention of capacity ($/MW)	✓	
Electricity demand estimates (MW)	✓	
Industrial Preference Coefficient (%)		✓
GDP Growth rate (%)		✓
Foreign Donor Support ($/Year)		✓
Net Births Rate (%)		✓
Net Deaths Rate (%)		✓
Objective Function weights	✓	

8.4 Graphic User Interface

The EGP-DSS provides a Graphical User Interface (GUI), developed using Microsoft Visual Basic for Applications (VBA) programming language as front-end and Microsoft Excel 2007 as back-end. These selections were made based on the user-friendliness of the windows environment for both the programmer and the EGP-DSS user. This GUI environment facilitates the interaction between the user and model base and to assist decision support for electricity planning. The model base of the EGP-DSS incorporates SD and MOLP models with interactive graphics capabilities to assist in strategic decision-making activities.

The GUI is established through a network of links and forms that clearly direct the user through the program functions. The EGP-DSS is designed to support relatively novice users by providing easy-to-use menus, pre-formatted data displays, and forms for data input. The GUI supports the data management and modeling functions.

The GUI shows the parameters that can be adjusted readily by the users experimenting with the models. Also scenario analysis can be undertaken by undertaking "what if" experiments with the interface.

The GUI is categorized into 5 blocks; **W**elcome, **T**echnical Information, **G**eneration Technology, **E**lectricity Demand, and **D**ecision Support. It focuses on data input, interface controls, running models, and viewing results. Details on the GUI are presented in Appendix C.

Throughout the GUI, the user may come across terms and specifications that are difficult to understand. To assist the user in performing the different functions of EGP-DSS, help files are available for each module. These files explain the concepts and throughly describe the requirements for inputting the parameters.

Technical Information interface

This block enables the user to input technical information on electricity generation and transmission namely investment factor (MW/$), availability factor (%), and minimum operating cost ($/MW). These parameters are relevant to the EGP-SD model, where the generation technologies are not explicitly considered.

Generation Technology interface

The Generation Technology interface is used to input parameters related to electricity technologies namely; Biomass, Geothermal, Wind, Solar PV, Thermal, Bagasse, Small and Large hydro power. This information is relevant to the MOLP model. The information required include investment cost ($/MW), availability factor (%), and cost for full retention of capacity ($/MW). They have an influence on the available electricity capacity.

Electricity Demand interface

Electricity demand estimates are input using the Electricity Demand interface. This is the forecast peak demand (MW) for each demand sector from 2008 up to 2028.

The user is expected to input the preference coefficient of the industrial sector on a scale of 0 for "least" to 1 for "best".

Decision Support interface

The Decision Support interface block is where the user can simulate and run models and views results. But first, the user has to input the importance levels for each objective on a scale of 0 for "least" to 100 for "best". This level provides the relative importance of each objective to the user against a numerical scale.

The inbuilt MOLP and EGP-SD models utilize the parameters supplied by the user, and generates efficient solutions and model behaviour graphs, thus enabling users to use their own criteria and value judgments in decision making. The MOLP model executed using the GAMS program saves the results in an Excel worksheet. The EGP-SD model is run using then VENSIM program. After running the MOLP model, the EGP-SD stock-and-flow diagram is opened in VENSIM. The user has to run it, and can then view the simulation results of the outcome variables using the graphs. The graph can be saved as a Windows Meta file for later use. To view the EGP-DSS results, the VENSIM diagram is first closed so as to regain access the GUI menu.

The EGP-DSS enables the visualization of the results calculated in the modeling stage for a given set scenarios. This tool helps the DM to understand the implications of the scenarios and to explore their effects in the EGP dimensions and in their dynamics over time. The visualization supports the DM in the comparative analysis of the model results. The comparison allows the DM to gain an easy understanding of the differences between the impacts of the scenarios with respect to EGP over time.

8.5 Installation and System Requirements

In order to run EGP-DSS, the user must create a directory (with the name of **EGPDSS**) in the root directory of the users hard disk C:. There should be two subdirectories namely **GAMS23.4** and **VENSIM** in the directory of **EGPDSS**. The subdirectories contain the installation files for GAMS 23.4 and VENSIM MODEL READER respectively. Also included in the **EGPDSS** directory are the following files, as shown in Figure 8.1;

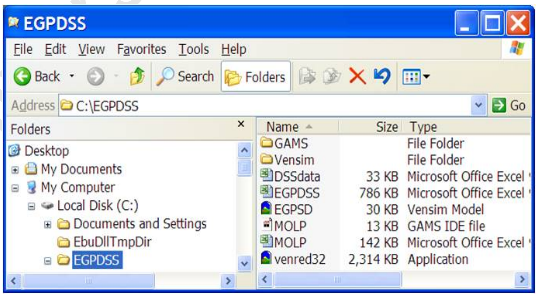


Figure 8.1: Contents of the EGPDSS Directory

1. **EGPDSS.XLS** : This is the EGP-DSS file with a GUI that is run using a macro-enabled Microsoft Excel 2007.

2. **EGPSD.VMF** : This is a vensim binary format model that can be read using the Vensim Model Reader to view and simulate the EGPSD vensim model.

3. **MOLP.GMS** : This is the GAMS file to run the MOLP model. This requires a GAMS license from the website; `http://www.gams.com`.

4. **MOLP.XLS** : This file contains the GAMS output for the MOLP model

5. **DSSDATA.XLS** : This is the input data file for the EGP-DSS GUI. The models read data from this file

The EGP-DSS was developed using the VBA program of Microsoft Excel. It is recommended to run the DSS in Windows XP or Windows 7 with a macro-enabled Microsoft Excel 2007. The provided programs (**GAMS** and **Vensim Model Reader**) need to be first installed into the program files directory. GAMS is installed such that the executable file is in path **C:/Program Files/GAMS23.4/GAMS.exe**. The vensim model reader is a free-ware that can be downloaded from the vensim website (**http://www.vensim.com**). The vensim model reader is installed such that the executable file is in path **C:/Program Files/Vensim /Venread.exe**.

8.6 Scenarios for comparison

The development of a scenario evolves from where we are now and what the future might be, having considered not only history or current trends, but also the possibility of other socio-economic occurring in the future. As scenario planning is based on many possible future events, [Rachmatullah et al., 2007, Soontornrangson et al., 2003], all possibilities have to be considered as having an equal potential to occur. Therefore, several options have to be prepared and a decision is then made to select an appropriate option that provides an outcome with minimum mismatch under any possible scenario.

The identified set of scenarios describes a range of possible socio-economic developments envisaged up to 2030. The basic idea of using these scenarios in EGP-DSS is to introduce wider contextual factors and consideration of uncertainty into the analysis of the MOLP and EGP-SD models. Three scenarios have been developed as possible "future world", and from those visions of possible futures, variables describing factors within those "worlds" have been devised, to illustrate the DSS.

In a developing country context, we assume continued economic development aimed at addressing energy planning problems. The economic development cannot be determined by the DM, but it does exert an influence on the budget allocated to the electricity sector. Here different conditions of economic development are introduced as different scenarios which may affect the outcomes of the models.

GDP growth rate, as one of the indexes of economic development, is used to define the scenarios. In the EGP-SD model GDP growth rates assume the same level of growth during the time span of the scenarios but with some variation between scenarios. In the MOLP model electricity demand is an explicit input, while in the EGP-SD model, industrial electricity demand is indirectly influenced by GDP growth rate and population growth rate influences non-industrial electricity demand. The GDP and electricity demand growth rates were assumed after inspection of the projections made by various other authors and authorities, [BMI, 2010, UBOS, 2010, MEMD, 2009].

The purpose of the scenarios is to provide a series of contexts within which to compare and contrast the consequences of the scenarios and performance of the MOLP and EGP-SD models. We analyse model behaviour and policy implications of the model results. In fact, scenarios are differently interpreted in the two models but with some consistency.

Scenario 1: Business-As-Usual (BAU)

This scenario keeps the present assumptions and technical and socio-economic characteristics for the base case. The parameters assume average values of the recent periods. The parameter values for the BAU are fixed by definition. Simulations results for this scenario have been presented in the previous Chapter. The results of the scenarios are compared to BAU where current parameters remain unaltered in the future. The Business-As-Usual (BAU) scenario is used for comparison and to explore the effects of scenario parameter variations to the model outcomes.

Scenario 2: High Economic Growth

This is the main government priority in the present and future for a long period of time. We assume a 15% increase in GDP growth rate, considering Uganda's economic outlook, [BMI, 2010]. We further assume that this economic growth will lead to 10% decrease in the minimum generation and transmission operating costs, and at the same time an increase in the generation and transmission investment factor of 10%. We also expect an increase in sectoral electricity demand = 9% per annum from the base year 2008, and project a 10% increase in net births and deaths rates respectively. This is the optimistic scenario. Details of the parameter variations are as showed in Table 8.2.

