

Investigating investment risk factors in biomass embedded power generation projects

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Abstract

During the last decade, commercial and industrial businesses in South Africa have been severely impacted by increased load-shedding and rising electricity prices. This has, in part, contributed to an increase in the number of companies investing in embedded generation. Sunflower-crushing plants present unique opportunities for embedded generation in the agro-processing industry. The husks produced by these plants can serve as a high-energy content fuel source, which, if correctly utilised, can be converted to power for use by the crushing plant. Unfortunately, information regarding biomass power generation in the South African context is sparse, and no known source investigates renewable energy for sunflower-crushing plants in particular. As such, crushing-plant owners and other investors have little information available to evaluate the possible risks associated with investing in the opportunity of embedded generation in this industry.

This study aims to partially address the gap in research by identifying and assessing risks unique to the opportunity. A literature review was used as the basis for identifying risks. Statistical evaluation of relevant data enabled the development of models considering several variables' stochastic nature. Monte-Carlo simulations (MCS) of the financial performance allowed the calculation of risk metrics such as value at risk (VaR). Risk mitigation strategies were also identified through the literature study and serve as a framework for risk mitigation strategies suggested in this study.

The results revealed several inherent risks that need to be accepted by investors. Factors include uncertainty in production levels, the possible impact of load-shedding, and the future escalation in Eskom electricity tariffs. Risks that could have a significant effect but can be mitigated were also identified, with strategies proposed to either transfer or control risks. The risks were further mapped according to impact, likelihood, and level of mitigation, and together with the recommendations give decision makers insight into the most pertinent risks and focus areas for risk management. The study forms a basis for further research in biomass renewable power generation and risk management.

Key terms: renewable power, embedded generation, risk management

Opsomming

Besighede en industrië in Suid-Afrika is gedurende die laaste dekade nadelig beïnvloed deur stygende elektrisiteitskoste en toenemende kragonderbrekings. Hierdie faktore dra in deels daartoe by dat 'n groeiende aantal besighede in hernubare kragbronne belê om elektrisiteit vir eie gebruik op te wek. Sonneblompersaanlegte bied unieke geleenthede vir die opwekking van elektrisiteit met hernubare bronne. Die doppies wat as byproduk geproduseer dien as 'n hoë energie brandstof gebruik kan word om krag op te wek. Daar is egter 'n tekort aan literatuur wat die potensiaal van biomassa as hernubare bron vir elektrisiteitsopwekking in Suid-Afrika bespreek. Verder is daar geen literatuur bekend wat fokus op hernubare elektrisiteitsopwekking vir sonneblompersaanlegte nie. Die tekort aan inligting lei daartoe dat eienaars van aanlegte, asook moontlike beleggers, weinig inligting tot hulle beskikking het om die spesifieke geleentheid te ondersoek en te oorweeg.

Hierdie studie poog om die tekort aan literatuur gedeeltelik aan te spreek deur die risiko's wat gekoppel is aan die opwekking van elektrisiteit vir sonneblompersaanlegte te identifiseer en te kwantifiseer. 'n Literatuur studie dien as grondslag vir die identifisering van risiko faktore. Statistiese metodes is gebruik om die ewekansigheid van sekere risiko faktore in modelle te omskep. Deur middel van Monte-Carlo simulaties (MCS) is die impak van die faktore op die risiko maatstawwe bepaal. Die literatuur studie is ook gebruik om risiko vermindering strategieë te identifiseer. Die geïdentifiseerde strategieë dien as 'n raamwerk om voorstelle te maak aangaande die risiko faktore wat in hierdie studie ontleed is.

Die resultate lig spesifieke ondeliggende risiko's uit wat beleggers moet aanvaar. Die faktore sluit in die onsekerheid in produksie vlakke, die moontlike impak van kragonderbrekings, en die onsekerheid in Eskom se toekomstige elektrisiteitsverhogings. Risiko's met 'n beduidende impak wat wel versag kan word is ook geïdentifiseer. Strategieë is voorgestel om hierdie risiko's te bestuur of oor te dra aan 'n derde party. Die risiko's is grafies voorgestel na aanleiding van elke risiko se impak, waarskynlikheid, en die potensiaal om die impak te versag of te verminder.

Die grafiese voorstelling van die risiko's, te same met die aanbevelings, gee besluitnemers 'n beter verstaan van die belangrike risiko's en waar die fokus van risiko bestuur moet wees. Die studie dien ook as 'n grondslag vir verdere navorsing in hernubare kragopwekking met biomassa asook risikobestuur van kragopwekkingsprojekte.

Sleutel terme: hernubare energy, kragopwekking vir eie gebruik, risiko bestuur

List of abbreviations

BFAP	Bureau for Food and Agricultural Policy
BW	Bid window
CAPEX	Capital expenditure
CDF	Cumulative distribution function
CHP	Combined heat and power
CV	Calorific value
ED	Economic development
EPC	Engineering procurement and construction
FOB	Freight on board
FS	Free State
FWHM	Full width at half maximum
ICE	Internal combustion engine
IPP	Independent Power Producers
IRR	Internal rate of return
kWh	Kilowatt-hour
LCOE	Levelised cost of electricity
LS	Load-shedding
MCS	Monte-Carlo simulation
MW	Megawatt

MWe	Megawatt electric
MWh	Megawatt hour
MWp	Megawatt peak
NAMC	National Agricultural Marketing Council
Nersa	National Energy Regulator of South Africa
NPV	Net present value
NW	North West
OEM	Original equipment manufacturer
OPEX	Operational expenditure
ORC	Organic Rankine cycle
O&M	Operating and maintenance
OTC	Over the counter
PB	Payback
PDF	Probability density function
PT	Payback time
PV	Photovoltaic
RE	Renewable Energy
REIPPPP	Renewable energy independent power producer's procurement programme
RO	Real option
ROI	Return on investment

SAFEX	South African Future Exchange
SAGIS	South African Grain Information Services
SSEG	Small scale embedded generation
TPC	Total plant cost
VaR	Value at risk
USD	United States dollars

TABLE OF CONTENTS

Acknowledgements	i
Abstract	ii
Opsomming	iii
List of abbreviations	v
Chapter 1	1
Introduction	1
1.1 Introduction and background	1
1.2 Problem statement	3
1.3 Research questions.....	4
1.3.1 Main research question	4
1.3.2 Specific research questions	4
1.4 Objectives	5
1.4.1 General objective.....	5
1.4.2 Specific objectives	5
1.5 Scope of the study/Delimitations	5
1.5.1 Field of study	5
1.5.2 Geographical and industry demarcation.....	6
1.6 Chapter layout	6

Chapter 2	8
Literature review	8
2.1 Introduction	8
2.2 Renewable power generation in South Africa	9
2.3 Embedded power generation opportunities in the sunflower value chain	15
2.4 Overview of the sunflower production and crushing market in South Africa	19
2.5 Risks in renewable energy power generation	24
2.5.1 Identification and classification of risks	27
2.5.2 Risk assessment and management	32
2.5.3 Summary of risks	36
2.6 Risk evaluation methods and metrics	42
2.7 Conclusion	44
Chapter 3	46
Methodology	46
3.1 Introduction	46
3.2 Methodology overview	46
3.3 Classification of the risks for the specific sector	48
3.4 Risk assessment	48
3.4.1 Risk quantification	49

3.4.2	Test to determine the required number of simulations	49
3.4.3	Metrics used to quantify the risks.....	50
3.4.4	Risk likelihood.....	51
3.5	Proposing risk management methodologies.....	51
3.6	Conclusion.....	51
Chapter 4		52
	Risk identification, data collection and processing	52
4.1	Introduction	52
4.2	Risk identification, classification, and grouping.....	52
4.3	Data collection for the risk assessment model	59
4.3.1	Utilisation risk due to production variation.....	59
4.3.2	Crushing plant electrical energy demand uncertainty.....	69
4.3.3	Power plant sizing uncertainty risk.....	70
4.3.4	Production loss risk	72
4.3.5	Technology selection risk	84
4.3.6	Investment cost (Total project cost) uncertainty	84
4.3.7	Conversion efficiency uncertainty	86
4.3.8	Power plant O&M cost uncertainty.....	88
4.3.9	Biomass price uncertainty.....	88
4.3.10	Construction risk.....	89
4.3.11	Lending and inflation rates.....	90

4.3.12	Eskom tariffs and tariff increase.....	92
4.3.13	Exchange rate risk.....	93
4.4	Conclusion.....	93
Chapter 5		94
Financial model and results		94
5.1	Introduction	94
5.2	Model description and assumptions	94
5.3	Analysis scenarios	97
5.4	Results	102
5.4.1	Introduction to the interpretation of the results	102
5.4.2	Scenario 1: Analyses 1a to 1c	104
5.4.3	Analyses 2a to 2d	109
5.4.4	Scenarios 3 and 4.....	112
5.4.5	Scenario 5	115
5.4.6	Scenario 6	116
5.4.7	Scenario 7	117
5.4.8	Scenario 8	118
5.5	Results summary.....	120
5.6	Discussion and implications for investors and decision-makers	126
5.7	Summary and conclusion	129

Chapter 6		130
Conclusions, recommendations, and future research		130
6.1	Introduction	130
6.2	Summary of the study and main findings	130
6.3	Recommendations for managing investment risks	133
6.4	Contribution of the field of study	134
6.5	Areas of further research	134
6.5.1	Improvements to the risk assessment method	134
6.5.2	Application of the risk assessment method	135
6.6	Concluding remarks	135
References		137

LIST OF TABLES

Table 2-1: Oilseed crushers in South Africa for sunflower seed in 2013	16
Table 2-2: Summary of the risks, risk drives, risk probability and risk management.....	38
Table 4-1: Identification, classification and grouping of risk factors.....	54
Table 4-2: Power plant peak capacity as a function of crushing plant production	72
Table 4-3: Calorific value of husk	89
Table 5-1: Model nominal assumptions and inputs	96
Table 5-2: Analysis scenarios.....	98
Table 5-3: Risk impact assessment from the results.....	103
Table 5-4: Basis on which risk likelihood, impact and mitigation are evaluated.....	103
Table 5-5: Results for analyses 1a to 1c.....	105
Table 5-6: Summary of the impact of the risk factors.....	122

