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A three-tier model for electricity generators and decision makers

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University of the Witwatersrand

Doctoral Thesis

A Three-Tier Model for Electricity Generators and Decision Makers

Mantombi Bashe

A thesis submitted in fulfilment of the requirements
for the degree of Doctor of Philosophy
in the

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September 2022

Declaration

I, **Mantombi Bashe**, declare that this thesis titled, "**A Three-Tier Model for Electricity Generators and Decision Makers**" and the work presented in it is my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.

Signed: 

Date: 28 September 2022

Abstract

The aim of this study is to develop, demonstrate and recommend a three-tier planning model for the electricity generation expansion planning (EGEP) which consists of: costs evaluation of the existing portfolio of power plants, the EGEP and evaluation of investment costs for new capacity technologies.

The long term EGEP problem is solved by optimisation models which determine energy technologies, size and when should the electricity generation plants be available during the planning horizon under certain constraints.

The first step seeks to influence the selection of potential technologies by assessing the fuel costs of existing fleet of power plants; where portfolio theory model is utilised for energy sources such as coal, hydro, nuclear and gas/diesel. The portfolio evaluation period ended in 2013, coinciding with the year the electricity generation capacity expansion planning period started. The results of portfolio evaluation showed that the 2013 portfolio fuel costs are not efficient because of both high costs and risks.

The second step is the actual planning for new electricity generation capacity. Two stage stochastic programming (TSSP) model is used for planning amidst of uncertainty in electricity demand. The TSSP model is contrasted with a traditional deterministic model for the EGEP which is used for the period, 2013 to 2050. The planning data is sourced from South African Integrated Resource Plan (IRP) update published in 2013. The cost results emanating from the TSSP model are lower than the deterministic model's cost results.

The third step evaluates the investment costs for projects emanating from TSSP results. Real option (RO) models are used in this tier to provide decision makers with options in projects implementation dates. Sequential compound RO model is applied to new capacity with increments and a binomial option pricing model is used for technologies where new capacity occurs once in the period. RO model is compared to the net present value (NPV) model. The NPV results suggest that all the investment projects be rejected; whereas the RO results show that they can also be deferred.

I dedicate this research to my mother,

Nosunday Muriel Bashe, and my late father,

Sicelo Bashe,

for their encouragement.

To Mlibo and Inkosi-Iyapha

for allowing me to be a part-time mother whilst carrying out this research.

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Symbols

i, j	energy sources
p	potential technology type
k	demand category
t	time period in Tier 1
$\tilde{t}$	time period in Tier 2
$\hat{t}$	time period in Tier 3
β	binary parameter
F	expected cash flow
$H_{\hat{t}}$	historical revenue less operating costs at time $\hat{t}$
l	number of investment projects
m	number of years from cash flow year to RO evaluation date
n	existing technology type
$\grave{n}$	the maximum number of times that u or d can go up or down, respectively
σ	volatility
r	interest rate
d	decreasing factor
$\hat{p}$	risk free probability
u	decreasing factor
z	last investment year
$C_{\hat{t}}$	running costs at time $\hat{t}$
$F_{\hat{t}}$	cash flow at time $\hat{t}$
$r_{\hat{t}}$	historical return up to time $\hat{t}$
$V_{\hat{t}}$	revenue at time $\hat{t}$
r_f	risk-free interest rate
f_i	fuel cost for energy source i

f_{it}	fuel cost for energy source i at time t
X_{f_i}	weight of fuel cost i
μ_{f_i}	average of fuel cost i
σ_{f_i}	standard deviation of fuel cost f_i
ρ_{f_i,f_j}	correlation coeffient between fuel costs f_i and f_j
$c_p^{\tilde{t}}$	annual capital costs for technology p at time $\tilde{t}$
$e_p^{\tilde{t}}$	existing capacity for technology p at time $\tilde{t}$
$u_p^{\tilde{t}}$	cost of unserved energy for technology p at time $\tilde{t}$
$b_p^{\tilde{t}}$	annual capacity factor for technology p at time $\tilde{t}$
$l_p^{\tilde{t}}$	annual fixed operation and maintenace cost for technology p at time $\tilde{t}$
$v_p^{\tilde{t}}$	annual variable operation and maintenace cost for technology p at time $\tilde{t}$
$f_p^{\tilde{t}}$	annual fuel cost for technology p at time $\tilde{t}$
$g^{\tilde{t}}$	sum of running costs ($u_p^{\tilde{t}}$, $l_p^{\tilde{t}}$, $v_p^{\tilde{t}}$, $f_p^{\tilde{t}}$) at time $\tilde{t}$
$d_k^{\tilde{t}}$	instantaneous electricity demand for demand category k at time $\tilde{t}$
$q_k^{\tilde{t}}$	duration of demand for demand catergory k at time $\tilde{t}$
$r_k^{\tilde{t}}$	required electricity for demand catergory k at time $\tilde{t}$
$x_k^{\tilde{p}}$	new capacity for technology p at time $\tilde{t}$
$y_{pk}^{\tilde{p}}$	allocation for technology p capacity to demand category k at time $\tilde{t}$
$z_k^{\tilde{p}}$	unserved energy for demand category k at time $\tilde{t}$
$m_n^{\tilde{p}}$	decommissioned capacity for technology m at time $\tilde{t}$
$y_{nk}^{\tilde{p}}$	allocation for technology n capacity to demand category k at time $\tilde{t}$
$e_n^{\tilde{t}}$	existing capacity for technology p at time $\tilde{t}$

Abbreviations

AIMMS	**A**dvanced **I**nteractive **M**ultidimensional **M**odeling **S**ystem
BOPM	**B**inomial **O**ption **P**ricing **M**odel
BS	**B**lack-**S**choles
BSM	**B**lack-**S**choles-**M**erton
c/kWh	South African **c**ents per **k**ilo**w**att **h**our
CCGT	**C**ombined **C**ycle **G**as **T**urbine
CCGTwCCS	**C**ombined **C**ycle **G**as **T**urbine **w**ith **C**arbon **C**apture and **S**torage
CCS	**C**arbon **C**apture and **S**torage
COP21	**21**st session of the **C**onference **o**f the **P**arties
CRO	**C**ompound **R**eal **O**ptions
CO_2	**C**arbon **dio**xide
COUE	**C**ost **o**f **U**nserved **E**nergy
CSP	**C**oncentrated **S**olar **P**ower
DEA	The South African **D**epartment of **E**nvironmental **A**ffairs
EDC	**E**xpected **D**eterministic **C**ost
EG	**E**lectricity **G**eneration
EGEP	**E**lectricity **G**eneration **E**xpansion **P**lanning
FBwCCS	**F**luidized **B**ed Combustion **w**ith **C**arbon **C**apture and **S**torage
FBwFGD	**F**luidized **B**ed Combustion **w**ith **F**lue **G**as **D**esulfurization
FGD	**F**lue **G**as **D**esulfurization
GBM	**G**eometric **B**rownian **M**otion
GJ	**G**iga**j**oule
GDP	**G**ross **D**omestic **P**roduct
GHG	**G**reen**h**ouse **G**as
GVP	**G**ross **P**roject **V**alue

GW	**G**iga**w**att
GWh	**G**iga**watt h**our
h	**h**our
HYOYIR	**H**istoric **Y**ear-**o**n-**Y**ear **I**nflation **R**ate
IEA	**International Energy Agency**
ICCC	**I**ntegrated **G**asification **C**ombined **C**ycle
IGCCwCCS	**I**ntegrated **G**asification **C**ombined **C**ycle **w**ith **C**arbon **C**apture and **S**torage
IPO	**I**nitial **P**ublic **O**ffering
IRP	**I**ntegrated **R**esources **P**lan
kW	**k**ilo**w**att
LP	**L**inear **P**rogramming
MAD	**Market A**sset **D**isclamer
MWh	**M**ega**w**att **h**our
MILP	**M**ixed **I**nteger **L**inear **P**rogramming
Moz	**Moz**ambique
MR	**M**ean **R**eversion
NERSA	**N**ational **E**nergy **R**egulator of **S**outh **A**frica
NF	**N**uclear **F**leet
NPV	**N**et **P**resent **V**alue
OCGT	**O**pen **C**ycle **G**as **T**urbine
PCC	**P**earson's **C**orrelation **C**oefficient
PCwCCS	**P**ulverized **C**oal **w**ith **C**arbon **C**apture and **S**torage
PCwFGD	**P**ulverized **C**oal **w**ith **F**lue **G**as **D**esulfurization
PDD	**P**eak **P**lateau **D**ecline
PIPs	**P**hysical **I**nvestment **P**rojects
PT	**P**ortfolio **T**heory
PV	**P**hoto**v**oltaics
R	**R**and
R&D	**R**esearch and **D**evelopment
RDMIP	**R**esearch and **D**evelopment **M**anufacturing

	Investment **O**pportunities
RE	**R**enewable **E**nergy
RLOC	**R**evenue **L**ess **O**peration **C**osts
RES	**R**enewable **E**nergy **S**ources
RNA	**R**isk **N**eutral **A**pproach
RO	**R**eal **O**ptions
SA	**S**outh **A**frica
SAn	**S**outh **A**frica**n**
SP	**S**tochastic **P**rogramming
TSSP	**T**wo **S**tage **S**tochastic **P**rogramming
TSSLP	**T**wo **S**tage **S**tochastic **L**inear **P**rogramming
TSSMILP	**T**wo **S**tage **S**tochastic **M**ixed **I**nteger **L**inear **P**rogramming
TSSPS	**T**wo **S**tage **S**tochastic **P**rogramming **S**olution
SADC	Southern **A**frican **D**evelopment **C**ommunity
SCRO	**S**equential **C**ompound **R**eal **O**ptions
SO	**S**ystem **O**perator
SU	Nuclear **S**ingle **U**nit
VSS	**V**alue of **S**tochastic **S**olution
Zam	**Zam**bia

CHAPTER 1

Introduction

Electricity generation expansion planning (EGEP) is an activity that is required for sustainable delivery of electrical energy. Fossil fuels such as coal, gas, oil, and renewable energy sources play a major role in EGEP. Lately, the focus is more on renewable energy sources than fossil fuels, due to the mitigation of climate change effects encompassed in COP21. In COP21, the aim is to make sure that the average temperature does not increase by more than 2° Celsius by 2050 [1]. The Greenhouse Gas (GHG) emissions are released during the combustion of fossil fuels when electricity is being generated. Renewable energy sources reduce the GHG emission from electricity generation. Carbon capture and storage (CCS) captures the CO_2 (one of the GHG emissions) after fossil fuel combustion before it is released to the atmosphere for storage. CCS contributes towards the reduction of GHG emissions. Flue gas desulphurization (FGD) is another technology which reduces GHG emissions by reducing SO_2 from coal combustion before emission is released to the atmosphere.

As a result of COP21, new electricity capacity expansion plans should utilise less of traditional fossil fuels and increase use of renewable energy sources and implementation of technologies that minimise GHG emissions.

1.1 Background of the EGEP

The EGEP is one of the most researched topics as electricity generation (EG) industry is evolving continuously. The changes in EG landscape started in mid-1980s, where vertical integrated structures moved to semi regulated and liberalised. The discussion of more details on the early changes in the electricity industry are in [2] and [3].

For climate change and environmental protection concerns, the supply side established renewable energy sources, mainly from wind and solar, CCS and FGD, clean coal technologies, and emission constraints [3]. Similar to the electricity supply side, the demand side introduced initiatives that reduce electricity usage. Smart grids which work hand in hand with smart meters is one of electricity demand side innovations. Smart meters allow electricity users to monitor their electricity usage. More details in electricity demand management initiatives are discussed in details in [3], [4] and [5]. In different countries there are polices which promote renewable energy sources and GHG emissions [3]. The above evolution in the electricity industry resulted in new developments in the EGEP models. Planning for EG capacity expansion is an ongoing important part of electricity generation, driven by expected growth in electricity demand and ageing power plants.

The EGEP problem is a power plant mix problem that identifies what, where, when and how much new generation expansion facilities shall be installed. This definition does not include capacity to be decommissioned. Decommissioning is where the electrical generating units are shut down and all operating permits are terminated for the power stations [6]. In this study most coal power stations have a set decommissioning date, due to retirement, during the EGEP period [7]. The power station retirement is not the only reason that leads to plant decommissioning, others reasons include the following for coal plants [8]: policy and regulations, cost competition with other fuels, and corporate emissions reduction goals. *What* is defined as the type of generation technologies to be added to the grid; *how* much is the size of each generation plant; *where* is the location of these plants and when

is the stages of the planning horizon when the new technologies will be implemented? The EGEP problem can also be defined as a problem that determines the optimal type of energy technologies, size (how much), location (where) and time (when) of construction of new generation plants while minimising total costs over a long term horizon and being subject to a series of constraints. More details on the above definitions are in [2], [9], [10] and [11].

The EGEP problem definitions discussed above are similar; however, there are few differences due to the type of data used, availability of data and assumptions used by the authors. If, for example, the assumption is that there is no existing capacity, decommissioning capacity would not be included in the EGEP problem definitions. Furthermore, if, for example, the data available has power plants' locations for potential technologies, then location forms part of the EGEP problem definition. The EGEP problem adopted in this thesis includes what, when and how, and the decommissioning dates for existing capacity. The where is excluded in this thesis because of data constraints.

1.2 Objectives and Constraints in EGEP models

The vast experience obtained by engineers from EGEP became a mathematical model [3]. The first EGEP problem's objective was to minimise total costs (capital or investment and operating costs) in the electricity industry [12].

The EGEP objectives have evolved since then to multi-objectives which include economic, technological, environmental, reliability, social, policy and regulatory aspects. Some of the above multi-objective functions include total cost, emission cost, emission quantity, imported electricity or fuel cost, cost of unserved demand, and energy price. In [2], [3], [9], [10] and [13] there are further details on the objectives and constraints of the EGEP problem.

The mathematical models that solve the EGEP problem have also evolved with the evolving electricity industry. Objective functions play a huge role in EGEP models, which are in turn influenced by the availability of data. All the EGEP

models objective functions have constraints, as shown below [9],

$$\min \text{ (max)} \quad f(x),$$

subject to constraint(s)

$$g(x) \geq 0.$$

In cases when one or more objective functions are to be minimised and the other(s) is (are) maximised, this is known as conflicting multi-objective functions. Conflicting multi-objectives are discussed further in [2] and [9].

Constraints for a cost minimising EGEP problem typically consists of reliability, security, flexibility, environmental considerations, social acceptability and existing generation capacity. Some of the above constraints include emission level, reliability margin, budget, peak demand, spin reserve, generation capacity, number of units and renewable penetration levels. Similarly, some constraints can be imposed on the data used in the EGEP model. In regulated electricity markets, the objectives of EGEP models are to minimise costs and in unregulated or competitive markets the objectives are to maximise profits. Further discussion on objective functions and constraints are in [9], [11], [12] and [14].

In EGEP mathematical models simulate the desired objective function(s) and constraints. The static models are when the decisions are taken once at the beginning of the period [15]. However, when a decision is broken down into a sequence of decisions over time, such models are called dynamic [9]. In [9], there are more details about static and dynamic models.

EGEP models are long term models which try to simulate what will happen in the future; as a result, for such models to work, assumptions are made about the future. Assumptions are about the data used in the model which include but not limited to future electricity demand, technology costs, fuel costs, investments and operation costs and economic conditions. [12] and [16] provide more details on the data used for EGEP models.

Another set of assumptions in EGEP models is on whether the variables used, are continuous or discrete and if the problem is linear or non-linear. Linear and

non-linear variables are in [2], [13], [16] and [17].
Other data related assumptions in EGEP models are on the risks and uncertainties.

1.2.1 Risks in the EGEP models

The energy crisis in the 1970s introduced risk to the EGEP problem. Broad sources of risks in EGEP problem which decision makers should consider are typically economic, political, regulatory, environmental, technical, social, and climate risks. The following definitions of risks are in [16]: variance, expected excess, excess probability and conditional value at risk. Variance is a risk measure in EGEP problems, which is the deviation from expected value. Expected excess or regret is another measure of risk used in EGEP problem and is defined as the expected value over a predefined target level. Similarly, excess probability also measures EGEP risk and is defined as the probability of exceeding a predefined target [16]. Value at risk (VaR) is another risk measure of EGEP risk, which means a potential value of loss over a predefined period for a given confidence interval. Conditional value at risk (CVaR) is a conditional expectation of losses with a value higher than VaR and maximum regret risk measures. Sharpe's risk definition, which is the sum of systematic and specific risks, is also used in EGEP problem. Variance is a risk measure in this thesis because it is the only risk that can be determined with the available data. More details on risks in EGEP problems are in [3], [10], [16], [18], [19], [20], [21], [22], [23] and [24].

1.2.2 Uncertainties in the EGEP models

Uncertainty refers to a situation where the outcomes and/or their probability of occurrence are unknown to decision makers. It is a lack of exact knowledge, regardless of the cause of deficiency.
The broad sources of uncertainties for the EGEP problem are in costs, load growth,

performance of electrical network and in socio-political influences. Other uncertainties in the EGEP problem include access to natural resources, rising fossil fuel prices, policies for climate change mitigation, technological innovation, replacement of ageing facilities and shareholder value. There are also uncertainties in emission factors. The introduction of renewable energy sources into EGEP also introduced more uncertainties, because of the difficulty to predict the renewable energy sources (RES) electricity supply. The uncertainty considered in this thesis is on load growth, since it is the only uncertainty on the data available. More details on uncertainties in the EGEP are obtainable from [2], [9], [22], [25], [26] and [27].

Scenario analysis, sensitivity analysis and probabilistic analysis evaluate uncertainties in the EGEP problem. In scenario analysis, a range of potential future (scenarios) is generated and for each scenario is the EGEP problem evaluation, and the decision makers choose favourable outcomes. Sensitive analysis identifies areas of vulnerability (sensitivities) in the EGEP problem, which requires the monitoring of model results for changes in sensitivities. Probabilistic analysis is about allocation of probabilities to the occurrence of sensitive variables and determination of optimal output. Probabilistic analysis is superior to both scenario and sensitivity analysis. More details on uncertainty evaluation are available in [3] and [2].

The uncertainties at planning stage remain even post planning when decision makers have to implement the plans. However, not all the models that are utilised to solve the EGEP problem incorporate uncertainties.

This thesis considered, electricity demand uncertainty and evaluated it through probabilistic analysis. Nonetheless, the thesis assumed that even at the stage of capacity implementation, the electricity demand uncertainty still exists.

1.2.3 Techniques for solving the EGEP problem

The discussion in sections 1.2, 1.2.1 and 1.2.2 is used in selecting a technique that solves an EGEP problem. Optimisation is a popular technique utilised for solving

the EGEP problem. The application of optimisation techniques are in both single and multi-objectives EGEP problems. If both the objective and constraint functions are linear, then, the utilisation of a linear programming (LN) optimisation technique is appropriate. However, if the objective and/or constraint functions are linear and have both integer and continuous variables, then, mixed integer linear programming (MILP) optimisation technique is relevant. Sometimes the modelling of the EGEP problem includes a nonlinear programming, nonlinear mixed integer or nonlinear integer programming. Interested readers can consult [3], [2], [9], [10], [11], [28] and [29], for more information on optimisation techniques utilised in the EGEP problem.

The EGEP problems are large scale problems which can execute for long hours in an ordinary computer, hence the use of decomposition methods to overcome these challenges. The utilisation of Dantzig-Wolfe decomposition and Benders decomposition is common for the EGEP problems. More details on decomposition methods are in [3], [9] and [11].

The optimisation techniques utilise mathematical models and are able to provide a global optimal solution to the EGEP problem. Mathematical based optimisation techniques discussed above fail to solve non-continuous and non-differentiable EGEP problems [9]. Another shortfall of optimisation techniques discussed so far is the incorporation of risk and uncertainty. These shortfalls resulted in utilisation of other techniques for solving the EGEP problem. More details on optimisation techniques are in [3] and [9].

The utilisation of heuristic and meta-heuristic techniques in the EGEP problems incorporate non-continuous and non-differentiable. However, heuristic and meta-heuristic techniques do not guarantee global optimal solution for the EGEP problem. More details on heuristic and meta-heuristic techniques are in [2], [3] and [9].

Stochastic programming (SP) is an optimisation technique which is able to address the uncertainties in the EGEP problems. Uncertainties on fuel costs, market electricity prices, prices on green certificates, CO_2 emission allowances, market share and capital cost. More details on SP and uncertainties are in [30] and [31].

The modern portfolio theory (PT) approach minimises either the cost or the risk

of a portfolio of electricity generation assets, where the EGEP problem is in investment selection. Other than quantifying risk, PT models provide decision makers with a range of optimal (efficient) portfolios, as opposed to just one optimal solution. More details on PT models are in [14] and [19]. The criticism against PT models is simplicity and less robust because such models do not consider the technical aspects of a power system. PT models cannot be applied practically for determining optimal portfolios of electricity supply. More details on the shortfalls of PT models are in [14] and [28].

Real Options (RO) are also used to evaluate uncertainties in the EGEP problems. The following uncertainty factors, which include electricity price, cost, demand, technology, policy and demand response, are considered in RO models. More details on the applications of RO models to the EGEP problems are in [23], [32] and [33].

However, most if not all uncertainties identified at the planning stage remain at post planning stage. The post planning stage is where the EGEP new capacity results become real projects. The RO model evaluated the following post planning uncertainties which include production of electric power, investment costs, price of electricity, consumer price index, climate change policy and fuel price. More applications of RO models on post planning uncertainties are in [34] and [35].

Most of the literature about risks and uncertainties in EGEP problem is from competitive or deregulated energy markets. One may assume or conclude that risks and uncertainties do not exist in regulated energy markets, which is not the case. This thesis utilised models based in PT, SP and RO.

1.2.4 Risks, Uncertainty, and Solution Techniques in Objectives and Constraints

Moving a step further from the form of objective functions represented in section 1.2 only the minimisation objective functions which involve risk and uncertainty are discussed in this section. The uncertainty is utilised for objective functions that have one or more functions, but risk operates only when there are

conflicting objective functions. The following is a deterministic setting where both the objective function and constraints do not have risk or uncertainty [36],

$$\begin{aligned} \min \quad & f(\mathbf{x}), \\ \text{s.t.} \quad & g_{\hat{l}}(\mathbf{x}), \end{aligned}$$

where $\hat{l} = 1, \ldots, \hat{L}$, $\mathbf{x}$ is a decision vector from $\mathbb{R}$ or $\mathbb{Z}$. Usually if $\mathbf{x} \in \mathbb{R}$, LN optimisation techniques are utilised to determine the values of $\mathbf{x}$. However, if $\mathbf{x} \in \mathbb{Z}$, techniques based on integer optimisation are employed. In some cases, $\mathbf{x} \in \mathbb{Z}_+$ for the objective function and $\in \mathbb{R}_+$ for constraints, then deterministic MILP is an appropriate technique.

Sometimes there is uncertainty in the data, and it is represented by a random variable ξ, which has a known probability or one that can be estimated [36] and [37]. As a result of the uncertainty, $f(\mathbf{x})$ is replaced by $f(\mathbf{x}, \xi)$ and $g_{\hat{l}}(\mathbf{x})$ by $g_{\hat{l}}(\mathbf{x}, \xi)$ [36], [37]. Once uncertainty is involved as mentioned above, then a two stage or multi-stage stochastic programming approach is appropriate [37]. The decomposition methods are usually utilised to simplify the solution of $f(\mathbf{x}, \xi)$ when the values of $\mathbf{x}$ are already determined.

The approach discussed above is regarded as a mathematical approach, and the same problem could be solved by meta-heuristic approach [38].

Risk could be incorporated for both deterministic and uncertain objective functions, however it is added to deterministic objective function below. Assuming that there is a risk parameter λ, then an objective function can be presented as follows [39],

$$\min C = f(\mathbf{x}) + \lambda \text{Var}(f(\mathbf{x})),$$

where C denotes a risk weighted total cost, $f(\mathbf{x}))$ is assigned to a total cost, λ denotes a risk-averse parameter, $\text{Var}(f(\mathbf{x}))$ denotes the variance of the total cost function. A mean-risk function is represented by the following objective function [40],

$$\lambda f(Y_t) - (1 - \lambda)\mathbb{E}(Y_t),$$

where $t = 1, \ldots, T$, for a multi-period risk, $\lambda \in (0, 1)$ and $\mathbb{E}(Y_t)$ denotes the expected value of Y_t. The next section discusses the available software for solving the objective functions with constraints, as discussed in this section.

1.3 Modelling Software for the EGEP

There is a good deal of off the shelf software that could be utilised for solving the EGEP problems, which are different in many ways. In [41] there is a detailed list of some of these software. Plexos is discussed briefly because it is a powerful and popular software for modelling the EGEP problems [42]. AIMMS is also discussed because it is used in this thesis. Even though Plexos is popular, it has some flaws, one of them is the computational cost for long term simulations [41]. Plexos is unable to model stochastic programming problems. AIMMS is one of the optimisation software that can handle difficult types of stochastic programming problems [43]. AIMMS software also allows model developers to code complicated optimization models in a clear, concise, and efficient way [44]. The disadvantage of AIMMS is that its applications are not well documented, and it is not as detailed as Plexos.

Optgen is a computational tool for determining the least-cost expansion (generation and interconnections) of a multi-regional hydrothermal system [45]. Even though the Optgen was utilised in expansion planning for Brazil and Venezuela [45], there are no publications that the authors is aware of. As a result, the advantages and disadvantages of this software remain difficult to establish. In [46] the Optgen was compared to Plexos software, and the conclusion was Plexos is far superior to Optgen.

Engage is one of NREL's models [47]. It is a modelling tool which makes cross-sectoral energy system planning and simulation easier and more accessible [47]. Similar to Optgen, there is not much information available about Engage which is independent of NREL.

1.4 Purpose and Significance of the Study

The EGEP problem is an old problem in the electricity industry, which has been evolving because of changes in the industry. So far, there is no model that is able to optimise the EGEP problem and also incorporate risk and uncertainty, starting from pre-planning stage to post planning period. The purpose of this study is to introduce a new approach for solving the EGEP problem based on mathematical models which incorporate both risk and uncertainty. The new approach uses three models.

1.4.1 Definition of the Three-Tier Planning Process

This thesis introduces a new approach for the EGEP. The three-tier model is demonstrated in regulated electricity industry. The thesis develops, demonstrates, validates and recommends a new approach to the EGEP consisting of three tiers as shown in Figure 1.1. In Figure 1.1, input A represents historic fuel costs for

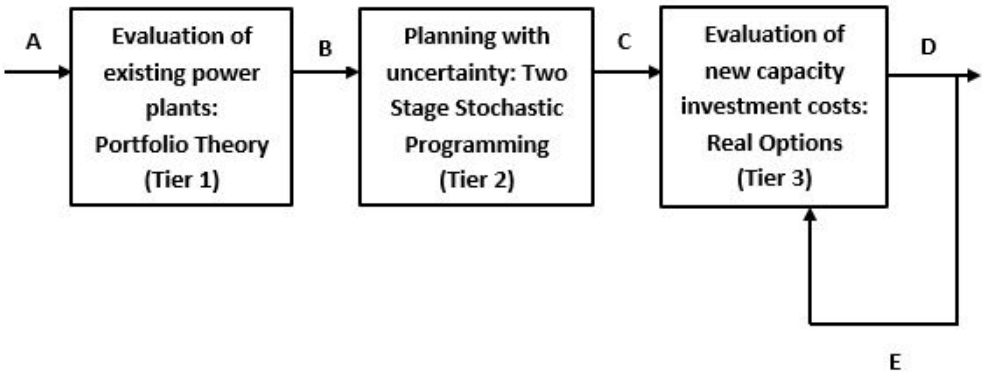


FIGURE 1.1: Three tier planning process

existing power plants, which are used for risk evaluation. However, fuel costs are not the only operating costs that are risky. Maintenance costs and other operating costs can also be evaluated [48]. The second tier is supposed to consider the information obtained from the evaluation of existing power plants, which is

represented by B in Figure 1.1, to selecting new energy sources for the new capacity expansion. The output C in Figure 1.1 is the second tier output which consists of the technologies that are selected in the second tier, the corresponding data such as energy sources, capital and operational costs, new capacity and dates when the new capacity is anticipated. The output D in Figure 1.1 is when the decision makers have taken a decision to invest or not to invest on a particular investment project. However, there is a possibility to re-evaluate the RO values for the investment project at a later date, then input E is utilised in Figure 1.1. The re-evaluation is considered in RO because its values depend on certain economic values, which change frequently. However, the frequency of re-evaluating the RO models is decided upon by decision makers. The implementation of each tier uses an appropriate mathematical model. The individual models in Figure 1.1 have been introduced in section 1.2.3.

In the first tier, the evaluation of existing power plants using PT will be performed by assessing the fuel costs and their risks before the planning for the EGEP. The aim of the first tier is to inform the decision-making process by determining the fuel risks of the present energy sources. When possible, the energy sources with fuels that are risky can be replaced or supplemented with energy sources that have fuels with less risk. The outcome of the energy source's deliberation is supposed to be passed to the second tier, where the planning with uncertainty using TSSP takes place.

The evaluation of new capacity investment costs, using RO, evaluates the investment cost for technologies which are selected by the TSSP in the second tier. In the third tier, the selected technologies become investment projects, which involve building power plants. The conversion of selected technologies to investment projects sometimes takes years, and during this time some assumptions used at the planning stage are realised partially. This thesis focuses on the assumption about future electricity demand. The partially realised electricity demand can either be lower, higher or at the same level as the assumed one. If the demand is lower than expected, then the new capacity installation dates could be delayed; if the demand is at the same level as assumed, then dates can be left as they are. If the

demand is higher, then new capacity installation dates can be brought forward.
According to the knowledge of the author, the electricity expansion planning approach shown in Figure 1.1 is new, and it is used for the first time in this thesis. Models based in portfolio theory (PT), two stage stochastic programming (TSSP) and real options (RO) were used as individual models before in the EGEP; however, these models have never been used together for the purpose explained and shown in Figure 1.1.
The planning process in Figure 1.1 borrowed from strategic planning, is defined as a series of concepts, procedures, and tools that are designed to help leaders, managers, and planners to think and act strategically [49]. Rewriting the strategic planning definition in terms of Figure 1.1, resulted in a series of models that are designed to help the EGEP decision makers and planners to think and act strategically. According to Maleka [50] and Andrade and Loureiro [51], strategic planing is a process which starts with goal setting (strategic conception), analysis of strategic formation (strategic knowledge management), then strategy formation (formulation), followed by strategy implementation and strategy monitoring (validation and strategy reassessment). Figure 1.1 dropped the first and the last steps of strategic planning, because the goal is to expand EG capacity, which is the first step. The last step is equivalent to monitoring the performance of newly implemented power plants beyond the EGEP planning scope.
The evaluation of existing power plants (Tier 1) in Figure 1.1 is about the analysis of strategic formation because this is where internal and external analysis of factors such as emerging technology and new competition occur. The planning with uncertainty (Tier 2) relates to the strategy formation. This is the case because strategy formation entails developing of specific actions that will enable an organisation to meet its goals. The goal in this case is to expand EG capacity. The evaluation of new capacity investment costs (Tier 3) is associated with strategy implementation to meet organisational goals. More details on strategic planning are in [50].

1.4.2 Research Questions

This thesis attempts to answer the following major question: How can a three-tier electricity expansion plan with the objective of minimising costs and re-evaluate investments be implemented? This question can be subdivided into three sub-questions:

- How can a PT model be utilised as a first tier in a three-tier model for electricity generation portfolio evaluation?
- How can a TSSP model which includes uncertainty in future electricity demand be implemented as a second tier in electricity capacity expansion?
- How can decision makers apply RO models to evaluate investment costs amidst changes in assumption taken at the second tier?

To the know of the author, the three-tier model is introduced and applied for the first time in the EGEP.

1.5 Organisation of the Thesis

The thesis organisation is as follows: Chapter 2 provides a literature scan for the three tiers. The development of three-tier methodology is in chapter 3. The analysis of methodology models is in chapter 4. The data for developing the three-tier model is discussed in chapter 5. Chapter 6 discusses the results of this study. The validation of the three-tier model is presented in chapter 7. In chapter 8, there is the discussion of the results, while chapter 9 presents the conclusion and recommendations based on the drawn conclusion. Appendix A has tables of 200 efficient portfolios' costs and risks. In appendix B there are tables for energy sources corresponding to the efficient portfolios in appendix A. Appendix C has the Matlab code for the efficient portfolios in appendices A and B. Appendix D has some three-tier model valuation data not included in [52]. In appendix E are

the South African historic and simulated year-on-year inflation rates from January 2009 to December 2105. Appendices F, G and H are published papers emanating from this research.

CHAPTER 2

Three-Tier Literature

The aim of this chapter is to provide a background on the portfolio theory, two stage stochastic programming and real options models. The chapter also demonstrates the use of the above models in the EGEP.

2.1 The Portfolio Theory

As discussed in chapter 1, the PT is one of the techniques that are used in the EGEP, mainly for risk determination. This thesis used the PT in the first tier which is discussed in details in chapter 3, hence its background is provided.

2.1.1 The Portfolio Theory in Financial Industry

The PT discussed and utilised in this thesis is from the Markowitz theory, not on Maslow. This is the case because the Maslowian PT uses an individual's psychological needs, which makes it more appropriate for individual investors than corporate investors. The background and differences between the Markowitz and Maslow theories are in [53], [54] and [55]. However, the Markowitz' PT uses assets' historic performance, which is appropriate for this study because the PT is used to assess the historic performance of existing power plants.

The PT utilises a utility function $U(R)$ where R denotes the rate of return for the investment period; or efficient portfolios. However, the determination of $U(R)$ is more expensive than efficient portfolios, which are as good as the best $U(R)$. More details on $U(R)$ and efficient frontiers are in [56]. As a result, this thesis utilised

the PT based on efficient frontiers rather than on a utility function because of data constraints.

Markowitz [57] defines a good financial portfolio as more than just a long list of financial securities and bonds, but a balanced whole that provides the investor with protections and opportunities with respect to a wide range of contingencies. An efficient portfolio is a portfolio P which is obtainable; there is another obtainable portfolio Q whose expected return is greater than P's, then its risk must be greater than P's. If there is also another obtainable portfolio S whose risk is less than P's, its expected return must be less than P's.

Efficient frontier is a curve that connects all the efficient portfolios. All other portfolios that are not on the efficient frontier are inefficient portfolios. More details on efficient frontier and mathematical models for determining efficient frontiers are in [57].

The Portfolio theory is about reducing a portfolio risk, not an individual security's risk. Diversification is about investing in a portfolio whose underlying securities are from different industries. More details on portfolio risk and diversification are in [57]. In this thesis, diversification is about investing in different electricity energy sources.

2.1.2 The Portfolio Theory in Electricity Generation

The PT models are not new in electricity generation. The following continents have used the PT models in electricity generation, notably, North America [58], [59], [60] and [61]; South America [62], Europe [60], [63], [64] and [65] and Asia [66] as well as [39].

Most of the authors cited above utilised PT models to determine if an existing or an already planned EG portfolio is efficient. The exception is in [65] and [39] where the authors utilised PT model for electricity generation planning.

The review discussed in this section covers continents with deregulated electricity industry, except in [58] where the study took place before. This shows that the PT

can be utilised for risk evaluation for both regulated and deregulated electricity industries.

2.2 Two Stage Stochastic Programming

Two stage stochastic programming (TSSP) is one of the SP techniques utilised in the EGEP which is discussed briefly in chapter 1. The SP models are popular for evaluating uncertainty in the EGEP. In this thesis the TSSP is used in Tier 2 which is discussed in details in chapter 3, hence the TSSP background is discussed in section 2.2.1.

2.2.1 Stochastic Programming Background Theory

Bellman [67] and Dantzig [68] introduced stochastic programming (SP). There are differences in their definitions. SP is a dynamic programming as a mathematical theory devoted to the study of multi-stage processes [67]. A dynamic programming is defines in [67] as a time dependent programming, where the order of operations is important.

The SP is a general model where there are activities that take place in two or more stages [68]. In [68], the first stage activities are determined in advance and the other stages' activities could not be determined in advance since they are dependent on the first stage. The activities for stages that follow the first stage also depend on the outcome of random events representing uncertainty [68]. Even though there are similarities in the SP definitions in [67] and [68], the practitioners use them independently.

The SP has different but related definitions from different authors, and a few of them are mentioned below. The SP is a class of optimisation models and algorithms in which some data may be subject to significant uncertainty [69]. The SP models are appropriate when data evolved over time and decisions needs to be made prior to observing the entire data stream [70]. The SP is a part of

mathematical programming and operations research that study how to incorporate uncertainty into decision problems [70]. It provides modelling and solution approaches that harnessed the power of optimisation to solve models that are sensitive to the impact of uncertainty [70].

2.2.2 Two Stage Stochastic Linear Programming and Deterministic Linear Programming Models

The deterministic linear programming (LP) models play an important role in the derivation of the two stage stochastic linear programming (TSSLP). A detailed background of LP and how it evolved to the SP is in [71]. The SP introduced uncertainty aspect to the LP models. The general TSSLP model is in [68] and [72].

2.2.2.1 Applications of deterministic LP models in the EGEP

A detailed deterministic LP models for the EGEP are in [15], [73] and [74]. The electricity capacity expansion problem in both [73] and [74] is about minimising the capital, imported electricity, and operating costs. The deterministic models for the EGEP use one scenario at a time, this is equivalent to a probability of 1 for each scenario. This means that the deterministic model, in this case, assumes that the electricity demand will follow one scenario.

According to Wallace and Fleten [75], the first step of making sure that the model is realistic is by introducing several possible future demand scenarios. Scenario analysis is important for checking the robustness of the deterministic model when there is uncertainty about the future behaviour of the data in [76].

2.2.2.2 Applications of two stage stochastic linear programming models in the EGEP

The derivation of TSSLP models starts from the deterministic LP in [15], [73], [74], [77] and [78] utilising the deterministic LP models mentioned in section 2.2.2.1. The TSSP models take care of the unknown future. The TSSLP model in [73] and [74] is similar to the one in [15], except that the total investment cost had a limiting budget in [15]. Another exception is the consideration of existing capacity in [73] and [74] but not in [15]. The applications of TSSP models are in [79] in a regulated electricity industry. The uncertainty in [79] is the future availability of the thermal power plants which are in operation. In [15] and [80] the TSSP models were applied where the sources of uncertainty were electricity demand and costs of various power plants to meet future electricity demand.
In [75] Wallace and Fleten argued that the SP models can be utilised in long term electricity planning.

2.2.3 Two Stage Stochastic Mixed Integer Linear Programming and Deterministic MILP Models

The mixed integer linear programming (MILP) addresses the LP short falls. The general form of a two stage stochastic mixed integer linear programming (TSSMILP) model is in [81], [82] and [83]. What separates TSSMILP to TSSLP are variables that impose non-negativity and discrete, binary or continuous restriction of the first and second stage variables, respectively [82]. Similarly, there is no major difference between deterministic LP and MILP models, except for the variables which are linear in the LP model, are either discrete, binary or continuous restricted in the MILP model [82].

2.2.3.1 Applications of TSSMILP and deterministic MILP models in EGEP

The utilisation of both the TSSMILP and deterministic MILP models in the EGEP is in the minimisation of total costs [84], [85], [86] and [87]. However, the above authors considered different uncertainties. Most of the MILP applications in the literature do not only consider the generation expansion but also the transmission expansion, which is not considered in this thesis due to data constraints.

2.2.3.2 Value of SP solution

The aim of determining the value of the SP solution is to show the superiority of SP over the deterministic models. Birge [77] defines the value of SP solution (VSP) as the difference between the expected deterministic cost and the stochastic programming solution. The application of the VSP concept is in financial planning [70]. The VSP is considered in this thesis for the comparison of deterministic to TSSP costs results.

2.2.4 Scenario Analysis

This subsection provides a background and applications of scenarios, scenario planning and/or scenario analysis. The definition of one of these terms is in [88] where scenarios are defined as vivid description of plausible futures. Another definition is in [88] where scenario planning is a combination of scenario analysis and strategic planning. According to Schoemaker [89], "scenario planning stands out for its ability to capture a whole range of possibility in rich details", when compared to other managerial tools for strategic planning.

There is no optimal number of scenarios; however, the recommended number of scenarios ranges from 3 to 6 [90]. The definitions of the following scenarios: optimistic, basic, pessimistic and realistic, are in [91]. There are qualitative or quantitative scenarios. Qualitative scenarios are when the possible futures are in

the form of narrative text or story lines [92]. Quantitative scenarios provide tables and figures incorporating numerical data [92]. The application of scenarios in the EGEP are in [73], [74] and [93].

2.2.5 Cost of Unserved Energy

The introduction to the cost of unserved energy (COUE) is important because it is used in chapter 3 and in the subsequent sections. COUE emanated from load shedding, where load shedding is a controlled way of reducing the electricity demand with the aim of protecting the electricity system from a total blackout [94]. The COUE is the opportunity cost to electricity consumers and the economy from electricity supply interruptions [95]. The COUE is supposed to be higher than other electricity suppliers' running costs [15] and [73].

2.3 Real Options

Real options (RO) is one of the techniques utilised in the EGEP which is discussed briefly in chapter 1. RO models are also popular for evaluating uncertainty in the EGEP. This thesis utilised RO models in Tier 3 which is discussed in details in chapter 3.

The RO value depends on the following variables [96]: the value of an underlying risky asset, the exercise price, the time to expiration of the option, standard deviation of the underlying asset value (volatility) and risk-free rate of interest over the option lifetime. The RO value increases with the increasing: value of the underlying asset, time to expiration, volatility and risk-free rate. It decreases when the exercise price increases.

2.3.1 Real Options and Net Present Value

Having a reliable investment project assessment tools is important because investment projects have a huge impact on the company's future. Investments that add

value to the company are more desirable. There are models which are used to determine if a project will add value or not. The discounted cash flow (DCF) model is a traditional model which is used to value new investments. DCF model has three parts namely: net present value (NPV), internal rate of return (IRR) and risk weighted cost of capital. The NPV is the most popular methodology for evaluating project investments. More details on project investments and models that are used to value new investments are in presented [97] and [98].
NPV and IRR models are popular in South African industrial companies, as in [99] and [100]. However, when uncertainty is high DCF models, which perform well when expected cash flows are deterministic, fails to provide decision makers with adequate investment support. Therefore, there is a growing interest in models based on real options (RO), because these models guide decision makers better in dynamic environments. More details on the DCF model's shortcomings are in [98].

2.3.1.1 Net present value

The NPV of a project is the present value of its future expected cash flows [101]. The NPV model has shortcomings and one of them is its failure to incorporate uncertainties [96], [102], [103] and [104]. An approach which includes uncertainty is important in this thesis because of the uncertain expected cash flows based on the uncertainty in electricity demand.

2.3.1.2 Real options background

Derivatives are financial instruments whose value depends on the value of another underlying variable; they are generally called financial derivatives. The roots of RO are in financial derivatives introduced in the 20th century. Derivatives are able to protect the financial investors against future uncertainties. Similarly, RO protect physical asset investors against future uncertainties. Further details on RO are in [105], [106], [107] and [108].

The valuation of RO models utilise an option-pricing model [106]. RO can add a considerable value to physical investment projects (PIPs), but are often ignored or valued incorrectly [106]. RO capitalises on the NPV shortcomings [96] and [102], hence the utilisation of the RO models in this thesis.

2.3.1.3 Options embedded in physical investment projects

Options embedded in PIPs are categorised as American or European options. RO which can be exercised at any time up to maturity date are American option. However, a European RO can be exercised only at maturity date. The date in which the call or put RO comes to an end is the expiry or maturity date.
The following are the definitions of options embedded in PIPs. Abandonment option is an option to sell or close down a PIP, while expansion option is an option to make further investments and increase output when the conditions are favourable. It is also noted that a contraction option is an opposite of an expansion option, as it reduces the scale of a PIPs' operation. An option to defer is an option which allows the PIPs to be deferred to a later date, and an option to extend is used to extend the life of PIP. Further details on the above terms and definitions are in [96], [102], [106], [109], [110].
This thesis has adopted the option to defer because decision makers can have new capacity implementation dates due to changes in assumptions taken at the planning tier. The uncertainty considered in this thesis is electricity demand. The thesis employed SCRO models because some new capacity technologies have sequential capacity increases which require further investments.

2.3.1.4 Call options and compound real options

This section introduces the RO call option and compound real options. A call option is as an option which gives the holder the right but not the obligation to buy or invest in the underlying asset by a certain date (expiration or maturity date) for a certain price (exercise price or strike price). This study considered

a call option because it provides decision makers with flexibility in the dates of building new power stations. The deferred real options allow a decision maker to defer the investment date of any project [102]. More details on call options are in [96], [102], [106] and [109].

The study utilised call options and compound sequential real options (CRO) together. CRO are options whose value depends on the value of other options. They are options on options or nested options. More details on CRO are in [96], [102], [111], [112].

However, this study did not just use an CRO, but a SCRO. The SCRO is when the creation of the second option follows after the first option is exercised [96]. It can be applied when a project has multiple phases and the latter phases depend on the success of previous phases [112]. SCRO allows decision makers to learn from the first option before moving to the second option.

2.3.2 Models for Valuing Real Options

The models for valuing RO are from financial options. Black-Scholes and binomial option pricing models (BOPM) are discussed because BOPM is used for the evaluation of new projects investment costs. BOPM is utilised in the study because it is a powerful technique for solving option pricing problem [113]. There are linkages between the Black-Scholes and BOPM models and are discussed in section 2.3.2.1. There are other models which are used for valuing options as in [114], [115], [116] and [117].

2.3.2.1 Black-Scholes model

The Black-Scholes model is the first option pricing model derived under certain assumptions to value European options only [118]. Later on, the Black-Scholes model extension in [119] allowed the model to evaluate any option. The model has several solutions and one of them is used in [120] to value an investment opportunity. It provides a background for the binomial option pricing model.

2.3.2.2 Binomial option pricing model (BOPM)

Cox *et al.* [121] felt that the Black-Scholes model required further mathematical analysis as a result, in [121], a binomial option pricing model (BOPM) is in traduced as a simplified model of valuing options based on discrete time periods. The BOPM is a powerful technique for solving option pricing problems [113]. It utilises binomial trees and formulae [102], [105], [122] and [117].

One important aspect on valuing BOPM is a risk-free interest rate, which result in a risk neutral probability. Risk neutral probability is not the same as the probability that an event will occur. However, the risk neutral probability provides a mathematical convenience for adjusting cash flows such that they may be discounted at a risk-free interest rate. Risk neutral valuation is an assumption that the investors are risk neutral, meaning that the investors do not increase the expected return on an investment to compensate for an increased risk [102]. The reality is that the investments have risk, but the risk-free valuation provides a correct option value for both risk neutral and for investors who expect a compensation for risky investments [102]. The RO evaluates the underlying asset; as a result, the investors' risk preferences are unimportant [102]. Further details on risk neutral probability are in [96] and [102]. The BOPM break the option duration into sub-periods. As these sub-periods get smaller and smaller, the option values approach the call option values determined by the Black-Scholes model [96], [117], [121].

The BOPM is utilised to value one or several underlying assets [105]. The BOPM is used in this study for valuing options where new capacity occurred once during the investigation period. The reason BOPM is used is that it forms a basis for SCRO models.

2.3.2.3 Sequential compound real options background and applications

The approach of using BOPM for evaluating SCRO is developed in [96]. Two approaches of evaluating SCRO using BOPM are risk neutral approach (RNA)

and replicating portfolio approach [96]. It is noteworthy that replicating portfolio approach assumes that the underlying asset is a portfolio of assets. This study demonstrates that the RNA approach is similar to the BOPM explained section 2.3.2.2, the only difference is that the underlying asset has several sequential investments. It is noted that the RNA approach is easier to implement than the replicating portfolio approach, as shown in [96]. This study employed RNA because it is more orderly than the replicating portfolio approach.
The following authors employed RNA in valuing different PIP. For example, Copeland and Antirakov [96] applied the RNA to value an American call on a multiphase construction project, while Radjenovic [103] utilised the RNA approach in valuing a PIP. Moreover, Herath and Park [123] used RNA to a research and development manufacturing investment project.

2.3.2.4 Real options and portfolios of investment projects

This study applied RO models to a portfolio of new power plant technologies. It is worth noting that the following authors utilised RO models in different portfolios. On the one hand, Hlouskova [124] applied RO to a portfolio of generation assets in liberalised markets. On the other hand, Brosch [105] discussed a detailed literature on RO analysis in a portfolio which is a combination of multiple risky assets, while Csapi [125] used PT and RO models to Hungary's ten power generating plants. This study considered a portfolio of underlying assets not a portfolio of real options, and the underlying assets did not switch from one option to the next as in [105].

CHAPTER 3

Three-Tier Methodology Development

3.1 Tier 1: Methodology Development Based on PT

The first tier in Figure 3.1 is evaluating the existing power plants as there are lessons that decision makers could learn from existing power plants including the costs' risks. In Figure 3.1, input A represents historic fuel costs for existing power plants used for risk evaluation. However, fuel costs are not the only operating costs that are risky. Maintenance costs and other operating costs could also be evaluated. Maintenance costs are excluded because the study in [48] showed that the inclusion of fuel levy, operation, and maintenance costs did not make a huge difference on the results of the fuel study alone. The PT models only use a single cost input at a time, when different costs from different sources, other than fuel are utilised, they should be added together before the analysis.