Table 8.2: Parameter variations for Scenario 2

Base case scenario		**Scenario 2**	
Parameter	Value	Scenario effect	Value
Minimum generation operating costs	90000	10% decrease	81000
Minimum transmission operating costs	99000	10% decrease	89100
Generation investment factor	3.1e-07	10% increase	3.41e-07
Transmission investment factor	2.05e-07	10% increase	2.26e-07
Electricity demand rate	Table 5.3	10% increase	Table 8.3
GDP growth rate	0.065	15% Increase	0.075
Net births rate	0.0465	10% Increase	0.0512
Net deaths rate	0.0147	10% Increase	0.0162

Scenario 3: Low Economic Growth

Assuming a pessimistic scenario, with a low economy growth, leading to a 10% increase in the minimum generation and transmission operating costs, and at the same time a decrease in the generation and transmission investment factor of 20%. We also expect a lower growth rate in electricity demand (9%) due to the stagnant economy, as showed

Table 8.3: Scenario 2: Electricity demand estimates (MW) by sector

Demand	**Planning periods**				
Sector	2008	2013	2018	2023	2028
Domestic	101	152	227	341	511
Commercial	53	80	119	179	268
Medium industry	73	110	164	246	370
Large industry	162	243	365	547	820
Street light	2	3	5	7	10
Total	391	587	880	1320	1979

in Table 8.4 below. However, we also assume no significant changes in the GDP growth rate, net births rate and net deaths rate.

Table 8.4: Parameter variations for Scenario 3

Base case scenario		**Scenario 3**	
Parameter	Value	Scenario effect	Value
Minimum generation operating costs	90000	10% increase	99000
Minimum transmission operating costs	99000	10% increase	108900
Generation investment factor	3.1e-07	20% decrease	2.48e-07
Transmission investment factor	2.05e-07	20% decrease	1.64e-07
Electricity demand rate	Table 5.3	9% increase	Table 8.5
GDP growth rate	0.065	Same	0.065
Net births rate	0.0465	Same	0.0465
Net deaths rate	0.0147	Same	0.0147

Table 8.5: Scenario 3: Electricity demand estimates (MW) by sector

Demand	**Planning periods**				
Sector	2008	2013	2018	2023	2028
Domestic	101	146	206	289	403
Commercial	53	77	107	151	212
Medium industry	73	106	149	209	291
Large industry	162	235	329	460	644
Street light	2	3	4	6	7
Total	391	567	796	1114	1557

8.7 Comparison of EGP-DSS Results

This section discusses the results of optimization and simulations in the EGP-DSS under different scenarios, to distinguish the effects of some parameters on MOLP and EGP-SD model outcomes. The model results are analysed with the aim of identifying further differences in the two modeling approaches and to illustrate how they can be interpreted. The comparison of model results for the different scenarios allows conclusions as to what answers can be queried from the models if they are applied to same questions.

In assessing the EGP-DSS results, it is important to consider a number of factors. First, in a developing country context, many of the model parameters are not known with certainty by the energy planners themselves. They are estimated through energy studies and reports. For the models to run, the estimated parameters were always kept within a realistic range.

8.7.1 Available generation capacity

On comparing the EGP-DSS results of the available generation capacity by the MOLP model and the EGP-SD model, we find that, for the high and low economic growth scenarios, the results generally depict a similar shape and have the same tendency.

In the results from MOLP model, after the year 2018, the available generation capacity begins to increase steadily at a slower rate than in the EGP-SD model, as depicted in Figure 8.2. This could be explained by EGP-SD model keeping a fixed proportion of GDP growth, whereas the MOLP model objective minimizes the expected electricity capital investments costs for each year of the planning period. The long term effect of minimizing capital investment costs is reduced electricity generation capacity.

In Figure 8.3, the simulations of the EGP-SD model shows an increasing trend in the available generation capacity for both high and low economic growth scenarios. GDP growth is often accompanied by increased total energy funds, that are subsequently

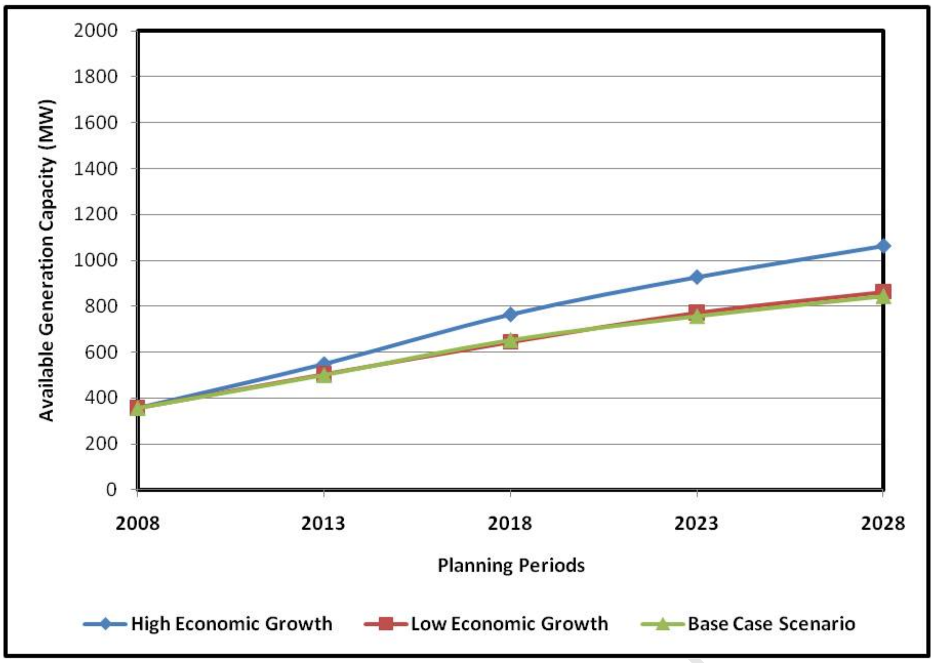


Figure 8.2: Available generation capacity - MOLP model

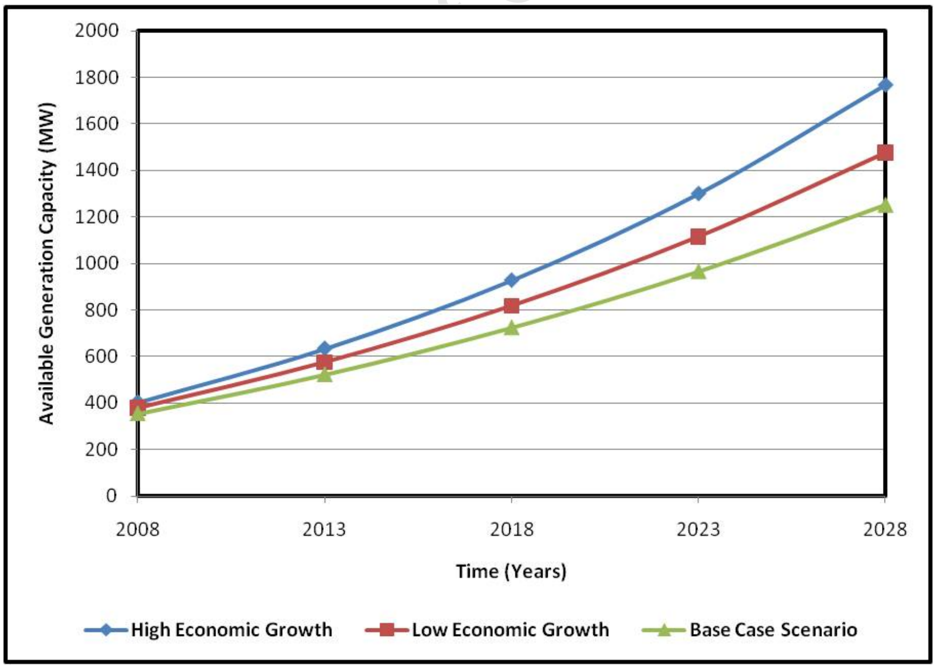


Figure 8.3: Available generation capacity - EGP-SD model

invested in electricity generation capacity. Thus, in running the EGP-SD model, GDP growth and available generation capacity change in the same direction. GDP growth is the primary driver of electricity generation capacity. For both scenarios, there is an increasing trend in available generation capacity in both MOLP and EGP-SD model.

8.7.2 Electricity Allocation strategy

The proportion of allocation to industry sector in the MOLP model was obtained by dividing electricity provided (MW) by electricity demanded (MW) for the large and medium industry sectors, for each of the planning periods.