LIST OF FIGURES

Figure 2-1: Average electricity price in South Africa (real and inflation-adjusted).....	9
Figure 2-2: Annual forced load reduction capacity (load-shedding).....	10
Figure 2-3: Annual electricity production in South Africa.....	10
Figure 2-4: Energy produced through primary renewable sources.....	11
Figure 2-5: Average tariffs for bid windows 1 to 4 of SA's REIPPPP for various technologies.....	12
Figure 2-6: Annual installed embedded generation capacity.....	13
Figure 2-7: Breakdown of embedded generation capacity per industry and province	14
Figure 2-8: Drivers for the implementation of SSEG	15
Figure 2-9: Production of electricity using sunflower husk	18
Figure 2-10: Sunflower planted in the North West and Free State	19
Figure 2-11: Comparison of sunflower production between countries.....	20
Figure 2-12: Sunflower oil and oilcake produced and seed prices for 2000 to 2020.....	21
Figure 2-13: Correlation between sunflower oil price and seed price	22
Figure 2-14: Sunflower and soybean crude oil prices in Argentina	23
Figure 2-15: Comparison between installed cost per kW for solar PV (left-hand side) and biomass (right-hand side).....	24
Figure 2-16: Comparison between LCOE for solar PV (left-hand side) and biomass (right- hand side).....	26
Figure 2-17: Ranking of the significance of risks as per stakeholder evaluation for IPP renewable energy projects	33

Figure 2-18: Ranking of the likelihood of occurrence of risks as per stakeholder evaluation for IPP renewable energy projects	34
Figure 2-19: Renewable energy technology risk transfer map	35
Figure 2-20: Summary of the risk classifications	37
Figure 3-1: Overall methodology of the risk analysis	47
Figure 4-1: Monthly national production figures for sunflower	60
Figure 4-2: Monthly production rates for each month of the year	61
Figure 4-3: Normalising factor to determine the average monthly production	63
Figure 4-4: CDF for the average annual production data	63
Figure 4-5: Comparison between the CDF for the annual production between the actual and simulated data	65
Figure 4-6: Comparison between simulated and actual annual data	66
Figure 4-7: Distribution of the simulated 24-year average annual production rate	67
Figure 4-8: Original annual production rates compared with simulated production rate (1)	68
Figure 4-9: Original annual production rates compared with simulated production rate (2)	68
Figure 4-10: Specific electricity consumption of twelve sunflower-crushing plants	70
Figure 4-11: Peak power requirements for different crushing capacity plants	71
Figure 4-12: Trend in the cumulative number of load-shedding events	73
Figure 4-13: CDF for the duration of load-shedding events	74
Figure 4-14: Cumulative number of load-shedding hours from the model and original data	75
Figure 4-15: Distribution of the total simulated hours of load-shedding over 51 months	76
Figure 4-16: Example of a load reduction event	77

Figure 4-17: Cumulative distribution function for the average forced load-shedding per event	78
Figure 4-18: Example of a load-shedding schedule	79
Figure 4-19: Relationship between the producer price (sunflower seed) and the price of sunflower oil and oilcake	80
Figure 4-20: Sunflower seed producer price and simulated price	81
Figure 4-21: CDF for the normalised difference between actual and average sunflower seed prices	82
Figure 4-22: Actual and simulated sunflower oil and oilcake prices	83
Figure 4-23: Specific capital cost for combustion power plants.....	85
Figure 4-24: Total plant cost as a function of the plant capacity.....	86
Figure 4-25: Conversion efficiency for biomass combustion power generation plants	87
Figure 4-26: Probability of the percentage cost overrun for projects between A1\$ and \$10 million (R11M to R121M at R11/A\$).....	90
Figure 4-27: Historical interest rate data.....	91
Figure 4-28: Inflation rate for the past 25 years	91
Figure 4-29: Annual increase in commercial and industrial tariffs	92
Figure 5-1: Overview of the financial model.....	95
Figure 5-2: Comparison between the results obtained from 1000 and 10000 simulations.....	101
Figure 5-3: Comparison between the NPV for analyses 1b and 1c.....	106
Figure 5-4: Comparison between estimated returns for analyses 3 and 8.....	107
Figure 5-5: Examples of cash flows	108
Figure 5-6: Most likely NPV as a function of crushing plant capacity, with FWHM and VaR ..	110

Figure 5-7: IRR and LCOE as a function of crushing plant capacity.....	110
Figure 5-8: NPV, IRR, LCOE and PB of the smallest and largest crushing plants (Analyses 2a and 2d).....	111
Figure 5-9: NPV and VaR for various specific energy consumptions at the nominal crushing capacity	113
Figure 5-10: NPV and VaR for various power plant capacities at the nominal crushing capacity.....	114
Figure 5-11: Sensitivity of the NPV and VaR to changes in the biomass price.....	115
Figure 5-12: Impact of interest rate on NPV and VaR.....	117
Figure 5-13: Impact of Eskom electricity price on NPV and VaR	118
Figure 5-14: Impact of O&M costs on the NPV and VaR	119
Figure 5-15: Risk map	121

Chapter 1

Introduction

1.1 Introduction and background

Sunflower-crushing plants are very power- and energy-intensive, and this significantly impacts production costs (Havrysh *et al.*, 2020:2). The crushing margins of sunflower-crushing plants in South Africa have been under severe pressure due to various market factors, including rising electricity prices and increased frequency of load-shedding (BFAP, 2020:77; Inglesi-Lotz & Blignaut, 2011:459). South African legislation changed in June 2020 to allow small-scale embedded generation (SSEG) implementation of up to 100MW without a license (Smith, 2021). This change in legislation presents sunflower-crushing plants with a unique opportunity to be power independent by generating electricity with the biomass waste stream from the crushing operation while possibly generating revenue from power sales.

In South Africa, the production levels of crushing plants depend on seed production levels (crushing plants have excess capacity (NAMC, 2004:234)). Seed production, in turn, depends on various local and international market factors and changes significantly over time (van der Burgh *et al.*, 2015:12). There might be a causal link between the local seed production levels and the electricity demand of a crushing plant. Such factors must be considered when investing in power generation capacity and may significantly influence the return on investment. Biomass renewable energy is capital-intensive compared to other renewable energy sources and has inherent risks and uncertainties that affect investment profitability (UNEP, 2004:14-18).

The Bioenergy Atlas for South Africa (Hugo, 2016) gives a comprehensive overview of the possible sources of bioenergy in South Africa. It includes references to sunflower husk as a source of lignocellulose that can be used for combustion and power generation (Hugo, 2016). Furthermore, the report provides the technology options and costs for lignocellulose power conversion on a high level. Still, agricultural residue sources mainly focus on wheat and maize, with further emphasis on invasive plant species and forestry residues (Hugo, 2016:25). There is however a lack of

academic information on the cost of electricity production from sunflower husks as a biomass fuel source. This lack of research makes it difficult for investors to quickly determine the profitability of investing in such a project and the risk associated with such an investment. In addition, crushers and refineries have to deal with the volatile retail markets and fluctuations in price (van der Burgh *et al.*, 2015:40). International sources report a large variability in the LCOE for biomass projects. The data emphasise that such projects do not have a one-size-fits-all profitability analysis. Risks specific to a particular project or opportunity must be better quantified and compared to renewable energy (RE) technologies such as solar photovoltaic (PV). Further research is required into the factors influencing the profitability of investing in power generation projects with sunflower husk as a fuel source while considering more advanced methods of estimating the risks of such investments.

The profitability of power generation projects is usually evaluated by looking at the project's net present value (NPV) and levelised cost of electricity (LCOE). This is also the case for existing international evaluations of power generation using sunflower husk (Havrysh *et al.*, 2019; Havrysh *et al.*, 2020; Jiang *et al.*, 2019). It is generally done by looking at various scenarios to incorporate the factors influencing profitability. This approach, however, doesn't account for all the uncertainties (Heck *et al.*, 2016; Ioannou *et al.*, 2017). For example, the inputs to the calculation of the LCOE are usually point values. It effectively neglects the inherent uncertainty in power generation investment (Heck *et al.*, 2016:21). Other methods of incorporating the risk factors when evaluating profitability include Monte-Carlo simulation (MCS) techniques for financial modelling (O'Donnell *et al.*, 2002:94).

This study will investigate and quantify the risk and uncertainty factors influencing the profitability of generating power for a sunflower-crushing plant using the biomass waste stream as a fuel source. A financial model will include the identified risk and uncertainty factors to quantify the investment risks. The identified risks will provide investors and plant owners with a more accurate representation of the investment opportunity of Small-Scale Embedded Generation (SSEG) in sunflower-crushing plants. It will also highlight which risks are inherent to the investment opportunity and which risks can and should be managed.

1.2 Problem statement

South Africa's power generation situation is dire, with electricity costs rising and load-shedding implemented frequently. The power generation situation results in the price elasticity of electricity demand for the industrial sector being highly significant and negative (Inglesi-Lotz & Blignaut, 2011:459). The increased cost of procuring electricity from municipalities or Eskom, as well as the changes in legislation concerning SSEG, has opened up numerous opportunities for commercial and industrial businesses to invest in renewable energy. One such opportunity is in the agro-processing industry, where sunflower seeds are processed. In sunflower-crushing plants, the high-energy content husk is a waste stream that can potentially be used as a fuel source for power generation.

The academic literature does not provide comprehensive information on biomass power generation in the South African context (Visser *et al.*, 2019:10). Risk assessment studies for biomass power generation with sunflower husk are not readily available in academic literature for South Africa. Furthermore, unique market conditions and local factors need to be considered. The electricity generation costs of biomass RE projects depend on various parameters that contain inherent risks and uncertainties, such as the technology used, significant capital cost, the capacity factor, long construction periods, and variability of fuel availability, price and energy content (Agrawal, 2012:15; Taylor *et al.*, 2020; UNEP, 2004).

Various market factors influence the annual sunflower production output. These include international oilseed prices of palm oil, soybean oil and sunflower oil (Lemmer, 2019; van der Burgh *et al.*, 2015:30). Other factors influencing crushing plant production rates are the seed oil content and the annual weather conditions (BFAP, 2020:77,78; NAMC, 2004:236). These factors result in significant variability in crushing plant production rates and put severe pressure on crushing margins (BFAP, 2020:77; Strydom, 2016:24).

Crushing plants aiming to invest in SSEG using sunflower husk need to consider the production variability and uncertainties associated with biomass RE. The uncertainties and risks involved are easily neglected using the standard method of calculating the

LCOE (Heck *et al.*, 2016; Ioannou *et al.*, 2017). It is difficult for decision-makers to evaluate the possible uncertainty in the expected cashflows and yield of such an investment without considerable simplifications and assumptions. This uncertainty in the investment yield can potentially lead to lost investment opportunities or over-optimistic investment. The influence of the risks and uncertainties associated with these projects can only be quantified using more complex investment analysis tools.

Owners of sunflower-crushing plants, therefore, face not only a possibly unique opportunity to produce power for themselves while utilising the waste stream from the process but also the risk of investing in a project where the risks are not adequately quantified. With other renewable energy options available, careful consideration should be given to the profitability and the risks involved to ensure more informed decision-making.

Therefore, by considering all of the above, this research study will aim to address and answer the following research questions and objectives stated below.

1.3 Research questions

1.3.1 Main research question

The main research question of the study is what are the primary factors influencing the investment risks in embedded power generation for sunflower-crushing plants when using biomass as a fuel source, and how will they influence decision-making?