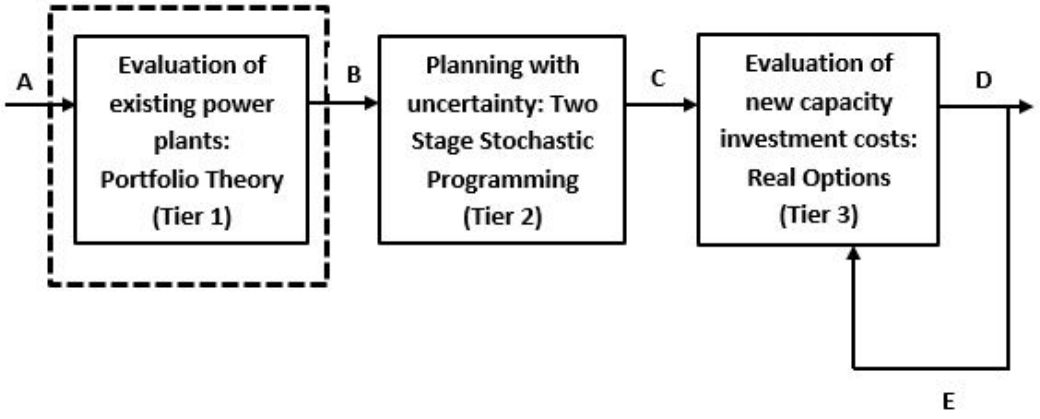


FIGURE 3.1: First tier of planning process

The PT is a theory that is developed for risk evaluation in financial portfolios. The

application of PT models in the past few decades, was in electricity generation portfolios or mixes for risk evaluation, as discussed in section 2.1.1. This study utilised the PT model to evaluate risk of the existing electricity generation mix before the EGEP begins, as shown in Figure 3.1.

In this study, risk measures the variability of fuel costs during the investigation period.

3.1.1 Portfolio Theory Mathematical Model Adjusted for Electricity Generation

There are major differences between financial market portfolios and portfolios in electricity generation. The major differences are that financial market portfolios focus on returns, whereas electricity generation portfolios focus on costs. Financial assets are more easily disposable than electricity generation assets like coal-fired plants [126] and financial securities are almost infinitely divisible such that a portfolio could contain between 0% and 100% of a given security, which is not the case with electricity generation assets [126]. The other difference is that the objective of financial markets is to maximise portfolio returns, whereas the objective of the electricity generation is to minimise portfolio costs [48]. Irrespective of the differences listed above, the use of PT models is common for evaluation of electricity portfolios, as shown in section 2.1.2 of chapter 2.

$$\min \quad C = \sum_{i=1}^{N} X_{f_i} \mu_{f_i}, \tag{3.1}$$

subject to the following constraints

$$\sum_{i=1}^{N} X_{f_i} = 1, \tag{3.2}$$

$$X_{f_i} \geq 0 \; \forall \; i, \tag{3.3}$$

where,

$$\mu_{f_i} = \mathbb{E}(f_i) = 1/T \sum_{t=1}^{T} f_{it}, \tag{3.4}$$

$$\rho_{f_i,f_j} = \text{cov}(f_i, f_j)/\sigma_{f_i}\sigma_{f_j}, \tag{3.5}$$

$$\text{cov}(f_i, f_j) = \mathbb{E}[(f_i - \mu_{f_i})(f_j - \mu_{f_j})] \; \forall \; f_i \neq f_j, \tag{3.6}$$

$$\sigma_i = \sqrt{\mathbb{E}(f_i - \mu_{f_i})^2}, \tag{3.7}$$

$$\sigma = \left[\sum_{i=1}^{N} \sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j \right]^{1/2}. \tag{3.8}$$

illustratively $i \in \mathbb{R}_+$ denotes energy source, while $X_{f_i} \in \mathbb{Q} \in \mathbb{R}_+$ denotes the weight of fuel cost of energy source i in the portfolio and $f_i \in \mathbb{R}_+$ denotes fuel cost. $\mu_{f_i} \in \mathbb{R}_+$ denotes the average of fuel cost of energy source i over the given period $t \in \mathbb{Z}_+$, which is from a year $t = 1, \ldots, T$. $f_{it} \in \mathbb{R}_+$ denotes the actual fuel cost for energy source i for a year t, $\sigma_i \in \mathbb{R}_+$ denotes the risk for fuel cost f_i. $\rho_{f_i,f_j} \in \mathbb{Q} \in \mathbb{R}_+$ denotes the correlation coefficient between fuel costs for energy sources i and j, $-1 \leq \rho_{ij} \leq 1$. There is a portfolio risk reduction when investing in fuel costs that have a low correlation coefficient with each other [127].

The output B in Figure 3.1 are the results obtained from equations (3.1) to (3.8) which should inform decision makers if the existing portfolio of energy sources of fuel costs is efficient or not. If it is not efficient, what contributed to the inefficiency and what could be done in the second tier to make sure that the new portfolio is closer to efficiency than the existing one. If it is efficient, then the capacity from the same energy sources could be expanded, without missing out on the new emerging energy sources. The output B is the information that decision makers take to the planning tier after evaluating the portfolio of existing energy sources, which are fuel costs.

3.1.2 Data Requirements for First Tier Model

The developed first tier model utilises annual historic data collected from the energy sources and the corresponding fuel costs for each energy source per kWh.

Annual data is utilised for consistency, since this thesis analysed annual data throughout. If there are n energy sources, there should be n corresponding fuel costs, except for renewable energy sources with no fuel costs. The renewables are excluded in Tier 1 analysis, because they do not have fuel costs.

3.1.3 Critical Analysis of the First Tier Model

As discussed in section 3.1.2, if energy sources do not have fuel costs like wind and solar, their corresponding fuel cost risk utilising cannot be determined by standard deviation. Nevertheless, in such cases different risk measures like VaR [23] and CVaR in [65] and [23], can be used.

However, each of these risk measures has different data requirements and if such data is not available, one might not be able to utilise PT.

Similarly, new technologies might not have enough historical fuel costs data for determining standard deviations. In such cases, proxy data and simulated techniques [19] might be used.

PT models measure diversification by correlation coefficients, represented by ρ_{f_i,f_j} in equation (3.5). According to Stirling, [128] ρ_{f_i,f_j} has flaws because it considers only two energy sources at a time. Shannon-Wiener diversity index utilised in [128] measures the diversity of the entire portfolio. The higher the value of Shannon-Wiener diversity index, the greater the diversity [128]. Nevertheless, there is no absolute value of Shannon-Wiener diversity index for diversity or greater diversity. PT outperformed the Shannon-Wiener diversity index in the analysis in [14].

Even though PT has critics in electricity generation, it is widely accepted [19]. This study also used a PT model in the first tier of the three-tier model to carry out the evaluation of the existing energy sources fuel costs.

3.1.4 Limitations of the First Tier Model

The first tier model in equations (3.1) to (3.8), is based on LP. LP models are simple and easy to solve, as are result are utilised as benchmarks [129]. As discussed

in section 2.1.2, the first tier model is utilised in other continents. However, LP models do not capture all the complications of real world models. The first tier model is minimising the average fuel cost for a given risk, and has minimal data requirements.

The decision makers can optimise the fuel portfolio risk, which is measured by the standard deviation in this study. Alternatively, decision makers can optimise both the average fuel portfolio cost and risk. These two options change the objective function of the first tier models to equation (3.9) [129] and equation (3.10) [130], respectively.

$$\min \quad C^1 = \sum_{i=1}^{N} \sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j \tag{3.9}$$

In equation (3.9) the objective function is minimising the variance of fuel costs, which is σ^2, where σ is from equation equation (3.8).

$$\min \quad C^2 = \sum_{i=1}^{N} X_{f_i} \mu_{f_i} - \lambda \sum_{i=1}^{N} \sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j \tag{3.10}$$

Equation (3.10) is derived from equations (3.1) and (3.9) and λ is a scalar representing the decision makers' attitude to risk [130]. Both equations (3.9) and (3.10) are nonlinear because of the variance and are not discussed further in this study. However, nonlinear models have different challenges which include making the model more complex and difficult to explain and solve because the solution might diverge [129].

3.2 Tier 2: Methodology Development Based on TSSP

The electricity capacity expansion is about increasing the existing capacity because of anticipated electricity demand increase and decrease of existing capacity due to power plant decommissioning. The second tier is planning for capacity expansion amidst of electricity demand uncertainty. There are other uncertainties in the EGEP which are not considered in this study, such as future investment costs, future inflation, future policies and regulations, to mention a few.

The second tier used TSSP model because it focuses on future uncertainties. Fig-

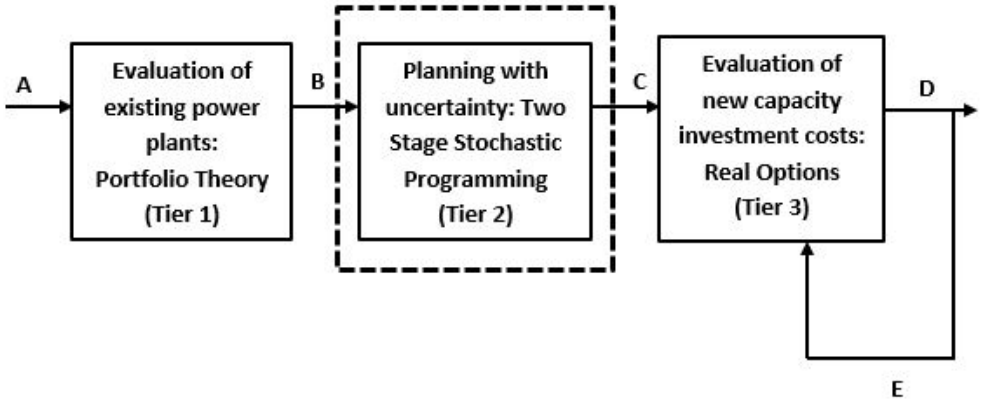


FIGURE 3.2: Second tier of planning process

ure 3.2 shows how the second tier fits into the three-tier model. The second tier is supposed to consider the information obtained from the evaluation of existing power plants, which is represented by B in Figure 3.2 in selecting new energy sources for the new capacity expansion.

In the second tier, the favoured deterministic and the two stage stochastic models, are compared and contrasted.

3.2.1 Adjusted Deterministic Model

The author of this thesis adjusted the deterministic LP model in [73] and [74] as follows: the objective function in this study minimised annual costs which spanned over several years; both existing and new capacities have capacity factors because electricity generating technologies do not generate 100% of the capacity throughout due to planned and unplanned maintenance; the existing capacity is not available throughout the planning because some of it is decommissioned; the running costs consist of fuel, fixed and variable maintenance, and the cost of unserved energy.

The adjusted mixed integer deterministic model for potential new technologies is equation (3.11) to equation (3.20).

$$\min \quad \sum_{\tilde{t}=1}^{\tilde{T}} \Big(\sum_{p=1}^{P} (c_p^{\tilde{t}}\ x_p^{\tilde{t}}) + g^{\tilde{t}} \Big) \tag{3.11}$$

subject to the following constraints,

$$\sum_{k=1}^{K} y_{pk}^{\tilde{t}} \leq b_p^{\tilde{t}}\ e_p^{\tilde{t}} \quad \forall\ \tilde{t}, p, \tag{3.12}$$

$$x_p^{\tilde{t}} \geq x_p^{\tilde{t}-1} \quad \forall \tilde{t}, p, \tag{3.13}$$

$$e_p^{\tilde{t}} = e_p^{\tilde{t}-1} + x_p^{\tilde{t}} \quad \forall \tilde{t}, p, \tag{3.14}$$

$$\beta\ z_k^{\tilde{t}} + q_k^{\tilde{t}} \sum_p y_{pk}^{\tilde{t}} = r_k^{\tilde{t}} \quad \forall\ \tilde{t}, k, \tag{3.15}$$

$$r_k^{\tilde{t}} = \begin{cases} (d_k^{\tilde{t}})\ q_k^{\tilde{t}} \text{ if } k = 1 \\ (d_k^{\tilde{t}} - d_{k-1}^{\tilde{t}})\ q_k^{\tilde{t}} \text{ if } k = 2 \end{cases}, \tag{3.16}$$

$$\sum_{k=1}^{K} \left(u_k^{\tilde{t}}\ z_k^{\tilde{t}} + q_k^{\tilde{t}} \sum_p (l_p^{\tilde{t}} + v_p^{\tilde{t}} + f_p^{\tilde{t}}) y_{pk}^{\tilde{t}} \right) = g^{\tilde{t}} \quad \forall\ \tilde{t}, p, \tag{3.17}$$

$$x_p^{\tilde{t}} \in \mathbb{Z}_+ \quad \forall\ \tilde{t}, p, \tag{3.18}$$

$$y_{pk}^{\tilde{t}} \in \mathbb{R}_+ \quad \forall\ \tilde{t}, p, k, \tag{3.19}$$

$$z_k^{\tilde{t}} \in \mathbb{R}_+ \quad \forall\ \tilde{t}, k, \tag{3.20}$$

where the indices are: $p \in \mathbb{Z}_+$ denotes a technology type, which is associated with an energy source, $k \in \mathbb{Z}_+$ denotes the demand category and for base ($k = 1$) or peak ($k = 2$) and $\tilde{t} \in \mathbb{Z}_+$ denotes years. The parameters are: β denotes a binary number which is equal to 0 or 1, $c_p^{\tilde{t}} \in \mathbb{R}_+$ denotes annual capital cost for technology p in year $\tilde{t}$ in R/kW, $e_p^{\tilde{t}} \in \mathbb{Z}_+$ denotes existing capacity for technology p in year $\tilde{t}$ in GW, $u_k^{\tilde{t}} \in \mathbb{R}_+$ denotes cost of unserved energy for category k at year $\tilde{t}$ in R/kWh, $b_p^{\tilde{t}} \in \mathbb{Q} \in \mathbb{R}_+$ denotes annual capacity factor for technology p in year $\tilde{t}$, $l_p^{\tilde{t}} \in \mathbb{R}_+$ denotes fixed operation and maintenance cost for technology p in year $\tilde{t}$ in R/kW per year, $v_p^{\tilde{t}} \in \mathbb{R}_+$ denotes variable operation and maintenance cost for technology p in year $\tilde{t}$ in R/MWh, $f_p^{\tilde{t}} \in \mathbb{R}_+$ denotes fuel cost for technology p in year $\tilde{t}$ in R/GJ, $d_k^{\tilde{t}}$ denotes instantaneous electricity demand for k in year $\tilde{t}$ in GW, $q_k^{\tilde{t}} \in \mathbb{R}_+$ denotes duration of demand for category k in year $\tilde{t}$ and $r_k^{\tilde{t}} \in \mathbb{R}_+$ denotes required electricity for k in year $\tilde{t}$. The variables are: $x_p^{\tilde{t}}$ denotes new design capacity for

technology p in year $\tilde{t}$ in GW, $y_{pk}^{\tilde{t}}$ denotes allocation of technology p capacity to demand k in year $\tilde{t}$ in GW, $g^{\tilde{t}}$ denotes the sum of running costs in year $\tilde{t}$ made up of the cost of unserved energy, fuel, fixed and variable maintenance costs in year $\tilde{t}$ and $z_k^{\tilde{t}}$ denotes unserved energy for demand category k in year $\tilde{t}$ in GW.
The objective function in equation (3.11) minimises the capital cost for new capacity and the corresponding running costs. The equation for running costs $g^{\tilde{t}}$ is in equation (3.17). The constraint in equation (3.12) ensures that allocated capacity is not more than the available capacity in a year, $\tilde{t}$ which is the existing capacity multiplied by the capacity factor. In equation (3.15) the allocated capacity is more than the electricity required. The association between year $\tilde{t}$ and year $\tilde{t}$-1 capacity is in equation (3.14), which confirmed that the capacity allocated in each year is including the existing capacity from the previous year. The required electricity per demand category is in equation (3.16). This equation differentiates the required electricity that is met by the base from the one met by peak load technologies.

$$\sum_{k=1}^{K} y_{nk}^{\tilde{t}} \leq b_n^{\tilde{t}} e_n^{\tilde{t}} \quad \forall \tilde{t}, n, \tag{3.21}$$

$$e_n^{\tilde{t}} = e_n^{\tilde{t}-1} - m_n^{\tilde{t}-1} \quad \forall t, n, \tag{3.22}$$

$$q_k^{\tilde{t}} \sum_{n}^{8} y_{nk}^{\tilde{t}} = r_k^{\tilde{t}} \quad \forall \tilde{t}, k, \tag{3.23}$$

$$y_{nk}^{\tilde{t}} \in \mathbb{R}_+ \quad \forall\ \tilde{t}, n, k, \tag{3.24}$$

$$e_n^{\tilde{t}} \in \mathbb{Z}_+ \quad \forall\ \tilde{t}, n, \tag{3.25}$$

$$m_n^{\tilde{t}} \in \mathbb{Z}_+ \quad \forall\ \tilde{t}, n, \tag{3.26}$$

where $n \in \mathbb{Z}_+$ denotes the number of energy sources, $m_n^{\tilde{t}}$ denotes the decommissioned capacity for plant type of energy source n at time $\tilde{t}$, $e_n^{\tilde{t}}$ denotes an existing capacity for energy source n at year $\tilde{t}$, $y_{nk}^{\tilde{t}}$ denotes capacity allocation for technology n to demand k at year $\tilde{t}$ in GW. All other indices, parameters and variables are as defined in equation (3.11) to equation (3.20).

3.2.2 Adjusted TSSP Model

The current study also adjusted the TSSLP model in [73] and [74] by including the demand uncertainty, to form a TSSMILP model as shown in equation (3.27) to equation (3.38). The TSSLP models adjustment incorporated the deterministic MILP model in section 3.2.1. The aim of adjusting both the deterministic LP and the TSSLP models was to ensure that the models are realistic than in [73], [74]. The adjusted model is in equation (3.27) to equation (3.39).

$$\min \quad \sum_{\tilde{t}=1}^{\tilde{T}} \sum_{p=1}^{P} \left(c_p^{\tilde{t}} \; x_p^{\tilde{t}} + \sum_{s=1}^{S} (\hat{p}_s g_s^{\tilde{t}}) \right), \tag{3.27}$$

subject to the following constraints,

$$\sum_{k=1}^{K} y_{pks}^{\tilde{t}} \leq b_p^{\tilde{t}} \; e_p^{\tilde{t}} \quad \forall \; \tilde{t}, p, s, \tag{3.28}$$

$$x_p^{\tilde{t}} \geq x_p^{\tilde{t}-1} \quad \forall \; \tilde{t}, p, \tag{3.29}$$

$$e_p^{\tilde{t}} = e_p^{\tilde{t}-1} + x_p^{\tilde{t}} \quad \forall \; \tilde{t}, p, \tag{3.30}$$

$$\beta z_{ks}^{\tilde{t}} + q_{ks}^{\tilde{t}} \sum_{p} y_{pks}^{\tilde{t}} = r_{ks}^{\tilde{t}} \qquad \forall \; \tilde{t}, k, s, \tag{3.31}$$

$$r_{ks}^{\tilde{t}} = \begin{cases} (d_{ks}^{\tilde{t}}) \; q_{ks}^{\tilde{t}} \text{ if } k = 1 \\ (d_{ks}^{\tilde{t}} - d_{k-1,s}^{\tilde{t}}) \; q_{ks}^{\tilde{t}} \text{ if } k = 2 \end{cases}, \tag{3.32}$$

$$\sum_{k=1}^{K} \left(u_{ks}^{\tilde{t}} \; z_{ks}^{\tilde{t}} + q_{ks}^{\tilde{t}} \sum_{p=1}^{P} (l_{ps}^{\tilde{t}} + v_{ps}^{\tilde{t}} + f_{ps}^{\tilde{t}}) \; y_{pks}^{\tilde{t}} \right) = g_s^{\tilde{t}} \quad \forall \; \tilde{t}, s, \tag{3.33}$$

$$x_p^{\tilde{t}} \in \mathbb{Z}_+ \qquad \forall \; \tilde{t}, p, \tag{3.34}$$

$$y_{pks}^{\tilde{t}} \in \mathbb{R}_+ \qquad \forall \; \tilde{t}, p, k, s, \tag{3.35}$$

$$z_{ks}^{\tilde{t}} \in \mathbb{R}_+ \qquad \forall \; \tilde{t}, k, s, \tag{3.36}$$

$$g_s^{\tilde{t}} \in \mathbb{R}_+ \qquad \forall \; \tilde{t}, s, \tag{3.37}$$

$$e_p^{\tilde{t}} \in \mathbb{Z}_+ \qquad \forall\ \tilde{t}, p, \tag{3.38}$$

$$m_p^{\tilde{t}} \geq 0 \qquad \forall\ \tilde{t}, p, \tag{3.39}$$

where the indices are exactly the same as defined for the deterministic model in section 3.2.1. The only difference is $s \in \mathbb{Z}_+$ which denotes scenarios, each with probability, $\hat{p} \in \mathbb{Q} \in \mathbb{R}_+$. The parameters are exactly the same as defined for the deterministic model, except for $u_{ks}^{\tilde{t}} \in \mathbb{R}_+$ which denotes the cost of unserved energy for demand k and scenario s at time $\tilde{t}$ in R/kWh, $d_{ks}^{t} \in \mathbb{R}_+$ denotes instantaneous electricity demand for k and scenario s at time $\tilde{t}$ in GW, $q_{ks}^{\tilde{t}} \in \mathbb{R}_+$ denotes duration of demand for demand k and scenario s at time $\tilde{t}$, duration for base is 24 hours per day and 6 hours for peak; $r_{ks}^{\tilde{t}} \in \mathbb{R}_+$ denotes the required electricity for k and s at year $\tilde{t}$ in GWh. Variables are $x_p^{\tilde{t}}$ which denotes new design capacity for technology p in year $\tilde{t}$ in GW, $y_{pks}^{\tilde{t}}$ denotes allocation of capacity for technology p to each demand k realisation and for each scenario s in year t in GW, $z_{ks}^{\tilde{t}}$ is the unserved energy for k and s in year $\tilde{t}$ in GW, $g_s^{\tilde{t}}$ denotes the sum of the running cost for scenario s in year $\tilde{t}$: cost of unserved energy, fuel, fixed and variable maintenance. Similar to the deterministic model, the SP model for existing power plants is in equations (3.40) to (3.45).

$$\sum_{k=1}^{K} y_{nks}^{\tilde{t}} \leq b_n^{\tilde{t}} e_n^{\tilde{t}} \quad \forall \tilde{t}, n, s, \tag{3.40}$$

$$e_n^{\tilde{t}} = e_n^{\tilde{t}-1} - m_n^{\tilde{t}-1} \quad \forall \tilde{t}, n, \tag{3.41}$$

$$q_{ks}^{\tilde{t}} \sum_{n=1}^{8} y_{nks}^{\tilde{t}} = r_{ks}^{\tilde{t}} \quad \forall \tilde{t}, k, s, \tag{3.42}$$

$$y_{nks}^{\tilde{t}} \geq 0 \quad \forall\ \tilde{t}, n, k, s, \tag{3.43}$$

$$e_n^{\tilde{t}} \geq 0 \quad \forall\ \tilde{t}, n, \tag{3.44}$$

$$m_n^{\tilde{t}} \geq 0 \quad \forall\ \tilde{t}, n, \tag{3.45}$$

where the indices, parameters, and variables in equation (3.40) to equation (3.45) are as defined in equation (3.21) to equation (3.26) and equation (3.27) to equation (3.38).

The first tier output B is supposed to influence the selection of technologies which

are associated to the corresponding energy sources, p, for both the deterministic MILP and the TSSMILP models, because each technology has a corresponding energy source fuel.

3.2.3 Data Requirements of the Second Tier Models

There are two data sets required for the deterministic MILP and TSSMILP models. The first set is for potential technologies' data which consists of: technology name, corresponding energy source, lead time, capital phasing in percentages, life of plant, capital costs, fixed and variable operating costs, fuel costs and CO_2 emissions.
The second data set is for existing plants where the following data is required: energy sources, existing capacity, commissioning dates (especially for power plants which are not existing, but committed at the beginning of the investigation period), because the capacity of these power plants formed part of existing capacity from the respective commission dates, decommissioning dates and corresponding capacity. The following data could also be collected: fixed and variable operating costs, fuel costs, CO_2 emissions.
The data for forecasted electricity demand scenarios; corresponding probabilities for each scenario; capacity factors for energy sources, was collected and the determination of the cost of unserved energy is in [71].

3.2.4 Critical Analysis of the Second Tier Models

Both the deterministic MILP and TSSMILP models require a lot of detailed data, as shown in chapter 5 and in appendix D. If some of this data is missing, the use of these models is impossible without compromising the results. The data utilised for the above models was free of contamination or inaccuracy, since it was secondary data collected from reliable publishers, as discussed in section 5.3 in chapter 5. However, sometimes raw data would be available for use. In such cases, data cleaning would be the first step before analysis is performed. Data

cleaning is a process of correcting conflicting and invalid data, identify missing or incomplete data, deleting inaccurate or contaminated records [131], [132] and [133]. The deletions of inaccurate records would result in data gaps, which could be completed by the mean or median of available data, linear interpolation, hot Deck and cold Deck, carrying forward the last observation [134].

The TSSP model requires the probability of occurrence for each scenario to be able to incorporate all the scenarios, at once. The scenario probabilities can be affected by decision makers' biases, where more weight can be assigned to a favourable scenario.

3.3 Tier 3: Methodology Development Based on RO and NPV

The third tier is important for decision makers because after the second tier evaluation, the reality is different from the assumptions utilised in the second tier. That is, the second tier results cannot be implemented as they are. In this study, the actual electricity demand is below the forecasted scenarios as discussed in section 5.3.4. The RO models are the best models for uncertainties. These are proposed for the third tier because the uncertainty of electricity demand will affect the revenue from the new investment projects.

The output C in Figure 3.2 is the second tier output, which consists of the technologies that are selected in the second tier and corresponding: energy sources, capital and operational costs, new capacity and dates when the new capacity is anticipated. The output D in Figure 3.3 is when the decision makers have taken a decision to invest or not to invest on a particular investment project. However, if it is still possible to re-evaluate the investment project at a later date, the input E is utilised in Figure 3.3. RO models [102] are used to evaluate the investment projects from the second tier results because of the electricity demand uncertainties after the planning in the second tier is completed.

Both the BOPM and SCRO are utilised to evaluate the investment projects. New

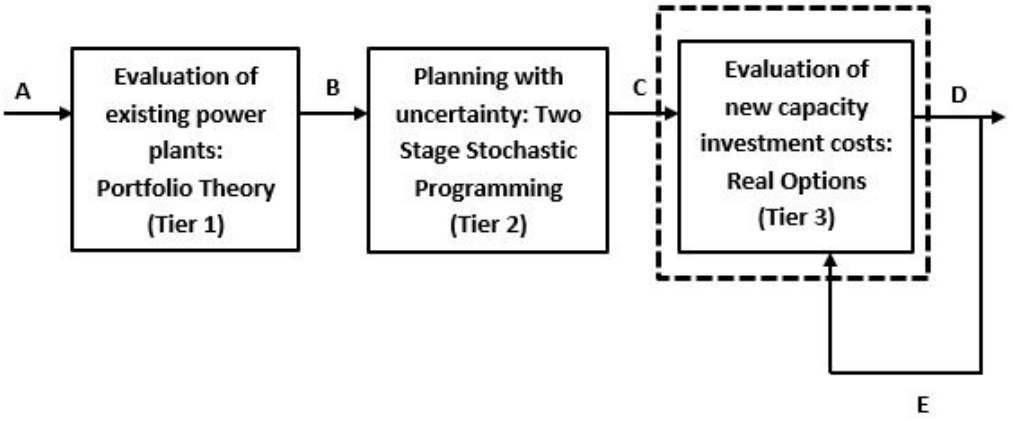


FIGURE 3.3: Third tier of planning process

capacity can be added once or several times during the period considered in section 3.2 from the potential technologies. The new capacity is regarded as investment project in Tier 3. These investment projects are evaluated by BOPM if the new capacity is added once and by SCRO if it is added more than once. The risk neutral approach (RNA) of valuing SCRO is formulated into three steps discussed below. The NPV [101] is the popular technique for evaluating investment projects. This technique is also employed in this study and compared to both BOPM and RNA results.

3.3.1 Step 1: Determination of the RO Factors

The RO factors σ, u, d and $\hat{p}$, are determined because they are used for determining other factors used to evaluate the BOPM and RNA models. Volatility, σ, is a standard deviation of historical returns, $r_{\hat{t}}$, in [122]. The assumption utilised is that historic revenues less operating costs ($H_{\hat{t}}$) follows a log normal distribution [122]. Values of $r_{\hat{t}} \in \mathbb{R}_+$, are derived from equation (3.46) [122].

$$r_{\hat{t}} = \ln(H_{\hat{t}}/H_{\hat{t}-1}) \tag{3.46}$$

In equation (3.46) $\hat{t} \in \mathbb{Z}_+$ represents the years. More factors are derived from equation (3.47) to equation (3.50).

$$r = 1 + r_f \tag{3.47}$$

In equation (3.47) [96] $r \in \mathbb{R}_+$ is the interest rate and $r_f \in \mathbb{R}_+$ is the risk-free rate.

$$d = e^{\sigma\sqrt{\Delta\tilde{t}}} \tag{3.48}$$

In equation (3.49) [96] $d \in \mathbb{R}_+$ is a decreasing factor and $\Delta\tilde{t} \in \mathbb{R}_+$ is the time frequency.

$$u = e^{-\sigma\sqrt{\Delta\tilde{t}}} \tag{3.49}$$

In equation (3.48) [96] $u \in \mathbb{R}_+$ is a decreasing factor.

$$\hat{p} = (r - d)/(u - d) \tag{3.50}$$

In equation (3.50) [96] $\hat{p} \in \mathbb{Q} \in \mathbb{R}_+$ is a risk-free probability.

3.3.2 Step 2: Determination of Gross Project Values

The expected cash flows are used to determine $V_0 \in \mathbb{R}_+$, the underlying value of the investment projects (gross project values). The gross project value is supposed to be greater than the investment cost for the real option to be valuable. Since there is no data for expected cash flows for these new investment projects, the expected cash flows are determined from equation (3.51).

$$F_{\hat{t}} = V_{\hat{t}} - C_{\hat{t}}, \tag{3.51}$$

where $\hat{t} \in \mathbb{Z}_+$ denotes the cash flow year from the year the new capacity from the new technology is allocated to meet demand, $F_{\hat{t}} \in \mathbb{R}$ denotes cash flows, $V_{\in}\mathbb{R}_+$ denotes revenue and $C_{\hat{t}} \in \mathbb{R}_+$ dnotes running costs. To be able to determine both revenue and running costs, generated electricity (GWh) is determined from the

technology's allocated capacity in chapter 6.

$$V_{\hat{t}} = S_{\hat{t}} \times P_{\hat{t}}, \tag{3.52}$$

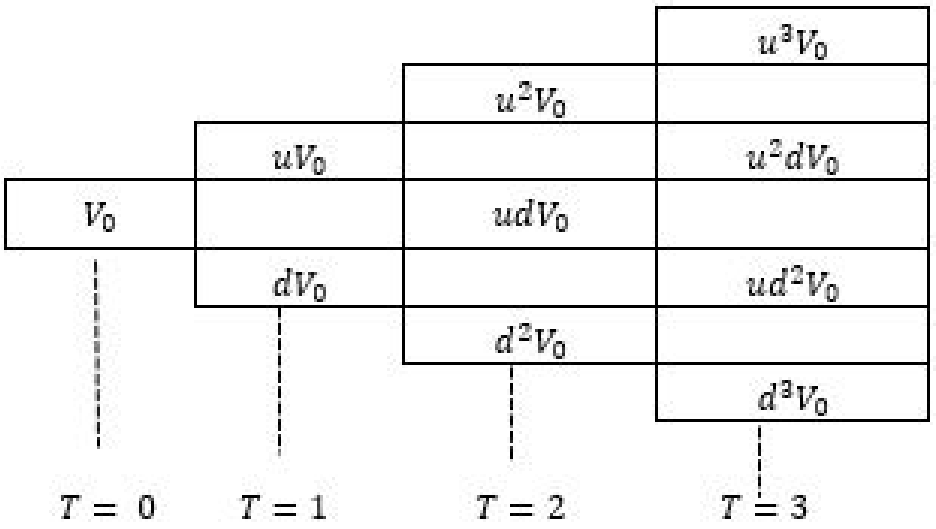
where, $S_{\hat{t}} \in \mathbb{R}_+$ for electricity sold and $P_{\hat{t}} \in \mathbb{R}_+$ for sales price. History showed that not all electricity generated is sold [135]. To accommodate uncertainty in future values of $V_{\hat{t}}$, Chebyshev's Theorem [136] is used, assuming that the percentage of electricity sold to electricity generated moves randomly between two standard deviations above and below the historic average. This assumption accommodated 75% of the future values of $V_{\hat{t}}$, the other 25% lies outside the two standard deviation boundary. The determination of random values for each investment project for each year is performed in MS Excel using the RANDBETWEEN function [137]. The revenue, $V_{\hat{t}}$ is determined from an average of 500 simulation for each investment project yearly [137]. The sales price, $P_{\hat{t}}$, is adjusted by simulated inflation rates.

The value of the initial gross project value, V_0, is determined from equation (3.53) and is utilised as the underlying value of investment projects.

$$V_0 = \sum_{l=1}^{\hat{n}} \left(\sum_{m=1}^{y} \frac{F_m}{r^m} \right)_l \tag{3.53}$$

In equation (3.53), $F_m \in \mathbb{R}_+$ denotes the expected cash flow, m denotes the number of years from the cash flow year to the evaluation date [96] while $l \in \mathbb{Z}_+$ denotes the number of investment projects. The value of V_0, goes up by a factor u and down by d, until the last investment year [122], which is denoted by $z \in \mathbb{Z}_+$. The up and down movements of V_0 form a binomial tree [122], [96] which is shown 3.1 for the first 3 years. The binomial tree is used because it embodies the uncertainty associated with each V_0 [123]. The values of V_0 are not kept constant, but are to be adjusted as new information emanates [123]. In Table 3.1, the order of ups and downs do not matter. As an example: $dududV_0 = uuddd V_0 = dddduuV_0 = d^3u^2V_0$. Table 3.2 shows the last 3 years, $z-2, z-1$ and z of the same binomial tree in Table 3.1. The $\grave{n} \in \mathbb{Z}_+$ in Table 3.2 is the maximum times that the factor u or d can increase or decrease, respectively. The values of V_0 at $T = z, z-1, z-2$ are

TABLE 3.1: V_0 values for the first three years



utilised for the determination of SCRO values because these years correspond to the actual investment years for the project [96].

3.3.3 Step 3: SCRO Values for the Investment Projects

In this step, decisions are made about the l investment projects. The information determined in the previous steps is utilised for determining the call option values corresponding to the investment projects. The call option values are considered in this case, because the investors are planning to build new stations, which is similar to buying than selling.

3.3.3.1 SCRO Values for the Investment at $T = z$

Starting with the investment project that expires at $T = z$, all the call option values corresponding to the investment cost I_l, at, $T = z$ are assigned to $C_{l,z}$. The values of $C_{l,z} \in \mathbb{R}_+$ are derived from equation (3.54) [96].

$$C_{l,z}^{\grave{i}} = \max(G_z^{\grave{i}} - I_l, 0) \tag{3.54}$$

TABLE 3.2: V_0 values for the last three years

		$u^{\grave{i}}V_0$
	$u^{\grave{i}-1}V_0$	
$u^{\grave{i}-2}V_0$		$u^{\grave{i}-1}dV_0$
	$u^{n-2}dV_0$	
$u^{\grave{i}-3}dV_0$		$u^{\grave{i}-2}d^2V_0$
	$u^{\grave{i}-3}d^2V_0$	
$u^{\grave{i}-4}d^2V_0$		$u^{\grave{i}-3}d^3V_0$
$\vdots$	$\vdots$	$\vdots$
	$u^3d^{\grave{i}-4}V_0$	
$u^2d^{\grave{i}-4}V_0$		$u^3d^{\grave{i}-3}V_0$
	$u^2d^{\grave{i}-3}V_0$	
$ud^{\grave{i}-4}V_0$		$u^2d^{\grave{i}-2}V_0$
	$ud^{\grave{i}-2}V_0$	
$d^{\grave{i}-2}V_0$		$ud^{\grave{i}-1}V_0$
	$d^{\grave{i}-1}V_0$	
		$d^{\grave{i}}V_0$
$T = z-2$	$T = z-1$	$T = z$

In equation (3.54), $\grave{i} \in \mathbb{Z}_+$ denotes the number of rows in each column of Table 3.2, for example, for $T = z$, $\grave{i} = 1, \ldots, z+1$. The call options values at $T = z$ are used

to determine the call option values at $T = z - 1$, using equation (3.57) [29].

$$C_{l,z-1}^{\acute{i}} = \frac{\left(\hat{p}C_{l,z}^{\grave{i}} + (1-\hat{p})C_{l,z}^{\grave{i}+1}\right)}{r} \tag{3.55}$$

In equation (3.55) $\acute{i} \in \mathbb{Z}_+$ and $\acute{i} = 1, \ldots, z$. Equation (3.55) is used to determine the call options values at $T = z - 1$. Similarly, call option values at $T = z - 2$ are determined from the call option values at $T = z - 1$. The determination of call option values from the previous year's call option values continue until $T = 0$. Similar to the values of V_0,the call options determined in this subsection also form a binomial tree.

The information provided from subsection 3.3.1 to this subsection is exactly the same information that was utilised to evaluate RO values from BOPM. The only exception is in equation (3.53) where the value of l is one.

3.3.3.2 SCRO values for the investment at $T = z - 1$

The call option values for the investment project cost, $I_{l-1} \in \mathbb{R}_+$, are determined from the resultant binomial tree in section 3.3.3.1. The call option values at $T = z - 1$, is $C_{l-1,z-1}^{\grave{j}} \in \mathbb{R}_+$, where $\grave{j} = 1, \ldots, z$, are determined from equation (3.56). Similar to section 3.3.1, $\grave{j} \in \mathbb{Z}_+$.

$$C_{l-1,z-1}^{\grave{j}} = \max(C_{l,z-1}^{\grave{j}} - I_{l-1}, 0) \tag{3.56}$$

Similar to equation (3.55), equation (3.57) is used to determine call option values at $T = z - 2$, which are determined from the call option values at $T = z - 1$. In equation (3.57), $\acute{j} \in \mathbb{Z}_+$ and $\acute{j} = 1, \ldots, z - 1$.

$$C_{l-1,z-2}^{\acute{j}} = \frac{\left(\hat{p}C_{l-1,z-1}^{j} + (1-\hat{p})C_{l-1,z-1}^{\acute{j}+1}\right)}{r} \tag{3.57}$$

Similar to subsection 3.3.3.1, the call option values determined in this section result in a binomial tree.

3.3.3.3 SCRO values for the investment at $T = z - 2$

The call option values for investment at $T = z - 2$, $I_{l-2} \in \mathbb{R}_+$, are determined from the call option values in subsection 3.3.3.2. However, only the call option values from $T = z - 2$ are considered because this is where I_{l-2} is invested. The call option values for I_{l-2} at $T = z - 2$ are determined from equation (12) where $\hat{k} = 1, \ldots, z - 1$.

$$C^{\hat{k}}_{l-2,z-2} = \max(C_{1-1,z-2} - I_{l-2}, 0) \tag{3.58}$$

Similar to sections 3.3.3.1 and 3.3.3.2, the call option values at $T = z - 3$ are derived from the call option values at $T = z - 2$, as shown in equation (3.59) where $\acute{k} = 1 \ldots, z - 2$.

$$C^{\acute{k}}_{l-3,z-3} = \frac{\left(pC^{\acute{k}}_{l-2,z-2} + (1-p)C^{\acute{k}+1}_{l-2,z-2}\right)}{r} \tag{3.59}$$

The call option values determined in equation (3.59) are utilised to determine the call at $T = z - 3, z - 4, \ldots, 0$. The call option value for the investment, I_{z-2}, at, $T = 0$ is utilised to determine if the total investment for the l projects should be invested or deferred.

3.3.4 NPV Model

The factors, expected cash flows and investment costs determined in sections 3.3.1 to 3.3.3 are also utilised to determine the net present value for each investment project. NPV formula is in equation (3.60) [101].

$$NPV = \sum_{\hat{t}=0}^{\hat{T}} F_{\hat{t}}/(r)^{\hat{t}} \tag{3.60}$$

However, in this case the $F_{\hat{t}} \in \mathbb{R}$ is inclusive of the capital investments, which are taken from the TSSMILP results for each project. Typically, to differentiate the cash-out flows to cash inflows, a negative sign is utilised to cash-out flows.

3.3.5 Data Required for Third Tier Models

The data required for RO models is the investment lifetime t, n which is the number of sub-periods in which the investment period is divided into, the information for determining the volatility, σ and risk-free rate to determine r. The information above is used to determine u, d and p. The other required information is the output from the second tier.

Similar to the RO models, the NPV model requires investment lifetime, discount rate, the investment cost and the cash flows. Both the investment cost and cash flows are determined from the second tier results.

3.3.6 Critical Analysis of the Third Tier Models

In this section, only the critical analysis for RO models is provided, because NPV model is not a recommended model for the third tier. RO models are regarded as the best for valuing an investment project when there are uncertainties, when compared to NPV. There is no RO model for valuing a portfolio of projects. The same approach that is used for one project is utilised for each project in the portfolio. As a result, valuing a portfolio of investment projects using RO models can be tedious because each project is valued independent of the next project. However, the formulas are simple, and the errors can be detected easily.

The RO models require output from the second tier, which means that without the output from the second tier, there are no investment projects to be evaluated.

3.4 The Summary of the Three-Tier Methodology

In this chapter, the methodology of evaluating the three tier models is developed. Utilisation of the same period within the three-tier model is important for consistency. The methodology started by focusing on the existing energy sources that are utilised before planning for capacity expansion. In Tier 1, the decision makers evaluated the efficiency of the fuel costs of these energy source by the PT model.

The output of the PT model analysis is supposed to be utilised to decide if the current energy sources should be increased or decreased, where they would be replaced by alternative energy sources.

Once this decision is taken, decision makers analysed the potential technologies, paying more attention on their energy sources. The deterministic MILP and the TSSMILP models are utilised in Tier 2, to analyse the potential technologies, with the aim of minimising both their investment and running costs. The aim of using two models is to compare and contrast their results. In Tier 2 there is also an electricity demand uncertainty, which is presented by scenarios with known probabilities. Both the deterministic MILP and the TSSMILP models also incorporated the load shedding variable and the corresponding costs. The TSSMILP model is well known for analysing uncertainty, as a result, the results of this model are utilised as an input to the Tier 3 models. Even though all the tiers require data, Tier 2 requires most data than other tiers and Tier 3 utilises Tier 2 output and some economic data.

The potential technologies selected by the TSSMILP model and their corresponding output data are converted to investment projects. In Tier 3 these investment projects are evaluated by the RO and popular NPV models. The two RO models are utilised, the BOMP which is for investment projects which have a once off capital investment during the period under consideration for capacity expansion, and the RNA is for the investment projects that require more than one capital investment during this period. The NPV model is utilised to evaluate both projects with once off and several investments. The results from the RO models are utilised to assist the decision makers with the following decision: to invest in the investment project now, discard the investment project or re-evaluate the RO value of the investment project at a later date. The models in this chapter are analysed in chapter 4.

CHAPTER 4

Analysis of the Three-Tier Model

In this chapter, the models in chapter 3 are analysed with the aim of providing more details that could not be incorporated earlier in this study.

4.1 Analysis of the Tier 1 Model

The PT model, utilised in the Tier 1, focused on a portfolio of fuel costs for the energy sources. The PT analysis starts with one cost and end up with a portfolio of costs. This can be observed in equation (3.1) which is a sum of individual fuel costs for energy sources. The aim of the PT model is to compute the portfolio efficient sets of minimum cost and corresponding standard deviation, given by C and σ in equations (3.1) and (3.8), respectively.

4.1.1 Determination of the Portfolio Efficient Sets

The objective function in equation (3.1) is minimising the portfolio cost. The portfolio cost is determined from a weighted sum of individual energy fuel costs. In equation (3.1) both the costs and corresponding weights are vectors, which result in a portfolio cost when multiplied. The constraints in equations (3.2) and (3.3) allow for portfolios consisting of one cost, as an example, $X_1 = 1$ as in vector (4.1) [57]. This means that other weights are equal to zero. As much as,

$X_1 = 1$ in vector (4.1), any of the $X_i,\ i = 1, \ldots, N$, can be equal to one.

$$\begin{bmatrix} 1 \\ X_2 \\ X_3 \\ \vdots \\ X_N \end{bmatrix} \tag{4.1}$$

The constraints in equations (3.2) and (3.3) also result is several portfolios [57] because there are several combinations of X_i's which can satisfy these constraints. These several combinations of portfolios are bounded below by a vector (4.1) and above by a vector (4.2).

$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ \vdots \\ 1 \end{bmatrix} \tag{4.2}$$

Corresponding to each portfolio cost is a portfolio risk, which is determined from the standard deviation in equation (3.8). Equation (3.8) depends on the standard deviations of individual fuel costs in equation (3.7) and the corresponding correlation coefficient in equation (3.5). Both the individual fuel costs standard deviations and correlation coefficients are constant, as they are determined from one set of historical data. What causes the portfolio risks to change are the weights determined from equation (3.1).

Once the portfolio costs and corresponding standard deviation are determined, they are not efficient until they fulfil the following conditions [57]: both the C and σ are obtainable; no other obtainable set, C^1, σ^1, exist such that $C^1 < C$ and $\sigma^1 \leq \sigma$ or else $C^1 \leq C$ and $\sigma^1 < \sigma$.

4.2 Analysis of the Tier 2 Models

Both the deterministic MILP and TSSMILP models are analysed in this subsection, but the emphasis is on the TSSMILP model because the deterministic model is a special case of TSSMILP when only one scenario is considered at a time. The TSSMILP model in chapter 3 is compared to the standard TSSMILP model. The analysis also included the feasible and utilisation of Benders decomposition in solving the TSSMILP model.

4.2.1 Standard TSSMILP and Deterministic MILP Models

The standard form of the TSSMILP models is in equations (4.3) to (4.6) [81], [82], [83], [138] and [139].

$$\min \quad c^{\intercal}x + \sum_{k'=1}^{K'} (\hat{p}_{k'} q_{k'}^{\intercal} y_{k'}), \tag{4.3}$$

subject to the following constraints,

$$Ax \geq b, \tag{4.4}$$

$$W_{k'} y_{k'} \geq h_{k'} - T_{k'} x, \ for \ k' = 1, \ldots, K', \tag{4.5}$$

$$x \in \mathcal{X}, \tag{4.6}$$

$$y_{k'} \in \mathcal{Y}, \tag{4.7}$$

where x is a decision vector whose values are determined in stage one, from the first term of equation (4.3) and the inequality in equation (4.4), c and b are known vectors, A is a known $m \times n$ matrix, T and W are $\bar{m} \times n$ and $\bar{m} \times \bar{n}$ matrices, respectively. The second term of equation (4.3) determines the second stage decision vector, $y_{k'}$. The $\xi_{k'} = q_{k'}$, $W_{k'}$, $h_{k'}$, $T_{k'}$, with respect to positive probabilities $\hat{p}_{k'}$ is finite number of realisation (scenarios) is the second stage. $\xi = \xi_{k'}, \ldots, \xi_{K'} \subset \Xi$ is a random vector defined on a probability space ($\tilde{k'}$, $\tilde{A}$, $\tilde{P}$) which denotes the set of all outcomes, a collection of random variables and their associated probability

distributions, respectively [81]. For a given realisation of k', $q_{k'}$, $W_{k'}$, $h_{k'}$ and $T_{k'}$ become well known. The sets $\mathcal{X} \subseteq \mathbb{R}_+^{n_1}$ and $\mathcal{Y} \subseteq \mathbb{R} \times \mathbb{R}_+^{n_2}$ impose non-negativity and discrete, binary or continuous restriction of the first and second stage variables, respectively [82].

The feasibility of equation (4.5) puts a limitation on the first stage decision vector, x, such that the second term of equation (4.3) is minimised [138].

Similarly, the standard form of the deterministic MILP model is in equations (4.8) to (4.12) [81], [82] and [83].

$$\min \quad c^\intercal x + q^\intercal y, \tag{4.8}$$

subject to the following constraints,

$$Ax \geq b, \tag{4.9}$$

$$Tx + Wy \geq h, \tag{4.10}$$

$$x \in \mathcal{X}, \tag{4.11}$$

$$y \in \mathcal{Y}, \tag{4.12}$$

where variables and parameters are as defined in equations (4.3) to (4.7). The only difference is that here is no uncertainty which is represented by ω in the TSSMILP model and the probability, $\hat{p}$, which is equal to one, in the deterministic MILP.

4.2.2 Comparison of the Tier 2 Models to the Standard MILP Models

This section establishes which part of equations (3.27) to (3.45) correspond to equations (4.3) to (4.7). Since the deterministic MILP and TSSMILP models are similar with the scenarios and their corresponding probability being the only difference, only the TSSMILP model is discussed. The first term of the objectivity function in equation (3.27) [73], [74] corresponds to the first term of equation (4.3). The corresponding constraints are in equations (3.29), (3.30) [15], (3.34) and (3.38). In the first stage, new capacity is required per new potential technology, p and per

year t. According to equation (3.29), the new capacity should be more or equal to the one that was added in the previous year because accumulated capacity is of interest. Equation (3.30) is keeping the total of how much new capacity is added so far. Equation (3.34) restricts the new capacity to positive integers only. Equation (3.38) makes sure that the accumulated existing new capacity is positive.

The second stage objective function is the second term of equation (3.27) which corresponds to the second term of equation (4.3). The expansion of the second term of equation (3.27) is in equation (3.33) [73] and [74]. The expansion equation has two variables, $y^{\bar{t}}_{pks}$ and $z^{\bar{t}}_{ks}$ and their respective costs. The costs that correspond to $y^{\bar{t}}_{pks}$ occur when the allocated capacity is from the new technologies, and the costs that correspond to $z^{\bar{t}}_{ks}$ occur only when there is a shortage of allocated capacity from the new technologies. The constraints for the second term objective are in equation (3.28) [15], equation (3.31) [73] [74], equation (3.35), (3.36), (3.37), (3.40), and all the constraints corresponding to equation (3.40). Equations (3.28) and (3.40) work hand in hand, in making sure that the new and old allocated capacity from new potential technologies and existing power plants, is not more than the new and old accumulated capacity, respectively, multiplied by the corresponding capacity factor. The electricity demand is met by equations (3.31) and (3.42). The first term of equation (3.31) on the left side of the equal sign also includes the unserved energy which is not there all the time, hence the binary number, β. The current study introduced the first term of equation (3.31) because in some instances, the allocated capacity is not enough to meet the electricity demand.