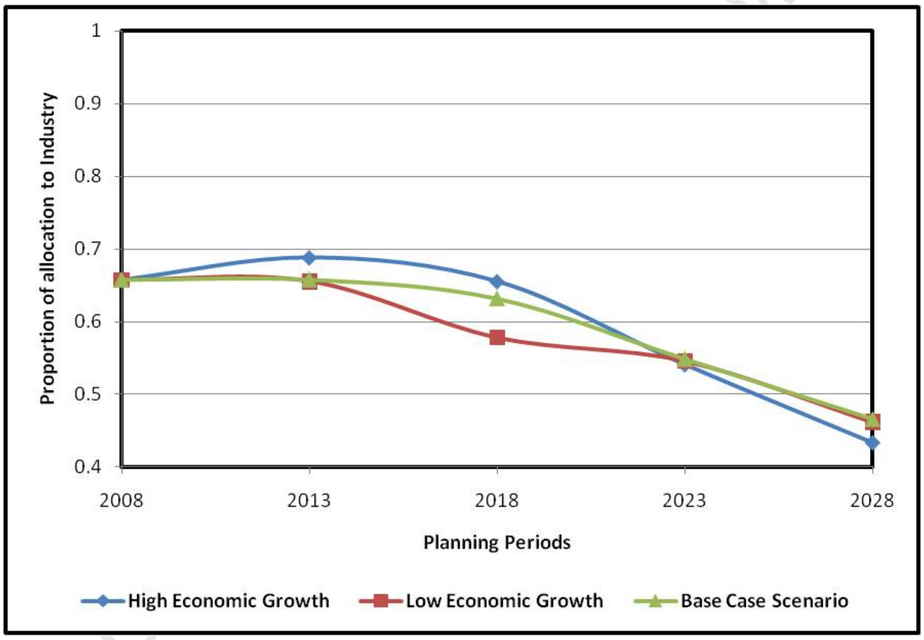


Figure 8.4: Proportion of allocation to industry - MOLP model

Figure 8.4 shows the MOLP model optimization results for all the scenarios. Results indicate a decreasing trend in electricity capacity allocated to industry sector for each scenario. This arises as a result of available electricity capacity decreasing while industrial electricity demand is increasing at a constant growth rate. The high economic growth scenario postulates a high GDP growth rates, leading to a higher increase in industrial electricity demand compared to the industrial available electricity. This means that as the industrial electricity demand increases, the ratio of industrial available electricity-to-industrial electricity demand will keep decreasing.

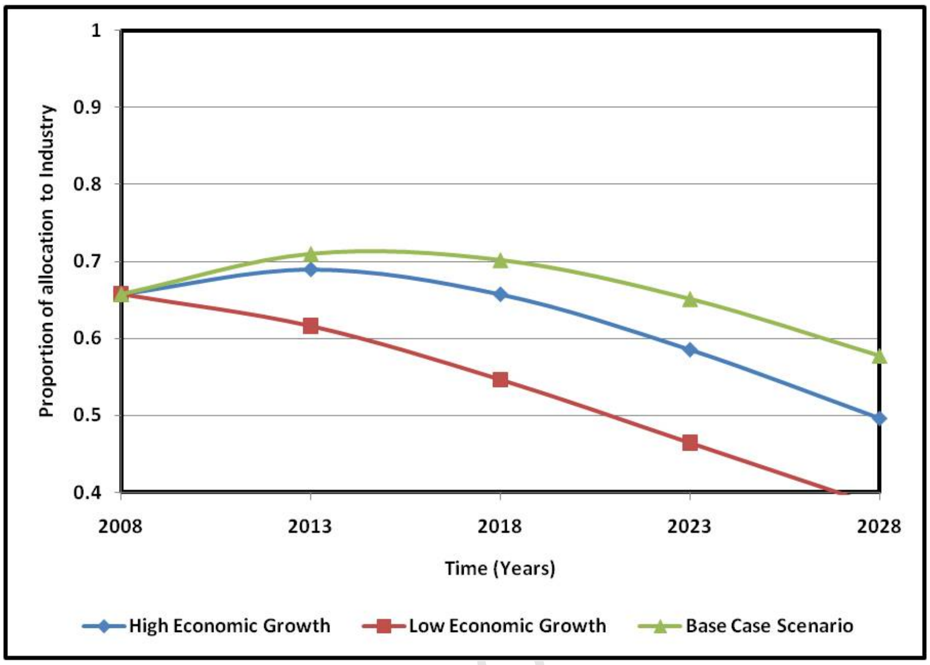


Figure 8.5: Proportion of allocation to industry - EGP-SD model

The simulations from EGP-SD model shows that after the year 2013, there is a decreasing trend in the proportional allocation to the industrial sector, (see Figure 8.5). In both high and low economic growth scenarios, after the year 2013, the industrial electricity demand increases sharply compared to the industrial available electricity. This is influenced by the increase in GDP growth as a primary driver of industrial electricity demand.

The scenario patterns in the EGP-SD model are more spread than in the MOLP model. The proportions are clearly lower in the MOLP model than in the EGP-SD model. The reason for this is that minimizing capital investment and maintenance costs in the MOLP model leads to a reduction in available electricity capacity, and thus lower proportions of electricity capacity are allocated to industry. Additionally, the EGP-SD model considers more factors characterized by non-linearities that are inherent in the SD models.

8.8 Insights Learned

The models generate information on available electricity capacity and the allocation strategy to demand sectors as a reaction to changes in economic conditions. This study is therefore especially suited as a decision support tool for policy makers elaborating national policy concepts and optimal sectoral policy measures for given goals.

Using both models to analyze the same scenarios gives us a unique basis to understand how different model configurations and model boundaries affect the results. No model captures the whole picture. The scenario simulations show that some results are quite similar for both models. The main differences between the models are hence issues of magnitude, not direction or trend. This is reassuring.

The analysis found that the results from the MOLP and EGP-SD models vary slightly because each methodology has its underlying assumptions. Sometimes these assumptions may not be applicable to the particular situations. Whereas the EGP-SD model provides a systems behaviour, MOLP model gives a more specific detailed output. The MOLP seeks to determine the type and capacity of electricity generation options to satisfy future electricity demand. The MOLP model goes further to determine a feasible electricity allocation strategy to the demand sectors for given goals.

Industrial electricity demand levels vary between the models, mainly due to the extent to which demand is assumed to be GDP growth rate and price sensitive or not. The variation in demand levels is however not dramatic. Industrial electricity allocation is very sensitive to model features. It should be noted that the models are particularly sensitive to small changes in electricity demand and GDP growth rate.

Although both models depict a very similar increasing pattern in available generation capacity, the MOLP model has a lower generation capacity than the EGP-SD model. The reasons why generation capacity is higher in the EGP-SD model are associated with model configurations. Whereas SD considers fixed parameters and simulates the over time, the MOLP parameters are subjected to greater level of detail through optimization in order to provide optimal values. For example, it is not surprising that variations in GDP, which is the primary driver of electricity generation capacity, results in significantly higher levels of available generation capacity in the EGP-SD model than in the MOLP model.

The comparison scenarios inform the development of key parameters, which are used within the models in EGP-DSS. This approach, of using scenario descriptions to impact directly on a modeling system, is one of the key innovations of this study. To deal with the complexity that DM may be interested in exploring and assessing, a EGP-DSS has been developed, based on the integration of MOLP and EGP-SD models and an easy-to-operate graphical user interface.

Conceptually, a DSS always involves subjective parameters such as objective preferences and importance levels. It is possible to find an ideal compromise solution with a particular set of inputs for a DM, but a different solution could just as well result from another set. Fortunately, inconsistent results from different sets of inputs have not been very significant in this study.

The EGP-DSS provides the DM with powerful capabilities in analyzing, exploring and comparing a set of results from both models. It helps decision makers gain insight on the problem as well as confidence when making decisions. The tool is used to help DM explore a set of decisional problems, by allowing comparison of scenario options and supporting users in strategic decision-making processes.

This chapter has described an EGP-DSS that integrates the MOLP and EGP-SD models, to study different scenarios in order to analyse the behaviour and implications of model results. The main aim was to identify and differentiate the suitability of the two model approaches for decision support in electricity planning.

Chapter 9

Conclusions and Recommendations

9.1 Introduction

The goal of this thesis was to compare MP and SD approaches, and to apply models in the domain of EGP, in a developing country context. The thesis addresses the following fundamental questions; how MP and SD models can be used in explaining how EGP systems behave in the long term, specifically for developing countries with insufficient electricity capacity?; To what extent can the behaviour of EGP systems operating under insufficient electricity capacity be explained using SD methodology as a complement to MP approach?; What effect do changes in various policy parameters have on the long term behaviour of EGP systems?; How can the integration of MP and SD models be used to identify policy combinations to aid comprehensive decision making in EGP?

The motivation of this research stemmed from the relevance of the issue of EGP in a developing country context, characterized by insufficient electricity capacity due to lack of financial resources and poor operational and maintenance performance.

The research consists of three major components;

- Using MP approach to develop and implement a MOLP model to evaluate electricity generation alternatives in order to obtain the configuration mix of generation technologies and strategies to allocate the available electricity capacity, presented in Chapters 4 and 5;

- Developing a SD model that explores the dynamic interactions found in the electricity generation systems, presented in Chapters 6 and 7;

- Integrate MOLP and SD models into a DSS framework to aid decision making, presented in Chapter 8.

The conclusions made in this chapter are based on the model tuned to Uganda. However for reasons such as inadequate and limited financial resources and demand growth far exceeding the capacity additions, Uganda is not unique, and the basic modeling process should be applicable to other developing countries as well. It could also be adapted to other natural resources planning like water, environmental management, forestry, and land use, characterized by insufficient capacity utilization.

The MOLP model provides high level of detail and precision within assumptions about input data, while the EGP-SD model is more flexible due to a holistic view. The benefits of EGP-SD model for MOLP model lies in the identification inter-dependencies among the key variables and parameters in the EGP system. The joint use of these two approaches helps DM to make justifiable decisions, in the sense that they will better understand the problem than if the approaches were being used separately. The MOLP model requires detailed and accurate information about the electricity generation system. In situations where such information is lacking, the EGP-SD model is used to provide the decision support for the development of effective and efficient policy measures.