1.3.2 Specific research questions

- What unique factors will influence the investment uncertainty and risk for SSEG in sunflower-crushing plants?
- How can these uncertainties and risks be quantified?
- How can these risks be incorporated into a model to determine their influence on decision-making?
- How probable are the risks, and what mitigation strategies are there?
- What are the implications of these risks for decision-making in the feasibility phase of a project?

1.4 Objectives

1.4.1 General objective

The primary objective of this study is to identify and quantify the factors that will influence the LCOE of power generation for a crushing plant when using sunflower husk as a fuel source. When these factors are identified and quantified, they can be used to estimate better the uncertainty in the profitability of investing in a power generation facility for crushing plants. The study should highlight the significant risks and uncertainties when investing in this type of RE project, providing a framework for better decision-making and comparing investment alternatives.

1.4.2 Specific objectives

The specific objectives of this study are the following:

- Identify the factors influencing the uncertainty and risks in the investment returns.
- To quantify these uncertainties and risks.
- To develop a financial model that can incorporate all the risks in such a way that it can be used to analyse the influence on decision-making during the feasibility phase.
- To analyse the impact of risks and whether there are ways to mitigate these risks.
- To use the analysis to inform the implications for decision-making before investment in the power generation project.

A further objective of this study is to contribute to the available literature concerning biomass power generation in South Africa, specifically to power generation using sunflower husk.

1.5 Scope of the study/Delimitations

1.5.1 Field of study

This study is in the field of industrial and energy economics. The study is focused on the feasibility stage of evaluating investments in renewable power projects for embedded electricity generation.

1.5.2 Geographical and industry demarcation

This study will focus on the sunflower production and processing industry, specifically sunflower-crushing and crude oil production plants in the South African context. The electricity generation cost will focus on South African crushing plants and local factors, but international prices for equipment will be considered since the equipment is not necessarily locally available. In addition, the technology and feedstock are specific to the sunflower industry; therefore, capital costs and overall energy conversion efficiency will be particular to this feedstock.

1.6 Chapter layout

The dissertation is divided into six chapters:

Chapter 1 is the introduction and provides the context for the problem statement. Next, the background is sketched, followed by the problem statement, study objectives, and research questions.

Chapter 2 provides an overview of the power generation situation, emphasising biomass fuel sources. The sunflower industry is discussed to highlight factors influencing production rates and profitability in the industry. These factors provide a backdrop for discussing the risks of implementing SSEG for sunflower-crushing plants. The classification of risks and risk drivers for renewable power generation, in general, is discussed. A review of the investors' perception of the relevance and probability of the risks follows. Risk management methodologies and instruments are also briefly discussed. Finally, the standard methods used to estimate risks in various power generation projects are reviewed, and the metrics commonly used to report these risks.

Chapter 3 discusses the methodology that will be used to achieve the objectives. It includes how risks are classified and which methods are used to evaluate the impact of the risks. The process followed to ensure the integrity of the model is also discussed.

Chapter 4 focusses on data collection and analysis. The chapter starts with identifying and classifying the risks according to the categories identified in the literature review.

The risks are also grouped according to the risk evaluation method, namely stochastic methods and sensitivity analysis. A detail discussion follows on how the data is processed to allow the development of statistical models that can be used in a stochastic simulation of future cashflows. The assumptions and limitations for each risk factor are discussed.

Chapter 5 discusses the financial model assumptions, the modelling process, and the scenarios that are evaluated to show the sensitivity of the critical parameters. The results from the simulations are shown and discussed. The chapter is concluded with a summary of the risk assessment and mitigation strategies which informs the implication for investors and decision-makers.

Chapter 6 is the conclusions and recommendations resulting from the study.

Chapter 2

Literature review

2.1 Introduction

Embedded power generation refers to electricity production by a smaller power station (through solar, wind or biomass) for use by the entity producing the power (DBSA, 2022). Examples of embedded generation include factories using rooftop solar PV, municipalities, and even homes. However, such projects do not form part of the government procurement programmes, such as the Renewable energy independent power producer's procurement programme (REIPPPP), and are not backed by government guarantees or offtake agreements. Therefore, these projects carry a higher investment risk (DBSA, 2022).

The opportunities for embedded generation are linked to the electricity price and availability in South Africa. Industrial enterprises are well aware of the importance of electricity for production and believe that current supply levels are insufficient (Ateba *et al.*, 2019). In most cases, there is a lack of mitigation strategies, despite the level of uncertainty that load-shedding brings (Ateba *et al.*, 2019). The legislation also plays a vital role in providing the framework within which embedded generation is allowed. Each industrial enterprise is different, and the risks associated with embedded generation differ depending on the technology used. The industry in which the enterprise functions is also of relevance.

The literature review provides an overview of the following aspects: 2.2) the power generation situation in South Africa and the general climate for embedded generation; 2.3) the opportunities that exist for embedded generation in the sunflower value chain; 2.4) an overview of the sunflower production and crushing market in South Africa; 2.5) risks in renewable power generation projects; 2.6) the methods used to estimate and report investment risks; and 2.7) the conclusion.

2.2 Renewable power generation in South Africa

Electricity prices in South Africa have been rising consistently above inflation rates since the inception of rolling blackouts, known as load-shedding, in 2008 (Goode, 2020:18; Labuschagne, 2020). Figure 2-1 indicates the real and inflation-adjusted electricity prices for South Africa and the average price increase compared to the inflation rate.

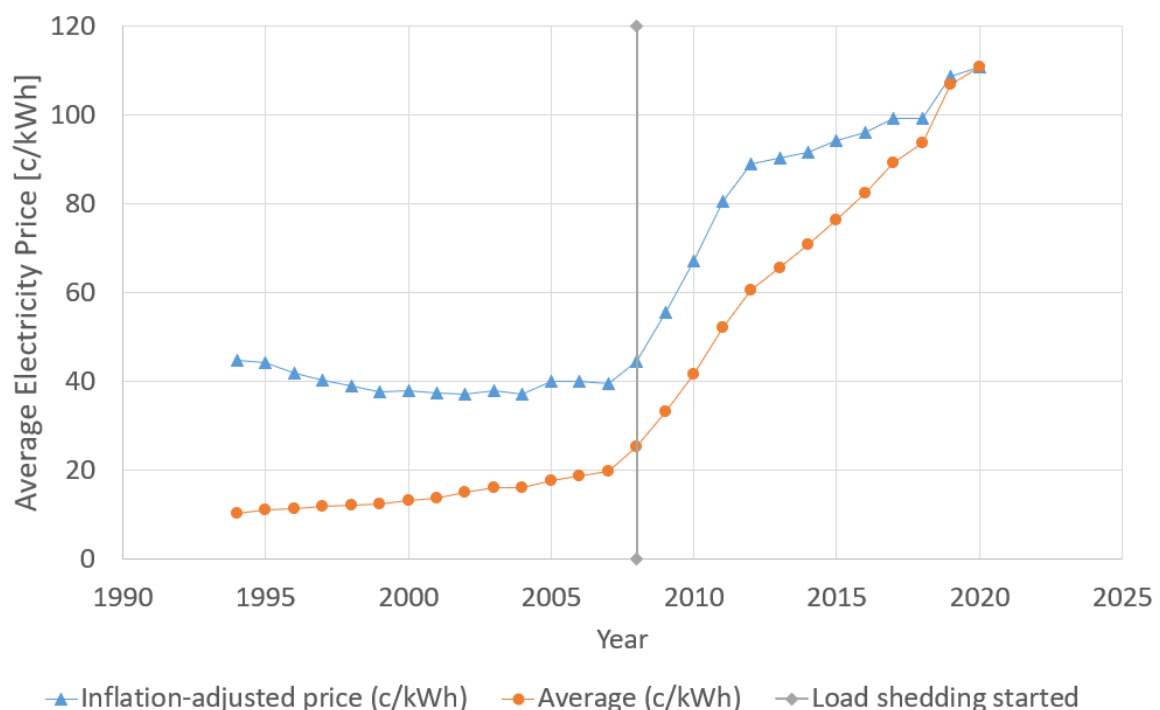


Figure 2-1: Average electricity price in South Africa (real and inflation-adjusted)

Source: Authors analysis; Labuschagne (2020)

The total power generation lost due to load-shedding has also increased since 2008, as shown in Figure 2-2 below. The increase in total lost power generation from 2020 to 2021 was more than 40%. There is also an increase in the frequency of high stages of load-shedding. The implication is that there are more occurrences where load-shedding was implemented for more extended periods (i.e. more hours per day per incident).

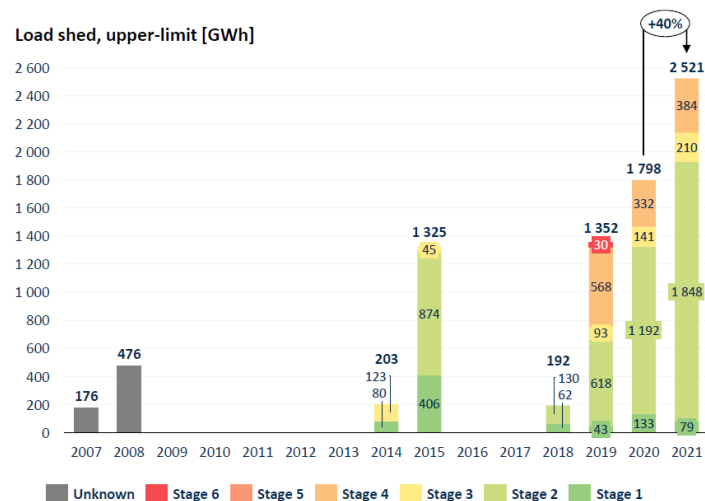


Figure 2-2: Annual forced load reduction capacity (load-shedding)

Source: Pierce and Ferreira (2022:171)

The dramatic increase in the electricity price made it more feasible for renewable energy (RE) power generation sources to enter the market. The loss in Eskom's coal generation capacity has also contributed to the increase in renewable energy. Figure 2-3 below shows a notable increase in the contribution of RE, highlighting that the total annual generation from coal has slowly decreased from 2010. The gap in demand has partly been filled with renewable sources, most notably wind and solar photovoltaic (PV).