There are different sets of capacities; the first one is the capacity from existing power plants, while the second one is from potential new technologies. The corresponding energy sources made it possible to add the two sources of capacities. The operating costs are excluded for the capacity from existing power plants, because their costs are very high when compared to the ones for new potential technologies. However, the capacity from the existing power plants is included, such that the model only adds necessary new capacity. The models of the new potential technology and existing power plants are separated for the reader's purposes. Equation (3.41) [15] is accumulating the total capacity from existing power

plants and also removing the decommissioned capacity.

Equations (3.35), (3.36), and (3.37) are there to make sure that allocated capacity from the potential technologies, unserved capacity and the total, respectively, are positive. Equation (3.43) for existing power plants is equivalent to equations (3.35). Constraints in equations (3.44) and (3.45) correspond to equation (3.41), and they make sure that the accumulated capacity from existing power plants and decommissioned capacity, respectively, are both positive.

The study also introduced equation (3.32) to differentiate between the base and peak required electricity that is met by both corresponding existing power plants and potential technologies.

4.2.3 Feasible Solution and Benders Decomposition for the Tier 2 Models

Starting with the standard form in equation (4.3) to equation (4.7), the feasible set of these equations is a vector x that satisfies the first stage constraint such that the determination of a feasible solution for the second stage problem is possible [138]. However, the vector x is expected to be feasible for all the realisations of $\xi_{k'}$ [15]. A set of feasible solutions is a convex set [138]. The feasible set for the TSSMILP model is the new capacity that satisfies the constraints in equations (3.29), (3.30), (3.34), (3.38) such that it is possible to find the feasible solution for the second term of equation (3.27). Not all the TSSMILP models, equivalent to the standard form, result in feasible solution for the second stage [78]. This is not the case with Tier 2 models, because the corresponding results for both deterministic MILP and TSSMILP models, are presented in section 6.2 in chapter 6. The aim of this section is not to provide the entire literature review on Benders decomposition (BD), but to provide literature that support what is discussed. The BD is used by default in this study because it is embedded in AIMMS software which is used to solve the Tier 2 problems. The BD is introduced to solve the complex TSSMILP second stage problem, which has four scenarios, that is $k' = 4$, twenty-five potential technologies and thirty-eight years. The BD is also employed

in the deterministic second stage problem, even though it is less complicated when compared to the TSSMILP.

The BD utilised in this thesis was introduced for a class of MILP [140]. However, it has extended to solve a wider range of problems in optimisation [140]. The decomposition methods are important because they provide an analytical approximation solution to complicated problems that can result in massive numerical computation [141].

4.3 Analysis of the Tier 3 Models

More information is provided for RO factors that utilise economic information. Since the new investment projects do not have cash flows, the derivation of expected cash flows is included in section 3.3.2. The RO factors are utilised for both BOMP and RNA and some for NPV models.

4.3.1 RO Factors

The RO factors are determined from the relevant economic information. Volatility $\sigma \in \mathbb{R}_+$ is a difficult factor to determine, because it requires historical information for projects to be evaluated by RO models. In this study, the returns are determined as a percentage of the current year historic revenue less operating expenses to the previous year's of an existing electricity utility. The determination of returns is done over several years, and the standard deviation of the return is volatility. Volatility changes with changes in revenue and operating expenses.

Risk-free return, $r_f \in \mathbb{R}_+$, is utilised to determine interest rates where r_f is another challenging factor. Typically, risk-free returns are estimated from bond yields. However, there are several bond yields and the bond with the same duration as the investment project is chosen. The bond yields change with time. Once these two factor are decided upon, other factors can be determined as shown in section 3.3.1. The volatility and risk-free rate changes, result in changes in the RO values. Hence, RO models are valued as often as the decision makers can afford,

with the aim of finding the best combination of volatility and risk-free rate which would result in RO value that favours the investment.

CHAPTER 5

SA Data Used for the Application of the Three-Tier Model

5.1 Background of Electricity Capacity Planning in SA

The key players in the South African electricity generation during the investigation period were Eskom, which is a state owned utility and independent power producers (IPPs). Eskom was the only player in electricity generation until the IPPs were introduced in 2010 [142]. The split between these key players in generated electricity (GWh) as at 31 March 2020 is 5.3% for IPPs and 94.7% for Eskom [143].

The South African Department of Mineral Resources and Energy (DMRE) is responsible for the EG capacity expansion planning, which produces the IRP. Once the IRP is authorised, the DMRE decides which key player(s) would build new power plants.

The year 2010 IRP (IRP2010) was promulgated in March 2011 [144]. In November 2013, the IRP2010 was updated (IRP2010 update) and published by DMRE [145] but was not promulgated. Similarly, there are IRP reports that were published in 2016 and 2018, IRP2016 [52] and IRP2018 [146], respectively, but were also not promulgated. The South African latest IRP (IRP2019) was promulgated in October 2019 [7]. The report for the latest IRP does not have detailed data, contrary to the IRP2010 update and IRP2016 reports; as a result, the model is developed from the IRP2010 update report data and the IRP2016 data for model validation in this study.

In this study, existing electricity power plants represented the existing electricity capacity.

5.2 SA Data Utilised in the First Tier

The data used for evaluation of existing power plants is collected from Eskom, which was generating 95% of electricity used in SA from April 2013 to March 2014 (2013/14) [147]. The collected data for first tier is indicated by input A in Figure 3.1. The data collected is the annual fuel costs in Rand for each energy source. The actual annual energy sent out in GWh for each of the 22 power plants owned by Eskom is also collected [148]. The collected data is used to determine fuel costs in South African cents per kWh (c/kWh), because the analysis in [48], showed that environmental levy and maintenance costs did not have much influence on the results of the analysis based on fuel costs only.

The energy sources, represented by i in the PT model in section 3.1.1, are coal, hydro, nuclear and gas/diesel in this case. Thus, f_1 is coal fuel cost, f_2 is hydro, f_3 is nuclear and f_4 is gas/diesel. X_{f_i} is the proportion for fuel cost i in the total of fuel costs. μ_{f_i} is the average of fuel cost f_i over the period which is financial years from 2008/09 to 2013/14 for the model development. f_{it} is the actual cost of a fuel cost i for financial year t, for example $f_{1,2009/10}$ is coal fuel cost in financial year 2009/10.

It is noteworthy that the period, 2008/09 to 2013/14, was when SA experienced load shedding for the first time [48]. The investigation ended in 2013/14 because this period coincided with the beginning of the EGEP which is discussed in Tier 2.

5.3 SA Data Utilised in the Second Tier

The data utilised in the second tier is sourced from the IRP2010 update [95]. This data is appropriate for this study because it contains demand scenarios which show that there is uncertainty in the future electricity demand. The IRP2010 update

also contains more detailed data about the potential technologies when compared to the previously published IRP report [95]. The availability of this complete data made the application of the TSSP and deterministic models possible. More details for the required data in the second tier are discussed in the following sections.

5.3.1 Data for Potential Technologies

The investigation period considered in this study started in 2013 to 2050. Data for potential technologies consists of the following costs: capital, $c_p^{\tilde{t}}$, fuel, $f_p^{\tilde{t}}$, fixed O&M, $l_p^{\tilde{t}}$, variable O&M, $v_p^{\tilde{t}}$ and other data. All this data is in [95] and [71]. The data discussed above is used in equations (3.11), (3.17), (3.27) and (3.33) in chapter 3.

5.3.2 Data for Existing Power Plants

Data for existing power plants in 2013 is in [71] and [95]. The existing capacity is increased by the committed capacity in [71] and [95]. The sum of existing and committed capacity is represented by e_n^t in equations (3.21), (3.22), (3.40) and (3.41). The existing power plants capacity data is decreased by the decommissioned capacity in [71] and [95] while decommissioned capacity is represented by $m_n^{\tilde{t}-1}$ in equations (3.22) and (3.41).

5.3.3 Capacity Factors

Capacity factors are used to adjust both potential and existing capacities, because the total capacity is not always available due to planned and unplanned outages. Equations (3.12), (3.21), (3.28) and (3.41) require capacity factors, $b_p^{\tilde{t}}$, to adjust the existing capacity, $e_p^{\tilde{t}}$. The capacity factors for renewable energy sources are in [149] since this is the only source with the recent renewable capacity factors. Capacity factors for other technologies are determined from Eskom's data. Due

to the confidentiality of Eskom data, only the renewable sources' capacity factors are in Table 5.1 [149].

TABLE 5.1: Average capacity factor

Energy source	Average capacity factor (%)
Solar PV	26
Wind	35
CSP	31

5.3.4 Scenario Data

The scenarios, s, in the equations in section 3.2.2 are based on electricity demand forecast scenarios in [95]. These scenarios are derived from the IRP2010 base case

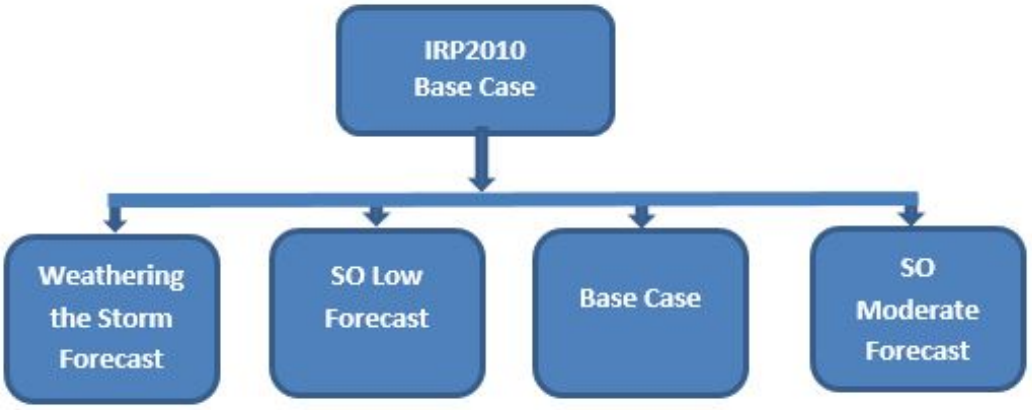


FIGURE 5.1: Scenarios considered in this study

scenario, as shown in Figure 5.1 [95]. The names given to the above scenarios are similar to the generic scenario names discussed in section 2.2.4. The only difference is in weathering the storm forecast and realistic scenario.

The actual data for each scenario is also shown in Figure 5.2 [95]. SO moderate forecast is the most optimistic scenario, followed by the base case and then the SO low scenario. The weathering the storm scenario is the most conservative scenario when compared to the above scenarios.

The differences amongst the scenarios in Figure 5.2 are the underlying assumptions on the electricity demand and economic outlook, as shown in Table 5.2 [95].

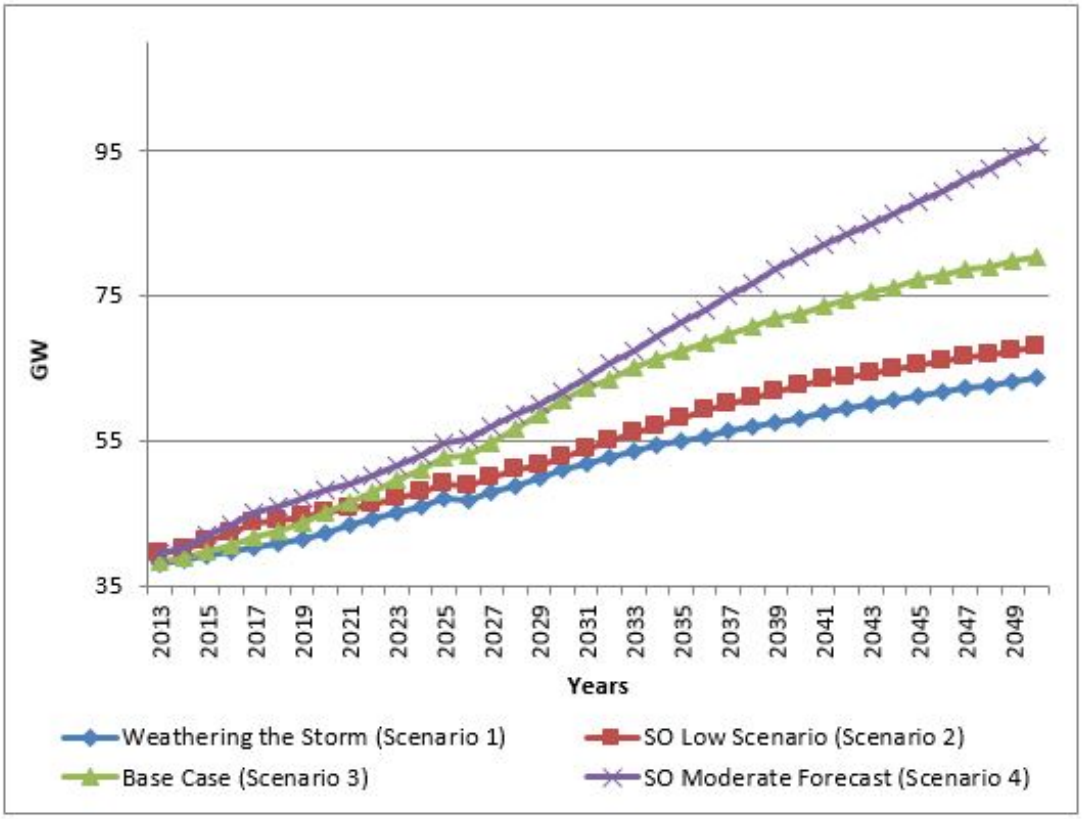


FIGURE 5.2: Electricity demand scenarios

In Table 5.2, S1 is weathering the storm forecast, S2 is system operator (SO) low forecast, S3 is the base case forecast and S4 is SO moderate forecast.

The demand scenarios in Figure 5.2 are used as random variable $\xi = S1,\ S2,\ S3,\ S4$, in equation (3.27). The four scenarios are equally weighted, that is, each scenario had a probability of 25%. Equal weights are used for the probabilities because the assumption is that decision makers are unbiased about the future electricity demand. These weights are used to determine E_ξ in equation (3.27). The scenarios data is also used for the deterministic model in section 3.2.1, however; one scenario is utilised at a time as deterministic models assume that the future is fully and perfectly known [15].

TABLE 5.2: Scenarios economic outlook

Scenario	Average annual electricity demand growth from 2013 to 2030 (%)	Average annual electricity demand growth from 2031 to 2050 (%)	Assumed average annual GDP growth to 2030 (%)
S1	1.8	1.3	2.9
S2	1.9	1.5	4.5
S2	2.7	1.9	5.4
S1	2.8	2.4	5.4

The actual South African average annual gross domestic product (GDP) growth rate from 2013 to 2020 is 0.16% [150], [151] and [152]. This suggested that at the end of 2020, all the scenarios in Table 5.2 had an optimistic outlook because the assumed respective average annual GDP growth rate for this period ranged from 2.9% to 5.4% which was way above the real average annual GDP growth of 0.16%. However, there is still another ten years to 2030, where higher GDP growth rates might be higher than the current ones.

TABLE 5.3: South African SOU total electricity sales growth

Year	Growth (%)
2012/13	-3.7
2013/14	0.6
2014/15	-0.7
2015/16	-0.8
2016/17	-0.2
2017/18	-0.9
2018/19	-1.8
2019/20	-1.2

The actual annual electricity growth is measured by annual electricity sales growth, shown in Table 5.3 [143]. Table 5.3 shows that the highest annual sales growth rate

is 0.6%, which is way below the least assumed average electricity growth of 1.8% before 2030 displayed in Table 5.2. Table 5.3 further showed that the expected average annual electricity growth assumptions were also optimistic, meaning that the model's results would also be optimistic.

5.3.5 Cost of Unserved Energy

The COUE is represented by u_k^t in equation (3.17) and by u_{ks}^t in equation (3.33). A COUE of R75 per kWh is used in [95]. This COUE is revised by the National Energy Regulator of South Africa's (NERSA's) consultation paper [153]. The revised COUE of R87.85 per kWh, taken from appendix A of the NERSA consultation paper [153], is used in this study.

Table 5.4 shows the COUE-1 values, which are based on the load shedding that was implemented in SA from 2018 to the beginning of 2019. Detailed derivation of the COUE-1 values in Table 5.4 is in [71]. The COUE-1 values in Table 5.4 are

TABLE 5.4: Cost of load shedding to electricity consumers and the economy

Case	COUE-1 (R/kWh)
A	2 935.93
B	15 352.25
C	205 657.81
D	206 602.43

based on the cost of load shedding to the South African economy and electricity users, which ranged between R18 billion to R102 billion [71]. The South African Council for Scientific and Industrial Research determined the same cost of load shedding as above for year 2019, which ranged between R59 billion and R118 billion [154]. The South African Council for Scientific and Industrial Research's cost of load shedding range is different from the one used in this study because it used a different period. It is also determined differently.

5.4 SA Data Utilised in the Third Tier

The technology data used in this chapter is taken from TSSMILP results in chapter 6. The data is only for potential technologies because once decision makers adopted the plan with new capacity from potential technologies, it becomes an investment project. The other data utilised in the third tier corresponded to the selected technologies in [71] and [95]. The economic data for determining risk-free rate and data for determining the volatility is discussed in section 6.3.1.1.

CHAPTER 6

Three-Tier Results Based on SA Data

This chapter discusses assumptions and results for the proposed three-tier model developed in chapter 3 based on the data discussed in chapter 5.

6.1 South African First Tier Results

In this section, the results of the first tier model from section 3.1.1 and the employed data discussed in section 5.2 are discussed. The PT model used in the first tier is developed in Matlab software and the script is in appendix C.
The results discussed in this section for existing energy sources are: correlation coefficients, efficient frontier and initial portfolio.

6.1.1 Assumptions for the Application of PT in Electricity Generation

The data collected for the first tier is assumed to represent the entire country's energy sources, because it was collected from Eskom which generated more than 90% of South African electricity during the investigation period [135]. A default portfolio optimisation model from the Matlab software is used. This model assumed that the investor is a long term investor who is fully invested in the assets, which are energy sources fuel in this study [155]. In the case of Eskom, the company invested in developing the power plants to the decommissioning date, which is about 50 years or more [7].
According to the study, the assumption is that efficient frontier is based on the

combination of E, the portfolio mean and V, the portfolio variance (risk) [56] and [127], E, is represented by C in equation (3.1) which is minimised when individual fuel average cost, μ_i, have small values. V is represented by σ in equation (3.8). If the value of the standard deviation is close to zero, this means the risk is low. The higher the value of standard deviation, the higher the risk.

The correlation coefficient, ρ_{ij}, measures a relationship between fuel costs from two (i, j) different energy sources. When the value of ρ_{ij} is close to zero, it contributes towards low portfolio risk. The relationship between σ and ρ_{ij} is shown by equation (3.8).

The initial portfolio is a portfolio that uses the fuel costs weights in a particular time period, which is 2013/14 in this study.

6.1.2 Results on Correlation Coefficients

The average fuel costs, μ_i, and fuel cost standard deviations, σ_i, are determined before the determination of correlated coefficients. The results are shown in Table 6.1, where gas/diesel has both the highest average fuel costs and risk measured

TABLE 6.1: Energy sources average costs and standard deviations

Energy source	Average fuel cost, μ_{f_i} (c/kWh)	Fuel cost standard deviation, σ_{f_i}(c/kWh)
Coal	12.34	2.96
Hydro	9.58	1.77
Nuclear	4.85	1.30
Gas/Diesel	243.96	46.49

by standard deviation, compared to other energy sources. The high average for gas/diesel indicate that this fuel costs more when compared to other fuels. The high standard deviation means that gas/diesel fuel cost fluctuated a lot more during the investigation period. Gas/diesel is utilised when there is a high electricity demand during emergencies. Additionally, gas/diesel is utilised for base load during the investigation period [48].

Pearson's correlation coefficient (PCC), ρ_{f_i,f_j}, is determined for the energy sources.

Values of the PCC range from -1 to +1. When PCC value is -1, it shows that f_i and f_j are perfectly related in a negative linear manner, but when PCC value is zero, it indicates that there is no linear relationship between f_i and f_j. When PCC value is +1, it shows that f_i and f_j are perfectly related in a positive linear manner.

The absolute magnitude of correlation coefficients are interpreted in [156] as shown in Table 6.2. There are other correlation coefficients that are discussed by Maturi

TABLE 6.2: Correlation coefficients interpretation

Absolute magnitude of correlation coefficient	Interpretation
0.00 to 0.01	Negligible correlation
0.01 to 0.39	Weak correlation
0.40 to 0.69	Moderate correlation
0.70 to 0.89	Strong correlation
0.90 to 1.00	Very strong correlation

and Elsayigh [157], Reshef *et al.* [158] and Gogtay and Thatte [159] but PCC is used in this study. Pearson's correlation coefficients results for the energy sources considered in this study are presented in Table 6.3. Comparing Table 6.3 to Table 6.2, one can observe that the correlation coefficients for the data used here range from moderate correlation (0.629) to very strong correlation (0.925). This means that the risk of the portfolio considered in this study cannot be reduced because there are no low or weak correlation coefficients, as shown in Table 6.3. This implies that decision makers are supposed to consider energy resources whose fuel costs are not only low, but also that do not fluctuate much at the planning stage. Renewable energy resources like wind and solar would be a good choice for decision makers because these energy resources have no fuel costs [95].

TABLE 6.3: Correlation coefficients of energy sources

	Coal	Hydro	Nuclear	Gas/Diesel
Coal	1.000	0.925	0.792	0.820
Hydro		1.000	0.759	0.729
Nuclear			1.000	0.629
Gas/Diesel				1.000

The correlation coefficient between gas/diesel and nuclear is the lowest compared to other correlation coefficients in Table 6.3. Table 6.1 shows that nuclear has the least average fuel cost and least standard deviation compared to other energy sources. Renewable energy sources have zero fuel costs lower than the nuclear fuel cost. Hence, it can be concluded that if there are renewable energy sources in the energy sources' portfolio, there would be low or weak correlation coefficients. Nevertheless, nuclear is utilised for base load, and this is not applicable to wind and solar energy sources.

The period of executing the first tier model is just before the second tier model investigation period. The first tier results discussed in section 6.1.2 suggest that renewable energy sources shall be considered in the second tier to reduce the correlation coefficients between fuel costs.

6.1.3 Results on Efficient Frontier

The results discussed in this section are derived from equations (3.1) to (3.7) in Section 3.1.1. The objective in equation (3.1) is to minimise the portfolio fuel cost. Figure 6.1 shows energy sources fuel costs' efficient portfolios as follows: the first efficient portfolio, located in the bottom left corner close to the axis of origin, has the lowest average cost (mean of portfolio costs), and risk (standard deviation of portfolio costs), inside this portfolio's circle is nuclear fuel cost. Next to nuclear is hydro and coal, as shown in a magnified box A in Figure 6.1. The last efficient portfolio, located in the top right corner, has the highest cost and risk. Inside this portfolio's circle is gas/diesel fuel cost; in between the first and the last efficient portfolios, are eight equally spaced efficient portfolios represented by empty circles. These portfolios are called efficient portfolios because they lie on the curve called efficient frontier [54] and [160].

The energy sources' share of the efficient portfolios in Figure 6.1 are in Figure 6.2. All the ten portfolios consist of one or two energy sources. There are four energy sources, and no efficient portfolio has three or four energy sources. The rest of the portfolios are dominated by hydro and gas/diesel except for portfolio 1 with

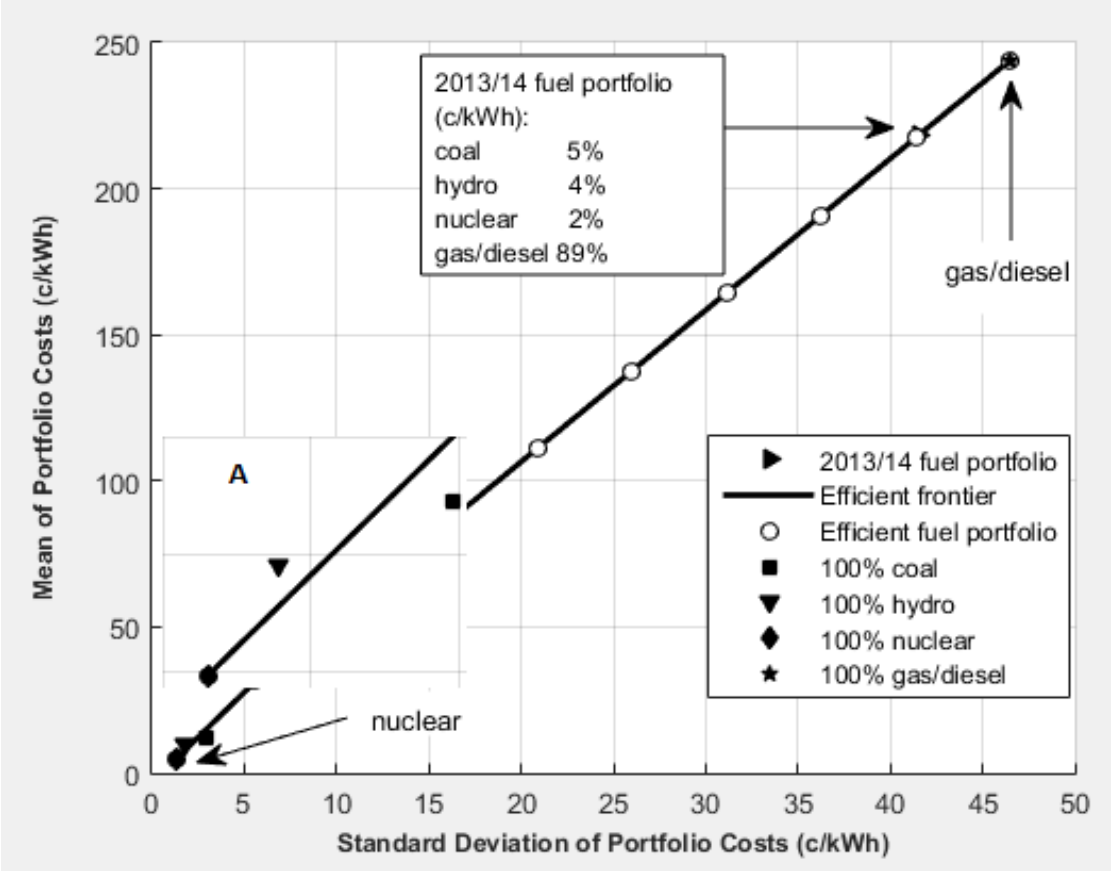


FIGURE 6.1: Energy sources efficient frontier

nuclear only. The average costs (costs) and the standard deviations (risks) for the efficient portfolios, both in c/kWh in Figure 6.1 are presented in Table 6.4. Portfolio 1's cost and risk in Table 6.4 is the same as nuclear's in Table 6.1. The

TABLE 6.4: Costs and risks of efficient portfolios

Portfolios	Cost (c/kWh)	Risk (c/kWh)
1	4.854	1.299
2	31.422	5.614
3	57.989	10.672
4	84.557	15.774
5	111.124	20.887
6	137.691	26.006
7	164.260	31.126
8	190.826	36.248
9	217.394	41.371
10	243.961	46.494

same applies to portfolio 10s cost and risk in Table 6.4 and gas/diesel's in Table 6.1.

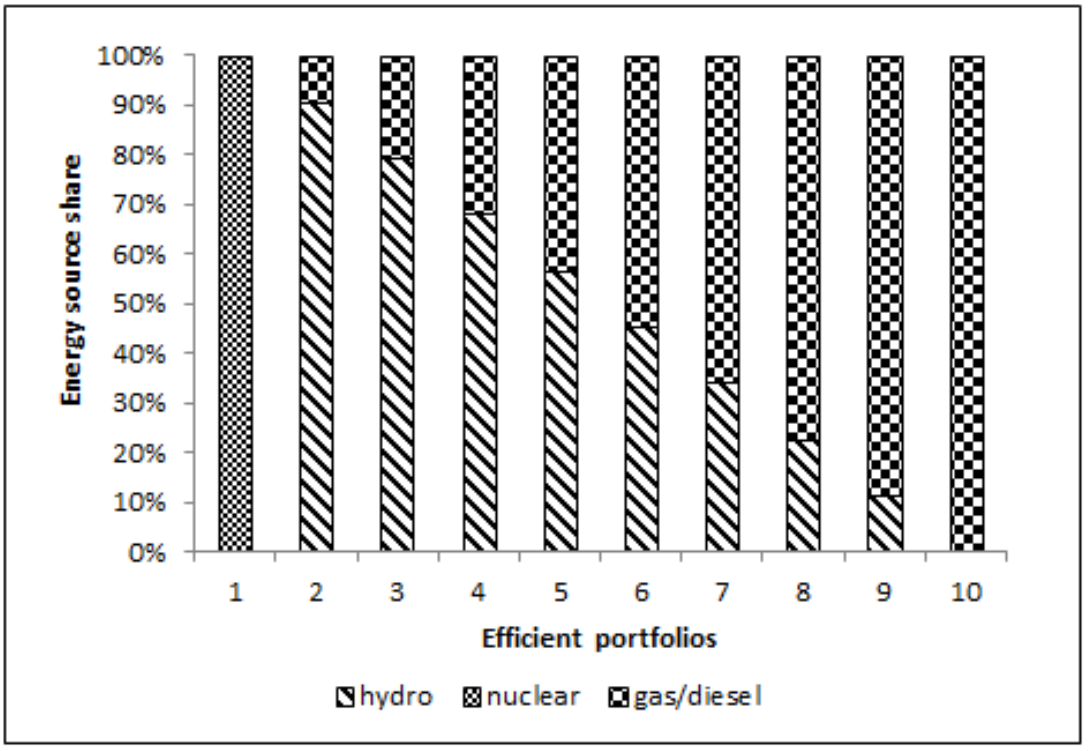


FIGURE 6.2: Energy source allocation for the ten portfolios in Figure 6.1

This means that both nuclear and gas/diesel fuel costs are on the efficient frontier. The 10 efficient portfolios in Figure 6.1 are the software's default number of efficient portfolios. The number of efficient portfolios displayed is possible to increase or decrease the number of efficient portfolios displayed; therefore, the number of efficient portfolios in 6.4 can be increased or decreased. Based on this, the number of efficient portfolios is increased arbitrarily to 200 with the aim of showing that there are more efficient portfolios with more energy sources. Appendices A and B show efficient portfolios with low costs and risks and those with high costs and risks, as well as the corresponding energy sources. These results show that the risk and cost of the initial portfolio can be reduced by decreasing the usage of gas/diesel. The gas/diesel energy source is utilised for both base and peak loads during the investigation period as the country is encountering load shedding [48]. The excessive use of gas/diesel resulted in high energy costs for Eskom, which is ultimately passed to the consumers through electricity price increases [161].

Figure 6.1 shows that coal is under the efficient frontier because of high risk; therefore it is not included in efficient portfolios. This means that even though

coal is used for base load, its fuel costs are not stable. Coal can move to the efficient frontier through a cost increase or risk decrease. However, risk decrease would benefit both the generator and electricity consumers.

6.1.4 Results on Initial Portfolio

Initial portfolio is the portfolio that shows fuel costs' shares in the energy sources under consideration as at 2013/14. This portfolio is labelled as 2013/14 fuel portfolio in Figure 6.1 in Section 6.1.3 and is behind the efficient portfolio with a star next to it.

In Figure 6.1, the initial portfolio looks like it is on the efficient frontier. However, Figure 6.3 shows that the initial portfolio is below the efficient frontier, which means that it is not efficient. The initial portfolio's cost is 218.2 c/kWh and risk is

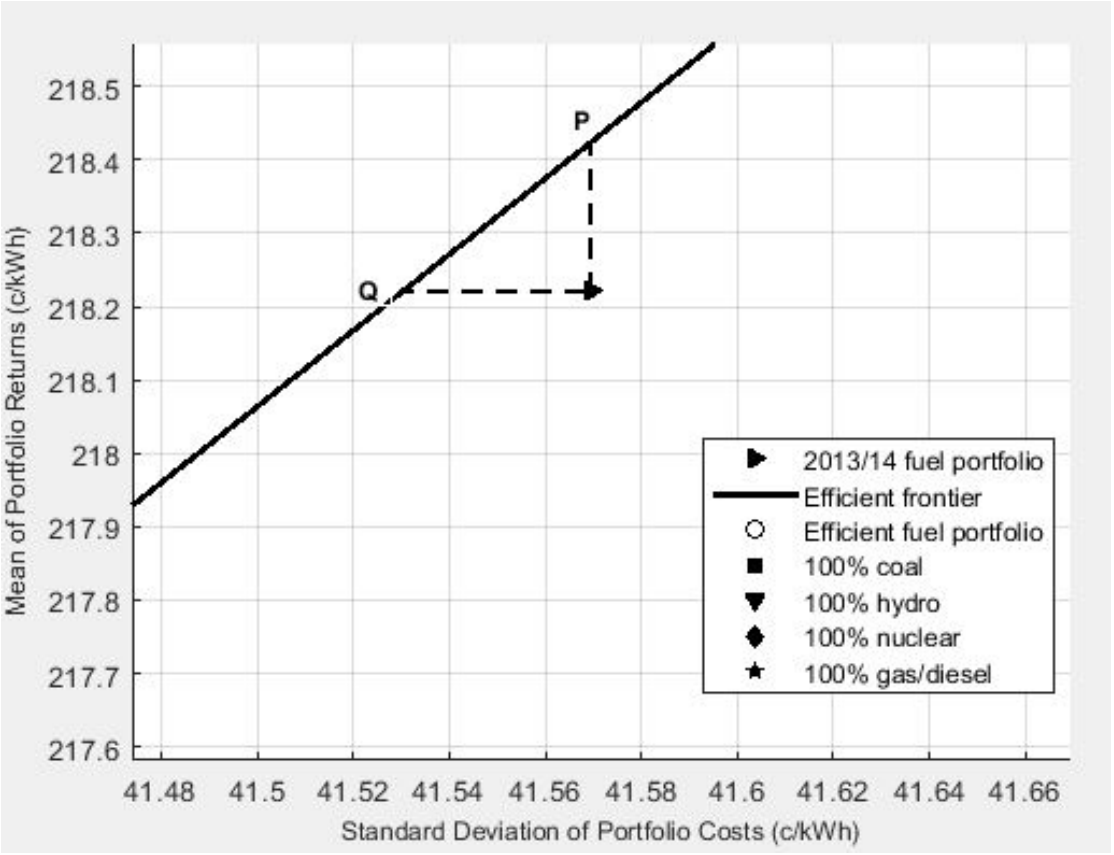


FIGURE 6.3: Efficient portfolios close to the 2013/14 fuel portfolio

41.57 c/kWh. There are efficient portfolios corresponding to the initial portfolio.

These portfolios are shown in Figure 6.3. There is an efficient portfolio P which has the same risk as the initial portfolio, and a slightly higher average cost of 218.41 c/kWh. There is another efficient portfolio Q which has the same cost as the initial portfolio and a slightly lower risk of 41.53 c/kWh. It is assumed that decision makers would choose portfolio Q, instead of P, due to its lower risk. If the individual fuel costs remain more or less constant during the investigation period, the initial portfolio risk will be reduced, and the initial portfolio will approach the efficient portfolio Q.

The efficient portfolios, P and Q, would not provide the decision makers with significantly lower costs or risks compared to the initial portfolio, because these portfolios are also dominated by gas/diesel, as shown in Table 6.4.

In the plan, high cost and risk of gas/diesel can be reduced by increasing renewable energy sources like hydro, which can be used for both base and peak loads. This output from the first tier is represented by B in Figure 3.1.

6.1.5 Summary on First Tier Results

The PT analysis results show that the fuel costs of the South African portfolio of energy sources during the investigation period are not well diversified because all the energy sources have moderate to high correlation coefficients. This indicates that the fuel costs increased or decreased together. What is ideal is a portfolio which has certain fuel costs that remain more or less constant when other costs moved up or down. This can be implemented by making sure that the costs of energy sources used for base load remain as constant as possible and the fuel costs for gas/diesel can vary because these stations are supposed to be utilised for peak load and emergencies. The results show that the initial portfolio is not efficient. However, there are efficient portfolios with both low cost and risk as shown in Figure 6.3, which can be considered.

It is noted that the model did not include coal in efficient portfolios because this energy source has high risk. For example, even though coal is cheap and utilised for base load for more capacity than other energy sources, its fuel costs are not as

stable as nuclear's.

A further analysis is performed where fuel and O&M costs are analysed together, and also where fuel and environmental levy costs are analysed together in [48]. The results for fuel and O&M costs analysis showed that the initial portfolio costs increased, but risk decreased when O&M costs are included. This means the fuel and O&M costs are more stable than fuel costs alone. The results for fuel and environmental levy costs showed that the environmental levy has little effect on discouraging the use of fuels which emit CO_2 by electricity generators.

The information that decision makers could use for planning from the evaluation of existing power plants is that the gas/diesel fuel cost is expensive for electricity consumers and that an alternative less expensive fuel is required which could be used for both peak load and emergencies. Even though coal is not efficient, it could be efficient if its risk is reduced. The fuel cost portfolio should have more energy sources with stable fuel costs to reduce the correlation coefficients. The coal risk can be reduced by keeping its cost as stable as possible. The cost and risk of gas/diesel can be reduced if the use of this fuel for base load can be reduced.

This chapter demonstrating how the PT model can be utilised as a first tier of the proposed EG expansion three-tier model.

6.2 South African Second Tier Results

The results in this section are based on the deterministic MILP model in section 3.2.1 and the TSSMILP model in section 3.2.2, together with the data discussed in section 5.3. Both models minimise the total annual capital cost and the running costs for the new capacity. The running costs comprised of fuel costs, fixed operating and maintenance (O&M) cost, variable O&M costs and cost of unserved energy.

The results discussed here are the total costs of new capacity determined from both deterministic MILP and TSSMILP models, the new capacity energy sources and dates when it is expected, the corresponding reserve margins and CO_2 emissions.

6.2.1 Assumptions for the Second Tier Models

The assumption is that all the costs remained constant throughout the planning period. Constant costs mean that the costs are in 2013 real terms. However, in reality, the capital costs for different technologies have increased at different rates since 2013 and will continue to increase until the power plants are built. Similarly, fuel costs and maintenance costs increase as well and will do so till the end of the power plant life. This implies that the resultant costs need to be adjusted by inflation.

The technologies adjusted overnight capital cost (R/kW) are used as the actual capital costs (R/kW) because actual costs are not available on the published data. Hydro, nuclear, solar and wind are assumed to be base load energy sources because they do not operate during peak hours only, whereas pump storage and gas/diesel are assumed to be peak load energy sources because they are suppose to operate during peak hours. Coal is allocated for both base and peak load; this is AIMMS software default. Low capacity factors for wind and solar compensate for the base load assumption.

The same average annual capacity factors are used throughout the investigation period for both potential technologies and existing capacity, because the forecasted capacity factors are not available. In reality, capacity factors are not expected to remain the same because the total energy over the investigation period per technology will not remain constant. The constant capacity factors' assumption might either overestimate or underestimate the actual energy produced per period by the models sometimes.

6.2.2 Deterministic MILP and TSSMILP Results

The results for deterministic MILP and TSSMILP models are discussed, with the aim of comparing and contrasting the two approaches. The results discussed in this section are: costs, new capacity, capacity allocation and CO_2 emission. The

reserve margins are discussed for the deterministic MILP model. The TSSMILP results are represented by output C in Figure 3.2.

6.2.2.1 Deterministic MILP model cost results for new capacity

This section discusses results based on MILP for the deterministic model discussed in section 3.2.1. Table 6.5 shows capital, total running and total cost for each of the four scenarios discussed in section 5.3.4. Plan 1 has optimal results for S1, Plan 2 for S2 and so forth. The capital costs increase from Plan 1 to Plan 4 because S1

TABLE 6.5: MILP deterministic model results for each demand scenario

Billion Rand	Plan 1	Plan 2	Plan 3	Plan 4
Capital cost	1 075.26	1 303.39	2 101.96	3 238.96
Total running cost	0.73	0.92	1.21	1.37
Total cost	1 075.99	1 304.31	2 103.17	3 240.33

has the most conservative while S4 has the most optimistic forecasted electricity demand when compared to other scenarios. All the COUE-1 values gave the same solution, as shown in Table 6.5. This means that the deterministic MILP model is not influenced by the cost of unserved energy.

The what if analysis results in Table 6.6 allow decision makers to cater for unknown demand that will materialise after the investment decision is taken. The results

TABLE 6.6: Results for what if scenario analysis - Case A

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**1 075.99**	12 398.19	103 444.20	248 202.26	91 280.16
Plan 2	1 304.12	**1 304.31**	8 1089.13	223 520.80	76 804.59
Plan 3	2 102.54	2 102.70	**2 103.17**	31 020.69	9 332.28
Plan 4	3 239.44	3 239.56	3 239.90	**3 240.33**	3 239.81

in Table 6.6 are for Case A where the COUE-1 value is R2 935.95/kWh, which is used for the $u_k^{\tilde{t}}$ in equation (3.17). The costs in bold text in Table 6.6 are the same as the total costs in Table 6.5. The other costs in Table 6.6 are derived from a what if analysis. The first row of Table 6.6 is where decision makers choose results based on S1 and the reality follows other S2, S3 or S4. For example, Table 6.6

shows that if S1 is chosen and the electricity demand reality followed S2, the cost increases from R1 175.99 to R12 398.19 billion and so on. The electricity demand not met by S1 capacity is compensated by the cost of unserved energy, because S1's capacity cannot be increased to meet higher electricity demand from other scenarios.

The expected costs in Table 6.6 are a weighted total cost of the plans' costs for all the scenarios, where the weights are 25% for each scenario. The expected costs decrease from Plan 1 to Plan 4 because Plan 4 has more capacity than the rest of the plans, and Plan 1 has the least capacity.

The what if analysis results for Case B are in Table 6.7 where a COUE-1 value of R15 352.25/kWh is used. In Table 6.8, results for Case C are presented based

Table 6.7: Results for what if scenario analysis-Case B

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**1 075.99**	52 422.04	448 941.98	1 202 465.20	426 226.31
Plan 2	1 304.12	**1 304.31**	194 082.48	776 766.86	243 364.44
Plan 3	2 102.54	2 102.70	**2 103.17**	239 010.90	61 329.83
Plan 4	3 239.44	3 239.56	3 239.90	**3 240.33**	3 239.81

on COUE-1 value of R205 657.81/kWh. Similarly, in Table 6.9 are the results for

Table 6.8: Results for what if scenario analysis-Case C

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**1 075.99**	688 902.62	6 000 656.74	16 094 807.08	5 696 360.61
Plan 2	1 304.12	**1 304.31**	2 583 743.35	10 389 344.72	3 243 924.12
Plan 3	2 102.54	2 102.70	**2 103.17**	3 175 699.59	795 502.00
Plan 4	3 239.44	3 239.56	3 239.90	**3 240.33**	3 239.81

Case D based on COUE-1 value of R206 602.43/kWh. Comparing results from

Table 6.9: Results for what if scenario analysis - Case D

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**1 075.99**	692 061.90	6 028 213.63	16 168 727.78	5 722 519.83
Plan 2	1 304.12	**1 304.31**	2 595 604.84	10 437 058.40	3 258 817.92
Plan 3	2 102.54	2 102.70	**2 103.17**	3 190 276.34	799 146.19
Plan 4	3 239.44	3 239.56	3 239.90	**3 240.33**	3 239.81

Table 6.6, Table 6.7, Table 6.8 and Table 6.9, all these tables show that even though Plan 1 had the lowest total costs as shown in Table 6.5, Plan 1 has the highest expected cost because of the capacity shortage and will result in unserved energy which will cost R2 935.95 for each kWh as shown in the results presented in Table 6.6. Capacity shortage is not desirable since it is costly. In contrary, if the decision makers choose Plan 4 which had the highest total cost in Table 6.5, it would cost the decision maker less if the actual demand follows S1, S2 or S3 instead of S4. If the actual demand followed a different scenario, the choice of Plan 4 will result in capacity surplus. Similar to the capacity shortage, capacity surplus is also not desirable because it is still costly. The expected cost increase with increasing COUE-1 values; nevertheless, the expected cost for Plan 4 remained the same for all the COUE -1 values.

6.2.2.2 TSSMILP model new capacity cost results

Costs for the TSSMILP model are determined for new capacity only as discussed in section 6.2.2.1 and results are presented in Table 6.10. The costs in Table 6.10 are for each element of ξ = S1, S2, S3, S4. For each case, the capital costs are the same for all the scenarios. What changes are the capacity allocations, hence the changes in running costs and the COUE costs. Table 6.10 shows that the capital costs are the same for all the elements of ξ in each case and do not vary per scenario as in the deterministic model. The capital costs are not influenced by scenarios, as shown in the first term of equation (3.27) in section 3.2.2. The COUE results in Table 6.10 show that there are instances where the model used COUE-1 values to allocate new capacity because the COUE-1 value is cheaper. The capacity allocation is discussed in sections 6.2.2.6 and 6.2.2.7. The model used COUE-1 values when the sum of fuel, fixed and variable O&M cost is higher than the COUE-1 value. This resulted in unserved energy, hence the COUE costs for S4 are greater than zero for all the cases, whereas S3 has COUE costs only in Case A.

Table 6.10 also shows that the COUE costs decreased with increasing value of COUE-1 (R/kWh) because the model is able to allocate new capacity that is

Table 6.10: TSSMILP total capital costs for new capacity

Rand (billion)	S1	S2	S3	S4	Solution
			Case A		
Capital Costs	1 631.85	1 631.85	1 631.85	1 631.85	
Running costs excluding COUE	0.70	0.90	1.42	1.96	
COUE costs	0.00	0.00	269.93	1 657.70	
Total	1 632.55	1 632.74	1 903.19	3 291.51	2 115.00
			Case B		
Capital Costs	2 562.33	2 562.33	2 562.33	2 562.33	
Running costs excluding COUE	0.54	0.67	1.08	1.57	
COUE costs	0.00	0.00	0.00	1 589.99	
Total Costs	2 562.86	2 563.00	2 563.40	4 153.88	2 960.79
			Case C		
Capital Costs	3 238.66	3 238.66	3 238.66	3 238.66	
Running costs excluding COUE	0.49	0.61	0.95	1.37	
COUE costs	0.00	0.00	0.00	0.97	
Total Costs	3 239.15	3 239.27	3 239.61	3 241.01	3 239.76
			Case D		
Capital Costs	3 238.66	3 238.66	3 238.66	3 238.66	
Running costs excluding COUE	0.49	0.61	0.95	1.37	
COUE costs	0.00	0.00	0.00	0.97	
Total Costs	3 239.15	3 239.27	3 239.61	3 241.01	3 239.76

cheaper than higher COUE-1 values.

The results in this section show that as the COUE-1 value increased from Case A to Case D, the TSSMILP model solution approached Plan 4 deterministic expected cost discussed in section 6.2.2.1. This shows that the most expensive cost of unserved energy is an indirect cost for Plan 4's expected cost.

In the last column of Table 6.10 is a solution which is a weighted total, where the weights are the weights allocated to the scenarios.

Table 6.10 shows that the cost results for Case C and Case D are the same. This implies that the Case C COUE-1 value is the highest COUE for the data used for these results. As a result, the two cases are referred to as Case C&D in the following sections.

6.2.2.3 Value of TSSMILP solution

This section quantifies the value of using the TSSMILP instead of the deterministic MILP model, introduced in section 2.2.3.2. Results are presented in Table 6.11 and are derived by subtracting the solutions in Table 6.10 from the corresponding expected costs from Table 6.6, Table 6.7, Table 6.8 and Table 6.9. The VSS for

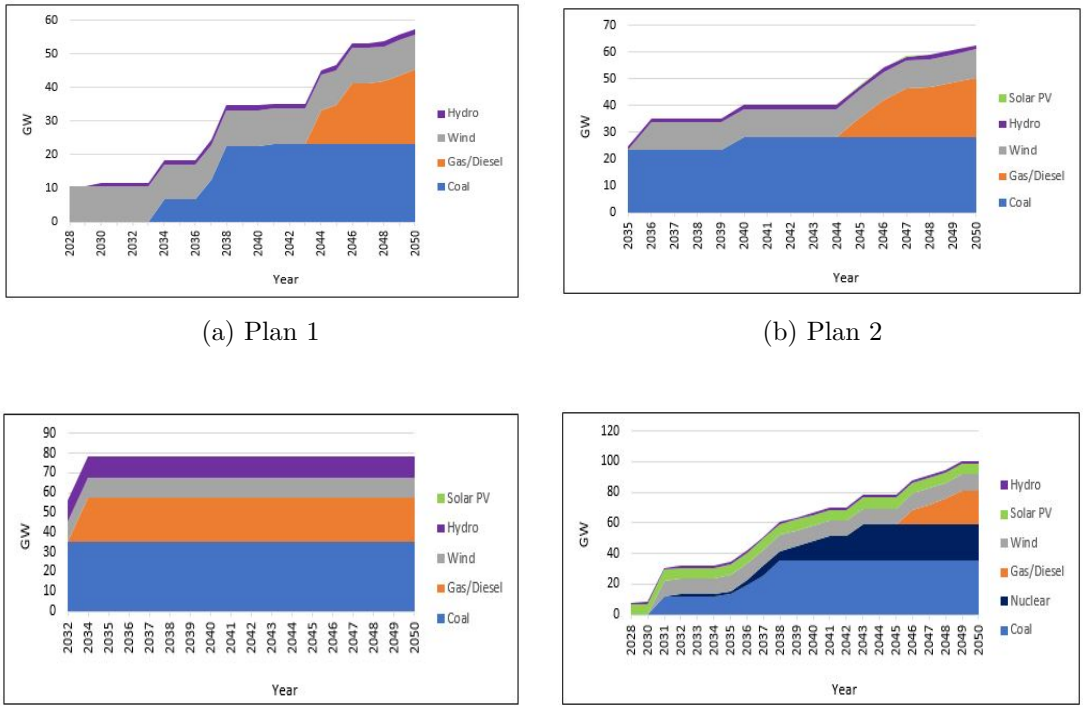
Table 6.11: Value of stochastic programming

Plan	EDC	VSS-A	VSS-B	VSS-C&D
		Using Table 6.6 results		
1	91 280.16	89 165.16	88 319.37	88 040.40
2	76 804.59	74 689.59	73 843.81	73 564.83
3	9 332.28	7 217.28	6 371.49	6 092.51
4	3 239.81	1 124.81	279.02	0.05
		Using Table 6.7 results		
1	426 226.31	424 111.31	423 265.52	422 986.54
2	243 364.44	241 249.44	240 403.66	240 124.68
3	61 329.83	59 214.83	58 369.04	58 090.07
4	3 239.81	1 124.81	279.02	0.05
		Using Table 6.8 results		
1	5 696 360.61	5 694 245.61	5 693 399.82	5 693 120.85
2	3 243 924.12	3 241 809.12	3 240 963.34	3 240 684.36
3	795 502.00	793 387.00	792 541.22	792 262.24
4	3 239.81	1 124.81	279.02	0.05
		Using Table 6.9 results		
1	5 696 360.61	5 694 245.61	5 693 399.82	5 693 120.85
2	3 243 924.12	3 241 809.12	3 240 963.34	3 240 684.36
3	795 502.00	793 387.00	792 541.22	792 262.24
4	3 239.81	1 124.81	279.02	0.05

plans 1 to 3 increased in Table 6.11 with increasing COUE-1 values. However, VSS for Plan 4 remained constant throughout. This shows that the deterministic MILP Plan 4 results are close to S4 results from the TSSMILP model. According to Wallace and Fleten [75], in general, even though the SP problem could not have the same solution as its corresponding deterministic problem, there is a possibility.