The MOLP model assumes linear relationships and uses quantitative data to generate optimal outcomes for a given set of policy goals. Whether these can at all be achieved is answered by the EGP-SD model. It identifies the scenarios that influence the effectiveness and efficiency of optimal policy measures and provides the information necessary for a successful implementation of the measures. Another important benefit is that the purely quantitative MOLP model can be expanded by the qualitative variables included in the EGP-SD model. The non-linearities in the EGP-SD model provide a potential of showing how sensitive the MOLP data is.

9.2 Conclusions

In this study, the optimization results of the MOLP model indicate that some degree of conflict exists between electricity generation cost and electricity supply benefits objectives. Section 5.3.3 indicates that, from the 7 investigated electricity generation technologies, hydro, thermal and bagasse appear to be the most promising because their average generation capacity potential over the entire is rather big. This is not a surprising finding as Uganda's current electricity generation is predominately hydro electricity, thermal, and some bagasse plants.

The electricity supply strategy shows how much electricity capacity is allocated to the demand sectors. In situations of insufficient capacity, electricity supply benefits goals for the large industry and domestic sectors are not easily achieved compared to the commercial and street light sectors, that required smaller electricity capacity.

In developing countries, electric utility systems with inadequate capital investments in generation capacity, and poor operational and maintenance performance are constantly resource constrained and the electricity capacity allocated to demand sectors will always be less than the desired demand. Section 5.3.3 shows that satisfying the ever increasing electricity demand becomes unattainable over the planning period of 20 years.

Alternatives that could still be investigated include increased funding, which needs to be explored. In the EGP-SD model, we represent funding by the proportion of GDP to the energy sector, which is easy to interpret, we believe. Increased funding would therefore mean higher GDP energy fraction, while in the MOLP model, increased funding means raising the goals for "costs" objectives. In fact, simulation results in Section 7.7 indicate that full industrial electricity demand satisfaction can be attained from the year 2013, when the GDP energy fraction is raised to 0.0045. The MOLP results in Section 5.3.3 indicate that relaxing the "costs" goals from 0 to 80 percent leads to electricity satisfaction of only commercial, street light, and medium industry demand sectors. However, a model is just a representation, the models way of increased funding is not what actually happens in reality.

Effective electricity planning policies are needed in developing countries to stimulate investment in electricity generation and in rationale electricity allocation strategies.

Validation of the EGP-SD model was accomplished by comparing model behaviour to the historical data collected in the "real world". This involved comparing model estimates of total demand (MW) and GDP ($) with observed data. The estimates generated by the EGP-SD model demonstrated an excellent correlation between the historical data and the model estimated data. The structural and dimensional tests were found to be correct.

The EGP-SD model simulates electricity capacity and used to analyze various scenarios (i.e. to conduct various "what-if" analyses). We look at different scenarios and see what need to be done under each and enable the identification of efficient policies for long-term electricity generation system. Primarily, the model provides a medium for better understanding into the nature of EGP systems. The EGP-SD model offers a valuable learning tool and decision support for electricity planners.

This research has combined the use of MP and SD into a DSS framework. In combining the use of two distinct approaches, this study has taken advantage of the strengths of each during the different stages of the modeling process. SD is used to formulate a model that simulates the consequences of different policies under various scenarios. MP is used as a computational engine to analytically arrive at the solution by simultaneously maximizing/minimizing objective functions under a set of constraints imposed by the problem. The presentation in Section 8.8 provides insights that enable the analysis and understanding of electricity impacts of various decisions, and thus improving on the quality of decision making in the electricity sector.

Both MOLP and EGP-SD model depict an increasing trend in available generation capacity. This is explained by the increase in GDP as the primary driver of electricity generation capacity. Additionally, both models portray a decreasing trend in electricity capacity allocated to the industry sector, mainly because industrial electricity demand grows faster than the available industrial electricity capacity.

The combination of these two approaches has some notable advantages. Firstly, the SD captures the most important cause-and-effect dependencies between the key variables and parameters in the model, and shed insight as to the time trajectory of the system as a result of these dependencies. Secondly, the framework takes advantage of the MOO technique, of simplifying the process of arriving at a solution for the DM. This analysis can help planners to make justifiable decisions, in the sense that they will better understand the problem and their own contribution to the decision and thus they would be able to justify their choices.

9.3 Limitations

One of the difficulties in conducting this study is the provision of reliable data of the electricity sector in Uganda. There is no independent organization for collecting energy-related data. Therefore, data used in the study has been collected from different sources such as MEMD, UMEME, Eskom, ERA, UETCL, UBOS, and international publications. To some extent data was used for illustration of the models.

In spite of lack of quantitative data, there is potential of generating useful models using SD approach. Subjectively assessed parameters are meaningfully used through scenario analysis, Monte Carlo simulations, and sensitivity analysis. This involves altering simultaneously the parameters to determine the impact of this change to the model.

9.4 Discussions

A framework for EGP has been developed taking into consideration the multiple objectives involved, using MP and SD procedures, and incorporating the DM preferences on the goals to achieve. The research has demonstrated the applicability of the models to a developing country's electricity generation system, leading to a DSS framework.

The value of this thesis lies in the integrated EGP-DSS tool for long term EGP, which provides assistance to making decisions in solving complex planning problems. It includes a quantitative process by using MOO, qualitative process by using SD and final decision process by scenario analysis. Its been found that SD serves as a framework to organize and filter knowledge thus leading to a better understanding of EGP problem complexity. It is in this sense that this thesis offers an extensive comprehension of complex EGP problems in developing countries.

Quality of life and human capital are adversely affected in case of frequent electricity outages of long durations. Huge investments are needed to enhance capacity of electricity generation. At the same time, renovation and maintenance of transmission and distribution lines is necessary to minimize electricity capacity losses.

There is need for sustained improvement of the technical and financial performance of electricity sector in developing countries, e.g. introduction of IPPs to boost national installed capacity. Establishment of dedicated electrification agencies with a mandate of providing electricity through the most appropriate least-cost options. The challenge of having reliable electricity in developing countries needs a set of technical, operational and financial solutions, particularly suitable to developing countries.

The structure of the electricity system in developing countries consists of large assemblages of semi-independent decision makers. If the MOLP and EGP-SD model results are to be used as a policy tool within the existing administrative setup, the model results should be implementable by the existing administration. This is only possible if the model decision variables match the decision making powers of the concerned policy makers in the energy sector. From the literature review, most of the models developed do not take this institutional dimension into consideration and hence may convey irrelevant messages to the energy planner.

9.5 Recommendations

Regardless of the previously described outcomes, much remains to be done and this work should be seen as a precursor of future research projects.

The MOLP model could be extended to include more objectives that might be necessary to the decision maker(s). For example, additional objectives could be minimizing fuel usage and gaseous emission levels resulting from electricity generation technologies. However, the more objectives in a MOO problem, implies a more complex problem to be solved. The additional objectives require more computational effort to generate the optimal solutions.

Uncertainty is a very important issue in energy planning. Uncertainty results from both the fact that it is difficult to forecast the future (external uncertainty) and also from the ambiguity inherent in human judgments (internal uncertainty). Scenarios for different growths of GDP and electricity demand can overcome such uncertainty but at the same time increase the complexity of the model. A scenario planning approach was described in Section 8.6 to consider the uncertainty in the electricity demand and GDP growth. Further research can be directed towards identifying the factors that induce uncertainty in the impacts at operational, tactical and strategic levels.

The implementation of the models relied on the characterization of the Uganda energy system obtained from official reports. A benchmarking study, over their capital investment requirements and operating and maintenance costs data to populate the models would be a particular benefit. The involvement of energy planners in the proposed EGP-DSS would be of great benefit, not only by ensuring the accuracy of the data used in the mathematical models but, in addition would contribute significantly to the participation of experts in the decision analysis. Such involvement of the energy planners would also assist in carrying out the above-mentioned benchmark study.