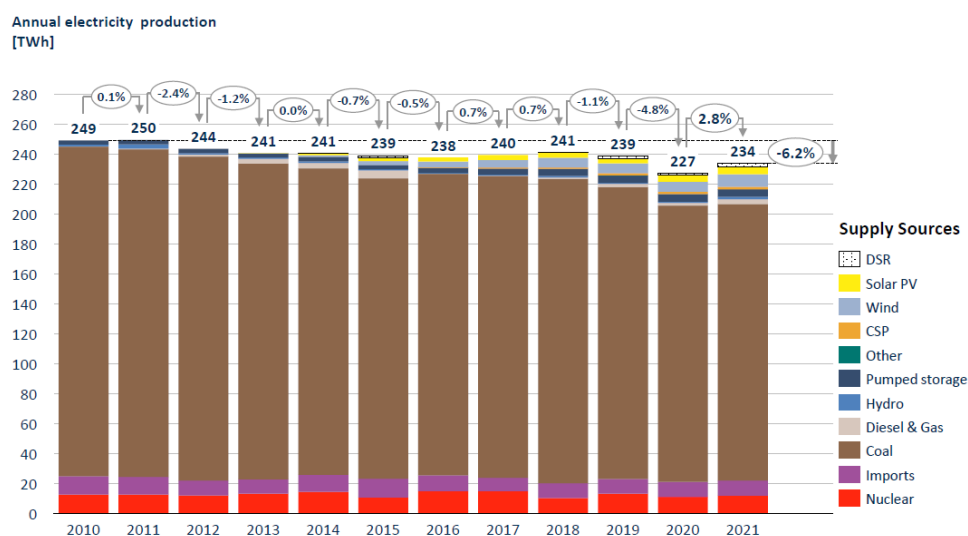


Figure 2-3: Annual electricity production in South Africa

Source: Pierce and Ferreira (2022:13)

Figure 2-4 below provides a more detailed breakdown of the increase in renewable energy supplying the grid, with Solar PV and wind being dominant. The contracted capacity awarded in Bid Window 4 (BW4) IPPs is between 40MW and 75MW for solar per contract and between 31MW and 140MW for wind per contract (REIPPPP Bid Window 4 Prices and economic development (ED) score). For biomass, only 17MW has been awarded in BW3 and 25MW in BW4 (Eberhard & Naude, 2017:28) (no capacity was awarded to biomass in BW1 and BW2).

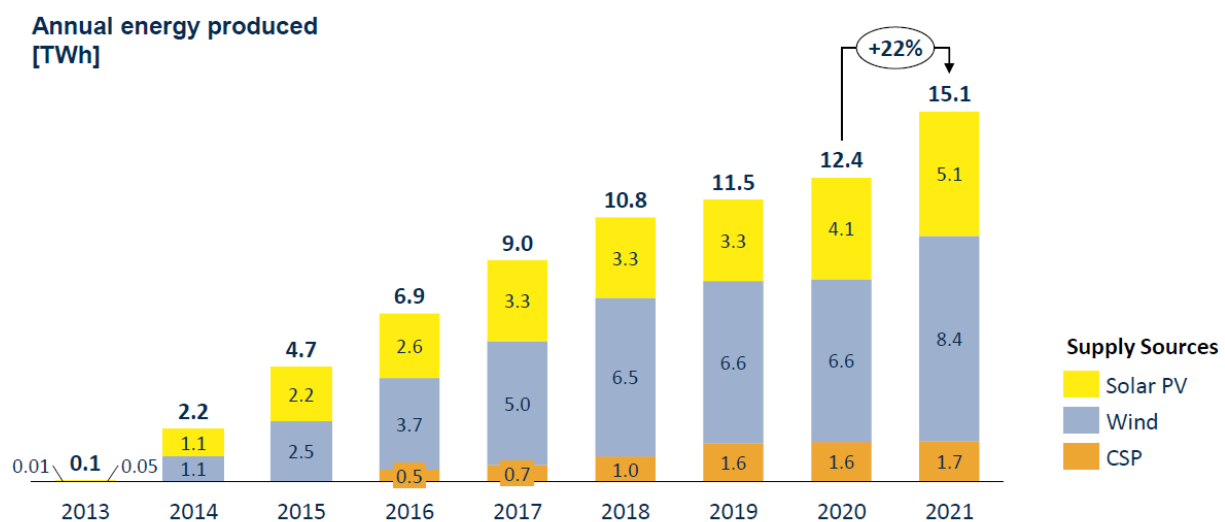


Figure 2-4: Energy produced through primary renewable sources

Source: Pierce and Ferreira (2022:12)

The progression of tariffs for each Bid Window (BW) in the South African Renewable Energy (RE) Independent Power Producer Procurement Programme (REIPPPP) is shown in Figure 2-5 below. The tariffs for solar and wind RE have notably declined and are competitive with the Eskom rates previously provided in Figure 2-1 (p 9). The decrease in tariffs is partially due to the decline in RE technology costs (Eberhard & Naude, 2017:31), specifically for solar (PV) and wind technology.

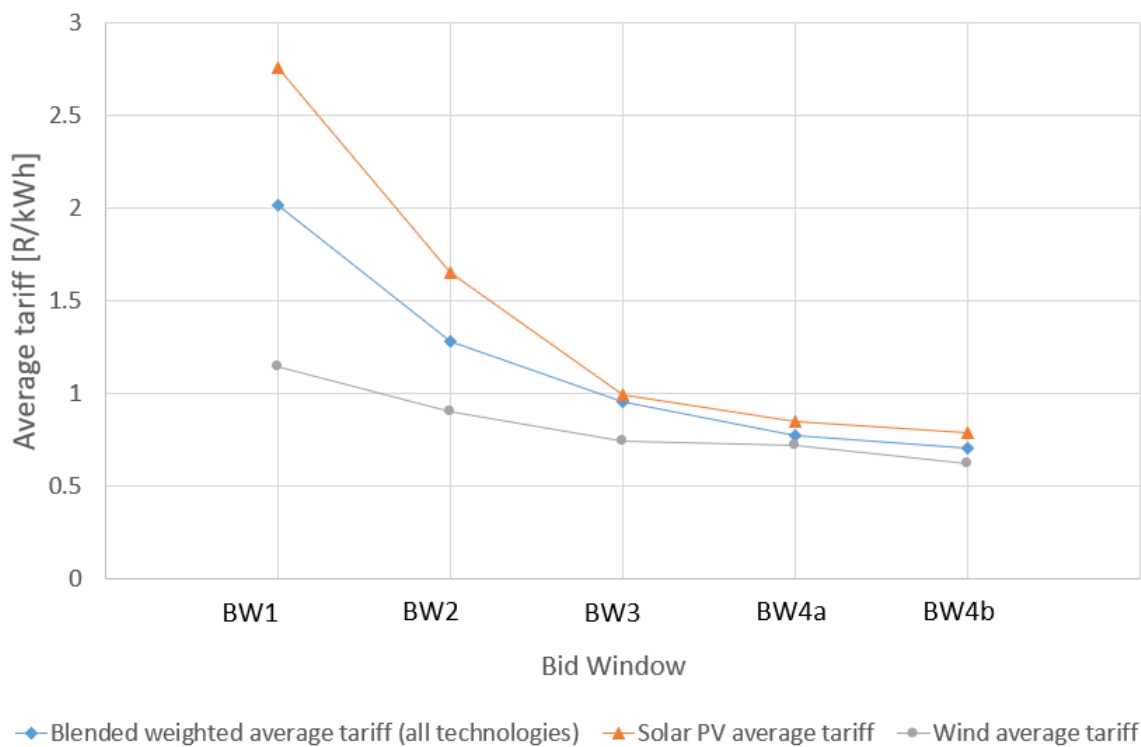


Figure 2-5: Average tariffs for bid windows 1 to 4 of SA's REIPPPP for various technologies

Source: Adapted from Eberhard and Naude (2017)

The power generation situation in South Africa has also opened opportunities for embedded generation. Embedded generation is the process whereby power is locally generated within the electricity distribution grid by households, commercial entities, municipalities, or industries. The significant decrease in the cost of solar PV and the sharp rise in Eskom tariffs has opened many opportunities for Small Scale Embedded Generation (SSEG) projects (Goode, 2020:13). Before 10 June 2021, SSEG projects were limited to a 1MW threshold before requiring a generation license. However, on 10 June 2021, it was announced that this threshold had been lifted to 100MW to encourage investment in embedded generation projects (Smith, 2021).

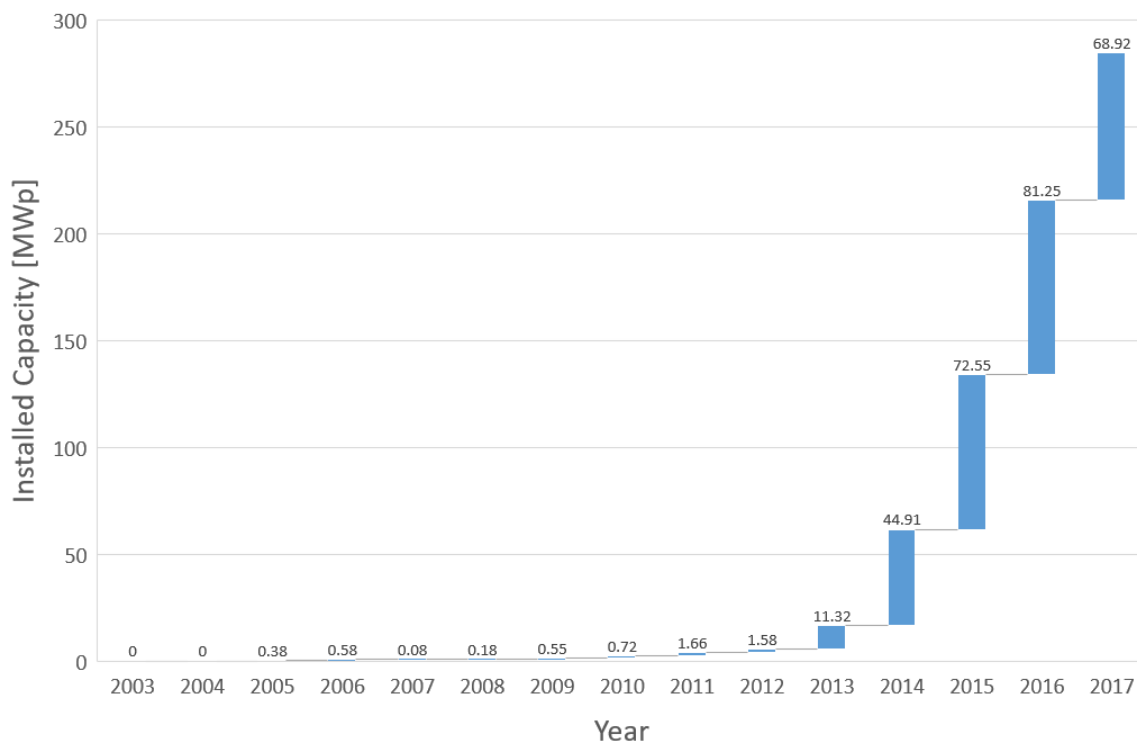


Figure 2-6: Annual installed embedded generation capacity

Source: Adapted from Pandarum *et al.* (2019)

Figure 2-6 above highlights the trend in embedded generation capacity between 2003 and 2017. Embedded capacity increased significantly over the last few years. This increase is mainly attributed to the decreasing cost of renewable technologies (i.e. solar PV) (Filipova & Morris, 2018). A breakdown of the installed capacity per province and sector for this period is provided in Figure 2-7 below. Embedded generation is predominantly taking place in the commercial and industrial sectors. Besides the cost, the predictability of electricity cost could also be a factor driving the adoption of PV solar for embedded generation (Pandarum *et al.*, 2019).