6.2.2.4 Deterministic MILP model new capacity results

The new capacity results discussed in this section correspond to the total costs results shown in Table 6.5. The model added new capacity to meet the forecasted electricity demand. In Figure 6.4, Plans 1 and 4 added new capacity as early as



(a) Plan 1

(b) Plan 2

(c) Plan 3

(d) Plan 4

FIGURE 6.4: Deterministic MILP model new capacity

2028. In the 2020s, more electricity capacity is decommissioned. The total new capacity in 2050 is 57.34 GW for Plan 1, 62.51 GW for Plan 2, 69.53 GW for Plan 3 and 100.19 GW for Plan 4.

Not all the existing capacity is decommissioned by 2050 since there is still 21.21 GW. The 2050 energy sources percentage constituents for each plan presented in Table 6.12 are inclusive of the 21.21 GW. The table shows that for almost all the plans, the energy sources' constituents are almost the same. The only exceptions are Plan 3 and Plan 4, both with nuclear, and Plan 4 also with solar PV energy sources. Solar energy source is one of the potential renewable energy sources. Only

TABLE 6.12: Deterministic MILP model energy source constituents (%)

Energy source	2013	Plan 1 - 2050	Plan 2 - 2050	Plan 3 - 2050	Plan 4 - 2050
Coal	76	50	53	52	42
Nuclear	4	0	0	8	20
Gas/Diesel	5	28	26	22	18
Wind	0	13	13	11	9
Hydro	8	9	8	7	5
Solar PV	0	0	0	0	6
Other	7	0	0	0	0

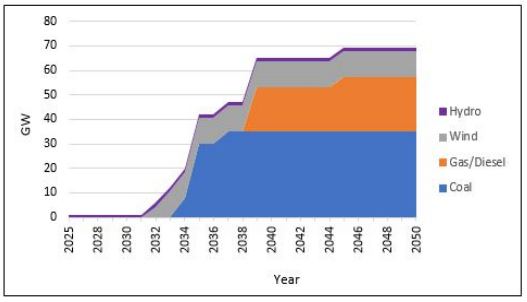
Plan 4 selected this energy source because of high anticipated electricity demand. Solar technologies were expensive at the time when the data was collected.

6.2.2.5 TSSMILP model results for new capacity

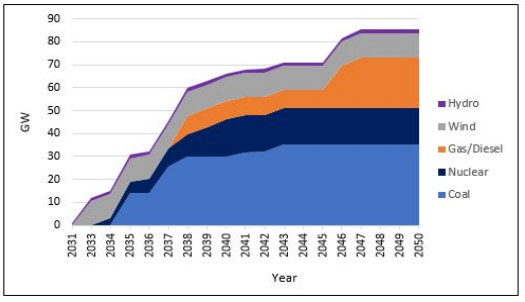
In this section, the new capacity corresponding to the TSSMILP capital costs are discussed in section 6.2.2.2 are presented in Figure 6.5. The TSSMILP model increased capacity for the same reasons that are discussed for the deterministic model in section 6.2.2.4. Figure 6.5a and Figure 6.5c show that the TSSMILP model added new capacity as early as in 2025. In fact, for all the cases in Figure 6.5, new capacity is added early when compared to Figure 6.4. If the planning results in Figure 6.5 are implemented, decision makers will need investment funds immediately.

The new capacity is based on the electricity demand forecast shown in Figure 5.2. However, section 5.3.4 showed that both GDP and electricity demand growth rates are below the forecast assumptions, as shown in Table 5.2. This means that the new capacity results cannot be implemented as they are. Hence, the third tier is proposed to evaluate the investment emanating from new capacity.

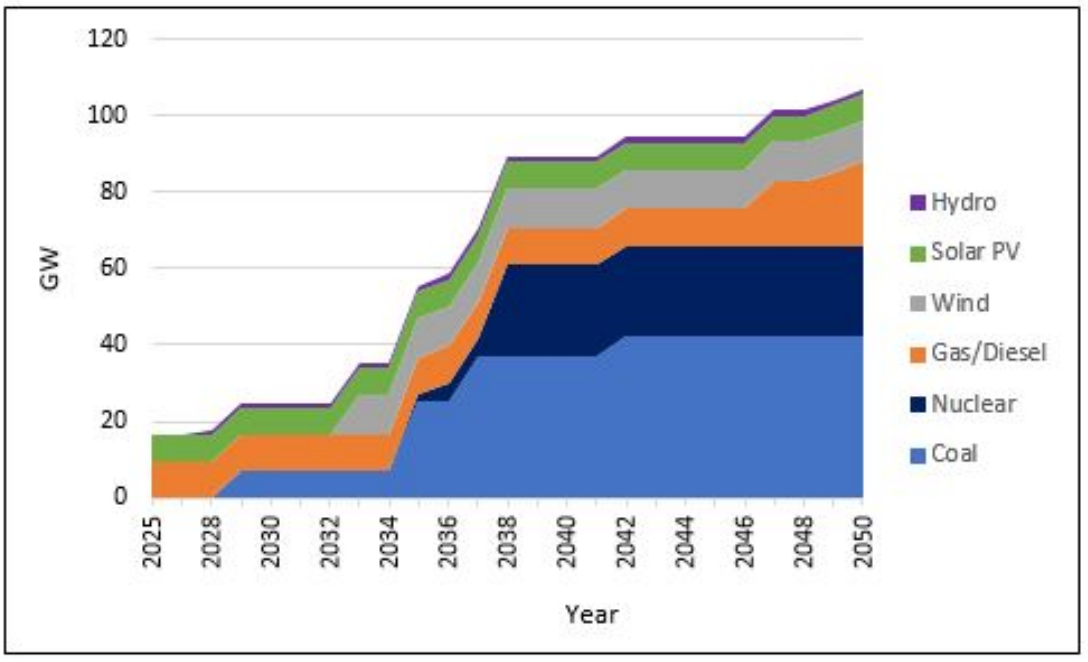
Nuclear is added to cases B and C&D in Figure 6.5 similar to Figure 6.4 where it is added for Plans 3 and 4. Like in Figure 6.4d, solar PV is added in Figure 6.5c. In the data used in this study, both nuclear and solar PV are expensive technologies; however, the model chooses these technologies for scenarios with high electricity demand.



(a) Case A



(b) Case B



(c) Case CD

FIGURE 6.5: TSSMILP model new capacity

At the end of the investigation period, Case A has a total capacity of 69.23 GW, 85.23 GW for Case B and 107.14 GW for Case C&D. It is, further, noted that the TSSMILP model has more capacity than the deterministic model in 2050 even though the TSSMILP model has cheaper total costs.

Table 6.13 shows the energy sources' percentage allocation for 2013 and for the new and existing capacity (total capacity) as at 2050 for each of the TSSMILP cases, while 2050 energy sources' constituents for both deterministic MILP and TSSMILP models are almost the same. The challenge with the selected renewable energy sources is that wind and solar PV are intermittent, and not easy to

TABLE 6.13: 2013 vs. 2050 TSSMILP total capacity allocation

Energy Source	2013	Case A: 2050 (%)	Case B: 2050 (%)	Cases C&D: 2050 (%)
Coal	76	57	48	42
Nuclear	4	0	15	20
Gas/diesel	5	24	21	18
Wind	0	12	10	9
Hydro	8	7	6	5
Solar PV	0	0	0	6
Other	7	0	0	0

dispatch without the energy storage [162]. The hydro new capacity is imported from Zambia and Mozambique [71] and [95].

One should bear in mind that the actual electricity demand has been slowing down from 2011 to 2020 as shown in Figure 6.6 derived from historic electricity generated and available for distribution [152] and [163]. There are various contributing

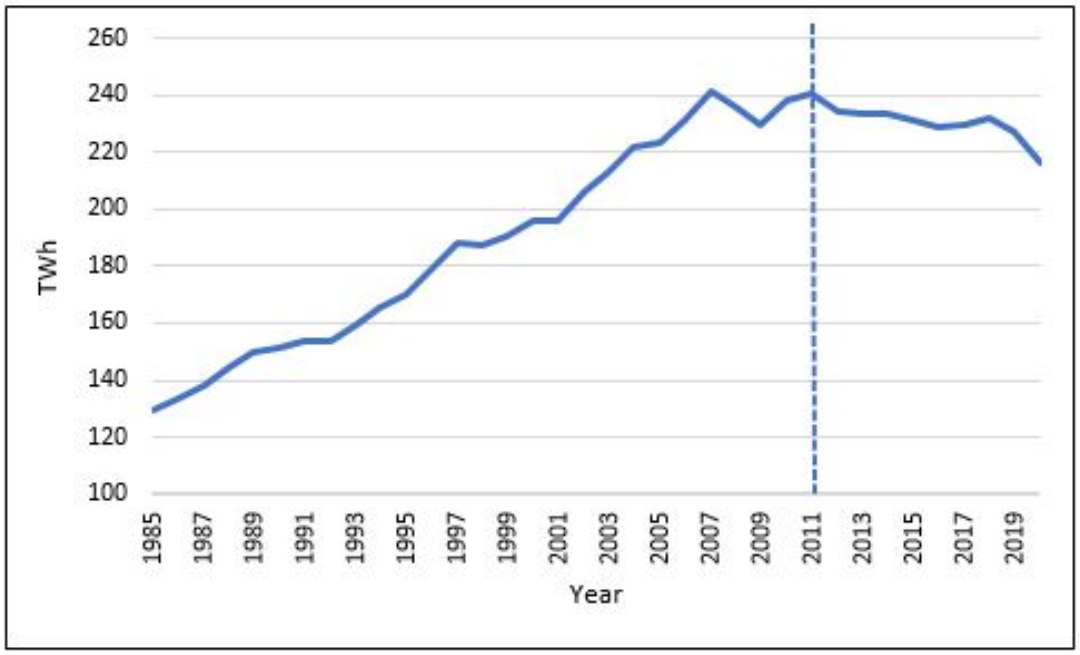
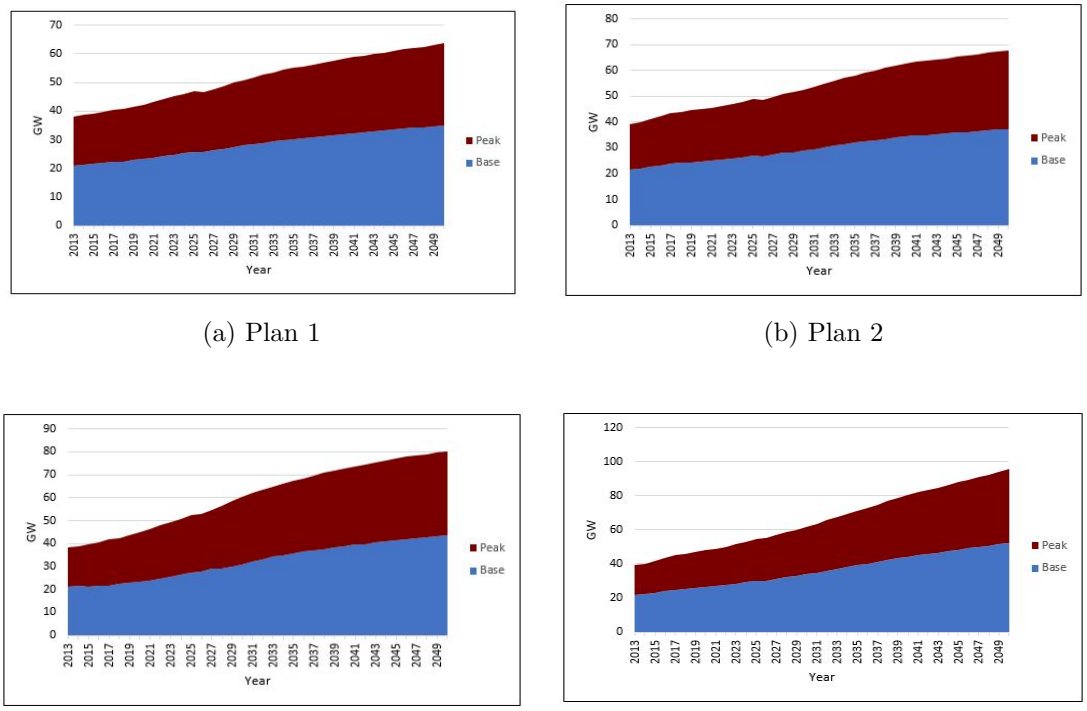


FIGURE 6.6: Historic electricity generated and available for distribution in SA

factors to the decline in electricity demand in SA. These are listed in [164]. If the decision makers choose results based on more optimistic demand scenarios like S3 and S4, and the trend in Figure 6.6 continues, this will result in reduced electricity revenues which will not be able to pay back the installed capacity.

6.2.2.6 Deterministic MILP model results for capacity allocation

In this section, the results of the deterministic MILP model total capacity allocation is discussed. Equations (3.12) and (3.21) from the deterministic model in section 3.2.1 determined the capacity allocation, and results are shown in Figure 6.7. The slight drop in the capacity allocation around 2027 in Figure 6.7



(a) Plan 1

(b) Plan 2

(c) Plan 3

(d) Plan 4

FIGURE 6.7: Deterministic MILP model capacity allocation

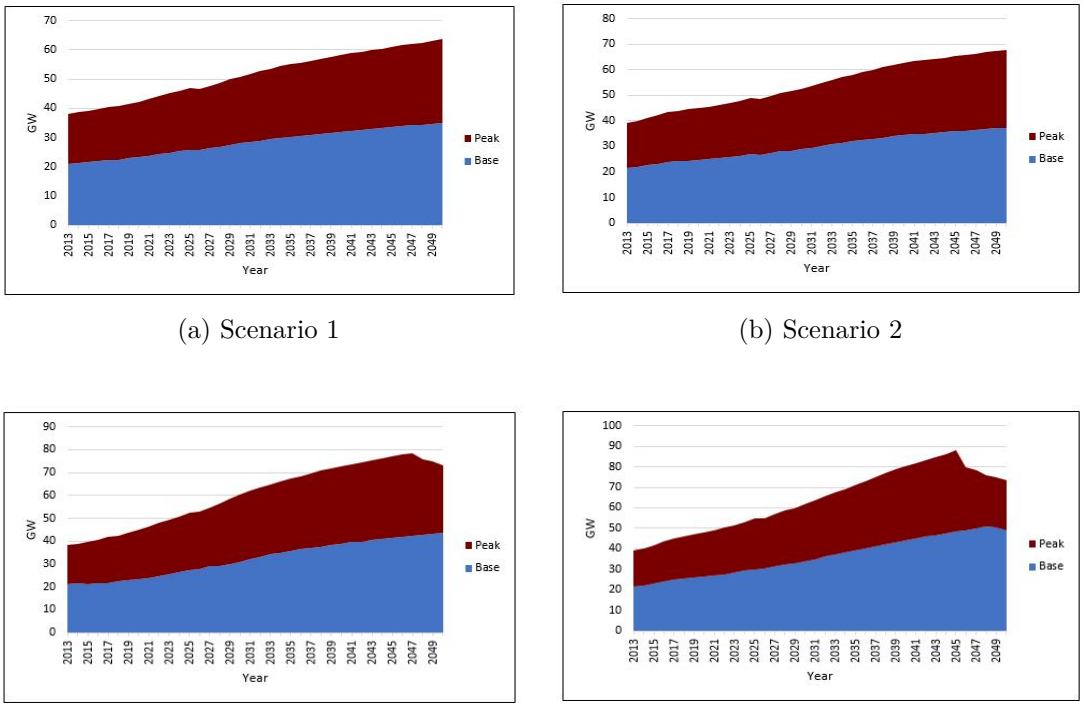
is due to decommissioning of existing power plants [71] and [95]. Nonetheless, the decommissioned capacity is replaced immediately by the model as shown in Figure 6.4. As expected, the capacity allocation increases from Figure 6.7a to Figure 6.7d, because of forecasted electricity demand.

6.2.2.7 TSSMILP model results for capacity allocation

The allocation of capacity for the TSSMILP model is discussed in this section. Similar to the deterministic case, equations (3.28) and (3.40) from the TSSMILP

model in section 3.2.2 are used to determine the capacity allocation and the results are shown in Figure 6.8, for Case A.

Similar to Figure 6.7, the 2027 plant decommissioning can be observed in Figure 6.8 and in Figure 6.9. The decommissioned capacity from 2026 to 2027 is 8 GW from coal. In both Figure 6.4 and Figure 6.5, there is no new coal capacity during this period. Figure 6.8c and Figure 6.8c showed that power plants that are



(a) Scenario 1

(b) Scenario 2

(c) Scenario 3

(d) Scenario 4

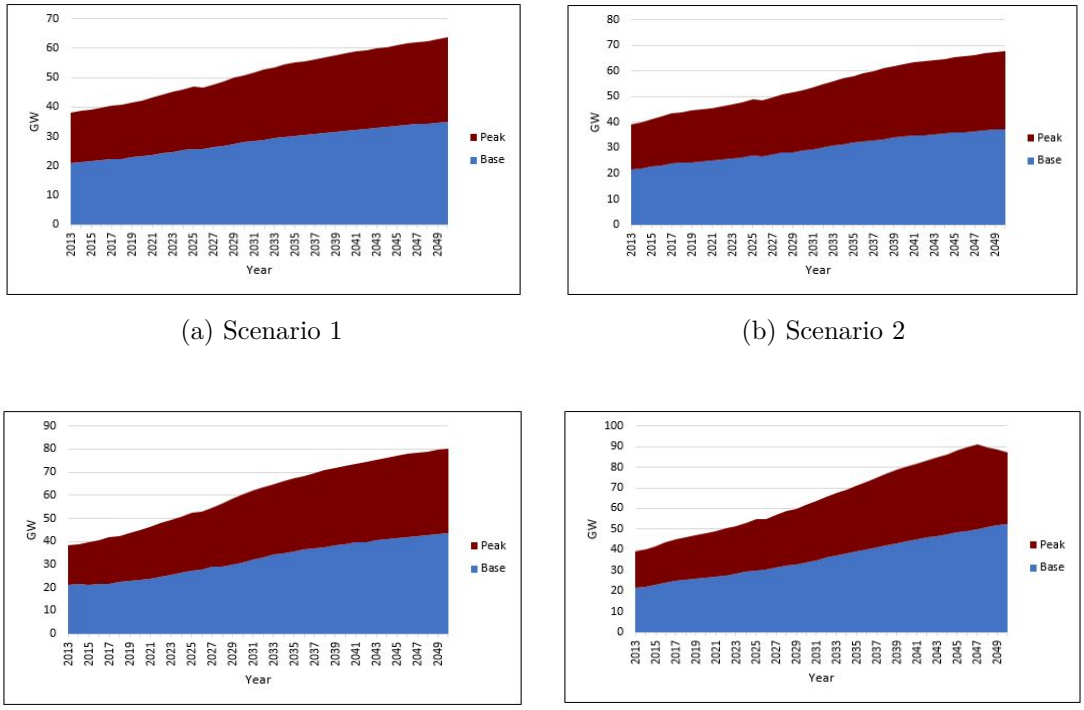
FIGURE 6.8: TSSLP model capacity allocation for Case A

decommissioned towards the end of the investigation period are not replaced with new capacity.

The TSSP cost results for Case A showed that there is COUE cost for scenarios 3 and 4, and this can be observed towards the end of the period in Figure 6.8c and Figure 6.8d, respectively. This means that for both scenarios, a COUE-1 value of R2 935.93 per kWh is cheaper than allocating more capacity. Figure 6.8d shows that scenario 4 unserved amounts of unserved energy is more than scenario 3's in Figure 6.8c. These results correspond to the COUE in Table 6.5 where the COUE for S4 is higher than S3's.

The capacity allocation for Case B is shown in Figure 6.9a. As expected, there is no COUE for S3 in this case, but only for S4. The COUE-1 value for Case B is R15 353.81. The capacity allocation for Case C&D is not shown because of minimal COUE value.

Other than the COUE impact on capacity allocation, the capacity allocation on both Figure 6.8 and Figure 6.9 increased with increasing electricity demand.



(a) Scenario 1

(b) Scenario 2

(c) Scenario 3

(d) Scenario 4

FIGURE 6.9: TSSLP model capacity allocation for Case B

6.2.2.8 Deterministic MILP model reserve margins

Reserve margins are determined for the deterministic MILP model, and the results are shown in Figure 6.10. The deterministic MILP is chosen because it has only one set of results as opposed to the TSSMILP with four sets. Figure 6.10 shows that Plans 1 and 3 have the highest reserves compared to other plans until mid-2020s. However, Plan 1 continued with high reserve margins till mid-2030s. This shows that even though Plan 1 added new capacity in 2020, most of it is not

allocated hence higher reserve margins. Such high reserve margins are costly to

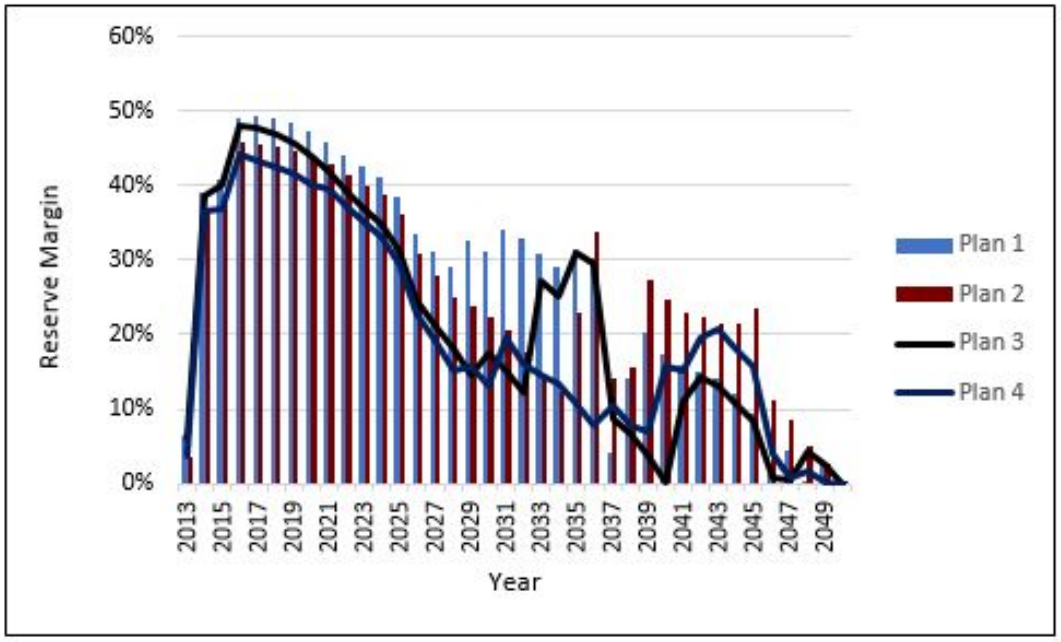


FIGURE 6.10: Deterministic MILP model reserve margins

the consumers because Plan 1 required more new power stations for reserve margin purposes.

Internationally, reserve margins requirements usually fall in the range of 15% to 25% [165]. Figure 6.10 shows that in 2013 the reserve margins were below 10% for all plans. The reserve margins increased from 2014 and reached the highest points in 2016 for all the plans. The increase in reserve margins is caused by the increase in capacity from the capacity that is committed before the planning period and the new capacity. The reserve margins started to decrease slightly afterwards and fell below 15% for Plan 4 and for other plans a couple of years later on. The decrease in reserve margins is caused by the decommissioned capacity. Even though new capacity is added, it did not replace all the decommissioned capacity. Figure 6.10 shows that in 2040, the reserve margins are equal to zero for Plan 3. This is the year where more capacity is decommissioned, and no new capacity is added by the model for Plan 3.

Reserve margins increased again before 2041 for Plans 3 and 4, but this was short-lived as the decrease can be observed from the early 2040s. In 2050, the reserve

margins are equal to zero again, for all the plans.

However, reserve margins requirements must be met every hour of a day, and every day of the year [166], which is not the case in Figure 6.10. High reserve margins cost the economy less than low reserve margins [167]. Low reserve margins can lead to load shedding, as this has been the case in SA [168]. Nonetheless, given the optimistic nature of the demand scenarios used in this study and the falling electricity sales, the actual reserve margins might be higher than the ones in Figure 6.10.

6.2.3 CO_2 Emission for New Capacity

This subsection complements the new capacity results discussed in sections 6.2.2.4 and 6.2.2.5, because CO_2 emissions reduction is a priority for electricity generators. The general move from fossil fuels to renewable energy sources is driven by the agreement which is taken on the 21st session of the Conference of the Parties (COP21) [1].

According to Eskom [169], historical electricity generation accounted for 42% of the nation's CO_2 emission in 2017/18. In an effort to make sure that the country abide by the COP21, the Carbon Tax Act was gazetted by the government of the Republic of South Africa on the 23rd of May 2019 and was effective from the 1st of June 2019 [170]. According to the South African National Treasury [171], the carbon tax was tol be applied in two phases initially. Phase 1 was applicable only to emissions that were direct emissions from owned or controlled sources. This phase was planned to start from 1 June 2019 and to continue till 31 December 2022. The carbon tax rate in phase 1 ranged from R6 to R48 per tonne of CO_2 equivalent emitted. There will to be tax-free emissions allowance in the first phase, ranging from 60% to 95%. Phase 2 is to commence in 2023 and continue until 2030. It is not clear yet how the above carbon tax work; as a result the carbon tax is not included in this study.

CO_2 emissions in kilo-tonnes (KT) are determined for both deterministic MILP and TSSMILP from the allocated capacity and the CO_2 emission data in [71] and

[95]. In Figure 6.11, CO_2 emissions starts in 2037 for all the plans, which is when

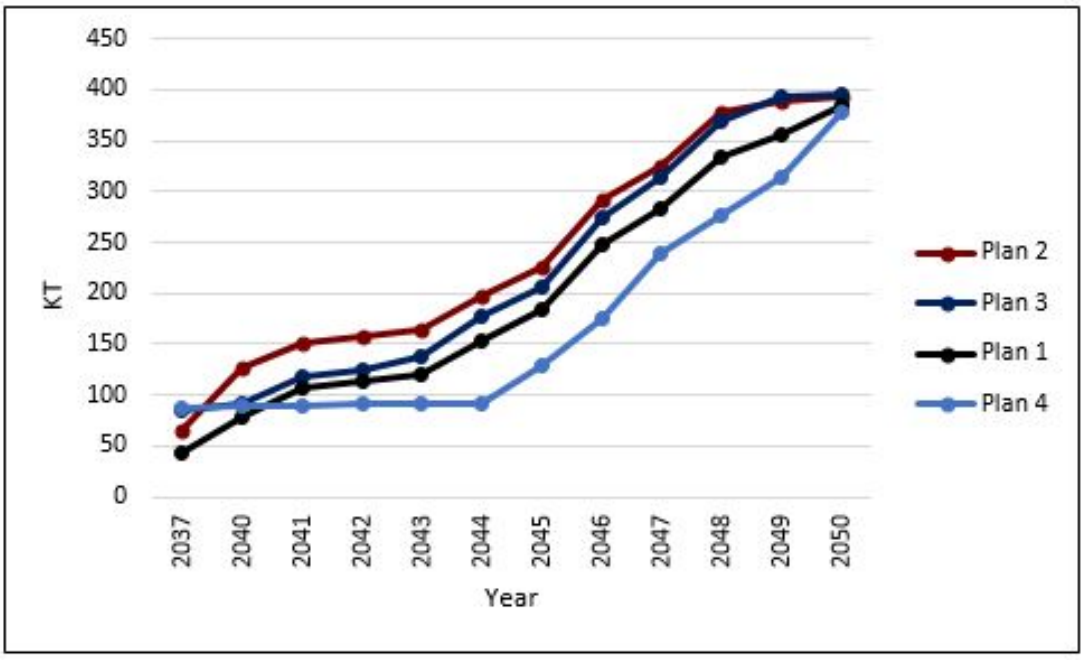
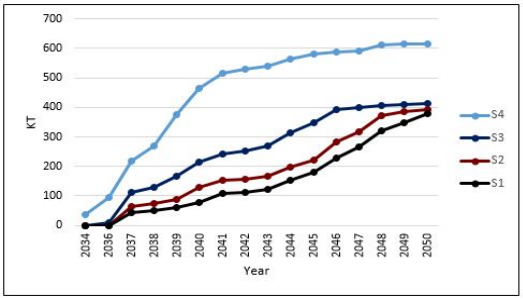


FIGURE 6.11: Deterministic MILP model CO_2 emission

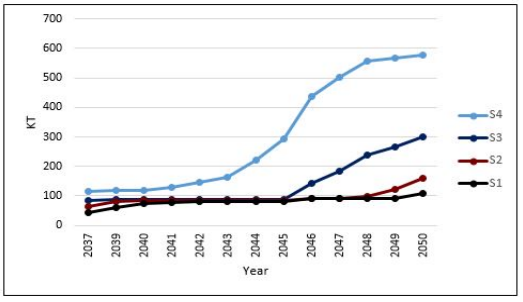
the CO_2 emitting technologies capacity are allocated for the first time. Figure 6.11 shows that Plans 1, 2 and 3 emit more CO_2 than Plan 4 because the three plans have more coal in the mix when compared to Plan 4 as shown in Table 6.12. Figure 6.11 shows that Plan 1, emit less CO_2 when compared to Plans 2 and 3 because Table 6.12 shows that Plan 1 has less coal. Plan 4 has low emissions because it has more nuclear in the mix when compared to other plans, as shown in Table 6.12.

In Figure 6.12, TSSMILP results show a different CO_2 emission picture when compared to the deterministic results in Figure 6.11. Case A shown in Table 6.10 has the least cost when compared to other cases, but Figure 6.12a shows that it has the highest CO_2 emissions when compared to other cases. This happened because Case A relied more on coal when compared to other cases. By 2050, all the scenarios in Case A have CO_2 emissions lying in the range, 378 to 615 KT.

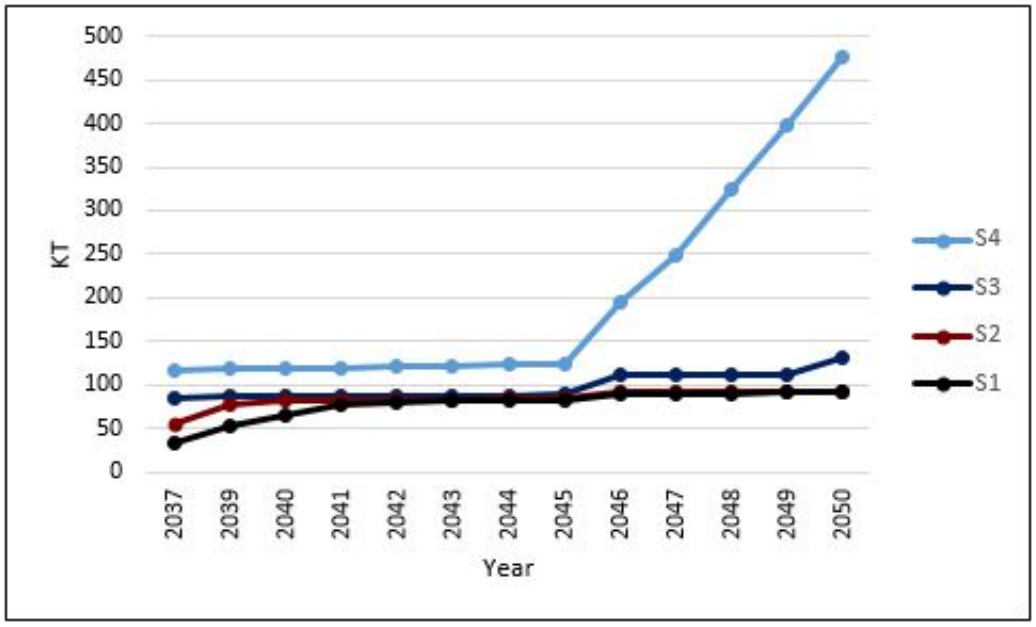
Figure 6.12b shows that for Case B in 2050, S4 has the highest CO_2 emissions lying between 500 and 600 KT. Similarly, in Case C&D, Figure 6.12c also shows that only S4 has the highest CO_2 emissions lying between 450 and 500 KT. This is because CO_2 emissions decreased from Case A to Case C&D because of corresponding coal constituent and increase in nuclear in the respective energy mixes



(a) Case A



(b) Case B



(c) Case C&D

FIGURE 6.12: TSSMILP model CO_2 emission

as shown in Table 6.13. Figure 6.12c also shows that between 2037 and 2045, all the scenarios' CO_2 emission is almost the same as there is the same amount of new capacity allocation from coal for all the scenarios at this period.

Comparing the South African long term emissions trajectory [172] in 2050,in Figure 6.11 and Figure 6.12's CO_2 emissions, all the plans and scenarios excluding existing capacity are within the electricity sector boundaries of CO_2 emissions, approximately 100 to 200 million tons (MT).

The CO_2 emissions recorded by Eskom in 2012/13 financial year is 227.9 MT [169]

and 220.9 MT in 2018/19 [135]. The South African long term emissions trajectory [172] shows that Eskom's CO_2 emissions as at 2018/19 are lying within the electricity sector lower and upper limits, of approximately 190 and 275 MT. The decommissioning of old coal plants together with new capacity which has less CO_2 emissions will reduce the South African CO_2 emissions.

According to DEA [172], electricity supply is the largest source of emissions. The carbon tax will enforce electricity generators to limit the emissions by shifting to sources of energy with lower carbon emissions. This shift is observed in Tables 6.12 and 6.13.

6.2.4 Summary of the Second Tier Results

The deterministic MILP and TSSMILP models are solved based on four different costs of unserved energy values and the corresponding results are referred to as Case A, B, C and D for the TSSMILP model. The TSSMILP results show that this model utilised the COUE, whereas the deterministic MILP model did not. The COUE values are only used for what if analysis in the deterministic MILP model.

The following sources of energy are selected by both models for new capacity: coal, gas/diesel, wind, hydro, solar PV and nuclear.

The new capacity's carbon emissions for both deterministic and TSSP models are within limits. The new South African carbon tax is expected to enforce the carbon emission reduction in electricity generation. The inclusion of renewable energy sources in new capacity will reduce the fuel risk that is highlighted in section 6.1.

The output C from the capacity planning with uncertainty using TSSMILP model in Figure 3.2 includes: new capacity, energy sources, underlying technologies, dates when the new capacity is expected to be available, corresponding capital costs and running costs.

The study demonstrated to the EGEP community by demonstrating how the TSSMILP model can be utilised as a second tier of the proposed three-tier model.

6.3 South African Third Tier Results

The results discussed in this section are based on the second tier results from section 6.2 and the methodology discussed in section 3.3.

6.3.1 Assumptions for the RO models

The technology data used in this section is from TSSMILP results in section 6.2. Scenario 4 (S4) results are used to demonstrate how the RO models, BOPM and RNA, as well as the NPV models are used in this study. S4 is chosen because the TSSMILP new technologies are the same for all scenarios in each case. The only difference in the scenarios in each case is in the allocation of the new capacity. S4 has the highest capacity allocation compared to all the other scenarios because of the highest electricity demand.
The details of both BOPM and RNA models are discussed and demonstrated in the later subsection, where CCGTwCCS and wind technologies from Case A are utilised, respectively. Subequently, the remaining technologies are evaluated by the two models demonstrated for the above two technologies and are presented together with their corresponding RO and NPV results.

6.3.1.1 Determination of real options parameters

The values of the parameters discussed in section 4.3.1 are determined in this subsection utilising formulae from section 3.3. The RO values are not evaluated once, but continuously with the aim of utilising the latest economic parameters. A risk-free rate of 7.5%, is determined from the South African thirty year annual bond yield as at 31 December 2020 of 10.797% [173] less the corresponding inflation rate of 3.3% [174]. The thirty years is chosen because incorporate the longest call option duration for the investment projects in Table 6.19. However, practically, a different annual bond yield would be used as at 31 December 2021 and so forth. An annual bond yield is chosen because the RO values are evaluated annually.

The values of $r_{\hat{t}}$, are determined by utilising Eskom's historical revenues from electricity sales less primary energy and other operating expenses of Eskom, from year 2000 to 2020, in equation (3.46). The standard deviation of the resultant values of, $r_{\hat{t}}$ result in the value of volatility, σ is 41.06%. The value of σ is utilised for all the investment projects. Similarly, σ changes from year to year, because with time more historical data would be obtained.

The value of σ is used to determine the values of u and d, using equation (3.48) and equation (3.49), respectively. $\sqrt{\Delta\hat{t}} = 1$ year, because RO values are determined annually. The resultant value of $u = 1.5077$ and $d = 0.6632$. The values of u and d are used to determine the value of p using equation (3.50). The resultant value of $p = 0.4875$.

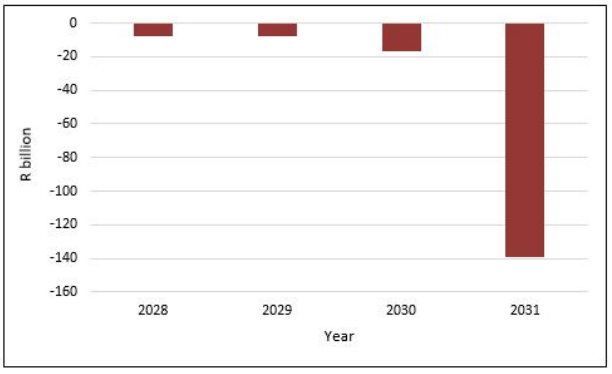
The above factors were utilised in the determination of all the RO values for the investment projects. With time, the annual inflation rate, bond yield, and historical data for determining $r_{\hat{t}}$ all change and so as the values of u, d and p. These changes result in the changes in RO values.

6.3.1.2 Capital costs for investment projects

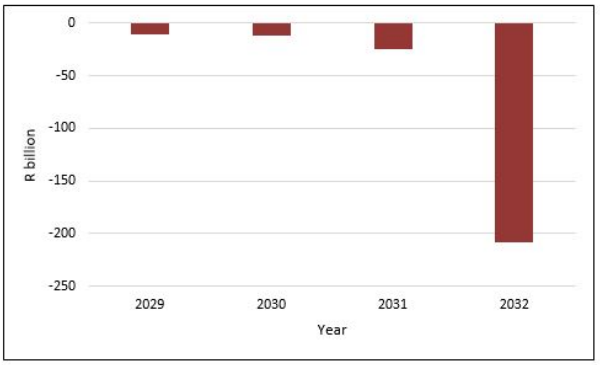
The capital costs are the investments for new power plants based on the technologies in TSSMILP results section 3.2. The lead time for each technology is shown in [52]. Wind technology required 4 years for construction before it can start to generate energy, and CCGTwCCS required 3 years. The actual investment costs for both technologies are shown in Figure 6.13 and Figure 6.14. The amount invested each year for each technology is influenced by the phasing in capital percentages.

6.3.1.3 Assumptions for converting new capacity into investment projects

Wind is one of the technologies with sequential new capacities during the investigation period, 2013 to 2050. It is chosen for demonstration because it is a renewable technology with no fuel costs. CCGTwCCS is a technology where new capacity was added in one year during the investigation period. It is chosen for



(a) Wind -1



(b) Wind-2

FIGURE 6.13: Investment costs for Wind

demostration because its capacity is required later in the planning period.
It should be noted that the number of units required in a particular year for each technology are considered to be the number of units in one power plant.

6.3.1.4 CCGTwCCS gross project values determination

In this step the values of the underlying assets, gross project values (V_0's) are determined, based on the parameters determined in section 6.3.1.1. The value of V_0 is determined from equation (3.53) in year 2020 for all the cash flows of the CCGTwCCS power plant. The resultant $V_0 = 22.93$ million Rand.The GPVs for the first 5 years of CCGTwCCS are shown in Figure 6.15. The GPV in Figure 6.15 and Figure 6.16 are used to determine the real call option values.

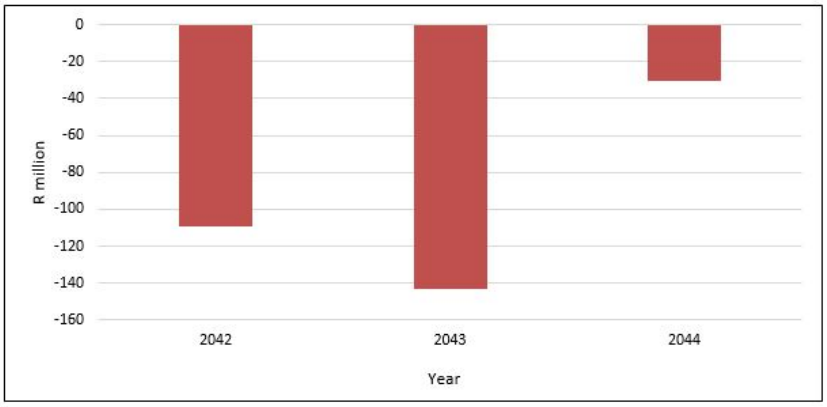


FIGURE 6.14: Investment costs for CCGTwCCS

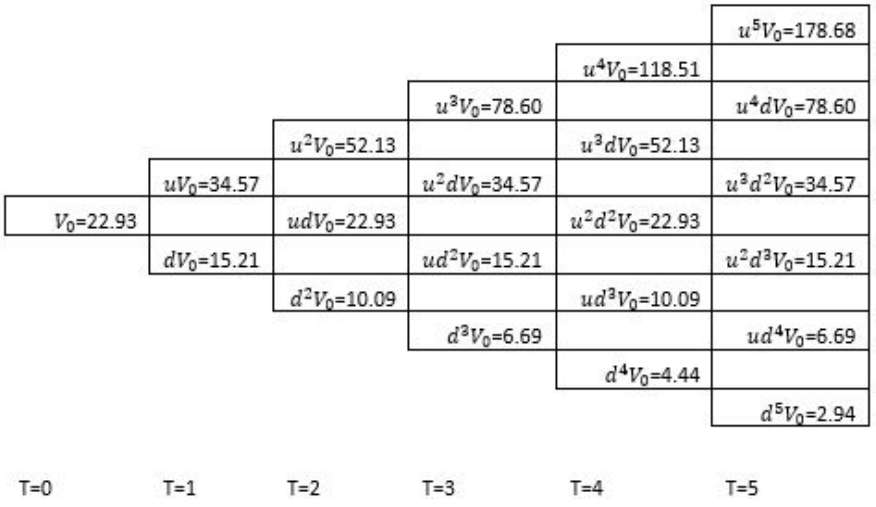


FIGURE 6.15: CCGTwCCS GPVs in R million for the first 5 years

6.3.1.5 CCGTwCCS real option determination

The call option value corresponding to the highest value of V_0, $u^{22}V_0$, in Figure 6.16 is $u^{22}C$ whose value is determined from equation (3.54).

$$u^{22}C = \max(u^{22}V_0 - I, 0) \tag{6.1}$$

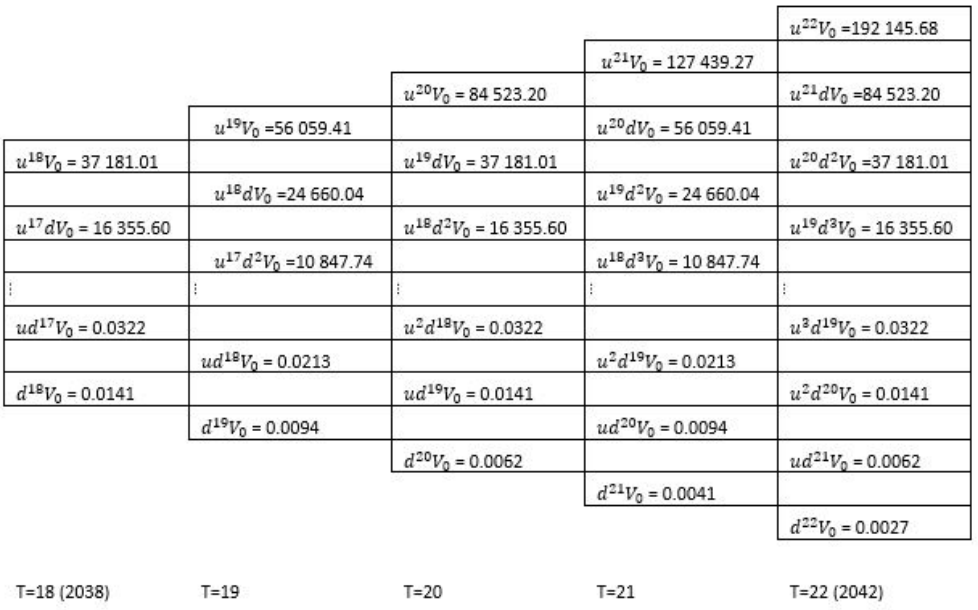


FIGURE 6.16: CCGTwCCS GPV in R million for the last 5 years

The value of I is the PV of the investments in Figure 6.14 as at 2020. Substituting the values of $u^{22}V_0$ and I into equation (6.1), the resultant is equation (6.2).

$$u^{22}C = \max(\text{R192.15 billion} - \text{R268.63 billion}, 0) = 0 \tag{6.2}$$

Since the call option values that corresponds to the highest value of V_0 is equal to zero, this means that all the call option values corresponding to the values of V_0 in both Figure 6.15 and Figure 6.16 are also equal to zero. This also implies that the call option value, C, corresponding to V_0 (T=2020), is also equal to zero.

6.3.1.6 RNA model for Wind technology

The first wind technology capacity is called power plant 1 (PT1), and the subsequent one is PT2. The number of years from 2020 (year zero) to 2028, the year of first investment for PT1, is 8 years. As a result, the call option duration for PT1 is 8 years and 1 year (2028 to 2029) for PT2.

The investment cost for PT1, is I_1, which is the sum of the PV of each investment costs, for PT1 as shown in Figure 6.13a. The PV for investment costs are

determined in the year of the first investment, which is 2028 and 2029 for PT1 and PT2, respectively. for the CCGTwCCS investment project. I_1 = R141.09 billion. Similarly, I_2 for PT2 is R210.37 billion, where the original investments are in Figure 6.13b.

6.3.1.7 Determination of wind gross project values

Wind investment project has successive investments dates in 2031 and 2032. Similarly, the initial V_0, for wind is determined from equation (3.53) in year 2020. Figure 6.17 shows how the value of V_0 changed from R41.03m at T=0 to T=5.

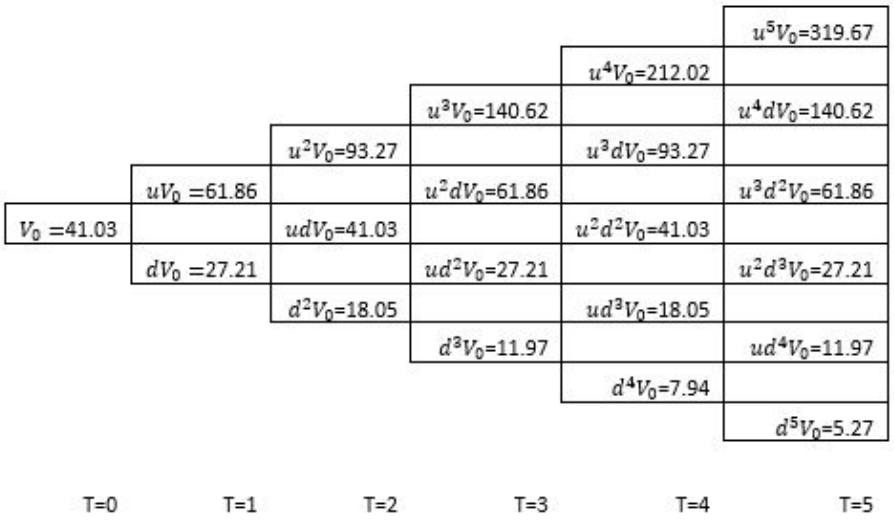


FIGURE 6.17: Wind GPV in R million for the first 5 years

R41.03m at T=0 either increased to R61.86m by the value of u or decreased to R27.21m by the value of d, at T=1. Figure 6.18 shows the last four years of the GVP. This part of the GVP is where the 2 power plants investments take place in years 2028 to 2029. The values of V_0 in Figure 6.17 and 6.18 are used in the determination of call option values.