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Appendix A:
MOLP GAMS code

```
option decimals=3
$inlinecom [ ]
$eolcom //
*$setglobal zeros yes

Sets
t       time periods
/1*5/
k       electricity generation options
        /Biomass,Geothermal,Wind,Solar,Thermal,Bagasse,Small_H,Large_H/
s       Electricity demand sectors
        /Domestic,Commercial,ind_M,Ind_L,Street/
d       Electricity supply segments
/1,2,3,4/
w       Objective functions
        /Inv,Mnt,Dom,Com,ind_M,Ind_L,Street/
x(w)    Cost objectives
        /Inv,Mnt/
y(w)    sector objectives
        /Dom,Com,Ind_M,Ind_L,Street/
;

Parameters
invc(k)    Investment costs($m\MW) of the generation options
icap(k)    Initial capacity(MW)of the generation options
capftr1(k) Availability factor of generation options at ideal gen mnt expend
capftr2(k) Availability factor of generation options at no proper gen mnt expend
gmcost(k)  minimum generation maintenance cost ($m\MW)
gfcost(k)  Cost for full retention of generation capacity ($m\MW)
glost(k)   Proportion of lost generation capacity if no maintenance
dem(s,t)   Demand estimates (MW)
GAMSdat(k,*)
GAMSdat1(*,k)
GAMSdat2(*,*)
GAMSdat3(*,*);

* Fixed electricity generation parameters
```

```
$CALL GDXXRW.EXE "C:\TuyiRichDocs\TuyiRich2010
\PhDGAMS\GAMSOOdata.xls" par=GAMSdat rng=A1:E9
$GDXIN GAMSOOdata.gdx
$LOAD GAMSdat
$GDXIN
icap(k) = GAMSdat(k,"icap");
capftr1(k)= GAMSdat(k,"capftr1");
glost(k) = GAMSdat(k,"glost");
gmcost(k) = GAMSdat(k,"gmcost");

* Electricity generation parameters
$CALL GDXXRW.EXE "C:\TuyiRichDocs\TuyiRich2010
\PhDGAMS\GAMSOOdata.xls" par=GAMSdat1 rng=Sheet2!A3:I6
$GDXIN GAMSOOdata.gdx
$LOAD GAMSdat1
$GDXIN
invc(k) = GAMSdat1("invc",k);
capftr2(k)= GAMSdat1("capftr2",k);
gfcost(k) = GAMSdat1("gfcost",k);

*call electricity demand data
$CALL GDXXRW.EXE "C:\TuyiRichDocs\TuyiRich2010
\PhDGAMS\GAMSOOdata.xls" par=GAMSdat2 rng=Sheet5!A2:F7
$GDXIN GAMSOOdata.gdx
$LOAD GAMSdat2
$GDXIN
dem(s,t) = GAMSdat2(s,t);


display invc,icap,capftr1,capftr2,gmcost,gfcost,glost,dem;

$ontext
Table dem(s,t)  demand (MW)
             1        2        3        4          5
Domestic     101      141      198      278        389
Commercial   53       74       103      145        203
Ind_M        73       102      143      201        281
Ind_L        162      226      317      444        621
Street       2        3        4        5          8
;

$offtext

Table Addr(s,d)  Proportional value increments in supply level per
*                    MW load allocated to segment d
              1          2          3          4
Domestic      0.13       0.54       0.24       0.09
Commercial    0.12       0.49       0.28       0.11
Ind_M         0.10       0.55       0.25       0.10
Ind_L         0.15       0.50       0.20       0.15
Street        0.12       0.58       0.21       0.09
;
```

```
$ontext
Parameter
weightx(x)    Input data for objective function weights
*importance level (i.e. 70)/range from GAMSpayoff table.xls
/Inv     0.065
 Mnt     1.1744
/;

Parameter
weighty(y)    Input data for objective function weights
*importance level/range from payoff table   \
/Dom     0.700
 Com     0.450
 Ind_M   0.800
 Ind_L   0.700
 Street  0.300
/;
$offtext

Parameter
weightx(x)    Input data for objective function weights;
Parameter
weighty(y)    Input data for objective function weights;

*call data on weights
$CALL GDXXRW.EXE "C:\TuyiRichDocs\TuyiRich2010
\PhDGAMS\GAMSOOdata.xls" par=GAMSdat3 rng=Sheet7!A3:B10
$GDXIN GAMSOOdata.gdx
$LOAD GAMSdat3
$GDXIN

weightx(x)= GAMSdat3(x,"weight");
weighty(y)= GAMSdat3(y,"weight");

display weightx,weighty;


Table Tgoalsx(x,t) input data for performance goals
*Half way the min and max achievements
        1           2            3            4            5
Inv     0           0            0            0            0
Mnt     0           0            0            0            0
;

Parameter
goalsx(x,t)    performance goals;
goalsx(x,t)= Tgoalsx(x,t);

Table Tgoalsy(y,t) input data for performance goals
        1           2            3            4            5
Dom     100         100          100          100          100
```

```
Com       100          100          100          100          100
Ind_M     100          100          100          100          100
Ind_L     100          100          100          100          100
Street    100          100          100          100          100
;

Parameter
goalsy(y,t)    performance goals;
goalsy(y,t)= Tgoalsy(y,t);

Scalar
R          reserve margin [5% per annum] /0.25/
tcost      cost of new transmission capacity ($m\MW) /0.091282/
itcap      initial transmission capacity /700/
growth     capacity growth rate /1.05/
rtm        reserve transmission capacity[2% per annum] /0.1/
fullt      cost of full retention of transmission capacity[$m\MW] /0.012/
propt      percentage of transmission capacity lost [3.5% per annum] /0.225/
;

variables
gcap(k,t)      generated capacity of option k in period t       (MW)
ngcap(k,t)     new generated capacity of option k in period t   (MW)
techalloc(k,t) available capacity of option k in period t
src(k,t)       loss of generation capacity                      (MW)
cxp(k,t)       expenditure on generation capacity maintenance   [$m\MW]
avl(k,t)       availability of option k in period t             [MW]
tcap(t)        transmission capacity n period t                 (MW)
ntcap(t)       new transmission capacity                      (MW)
stc(t)         loss in transmission capacity                  (MW)
txp(t)         expenditure on transmission capacity maintenance [$m\MW]
pcs(s,t)       Electricity supply level
ppss(s,d,t)    proportion of electricity supply level
b(s,d,t)       binary allocation variable      (0 or 1)

***********Objective function declarations
zx(x,t)       cost-type objective function variables
zy(y,t)       supply-type objective function variables
devnx(x,t)    deviational variables
devny(y,t)    deviational variables
bigD          maximum weighted deviation
Aggr          overall objective function
;

Positive variables
gcap,ngcap,techalloc,src,cxp,avl,tcap,ntcap,stc,txp,pcs,ppss,zx,zy;

Binary variable
b;

Equations
newgcap(k,t)   generated capacity in period t
```

```
lmtgcap(t)      limit in generated capacity
lgcap(k,t)      lost generation capacity in period t
lgexp(k,t)      lower limit on generation maintenance expenditure in period t
ulgexp(k,t)     upper limit on generation maintenance expenditure in period t
*techlmt(k,t)    limit in available capacity of option k in period t
capalloc(t)     capacity allocated in period t
avail(k,t)      availability factor of option k in period t
lastgcap(k,t)   generation capacity of the last period
newtcap(t)      new transmission capacity in period t
lasttcap(t)     transmission capacity of the last period
ltcap(t)        loss in transmission capacity in period t
ltexp(t)        limit on transmission maintenance expenditure in period t
tcapalloc(t)    transmission capacity allocation in period t

***********Electricity supply levels model
segalloc(s,t)      electricity segment allocation
Qsegd11(s,d,t)     proportion  allocated to segment 1
Qsegd12(s,d,t)     limit in allocation to segment 1
Qsegd21(s,d,t)     proportion  allocated to segment 2
Qsegd22(s,d,t)     limit in allocation to segment 2
Qsegd31(s,d,t)     proportion  allocated to segment 3
Qsegd32(s,d,t)     limit in allocation to segment 3
Qsegd4(s,d,t)      proportion  allocated to segment 4

Domestic(t)      domestic sector electricity supply level
Commercial(t)    commercial sector electricity supply level
Ind_M(t)         industry_M sector electricity supply level
Ind_L(t)         industry_L sector electricity supply level
Street(t)        street lighting electricity supply level

*************Multi-objective equations
Investment(t)    investment costs
Maintenance(t)   maintenance costs
Domestic(t)      domestic sector electricity supply level
Commercial(t)    commercial sector electricity supply level
Ind_M(t)         industry_M sector electricity supply level
Ind_L(t)         industry_L sector electricity supply level
Street(t)        street lighting electricity supply level

*************Goal programming equation declarations
deviationsx(x,t)  defining deviational variables
deviationsy(y,t)  defining deviational variables
maxwtdevx(x,t)     defining maximum weighted deviation
maxwtdevy(y,t)     defining maximum weighted deviation
Qaggr              aggregate objective function
;

*generated capacity
gcap.fx(k,'1')=icap(k);
newgcap(k,t)$(ord(t) LT 5)..  gcap(k,t+1)=e=gcap(k,t)+ ngcap(k,t)-src(k,t);
lastgcap(k,t)..  gcap(k,'5')+ ngcap(k,'5')-src(k,'5')=g= growth*gcap(k,'4');
lmtgcap(t)..sum(k,gcap(k,t))+ sum(k,ngcap(k,t)) =l= 2000;
```

```
*loss in generation capacity
lgcap(k,t).. src(k,t)=e=glost(k)*gcap(k,t)-(glost(k)/(gfcost(k)-gmcost(k)))
                                          *(cxp(k,t)- gmcost(k)*gcap(k,t));
lgexp(k,t).. cxp(k,t)=g=gmcost(k)*gcap(k,t);
ulgexp(k,t).. cxp(k,t)=l=gfcost(k)*gcap(k,t);
avail(k,t).. avl(k,t)=e=Capftr2(k)*gcap(k,t)-((Capftr2(k)
                          -Capftr1(k))/gfcost(k))*cxp(k,t);

*capacity allocation
*techlmt(k,t).. techalloc(k,t) =l= avl(k,t);
*capalloc(t).. sum(k,techalloc(k,t))=g= (1 + R)*sum(s,pcs(s,t));
capalloc(t).. sum(k,avl(k,t))=g= (1 + R)*sum(s,pcs(s,t));

*transmission capacity
newtcap(t)$(ord(t) LT 5).. tcap(t+1)=e= tcap(t)+ntcap(t)-stc(t);
lasttcap(t).. tcap('5')+ ntcap('5')-stc('5')=g=growth*tcap('4');
tcap.fx('1') = itcap;

*loss in transmission capacity
ltcap(t).. stc(t)=e=Propt*tcap(t)-(Propt/Fullt)*txp(t);
ltexp(t).. txp(t)=l=Fullt*tcap(t);
tcapalloc(t).. tcap(t)=g=(1 + rtm)*sum(s,pcs(s,t));

*demand sector capacity allocations
segalloc(s,t)..    pcs(s,t) =e= sum(d,ppss(s,d,t))*dem(s,t);

Qsegd11(s,d,t)..   1/4*b(s,'1',t) =l= ppss(s,'1',t);
Qsegd12(s,d,t)..   ppss(s,'1',t) =l= 1/4;

Qsegd21(s,d,t)..   1/4*b(s,'2',t) =l= ppss(s,'2',t);
Qsegd22(s,d,t)..   ppss(s,'2',t) =l= 1/4*b(s,'1',t);

Qsegd31(s,d,t)..   1/4*b(s,'3',t) =l= ppss(s,'3',t);
Qsegd32(s,d,t)..   ppss(s,'3',t) =l= 1/4*b(s,'2',t);

Qsegd4(s,d,t)..    ppss(s,'4',t) =l= 1/4*b(s,'3',t);

Investment(t).. zx('Inv',t)=e= sum(k,invc(k)*ngcap(k,t)) + tcost*ntcap(t);

Maintenance(t).. zx('Mnt',t)=e= sum(k,cxp(k,t)) + txp(t);

Domestic(t)..  zy('Dom',t)=e=400*sum(d,Addr('Domestic',d)*ppss('Domestic',d,t));

Commercial(t).. zy('Com',t)=e=400*sum(d,Addr('Commercial',d)*ppss('Commercial',d,t));

Ind_M(t).. zy('Ind_M',t)=e=400*sum(d,Addr('Ind_M',d)*ppss('Ind_M',d,t));

Ind_L(t).. zy('Ind_L',t)=e=400*sum(d,Addr('Ind_L',d)*ppss('Ind_L',d,t));

Street(t).. zy('Street',t)=e=400*sum(d,Addr('Street',d)*ppss('Street',d,t));
```

```
deviationsx(x,t).. devnx(x,t) =g= (zx(x,t)- goalsx(x,t))*weightx(x);
deviationsy(y,t).. devny(y,t) =g= (goalsy(y,t)-zy(y,t))*weighty(y);
maxwtdevx(x,t)..  bigD =g= devnx(x,t);
maxwtdevy(y,t)..  bigD =g= devny(y,t);
Qaggr..  Aggr =e= bigD + 0.02*(sum((x,t),devnx(x,t))+ sum((y,t),devny(y,t)));

Model GAMS /all/;

*********Goal programming************

Solve GAMS using MIP minimizing Aggr;

Display gcap.l,ngcap.l,src.l, cxp.l,avl.l;
Display tcap.l,stc.l,txp.l;
Display zx.l,zy.l,pcs.l;
execute_unload 'C:\TuyiRichDocs\TuyiRich2010
\PhDGAMS\costs.gdx' zx.l zy.l,gcap.l,ngcap.l,avl.l,pcs.l,stc.l;

execute 'gdxxrw.exe C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.gdx var=zx.l
o=C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.xls rng=Sheet1!A2:F4';
execute 'gdxxrw.exe C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.gdx var=zy.l
o=C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.xls rng=Sheet1!A7:F12';
execute 'gdxxrw.exe C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.gdx var=gcap.l
o=C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.xls rng=Sheet1!A15:F19';
execute 'gdxxrw.exe C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.gdx var=ngcap.l
o=C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.xls rng=Sheet1!H15:M19';
execute 'gdxxrw.exe C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.gdx var=avl.l
o=C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.xls rng=Sheet1!A22:F26';
execute 'gdxxrw.exe C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.gdx var=pcs.l
o=C:\TuyiRichDocs\TuyiRich2010\PhDGAMS\costs.xls rng=Sheet1!A29:F34';
```