Many embedded generators fall within municipal boundaries, and municipalities are increasingly forced to accommodate industrial and commercial enterprises that want to implement embedded generation. The total legally installed embedded generation capacity in the four main metros was 38.46MWp in 2018 and was predominantly for commercial enterprises (Filipova & Morris, 2018).

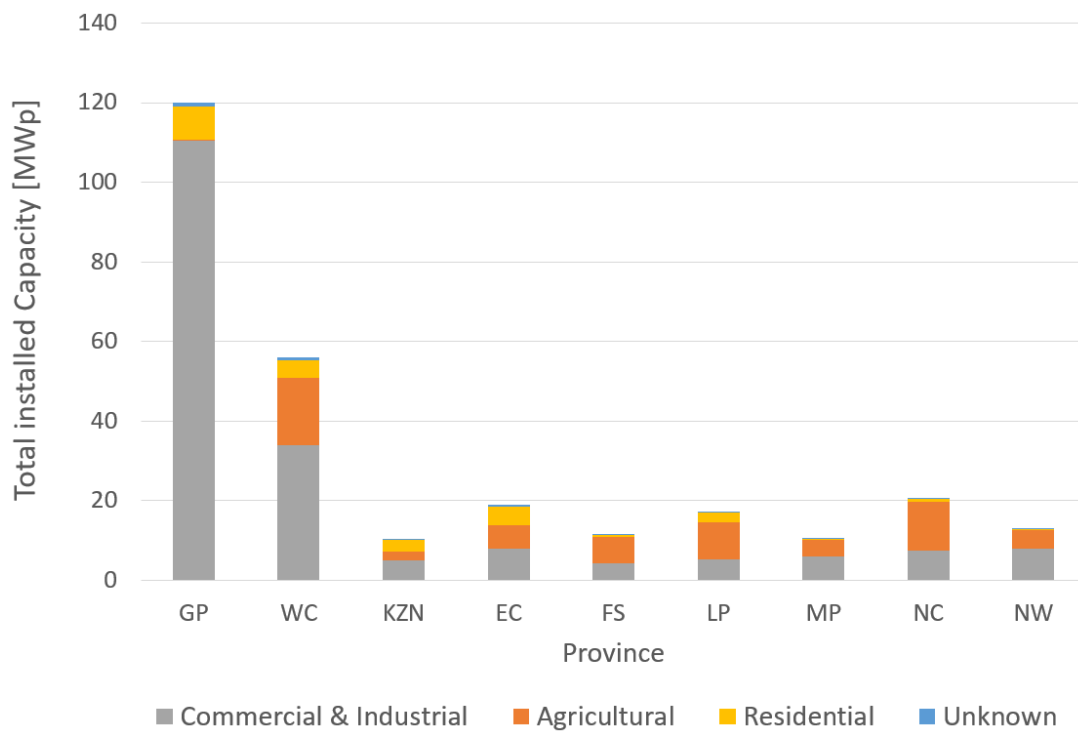


Figure 2-7: Breakdown of embedded generation capacity per industry and province

Source: Adapted from Pandarum *et al.* (2019)

Figure 2-8 below shows the drivers for implementing SSEG from the perspective of the four major metropolitan municipalities (Cape Town, eThekwin, Johannesburg and Ekurhuleni). The motivations to promote SSEG vary between the municipalities. Factors such as the security of supply, the cost of electricity, and the change in the electricity value chain are all factors that result from the general power situation in South Africa. The underlying risk that load-shedding and rising electricity costs bring is evident in all the metropolises. Embedded generation in municipalities is almost exclusively solar PV. Other factors, such as climate change mitigation and being “green”, are also important.

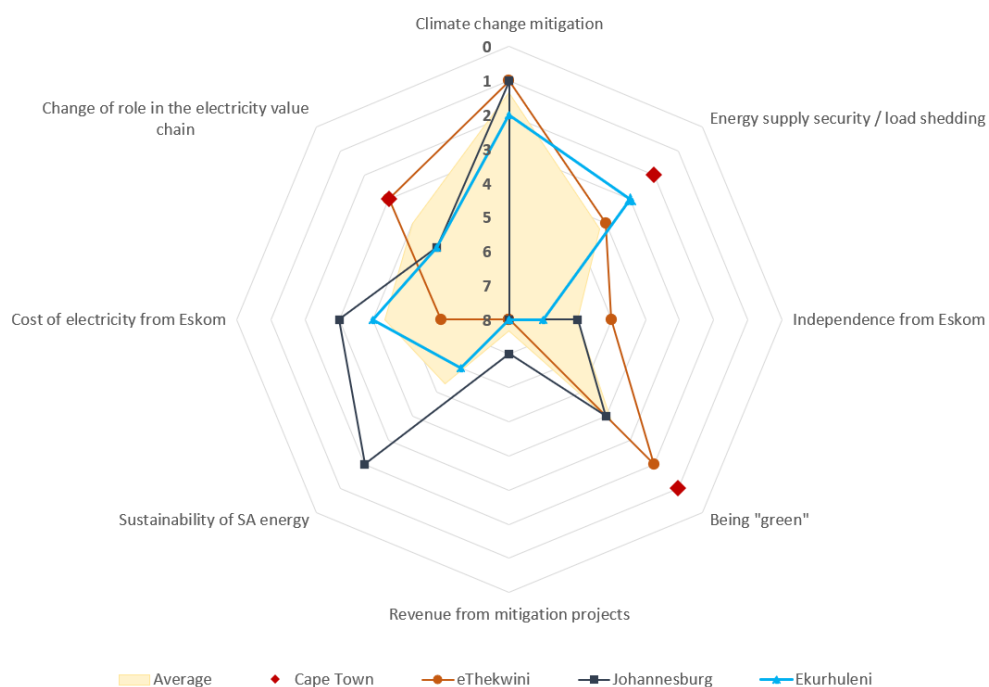


Figure 2-8: Drivers for the implementation of SSEG

Source: Adapted from Filipova and Morris (2018)

2.3 Embedded power generation opportunities in the sunflower value chain

With the threshold for SSEG lifted to 100MW, numerous opportunities open up for enterprises to generate power for themselves and become less dependent on Eskom. The possibilities include agro-processing facilities that generate biomass waste streams. Such waste streams can be used as feedstock for power generation. Furthermore, additional cost savings can be realised when the steam produced by combustion can be used to provide process heat.

In 2015 there were twelve sunflower oil and oilcake producers in South Africa, with a total capacity to process at least 1.7 million tons per annum (van der Burgh *et al.*, 2015:9). Table 2-1 below summarises the oilseed crushers in South Africa that can process sunflower seeds and soybeans in 2013. Oilseed crushing plants produce sunflower husk as a high-energy content by-product that can be used as a fuel for both steam and power (Havrysh *et al.*, 2020:2). These plants are very electricity and energy intensive, and this significantly impacts production costs (Havrysh *et al.*, 2020:2). The

profitability of sunflower-crushing plants depends on various factors that are specific to the sunflower industry as well as the local and international oilseed markets. The South African Bureau for Food and Agricultural Policy (BFAP) reports that crushing margins have been under severe pressure due to a combination of low oil content, high seed prices and low oil selling prices (BFAP, 2020:77). Crushing margins were negative in some months in 2010-2013, with negative crusher profits reported relative to retail prices in the 2011-2012 period (van der Burgh *et al.*, 2015:40). BFAP (2020:77) also reports negative crushing margins in 2016. According to reported data, average sunflower crop yields indicate that the relative profitability of sunflower production changes rapidly and that it is considered a “catch” crop (van der Burgh *et al.*, 2015:3).

Table 2-1: Oilseed crushers in South Africa for sunflower seed in 2013

Oilseed Crushers in South Africa		Sunflower	Soybean	Total
Name	Location	1000t / month	1000t / month	1000t / month
Continental Oil Mills	Viljoenskroon	10	15	25
Continental Oil Mills	Randfontein	16		16
EPKO Oil Seed Crushing	Lichtenburg	10		10
Nola Industries	Randfontein	10		10
Gauteng Oil	Gauteng	10		10
Willowton Oil Mills	Pietermaritzburg	14		14
Willowton Oil Mills	Isando	20	23	46
CEOCO	Boksburg	16		16
Nedan Oil	Potgietersrus	8		8
Noble	Standerton	26	28	54

Oilseed Crushers in South Africa		Sunflower	Soybean	Total
Majesty	Krugersdorp	10	16	26
Russel Stone	Bethlehem	Starting-up		

Source: Adapted from van der Burgh *et al.* (2015:37)

The initiation of load-shedding in 2008 and the subsequent electricity insecurity has resulted in a significant change in the price elasticity of electricity demand for most industry sectors (Blignaut *et al.*, 2015:6). The price elasticity for the industrial sector is highly significant and negative (Inglesi-Lotz & Blignaut, 2011:459). The impact of electricity on sunflower-crushing costs is not readily available. It would be specific to each crushing plant, depending on the crushing plant technology, plant age and operation of the plant. It can be expected that sunflower-crushing plants are sensitive to electricity prices, similar to any industrial plant that relies on large amounts of electricity. The availability of a high-energy content by-product in the form of husk and the increased allowed power generation threshold of SSEG projects are both positive drivers for considering embedded power generation. The steep increase in Eskom electricity prices is a further motivation for considering such an investment.

Figure 2-9 below presents schematically the process through which sunflower seeds are hulled, with the husk used to generate power through combustion. Examples of utilising the waste husk as an energy source for sunflower-crushing plants are available in other parts of the world, especially for steam generation. There are examples of power and steam generation in Paraguay and steam generation in France and Turkey (Berkes, 2008). In addition, feasibility studies for embedded generation at sunflower-crushing plants have been conducted in countries with high sunflower production, most notably Ukraine (Havrysh *et al.*, 2019; Havrysh *et al.*, 2020; Jiang *et al.*, 2019). However, the literature lacks detailed information on the implementation of power generation projects using sunflower husks as a fuel source.