6.3.1.8 Wind second investment project RO value determination

Wind investment project has two consecutive investments and their corresponding RO value are evaluated individually as discussed in section 3.3. The call option expiring at T=9 is valued first using I_2 and the corresponding values of V_0 at T=9 in Figure 6.18.

$$u^9 C_2 = \max(u^9 V_0 - I_2, 0) \tag{6.3}$$

Substituting the values of $u^2 V_0$ and I_2, equation (6.3) becomes equation (6.4).

$$u^9 C_2 = \max(\text{R1 652 million} - \text{R210.37 billion}, 0) = 0 \tag{6.4}$$

The call option values corresponding to the values of V_0 at T=9 are determined as shown in equation (6.3). However, the call option values are all equal to zero because their corresponding values of V_0 are less than R1 652 m.

The call option values from T=8 to T=0 are determined from the call option values at T=9, and similarly, these call option values are all equal to zero. The zero call option values are used to determine the call option values for PT1.

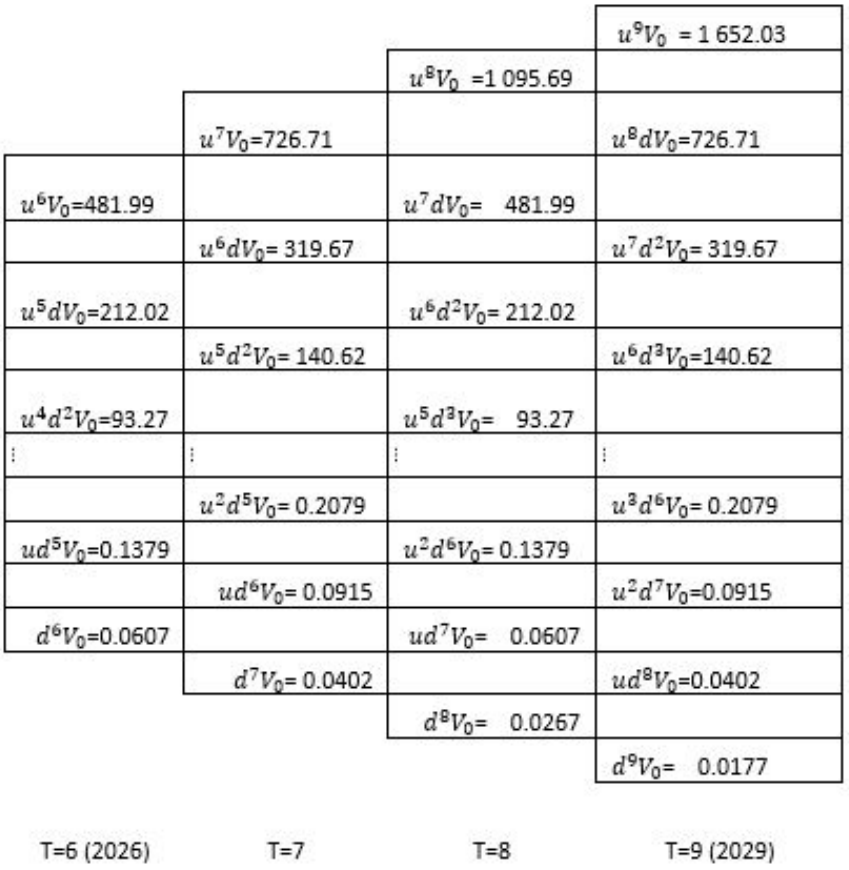


FIGURE 6.18: Wind GPV in R million for the last 4 years

The values of V_0 in Figure 6.17 and 6.18 are used in the determination of call option values.

6.3.1.9 Wind first investment project RO value determination

The call option values in year T=8, together with, I_1 are utilised to determine the call option values for PT1.

$$u^8C_1 = \max(u^8C_2 - I_1, 0) \tag{6.5}$$

However, the value of u^8C_2, the call option from section 6.3.1.8 is equal to zero. Similar to section 6.3.1.8, all the call option values corresponding to the PT1, C_1, are determined and are equal to zero.

The RO values for both CCGTwCCS and wind show that the output D in Figure 3.3 would advise the decision makers not to invest, but to defer the investment and revalue the options later on, as shown by input E.

6.3.1.10 Determination of NPV for wind and CCGTwCCS investment projects

The NPV's for both technologies are determined in year 2020 from equation (3.60. Starting with the wind technology, the NPV is determined for the entire project, utilising equation (3.60). The NPV for wind is -R188.84 billion and the resultant NPV for CCGTwCCS is -R54.73 billion.
Since both NPV's are negative, then the decision makers are advised not to invest in these projects. NPV results do not have a defer option or revalue later. Hence, the NPV models is not recommended for the third tier, but is utilised for comparison purposes.

6.3.2 Technologies Evaluated in the Third Tier Models

Table 6.14 shows the technologies evaluated from Case A TSSMILP results. The technologies on the first column are the ones with new capacities on several dates, during the investigation period. However, the technologies on the second column are the ones where there is only one date for new capacity.

TABLE 6.14: Technologies considered for RO analysis

Technologies with increments on new capacity	Technologies with no increments on new capacity	
PCwFGD	CCGT	MozC
Wind	CCGTwCCS	OCGT
	FBwCCS	PCwCCS
	FBwFGD	ZamA
	IGCCwCCS	ZamB
	IGCC	ZamC
	MozB	

The new capacity for the technologies on the first column of Table 6.14 is converted to the number of units as shown in Table 6.15 using the TSSMILP capacity results and corresponding rated capacity net in [71] and [95].

TABLE 6.15: Number of units for technologies with increments

Years	PCwFGB	Wind
2032		87
2033		123
2034	3	
2035	6	

Table 6.15 shows that by 2032, 87 units of wind technology are required and each unit had a capacity of 50 MW. Later on in 2033 further 123 units are required from wind technology.

Similarly, the new capacity for the technologies on the second column of Table 6.14 is converted to the number of units and the results are shown in Table 6.16.

TABLE 6.16: Number of units for technologies with no increments

Year	2026	2031	2032	2034	2035	2037	2038	2045
MozB	1							
ZamB		1						
MozC			1					
ZamA			1					
ZamC			1					
IGCC				9				
PCwCCS					9			
FBwFGD					20			
IGCCwCCS					9			
FBwCCS						20		
OCGT							70	
CCGT							14	
CCGTwCCS								7

Table 6.15 shows that by 2032, 87 units of wind technology are required, where each unit had a capacity of 50 MW. Later on in 2033 further 123 units are required from wind technology.

6.3.3 RNA and NPV Results

The RNA model discussed in three steps in section 3.3 was utilised for the PCwFGD technology, and the results are in Table 6.17. Table 6.17 shows that the PCwFGD investment has a zero call option values. Similar to the wind technology, this means that decision makers could abandon or defer this investment. The call option duration is just below 10 years for the first investments. The call option value could grow during this time; consequently, decision makers could defer this option. The RO results show that the decision makers are discouraged to build a

TABLE 6.17: Case A SCRO results

	PCwFGD
Investment year 1	2025
I_1 (R billion)	97.57
Call option duration (y)	8
Investment year 2	2026
I_2 (R billion)	205.89
Call option duration (y)	1
Year 0 (2020)	
NPV (R billion)	-201.35
Call option value (R billion)	0

power plant using the PCwFGD technology in Table 6.17 because its RO value is zero.

Technologies that are evaluated by RNA model in Case B are in Table 6.18 and in Table 6.19 for Case C&D. Most technologies in both Tables 6.18 and 6.19 have high investment costs and low capacity cash flows hence zero real option values and negative NPV. It is noted that low electricity tariffs and low capacity allocation contributed to low cash flows.

The RO values in Tables 6.18 can grow during the first investment option duration making option deferment a better option. The RO results suggest that decision makers are discouraged to build a power plant in 2020 using the technologies in Table 6.18 because their RO values are equal to zero. Therefore, the negative NPV values in Tables 6.18 advise the decision makers to ignore all the investments despite the fact that there is a need for the new capacity from these technologies investments. In the light of this, RO results which allow the decision makers to defer the investments are better than the NPV results.

Similar to Table 6.18, the SU RO value in Table 6.19 can be deferred because the first investment has a duration of 9 years. Nevertheless, the CCGT's investment duration for the first investment is 2 years. There is no much growth that can be expected during this time. As a result, the decision makers have to monitor this investment closely.

The only exception is CCGTwCCS in Table 6.19 which has a real option value

TABLE 6.18: Case B results

	SU	FBwCCS	PCwCCS	Wind
Investment year 1	2028	2037	2026	2028
I_1 (R billion)	166.83	249.57	176.80	137.00
Call option duration (y)	8	17	6	8
Investment year 2	2029	2038	2029	2029
I_2 (R billion)	194.85	37.63	123.89	204.31
Call option duration (y)	1	1	3	1
Investment year 3	2030			
I_3 (R billion)	205.28			
Call option duration (y)	1			
Investment year 4	2031			
I_4 (R billion)	216.13			
Call option duration (y)	1			
Investment year 5	2032			
I_5 (R billion)	227.68			
Call option duration (y)	1			
Investment year 6	2033			
I_6 (R billion)	239.71			
Call option duration (y)	1			
Investment year 7	2034			
I_6 (R billion)	252.39			
Call option duration (y)	1			
Year 0 (2020)				
NPV (R billion)	-670.43	-83.24	-238.42	-183.38
Call option value (R billion)	0	0	0	0

of R685 932. The CCGTwCCS for S4 in Case C&D has high capacity allocations, which resulted in high cash flows; the long call option duration of 26 and low investment costs also contributed towards a positive real option value. Decision makers are discouraged to build a power plant in 2020 based on the SU technology in Table 6.19, because its RO value is equal to zero. Both CCGT and CCGTwCCS are exempted because of the special condition discussed above. However, the NPV for the CCGTwCCS technology is negative.

Table 6.19: Case C&D results

	SU	CCGTwCCS	CCGT
Investment year 1	2029	2046	2022
I_1 (R billion)	166.83	91.55	15.32
Call option duration (y)	9	26	2
Investment year 2	2030	2047	2045
I_2 (R billion)	389.70	110.52	50.54
Call option duration (y)	1	1	23
Investment year 3	2032		2047
I_3 (R billion)	1 026.39		10.10
Year 0 (2020)			
NPV (R billion)	-707.03	-48.05	-22.94
Call option value (R)	0	R685 932	0

According to [103], the meaning of the RO value of R685 932 is that if the project's initial costs are more than R685 932, the project should be rejected or otherwise accepted. The initial costs for CCGTwCCS investment project are unknown. If the initial costs are more than R685 932, this option could be deferred and this would allow the RO value to grow due to long duration.

6.3.4 BOPM and NPV Results

The technologies evaluated in this subsection are for S4 for the same reasons explained earlier in section 6.3.3. The real option value for the CCGTwCCS technology is valued by BOPM discussed in section 3.3.3.1. The results show that the RO value for the CCGTwCCS technology is zero. The BOPM utilised to evaluate the RO values for Case A technology in the second column of Table 6.14 and the results are in Table 6.20.

The results in Table 6.20 show that the call option values are equal to zero for all technologies. However, most call option durations are above 5 years. There are chances that the call option values will grow during the call option duration.

Instead of abandoning these options because of low call option values, the decision makers can defer the investments. The options with low durations such as ZamA

Table 6.20: Case A SCRO results

Technology	Investment year	Investment (I) (R billion)	Call option duration (y)	Call option value in 2020	NPV (R billion) in 2020
CCGT	2037	208.62	17	0	-70.46
FBwCCS	2033	578.73	13	0	-226.08
FBwFGD	2031	282.52	11	0	-125.67
IGCC	2029	393.64	9	0	-205.32
ICGGwCCS	2030	583.06	10	0	-282.93
MozB	2014	-	-	-	-
MozC	2028	5.61	8	0	-3.09
OCGT	2036	118.39	16	0	-37.18
PCwCCS	2026	569.07	6	0	-368.75
ZamA	2023	1.9	3	0	-1.49
ZamB	2023	1.9	3	0	-1.44
ZamC	2028	1.19	8	R58 926.59	-0.62

and ZamB will require more attention from the decision makers by evaluating them on annual basis to determine possible changes on the RO values. The RO value decreased for the options with a short call option duration.

However, nothing can be done about MozB, since its investment date is before the real option evaluation date. RO models cannot be utilised for these investments.

Table 6.20 shows that ZamC is an exception with a positive call option value. This technology has the lowest investment cost when compared to other technologies in Table 6.20. Similar to the CCGTwCCS in Table 6.19, the RO for ZamC can be exercised if the initial costs are less or equal to R58 926.59. Otherwise, the ZamC RO can be deferred, and this will allow the RO value to grow during the option duration period. Decision makers are discouraged to build power plants in 2020 based on the technologies in Table 6.20 because their RO values are equal to zero. However, CCGT, MozB, NF, ZamA, ZamB and ZamC are exempted because of special conditions discussed above.

The last column of Table 6.20 has the NPVs for all the technologies. All the NPVs are negative, which means that all the technologies' investment must be abandoned. As discussed in section 6.3.3 the new capacity investments cannot be abandoned, since there is a need for new capacity. Hence, the RO results of

deferring the investments shall be considered.

Table 6.21: Case B SCRO results

Technology	Investment year	Investment (I) (R billion)	Call option duration (y)	Call option value in 2020	NPV (R billion) in 2020
CCGT	2043	319.60	23	R52 740 373	-60.55
CCGTwCCS	2042	37.15	22	0	-7.57
FBwFGD	2031	278.45	31	0	-125.67
IGCC	2032	393.64	12	0	-165.28
ICGGwCCS	2032	244.84	12	0	165.28
MozB	2022	11.63	2	0	-9.76
MozC	2022	5.61	2	0	-3.09
NF	2018	-	-	-	-
OCGT	2036	118.39	16	0	-37.22
PCwFGD	2028	333.42	8	0	-186.93
ZamA	2023	1.90	3	0	-1.49
ZamB	2023	2.69	3	0	-2.08
ZamC	2028	1.19	8	R60 563.41	-0.62

Results for technologies that qualified to be evaluated using BOPM for Case B and Case C&D are in Table 6.21 and Table 6.22, respectively. Even though for Case B and Case C&D, TSSMILP results have higher capacity compared to Case A, these cases also have higher investment costs when compared to Case A. On this basis, all the technologies in both cases have zero call option values and negative NPVs. High investment costs and low cash flow because of both low capacity allocation and low electricity prices contributed towards low option values.

The only exception is CCGT in Case B which has a call option value of R52 740 373. This call option value is higher than ZamC's call option values, possible decision makers can exercise this option. If the decision makers exercise this option, this will form part of output D in Figure 3.3. The high call option duration, of 23 years contributed towards the positive call option value. CCGT is one of the cheapest technologies but the high investment cost in Table 6.21 is due to more capacity that is invested in this technology by the TSSMILP model, as indicated by the number of units in Table 6.16. The high investments on the CCGT technology in turn contributed towards high cash flows, which contributed towards a positive

call option value.

Similar to Table 6.20 ZamC also has a positive call option value in Table 6.21 and in Table 6.22. The call option values are R60 563.41 and R59 432.24 for cases B and C&D, respectively. The low investment costs contributed to these positive investment costs. The call option duration is 8 years for both cases, which is enough for the call option value's growth. Decision makers are discouraged to

Table 6.22: Case C&D SCRO results

Technology	Investment year	Investment (I) (R billion)	Call option duration (y)	Call option value in 2020	NPV (R billion) in 2020
FBwCCS	2037	713.07	17	0	-208.61
FBwFGD	2031	278.45	11	0	-125.67
IGCC	2032	393.64	12	0	-165.28
ICGGwCCS	2032	583.06	12	0	-244.84
MozB	2019	-	-	-	-
MozC	2024	4.56	4	0	-3.36
NF	2022	615.26	2	0	-527.82
OCGT	2023	60.79	3	0	-48.89
PCwCCS	2026	569.07	6	0	-368.75
PCwFGD	2026	333.42	6	0	-216.02
Solar PV	2022	306.17	2	0	-264.93
Wind	2029	348.87	9	0	-181.94
ZamA	2019	-	-	-	-
ZamB	2024	2.83	4	0	-2.11
ZamC	2028	1.19	8	R59 432.24	-0.62

build power plants in 2020 based on the technologies in Table 6.22 because the RO values are equal to zero. However, the MozB and ZamA technologies are exempted on the account that the investment dates have passed ZamC because of a positive RO value and technologies with a duration that is less than 5 years. The NPV results are negative for all technologies and cases. These results suggest that all the investments for the technologies in Tables 6.20 to 6.22 must be abandoned. The low side of abandoning all investments is electricity capacity deficit. Hence, decision makers would be better off when they use RO results which allow for the deferment of the investments with low option value. The deferred investments

form part of output E in Figure 3.3, because deferred options will be re-evaluated again later on.

6.4 Summary of the Third Tier Results

Sequential compound real option model is used for technologies which have new capacity increments while binomial option pricing model is used for technologies where new capacity but no increments during the investigation period. NPV is also determined for both groups of technologies.

Results for both the SCRO model and BOPM show that all the new technologies' investments can either be abandoned or deferred, except for CCGT and ZamC, in certain cases. Similarly, the NPV results for all technologies show that all the new technologies' investments must be abandoned.

The technologies' call option values can increase during the call option duration. Hence, decision makers should defer the option to invest. Conversely, technologies with short call option durations must be monitored closely and those whose investment dates fall before 2020 cannot be valued by RO models. Decision makers are also discouraged from building power plants based on technologies with zero options. Nonethesless, decision makers are encouraged to pay attention to technologies with low option duration and the ones with positive RO values. It is observed that technologies whose investment dates are before 2020, cannot be evaluated by RO models.

Low electricity prices in South Africa contributed to low cash flow values as a result the value of the underlying generation technology might take a while to be greater than the investment value, which is a requirement for high real option values. A model based in RO can have better results when applied to the EGEP results, where the electricity prices are cost reflective. The high investment costs also contributed to low call option values.

CHAPTER 7

Validation of the Three-Tier Model

The main aim of the three-tier model validation is to determine if the model will produce the expected results when the validation data is used. Both data sets that are used to develop the three-tier model and the validation data sets are not validated.The reports where both data sets are collocated from are assumed to be credible sources, hence no data validation is performed.

7.1 Data Utilised for the Three-Tier Model Validation

The investigation period for validation started from 2014 to 2050. The three-tier model has three sub models, corresponding to each tier as shown in Figure 3.1, Figure 3.2 and Figure 3.3 in chapter 3. The data for each tier discussed in the section is for each tier.

7.1.1 Data for First Tier Model Validation

The data discussed in this section is utilised for the PT model, which is used in the first tier of the proposed planning methodology. Most of the fuel cost data for the first tier validation, is from 2008/09 to 2013/14 which is discussed in section 5.2 and added to the 2014/15 data. The 2014/15 data in c/kWh is derived from the data in Table 7.1.

TABLE 7.1: Data for determining fuel costs

2014/15	coal	gas/diesel	nuclear
Cost (R million)	51 554	9 546	530
Energy sent out (GWh)	204 838	3 709	13 794

The cost from hydro is not provided in [175] like the other fuel costs in Table 7.1. These costs are estimated from the historic data discussed in section 5.2. The energy sources in [175] included renewable energy sources (small hydro, solar and wind) and gas/diesel from IPPs. Both solar and wind do not have fuel costs but gas/diesel and hydro have. The fuel costs for IPPs or data where they can be derived from is not provided in [175]; as a result, the IPPs' fuel costs are excluded in this validation.

This period coincided with the beginning of the IRP2016 period. Similar to the period, 2008/09 to 2013/14, load shedding was also experienced in 2014/15 [175].

7.1.2 Validation Data for the Second Tier

The data utilised for validating the second tier has the same format as the data discussed in section 5.3. The validation data is collected from the IRP2016 report [52], which is also appropriate for this study because it contained all the necessary data. Similar to chapter 6, the demand scenarios had equal weights.

7.1.2.1 Validation data for potential technologies

Potential data consisted of the following costs for potential technologies: capital, fuel, fixed O&M and variable O&M. The costs and capacities for different technologies are in [52]. These costs are used in the equations in sections 3.2.1 and 3.2.2.

The potential technologies included demand management technology, which do not have capital cost. Demand management technology is the best technology for

the second tier model because it has no capital cost; however, it cannot be evaluated in the third tier without the capital costs. Hence, this technology is excluded in the validation analysis.

7.1.2.2 Existing power plants data

Data for existing power plant in 2014 is in [52]. The existing power plant data is increased during the investigation period by the IPP capacity in section D.1 and Eskom new build capacity in section D.2 in appendix D. The existing data is decreased by the decommissioned capacity in [52] and [7]. The IPP wind and PV capacity is decommissioned after 20 and 25 years, respectively, according to the economic life data in [52]. More details for the required data in the second tier are discussed in the following sections.

7.1.2.3 Capacity factors for validation data

The capacity factors for renewable energy sources and other energy source are collected from different sources as shown in Table 7.2.

Table 7.2: Capacity factors

Energy Source	Capacity factor (%)	Source
Biogas	71	[176]
BioMSM	82	[176]
Bagasee	92	[177]
CAES	85	[178]
CSP	43	[176]
ICE	11.5	[179]
Landfill	71	[176]
Lithium-Ion	40	[180]
Solar PV	25	[176]
Wind	39	[176]

All the capacity factors collected in [176] are average capacity factors. The capacity factors for other technologies are determined from Eskom data, as discussed in section 5.3.3.

7.1.2.4 Validation scenario data

The data in this section is used in the model exactly the same way as the data in section 5.3.4 but, the actual data was different.

The scenarios considered are [181]: low (S1), high (less energy intensive, S2), moderate (S3) and high (same sector, S4), as shown in Figure 7.1. The differences

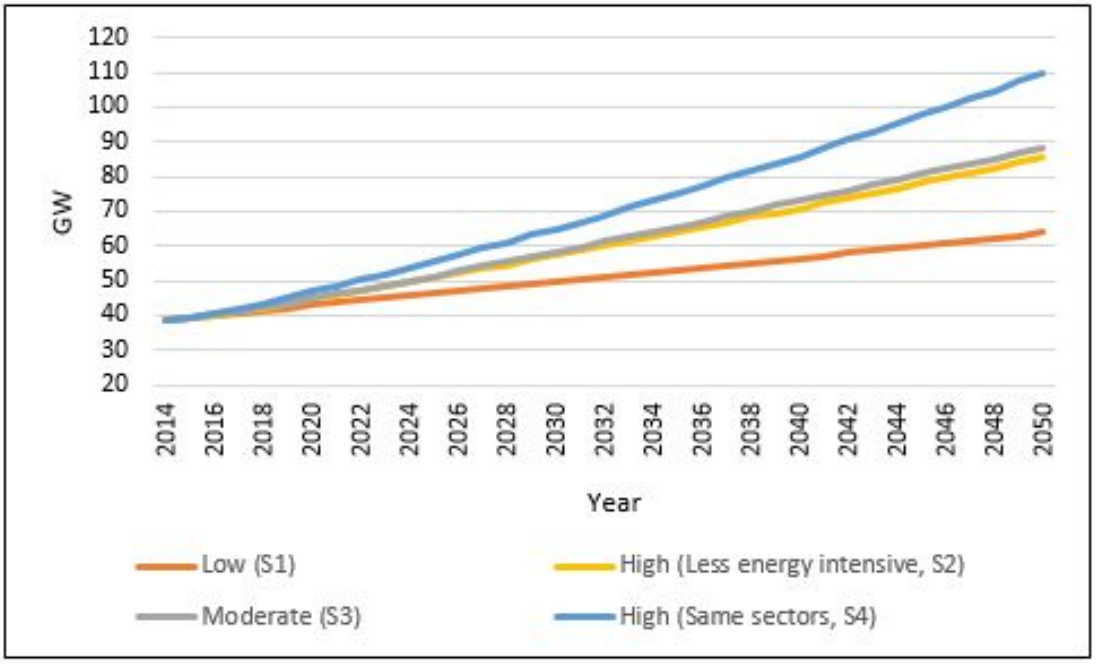


FIGURE 7.1: Electricity demand scenarios

amongst the scenarios in Figure 7.1 are the expected growth in [181]: value of GDP, final consumption expenditure of households and relevant manufacturing and mining indices.

7.1.3 Validation Data for the Third Tier

The data for technologies used in this section is obtained from the second tier results. The expected cash flow data is derived as discussed in section 3.3.2. Similarly, the parameters derived in section 3.3.1 are used for the model validation.

7.2 Validation Methodology

The models from chapter 3 are utilised and data discussed in section 7.1 is used for the three-tier model evaluation.

As discussed in section 3.1.1 the PT model is used for the first tier together with the assumptions discussed in section 6.1.1. The only difference is that the portfolio of fuel costs is evaluated in 2014/15.

Both the deterministic MILP and TSSMILP developed in AIMMS software are used for the second tier validation, together with the assumptions discussed in section 6.2.1.

The technology data used for the third tier valuation is taken from TSSMILP snd Case B results in section 7.3.2.2. Case B and scenario 4 (S4) results are used to demonstrate how the RO models can be used. Case B is chosen because it consists of almost all the technologies and yet it is less expensive when compared to cases C and D. The TSSMILP new technologies are the same for all scenarios, so, S4 is used for validation because it has highest capacity allocation compared to all the other scenarios of the highest electricity demand. The assumptions discussed in section 6.3.1 are also used for the model validation. The RO model is developed in Microsoft Excel and validated in Python software.

7.3 Validation Results

The results for each tier are discussed in this section. The initial portfolio results are discussed for the first tier. For the second tier, the new capacity costs for both

models, the values of TSSMILP solution and new capacity results are discussed. The RO and NPV results are discussed for the third tier.

7.3.1 First Tier Validation Results

Results are obtained by using the model discussed in section 3.1.1 and the data discussed in section 7.1.1. The initial portfolio is labelled as 2014/15 initial port-

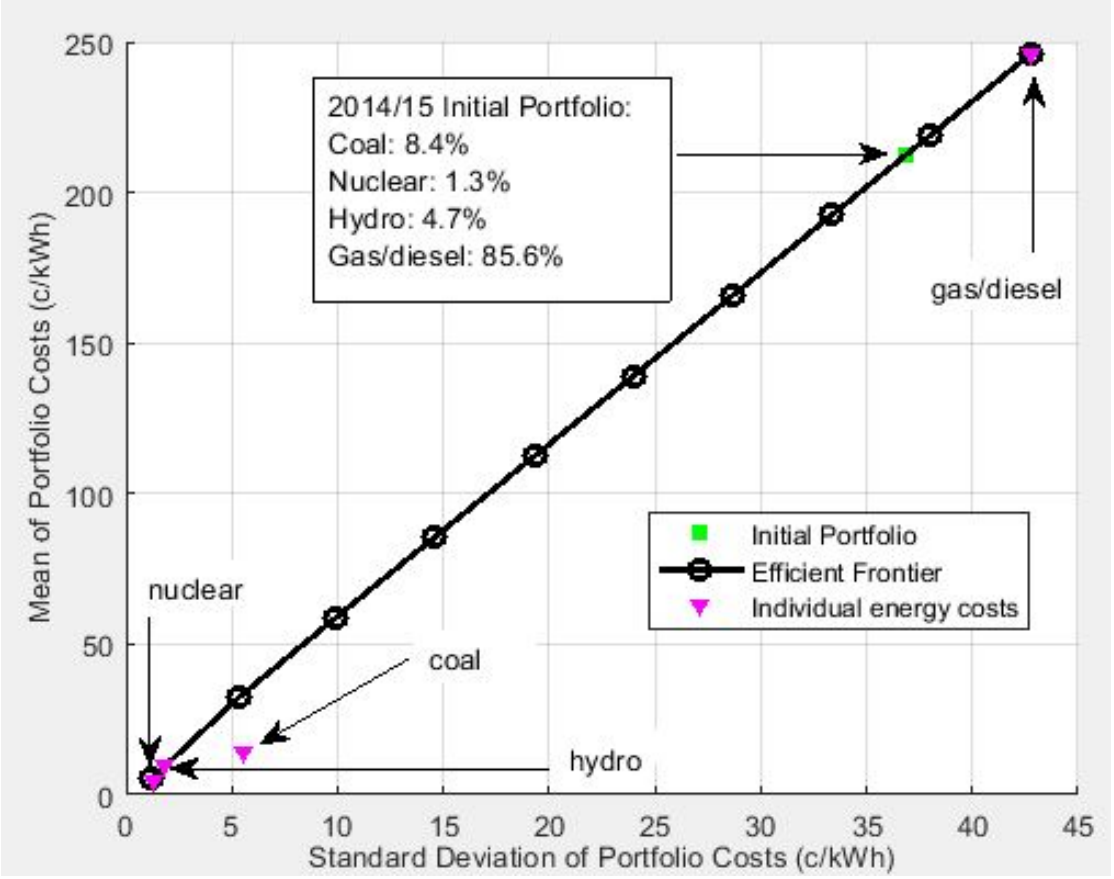


FIGURE 7.2: Validation of energy sources efficient frontier

folio in Figure 7.2. It is a portfolio made up of the existing energy sources in 2014/15 and weighted by the respective fuel costs. In Figure 7.2 the initial portfolio looks like it is on the efficient frontier. However, Figure 7.3 shows that the initial portfolio is below the efficient frontier. This means that the initial portfolio is not efficient.

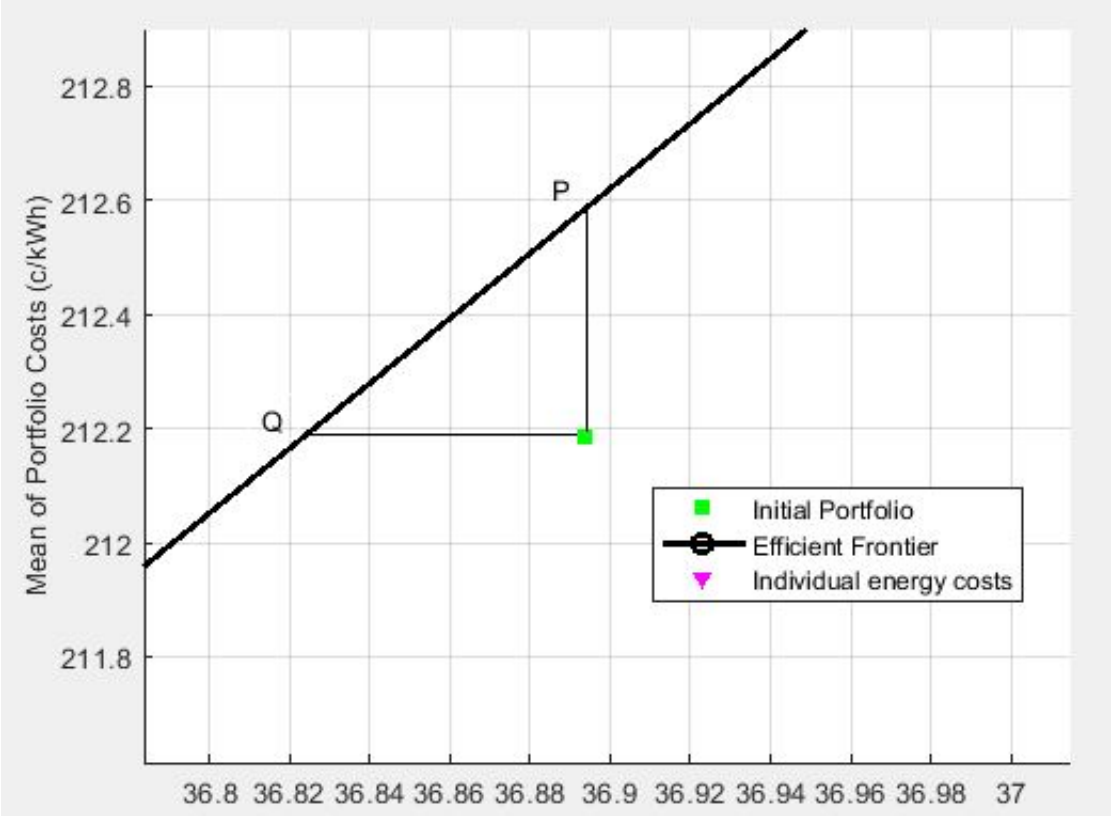


FIGURE 7.3: Efficient portfolios close to the 2014/15 fuel portfolio

The initial portfolio's average cost is 212.2 c/kWh and risk is 36.89 c/kWh. There are efficient portfolios corresponding to the initial portfolio which are shown in Figure 7.3 as P and Q. Efficient portfolio, P, has the same risk as the initial portfolio, and a slightly higher average cost of approximately 212.6 c/kWh. The efficient portfolio, Q, has the same cost as the initial portfolio, and a slightly lower risk of approximately 36.82 c/kWh.

The assumption is that decision makers will choose portfolio Q, instead of P because portfolio Q has a lower risk. If the individual fuel costs remain more or less constant during the investigation period, the initial portfolio risk will be reduced, and the initial portfolio will approach the efficient portfolio Q.

Nonetheless, the efficient portfolios P and Q, will not provide the decision makers with significantly lower costs or risks compared to the initial portfolio, as these portfolios are also dominated by gas/diesel.

In the second tier, high cost and risk of gas/diesel can be reduced by increasing

renewable energy sources with energy storage systems. This first tier output is labelled as Bin Figure 3.1.

7.3.2 Second Tier Validation Results

The results discussed in this section compare and contrast the deterministic MILP to TSSMILP results.

7.3.2.1 Deterministic MILP model cost results for new capacity

The deterministic results in Table 7.3 show capital, total running and total cost for each of the four scenarios discussed in section 7.1.2.4. The total cost results in

TABLE 7.3: MILP deterministic model results for each demand scenario

Billion Rand	Plan 1	Plan 2	Plan 3	Plan 4
Capital cost	4 389.76	15 242.21	16 527.02	27 131.60
Total running cost	1.94	2.05	2.09	2.44
Total cost	4 391.70	15 244.26	16 529.11	27 134.04

Table 7.3 are higher when compared to the results presented in Table 6.5 because 2014 costs are higher than 2013 costs used in chapter 6. For example, the total optimal cost corresponding to Plan 1 is R4 391.70 whereas it was R1 075.99 billion in 2013.

The results presented in Table 7.4 are for Case A and are based on a COUE-1 value of R2 935.95/kWh. The expected cost in Table 7.4 is derived exactly the same as the ones in Table 6.6. A similar pattern is observed even for cases B, C&D.

For deterministic MILP based models, decision makers will choose Plan 4 because this plan had the least expected cost. Plan 4 results in Table 7.4 show that there is the least cost variation if this plan was chosen and the actual demand follows S1, S2 or S3 instead of S4. The what if analysis results in Table 7.4 allowed decision makers to cater for the unknown demand that would materialise after the investment decision is taken. The results in Table 7.5 are similar to those presented

Table 7.4: Results for what if scenario analysis - Case A

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**4 391.70**	134 256.58	166 433.89	542 109.44	211 797.90
Plan 2	15 243.36	**15 244.26**	19 747.67	104 912.17	38 786.86
Plan 3	16 528.14	16 528.98	**16 529.11**	85 849.52	33 858.94
Plan 4	27 132.68	27 133.22	27 133.30	**27 134.04**	27 133.31

Table 7.5: Results for what if scenario analysis - Case B

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**4 391.70**	683 461.10	851 718.49	2 816 156.56	1 088 931.96
Plan 2	15 243.36	**15 244.26**	38 792.43	484 120.99	138 350.26
Plan 3	16 528.14	16 528.98	**16 529.11**	379 007.69	107 148.48
Plan 4	27 132.68	27 133.22	27 133.30	**27 134.04**	27 133.31

in Table 7.4 but are for Case B where COUE-1 value is R15 352.25/kWh. Table 7.6 results are for Case C based on COUE-1 value of R205 657.81/kWh. Similarly,

Table 7.6: Results for what if scenario analysis – Case C

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**4 391.70**	9 101 150.18	11 355 114.75	37 670 606.68	14 532 815.83
Plan 2	15 243.36	**15 244.26**	330 692.60	6 296 276.16	1 664 364.10
Plan 3	16 528.14	16 528.98	**16 529.11**	4 872 259.72	1 230 461.49
Plan 4	27 132.68	27 133.22	27 133.30	**27 134.04**	27 133.31

Table 7.7 results are for Case D based on COUE-1 value of R206 602.43/kWh. Table 7.4 to Table 7.7 show that the plans are less expensive only if the reality

Table 7.7: Results for what if scenario analysis - Case D

Billion Rand	S1	S2	S3	S4	Expected Cost
Plan 1	**4 391.70**	9 142 932.83	11 407 250.16	37 843 612.73	14 599 546.85
Plan 2	15 243.36	**15 244.26**	332 141.50	6 325 125.79	1 671 938.73
Plan 3	16 528.14	16 528.98	**16 529.11**	4 894 562.75	1 236 037.24
Plan 4	27 132.68	27 133.22	27 133.30	**27 134.04**	27 133.31

followed the scenario corresponding to the plan or a scenario with less electricity demand, otherwise the costs become more expensive.

7.3.2.2 TSSMILP model new capacity cost results

Costs for the TSSMILP model are determined for new capacity only as discussed in section 6.2.2.5. Results are presented in Table 7.8. The COUE results in Table 7.8

Table 7.8: TSSMILP total capital costs for new capacity

Rand (billion)	S1	S2	S3	S4	Solution
			Case A		
Capital Costs	1 655.05	1 655.05	1 655.05	1 655.05	
Running costs excluding COUE	2.27	3.65	3.79	4.46	
COUE costs	90.73	3 854.81	4 820.04	14 201.54	
Total	1 748.05	5 513.51	6 478.87	15 861.04	7 400.37
			Case B		
Capital Costs	11 874.18	11 874.18	11 874.18	11 874.18	
Running costs excluding COUE	1.18	2.23	2.38	3.49	
COUE costs	0.00	596.97	1 352.60	14 508.66	
Total Costs	11 875.36	12 473.38	13 229.16	26 386.32	15 991.06
			Case C		
Capital Costs	24 379.17	24 379.17	24 379.17	24 379.17	
Running costs excluding COUE	1.00	1.54	1.63	2.40	
COUE costs	0.00	0.00	0.00	3 743.60	
Total Costs	24 380.17	24 380.72	24 380.81	28 125.18	25 316.72
			Case D		
Capital Costs	24 379.17	24 379.17	24 379.17	24 379.17	
Running costs excluding COUE	1.00	1.54	1.63	2.40	
COUE costs	0.00	0.00	0.00	3 760.79	
Total Costs	24 380.17	24 380.72	24 380.81	28 142.37	25 321.02

show that there are instances where the model used the COUE-1 values than to add new capacity because it was cheaper. This resulted in unserved energy, hence the COUE costs are greater than zero for all the cases. There are more scenarios in Table 7.8 with positive COUE costs than in Table 6.10 because the validation data has higher capital costs than the model building data.

Table 7.8 also shows that the COUE costs decreased with increasing value of COUE-1 (R/kWh) because the model is able to allocate more new capacity with cheaper running costs than the COUE-1 values.

The results in this section show that as the COUE-1 value increased from Case

A to Case D, the TSSP model solution approached Plan 4 deterministic expected cost discussed in section 6.2.2.2. This showed that the most expensive cost of unserved energy is an indirect cost for Plan 4's expected cost.

7.3.2.3 Value of TSSMILP solution

This section quantifies the value of using the TSSMILP model as discussed in section 2.2.3.2 for the TSSLP model. Results are presented in Table 7.9 and were derived from Table 7.4, Table 7.5, Table 7.6 and Table 7.7. The VSS for Plans

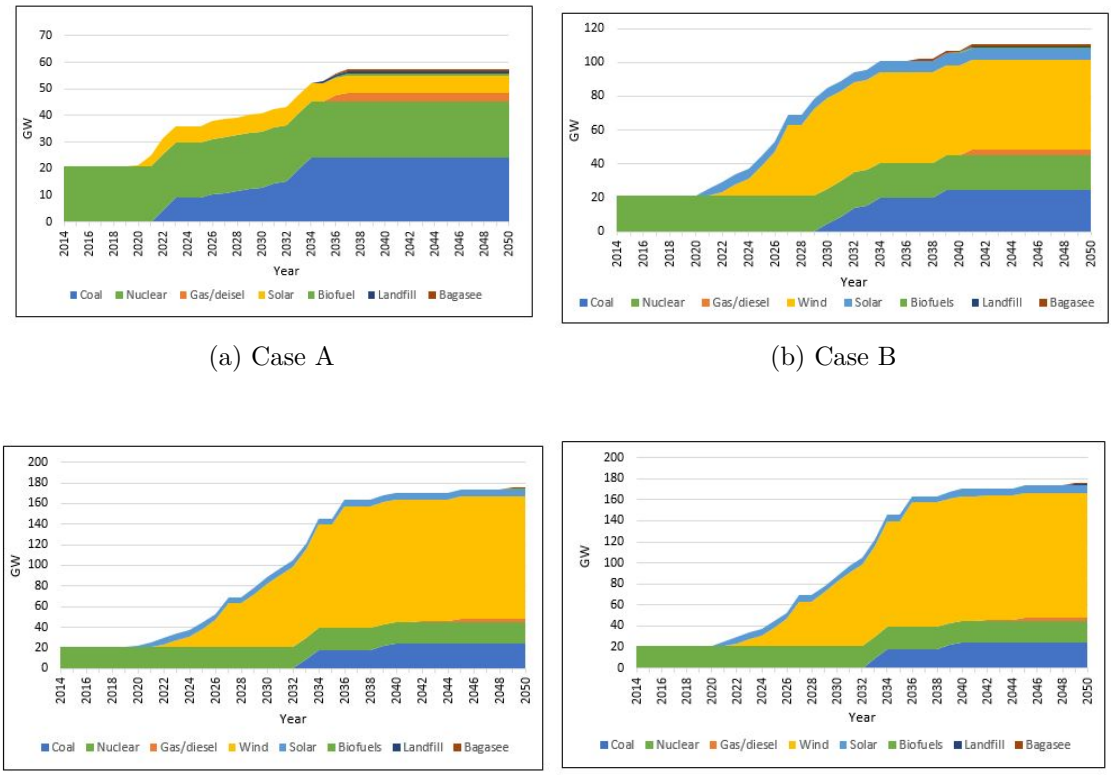
Table 7.9: Value of stochastic programming

Plan	EDC	VSS-A	VSS-B	VSS-C	VSS-D
Using Table 7.4 results					
1	211 797.90	204 397.54	195 806.85	186 4871.18	186 476.89
2	38 786.86	31 386.50	22 795.81	13 470.15	13 465.85
3	33 858.94	26 458.57	17 867.88	8 542.22	8 537.92
4	27 133.31	19 732.95	11 142.26	1 816.60	1 812.30
Using Table 7.5 results					
1	1 088 931.96	1 081 531.60	1 072 940.91	1 063 615.25	1 063 610.95
2	138 350.26	130 949.89	122 359.20	113 033.54	113 029.24
3	107 148.48	99 748.11	91 157.42	81 831.76	81 827.46
4	27 133.31	19 732.95	11 142.26	1 816.60	1 812.30
Using Table 7.6 results					
1	14 532 815.83	14 525 415.46	14 516 824.77	14 507 499.11	14 507 494.81
2	1 664 364.10	1 656 963.73	1 648 373.04	1 639 047.38	1 639 043.08
3	1 230 461.49	1 223 061.12	1 214 470.43	1 205 144.77	1 205 140.47
4	27 133.31	19 732.95	11 142.26	1 816.60	1 812.30
Using Table 7.7 results					
1	14 599 546.85	14 592 146.48	14 583 555.79	14 574 230.13	14 574 225.83
2	1 671 938.73	1 664 538.36	1 655 947.67	1 646 622.01	1 646 617.71
3	1 236 037.24	1 228 636.88	1 220 046.19	1 210 720.53	1 210 716.23
4	27 133.31	19 732.95	11 142.26	1 816.60	1 812.30

1 to 3 increased in Table 7.9 with increasing COUE-1 values. However, VSS for Plan 4 remained constant throughout. The VSS inform the decision makers that the deterministic MILP costs more than the TSSMILP and the cost increases with the increasing value of unserved energy. The remaining results are discussed only for the TSSMILP model since it has better costs results than the deterministic MILP model.

7.3.2.4 TSSMILP results for new capacity

In this section, the new capacity corresponding to the TSSMILP capital costs that are discussed in section 7.3.2.2 is presented in Figure 7.4. In Figure 7.4, the new



(a) Case A

(b) Case B

(c) Case C

(d) Case D

FIGURE 7.4: TSSMILP new capacity

capacity is added as early as 2014 for all the cases, and it consists of nuclear. As expected, the new capacity is increasing with increasing demand; however, the Case C and Case D new capacity is the same because even the capital costs for these cases are the same in Table 7.8. The solar energy source consists of PV and CSP in Figure 7.4a. In Figure 7.4, the energy storage (pumped storage, Lithium1hr, Lithium3hrs, CAES8hrs) capacity which is 2.85 GW for each case is not included because they store an already generated energy. The exception is pumped storage, which also consumes some of the generated energy before it can generate energy. Nonetheless, the costs for energy storage are included in Table 7.8.

Table 7.10 shows the energy sources' percentage allocation for 2014 and for the new and existing capacity (total capacity) as at 2050 for each of the TSSMILP cases while in Table 7.10, wind is a dominating energy source for cases B, C and D. However, there is no wind in Case A but more coal and nuclear because wind is more costly on the validation data than the coal and nuclear. Coal is below 20% for cases C and D. This drop in coal is not seen in the results of the data that is used to develop the model. In the validation data, all the technologies costs are on par, which is not the case with the data used to develop the model. Table 7.10 also shows that the validation data has more renewable energy sources, however, as discussed before, there is also energy storage which make renewable energy more competitive to other energy sources.

TABLE 7.10: 2013 vs. 2050 TSSMILP total capacity allocation (%)

Energy Source	2014	Case A: 2050	Case B: 2050	Cases C: 2050	Cases D: 2050
Coal	72.5	47.1	26.3	17.1	17.1
Nuclear	4.1	31.2	17.4	11.3	11.3
Gas/diesel	5	4.4	2.5	1.6	1.6
Wind	0	0	44.11	63.7	63.7
Hydro	5.5	3.7	2.1	1.3	1.3
Solar	2.3	10	5.6	3.6	3.6
Other	3.7	0	0	0	0
Biofuels	0.0	1.1	0.6	0.4	0.4
Landfill	0.0	1.0	0.5	0.4	0.4
Bagasee	0.0	1.4	0.8	0.5	0.5

7.3.3 Third Tier Results

The new capacity for technologies is converted into projects in this section, as demonstrated in section 6.3.1.3. The technologies considered in this section are in Table 7.11 and are divided into two groups of technologies whose new capacity have increments and technologies whose new capacity have no increments during the investigation period.

TABLE 7.11: Technologies considered for RO analysis

Technologies with increments on new capacity	Technologies with no increments on new capacity	
Pumped Storage*	BagasseFel	CSPTr6hrs
PCwCCS	BagasseGen	CSPTr9hrs
PCwFGD	BioFo	FBwFGD
PVconc*	Biogas	ICE2
WindREBID*	BioMSM	ICE10
	CAES8hrs*	IGCC
	CCGT	Landfill
	CSPTo3hrs	Lithium1hr*
	CSPTo6hrs	Lithium3hr*
	CSPTo9hrs	Nuclear*
	CSPTr3hrs	OCGT

In Table 7.11, the * represents technologies whose investment date is on or prior to 2020. The technologies are excluded on the RO analysis because their real options have a duration of zero or less.

The new capacity for the technologies on the first column of Table 7.11 is converted to the number of units as shown in section 6.3.2. The investment cash flows are determined for all the technologies in Table 7.11, excluding the excluded technologies, as in section 6.3.3. The data corresponding to the technologies in Table 7.11 from section 7.3.2.1 and in [52] is used to determine the cash flows.

The RNA model and BOPM are applied to the new investment projects in Table 7.11, as discussed in section 3.3.

7.3.4 Third Tier Validation Results

The results in Table 7.12 are for the technologies with increments on new capacity in Table 7.11. These technologies are valued as sequential compound real option (SCRO) using risk neutral approach (RNA) model, as in section 6.3.1.6. Table 7.12 shows that both PCwCCS and PCwFGD investments have a zero call

Table 7.12: Case B SCRO results

	PCwCCS	PCwFGD
Investment year 1	2025	2021
I_1 (R billion)	463.02	239.36
Call option duration (y)	5	1
Investment year 2	2029	2022
I_2 (R billion)	569.55	252.10
Call option duration (y)	4	1
Year 0 (2020)		
NPV (R billion)	-619.66	-440.76
Call option value (R billion)	0	0

option values. The call option duration for PCwFGD is one year for the first investments, which means that this call option value does not have much time to grow. Decision makers can exercise an option to abandoning this investment. However, the PCwCCS has a 5-year call option duration which is enough for call option value to grow. So, decision makers are better off when deferring this call option.

Real options for technologies on the second column of Table 7.11 are valued by a binomial option pricing model (BOPM), as presented in section 6.3.4. The CCGT investment costs are the highest in Table 6.20 because this was one of the cheapest technologies. Consequently, more capacity was added by the model.

The results in Table 6.20 show that the call option values are equal to zero for all technologies. However, the call option durations range from 8 to 20 years. There are chances of seeing changes in option values where the call option duration is more than 5 years.

Instead of abandoning these call options because of call option values, the decision

Table 7.13: Case B SCRO results

Technology	Investment year	Investment (I) (R billion)	Call option duration (y)	Call option value in 2020	NPV (R billion) in 2020
BagasseFel	2035	23.61	15	0	-7.98
BagasseGen	2034	45.28	14	0	-16.40
BioFo	2033	54.75	13	0	-16.20
Biogas	2039	65.33	19	0	-16.54
BioMSM	2035	94.52	15	0	-31.96
CCGT	2038	2 702.39	18	0	-683.28
CSPTo3hrs	2030	20.76	10	0	-10.07
CSPTo6hrs	2030	25.53	10	0	-12.39
CSPTo9hrs	2030	28.92	10	0	-14.03
CSPTr3hrs	2030	23.26	10	0	-11.29
CSPTr6hrs	2030	28.72	10	0	-13.94
CSPTr9hrs	2030	35.23	10	0	-17.10
FBwFGD	2028	394.32	8	0	-79.02
ICE2	2036	0.06	16	0	-0.02
ICE10	2040	0.46	20	0	-0.11
IGCC	2029	137.47	9	0	-71.71
Landfill	2040	73.22	20	0	-17.24
OCGT	2039	21.85	19	0	-5.53

makers could defer the investments.