Appendix B: EGP-SD Model VENSIM Equations

```
%\label{VensimEquations}
annual donor repayment=
FOREIGN DONOR SUPPORT*DONOR REPAYMENT RATE
~ Dollars/year
~ Annual donor repayment
|
DONOR REPAYMENT RATE=
0.045
~ Dmnl
~ Donor repayment rate per year
|
total operating funds=
total energy fund*ENERGY FUND OPERATING
FRACTION-annual donor repayment
~ Dollars/year
~ Total operating fund
|
Population= INTEG (
births rate-deaths rate,
2.25754e+007)
~ People
~ Total population
|
births rate=
Population*NET BIRTHS RATE
~ People/year
~ Births
|
NET DEATHS RATE=
0.0179
~ 1/year [0,1]
~ Net deaths rate
|
deaths rate=
Population*NET DEATHS RATE
~ People/year
~ Deaths
```

```
|
NET BIRTHS RATE=
0.0465
~ 1/year [0,1,0.001]
~ Net births rate
|
direct government funding=
Gdp*GDP ENERGY FRACTION
~ Dollars/year
~ Direct Government funding per year
|
total energy fund=
direct government funding+electricity revenue
~ Dollars/year
~ Total energy fund
|
AVERAGE ELECTRIFICATION RATE=
2920
~ hours/year
~ Average electricification time (hours) per year;
assuming 8 hours per day
|
total investment fund=
total energy fund*(1-ENERGY FUND OPERATING FRACTION)
+FOREIGN DONOR SUPPORT
~ Dollars/year
~ Total investment fund as a fraction of GDP Energy fund
|
industrial electricity demand=
Gdp*STANDARD MW per GDP*industrial electricity demand multiplier
~ MW
~ Industrial sector electricity demand
|
"non-industrial electricity demand"=
"non-industrial electricity demand multiplier"*Population
*STANDARD MW per POPULATION
~ MW
~ Other electricity demand
|
FOREIGN DONOR SUPPORT=
1.1e+008
~ Dollars/year
~ Donor support
|
"non-industrial electricity demand multiplier"= WITH LOOKUP (
relative electricity price,
([(0,0.95)-(6,1)],(0,1),(0.366972,0.992105),(1.24771,0.980921)
,(2.6789,0.969737),(4\
,0.967105),(4.97248,0.967544),(5.85321,0.967325) ))
~ Dmnl
~ Other electricity demand multiplier
|
```

```
"non-industrial available electricity-to-demand ratio"=
"non-industrial available electricity"/"non-industrial
electricity demand"
~ Dmnl
~ "Other available electricity-to-demand ratio"
|
BASE YEAR ELECTRICITY PRICE=
92.64
~ Dollars/(MW*hours)
~ Base year 2008 electricity tarrif
|
INDUSTRIAL PREFERENCE COEFFICIENT=
0.75
~ Dmnl [0,1]
~ Industrial sector preference coefficient
|
TRANSMISSION CAPACITY INVESTMENT FACTOR=
2.1e-007
~ MW/Dollars
~ Transmission capacity per fund invested factor
|
GENERATION CAPACITY INVESTMENT FACTOR=
3.1e-007
~ MW/Dollars
~ Generation capacity per fund invested factor
|
industrial electricity demand multiplier= WITH LOOKUP (
relative electricity price,
([(0,0.95)-(8,1)],(0.0856269,1),(1.27217,0.987281),
(2.2263,0.981579),(3.69419,0.975439\
),(4.81957,0.972807),(5.70031,0.971491),(6.6055,0.971272),
(7.92661,0.971053) ))
~ Dmnl
~ Industrial electricity demand multiplier
|
transmission operating fund=
total operating funds*(1-GENERATION OPERATING FRACTION)
~ Dollars/year
~ Transmission operating fund as a fraction of Total operating fund
|
available generation capacity=
Electricity generation capacity*GENERATION AVAILABILITY FACTOR
~ MW
~ Available generation capacity
|
IDEAL GENERATION OPERATING COSTS=
90000
~ Dollars/MW/year
~ Ideal generation operating costs
|
available transmission capacity=
Electricity transmission capacity*TRANSMISSION AVAILABILITY FACTOR
```

```
~ MW
~ Available transmission capacity
|
STANDARD MW per GDP=
3.13917e-008
~ MW/Dollars
~ Standard MW per GDP=Base year Industrial demand/Base year GDP
|
STANDARD MW per POPULATION=
4.4296e-006
~ MW/People
~ Standard MW per population=Base year Other demand/Base year population
|
industrial available electricity to demand ratio=
industrial available electricity/industrial electricity demand
~ Dmnl
~ Industrial sector available electricity-demand ratio
|
GENERATION INVESTMENT FRACTION=
0.45
~ Dmnl [0,1]
~ Generation investment fraction
|
transmission investment funds=
total investment fund*(1-GENERATION INVESTMENT FRACTION)
~ Dollars/year
~ Transmission investment fund
|
GENERATION AVAILABILITY FACTOR=
0.9
~ Dmnl [0,1]
~ Generation availability factor(%)
|
GENERATION AVERAGE LIFETIME=
50
~ years
~ Generation average lifetime in years
|
GDP ENERGY FRACTION=
0.002525
~ 1/year [0,1]
~ GDP energy fraction per year
|
new generation capacity rate=
generation investment funds*GENERATION CAPACITY INVESTMENT FACTOR
~ MW/year
~ |
TRANSMISSION AVERAGE LIFETIME=
35
~ years
~ Transmission average lifetime in years
|
```

```
new transmission capacity rate=
transmission investment funds*TRANSMISSION CAPACITY INVESTMENT FACTOR
~ MW/year
~ New transmission capacity rate
|
IDEAL TRANSMISSION OPERATING COSTS=
99000
~ Dollars/MW/year
~ Ideal transmission operating costs
|
TRANSMISSION AVAILABILITY FACTOR=
0.9
~ Dmnl [0,1]
~ Transmission availability factor(%)
|
electricity shortages multiplier= WITH LOOKUP (
industrial available electricity to demand ratio,
([(-6,0.6)-(6,1)],(-6,0.801754),(-4.75229,0.798246),
(-2.80734,0.829825),(-0.899083,\
0.889474),(1.37615,0.94386),(3.3211,0.966667),(5.9633,0.984211) ))
~ Dmnl
~ Electricity shortages multiplier
|
total electricity provided=
MIN(available generation capacity, available transmission capacity )
~ MW
~ Total electricity provided
|
generation operating expenditure ratio=
generation operating fund/ideal generation operating expenditure
~ Dmnl
~ Generation operating expenditure ratio
|
ideal transmission operating expenditure=
IDEAL TRANSMISSION OPERATING COSTS*Electricity transmission capacity
~ Dollars/year
~ Actual transmission operating expenditure
|
generation investment funds=
total investment fund*GENERATION INVESTMENT FRACTION
~ Dollars/year
~ Capital generation investment fund as a fraction of
Total investment fund
|
Electricity generation capacity= INTEG (
new generation capacity rate-loss in generation capacity rate,
200)
~ MW
~ Electricity generation capacity
|
ELECTRICITY PRICE:=
GET XLS DATA('ElectricityTariffs.xls', 'Sheet1', '1', 'A2')
```