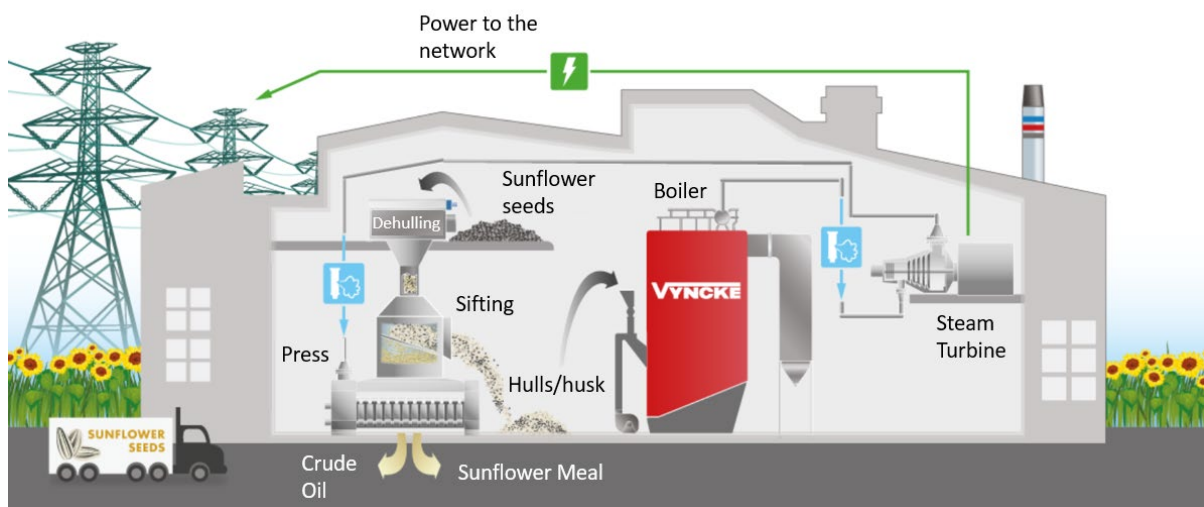


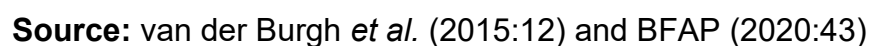
Figure 2-9: Production of electricity using sunflower husk

Source: Adapted from Vyncke (2021)

Rice processing similarly produces high energy content residue in the form of a risk husk or straw that can be used as a fuel source. Several studies in the literature investigate the feasibility of producing power with risk husk (Abdelhady *et al.*, 2018; Delivand *et al.*, 2011; Nguyen, 2014). However, it is noted that the primary method of power conversion is through combustion for steam generation and expansion through a steam turbine for power generation.

There are very few reports on the use of biomass as a fuel source for power generation in South Africa, and in most cases, only applied on a small scale (Visser *et al.*, 2019:10). A reason for the lack of academic literature is the limited biomass generation capacity under the REIPPPP. Under round 4, only 41MW, or 0.81% of the 5037MW, were procured through biomass combustion (Visser *et al.*, 2019:10). Studies that focus on biomass energy in South Africa and Sub-Saharan Africa include gasification as a technology, sugarcane residues for energy generation, and maize and wheat residues as source (Batidzirai *et al.*, 2016; Mamphweli & Meyer, 2009; Roder *et al.*, 2017). Further overviews of the potential for biomass energy in South Africa are given by Aliyu *et al.* (2018), Winkler *et al.* (2017), Valk (2014), Akinbami *et al.* (2021) and Dasappa (2011). None of these overviews, however, includes a specific emphasis on sunflower husk as a fuel source for power generation.

In South Africa, sunflowers account for approximately 3.8% of the total area cultivated (or about 13.2 million hectares), compared to 20.5% and 3.7% for maize and soybeans, respectively (van der Burgh *et al.*, 2015:3). The main areas where sunflower is grown is in the Southern and western Free State, as well as the drier parts of North West (van der Burgh *et al.*, 2015:3). Figure 2-10 shows the relative areas in the North-West and Free State used for sunflower production. The North-West and Free State account for 79% of the total national area used to plant sunflowers (van der Burgh *et al.*, 2015:12).



South Africa was the world's 13th largest producer of sunflower seed in 2018 (BFAP, 2020:12). Figure 2-11 compares the production in various countries. The countries that are major sunflower producers or exporters are Argentina, Ukraine and Russia (van der Burgh *et al.*, 2015:3,56). Production in Argentina is especially important for the South African context since they are also in the Southern hemisphere, and its production and market cycle is therefore aligned with South Africa (NAMC, 2004:236).

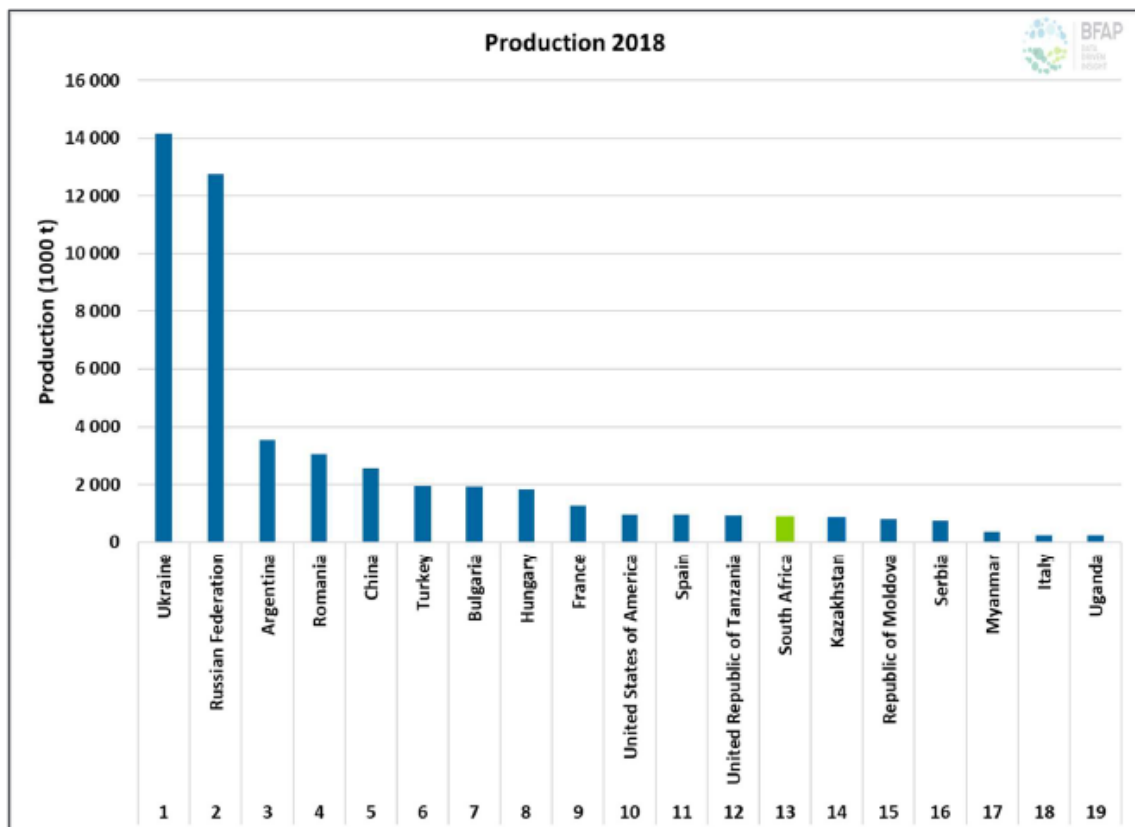


Figure 2-11: Comparison of sunflower production between countries

Source: BFAP (2020:12)

Figure 2-12 below compares the oil and oilcake quantity produced from 2000-2020 and the seed price paid to producers in South Africa. It is evident from the data that there is a large variability in the total annual production of oil and oilcake over time. The producer prices also fluctuate considerably, but shows a general linear increase over time. Various South African companies have ample crushing capacity, and price and production fluctuation invariably influence the profitability of crushing operations.

There also seems to be tight competition for the sourcing of sunflower (van der Burgh *et al.*, 2015:39). The total annual production could be expected to play an essential role in a crushing plant's power requirements.

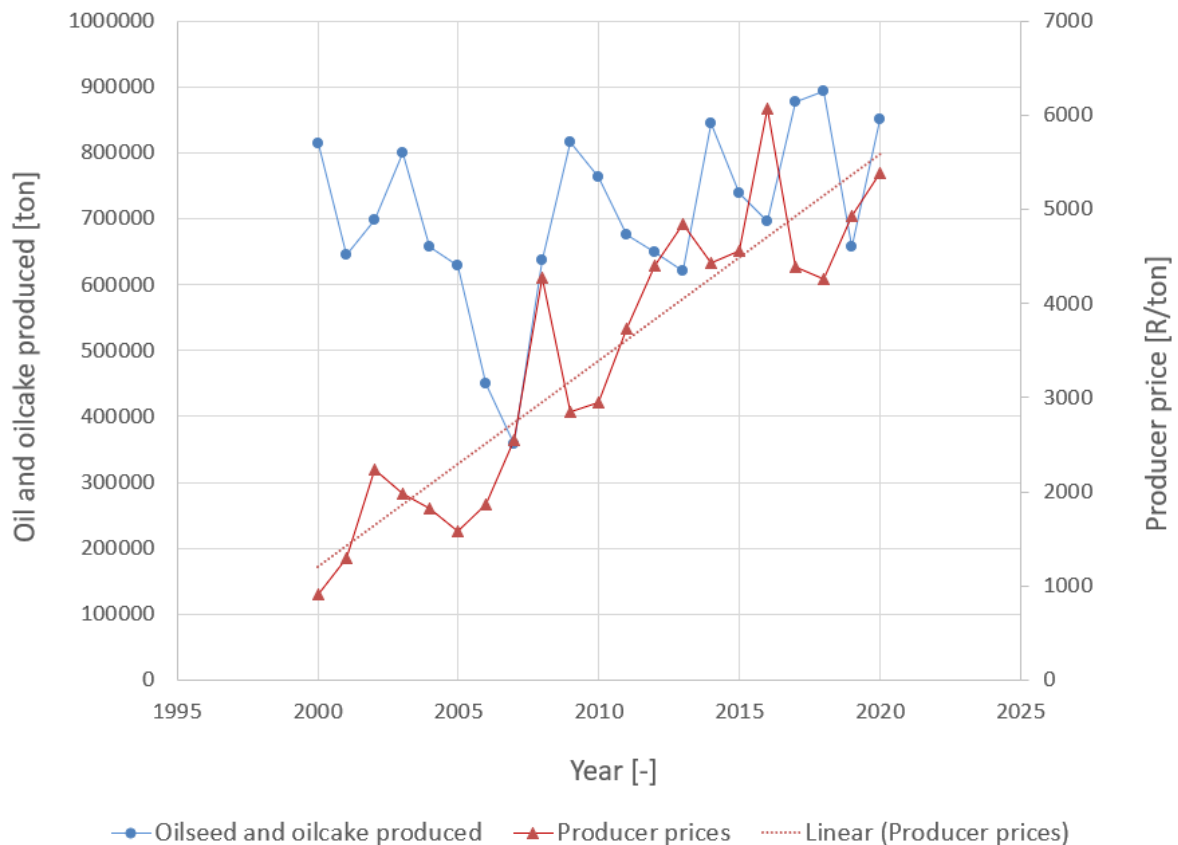


Figure 2-12: Sunflower oil and oilcake produced and seed prices for 2000 to 2020

Source: EasyData (2021)

South Africa is not a significant player in international oilseed production and trade and is therefore considered a price taker (NAMC, 2004:236). The South African National Agricultural Marketing Council (NAMC) report notes that the international oil price acts as a guideline for domestic seed and oil prices. The Argentinean oil market is critical since it has the same marketing period (NAMC, 2004:236). Figure 2-13 below compares the relationship between the South African Foreign Exchange (SAFEX) sunflower seed price and the crude oil price. The graph highlights that the local sunflower seed and oil prices depend on international markets and are usually traded very close to the import parity (NAMC, 2004:236).