The options with low durations as seen in Table 7.12 would require more attention from the decision makers because they do not have much to grow. Decision makers have an option of holding these options till their duration reach zero and abandon them then. However, the real option models cannot be used for projects where the investment dates are on or before the evaluation dates since the real option value increases with long duration [96].

Both Table 7.12 and Table 7.13 show NPV results. The NPV are determined in section 6.3.1.10.

The real option values for other cases are deduced from the results in section 7.3.3 because the investment costs used in this chapter are higher than the investment costs utilised in chapter 6.

7.4 Validation Conclusion

Validation results showed that the 2014/15 energy sources fuel portfolio is inefficient. Nonetheless, the stochastic programming cost results outperformed the deterministic results.

The third tier validation results showed that the investment on the selected technologies in 2020 is impossible, because of low real option values which resulted from low cash flows generated by each technology. Based on this, decision makers should defer the investments and re-evaluate them at a later date and abandon the investments with zero duration and the ones that have passed the investment dates.

The current study contributed in this chapter by formulating the adjusting the TSSMILP and formulating the NRA model developed in chapter 3 and demonstrated in chapter 6.

CHAPTER 8

Discussion

This study has demonstrated how can one apply the three tier planning process, and the results are discussed in this chapter. The results of each tier of the three-tier planning process tier were discussed in chapter 6. The three-tier model was validated and the results were discussed in chapter 7. The three-tier model is based on linear programming for both the first and second tier models. However, not all the problems can expressed as linear programming, but also as nonlinear programming. In such cases, the three-tier model developed in this study can be utilised as a benchmark.

Two papers were published on Tier 1 content, a paper that was presented in an IEEE conference labelled appendix F and another paper that was published in the Journal of Energy in Southern Africa labelled appendix G. A paper emanated from Tier 2 content and was published in the ORiON Journal and is labelled appendix H. A further paper resulting from Tier 3 content is being submitted for publication.

8.1 Evaluation of Existing Power Plants

The first tier showed the importance of evaluating the costs and risks of the existing energy sources. The outcome of the first tier was that the reliance on gas/diesel as a peak and emergency energy source was risky. Even though the OCGT plants could use gas as well as diesel, these plants used only diesel [30]. Pumping storage (PS) technologies were used for peak and emergencies. The downside was PS technologies which used electricity to pump water to the upper dam, making

this technology less useful during emergencies. The first tier model suggested that South African decision makers should consider other sources of energy for peaking and emergencies that are cheaper than diesel. Gas is an alternative energy that could be considered for peaking power plants, and this was proposed in IRP2019 [7]. SA could make arrangements with countries like Mozambique and Tanzania for gas supply [182].

Energy storage technologies were not included in the data for building the three-tier model but the energy storage data was added to the validation data. The energy storage technologies included were inclusive of lithium-ion battery, compressed air energy storage and pumped storage.

The energy storage are expensive investments, which do not generate energy if there is no energy stored. Battery energy storage system (BESS) was another alternative that could be used for peaking. Lithium-ion battery was used for BESS and its efficiency and life cycle are improving [183]. The cost of lithium-ion battery has also decreased drastically, from 1000 $/kWh in 2010 to below 300 $/kWh in 2016 [184]; however, this cost is still high [7] and [183]. In South African Rand (Rand=100c) the 2016 BESS cost was below 4 412 R/kWh, using 2016 exchange rate of R14.71 per $ [185]. Nevertheless, energy users could benefit from using the BESS by saving self-generated electricity from solar and wind [184]. The benefits of investing in BESS were being experienced by industrial energy users [183]. Eskom had already invested R6 billion into BESS projects which would comprise 360 MW [186]. The Eskom's BESS projects aimed at storing energy generated from solar and wind and release it during the peak period [7] and [186].

The data requirements for successful implementation of the proposed evaluation process were the cost of fuel for each energy source in Rand and energy sent out from each energy source in GWh. Any software with a portfolio theory model could be used; the Matlab software with financial toolbox was used in this study. PT was utilised successfully to show that the South African energy sources were not efficient in 2013. The risk measures used in this study would have shortcoming for measuring the risks of renewable energy sources and in cases where there was no historical data. However, in such cases other risk measures such as VaR and

CVaR could be used. Proxy or simulated data could be used when there is no historical data.

8.2 Planning with Uncertainty

The implementation of EGEP with uncertainty demonstrated that a TSSMILP model was more realistic when compared to TSSLP model and had lower costs than the deterministic MILP. The values of stochastic programming (VSP) showed that the costs results for the TSSMILP model were lower than the deterministic model's costs. The VSP results in this study concurred with VSP of a financial application in [77].

The models selected wind, hydro and solar PV renewable energy sources even though the input data also had other solar energy technologies. The objective function of the models was to minimise costs; consequently, the models did not select technologies that use expensive renewable energy source. To examplify, the wind technology was cheaper when compared to solar technologies, and wind also had a higher capacity factor compared to solar renewable energy source. Solar PV was only selected by scenario 4 with the highest electricity demand forecast. However, both solar PV and wind energy is intermittent and non-dispatchable. The hydro technologies were all based in neighbouring countries, Mozambique and Zambia. The IRP2010 results had wind, hydro and solar PV [95] for all the scenarios considered in this study. However, the results in [95] showed that hydro imports were constrained at 1 500 MW, which was also the case in this study. In the IRP2019, hydro imports were constrained at 2 500 MW, and 2030 appeared as a set date for its new capacity [7]. In this thesis, the hydro new capacity started way earlier than 2030.

Scenario 4 new capacity included nuclear. The IRP2010 update also had new capacity from nuclear for three of the four scenarios, except for weathering the storm scenario [95]. There was no new capacity from nuclear in the IRP2019 [7]. Possibly this was the case because of the 9 600 MW which was determined from

the IRP2010; however, is not built yet [146]. Eskom was also considering the extension of life for the existing nuclear power plant, which would reach end of life in 2024 [7].

There was a decrease in coal new capacity in this study. Certain scenarios in IRP2019 had less new capacity from coal [7]. There were financial constraints for coal new power plants because lenders only consider coal technologies that have high efficiency and low emission (HELE) [7]. This meant that there might be delays in building new coal power plants and this might have a negative effect in electricity supply.

The coal new capacity CO_2 emissions were within the South African CO_2 emission limits. However, the coal technologies used in this syudy did not all satisfy the HELE requirements. The coal technologies which satisfy HELE requirements included coal underground gasification, integrated gasification combined cycle, carbon capture utilisation and storage, ultra-super critical and super critical [7].

The falling electricity demand was discussed in this study. The improved energy efficiency by large energy consumers was also contributing towards falling electricity demand [7]. The electric vehicles were expected to counteract the falling electricity demand, but only after 2030 [7].

In this study, the actual electricity demand was below all the forecasted electricity demands. However, the actual electricity demand could fall in-between the scenarios or even above.

Electricity demand was the only uncertainty considered in this study and also in the IRP reports [144], [145], [146] and [7]. However, in reality, there were other uncertainties which could be considered such as the technologies' capital costs, the operating and maintenance costs and the fuel costs.

The data that was used for this study was collected in 2012 and was published in [95]. The data that was used in the IRP2019 was not published, but there were uniform resource locator (URL) links for the raw data used in [7] even though, some were not accessible. Even if the raw data was all available, the data adjustment was impossible, as was the case in [7]. Data availability benefits the research fraternity and expands the body of knowledge.

For the planning with uncertainty tier to be successful, the following data is required: electricity demand forecast scenarios, existing capacity with corresponding energy sources, decommissioning dates for existing capacity, potential new technologies names and the corresponding energy source, costs (capital, maintenance (variable and fixed), fuel costs and cost of unserved energy), life of plant, lead time, technology capacity, capacity factors and CO_2 emissions. A software that has both stochastic programming and deterministic models is ideal. In the context of this study, AIMMS software was used.

8.3 Evaluation of New Capacity Investment Costs amidst Changes in Planning Assumptions

The TSSMILP results from the planning tier were used for the evaluation of investment costs tier. The TSSMILP results included a list of technologies, corresponding energy sources, new capacity and the corresponding dates which indicated when the new capacity was expected. The planning tier results were based on the planning tier assumptions, which influenced the new capacity expected dates. The forecasted electricity demand assumption had the most influence on the new capacity expected dates. However, from 2013 to 2019, the actual electricity demand was below all the forecasted electricity demand scenarios. Due to this difference between the forecast and the realised electricity demand, the new capacity dates from the plan required an alteration.

Real option models were used in this study to manage the planning tier unrealised assumptions after the plan has been authorised. These changes, especially the demand forecast, were also acknowledged as a risk in the IRP2019 report [7]. However, this risk would be mitigated by managing the pace and scale of new capacity implementation in the [7]. In this study, RO models that could be used to mitigate the risk of unrealised electricity demand assumptions were proposed and demonstrated.

The former chairman of Eskom once quoted the cost of completing the building of Medupi and Kusile power stations [187]. The proposed RO model could have

been utilised to evaluate the cost of not completing the building of Medupi and Kusile power stations, because it was not provided in [187].

The implementation of a plan results without using an evaluation of new capacity investment costs tier could lead to costly capacity surplus or deficit. The real option results in this study provided the decision maker with the option to defer or to abandon the investment project which resulted from the TSSMILP new capacity. NPV model, which was used by industrial companies [99], was also used, and the results only provided the decision makers with the decision to abandon the investments.

The option to defer was recommended because it provided the decision makers with the option of delaying the investment and re-evaluating the real option in the remaining life of option years.

Low revenues contributed to the values of the underlying assets. Revenues were low because of low electricity prices. South African electricity price was one of the lowest electricity prices in the world in 2018 [188]. It is significant to mention that the South African electricity tariff was not cost-reflective at the time of undertaking this study [189]. High investment costs also contributed to low real option values.

Assuming that the RO results gave decision makers option to invest all the technologies, this would raise a different challenge because the investment years were close to each other. It would require decision makers to have huge investment capital funds available for a long period. The availability of skills almost at the same time for different projects would also be another challenge [190]. Usually, mega-projects like Kusile and Medupi power plants were associated with cost overruns and schedule delays [187] and [191].

The planning tier input data and output was required for the RO model, together with some economic data (risk-free rate, risk premium, expected cash flow volatility). RO models could be developed in MS Excel. In the case of this study, MS Excel and Python software were used.

If the proposed three tier process was ignored, firstly, decision makers would invest in energy sources without understanding the financial risk of the energy sources;

secondly they would continue to utilise deterministic models even when there were better models like the stochastic programming model. Lastly, decision makers would continue to implement outdated plan results, even when the evidence shows that the plan assumptions have changed.

8.4 Three-Tier Model Data Requirements

Data played a huge role in this study. The South African data was utilised which was collected mainly from published documents. There are no companies in SA that collect comprehensive energy industry data, this make result in this area difficult. Companies like International Energy Agency, try to collect African data, but is it not comprehensive enough. Countries with companies that collect energy industry data would be able to implement the proposed three-tier model, within a short space of time because software is available as discussed in section 1.3. As a result of data challenges, most studies utilise simulated data, which would be a challenge for the three-tier model.

8.5 Contribution of the Study

The current study introduced, developed, demonstrated and recommends a three-tier electricity generation capacity expansion planning model. This study contributed by demonstrating how PT, TSSMILP and RO models are utilised together in the three-tier model. This study contributed further in Tier 2 by extending the EGEP model to also take care of load shedding and the corresponding costs. This study also contributed in Tier 2 by deriving the cost of unserved energy which was not available on the collected data. The contribution of the study in Tier 3 was to formalise the risk neutral approach which is utilised to evaluate new capacity added several times during the investigation period.

CHAPTER 9

Conclusion and Recommendations

The current study proposed, demonstrated and validated a three tier process in electricity capacity expansion.

9.1 Conclusion

The Portfolio Theory model was used for evaluating the existing power plants in the first tier. The aim of this tier was to inform decision makers before planning for electricity generation capacity expansion about the costs and risks of energy sources used by existing power plants. The evaluation of existing power plants results showed that the South African portfolio made up of energy sources fuel costs during the investigation period 1 April 2007 to 31 March 2014 was not well diversified. This was the case because all the energy sources fuel costs had moderate to high correlation coefficients.

The initial portfolio was not efficient because it had both high cost and risk. Gas/diesel contributed to the initial portfolio's high costs. Both coal and gas/diesel contributed to the initial portfolio's high risk. The information to take from the planning tier was that coal was a base load energy source, but its cost was not constant and an alternative cheaper peak energy sources was necessary to reduce gas/diesel costs.

This study brought in the use of portfolio mtheory model as a pre-planning model in electricity generation capacity expansion.

The planning with uncertainty was demonstrated by a two stage stochastic linear programming (TSSLP) model, for the period 2013 to 2050. The TSSLP model

was used because of uncertainties in electricity demand. The availability of a comprehensive data set made this study possible. The TSSLP model was contrasted with the traditional deterministic linear programming model. Later on, the LP models were converted to mixed integer LP (MILP) models. The TSSLP became TSSMILP and the deterministic linear programming model became the deterministic MILP model. The MILP results were used because the new capacity results were integers as opposed to continuous LP's new capacity. The following sources of energy were selected for both models of new capacity: coal, gas/diesel, wind, hydro, solar PV and nuclear.

The inclusion of renewable energy sources in new capacity would reduce the fuel risk that was highlighted by the PT results. There were costs savings when TSSMILP cost results were compared to deterministic results.

The carbon emissions for new capacity for both deterministic MILP and TSSMILP models were within limits. However, the picture might differ for the total capacity (existing and new capacity). The South African carbon tax was expected to enforce the carbon emission reduction, especially for electricity generators.

The reserve margins were more than enough for the better part of the planning period and began to drop below 15% from 2028 for Plan 4, 2036 for Plan 2 and 2046 for plans 1 and 3, as the existing capacity was decommissioned.

This study contributed in the second tier by adjusting the TSSMILP model to incorporate load shedding when necessary.

Real options (RO) models were used for the evaluation of new capacity investment costs and admist of changes in planning assumptions. The data used for RO models was taken from TSSMILP results, which had new capacity from different technologies and the dates when each capacity was required.

Sequential compound real option (SCRO) model was used for technologies with new capacity increments and binomial option pricing model (BOPM) was used for technologies where new capacity occurs once. Traditional NPV model was also used to evaluate the investments for all the technologies with new capacity.

Results for both the SCRO model and BOPM showed that all the investments for new technologies could be abandoned or deferred. NPV results for all technologies

showed that all the investments for new technologies should be abandoned.
The RO values could increase because most projects had option durations which were more than ten years. However, in technologies with option durations which were less than ten years, the recommendation is that decision makers should defer and monitor them closely. The high investment costs and low values of the underlying assets due to low electricity prices contributed to low option values.
The current study contributed in the third tier by formulating the RNA model, which is a branch of SCRO models. The study answered the research questions in section 1.4.2 in chapter 1.

9.2 Recommendations

Based on the results found in this study, it is recommendation that the planning process proposed and demonstrated in this research should be used by the decision makers in the electricity industry. The implementation of the three tier process can be applied with exactly the same skills that prepare the IRP. Moreover, the South African Department of Minerals Resources and Energy should continue to publish detailed adjusted data when publishing integrated resources plan reports. In this research, only one uncertainty in the electricity demand was considered. However, there are other uncertainties that can be considered like the future investment, maintenance and fuel costs. It is also recommended that future research considers the above uncertainties. The observed actual electricity demand in this study lied below all the electricity demand scenarios. In the light of the above the other recommendation is to apply the three tier process when the actual demand lies in-between or above the forecasted electricity demand. Both the first and the second tiers are based on linear programming in this study, it is recommended that these tiers be expanded further for non linear programming.
The data used for the first tier did not include renewable resource data, further research is recommended which includes all the available energy sources in this tier. In addition, a software for evaluating a portfolio of RO using RNA is recommended.

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Appendix A

Efficient Portfolios' Costs and Risks

This appendix which shows the average cost (cost) and standard deviation (risk) of the 200 efficient portfolios. In chapter 6 only 10 of the 200 efficient portfolios could be visualised in Figure 6.1 and in Table 6.4. The 200 efficient portfolios provide decision makers with a wider choice than the 10 efficient portfolios observed in chapter 6.

Portfolio	Cost (c/kWh)	Risk (c/kWh)
1	4.85	1.30
2	6.06	1.34
3	7.26	1.45
4	8.46	1.60
5	9.66	1.77
6	10.86	1.95
7	12.06	2.14
8	13.27	2.33
9	14.47	2.53
10	15.67	2.74
11	16.87	2.94
12	18.07	3.16
13	19.27	3.37
14	20.47	3.59
15	21.68	3.80
16	22.88	4.02
17	24.08	4.24

Portfolio	Cost (c/kWh)	Risk (c/kWh)
18	25.28	4.47
19	26.48	4.69
20	27.68	4.91
21	28.89	5.14
22	30.09	5.36
23	31.29	5.59
24	32.49	5.82
25	33.69	6.04
26	34.89	6.27
27	36.09	6.50
28	37.30	6.72
29	38.50	6.95
30	39.70	7.18
31	40.90	7.41
32	42.10	7.64
33	43.30	7.87
34	44.51	8.09
35	45.71	8.32
36	46.91	8.55
37	48.11	8.78
38	49.31	9.01
39	50.51	9.24
40	51.71	9.47
41	52.92	9.70
42	54.12	9.93
43	55.32	10.16
44	56.52	10.39
45	57.72	10.62
46	58.92	10.85
47	60.13	11.08

Portfolio	Cost (c/kWh)	Risk (c/kWh)
48	61.33	11.31
49	62.53	11.54
50	63.73	11.77
51	64.93	12.00
52	66.13	12.23
53	67.33	12.46
54	68.54	12.70
55	69.74	12.93
56	70.94	13.16
57	72.14	13.39
58	73.34	13.62
59	74.54	13.85
60	75.75	14.08
61	76.95	14.31
62	78.15	14.54
63	79.35	14.77
64	80.55	15.00
65	81.75	15.23
66	82.95	15.47
67	84.16	15.70
68	85.36	15.93
69	86.56	16.16
70	87.76	16.39
71	88.96	16.62
72	90.16	16.85
73	91.37	17.08
74	92.57	17.32
75	93.77	17.55
76	94.97	17.78
77	96.17	18.01

Portfolio	Cost (c/kWh)	Risk (c/kWh)
78	97.37	18.24
79	98.57	18.47
80	99.78	18.70
81	100.98	18.93
82	102.18	19.17
83	103.38	19.40
84	104.58	19.63
85	105.78	19.86
86	106.99	20.09
87	108.19	20.32
88	109.39	20.55
89	110.59	20.78
90	111.79	21.02
91	112.99	21.25
92	114.19	21.48
93	115.40	21.71
94	116.60	21.94
95	117.80	22.17
96	119.00	22.40
97	120.20	22.64
98	121.40	22.87
99	122.61	23.10
100	123.81	23.33
101	125.01	23.56
102	126.21	23.79
103	127.41	24.02
104	128.61	24.26
105	129.81	24.49
106	131.02	24.72
107	132.22	24.95

Portfolio	Cost (c/kWh)	Risk (c/kWh)
108	133.42	25.18
109	134.62	25.41
110	135.82	25.65
111	137.02	25.88
112	138.23	26.11
113	139.43	26.34
114	140.63	26.57
115	141.83	26.80
116	143.03	27.03
117	144.23	27.27
118	145.43	27.50
119	146.64	27.73
120	147.84	27.96
121	149.04	28.19
122	150.24	28.42
123	151.44	28.66
124	152.64	28.89
125	153.85	29.12
126	155.05	29.35
127	156.25	29.58
128	157.45	29.81
129	158.65	30.05
130	159.85	30.28
131	161.05	30.51
132	162.26	30.74
133	163.46	30.97
134	164.66	31.20
135	165.86	31.43
136	167.06	31.67
137	168.26	31.90

Portfolio	Cost (c/kWh)	Risk (c/kWh)
138	169.47	32.13
139	170.67	32.36
140	171.87	32.59
141	173.07	32.82
142	174.27	33.06
143	175.47	33.29
144	176.67	33.52
145	177.88	33.75
146	179.08	33.98
147	180.28	34.21
148	181.48	34.45
149	182.68	34.68
150	183.88	34.91
151	185.09	35.14
152	186.29	35.37
153	187.49	35.60
154	188.69	35.84
155	189.89	36.07
156	191.09	36.30
157	192.29	36.53
158	193.50	36.76
159	194.70	36.99
160	195.90	37.23
161	197.10	37.46
162	198.30	37.69
163	199.50	37.92
164	200.71	38.15
165	201.91	38.38
166	203.11	38.62
167	204.31	38.85

Portfolio	Cost (c/kWh)	Risk (c/kWh)
168	205.51	39.08
169	206.71	39.31
170	207.91	39.54
171	209.12	39.77
172	210.32	40.01
173	211.52	40.24
174	212.72	40.47
175	213.92	40.70
176	215.12	40.93
177	216.33	41.16
178	217.53	41.40
179	218.73	41.63
180	219.93	41.86
181	221.13	42.09
182	222.33	42.32
183	223.53	42.56
184	224.74	42.79
185	225.94	43.02
186	227.14	43.25
187	228.34	43.48
188	229.54	43.71
189	230.74	43.95
190	231.95	44.18
191	233.15	44.41
192	234.35	44.64
193	235.55	44.87
194	236.75	45.10
195	237.95	45.34
196	239.15	45.57
197	240.36	45.80

Portfolio	Cost (c/kWh)	Risk (c/kWh)
198	241.56	46.03
199	242.76	46.26
200	243.96	46.49

Appendix B

Energy Source Share for Efficient Portfolios

This appendix shows the energy source share for the 200 efficient portfolios whose costs and risks are in appendix A. It can be observed that only the first 7 portfolios have a share for nuclear energy source. The majority of portfolios have only hydro and gas/diesel energy sources.

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
1	0	100	0
2	25.42	74.58	0
3	50.84	49.16	0
4	74.02	25.93	0.04
5	81.57	18.03	0.40
6	89.11	10.14	0.75
7	96.66	2.24	1.10
8	98.43	0	1.57
9	97.92	0	2.08
10	97.4	0	2.60
11	96.89	0	3.11
12	96.38	0	3.62
13	95.86	0	4.14
14	95.35	0	4.65
15	94.84	0	5.16
16	94.33	0	5.67
17	93.81	0	6.19

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
18	93.30	0	6.70
19	92.79	0	7.21
20	92.28	0	7.72
21	91.76	0	8.24
22	91.25	0	8.75
23	90.74	0	9.26
24	90.23	0	9.77
25	89.71	0	10.29
26	89.2	0	10.80
27	88.69	0	11.31
28	88.18	0	11.82
29	87.66	0	12.34
30	87.15	0	12.85
31	86.64	0	13.36
32	86.12	0	13.88
33	85.61	0	14.39
34	85.10	0	14.90
35	84.59	0	15.41
36	84.07	0	15.93
37	83.56	0	16.44
38	83.05	0	16.95
39	82.54	0	17.46
40	82.02	0	17.98
41	81.51	0	18.49
42	81.00	0	19.00
43	80.49	0	19.51
44	79.97	0	20.03
45	79.46	0	20.54
46	78.95	0	21.05

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
47	78.43	0	21.57
48	77.92	0	22.08
49	77.41	0	22.59
50	76.90	0	23.10
51	76.38	0	23.62
52	75.87	0	24.13
53	75.36	0	24.64
54	74.85	0	25.15
55	74.33	0	25.67
56	73.82	0	26.18
57	73.31	0	26.69
58	72.80	0	27.20
59	72.28	0	27.72
60	71.77	0	28.23
61	71.26	0	28.74
62	70.75	0	29.25
63	70.23	0	29.77
64	69.72	0	30.28
65	69.21	0	30.79
66	68.69	0	31.31
67	68.18	0	31.82
68	67.67	0	32.33
69	67.16	0	32.84
70	66.64	0	33.36
71	66.13	0	33.87
72	65.62	0	34.38
73	65.11	0	34.89
74	64.59	0	35.41
75	64.08	0	35.92

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
76	63.57	0	36.43
77	63.06	0	36.94
78	62.54	0	37.46
79	62.03	0	37.97
80	61.52	0	38.48
81	61.00	0	39.00
82	60.49	0	39.51
83	59.98	0	40.02
84	59.47	0	40.53
85	58.95	0	41.05
86	58.44	0	41.56
87	57.93	0	42.07
88	57.42	0	42.58
89	56.90	0	43.10
90	56.39	0	43.61
91	55.88	0	44.12
92	55.37	0	44.63
93	54.85	0	45.15
94	54.34	0	45.66
95	53.83	0	46.17
96	53.32	0	46.68
97	52.80	0	47.20
98	52.29	0	47.71
99	51.78	0	48.22
100	51.26	0	48.74
101	50.75	0	49.25
102	50.24	0	49.76
103	49.73	0	50.27
104	49.21	0	50.79

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
105	48.70	0	51.30
106	48.19	0	51.81
107	47.68	0	52.32
108	47.16	0	52.84
109	46.65	0	53.35
110	46.14	0	53.86
111	45.63	0	54.37
112	45.11	0	54.89
113	44.60	0	55.40
114	44.09	0	55.91
115	43.57	0	56.43
116	43.06	0	56.94
117	42.55	0	57.45
118	42.04	0	57.96
119	41.52	0	58.48
120	41.01	0	58.99
121	40.50	0	59.50
122	39.99	0	60.01
123	39.47	0	60.53
124	38.96	0	61.04
125	38.45	0	61.55
126	37.94	0	62.06
127	37.42	0	62.58
128	36.91	0	63.09
129	36.40	0	63.60
130	35.89	0	64.11
131	35.37	0	64.63
132	34.86	0	65.14
133	34.35	0	65.65

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
134	33.83	0	66.17
135	33.32	0	66.68
136	32.81	0	67.19
137	32.30	0	67.70
138	31.78	0	68.22
139	31.27	0	68.73
140	30.76	0	69.24
141	30.25	0	69.75
142	29.73	0	70.27
143	29.22	0	70.78
144	28.71	0	71.29
145	28.20	0	71.80
146	27.68	0	72.32
147	27.17	0	72.83
148	26.66	0	73.34
149	26.14	0	73.86
150	25.63	0	74.37
151	25.12	0	74.88
152	24.61	0	75.39
153	24.09	0	75.91
154	23.58	0	76.42
155	23.07	0	76.93
156	22.56	0	77.44
157	22.04	0	77.96
158	21.53	0	78.47
159	21.02	0	78.98
160	20.51	0	79.49
161	19.99	0	80.01
162	19.48	0	80.52

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
163	18.97	0	81.03
164	18.46	0	81.54
165	17.94	0	82.06
166	17.43	0	82.57
167	16.92	0	83.08
168	16.40	0	83.60
169	15.89	0	84.11
170	15.38	0	84.62
171	14.87	0	85.13
172	14.35	0	85.65
173	13.84	0	86.16
174	13.33	0	86.67
175	12.82	0	87.18
176	12.30	0	87.70
177	11.79	0	88.21
178	11.28	0	88.72
179	10.77	0	89.23
180	10.25	0	89.75
181	9.74	0	90.26
182	9.23	0	90.77
183	8.71	0	91.29
184	8.20	0	91.80
185	7.69	0	92.31
186	7.18	0	92.82
187	6.66	0	93.34
188	6.15	0	93.85
189	5.64	0	94.36
190	5.13	0	94.87
191	4.61	0	95.39

Portfolios	Hydro share (%)	Nuclear share (%)	Gas/Diesel share (%)
192	4.10	0	95.90
193	3.59	0	96.41
194	3.08	0	96.92
195	2.56	0	97.44
196	2.05	0	97.95
197	1.54	0	98.46
198	1.03	0	98.97
199	0.51	0	99.49
200	0	0	100

Appendix C

Matlab Code for Portfolio Theory

The Matlab code in this appendix was used to produce the results in chapter 6, appendix A and appendix B.

```
%This model uses a default portfolio optimization problem which has a risk
%(standard deviation) and return (mean) proxy associated with a given
%problem, and a portfolio set that specifies a portfolio weights to be
%positive and sum up to 1.
% This model is executed only after importing the data, with energy source
%name and corresponding fuel cost vector, from Excel to Matlab
% Renaming the technologies with shortnames
C  = Coal;
H  = Hydro;
N  = Nuclear;
G  = Gas;
% Forming a matric from the energy sources' data
MAT =[C, H, N, G];
% Calculating covariance for the energy sources' data
Cov = cov(MAT);
%Calculating correlation coefficient for the energy sources' data
% rho = corrcoef(Cov);
% display (rho)
% Calculating means for the energy sources' data
MC  = mean(C);
MH  = mean(H);
MN  = mean(N);
MG  = mean(G);
m = [MC, MH, MN, MG];
% Calculating standard deviations for the technologies
STDC = std(C);
STDH = std(H);
STDN = std(N);
STDG = std(G);
%Initial portfolio weights for fuel costs
pwgt0 = [ 0.05; 0.04; 0.02; 0.89];
```

```
%Portfolio object, InitPort, identifies the initial portfolio
p = Portfolio('InitPort',pwgt0);
% Adding to the previous portfolio, p, expected portfolio mean, m and expected
% portfolio covariance, Cov.
p = setAssetMoments(p, m, Cov);
%p = Portfolio('NumAssests',10);
% setDefaultConstraints allow one to view the portfolio constraints. The defaults
% portfolio optimization problem has 2 constraints: portfolio weights must be positive
% and portfolio weights must sum up to 1.
 p = setDefaultConstraints(p);
% plotFrontier plot the efficient frontier based on the mean ann covariance
% provided. Initial portfolio is also plotted.
 plotFrontier(p);
% hold on means do not display the plotted graph
 hold on
% scatter plot of standard deviation and mean for each energy source
scatter([STDC,STDH,STDN,STDG],[MC, MH, MN, MG],'m','Filled');
% Display the efficient frontier with initial portfolio and scatter plot
% for energy sources' standard deviation (x-axis) and mean (y-axis)
hold off
% The following part of the model does not form part of the efficient frontier,
% but is derived from the efficient frontier calculations
%
%Calculating and displaying the correlation coefficient matrix, rho, for the
%matrix of energy sources data
rho = corrcoef(MAT);
%NumPort is for the number of portfolios on the efficient frontier. This
%number can be changed from 10 which is a default, but it should be greater than zero.
NumPorts = 10;
%PortWts is for the weights of the 10 efficient portfolios. That is a percentage of
%each fuel cost
PortWts = estimateFrontier(p, NumPorts);
% PortRisk is for the risks (standard deviations)of the 10 efficient
% portfolios.
PortRisk = estimatePortRisk(p,PortWts);
% PortReturn is for the returns (means) of the 10 efficient
% portfolios.
PortReturn = estimatePortReturn(p,PortWts);
% Display show the values for the above calculations
display(rho);
display(PortWts);
display(PortRisk);
display(PortReturn);
% End
```

Appendix D

Some SA Validation Data for Existing Power Plants and Potential Technologies

D.1 IPP Commissioned Capacity

The IPP new capacity is not included directly on the data in [52].

Year	Solar PV	CSP	Wind	Other renewable
2015[a]	964	100	639	10
2016[b]	1 325	200	1 360	12
2017[c]	1 474	200	1 468	19
2018[d]	1 980	300	1 474	22
2019[e]	1 980	500	1 474	22
2020[f]	2 181.9	500	2 405.22	22
2021[g]	2 436.9	500	3 133.05	26.7

The IPP data in is collected from the following sources:

a - [192] and [193]

b - [194] and [193]

c - [195]

d - [196]

e - [197]

f - [176] and bid window 4 projects which were commissioned after the report in [176] was published.

g - Bid window 4 projects that are in construction after the report in [176] is published.

D.2 Eskom New Build Capacity

The Eskom new build dates in [52] are outdated, hence new dates and corresponding capacity in MW are provided in this section.

Year	Ingula	Medupi	Kusile
2015		720[a]	
2016			993[a]
2017	1 440[b]	720[b]	331[a]
2019	1 440[cd]		
2021	720[d]	720[d]	
2022		720[d]	
2023		720[d]	
2024		1440[d]	

The new build data is collected from the following sources:

a - [189]

b - [135], [169]

c - [143]

d - [143]

Appendix E

SA Actual and Simulated Inflation Rates

The historic year-on-year inflation rates (HYOYIR) from January 2009 to December 2020 are taken from the reports in the Statistics South African website [198], [199], [200], [201], [151]. Year 2009 is chosen because it was the year where South Africa started to target the year-on-year inflation rates to fall between 3% and 6% [202].

The future inflation rates are simulated based on the HYOYIR. The distribution of the HYOYIR and the corresponding parameters are determines in R software [137]. The inverse distribution, $Y = F^{-1}(U)$, is used to simulate the year on year inflation rates for the period 2021 to 2105 [137]. In this appendix Y is the simulated year-on-year inflation rates; F^{-1} is the inverse of the distribution determined using the HYOYIR; and U is a random uniform variate generated by function RAND() in MS Excel [203]. It should be noted that the distribution and its inverse are determined on a transformed HYOYIR. The transformation is given by equation (E.1).

$$y = 100 \times \text{HYOYIR} \tag{E.1}$$

At the end the transformation in equation (E.1) is transformed back as shown in equation (E.2).

$$\text{HYOYIR} = y/100 \tag{E.2}$$

The annual inflation rates in this appendix are determined by taking an average of a calendar year values of HYOYIR [201], [151]. The results of the simulated inflation rates are shown in Figure E.1, as a solid line. The actual annual inflation rates are in square dots (2013 to 2020) in Figure E.1.

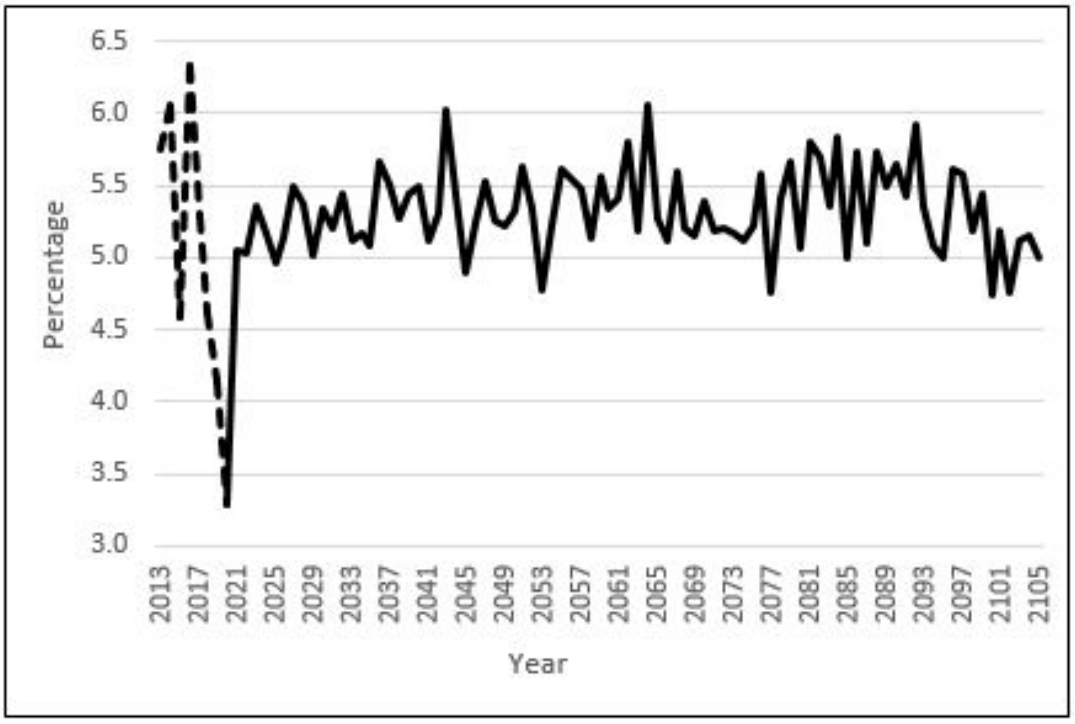

FIGURE E.1: SA actual and simulated inflation rates

Appendix F

IEEE Conference Paper

In appendix F is an Institute of Electrical and Electronics Engineers (IEEE) conference paper based in portfolio theory (PT) which is discussed in chapter 6.

Analysis of the South African Generation Fuel Mix Using Portfolio Theory

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***Abstract*—Markowitz' portfolio theory is applied to South Africa's electricity generation fuel mix problem. The results obtained suggest that SA's generation fuel mix is inefficient with high cost and high risk. It is proven that the reduction in the cost and risk of the SA's generation fuel mix is linked to the reduction of the use of OCGTs.**

***Keywords*—Portfolio theory, efficient portfolios, efficient frontier.**

I. Introduction

Portfolio theory (PT) has been used to evaluate electricity generation assets in other countries as discussed in [1], [2], [3], [4], [5] and [6], but not in South Africa (SA). In this paper an analysis of the SA's generation fuel mix using PT is presented. The focus is mainly on the cost of primary energy used because this constitutes approximately 80% of a utility's production expenses [1]. In this paper PT will be discussed as defined by Markowitz [7]-[8] and not by Maslowian in [9] and [10].

SA's generation mix includes coal, hydro, open cycle gas turbine (OCGT), nuclear, pumped storage and wind power stations.

A. Electricity Generation in South Africa

Electricity generation industry is regulated in SA. Eskom generates approximately 95% of the electricity used in SA [11]. Currently, Eskom has a total generating capacity of $41990\ MW$, [11]-[12] as shown in Table I:

TABLE I
SA'S ELECTRICITY GENERATION CAPACITY IN 2013

Technology	Capacity in MW
Coal	35718
Hydro	600
Open cycle gast turbines	2409
Nuclear	1860
Pumped Storage	1400
Wind	3

In 2013 Eskom also received $7698\ GWh$ from the South African Development Community (SADC) region [12]. The energy availability factor (EAF) for Eskom's financial year $2012/13$ (1 April 2012 to 31 March 2013) was 77.65% decreasing from 81.99% in $2011/12$ [12]. The decrease in EAF reduced the above effective capacity to about $32600\ MW$. Over the period $2012/13$ the peak demand was $35525\ MW$ [12]. The margin between Eskom's available capacity and peak demand was mitigated through [12]:

- Keeping the generating units in operation and deferring maintenance on power plants,
- Implementing demand-side management initiatives,
- Increasing the use of OCGT power stations, and
- Purchasing additional capacity from independent power producers (IPPs).

OCGT, pumped storage and hydro-electric stations are peaking stations, which are supposed to be operated during peak periods and in emergency situations [11]-[12]. Due to excessive use of OCGT stations the fuel cost for these stations increased by 281% in $2011/12$ [13] and by a further 21.6% in $2012/13$ [12].

B. Portfolio Theory

Markowitz [8] defined a good financial portfolio as more than just a long list of financial securities and bonds, but a balanced whole that provides the investor with protections and opportunities with respect to a wide range of contingencies. Portfolio P is efficient if [8]:

- it is an obtainable;
- there is any other obtainable portfolio whose expected return (R) is greater than P, its risk (σ) must also be greater than P's; and
- there is an obtainable portfolio whose risk is less than P, its expected return must also be less than P's.

It is possible to draw a curve that joins all the portfolios that behave like portfolio P, and this curve is called an efficient frontier [8]. All other portfolios that are not on the efficient frontier are called inefficient portfolios. Mathematically, PT reduce to the following equations in case of a portfolio made up from N securities [8]:

$$R = \sum_{i=1}^{N} X_i \mu_i, \ \ \sum_{i=1}^{N} X_i = 1, X_i \geq 0 \ \forall i \qquad (1)$$

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$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} r_{it} \tag{2}$$

$$\sigma = \left[\sum_{i=1}^{N}\sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j\right]^{1/2} \tag{3}$$

where:

- X_i is the weight of a financial security i in the portfolio, financial securities and their respective weights are chosen by the investor,
- μ_i is the average return of a financial security i over a given period T,
- r_{it} is the actual return of a financial security i at time t,
- σ_i is the standard deviation of a financial security i's historic returns, representing security's risk, and
- ρ_{ij} is the correlation coefficient between security i and j, $-1 \leq \rho_{ij} \leq 1$.
  Portfolio risk is reduced by investing in financial securities that have a low correlation coefficient with each other.
- T is the total historic period (number of: years or month or days, etc).

C. Portfolio Theory in Electricity Generation

PT has been used widely in electricity generation, but this section will be limited to cases where actual historic electricity generation fuel costs were used. Cases where estimated data was used like in [6] and also where proxy data was used like in [2], are not discussed.

Bar-Lev and Katz [1] used PT to determine if 1969 United States (US) electricity utilities were the efficient utilisers of the fossil fuels. The fuel mixes was made up of coal, oil and gas. The results showed that the fuel mix for 3 regions was on the respective efficient frontiers and for other 6 was below the efficient frontier.

Awerbuch [14] also applied PT to 1998 US electricity generating mix, made up of coal and gas. The results showed that this US mix was not on the efficient frontier. The efficient mix had less coal and more gas, but had high risk which Awerbuch recommended that it could be lowered by adding renewables to the mix.

Krey and Zweifel [3] determined if year 2003 electricity generation technology mix for Switzerland and US was efficient using PT. The Swiss generation mix consisted of nuclear, run of river, storage hydro and solar, whereas the US mix was made up of coal, nuclear, gas, oil and wind. The results showed that both the Swiss and the US generation mixes were inefficient. For Switzerland a move towards nuclear and away from run of rivers would lead to an efficient generation mix. US efficient generation mix contained more coal but no gas.

The review above shows that in all the cases irrespective of the fuel mixes used, the mixes were inefficient according to PT. Hence the need to determine the case of the South African generation fuel mix.

Section II discusses the methodology and data used; Section III presents the application of PT to Eskom's electricity generation fuel mix and Section IV is the conclusion.

II. Methodology and Data Used

It is important to note that there are major differences between financial market portfolios, for which PT was first developed, and portfolios of electricity generation. The major differences are:

- Financial market portfolios focus on returns whereas electricity generation portfolios focus on costs.
- It is easier to sell financial asset than electricity generating assets like coal fired plants [5].
- Financial securities are almost infinitely divisible such that a portfolio can contain between 0% and 100% of a given security, this is not the case with electricity generation assets [5].

Irrespective of these differences PT is commonly used for valuation of electricity generation mixes [5]. Equations 1 to 3 are modified as follows for a portfolio made up from N electricity generation technologies:

$$R = \sum_{i=1}^{N} X_i \mu_i, \;\; \sum_{i=1}^{N} X_i = 1, X_i \geq 0 \;\; \forall i \tag{4}$$

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} r_{it} \tag{5}$$

$$\sigma = \left[\sum_{i=1}^{N}\sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j\right]^{1/2} \tag{6}$$

where:

- R is the portfolio cost,
- X_i is the weight of technology i's fuel cost in the portfolio,
- μ_i is the historic average fuel cost for technology i,
- r_{it} is the actual fuel cost for technology i in year t,
- σ_i is the standard deviation for technology i's historic fuel cost, representing technology's fuel risk,
- T is the number of historic years, and
- ρ_{ij} is the correlation coefficient between technology i's fuel cost and technology j's fuel cost.

$-1 \leq \rho_{ij} \leq 1$. If i is always an exact positive multiple of j, then $\rho_{ij} = 1$. If i is always an exact negative multiple of j, then $\rho_{ij} = -1$. If i moves independent of j, then $\rho_{ij} = 0$. Portfolio risk is reduced when ρ_{ij} is close enough or equals to zero.

Data was collected from Eskom Holdings SOC Limited. Data collected was the actual annual fuel costs in Rands and actual annual energy sent out in GWh, for each of the 22 power plants [12]. The fuel cost was calculated from this data in $Rands/kWh$ (R/kWh) for each generation technology. Data was collected from 2002 till 2013, but the fuel cost data for open cycle gas turbines and hydro electric power stations

was available only from 2010. Hence, the PT analysis is based on the data from 2010 to 2013, which is common period for the data.

III. Portfolio Theory in South African Generation Mix

A Matlab software with the financial toolbox was used to analyse the data discussed in Section II and drawing of figures in this section. Firstly, the correlation coefficients amongst the technologies' fuel costs were calculated. Results are presented in Table II.

TABLE II
Correlation coefficients for Eskom's generation fuel mix in 2013

	Coal	**Nuclear**	**PS**	**Hydro**	**OCGT**
Coal	1.0000	0.8403	0.6963	-0.7219	-0.4982
Nuclear		1.0000	0.9742	-0.4432	-0.7692
PS			1.0000	-0.2287	-0.8071
Hydro				1.0000	-0.0499
OCGT					1.0000

The first row in Table II shows that the fuel cost for coal is highly correlated to nuclear, with $\rho_{coal,nuclear} = 0.8403$. $\rho_{coal,PS}$ is also high, but slightly lower at 0.6963. This means that the generation fuel mix risk cannot be reduced by investing in these technologies. However, $\rho_{coal,Hydro} = -0.7219$ and $\rho_{coal,OCGT} = -0.4982$. This means that coal fuel cost behaves in an opposite direction to hydro and OCGT's fuel costs. To a certain extent the generation fuel mix risk is reduced by investing in coal and OCGTs technologies because the magnitude slightly below 0.5. $\rho_{hydro,OCGT} = -0.0499$, this correlation coefficient is the closest to zero compared to all $\rho_{i,j}$'s in Table II. This helps to reduce the risk of the generation fuel mix. However, as shown in Table I the hydro capacity is currently limited to only $600\ MW$.

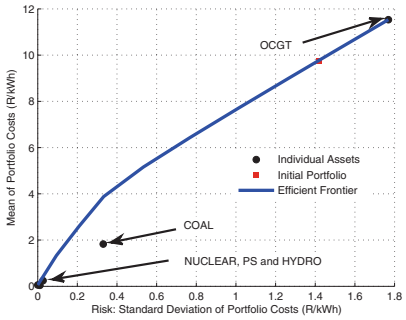

Fig. 1. Risk and cost of Eskom's generation mix fuel in 2013

Fig. 1 displays the efficient frontier using the individual assets' mean (average) costs and standard deviations of the individual assets' costs. Fig. 1 shows that the annual average fuel cost for OCGTs is extremely high, followed by coal. Nuclear, pumped storage and hydro all have least fuel costs. The same behavior is observed for the respective fuel cost risks.

The initial portfolio (the current generation mix) is made up of coal, hydro, OCGTs, nuclear and pumped storage fuel costs in $Rands/kWh$ and the respective weights of these technologies in the initial portfolio are as presented in Table III.

TABLE III
Eskom's annual fuel cost ($Rands/kWh$) split in 2013

Technology	**%**
Coal	15.7
Hydro	0.4
Open cycle gas turbines	81.8
Nuclear	0.3
Pumped Storage	1.8

It can be seen from Table III, that the initial portfolio fuel cost is dominated by open cycle gas turbines' fuel cost. What this means is that Eskom is spending more on the OCGTs' fuel than all other technologies.

In Fig. 1 it looks like the initial portfolio is on the efficient frontier, however zooming in Fig. 1, Fig. 2 is obtained. Fig. 2 shows that the initial portfolio is not on the efficient frontier. This means that the current electricity generation fuel mix is not efficient. The risk of the initial portfolio is 1.421 and the cost is $9.726\ R/kWh$. Two portfolios on the efficient frontier can be determined from the initial inefficient portfolio. One has the same risk as the initial portfolio and the other has the same cost as the initial portfolio. The portfolio with the same risk as the initial portfolio costs $9.781\ R/kWh$ and the one with the same cost as the the initial portfolio has a risk of 1.410. The portfolio with the same risk as the initial portfolio, cost slightly more and the one with the same cost has less risk.

Using the efficient frontier line in Fig. 1, 10 equally spaced portfolios are derived and presented in Table IV. Fig. 3 shows the contribution of each of the technologies in the 10 equally spaced portfolios.

The following can be derived from Fig. 3:

- Portfolio 1 consist of hydro only.
- Portfolio 2 is made up of 69% pumped storage, 25% coal and 6% OCGTs.
- Portfolio 3 has 59% coal, 28% pumped storage and 13% OCGTs.
- Portfolios 4 up to 10 are made up of coal and OCGTs, with coal decreasing from 79% in portfolio 4 to 0% in portfolio 10 and OCGTs increasing from 21% to 100%, respectively.

Table IV shows that the initial portfolio and the two corresponding efficient portfolios are all between portfolios 8 and 9 in Fig. 3. This area in Fig. 3 is dominated by OCGTs.

TABLE IV
COSTS AND RISKS OF THE 10 PORTFOLIOS ON THE EFFICIENT FRONTIER IN FIG. 1

Portfolio	1	2	3	4	5	6	7	8	9	10
Cost (R/kWh)	0.056	1.331	2.607	3.882	5.157	6.432	7.708	8.983	10.258	11.533
Risk	0	0.094	0.210	0.333	0.533	0.768	1.013	1.263	1.515	1.769

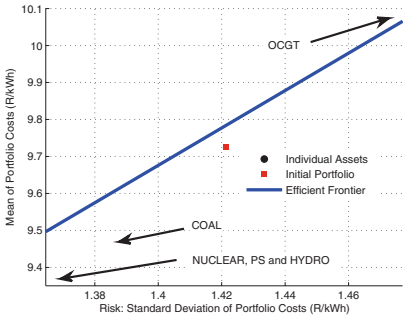

Fig. 2. Zooming in the initial portfolio in Fig. 1

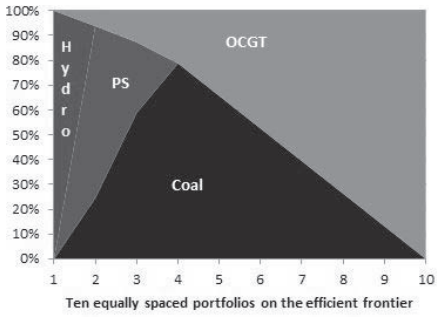

Fig. 3. Technology split of 10 portfolios on the efficient frontier

A. Reducing the Cost and Risk of SA Generation Fuel Mix

OCGT power stations were built to operate between 2 and 6 hours a day [15]. Different scenarios of using OCGTs from 2 hours a day (8%) to 6 hours a day (25%) are in Table V. For each scenario, an initial portfolio technology mix and the initial portfolio's cost and risk are presented. The case of using OCGTs for 6 hours a day is considered below. This seems to be a reasonable choice because there are 2 peak periods with a total of 7 hours a day.