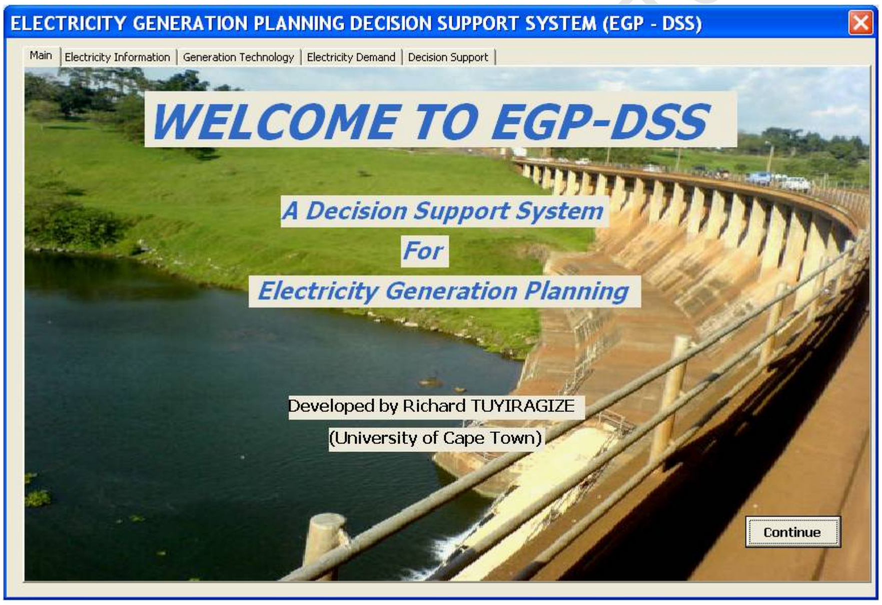
```
~ Dollars/MW/hours
~ Electricity price per MWh
|
Electricity transmission capacity= INTEG (
new transmission capacity rate-loss in transmission capacity rate,
230)
~ MW
~ Electricity transmission capacity
|
ENERGY FUND OPERATING FRACTION=
0.235
~ Dmnl [0,1]
~ Energy fund operating fraction
|
Gdp= INTEG (
gdp growth,
5.734e+009)
~ Dollars
~ |
transmission capacity loss multiplier= WITH LOOKUP (
transmission operating expenditure ratio,
([(-0.04,0)-(2,1)],(-0.030581,0.97676),(0.0847706,0.87447),
(0.140917,0.824561),(0.30581\
,0.76505),(0.608807,0.732456),(0.814679,0.719298),(1.17028,
0.70614),(1.44477,0.714912\
),(1.63817,0.701754),(1.78789,0.697368),(2.00624,0.710526) ))
~ Dmnl
~ Transmission capacity loss multiplier
|
generation capacity loss multiplier= WITH LOOKUP (
generation operating expenditure ratio,
([(0,0.3)-(5,1)],(0,0.726316),(0.244648,0.65614),
(0.412844,0.607018),(0.623853,0.542544\
),(1.02446,0.490351),(2.17125,0.401316),(3.19572,0.379825),
(4.02141,0.361404),(4.96942\
,0.349123) ))
~ Dmnl
~ Generation capacity loss multiplier
|
loss in transmission capacity rate=
(Electricity transmission capacity/TRANSMISSION AVERAGE LIFETIME)
*transmission capacity loss multiplier
~ MW/year
~ Loss in transmission capacity rate
|
ideal generation operating expenditure=
Electricity generation capacity*IDEAL GENERATION OPERATING COSTS
~ Dollars/year
~ Ideal generation operating expenditure
|
generation operating fund=
total operating funds*GENERATION OPERATING FRACTION
```

```
~ Dollars/year
~ Ideal generation operating fund
|
GENERATION OPERATING FRACTION=
0.55
~ Dmnl [0,1]
~ Generation operating fraction
|
transmission operating expenditure ratio=
transmission operating fund/ideal transmission operating expenditure
~ Dmnl
~ Transmission operating expenditure ratio
|
loss in generation capacity rate=
(Electricity generation capacity/GENERATION AVERAGE LIFETIME)
*generation capacity loss multiplier
~ MW/year
~ Loss in generation capacity rate
|
gdp growth=
Gdp*GDP GROWTH RATE*electricity shortages multiplier
~ Dollars/year
~ GDP variation
|
GDP GROWTH RATE=
0.065
~ 1/year [0,1]
~ GDP growth rate per year
|

********************************************************
.Control
********************************************************~
Simulation Control Parameters
|

FINAL TIME  = 2030
~ year
~ The final time for the simulation.
|
INITIAL TIME  = 2000
~ year
~ The initial time for the simulation.
|
SAVEPER  = 0.0625
~ year [0,?]
~ The frequency with which output is stored.
|
TIME STEP  = 0.0625
~ year [0,?]
~ The time step for the simulation.
|
```

Appendix C: EGP-DSS Graphical User Interface

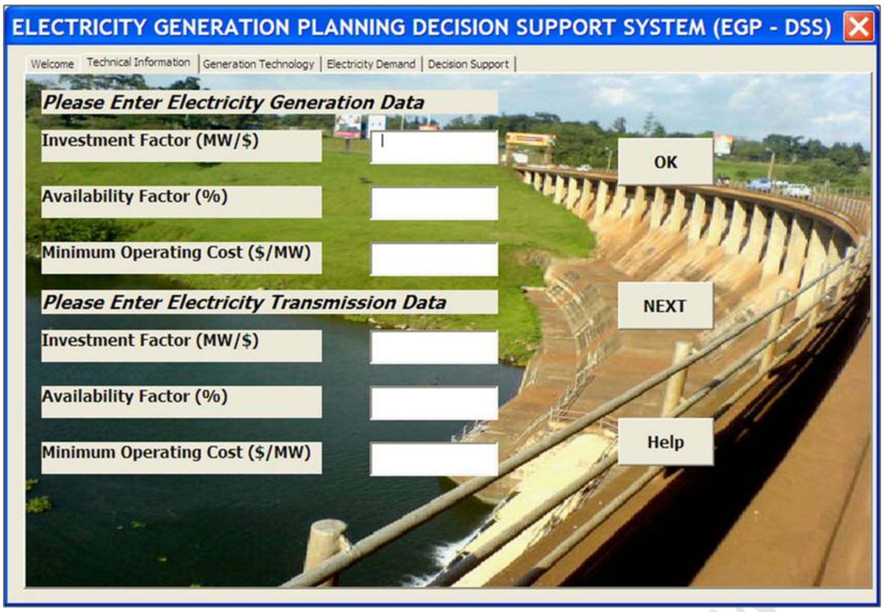
Welcome

The GUI starts with an animated Welcome interface that prompts the user to press the **CONTINUE** button to proceed to the rest of the blocks.



Technical Information interface

Generation Investment factor(MW/$): This determines how much electricity is generated per amount of invested funds in dollars. It is a measure of investment in new generation capacity. The higher the investment factor, the more likely increase in new generation capacity.