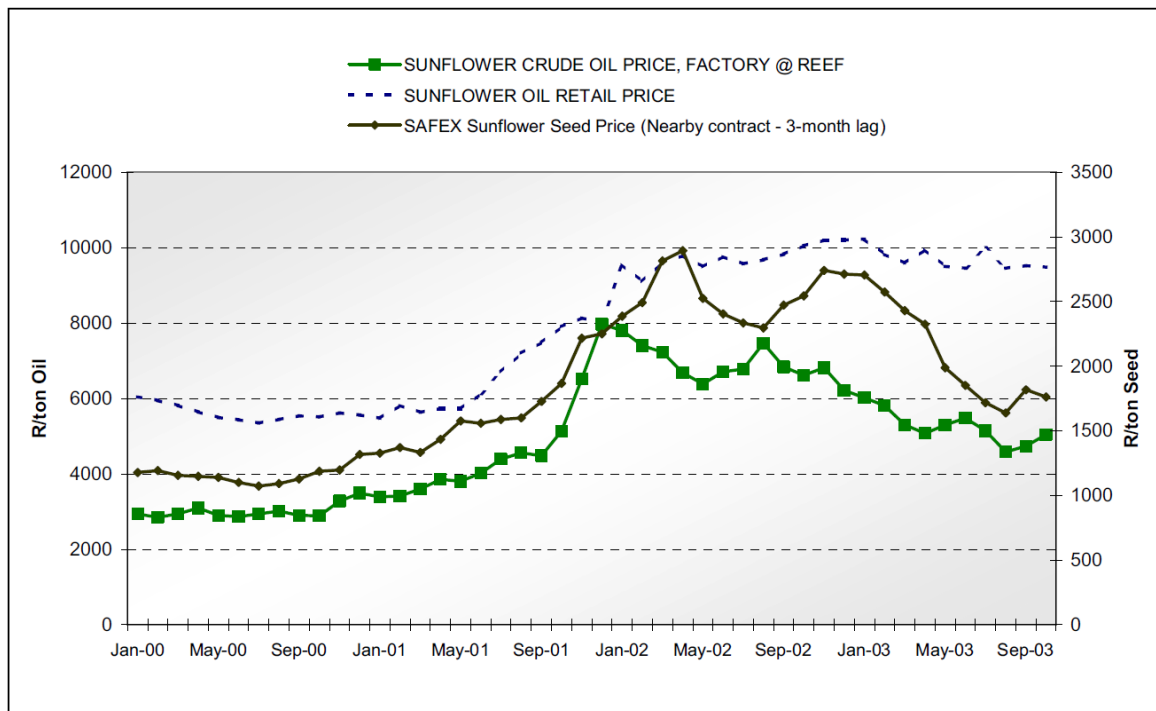


Figure 2-13: Correlation between sunflower oil price and seed price

Source: NAMC (2004:236)

The international prices of crude sunflower oil are further dependant on substitute oil prices, such as soybean oil. Figure 2-14 below shows Argentina's Freight-on-Board (FOB) prices for sunflower and soybean oils. The import parities of sunflower oil and substitute oils, such as soybean oil, are, therefore, drivers of the price that oilseed processors are willing to pay for sunflower seed (NAMC, 2004:236). Since 2012, crude soybean and palm oil have competed for the lowest-cost vegetable oil and are regarded as the drivers in the price formation of the other oils, including sunflower oil (van der Burgh *et al.*, 2015:30). Furthermore, South Africa is a major importer of vegetable oils and oilcake. The exchange rate has a significant impact on local producer prices and the crushing margins (Lemmer, 2019:1). There is a delicate balance between a sustainable price for the farmer and the price that crushing plants can pay while competing with imported oil and cake (Meyer & van der Burgh, 2015:29). Sunflower cake is regarded as a by-product with prices being determined by the local supply and demand in the cake market resulting in volatile prices (NAMC, 2004:237).

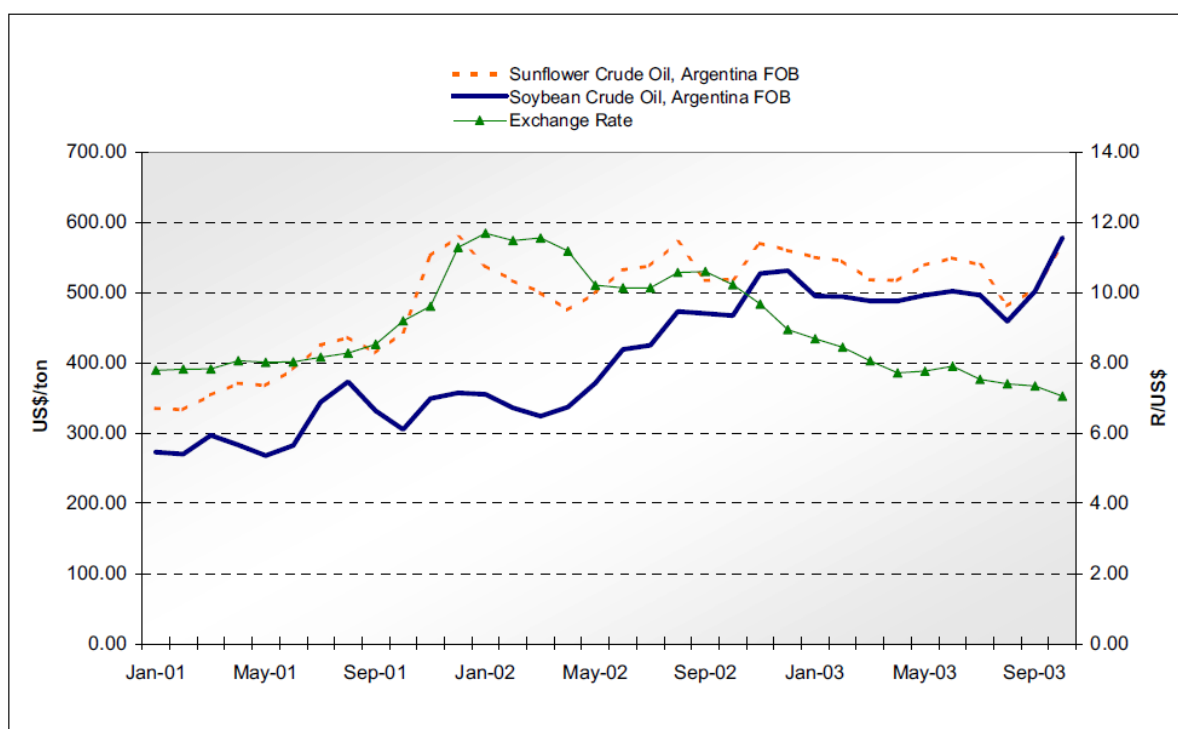


Figure 2-14: Sunflower and soybean crude oil prices in Argentina

Source: NAMC (2004:237)

Oil content in locally sourced sunflower seeds also plays a vital role in crushing margins and production rates of crushing plants. Oil content in South African sunflower seed has decreased below 38% in 2018 and 2019, which is substantially lower than oil content from producers in Argentina and Ukraine, which is on average between 42% and 44% (BFAP, 2020:77,78). When the oil content drops below 34%, it will be more expensive to produce crude oil in South Africa than to import it (when excluding the returns earned from cake) (BFAP, 2020:78). If refineries can import crude oil at a lower price than buying from local producers, then they will import the oil (NAMC, 2004:236).

Weather impacts the national sunflower production levels and the tons of sunflower crushed. For example, in 2016, the severe drought resulted in negative crushing margins as the sunflower seed price increased due to low production (BFAP, 2020:77). The increased demand in combination with the drought also resulted in negative crushing margins for soya beans in the 2015-2016 season (Strydom, 2016:24).

2.5 Risks in renewable energy power generation

The success of small-scale renewable energy projects is intricately connected with the financing available for such projects and the financing method used to structure the deal. Financiers are typically risk-averse, and the probability of risks negatively impacting the finances of a project must be minimised. Therefore, risk mitigation is a fundamental requirement in renewable energy projects to attract finance (UNEP, 2004:13).

While the opportunities for embedded power generation exist for both solar PV and biomass, different approaches are required to evaluate the investment opportunities for these technologies. Figure 2-15 illustrates the differences between Solar PV and biomass project investment (Taylor *et al.*, 2020). For Solar PV, the trend shows that the installed cost per kW is decreasing. The variation in cost is also reducing (i.e. the difference between the maximum cost and minimum cost per kW installed).

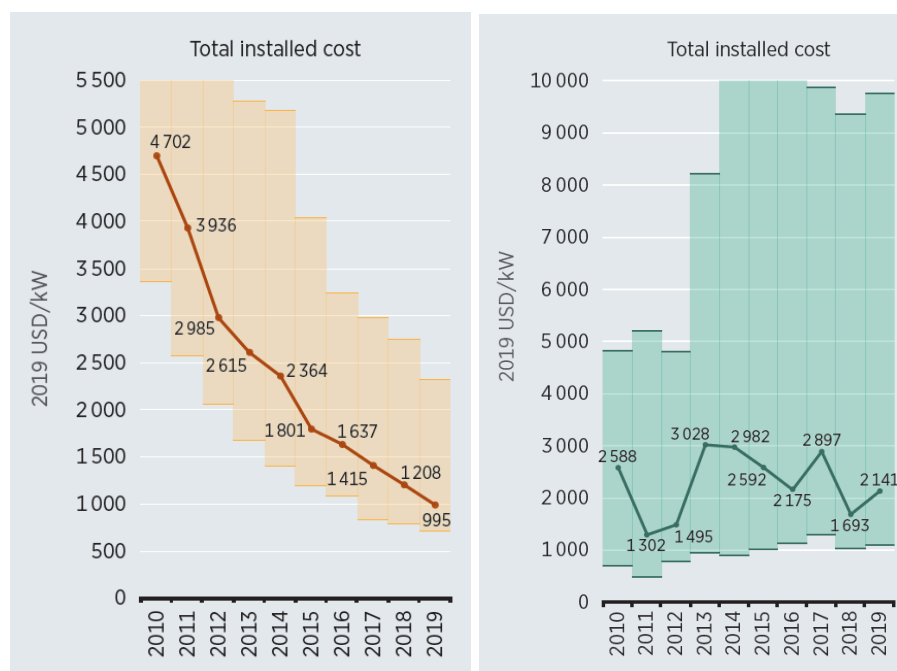


Figure 2-15: Comparison between installed cost per kW for solar PV (left-hand side) and biomass (right-hand side)

Source: Taylor *et al.* (2020:66,111)

For biomass, there is considerable variability in the installed cost, which reflects that each project is unique and that planning, engineering and construction costs are significant contributors to the total investment (Taylor *et al.*, 2020:113). The majority of biomass projects are furthermore small-scale (<25MW), and economies of scale are not achieved in the majority of projects (Taylor *et al.*, 2020:113). The risks of small-scale projects differ significantly from large-scale projects (Kristinsdottir, 2012).