If the OCGT cost in the initial portfolio in Fig. 1 is reduced by 75%, then the initial portfolio's cost and risk reduce as displayed in Fig. 4. The fuel split of the initial portfolio is on the last column of Table V. In Fig. 4 the cost of the initial portfolio has decreased to $6.842\ R/kWh$ and the corresponding risk has decreased to 0.874. Similar to Fig. 1, the initial portfolio in Fig. 4 is below the efficient frontier. The portfolio on the efficient frontier that has the same risk as the initial portfolio in this case costs $6.985\ R/kWh$. The portfolio that is on the efficient frontier but with the cost as the initial portfolio has a risk of 0.846. All the portfolios discussed here lie between portfolios 6 and 7 in Fig. 3. Portfolios between portfolio 6 and 7 in Fig. 3 use less OCGTs compared to portfolios between portfolio 8 and 9, where the initial portfolio in Fig. 1 lie.

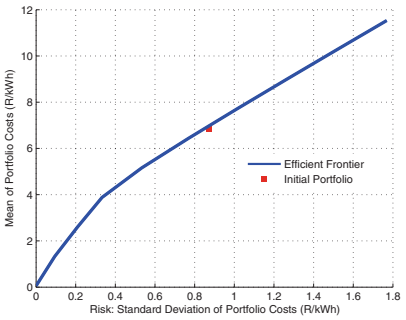

Fig. 4. Risk and cost of Eskom's generation mix - OCGTs fuel cost reduced by 75%

With the decrease in OCGT fuel, other technologies' fuel cost increased in the initial portfolio as shown in Table V.

It is possible to reach the initial portfolio fuel splits in Table V, as Eskom is currently building two coal stations, Medupi and Kusile with a combined total capacity of 9564 MW [13]. The primary energy cost for these new stations is expected to be higher than the current coal stations due to new coal contracts. A pumped storage station, Ingula with a total capacity of 1332 MW is also being built [13]. Ingula's primary energy cost is expected to remain at the same level as the current operation pumped storages, as the primary energy

TABLE V
INITIAL PORTFOLIO MIXES: SCENARIOS OF USING OCGTS BETWEEN 2 AND 6 HOURS A DAY

% of 24 hours	**8%**	**11%**	**14%**	**17%**	**20%**	**23%**	**25%**
Coal	63.2%	57.5%	52.8%	48.8%	45.3%	42.2%	40.5%
Nuclear	1.5%	1.3%	1.2%	1.1%	1.0%	1.0%	0.9%
PS	7.3%	6.7%	6.1%	5.7%	5.3%	4.9%	4.7%
Hydro	1.6%	1.5%	1.3%	1.2%	1.1%	1.1%	1.0%
OCGT	26.4%	33.0%	38.6%	43.2%	47.3%	50.8%	52.8%
Initial Portfolio Cost (R/kWh)	4.219	4.874	5.433	5.889	6.295	6.643	6.842
Initial Portfolio Risk	0.404	0.515	0.614	0.697	0.772	0.837	0.874

for pumped storages is water. The Department of Energy (DoE) has also entered into agreements with independent power producers (IPPs) to build renewable power stations, with a total capacity of $3916\ MW$ [16].

IV. CONCLUSION

PT has been applied to the case of Eskom's 2013 fuel generation mix. From the PT analysis carried out the results showed that:

- The correlation coefficients, $\rho_{i,j}$'s, between the technologies that form the SA's generation mix, are very high. $\rho_{hydro,OCGT}$ is the lowest at -0.0499. High $\rho_{i,j}$'s makes it impossible to reduce the generation mix risk.
- Along the efficient frontier, the portfolio with the lowest risk and lowest cost, consist of hydro only. Whereas, the portfolio with the highest risk and highest cost, consist of OCGTs only. The initial portfolio is closest to the portfolio with the highest cost and highest risk.

The Eskom's current fuel generation mix is not efficient because it has high cost and high risk. This is influenced by high cost of OCGTs fuel, which makes up 81.8% of the total generation mix fuel cost. By reducing the use of the OCGTs, the fuel cost and risk of the total generation mix also decreases. Also, by reducing OCGTs efficient portfolios with less risk and less cost become a possibility. This is possible as SA is currently building two coal, a pumped storage and renewables power plants.

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Appendix G

JESA Journal Paper

In appendix G is a paper that was published in the Journal of Energy in Southern Africa (JESA). This paper is also based in PT.

JOURNAL OF ENERGY IN SOUTHERN AFRICA

Assessing the costs and risks of the South African electricity portfolio: A portfolio theory approach

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Abstract
Portfolio theory is used to evaluate the cost and risk of the South African electricity generation portfolio in a bid to find out how the costs and risks of the South African electricity generation portfolio were managed following the 2007 and 2008 load-shedding events. The costs considered are fuel, environmental levy and operating and maintenance costs, for the Eskom power stations from 2008/09 to 2013/14. The results show that the current electricity generation mix is not efficient, due to high cost and risk; and following the 2007 and 2008 load shedding events the entire portfolio capacity was increased marginally and the open cycle gas turbine stations' fuel costs increased substantially. Future work would be to apply this study to the period following load-shedding in 2014 and 2015.

Keywords: efficient portfolio, risk, electricity, cost

Highlights
- The 2013/14 South African electricity-generating portfolio is not efficient.
- The portfolio has high cost and high risk.
- The OCGT's fuel cost and risk contributed to the 2013/14 portfolio's inefficiency.

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1. Introduction

1.1 South African generating landscape

Eskom generates approximately 95% of the electricity used in South Africa (Eskom, 2011). Eskom Holdings SOC Limited (Eskom) is a state-owned company. In the study period the South African electricity portfolio consisted of coal, hydro, open cycle gas turbine (OCGT), nuclear, pumped storage (PS) and wind stations. Table 1 presents the generation capacities that were used to assess the costs and risks of the South African electricity portfolio. It shows that from 2008/09 (1 April 2008 to 31 March 2009) to 2013/14 South Africa's electricity generation capacity increased slightly. Minor changes are observed in coal and nuclear capacities because Camden, Grootvlei, and Komati coal stations which had been mothballed were returned to service; Arnot coal station was upgraded; and Koeberg nuclear power station was enhanced. During the period covered in Table 1, total capacity increased by 1 492 MW.

Figure 1 presents the normalised electricity consumption met by each technology in the generating portfolio during the study period. Electricity consumption for coal was calculated using energy sent-out data and operating hours per coal power station. The power plants that were returned to service were excluded from the calculations as some of the units were commissioned during the period, 2008/09 to 2013/14. The data was normalised because of the huge differences in the technology capacities. Figure 1 indicates that the electricity consumption met by coal stations started to decrease from 2011/12. The coal stations' unplanned capacity loss factor increased from 2.95% in 2010/11 to 14.24% in 2013/14 as observed in the data provided by Eskom. It is possible that the consumption met by coal stations' decrease was influenced by the increase in the unplanned capacity loss factor, which is a measure of lost energy caused by unplanned production interruptions due to equipment failures and other plant conditions.

As seen in Figure 1, with the exception of the capacity met by OCGT stations, electricity consumption met by other technologies also decreased as from 2011/12. Consumption met by coal and hydro stations continued to decrease in 2012/13. In the period 2012/13 to 2013/14 the consumption met by OCGT stations continued to increase to 1.77. Consumption met by nuclear stations increased to 1.14 and that of PS stations increased to 0.65. This implies that, to a large extent, electricity consumption not met by the coal stations was met by OCGT stations and to a lesser extent by nuclear and PS stations. Normally, OCGT and PS stations are peaking stations, which are operated during peak periods and in emergency situations (Eskom, 2011; 2012; 2013), while coal stations are base stations.

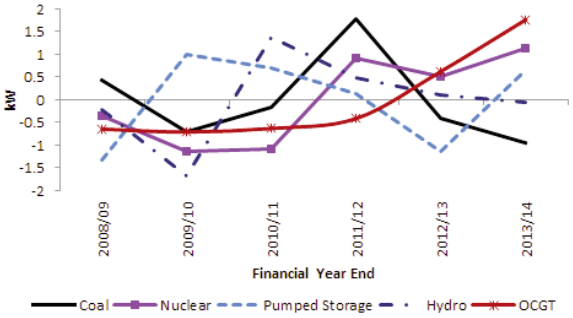

Figure 1: Normalised electricity consumption per technology.

Table 1: Generation capacities of South Africa's electricity portfolio, 2008–2014.

MW	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14
Coal	34 294	34 658	34 952	35 487	35 718	35 726
Hydro	600	600	600	600	600	600
Nuclear	1 800	1 800	1 830	1 830	1 860	1 860
OCGT	2 409	2 409	2 409	2 409	2 409	2 409
PS	1 400	1 400	1 400	1 400	1 400	1 400
Wind	3	3	3	3	3	3
Total	40 506	40 870	41 194	41 729	41 990	41 998

1.2 Portfolio theory

The objective of this paper is to apply portfolio theory to assess the costs and risks of the South African electricity generation portfolio following load-shedding in 2007 and 2008.

It can be noted that the application of portfolio theory (PT) to assess the costs and risks of the South African generating portfolio has not been done before. PT applied in this paper is as defined by Harry Markowitz in Markowitz (1952) and in Markowitz (1959) and not by Maslow (1943). Portfolio theory is sometimes referred to as modern portfolio theory (model), Markowitz model (theory), mean-variance model (theory), and portfolio optimisation theory (model) (Skarica & Lukac, 2012). PT has been used in other countries to evaluate electricity-generation portfolios and this is discussed in Bar-Levy and Katz (1976), Awerbuch (1993), (Awerbuch & Berger (2003), Beltran (2009), Krey and Zweifel (2006), Zhu and Fan (2010), and Cunha and Ferreira (2014).

1.3 Markowitz efficient portfolio

Markowitz (1959) defined a good financial portfolio as more than just a long list of financial securities and bonds, a balanced whole that provides the investor with protection and opportunities with respect to a wide range of contingencies. Markowitz defined portfolio as an efficient portfolio if:

- the *P* is obtainable;
- there is portfolio *Q* whose expected return is greater than *P*'s, then the risk of *Q* is greater than *P*'s; and
- there is portfolio *S* whose risk is less than *P*'s then the expected return of *S* is less than P's.

A curve that joins all the portfolios that behave like portfolio *P* is called an efficient frontier, and all other portfolios that do not lie on the efficient frontier are inefficient portfolios. Mathematically, PT reduces to Equations 1–5 in the case of a portfolio made up of *N* securities (Markowitz, 1959):

$$\text{Max } R = \sum_{i=1}^{N} X_i \mu_i,$$

$$\text{s.t. } \sigma = \left[\sum_{i=1}^{N}\sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j\right]^{1/2} \quad (1)$$
$$\sum_{i=1}^{N} X_i = 1, \text{ and } X_i \geq 0 \; \forall \; i$$

Where:

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} r_{it} \quad (2)$$

$$cov(r_i, r_j) = E\left[(r_i - \mu_i)(r_j - \mu_j)\right], i \neq j \quad (3)$$

$$\rho_{ij} = cov(r_i, r_j) \Big/ \sigma_i \sigma_j \quad (4)$$

$$\sigma_i = \sqrt{E(r_i - \mu_i)^2} \quad (5)$$

- X_i is the weight of a financial security in the portfolio, financial securities and their weights are chosen by an investor;
- μ_i is the average return of a financial security over a given period;
- r_{it} is the actual return of a financial security at time;
- T is the total historic period (number of: years or months or days, etc);
- σ is the portfolio standard deviation, representing portfolio risk;
- σ_i is the standard deviation for security;
- E is the expectation or average;
- ρ_{ij} is the correlation coefficient between securities; and
- $cov(r_i, r_j)$ is the covariance between securities and emphasises portfolio diversification.

Diversification is about investing in many securities from different industries, where securities' gains and losses will be influenced by different factors. Diversification also reduces the portfolio's risk, but does not eliminate it (Markowitz, 1959).

1.4 Portfolio theory in electricity generation

Although PT has been widely used in electricity generation, this section is limited to cases where actual historic electricity generation costs were used in the assessment. This approach excludes cases where: data was estimated (Zhu & Fan, 2010); proxy data was used (Beltran, 2009); and data was gathered from literature (Paz et al., 2014).

United States utility companies were facing a problem of optimising their fossil fuel mix. Bar-Lev and Katz (1976) applied PT on a regional basis to determine if the 1969 US electricity utilities were efficient users of fossil fuel. The regions were using a combination of coal, oil and gas. The results showed that, although the regions fuel mixes were efficiently diversified, fossil fuel mixes in three regions were on the respective efficient frontier, and below the efficient frontier in another six regions. The risk for these regional portfolios was also found to be high.

Awerbuch, 2000 applied PT to the 1998 US electricity portfolio, which was made up of coal and gas. The results showed that the US mix was not on the efficient frontier. Awerbuch showed that by adding 6% of renewables the 1998 portfolio risk would be reduced. The efficient portfolio reduced coal from 77% to 65% and increased gas from 23% to 35%. Awerbuch (2006) used PT in analysing the following portfolios: year 2000 and projected to 2010 for the European Union generating portfolio; year 2002 for the US, and year 2000 and projected to 2010 for Mexico. The results showed that all these portfolios were not efficient because of high costs and high risks. The efficient alternative portfolios replaced the fossil fuels with renewables.

Krey and Zweifel (2006) applied PT to determine if the year 2003 electricity generation technology mix for Switzerland and US were efficient. The Swiss portfolio consisted of nuclear, run-of-river, storage hydro, and solar, whereas the US portfolio was made up of coal, nuclear, gas, oil and wind. The results showed that Swiss portfolio was inefficient, due to high costs and high risk, and the US portfolio was not efficient due to high costs.

Cunha and Ferreira (2014) applied PT to Portugal's 2012 electricity generation portfolio, which was made up of renewable resources (wind, small hydro and photovoltaic), fossil fuels and imports. The results showed that the portfolio was not efficient, but close to the efficient frontier.

The review above shows that in almost all the cases, irrespective of the electricity portfolios used, the mixes are inefficient according to the PT. In this paper we seek to answer the question: What is the case of the South African electricity generation portfolio? Section 2 discusses the data used in the assessment period; Section 3 represents the methodology; Section 4 discusses the results and Section 5 is the conclusion.

2. Data

The costs focused on are the fuel costs used in the electricity generation plants, the generating maintenance costs, and the environmental levy.

2.1 Fuel costs, environmental levy and maintenance costs

The fuel costs data was obtained for coal, water, diesel, and uranium. There is no carbon tax in South Africa, but an electricity environmental levy was introduced in 2009 by the Department of Finance to apply to the sales of electricity generated from non-renewable sources (Eskom, 2009). Environmental levy rates are presented in Table 4.

Table 2: South African environmental levy rates (Gordhan, 2011; 2012; 2013; 2014; Eskom, 2009).

Effective date	*Cents/kWh*
1 July 2009	2
1 April 2011	2.5
1 July 2012	3.5

In the absence of carbon tax, the levy serves to promote energy efficiency and encourage lower greenhouse gas emission (Nene, 2015). According to Nene, steps are being taken to make sure that electricity users also pay the levy.

In 2015 a carbon tax bill was released for comment by the Treasury (Republic of South Africa, National Treasury, 2015). The bill states that the tax will be levied in respect of the sum of the greenhouse gas emissions expressed as carbon dioxide equivalent resulting from fossil fuel combustion, fugitive emissions in respect of commodity, and industrial process or product use. The carbon tax rate will be R120 per tonne of carbon dioxide equivalent of the greenhouse gas emissions from 1 January 2017. At this stage it is not clear if the environmental levy will be phased out when as the carbon tax becomes effective. The maintenance costs discussed in this paper are the operating and maintenance costs per power station, excluding head office operating costs.

2.2 Data collected for the study

Data collected was the actual annual fuel costs in rand, actual maintenance costs in rand, and actual annual energy sent out in GWh for each of the 22 power plants (Eskom, 2013). The maintenance and operating costs are made up of the respective stations' actual operating, repair and maintenance costs. The environmental levy costs in c/kWh were calculated using Table 4 and actual annual energy sent out for coal, nuclear and open cycle gas turbines stations. Fuel and maintenance costs in c/kWh were calculated from the costs in rand and the actual annual energy sent out for each generation technology.

Data was collected from 2008/09 to 2013/14, but the fuel cost data for OCGT, PS and hydroelectric power stations was available only from 2009/10. The 2008/09 fuel costs data for the OCGT, PS and hydroelectric power stations were derived by reducing the 2009/10 fuel cost data by 5.93%, which is the Eskom cost of electricity increase between the two years (Eskom, 2010). The start in period of 2008/09 data corresponds with Eskom's first financial year following load-shedding in 2007 and 2008. The data was analysed using Matlab software with the financial toolbox.

3. Methodology

It is important to note that there are major differences between financial market portfolios, for which PT was first developed, and portfolios in electricity generation. The major differences are that:

- financial market portfolios focus on returns whereas electricity generation portfolios focus on costs. The objective of the financial markets is to maximise portfolio returns whereas the objective of the electricity generation is to minimise portfolio costs;
- financial assets are more easily disposable than electricity generation assets like coal-fired plants (Awerbuch & Berger, 2003); and
- financial securities are almost infinitely divisible, such that a portfolio can contain between 0% and 100% of a given security, which is not the case with electricity generation assets (Awerbuch & Berger, 2003).

Irrespective of these differences, PT is commonly used for valuation of electricity portfolios (Awerbuch & Berger, 2003). Equations 1–5 are modified by replacing securities with the technology cost under consideration. In the case of fuel costs, Equations 6-11 are obtained, and used to analyse fuel and environmental costs and also fuel and maintenance costs.

Min total fuel cost (c/kWh) = coal fuel cost + hydro fuel cost + nuclear fuel cost + OCGT fuel cost + pumped storage fuel cost

$$\text{s.t } \sigma = \left[\sum_{i=1}^{N}\sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j\right]^{1/2}$$

I,j = fuel cost of coal, hydro, nuclear, OCGT and pumped storage

$$X_{coal} + X_{hydro} + X_{nuclear} + X_{OCGT} + X_{pumped\ storage} = 1,\ X_i \geq 0 \quad (6)$$

where Equation 7 was used to calculate the weight of coal fuel cost and the fuel cost weights for other technologies by substituting coal by the respective technologies.

$$X_{coal} = \frac{\text{Coal fuel cost}}{\text{Total fuel cost}} \quad (7)$$

Equation 8 was used to calculate the average of coal fuel cost and the average fuel costs for other technologies by substituting coal by the respective technologies.

$$\mu_{coal} = \frac{1}{6}\sum_{i=2008/09}^{2013/14} \text{coal fuel cost}_i \quad (8)$$

Equation 9 was used to calculate the standard deviation of coal fuel cost and the standard deviations of fuel costs for other technologies by substituting coal by the respective technologies.

$$\sigma_{coal} = \sqrt{E(\text{coal fuel cost} - \mu_{coal})} \quad (9)$$

The standard deviation is the measure of the fuel cost risk (Markowitz, 1959). The higher the standard deviation the higher is the risk and vice versa. Also, the more stable the fuel cost movement along the study period the less the fuel cost risk, and the more fluctuations on the fuel cost movement the higher the risk. Equation (10) was used to calculate the covariance between coal fuel cost and hydro fuel cost and the covariance of other pairs of fuel costs for other technologies.

cov(coal fuel cost, hydro fuel cost) = E[(coal fuel cost – μ_{coal}) (hydro fuel cost – μ_{hydro})] (10)

Covariance is a measure of the extent to which the pair of fuel costs moves up or down together. A portfolio with diversified electricity generation technologies will have low covariance, because the fuel costs for the generation technologies' fuel costs will not be affected by same factors. Low covariance also indicates lower portfolio risk (Markowitz, 1959).

$$\rho_{coal,hydro} = \text{cov(coal fuel cost, hydro fuel cost)}/\sigma_{coal}\,\sigma_{hydro} \quad (11)$$

The correlation coefficient in Equation 11 is derived from Equations 9 and 10. 'The correlation coefficient provides a more easily interpreted measure, than does the covariance, of the extent to which the two variables tend to move together' (Markowitz, 1959).

$$-1 \leq \rho_{coal,hydro} \leq 1 \quad (12)$$

Equation 11 shows that if coal fuel cost is always an exact positive multiple of hydro fuel cost, then $\rho_{coal,hydro} = 1$. If coal fuel cost is always an exact negative multiple of hydro fuel cost, then $\rho_{coal,hydro} = -1$. If coal fuel cost moves independent of , then $\rho_{coal,hydro} = 0$. Independence always imply zero correlation coefficient but zero correlation coefficient does not imply independence (Markowitz, 1959).

4. Results

4.1 Case 1: Fuel costs

Eskom generation fuel-mix cost data from 2008/09 to 2013/14 was used to obtain the correlation coefficients presented in Table 3 Pearson's correlation coefficient is used which measures the linear relationship between two variables (Stopher, 2012). Although there are other correlation coefficients which measure more relationships than the linear one, as discussed in Maturi and Elsayigh (2010) and Reshef et al. (2011), Pearson's was used by Markowitz (1959) for portfolio theory.

Table 3 shows that the fuel costs tend to move up and down together but not in perfect unison, hence their correlation coefficients lie between zero and one (Markowitz, 1959). Ideally, fuel costs that move independent of each other would be better, as they would reduce the portfolio risk. Correlation coefficients in Table 3 were calculated using Equation 11. Figure 2 displays the efficient frontier calculated using Equations 6–11.

The efficient frontier is a solid curve formed by the efficient portfolios. The average fuel costs and standard deviations (risks) of the different technologies displayed in Table 4 were obtained from Figure 2. From this point onwards, average fuel costs and costs will be used interchangeably.

Table 3: Correlation coefficients for Eskom's fuel mix.

	Coal	*Nuclear*	*PS*	*Hydro*	*OCGT*
Coal	1.000	0.792	0.893	0.741	0.820
Nuclear		1.000	0.740	0.690	0.629
PS			1.000	0.867	0.905
Hydro				1.000	0.575
OCGT					1.000

Table 4: Technologies' fuel average costs and standard deviations.

Technology	Fuel average cost (C/kWh)	Fuel costs risk (c/kWh)
Coal	12.34	2.96
Hydro	2.97	0.51
Nuclear	4.85	1.30
OCGT	243.96	46.49
PS	12.75	1.94

The centres of the circles in Figure 2 on the efficient frontier represent ten equally spaced efficient portfolios. Looking the efficient frontier from the bottom left to the top right, one can observe that:

- The centre of the first circle on the left has hydro. This shows that the efficient portfolio consisting of hydro only has less risk and cost compared to other nine efficient portfolios. Hydro's average fuel cost was calculated using Equation 8 and hydro's fuel cost standard deviation was calculated from Equation 9. Also, as can be seen in Table 4, hydro has both the least average cost and least risk compared to other technologies.
- The 2013/14 fuel portfolio is the square between the 8th and the 9th efficient portfolios. This part of the efficient frontier has portfolios with high cost and high risk. The 2013/14 fuel portfolio weights were derived from Equations 6 and 7, using 2013/14 fuel costs. The 2013/14 mix is dominated by OCGT's, this explains its location in Figure 2. The average cost of the 2013/14 fuel portfolio is 213.63 with a corresponding risk of 40.68 .
- The centre of the last circle on the right has OCGTs. This shows that the efficient portfolio with highest risk and cost compared to other nine efficient portfolios consist of OCGTs. Also, as can be seen in Table 4 OCGTs have both the highest average cost and the highest risk compared to other technologies.

Table 5 displays the average fuel costs and standard deviations (risks) of the ten efficient portfolios starting from bottom left to the top right of Figure 2. The first efficient portfolio on the left will be labelled

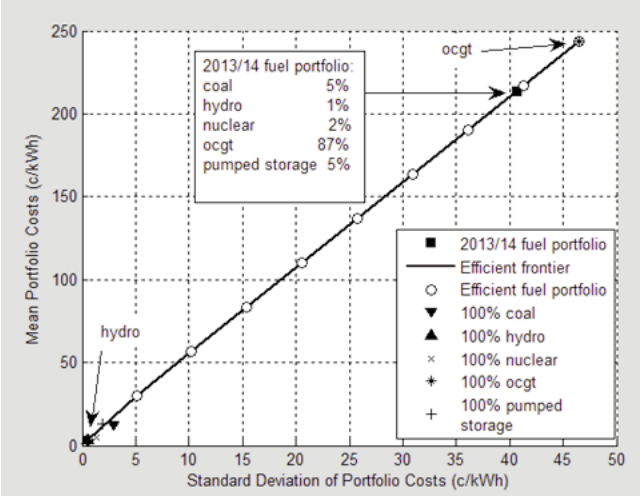

Figure 2: Technology allocation portfolio – fuel costs.

Table 5: Costs and risks of the 10 efficient portfolios in Figure 2.

Efficient portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Cost (c/kWh)	2.97	29.75	56.53	83.30	110.08	136.86	163.63	190.41	217.18	243.96
Risk (c/kWh)	0.51	5.11	10.25	15.42	20.60	25.77	30.95	36.13	41.31	46.49

as efficient portfolio 1, the next as efficient portfolio 2 and so on until efficient portfolio 10 on the top right.

Table 5 confirms that hydro is in the centre of efficient portfolio 1, as this efficient portfolio cost and risk matches hydros as displayed in Table 4. Similarly, OCGTs are in the centre of efficient portfolio 10, as this portfolio cost and risk matches OCGTs as displayed in Table 4. The actual technology allocation of the efficient portfolios in Table 5 is shown in Figure 3.

As seen in Figure 3, efficient portfolios 2–9 consist of pumped storage on a decreasing scale from 93% to 12% and OCGTs on an increasing scale from 7% to 88%, respectively.

Figure 3 and Table 5 show that the portfolios with less cost and risk are dominated by hydro and pumped storage. As seen in Table 1, the capacity of both these technologies will not be sufficient to provide electricity in South Africa. Figure 3 and Table 5 also show that the portfolios that are dominated by OCGTs have high cost and risk.

As per results, the efficient portfolios in Figure 3 suggest that South Africa has to move away from coal and nuclear completely. It would take a while for Eskom to do this because it is currently building two new coal power stations with a total capacity of 9564 MW. Also there are about five existing coal stations which are below 30 years and the nuclear station is about 30 years old. These stations still have another 20 to 30 years before decommissioning (Eskom, 2013). Currently, South Africa does not have much choice but to use all the technologies that are available due to electricity generation capacity constraints. Figure 4 is obtained by taking a closer look at the efficient frontier starting on the bottom left-hand side of Figure 2.

Figure 4 shows that the pumped storage is above the efficient frontier and both the nuclear and coal are below it. As we have seen in Figure 3, pumped storage appears on the efficient portfolios unlike coal and nuclear.

Figure 5 shows that the 2013/14 fuel portfolio is below the efficient frontier. Portfolios P and Q are the efficient alternatives to the 2013/14 fuel portfolio. Portfolio Q is desirable because of less cost and risk, compared to portfolio P. Even though portfolio Q is on the efficient frontier it is on the high cost side of the efficient frontier, which is not desirable.

4.2 Case 2: Fuel and environmental costs

In this section the same analysis presented in section 4.1 is performed, except that the environmental costs are added to the fuel costs for coal, nuclear and OCGT stations. Coal, nuclear and OCGT are the technologies affected by the environmental levies. From the data analysis Figure 6 is obtained. The average costs increased as follows:

- coal from 12.34 (fuel only) to 14.47 c/kWh (fuel and EL), a 17% increase;
- nuclear from 4.85 to 6.99 c/kWh, a 44% increase; and

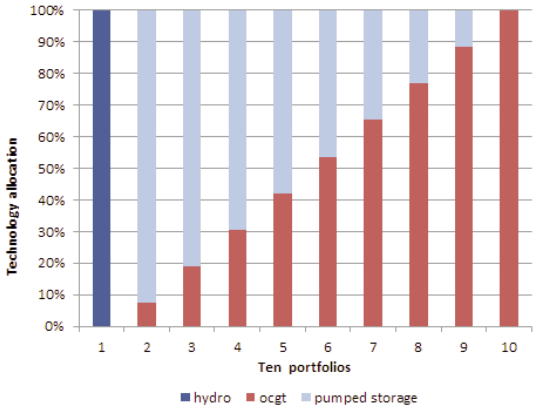

Figure 3: Technology allocation of the ten efficient portfolios.

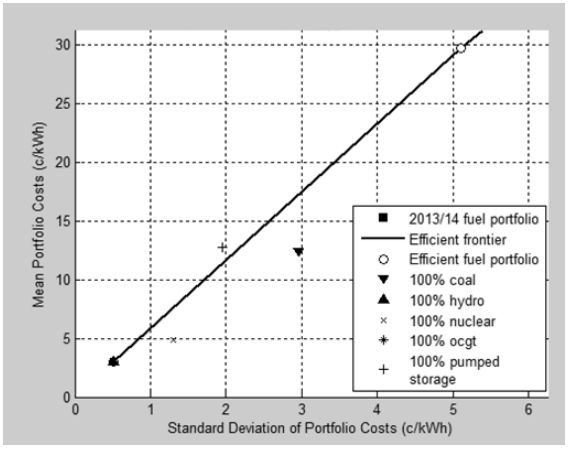

Figure 4: Figure 3 zoomed – 1.

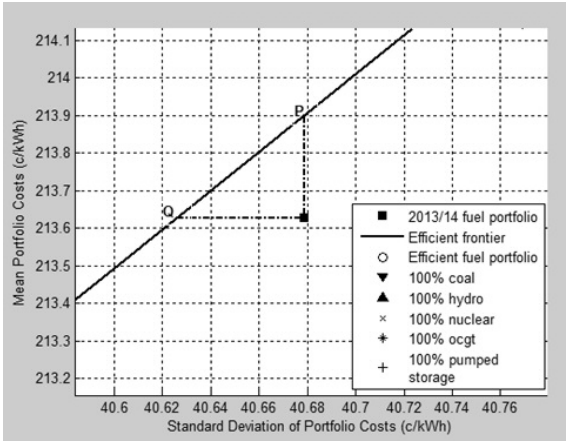

Figure 5: Figure 3 zoomed – 2.

- the OCGT from 243.96 to 246.17 c/kWh; a 1% increase.

The 2013/14 fuel and environmental levy portfolio's cost (210.99 c/kWh) decreased when compared to 2013/14 fuel portfolio's cost (213.63 c/kWh). This shows that environmental levy costs as currently determined have little effect in discouraging nonrenewable electricity generation.

4.3 Case 3: Fuel and operation and maintenance costs

Similarly to case 2, in this case the operation and maintenance (O&M) costs were also added to the fuel costs of each technology and the analysis results are shown in Figure 7. When adding the O&M costs to the fuel costs, the following major increases were observed when compared to fuel only costs:

- Nuclear's average cost increased from 4.85 (fuel only) to 11.48 (fuel and O&M), a 137% increase.
- Hydro's average cost increased from 2.97 (fuel only) to 5.44 (fuel and O&M), a 83% increase, and
- Coal's average cost increased from 12.34 (fuel

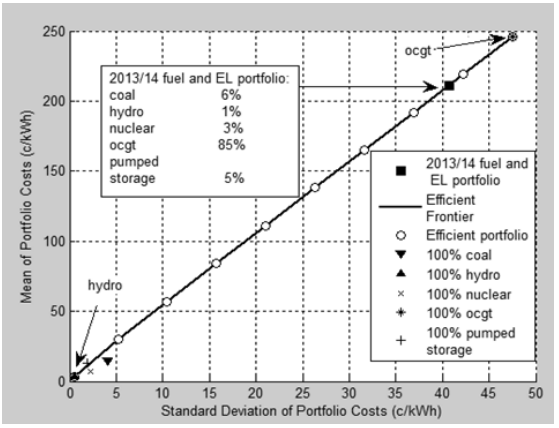

Figure 6: Technology allocation portfolio – Fuel and environmental costs.

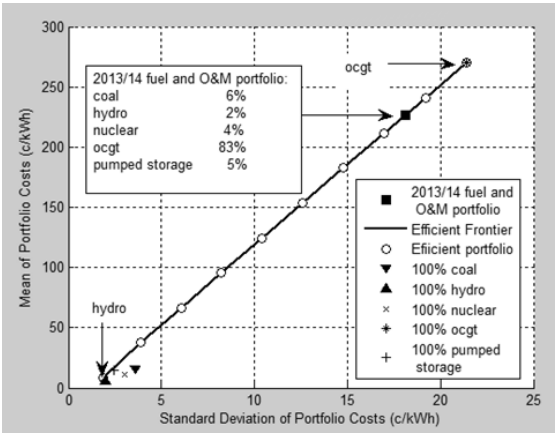

Figure 7: Technology allocation portfolio – fuel and O&M costs.

only) to 15.60 (fuel and O&M), an increase of 26%.

The 2013/14 fuel and O&M portfolio cost increased by 6% (226.18 c/kWh) when compared to 2013/14 fuel portfolio (213.63 c/kWh). Even though the 2013/14 fuel and O&M portfolio cost increased, the corresponding risk decreased from 40.68 to 18.14 c/kWh, 55% decrease. This shows that the fuel plus O&M costs were more stable compared to fuel only costs. The low risk is good, and it would have been better if it was observed in the case of fuel costs.

5. Conclusions

The analysis results show that South Africa's 2013/14 fuel portfolio is inefficient and has high risk. Following the 2007 and 2008 load-shedding, the entire portfolio capacity was increased by 3.7% and the OCGT stations fuel costs increased substantially. The high fuel costs have been incurred in producing electricity, when the electricity demand that was not met by coal stations was largely met by OCGT stations.

The efficient frontier based on fuel cost only shows that the efficient portfolios with minimum costs and low risk suggest that South Africa should move away from coal and nuclear, increase its exposure to hydro and pumped storage and reduce the exposure to OCGTs.

Adding environmental levy to the fuel costs, the analysis showed little to no impact in encouraging

the lower green emission technologies indicating the limited effect on the levy in promoting green technologies and suggesting the need to reconsider this policy approach.

Operation and maintenance costs were added to the fuel costs and the analysis showed that the initial portfolio cost increased slightly and the risk was reduced. This low risk is desirable for the fuel only portfolio.

Future work would be to apply this study to the period following the 2014 and 2015 load shedding events.

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Appendix H

ORiON Journal Paper

In appendix H is a paper which was published in the ORiON journal. This paper is based on two stage stochastic programming (TSSP) which is discussed in chapter 6.

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Application of stochastic programming to electricity generation planning in South Africa

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Abstract

A two-stage stochastic programming model is used to solve the electricity generation planning problem in South Africa for the period 2013 to 2050, in an attempt to minimise expected cost. Costs considered are capital and running costs. Unknown future electricity demand is the source of uncertainty represented by four scenarios with equal probabilities. The results show that the main contributors for new capacity are coal, wind, hydro and gas/diesel. The minimum costs obtained by solving the two-stage stochastic programming models range from R2 201 billion to R3 094 billion.

Key words: Two-stage stochastic programming, planning, electricity generation, scenario, expected cost, capacity.

1 Introduction

According to Sen & Zhou [34] stochastic programming (SP) deals with a class of optimisation models and algorithms in which some of the data may be subjected to significant uncertainty. The authors suggest that SP models are appropriate when data evolves over time and decisions need to be made prior to observing the entire data stream. This is also the case in this work since electricity generation expansion plans are made in advance and amidst uncertain future electricity demand. The approach followed in this paper is based on SP, which was introduced by Dantzig [9].

In this paper, a two-stage stochastic programming (TSSP) model for electricity generation expansion planning in South Africa, is proposed. Advantages of adopting SP are discussed

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by Higle [22] and Bisschop [6], and a general form of a linear TSSP problem is given by Shapiro *et al.* [32] as seen in equations (1) to (4):

$$\min \quad c^T x + E_\xi[q^T(\omega)y(\omega)], \tag{1}$$

$$\text{s.t.} \quad Ax = b, \tag{2}$$

$$T(\omega)x + W(\omega)y(\omega) = h(\omega), \tag{3}$$

$$x, y(\omega) \geq 0. \tag{4}$$

Where:

- x is a decision vector whose values are to be calculated in stage one;
- c, A, and b are known matrices corresponding to x, with sizes $n_1 \times 1$, $m_1 \times n_1$ and $m_1 \times 1$, respectively;
- $\xi = \xi(\omega)$ which emphasises that ξ is a random vector;
- $y(\omega)$ is the second stage decision variable whose values are to be calculated in stage two;
- $W(\omega)$, $q(\omega)$, $h(\omega)$ and $T(\omega)$ are matrices corresponding to $y(\omega)$ with sizes $m_2 \times n_2$, $n_2 \times 1$, $m_2 \times 1$ and $m_2 \times n_1$, respectively. For a given realisation of ω, the matrices $q(\omega)$, $h(\omega)$ and $T(\omega)$ become known;
- $\xi^T(\omega) = (q^T(\omega), h^T(\omega), T_1(\omega), \cdots, T_{m_2}(\omega))$; and
- E_ξ represents the mathematical expectation with respect to ξ.

In this work, stage one of the proposed TSSP model determines the investment costs for new capacity that will meet unknown future electricity demand. Stage two allocates available capacity to the future electricity demand. The objective is to minimise investment costs with uncertainty in future electricity demand. TSSP is adopted because the methodology:

- is appropriate when electricity demand unfolds over time and decisions need to be made prior to knowing what the entire electricity demand will be, and
- differentiates between what is known and what remains uncertain when decisions are made.

The paper is organised as follows, the application of SP in electricity generation planning is discussed in Section 2. A brief discussion about scenarios is provided in Section 3. The data used in the study is explained in Section 4 and the methodology followed is presented in Section 5. The results obtained are presented in Section 6 and the conclusion is in Section 7. Following the conclusion are Appendices A to J. Appendix A provides more details on existing capacity. Details for committed capacity are in Appendix B. Assumed capacity decommissioning schedules are in Appendices C to E. Input data for potential new technologies is in Appendices F to J.

2 Stochastic programming in electricity generation capacity planning

The WWF South Africa (WWFSA) [66] proposed an increase in renewable generation capacity into the South African system, from between 6% and 9% as suggested by [37],

to between 11% and 19% by 2030. The model used by WWFSA [66] was deterministic for system performance but probabilistic for cost analysis. The WWFSA results showed that the annual renewable energy production in the South African system can be as high as 25% in 2030, if the proposed increase is implemented. According to Birge & Louveaux [5] one of the shortcomings of a deterministic model is that it can only use one scenario at a time. SP models have the capability of solving all the scenarios simultaneously and provide an optimal solution [5]. Hence, an SP model is used in this paper.

TSSP was used by Albornoz *et al.* [2] in Chile over a ten year planning horizon. Even though the Chile electricity industry is privately owned, it is regulated. The uncertainty considered by the authors was the future availability of the thermal power plants which were in operation. Albornoz *et al.* concluded that the TSSP results were realistic and of a better quality compared to the deterministic approach. The TSSP discussed in this paper is implemented in the South African electricity industry, which is largely state owned unlike the Chile case but also regulated.

Birge & Louveaux [5] discussed multi stage SP models which was later reduced to two-stage programming models. Birge & Louveaux's discussion was based on the TSSP model, where electricity demand and costs of various power plants to meet future electricity demand were sources of uncertainty. Bisschop [6] applied TSPP with the aim of determining new power plant design capacities that will meet an increased electricity demand. Bisschop's objective function was minimising daily costs consisting of a fraction of capital costs for building new design capacity, operating cost associated with the allocation decision, and the cost of importing electricity.

The model by Bisschop is similar to the Birge & Louveaux [5] two-stage example, except that the total investment cost was not constrained to a budget and the existing capacity was considered, whereas Birge & Louveaux did not do so.

In this work, TSSP is applied to the South African electricity generation expansion planning problem for the period 2013 to 2050. The objective was to determine new capacities that will meet electricity demand at minimum cost. The TSSP is implemented for a regulated electricity industry, where existing capacity was considered but without a budget constraint.

3 Scenario analysis

According to Milligan *et al.* [28] scenario analysis is the most common representation of uncertainty in stochastic power systems research and this is also the approach used in this study.

Lindgren & Bandholding [27] defined scenario planning as a combination of scenario analysis and strategic planning. Amer *et al.* [1] used scenario, scenario planning and scenario analysis interchangeable. According to Schoemaker [33], "scenario planning stands out for its ability to capture a whole range of possibility in rich details", when compared to other managerial tools for strategic planning. According to Lindgren & Bandholding [27] there is more than one definition of scenarios. However, these authors define scenarios

as a vivid descriptions of a plausible future [27]. According to Lindgren & Bandholding scenario planning is not a well defined field.

There is no optimal number of scenarios according to Ameer *et al.* [1], however the most recommended range is from 3 to 6. The following four generic scenarios were defined by Zahradnickova & Vacik [67]:

- Optimistic scenario
- Basic scenario
- Pessimistic scenario
- Realistic scenario

There are both qualitative and quantitative scenarios [27]. The Forest of Broceliande [44] website defined qualitative scenarios as possible futures in the form of narrative text or story lines. Quantitative scenarios provide tables and figures incorporating numerical data [44]. The scenarios used in this study are quantitative. Although there is no one scenario development technique, generic steps for scenario development is proposed, see [1] for detail.

According to the South African Department of Energy [38] the IRP in the South African context is the national electricity long term plan which directs the expansion of electricity supply over a given period. In the South African Integrated Resources Plan (IRP) 2010-2030 update report [37] (IRP2010 update), scenarios were defined as a particular set of assumptions and set of future circumstances, providing a mechanism to observe the outcomes from these circumstances. The demand scenarios used in this study were taken from the IRP2010 update and details about these scenarios are shown in Figure 1.

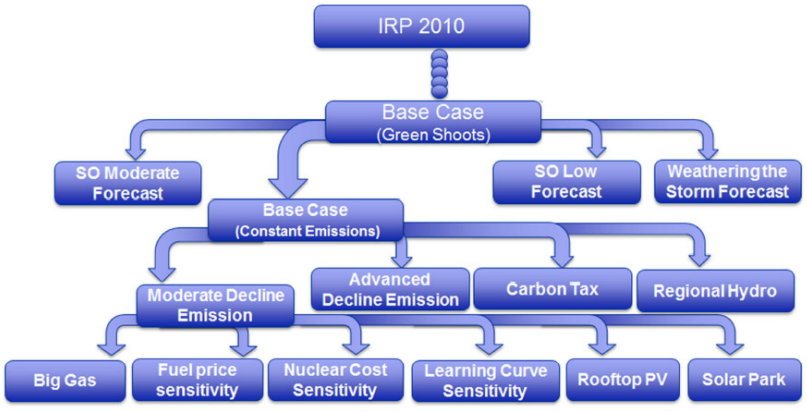


Figure 1: *All scenarios considered in the IRP 2010–2013 report [37].*

4 Data

The data used in this study was taken from the IRP2010 update report [37] since it contained demand scenarios which showed that there was uncertainty about the future demand. The IRP2010 update report also contained more detailed data about the potential technologies when compared to previously published IRP reports. The availability of this complete data made the application of the TSSP possible. The planning period used in the IRP2010 update report was 2013 to 2050, which was also used in this study. In the research work carried out the following data was used:

- The national electricity forecasted demand data. There were four demand scenarios and are presented in Figure 2 in Section 4.1.
- The national existing capacity which was meeting the demand in 2013. Details of this data are in Appendix A.
- The capacity that was committed by the minister of energy based on the IRP 2010-2030 (IRP2010) report [36] and the capacity committed by the public electricity utility in South Africa before the IRP2010 report. Details of this data are in Appendix B.
- A decommissioning schedule for the existing and committed capacity. Appendices C to E contain more details about this data.
- Potential technologies for meeting the forecasted demand together with the existing and committed capacity. The data used for the potential technologies is detailed in Appendices F to J.

4.1 Data for demand scenarios

The demand data was obtained from the IRP 2010-2030 update report [37]. The random variable, $\xi = S1, S2, S3, S4$ takes the values of the following demand scenarios with equal probability of 25%:

- Weathering the storm is represented by S1,
- System Operator (SO) Low Forecast by S2,
- Base Case Forecast by S3, and
- SO Moderate Forecast 4 by S4.

The demand data for the respective scenarios is displayed in Figure 2. The names given to the above scenarios are similar to the generic scenario names given by Zahradnickova & Vacik [67] in Section 3. The only difference is on weathering the storm forecast and the realistic scenario. Other scenarios in Figure 1 were not considered because they were all based on the same demand scenario. The demand data for the respective scenarios are shown in Figure 2.

As it can be seen in Figure 2, S1 has the lowest demand forecast compared to other scenarios from the middle to the end of the investigation period. Similarly, S4 has the highest demand forecast compared to the other scenarios within the same period. The underlying reason for these differences was due to the economic outlook of each scenario which is shown in Table 1. The actual South African average annual gross domestic

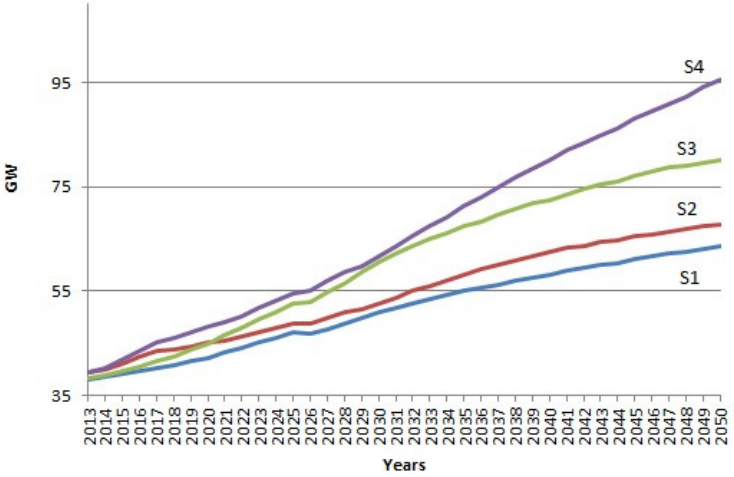


Figure 2: *Demand scenarios whose data was obtained from [37].*

Scenario	Average annual electricity demand from 2013 to 2030 (%)	Average annual electricity demand from 2031 to 2050 (%)	Assumed average annual GDP growth to 2030 (%)
S1	1.8	1.3	5.4
S2	1.9	1.5	5.4
S3	2.7	1.9	4.5
S4	2.8	2.4	2.9

Table 1: *Scenarios economic outlook [37].*

product (GDP) growth rate from 2013 to 2018 was 1.4% [43]. This suggests that at the end of 2018 all the scenarios in Table 1 had an optimistic outlook because their assumed respective average annual GDP growth for this period ranged from 2.9% to 5.4%, which is way above the real average annual GDP growth of 1.4%.

4.2 Data on existing and potential new capacity

To meet the national electricity demand scenarios discussed in Section 4.1, both existing and potential new capacity were considered. Existing capacity included in this research consisted of Eskom fleet, non-Eskom fleet and committed power plants over the period, 2013 to 2050 (see appendices A and B). The sources of energy considered were coal, gas/diesel, hydro, nuclear, solar, wind, and other sources.

The total existing capacity in 2013 was 48 220 megawatt (MW) (see appendix A). During the investigation the existing capacity was increased by the capacity that was committed by the South African public electricity utility before IRP 2010 [36] and the committed capacity from the 2011 ministerial determinations [37]. The committed capacities are presented in Appendix B. The existing capacity was decreased by the capacity of power plants which were expected to be decommissioned during the investigation period. The actual assumed decommissioning dates and the corresponding capacities are in Appendices C to E. Appendices F to J give more details of the new potential technologies, their respective capacities and the corresponding costs.

The same fuel-based annual capacity factors are used throughout the investigation period for both existing and new power plants [42]. This is because the forecasted capacity factors are not available. The assumption made about constant capacity factors might over estimate and sometimes under estimate the actual energy per period produced by the model in Section 5.

Capacity factors for renewable sources were obtained from Calitz *et al.* [7], since this was the only local source with recent renewable capacity factors. Capacity factor data for other power plants was obtained from the South African public electricity utility. Due to the confidentiality nature of the utility's data, only the renewable sources' capacity factors are presented in Table 2 [7].

Energy source	**Average capacity factor (%)**
Solar photo voltaic (PV)	26
Wind	35
Concentrated solar power (CSP)	31

Table 2: *Average capacity factor [7].*

5 Methodology

The TSSP model discussed in this section follows from the discussion in Section 2. The TSSP model implemented here applies SP to the electricity capacity expansion planning problem in South Africa. The two-stage SP model minimises

- The total annual capital cost for new capacity in the first stage.
- The running costs for new capacity in the second stage. The running costs consist of fuel costs, fixed operating and maintenance (O&M) costs, variable O&M costs, and cost of unserved energy.

The total annual capital cost belongs to the first stage because the decision to expand capacity is taken at this stage. At the time of making this decision the demand growth or decline in the period under consideration is unknown. This is only realised in the second stage. The running costs are allocated to the second stage because they vary according to the energy produced to meet demand.

5.1 Mathematical model

The following considerations were taken into account in the proposed model formulation:

- The objective function in this study minimises annual costs which spans over several years, 2013 to 2050.
- Both existing and new capacity are adjusted by capacity factors due to inefficiency of electricity generating technology.
- The existing capacity is not available throughout the entire planning horizon since some of it is decommissioned.
- The running costs are made up of fuel, fixed and variable maintenance, and the cost of unserved energy.