Generation Availability factor(%): This is the ratio of average available generation capacity (MW) over a period of time and the installed capacity (MW). It is measured as a percentage. The availability of power plants varies greatly depending on the design of the plant and how the plant is operated. Thermal and geothermal power plants have availability factors between 70% and 90%. This parameter requires an average availability factor for all generation technologies.

Minimum Generation operating cost ($/MW): These are expenses incurred during the operation of a generation system. They include fuel costs, service costs (maintenance and repairs), Personnel costs for technical plant operation, insurance, and administrative costs. They are measure in $ per MW output. In situations of financial constraints, this cost is expected to be less than the ideal operating cost.

Transmission Investment factor(MW/$): This determines how much electricity is generated per amount of invested funds in dollars. It is a measure of investment in new generation capacity. The higher the investment factor, the more likely increase in new generation capacity.

Transmission Investment factor(MW/$): This determines how much electricity is transmitted per amount of invested funds in dollars. It is a measure of investment in new transmission capacity. The higher the investment factor, the more likely increase in new transmission capacity.

Transmission Availability factor(%): This is the ratio of average available transmission capacity (MW) over a period of time and the installed transmission capacity (MW). It is measured as a percentage. The availability of transmission varies greatly depending on how the transmission installations are operated and maintained. This parameter requires an average availability factor for the whole transmission network.

Minimum Transmission operating cost (\$/MW): These are expenses incurred during the operation of a transmission system. They include fuel costs, Service costs (maintenance and repairs), personnel costs, insurance, and administrative costs. They are measure in \$ per MW output.In situations of financial constraints, this cost is expected to be less than the ideal operating cost.

Pressing the **HELP** button gives the detailed help information file associated with a given block.

The **OK** button has three functions:

1. check user's input so that all the required information has been supplied (that is called validation)
2. write the data on to the file
3. clear the form ready for the next entry

If the **OK** button is clicked without completing the form, an error message pops up.

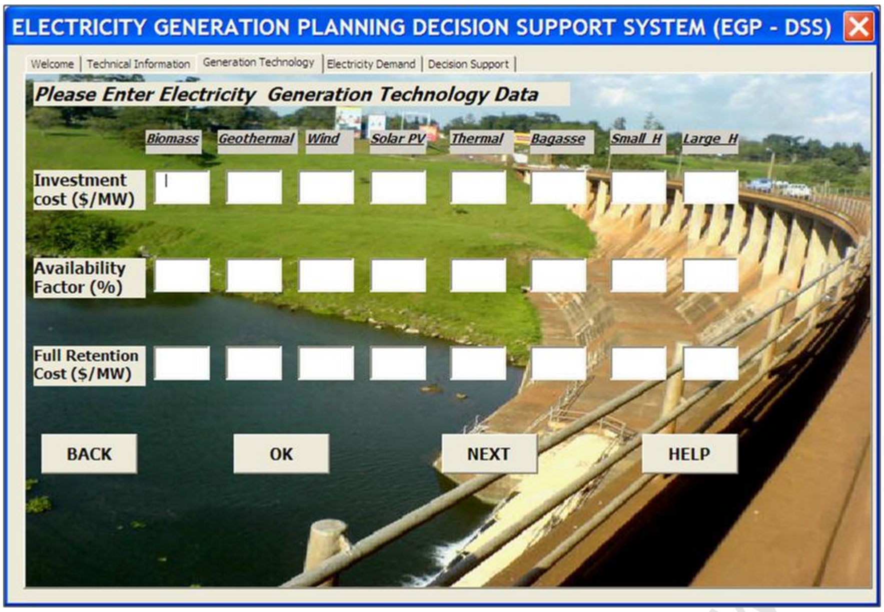
Dismiss the message box then type an entry in the "Investment Factor" box and try again. No message box should be displayed when you click the **OK** button. Click the **NEXT** button to proceed to the "Generation Technology" interface.

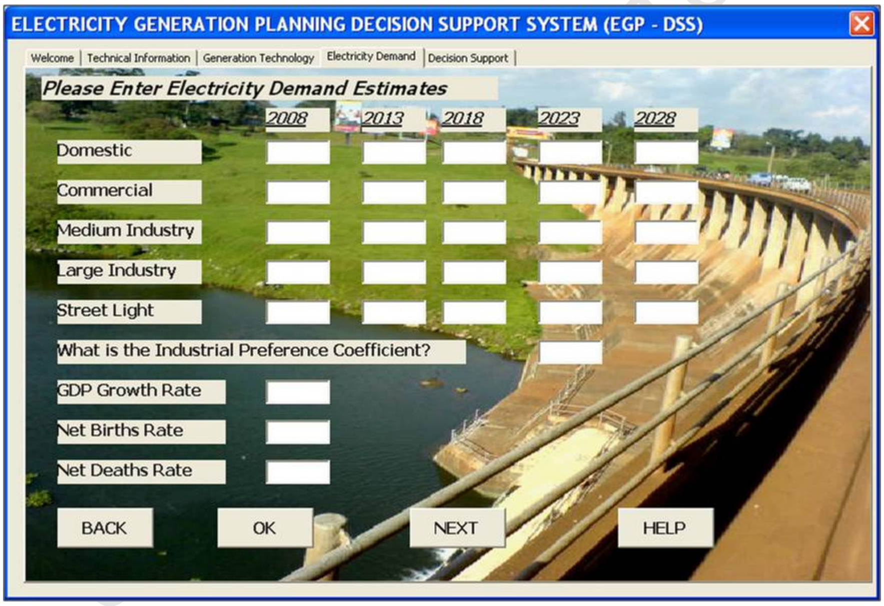
Generation Technology interface

The **OK** button validates the users' inputs and writes the generation technology data to a file. The **NEXT** button takes the user to the Electricity Demand interface, while the **BACK** button moves the user one step back to the Technical Information interface.

Electricity Demand interface

This shows the Electricity Demand Estimates interface. These are electricity peak demand estimates for each sector for the year 2008, 2013, 2018, 2023 and 2028, measured in MW.





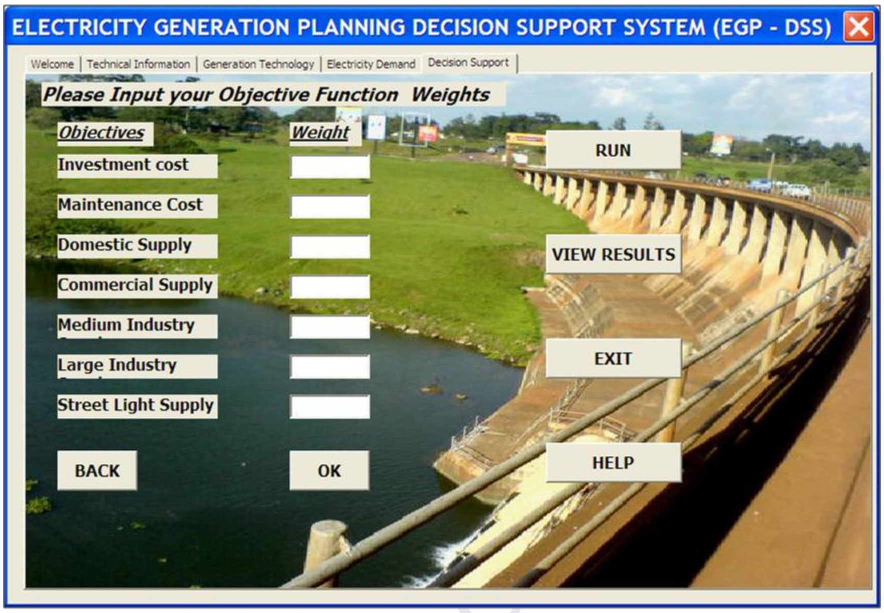
Industrial demand: The historical data on industrial electricity peak demand for the year 2000 is sought to simulate the electricity generation system. The industrial demand includes the medium and large industry sector.

Non-industrial demand: The historical data on non-industrial electricity peak demand for the year 2000 is sought to simulate the electricity generation system. The non-industrial demand includes domestic, commercial, and street light sectors.

Details of these parameters are presented in the Help file, obtained by pressing the

HELP button. The **OK** button validates the users' inputs and writes the electricity demand data to a file. The **NEXT** button takes the user to the Decision Support interface, while the **BACK** button moves the user one step back to the Generation Technology interface.

Decision Support interface



Objective Function Weights: With multiple objectives, decision makers may view different objectives as having different levels of importance. Therefore, we need to assess the relative importance of the each objective on a scale of 0 for "least" and 100 for "best".

The **BACK** button moves to the Generation Technology data screen.

After inputing all the parameters, the user presses the **OK** button to validate the inputs, write data to file, and finally save to an Excel workbook (*GAMSOOdata.XLS*). Once all the necessary parameters have been input, the user clicks the **RUN** button to initiate the sequence of algorithms used to produce the desired output saved to an Excel file, (*COSTS.XLS*).

The user can view the results by pressing the **VIEW RESULTS** button. The results can be viewed in table format or in graphics. If the data input is incomplete, the user is denied access to the EGP-DSS results. The results can be viewed on the screen or saved and printed out in hard copy.

The **EXIT** button closes the GUI.