Equation (5) to equation (15) are only for new technologies. Equations for existing power plants are provided by equation (16) to equation (21), later in this section.

$$\min \quad \sum_{t,p}[capc_p^t x_p^t + E_\xi \boldsymbol{v}^t], \tag{5}$$

$$\text{s.t.} \quad \sum_k \boldsymbol{y}_{pk}^t \leq e_p^t cap f_p^t \quad \forall (t,p), \tag{6}$$

$$\beta \boldsymbol{z}_k^t + \boldsymbol{du}_k^t \sum_p \boldsymbol{y}_{pk}^t = \boldsymbol{r}_k^t \quad \forall (t,k), \tag{7}$$

$$\boldsymbol{r}_k^t = \begin{cases} (\boldsymbol{d}_k^t)\boldsymbol{du}_k^t \text{ if } k=1 \\ (\boldsymbol{d}_k^t - \boldsymbol{d}_{k-1}^t)\boldsymbol{du}_k^t \text{ if } k=2 \end{cases}, \tag{8}$$

$$x_p^t \geq x_p^{t-1} \quad \forall (t,p), \tag{9}$$

$$e_p^t = x_p^t - x_p^{t-1} \quad \forall (t,p), \tag{10}$$

$$\sum_k \left(cue^t \boldsymbol{z}_k^t + \boldsymbol{du}_k^t \sum_p (fom_p^t + vom_p^t + f_p^t)\boldsymbol{y}_{pk}^t \right) = \boldsymbol{v}^t \quad \forall\ (t), \tag{11}$$

$$x_p^t \geq 0 \quad \forall\ (t,p), \tag{12}$$

$$\boldsymbol{y}_{pk}^t \geq 0 \quad \forall\ (t,p,k), \tag{13}$$

$$\boldsymbol{v}^t \geq 0 \quad \forall\ (t), \tag{14}$$

$$e_p^t \geq 0 \quad \forall\ (t,p), \tag{15}$$

Where:

- Indices:
  - p is technology type.
  - k is demand category; base (k=1) or peak (k=2).
  - t is year, from 2013 ($t = 1$) to 2050 ($t = n$).
- Parameters:
  - β is a binary parameter which is equal to 0 or 1.
  - e_p^t is the existing capacity for technology p at time t [gigawatt (GW)].

- $capc_p^t$ is annual capital cost for technology p at time t [Rand per kilowatt (R/kW)].
- $capf_p^t$ is annual capacity factor for technology p at time t .
- fom_p^t is fixed operation and maintenance cost for technology p at time t [R/kW] per year.
- vom_p^t is variable operation and maintenance cost for technology p at time t [Rand per megawatt hour (R/MWh)].
- f_p^t is fuel cost of technology p at time t [Rand per gigajoule (R/GJ)].
- cue^t is the cost of unserved energy for all demand category at time t [R/kWh].
- $\boldsymbol{d}_k^t$ is instantaneous electricity demand for k at time t GW.
- $\boldsymbol{du}_k^t$ is duration of demand for category k and at time t; duration for base is 24 hours per day and 6 hours for peak.
- $\boldsymbol{r}_k^t$ is the required electricity for k at time t [gigawatt hour (GWh)].

- Variables:

  - x_p^t is new design capacity of technology p at time t [GW]. This decision was taken just before time t, for the capacity to be available at time t.
  - $capf_p^t$ is based on fuel type [63]. Same capacity factor is used for all technologies and power plants that use the same fuel type. In this study the capacity factor based on fuel type is the quotient of all power plants that generated electricity using a particular fuel type in 2012 and the power plants availability capacity during the same period [63]. Power plant's available capacity is influenced by its planned and unplanned maintenance for each time t.
  - $\boldsymbol{y}_{pk}^t$ is allocation of capacity to each demand, k realization GW at time t for technology p. This decision was taken at time t.
  - $\boldsymbol{z}_k^t$ is the unserved capacity for k at time t [GW]. This decision was taken at time t.
  - $\boldsymbol{v}^t$ is the total cost of: unserved cost of unserved energy, fuel, fixed and variable maintenance.

β is equal to 1 when the available capacity is unable to meet electricity demand and equal to 0 when the capacity is able to meet demand. The variables in bold, in this section, are those that depend on the random variable $\xi = S1, S2, S3, S4$. Equation (5) is the objective function which minimises the capital cost for new capacity and operational costs. The running costs $\boldsymbol{v}^t$ as defined at the beginning of section 5 are expanded in equation (11). The constraint in equation (6) ensures that allocated capacity is less than the available capacity in year t, which is the installed capacity multiplied by the capacity factor. Equation (7) ensures that the required electricity is met by the allocated capacity. The year t capacity is linked to year $t-1$ capacity by equation (9). This is to ensure that the capacity allocated in each year, included what was existing in the previous year. The required electricity per demand category was expanded in equation (8). This equation is introduced to differentiate the required electricity that is met by the base load technologies from the peak load technologies as shown in Table 3.

Hydro under base demand category in Table 3 is classified as mid merit energy fuel source in [16]. Solar and wind are classified as non-dispatchables in [16]. The demand forecast

Base	Peak
Coal	Hydro (pumped storage)
Hydro	Gas/Diesel
Nuclear	
Solar	
Wind	

Table 3: *Fuel demand categories.*

used in this study was taken from [37] and was not categorised into mid merit and non-dispatchables. Hence hydro, wind and solar are classified as base. However, wind and solar have low capacity factors as shown in Table 2, which will be able to counteract the base demand category used. Equation (16) to equation (21) are for existing power plants.

$$\sum_{k} \boldsymbol{y}^{t}_{pop,k} \leq e^{t}_{pop} cap f^{t}_{pop} \quad \forall (t, pop), \tag{16}$$

$$e^{t}_{pop} = e^{t-1}_{pop} - dec^{t-1}_{pop} \quad \forall (t, pop), \tag{17}$$

$$\boldsymbol{du}^{t}_{k} \sum_{pop} \boldsymbol{y}^{t}_{pop,k} = \boldsymbol{r}^{t}_{k} \quad \forall (t, k), \tag{18}$$

$$\boldsymbol{y}^{t}_{pop,k} \geq 0 \quad \forall\ (t, pop, k), \tag{19}$$

$$e^{t}_{pop} \geq 0 \quad \forall\ (t, pop), \tag{20}$$

$$dec^{t}_{pop} \geq 0 \quad \forall\ (t, pop). \tag{21}$$

Where:

- pop is power plant.
- dec^{t}_{pop} is the decommissioned capacity for plant type pop at time t, as defined for new capacity.

All the other variables, parameters and indices in equation (16) to equation (21) are as defined for new technologies but used for existing power plants. It should be noted that no running costs were allocated to existing power plants, because existing capacity running costs were expensive compared to new technologies. The existing power plants are used to make sure that the model allocates electricity demand between existing power plants and new technology.

5.2 Cost of unserved energy

The cost of unserved energy (COUE) which emanates from load shedding, was referred to as backstop technology by Birge & Louveaux [5] and import cost by Bisschop [6]. Load shedding is a controlled way of reducing the electricity demand, with the aim of protecting the electricity system from a total blackout [14]. COUE is the opportunity cost to electricity consumers and the economy from electricity supply interruptions [37]. The COUE is represented by cue^{t}, which is in the first term of equation (11). The COUE is supposed to be higher than other running costs according to Bisschop and Birge & Louveaux.

A COUE of R75 per kWh was used in [37]. This COUE was revised by the National Energy Regulator of South Africa's (NERSA's) consultation paper [29]. The revised COUE of R87.85 per kWh which was taken from appendix A of the NERSA's consultation paper [29], is used in this paper.

5.2.1 Cost of load shedding to electricity consumers

According to the definition of load shedding in Section 5.2, load shedding affects both the electricity consumers and the economy. This section focuses on the cost of the recent past load shedding to the electricity consumers (COUE-1). In the recent past four stages of load shedding were experienced in South Africa. The four stages are presented in Table 4. The data with actual load shedding days and stages that were implemented by

Stage	Maximum capacity (MW)	Description	Average hours per day	Maximum kWh per day
1	1 000	3 times over 8 day period for 4 hours at a time.	1.5	1 500 000
2	2 000	6 times over 8 day period for 4 hours at a time.	3	6 000 000
3	3 000	9 times over 8 day period for 4 hours at a time.	4.5	13 500 000
4	4 000	12 times over 8 day period for 4 hours at a time.	6	24 000 000

Table 4: *Load shedding stages [14].*

the South African public electricity utility in the financial year 1 April 2018 to 31 March 2019 (2018/19) is in Appendix K. The information in Appendix K was used to calculate the actual number of days where a load shedding stage was implemented.

Stages	Actual kWh	COUE-1 (R)	COUE-1 (R/kWh)
1	9 000 000	790 650 000	527.10
2	72 000 000	6 325 200 000	1 054.20
3	27 000 000	2 371 950 000	175.70
4	168 000 000	14 758 800 000	614.95

Table 5: *Cost of load shedding to electricity consumers.*

The actual number of days were multiplied with the corresponding maximum kWh per day from Table 4, this product is called actual kWh in Table 5. The actual kWh values were multiplied by the COUE value of 87.85 R/kWh, this product is called COUE-1 (Rand (R)) in Table 5. The quotient in the last column of Table 5 is COUE-1 in R/kWh for each day where corresponding load shedding was implemented. The values in the last column of Table 5 were added to the cost of load shedding to the economy which is discussed in Section 5.2.2 and which were used in the model.

5.2.2 Cost of load shedding to the economy

In Section 5.2 it was discussed that electricity interruptions do not only affect the electricity consumer, but also the economy. This section focuses on the cost of the recent past load shedding to the economy. According to Investec's chief economist, Annabel Bishop, the load shedding that was implemented in the first quarter of 2019 in South Africa could wipe off between 33% and 50% of the gross domestic product (GDP) [55]. Bishop's claim was used to calculate the cost of load shedding to the economy for the period in Appendix K. To be conservative 33% was used.

For the load shedding period under consideration, corresponding quarterly GDP in Rand (R) was taken from the Statistics South Africa GDP report for the fourth quarter of 2018 [43]. The monthly GDP (R) was estimated by interpolating quarterly GDP using cubic splines function in Matlab [8]. Monthly GDP for December 2018 was also used for February and March 2019, because GDP for the first quarter of 2019 is not published yet. The daily GDP (R) was derived by dividing the monthly GDP by the number of days in each month. The economic cost (R) for each day of load shedding was derived by multiplying the daily GDP by 33%. Then the economic cost (R) was added for all the days where the same loading shedding stage was implemented, the results are in the second column of Table 6.

Stage	33% of daily GDP (R)	COUE-2 (R/kWh)
1	51 282 677 742	205 131
2	102 774 112 673	205 548
3	18 631 564 286	2 760
4	50 527 873 497	14 737

Table 6: *Cost of load shedding to the economy.*

The values in the second column of Table 6 were divided by the corresponding maximum kWh per day in Table 4. The quotient was multiplied by the number of days for each loading stage. The results are in the last column of Table 6, COUE-2 (R/kWh) for each day where corresponding load shedding stage was implemented. The COUE-2 (R/kWh) was added to the COUE-1 (R/kWh) in Table 5. The results are shown in Table 7. These values were used in the model and the results are presented in Table 8.

Case	COUE-3 (R/kWh)
A	2 935.93
B	15 352.25
C	205 657.81
D	206 602.43

Table 7: *Cost of load shedding to electricity consumers and the economy.*

However, it should be noted that the COUE -3 (R/kWh) in Table 7 cannot be used for other load shedding periods, because:

- the COUE -3 (R/kWh) values were derived from load shedding stages that implemented during the load period under consideration,

- GDP values used change from period to period, and
- the economist's view might also be different for load shedding which might be implemented in the future.

However, if a higher percent of GDP was used, say greater than 33% but less or equal to 50%, this percent of GDP would have resulted in higher values of COUE -3 (R/kWh).

6 Results and discussion

In this section, results for new capacity capital costs and corresponding running costs are presented. The new capacity and its corresponding CO_2 emissions are also presented.

6.1 Costs for new capacity

In this study, Advanced Interactive Multidimensional Modelling System (AIMMS) software was used in the modelling process. Solutions were computed by employing the commercial solver CPLEX 12.6. The determined costs are for the new capacity only as shown by the first term of the objective function in equation (5). Table 8 shows the capital costs, running costs and total cost, when a COUE values derived in Section 5.2 were used. The costs in Table 8 are for each element of ξ = S1, S2, S3, S4, provided as part of the solution.

Rand (billion)	**S1**	**S2**	**S3**	**S4**	**Solution**
		Case A			
Capital Costs	1 532.61	1 532.61	1 532.61	1532.61	
Running costs excluding COUE	0.37	0.49	0.79	1.17	
COUE costs	0.00	0.00	724.26	1 949.24	
Total	1 532.98	1 533.10	2 257.66	3 483.01	**2 201.69**
		Case B			
Capital Costs	2 746.55	2 746.55	2 746.55	2 746.55	
Running costs excluding the COUE	0.37	0.48	0.83	1.31	
COUE costs	0.00	0.00	0.00	764.78	
Total Costs	2 746.92	2 747.04	2 747.39	3512.64	**2 938.50**
		Case C			
Capital Costs	3 094.19	3 094.19	3 094.19	3 094.19	
Running costs excluding the COUE	0.36	0.47	0.81	1.28	
COUE costs	0.00	0.00	0.00	0.00	
Total Costs	3 094.55	3 094.66	3 095.00	3 095.47	**3 094.92**
		Case D			
Capital Costs	3 094.19	3 094.19	3 094.19	3 094.19	
Running costs excluding the COUE	0.36	0.47	0.81	1.28	
COUE costs	0.00	0.00	0.00	0.00	
Total Costs	3 094.55	3 094.66	3 095.00	3 095.47	**3 094.92**

Table 8: *SP total capital costs for new capacity.*

In Table 8 the running costs consist of 0% of the COUE (R) for:

- S1 and S2 in Case A.
- S1, S2 and S3 in Case B.
- All scenarios in Case C and D.

Table 8 shows that the capital costs are the same for all the elements of ξ in each case. This is the case because the capital costs are the first stage optimal results. For all the cases the running costs for S1 are the lowest compared to other scenarios, this was also expected because of the low electricity demand for S1. The results in Table 8 show that the solution to the objective function *i.e.* equation (5) is increasing from R2 201.69 billion in Case A to R3 094.92 in Cases C and D. The increase in objective function value is due to the increasing capital costs which is a result of high demand. However, one should bare in mind that the optimistic demand scenarios with equal probabilities and constant capacity factors were used when determining the results in Table 8.

The COUE results in Table 8 show that initially the model did not add new capacity, instead the COUE was used, hence COUE values are greater than zero for S3 and S4 in Case A, and S4 in Case B.

The results in Table 8 show that the COUE (R) decreased with increasing value of COUE (R/kWh). However, the COUE (R) did not decrease further for Case D. Table 8 also shows that any COUE (R/kWh) greater than Case C's will produce the same results as Case C. This was observed in Case D results. Results similar to C would have been obtained if the COUE -3 (R/kWh) values were derived from a GDP percent higher than 33%.

6.2 New capacity for SP model

In this section the new capacity corresponding to the capital costs discussed in Section 6.1 is presented. The model increased capacity because of more demand than the existing capacity. Existing capacity kept on decreasing even after the installation of committed capacity as shown in Appendix B, due to decommissioned power plants as shown in Appendices C to E.

Table 9, Table 10 and Table 11 show new capacity according to the technologies, x_p^t, based on sources of energy. As an example, the second column of Table 9 is the sum of x_p^t from technology p which use coal energy source as shown in Appendix F. The corresponding years, t, are in the first column.

It can be seen in Table 9 that new capacity started in 2026 with hydro energy sources. The hydro capacity was increased in 2031, where the wind energy capacity also started. The coal energy source capacity started in 2036 and then gas/diesel energy source capacity started in 2042. The total capacity for Case A kept increasing until 2045 and remained constant till the end of the period.

Unlike in Table 9, Table 10 shows that:

- new capacity started in 2021, with both gas/diesel and hydro energy sources;
- wind energy source came a year earlier.

Year	Coal	Gas/Diesel	Wind	Hydro	Total
2026	0.00	0.00	0.00	1.36	1.36
2027	0.00	0.00	0.00	1.36	1.36
2028	0.00	0.00	0.00	1.36	1.36
2029	0.00	0.00	0.00	1.36	1.36
2030	0.00	0.00	0.00	1.36	1.36
2031	0.00	0.00	12.14	3.53	15.68
2032	0.00	0.00	12.14	3.84	15.98
2033	0.00	0.00	12.14	7.68	19.82
2034	0.00	0.00	12.14	7.68	19.82
2035	0.00	0.00	12.14	7.68	19.82
2036	9.91	0.00	19.20	7.68	36.79
2037	21.43	0.00	19.20	7.68	48.31
2038	24.12	0.00	19.20	7.68	51.00
2039	28.20	0.00	19.20	7.68	55.08
2040	34.58	0.00	19.20	7.68	61.46
2041	37.16	0.00	19.20	7.68	64.04
2042	37.16	0.52	19.20	7.68	64.56
2043	37.16	5.31	19.20	7.68	69.36
2044	37.16	5.31	19.20	7.68	69.36
2045	37.16	5.56	19.20	7.68	69.61
2046	37.16	5.56	19.20	7.68	69.61
2047	37.16	5.56	19.20	7.68	69.61
2048	37.16	5.56	19.20	7.68	69.61
2049	37.16	5.56	19.20	7.68	69.61
2050	37.16	5.56	19.20	7.68	69.61

Table 9: *Case A: SP new capacity per technology (GW).*

The annual capacity allocation, y^t_{pk} and $y^t_{pop,k}$, results are shown in Figure 3 for Case A. For Case A, y^t_{pk} is based on the new capacity in Table 9, however $y^t_{pop,k}$ is based on existing power plants and committed capacity in Appendix A and Appendix B, respectively. Most of the existing capacity is decommissioned during the investigation period as shown in Appendix C to Appendix E.

Figure 3 shows the total capacity allocated to the demand categories k, for each year, t. The total capacity allocation is guided by the forecasted demand scenarios in Figure 2 for all the four scenarios. Case B, C and D will also show results similar to Figure 3.

Comparing Table 11 to Table 9 and Table 10:

- Similar to Table 9, hydro energy source capacity was installed first by the model. However, this capacity featured as early as 2014.
- The wind energy source capacity came next, but much earlier than in Cases A and B.
- Similar to Cases A and B, coal energy capacity featured in 2036.
- Unlike in Cases A and B, nuclear energy source capacity came after coal.
- Similar to Case A gas/diesel energy source capacity came last, but much later when compared to Case A.

Wind and hydro are the only renewable energy sources the model selected for all cases. The objective function of the model used in this paper minimises costs. As a result the

Year	Coal	Gas/Diesel	Wind	Hydro	Total
2021	0.00	2.27	0.00	2.18	4.45
2022	0.00	2.27	0.00	2.18	4.45
2023	0.00	2.27	0.00	2.18	4.45
2024	0.00	2.27	0.00	2.18	4.45
2025	0.00	2.27	0.00	2.18	4.45
2026	0.00	2.27	0.00	2.18	4.45
2027	0.00	2.27	0.00	2.18	4.45
2028	0.00	2.27	0.00	2.18	4.45
2029	0.00	2.27	0.00	2.18	4.45
2030	0.00	2.27	12.14	2.18	16.59
2031	0.00	2.27	12.14	3.12	17.54
2032	0.00	2.27	12.14	3.43	17.84
2033	0.00	2.27	12.14	7.68	22.09
2034	0.00	2.27	12.14	7.68	22.09
2035	0.00	2.27	12.14	7.68	22.09
2036	21.43	2.27	19.20	7.68	50.58
2037	32.95	2.27	19.20	7.68	62.10
2038	34.58	2.27	19.20	7.68	63.73
2039	34.58	2.27	19.20	7.68	63.73
2040	34.58	2.27	19.20	7.68	63.73
2041	36.09	2.27	19.20	7.68	65.24
2042	37.78	2.27	19.20	7.68	66.93
2043	39.79	5.56	19.20	7.68	72.23
2044	43.45	5.56	19.20	7.68	75.89
2045	46.76	5.56	19.20	7.68	79.20
2046	64.13	5.56	19.20	7.68	96.58
2047	64.13	5.56	19.20	7.68	96.58
2048	64.13	5.56	19.20	7.68	96.58
2049	64.13	5.56	19.20	7.68	96.58
2050	64.13	5.56	19.20	7.68	96.58

Table 10: *Case B: SP new capacity per technology (GW).*

model did not select technologies that use renewable energy with high costs. The costs for renewable energy sources' technologies are in Appendices H, I and J. It can be observed that wind technology was cheaper when compared to solar technologies. Also wind had a higher capacity factor compared to solar renewable energy source as shown in Table 2.

Case C and D also had capacity from nuclear energy source. Nuclear energy source in Appendix G has expensive capital costs but lower fixed costs and a higher capacity factor when compared to solar energy sources in Appendices H and I.

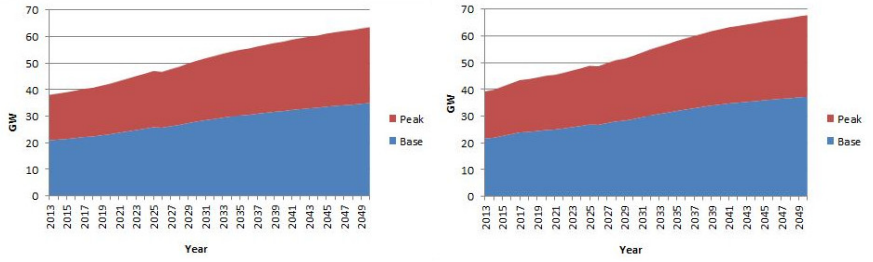
The data used in this study was collected before 2013, when solar technologies were still expensive. However, the solar PV prices have fallen by 80% between 2009 and 2017 [13]. The model was not adjusted with new data for PV prices because there was no latest comprehensive data as shown in appendices at the time of writing this paper. Unlike the PV technology there were no actual price decrease statistics for CSP technology in literature. This is possibly the case since according to the International Energy Agency (IEA), only 6 countries worldwide had installed the CSP technology by 2017. However, IEA expected the CSP technology uptake to increase from 2018 to 2023.

Year	Coal	Nuclear	Gas/Diesel	Wind	Hydro	Total
2014	0.00	0.00	0.00	0.00	2.59	2.59
2015	0.00	0.00	0.00	0.00	2.59	2.59
2016	0.00	0.00	0.00	0.00	2.59	2.59
2017	0.00	0.00	0.00	0.00	2.59	2.59
2018	0.00	0.00	0.00	0.00	2.59	2.59
2019	0.00	0.00	0.00	0.00	2.59	2.59
2020	0.00	0.00	0.00	0.00	2.59	2.59
2021	0.00	0.00	0.00	0.00	3.53	3.53
2022	0.00	0.00	0.00	0.00	3.53	3.53
2023	0.00	0.00	0.00	0.00	3.53	3.53
2024	0.00	0.00	0.00	19.20	3.53	22.73
2025	0.00	0.00	0.00	19.20	3.53	22.73
2026	0.00	0.00	0.00	19.20	3.53	22.73
2027	0.00	0.00	0.00	19.20	3.53	22.73
2028	0.00	0.00	0.00	19.20	3.53	22.73
2029	0.00	0.00	0.00	19.20	3.53	22.73
2030	0.00	0.00	0.00	19.20	3.53	22.73
2031	0.00	0.00	0.00	19.20	3.53	22.73
2032	0.00	0.00	0.00	19.20	3.84	23.04
2033	0.00	0.00	0.00	19.20	3.84	23.04
2034	0.00	0.00	0.00	19.20	3.84	23.04
2035	0.00	0.00	0.00	19.20	3.84	23.04
2036	9.91	0.00	0.00	19.20	7.68	36.79
2037	21.43	0.00	0.00	19.20	7.68	48.31
2038	24.12	0.00	0.00	19.20	7.68	51.00
2039	27.46	0.72	0.00	19.20	7.68	55.05
2040	34.58	1.76	0.00	19.20	7.68	63.22
2041	34.58	1.76	0.00	19.20	7.68	63.22
2042	35.95	1.76	0.00	19.20	7.68	64.59
2043	37.96	1.76	0.00	19.20	7.68	66.60
2044	49.03	1.76	0.00	19.20	7.68	77.67
2045	60.55	1.76	0.00	19.20	7.68	89.19
2046	60.55	1.76	0.00	19.20	7.68	89.19
2047	69.16	1.76	0.00	19.20	7.68	97.80
2048	69.16	1.76	0.00	19.20	7.68	97.80
2049	69.16	1.76	3.29	19.20	7.68	101.10
2050	69.16	1.76	5.56	19.20	7.68	103.37

Table 11: *Case C & D: SP new capacity per technology (GW).*

Table 12 shows the energy sources' percentage allocation for 2013 and for the new and existing capacity (total capacity) as at 2050 for each case. The total capacity is dominated by coal for all cases. However, this is clean coal since the underlying coal technologies have carbon capture and storage (CCS) and flue gas desulphurisation (FGD) [23].

It can be observed in Table 12 that from 2013 to 2050 there is a capacity shift from coal, nuclear and other for all cases. The shifted capacity moved to wind and hydro in Case A. However in Cases B, C and D, the new capacity for coal increased from 59% to 68%. The wind allocation decreased with increasing coal allocation for Cases B, C and D. In Cases C and D, nuclear's allocation increased when compared to Cases A and B.



(a) Case A - S1.

(b) Case A - S2.



(c) Case A - S3.

(d) Case A - S4.

Figure 3: *Annual capacity allocation for Case A.*

The challenge with the selected renewable energy sources is the intermittent nature of wind and hydro energy sources that are imported from Zambia and Mozambique as shown in appendix J. Hydro is imported since South Africa is one of the driest countries in the world, according to the South African Department of Water and Sanitation [61].

One should bear in mind that the electricity demand is slowing down in South Africa as shown in Figure 4 [12]. The declining electricity demand in South Africa has also been confirmed by the declining electricity sales as shown in Table 13.

If the trends shown by Figure 4 and Table 13 continue till the end of the investigation period and the actual electricity generation capacity expansion was based on more optimistic demand scenarios like S3 and S4, this would result in excessive electricity generation capacity surplus.

6.3 CO_2 emissions

The general move from fossil fuels energy sources to renewable sources is driven by the agreement which was taken on the 21st session of the Conference of the Parties (COP21) [62]. According to Eskom's 2017/18 integrated report [15] historical electricity generation accounted for 42% of the nation's CO_2 emission. In an effort to make sure that the country abide by the COP21 pledge, government departments have published the following documents:

Energy Source	2013	Case A: 2050 (%)	Case B: 2050 (%)	Cases C & D: 2050 (%)
Coal	76	59	68	68
Wind	0	21	16	15
Hydro	8	14	11	10
Gas/diesel	5	6	5	4
Nuclear	4	0	0	1
Other	7	0	0	0

Table 12: *2013 vs. 2050 SP total capacity allocation.*

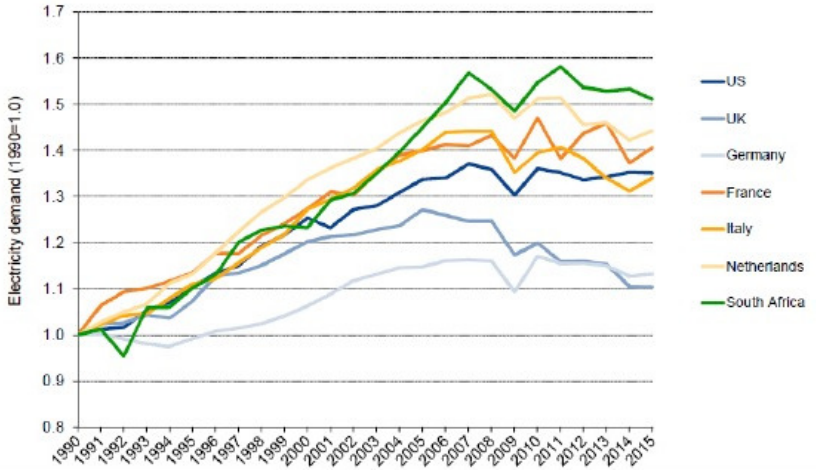


Figure 4: *Historic electricity demand - SA vs. other countries [12].*

Year	Growth (%)
2012/13	-3.7
2013/14	0.6
2014/15	-0.7
2015/16	-0.8
2016/17	-0.2
2017/18	-0.9

Table 13: *South African public utility total electricity sales growth[15].*

- Department of Environmental Affairs (DEA) has gazetted a draft National greenhouse gas emission reporting regulations in June 2016 [39].
- DEA has also gazetted a climate change bill in June 2018 [41].
- South African National Treasury has published a carbon tax bill draft for public comments [60].

The CO_2 emissions were determined only for the allocated new capacity. The model did not allocate the new capacity immediately. Hence the CO_2 in Table 14 started later than

2036, where the coal new capacity was introduced. Table 14 shows that S1 emit less CO_2 compared to other scenarios. This is because S1 has less demand when compared to other scenarios. Some of S1 demand was met by renewable energy resources with no emission.

Year	S1	S2	S3	S4
2037	0	15 222	69 565	99 017
2038	0	22 471	78 166	111 572
2039	11 989	36 038	91 747	141 604
2040	25 687	50 872	106 624	210 262
2041	36 909	61 801	120 146	253 242
2042	40 115	64 435	127 034	268,753
2043	44 020	68 246	145 405	290 229
2044	55 641	79 730	194 884	333 707
2045	65 263	89 090	231 931	366 428
2046	132 542	168 451	280 319	404 048
2047	144 664	203 435	314 368	442 539
2048	206 413	256 220	363 117	496 807
2049	231 275	281 593	386 605	530 560
2050	265 612	310 989	414 409	570 594

Table 14: *Case A: Total CO_2 emission per scenario (tonne).*

Year	S1	S2	S3	S4
2037	0	15 222	69 565	99 017
2038	0	22 471	78 166	111 572
2039	11 989	36 038	91 747	141 604
2040	25 687	50 872	106 624	210 262
2041	36 909	61 801	120 146	253 242
2042	40 115	64 435	127 034	267 248
2043	44 020	68 246	145 405	284 804
2044	55 641	79 730	194 884	327 459
2045	65 263	89 090	231 931	362 119
2046	132 542	168 451	276 995	410 868
2047	144 664	203 435	312 873	456 195
2048	206 413	251 141	364 053	514 948
2049	231 275	274 627	389 030	548 701
2050	262 132	304 848	418 618	588 735

Table 15: *Case B: Total CO_2 emission per scenario (tonne).*

For all the cases, CO_2 emissions increase from 2037 to 2050 as shown in Table 14 to Table 16. Furthermore, CO_2 emission also increase from S1 to S4.

However, CO_2 emissions increased from Case A to Case C and D. This is the case even though Table 12 showed that the coal energy source capacity was decreasing from Case A to Case C and D. The increased coal capacity observed for Case A is due to coal technologies with FGD. Appendix F shows that coal technology with FGD have high CO_2 emissions and is cheaper when compared to coal technology with CCS.

South African long term emissions trajectory, "peak, plateau and decline", is for the entire country [40]. However, DEA derived the electricity supply sector "peak, plateau and decline" (PPD), from the country's as shown in Figure 5.

Year	S1	S2	S3	S4
2037	0	15 222	69 565	99 017
2038	0	22 471	78 166	111 572
2039	11 989	36 038	91 747	127 658
2040	25 687	50 872	106 624	175 905
2041	36 909	61 801	120 146	225 246
2042	40 115	64 435	124 741	240 608
2043	44 020	68 246	126 377	258 163
2044	55 641	79 730	160 526	300 819
2045	65 263	89 090	197 573	335 894
2046	132 542	153 698	250 209	384 083
2047	143 719	175 241	286 087	425 250
2048	172 055	224 501	337 612	482 804
2049	203 801	247 986	362 452	523 338
2050	235 492	278 207	391 876	565 714

Table 16: *Cases C and D: Total CO_2 emission per scenario (tonne).*

Comparing the upper limit of Figure 5 in 2050 to Table 14, Table 15 and Table 16 2050's CO_2 emissions, it looks like the scenarios are above the upper limit. However, S1 is close enough for all the cases. One must bear in mind that all the demand scenarios were optimistic about electricity demand, low electricity demand will help with lowering CO_2 emissions.

The CO_2 emissions recorded by the South African electricity public utility [15] in 2012/13 financial year was 227.9 million tons and 205.5 million tons in 2017/18. According to Figure 5 the electricity public utility's emissions as at 2017/18 were between the lower and upper limits. However, as shown in Appendix A, the electricity public utility is not the only supplier of electricity.

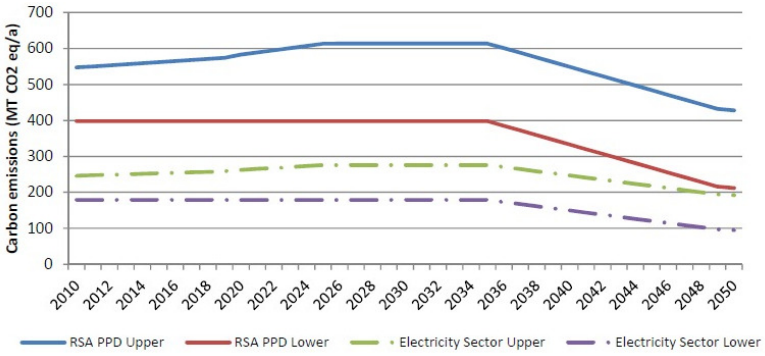


Figure 5: *SA and electricity supply sector PPD [37].*

According to the South African Department of Environmental Affairs (DEA) [40] electricity supply is the largest source of emissions. However, the electricity supplier can limit the emissions by shifting to lower carbon source of energy [40]. The emission results in Table 14, Table 15 and Table 16 show that the new capacity CO_2 emissions in Section 6.2 will be above the upper limit by 2050. This is before including the existing capacity's CO_2 emissions by 2050.

In future work, CO_2 emissions will be constrained in the model such that the new capacity emissions are aligned with DEA's recommendation of limiting emissions.

7 Conclusion

In this study TSSP modelling was applied to the South African electricity generation expansion planning for the first time. The random variable, ξ, was represented by four electricity demand scenarios, S1, S2, S3 and S4. Each demand scenario had 25% probability of occurring. As the actual demand is being realised the scenarios' probabilities can be adjusted to favour the most likely scenario. However, even though four scenarios were considered, the TSSP model incorporated all the scenarios at once. This resulted in optimal total costs ranging from R2 201 billion to R3 094 billion. The total costs from [37] range from R5 800 billion to R8 000 billion. However, these two sets of results are based on similar data up to an extent but assumptions, software and optimization models are not the same.

The costs constituencies as shown in Section 6 simplifies the decision makers' work because the capital costs are the same across all scenarios for each value of COUE (R/kWh) used; what changes per scenario are the running costs.

Results from Case A, S1 are considered to be more applicable, since these results are based on a more conservative demand scenario and have lower costs. Comparing 2013 and 2050 total capacities (existing and new) a decrease from coal, nuclear and other energy sources was observed. This decrease resulted in renewable energy sources' capacity increase. However, technologies that use solar renewable energy source were not selected because of high costs at the time when the data was collected and low capacity factors.

However, Case A's coal technologies emit more CO_2. This can be resolved by constraining the CO_2 emissions in the model.

An increased capacity from renewable energy sources in South Africa's electricity generation mix will contribute towards CO_2 emissions decrease. This will assist the country in fulfilling the COP21 pledge.

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Appendices

A. Existing capacity [37]

Plant name	Capacity (MW)	Source of energy
Eskom	**42 330**	
Camden	1 520	Coal
Grootvlei	1 080	Coal
Komati	900	Coal
Arnot	2 220	Coal
Hendrina	1 900	Coal
Kriel	2 880	Coal
Duvha	3 480	Coal
Matla	3 480	Coal
Kendal	3 840	Coal
Lethabo	3 540	Coal
Matimba	3 720	Coal
Tutuka	3 540	Coal
Majuba	3 840	Coal
Koeberg	1 860	Nuclear
Gariep	360	Hydro
Vanderkloof	240	Hydro
Colleywobbles	70	Hydro
Drakensberg	1 000	Hydro
Palmiet	400	Hydro
Acacia	180	Gas/ Diesel
Port Rex	180	Gas/ Diesel
Ankerlig	1 350	Gas/ Diesel
Gourikwa	750	Gas/ Diesel
Non-Eskom	**5 890**	
Cahorra Bassa	1 500	Hydro
Aggreko	90	Gas
Pretoria West	90	Coal
Rooiwal	180	Coal
Sasol Infrachem	150	Gas
Sasol SSF	500	Coal
Steenbras	180	Hydro
Co-generation	360	Other
MTPPP	280	Other
DR Peaking	500	Other
Interruptible Load	2 060	Other
TOTAL	**48 220**	

Table 17: *Existing capacity.*

Where:

- SSF is Sasol synthetic fuel
- MTPPP is Eskom's medium term power purchase programme
- DR is demand response
- Hydro is hydroelectric and pumped storage

B. Committed capacity [37]

The committed capacity was not yet built in 2013 but was already committed.

MW	Coal	Other	Gas	Wind	Other renewable
2010	**380**	**260**	0	0	0
2011	**679**	**130**	0	0	0
2012	**303**	0	0	400	100
2013	**823**	**333**	1020	400	25
2014	**722**	**999**	0	0	100
2015	**1444**	0	0	0	100
2016	**722**	0	0	0	0
2017	**2 168**	0	0	0	0
2018	**723**	0	0	0	0
2019	**1 446**	0	0	0	0
2020	**723**	0	0	0	0

Table 18: *Committed capacity [37].*

Where:

- The energy sources' capacities in bold are Eskom's commitments pre IRP.
- Other energy sources capacities which are not bold were committed in 2011 ministerial determinations.
- The wind energy source includes 100 MW for Eskom's Sere plant.

C. Assumed decommissioning schedule - 1 [37]

MW Year	Arnot	Camden	Duvha	Grootvlei	Hendrina	Kendal	Komati	Kriel	Lethabo
2013	0	0	0	0	0	0	0	0	0
2014	0	0	0	0	0	0	0	0	0
2015	0	0	0	0	0	0	0	0	0
2016	0	0	0	0	0	0	0	0	0
2017	0	0	0	0	0	0	0	0	0
2018	0	0	0	0	0	0	0	0	0
2019	0	0	0	0	0	0	0	0	0
2020	0	380	0	0	0	0	0	0	0
2021	0	190	0	0	380	0	0	0	0
2022	0	570	0	0	380	0	0	0	0
2023	0	380	0	0	190	0	0	0	0
2024	0	0	0	0	190	0	200	0	0
2025	740	0	0	180	190	0	100	0	0
2026	370	0	0	360	190	0	100	480	0
2027	370	0	0	180	380	60	300	480	0
2028	370	0	0	360	0	0	200	960	0
2029	370	0	0	0	0	0	0	960	0
2030	0	0	1 160	0	0	0	0	0	0
2031	0	0	580	0	0	0	0	0	0
2032	0	0	580	0	0	0	0	0	0
2033	0	0	580	0	0	0	0	0	0
2034	0	0	580	0	0	0	0	0	0
2035	0	0	0	0	0	0	0	0	590
2036	0	0	0	0	0	0	0	0	590
2037	0	0	0	0	0	0	0	0	0
2038	0	0	0	0	0	630	0	0	0
2039	0	0	0	0	0	0	0	0	1 800
2040	0	0	0	0	0	0	0	0	590
2041	0	0	0	0	0	1 890	0	0	590
2042	0	0	0	0	0	630	0	0	0
2043	0	0	0	0	0	630	0	0	0
2044	0	0	0	0	0	0	0	0	0
2045	0	0	0	0	0	0	0	0	0
2046	0	0	0	0	0	0	0	0	0
2047	0	0	0	0	0	0	0	0	0
2048	0	0	0	0	0	0	0	0	0
2049	0	0	0	0	0	0	0	0	0
2050	0	0	0	0	0	0	0	0	0

Table 19: *Assumed decommissioning schedule - 1 [37].*

D. Assumed decommissioning schedule - 2 [37]

MW Year	Majuba	Matimba	Matla	Tutuka	Pretoria West	Rooiwal	Sasol Infrachem	Sasol SSF	Koeberg
2013	0	0	0	0	0	0	0	0	0
2014	0	0	0	0	0	0	0	0	0
2015	0	0	0	0	0	0	0	0	0
2016	0	0	0	0	90	0	0	0	0
2017	0	0	0	0	0	0	0	0	0
2018	0	0	0	0	0	0	0	0	0
2019	0	0	0	0	0	0	0	0	0
2020	0	0	0	0	0	0	0	0	0
2021	0	0	0	0	0	0	0	0	0
2022	0	0	0	0	0	0	0	0	0
2023	0	60	0	0	0	0	0	0	0
2024	0	0	0	60	0	180	0	0	0
2025	0	0	0	0	0	0	0	500	0
2026	0	0	0	0	0	0	0	0	0
2027	0	0	0	0	0	0	0	0	0
2028	0	0	0	0	0	0	0	0	0
2029	0	0	580	0	0	0	0	0	0
2030	0	0	1 160	0	0	0	0	0	0
2031	0	0	580	0	0	0	0	0	0
2032	0	0	580	0	0	0	0	0	0
2033	0	0	580	0	0	0	0	0	0
2034	0	0	0	0	0	0	0	0	0
2035	0	0	0	580	0	0	0	0	0
2036	0	0	0	1 160	0	0	0	0	0
2037	0	1 220	0	580	0	0	0	0	0
2038	0	610	0	580	0	0	0	0	0
2039	0	610	0	0	0	0	0	0	0
2040	0	610	0	580	0	0	0	0	0
2041	0	610	0	0	0	0	0	0	0
2042	0	0	0	0	0	0	0	0	0
2043	0	0	0	0	0	0	150	0	0
2044	0	0	0	0	0	0	0	0	1 860
2045	0	0	0	0	0	0	0	0	0
2046	610	0	0	0	0	0	0	0	0
2047	610	0	0	0	0	0	0	0	0
2048	610	0	0	0	0	0	0	0	0
2049	670	0	0	0	0	0	0	0	0
2050	670	0	0	0	0	0	0	0	0

Table 20: *Assumed decommissioning schedule - 2 [37].*

E. Assumed decommissioning schedule - 3 [37]

MW Year	Acacia	Aggreko	Ankerlig	DoE IPP	Gourikwa	Port Rex	Co-generation	MTPPP
2013	0	0	0	0	0	0	0	0
2014	0	90	0	0	0	0	0	0
2015	0	0	0	0	0	0	0	0
2016	0	0	0	0	0	0	0	0
2017	0	0	0	0	0	0	0	0
2018	0	0	0	0	0	0	0	0
2019	0	0	0	0	0	0	0	0
2020	0	0	0	0	0	0	0	0
2021	0	0	0	0	0	0	0	0
2022	0	0	0	0	0	0	0	0
2023	0	0	0	0	0	0	0	0
2024	0	0	0	0	0	0	0	0
2025	0	0	0	0	0	0	0	0
2026	180	0	0	0	0	180	0	0
2027	0	0	0	0	0	0	0	0
2028	0	0	0	0	0	0	0	0
2029	0	0	0	0	0	0	0	0
2030	0	0	0	0	0	0	0	0
2031	0	0	0	0	0	0	0	0
2032	0	0	0	0	0	0	0	0
2033	0	0	0	0	0	0	0	0
2034	0	0	0	0	0	0	0	0
2035	0	0	0	0	0	0	0	0
2036	0	0	0	0	0	0	360	0
2037	0	0	1 350	0	750	0	0	0
2038	0	0	0	0	0	0	0	0
2039	0	0	0	0	0	0	0	0
2040	0	0	0	0	0	0	0	0
2041	0	0	0	0	0	0	0	280
2042	0	0	0	0	0	0	0	0
2043	0	0	0	0	0	0	0	0
2044	0	0	0	0	0	0	0	0
2045	0	0	0	0	0	0	0	0
2046	0	0	0	1 020	0	0	0	0
2047	0	0	0	0	0	0	0	0
2048	0	0	0	0	0	0	0	0
2049	0	0	0	0	0	0	0	0
2050	0	0	0	0	0	0	0	0

Table 21: *Assumed decommissioning schedule - 3 [37].*

F. Coal technologies [37]

Appendix F displays the new technology input data that was used in the model for technologies that use coal as a source of energy. The contents of this appendix were taken from the IRP update report [37].

	PC with FGD	PC with CCS	FBD with FGD	FBD with CCS	IGCC	IGCC with CCS
Rated capacity, net (MW)	4 500 (750x6)	4 500 (750x6)	250	250	1 288 (644x2)	1 288 (644x2)
Adjusted overnight capital cost (R/kW)	25 772	48 789	23 661	44 325	32 340	43 160
Fixed O&M cost (R/kW) per year	552	923	543	902	794	951
Variable O&M cost (R/MWh)	51.2	81.4	110.8	149.1	42.5	65.4
Variable fuel cost (R/GJ)	17.5	17.5	8.75	8.75	17.5	17.5
CO_2 emissions (kg/MWh)	947.3	136.2	978	150	930	120

Table 22: *Coal technologies [37].*

Where:

- PC is pulverised coal
- FGD is flue gas desulphurisation
- CCS is carbon capture and storage
- FBD is fluidised bed combustion
- IGCC is integrated gasification combined cycle
- O&M is operating and maintenance
- kg/MWh is kilogram per megawatt hour

G. Nuclear and gas/diesel technologies [37]

Appendix G displays the new technology input data that was used in the model for technologies that use nuclear and gas/diesel as a source of energy. The contents of this appendix were taken from the IRP update report [37].

	Nuclear single unit	**Nuclear fleet**	**OCGT**	**CCGT**	**CCGT with CCS**
Rated capacity, net (MW)	1 600	9 600 (1600x6)	115	711	591
Adjusted overnight capital cost (R/kW)	58 036	59 226	4 671	7 089	14 632
Fixed O&M cost (R/kW) per year	532	532	78	163	292
Variable O&M cost (R/MWh)	29.5	29.5	0.2	0.7	0.7
Variable fuel cost (R/GJ)	6.8	6.8	92	92	92
CO_2 emissions (kg/MWh)	0	0	618	388	47

Table 23: *Nuclear and gas/diesel technologies [37].*

Where:

- OCGT is open cycle gas turbines
- CCGT is closed cycle gas turbine

H. Technologies for renewable sources - 1 [37]

Appendix H displays the new technology input data that was used in the model for technologies that use renewable sources of energy. The contents of this appendix were taken from the IRP update report [37].

	Wind	**CSP Parabolic trough 3hrs**	**CSP Parabolic trough 6hrs**	**CSP Parabolic trough 9hrs**
Rated capacity, net (MW)	100 (50x2)	125	125	125
Adjusted overnight capital cost (R/kW)	15 945	44 626	56 381	67 512
Fixed O&M cost (R/kW) per year	310	582	599	616
Variable O&M cost (R/MWh)	0	1.9	2	2
Variable fuel cost (R/GJ)	0	0	0	0
CO_2 emissions (kg/MWh)	0	0	0	0

Table 24: *Technologies for renewable sources - 1 [37].*

Where:

- CSP is Concentrated Solar Power

I. Technologies for renewable sources - 2 [37]

Appendix I displays the new technology costs input data that were used in the model for technologies that use renewable energy sources. The contents of this appendix were taken from the IRP update report [37].

	CSP Central receiver 3hrs	**CSP Central receiver 6hrs**	**CSP Central receiver 9hrs**	**PV Crystalline silicon fixed tilt**
Rated capacity, net (MW)	125	125	125	10
Adjusted overnight capital cost (R/kW)	41 469	49 513	56 949	29 141
Fixed O&M cost (R/kW) per year	537	555	573	208
Variable O&M cost (R/MWh)	0	0	0	0
Variable fuel cost (R/GJ)	0	0	0	0
CO_2 emissions (kg/MWh)	0	0	0	0

Table 25: *Technologies for renewable sources - 2 [37].*

J. Import hydro [37]

Appendix J displays the new technology costs input that were used in the model for technologies that use hydro imports as a source of energy. The contents of this appendix were taken from the IRP update report [37].

	Import hydro (Moz A)	**Import hydro (Moz B)**	**Import hydro (Moz C)**	**Import hydro (Zam A)**	**Import hydro (Zam B)**	**Import hydro (Zam C)**
Rated capacity, net (MW)	1 500	850	160	120	250	120
Adjusted overnight capital cost (R/kW)	21 117	9 874	17 414	10 877	7 355	4 900
Fixed O&M cost (R/kW) per year	344	80.2	80.2	80.2	80.2	80.2
Variable O&M cost (R/MWh)	0	0	13.9	13.9	13.9	13.9
Variable fuel cost (R/GJ)	0	0	0	0	0	0
CO_2 emissions (kg/MWh)	0	0	0	0	0	0

Table 26: *Import hydro [37].*

Where:

- Moz is Mozambique
- Zam is Zambia

K. Load shedding days and stages

Appendix K shows the dates when the South African public electricity utility implemented load shedding, within 1 April 2018 to 31 March 2019 financial year. The stages are the highest load shedding stages implemented on that particular day. That is if the load shedding started at stage 1, then increased to stage 2 and ended in stage 3, stage 3 will be used for that day.

Date	Highest load shedding stage implemented	Source
14/6/2018	stage 1	[17]
15/6/2018	stage 1	[17]
16/6/2018	stage 1	[17]
31/7/2018	stage 1	[17]
18/11/2018	stage 1	[45]
1/12/2018	stage 2	[24]
2/12/2018	stage 2	[11]
3/12/2018	stage 2	[25]
4/12/2018	stage 2	[46]
5/12/2018	stage 2	[47]
6/12/2018	stage 2	[48]
7/12/2018	stage 2	[49]
8/12/2018	stage 1	[26]
10/2/2019	stage 2	[20]
11/2/2019	stage 4	[31]
12/2/2019	stage 3	[30]
13/2/2019	stage 3	[50]
14/2/2019	stage 2	[21]
15/3/2019	stage 2	[18]
16/3/2019	stage 4	[51]
17/3/2019	stage 4	[52]
18/3/2019	stage 4	[56]
19/3/2019	stage 4	[57]
20/3/2019	stage 4	[53]
21/3/2019	stage 4	[58]
22/3/2019	stage 2	[54]
23/3/2019	stage 2	[58]

Table 27: *Load shedding days and stages.*