The large variability in installed cost is further reflected in biomass's levelised cost of electricity (LCOE). As alluded to in Figure 2-16 below, the average LCOE of biomass is competitive compared to Solar PV, but the variation is significant. For biomass projects, LCOE is also related to the capacity factor, which is directly dependent on the availability of feedstock and the cost associated with the feedstock (Taylor *et al.*, 2020:119). For solar PV, yearly solar radiation can be estimated using commercial software (e.g. Solargis®), with typical bias in estimating the radiation being around 2.2%. Standard deviations on the bias are in the order of $\pm 5.3\%$ (ESMAP, 2019:19). Since the amount of solar radiation is the basis for estimating the electricity production in solar PV, the low uncertainties associated with estimating the radiation provides designers with remarkably accurate data for design purposes. The same accuracy applies to assessing generating capacity and revenue from generation. Such certainty is not possible for biomass power generation facilities, where feedstock availability, quality and price depend on many factors such as rainfall, commodity prices and demand for feedstock (Taylor *et al.*, 2020:119).

Commercial financiers consider various factors before investing in a power generation project. These include the maturity of the technology, the track record of implementation in the specific country, technology support in the country, and the project developer's reputation (UNEP, 2004:13). For small renewable energy projects, the use of unfamiliar technology could require a substantial equity component. The equity component could be as much as 50% of the project value (UNEP, 2004:14). Equity funding is costly. As a result, many renewable energy projects falling into this category do not go beyond the planning stage (UNEP, 2004:15).

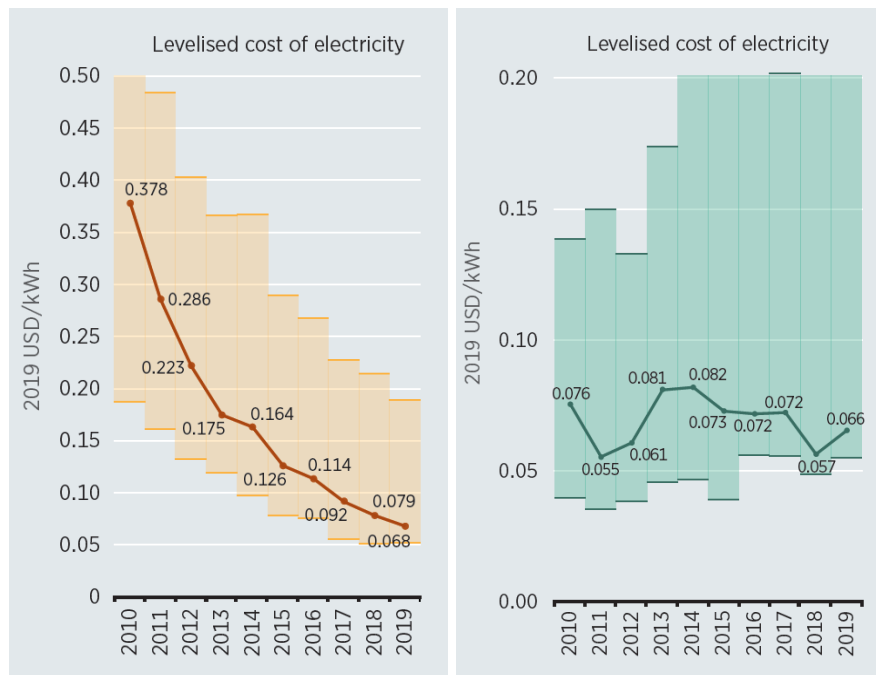


Figure 2-16: Comparison between LCOE for solar PV (left-hand side) and biomass (right-hand side)

Source: Taylor *et al.* (2020:66,111)

Agrawal (2012:12-13) suggests that project financing provides many benefits towards structuring renewable energy projects. However, risks need to be avoided or mitigated for successful financial closure (Agrawal, 2012:13). Some of the significant risks associated specifically with biomass projects are the security of supply of feedstock, fuel price volatility and emission controls (Agrawal, 2012:15; UNEP, 2004:18). Common risks in renewable energy projects are capital costs, construction risks, performance risks during operations, the lifetime of the plant, the capacity factor of the plant, future carbon prices, market risks, credit risks, legal risks, regulatory risks, political risks, and force majeure risks (Heck *et al.*, 2016:21; UNEP, 2004:14-18).

In the risk management process, the following steps are essential (Kristinsdottir, 2012):

- Risk identification: All risk exposure for the power plant project must first be identified.
- Risk assessment: The risk's impact (or cost) and the potential likelihood of occurrence need to be considered for each risk.

- Risk management methodology: Once the risks have been identified, various risk management methodologies must be considered. These typically avoid, control, accept and transfer methods.

The following section will review and classify risks typically associated with renewable power generation projects and provides an overview of the risk assessment and some of the literature discussing management methodologies. Finally, the risks identified from the literature review will be summarised according to the classification, assessment, and management methods.

2.5.1 Identification and classification of risks

The classification of risks associated with renewable projects varies in the literature. Egli (2020), Enzensberger *et al.* (2003), Frisari *et al.* (2013), and Gatzert and Kosub (2016) provide broad overviews of the classification of risks in energy projects. Risks can be grouped as exogenous and endogenous (Frisari *et al.*, 2013). Exogenous risks are those the project sponsor can control, such as technology selection, management and financial resources (Frisari *et al.*, 2013). Endogenous risks are those over which the project developer has little or no control. It is also risks that can't be easily mitigated, such as political risks, changes in policy, and currency devaluation (Frisari *et al.*, 2013). Alternatively, risks can be allocated into two main categories of investment risks – risks that influence the power plant's cost and risks that impact the revenues (Gross *et al.*, 2010).

Egli (2020:4) performed a comprehensive review of the risk classifications from 22 literature sources. A summary of the sources provides the following risk types: curtailment risks, policy risks, price risks, resource risks and technology risks, economic/commercial risks, and financial risks. These categories will be used to delineate the risks. However, it is essential to note that although risks can be broadly classified into different categories, risks can't be viewed as independent of each other.

Curtailment and utilisation risk

Curtailment risks refer to the risks arising from grid availability. The lack of grid availability leads to an oversupply of power generation that needs to be curtailed,

resulting in lower-than-expected revenue (Egli, 2020; Gatzert & Kosub, 2016; Gross *et al.*, 2010). In addition, low returns will be realised for the capital invested due to low utilisation without sufficient offtake. In this sense, curtailment and utilisation can be grouped. The risk associated with low capital utilisation is sometimes referred to as a volume risk (Mitchell *et al.*, 2006). Curtailment risks are, however, only associated with the demand side.

Neto *et al.* (2018) consider the influence of the capacity factor of wind farms on the economic viability and the risk resulting from the uncertainty in the capacity factor. The capacity factor is related to how well the equipment is utilised and is considered a utilisation risk in this context. The capacity factor can be influenced by both the demand and the supply side — a low need due to curtailment results in a low capacity factor. Unplanned downtime can also result in a low capacity factor. Gross *et al.* (2010) refer to utilisation as a technical risk.

Price risk

Electricity price fluctuations are a risk to stable and predictable revenue. In the case of embedded power generation, the purpose is to offset the power that would have been procured from the utility. As such, the utility price needs to be considered – if the utility price fluctuates considerably, there is a risk of the investment being less profitable.

The uncertainty in electricity prices can be classified as a market risk (Enzensberger *et al.*, 2003; Frisari *et al.*, 2013; Gatzert & Kosub, 2016). In cases where the price of electricity is determined by market forces (supply and demand), this classification makes sense. Neto *et al.* (2018) modelled the short-term price variation in the Brazilian energy market using stochastic methods. The risk underlying the price volatility, seasonality, and jumps or spikes can be evaluated in this way. Gross *et al.* (2010) also classify electricity price volatility as a price risk but expand the category to include fuel price volatility. In some cases, the electricity prices are based on the plant's performance, an example being wind plants in Germany that are remunerated based on their performance (Mitchell *et al.*, 2006).

In South Africa, the electricity price is determined by the National Energy Regulator of South Africa (Nersa), not supply and demand.

Resource risk

Resource risks include uncertainty in the characteristics of the exploitable reserve and the supply risk associated with the quality and availability of the resource when required (Enzensberger *et al.*, 2003). Reserve risks are typically associated with solar PV and wind, while supply risks are associated with biomass. Solar PV carries little to no resource risk after the site has been selected and meteorological data have been analysed (Kristinsdottir, 2012). In wind power generation, wind availability can be determined through wind measurements over a long period or, if possible, through historical data (Kristinsdottir, 2012).

Resource risks in biomass power plants can be mitigated through long-term contractual agreements, but this is not always viable. Indirect risk mitigation methods are proposed, such as selecting a site where the biomass resource is practically abundant (Enzensberger *et al.*, 2003). In the case of sunflower-crushing plants, the husk available is more than required for both heat and power, and the risk of resource availability is mitigated (Havrysh *et al.*, 2020).

Technical and technology risk

The technology chosen for the power conversion plant directly influences the risks involved. The level of technology readiness (i.e. how mature the technology is) could affect how long construction and commissioning take. The level of maturity in the country of installation, together with the skill level and experience, also play a role. The chosen technology could further influence the operating and maintenance costs, the level of downtime (which translates to capacity factor), and the conversion efficiency.

Factors that influence the uncertainty and investment risk include information asymmetry between the parties involved in the procurement and construction of the equipment and equipment quality (Lei *et al.*, 2020). In addition, the maturation of technologies, such as wind turbines, reduces construction periods and operating costs. New technology, for example, offshore wind turbines, could result in unreliable

operation (Gatzert & Kosub, 2016; Lei *et al.*, 2020). Kayser (2016) obtained opinions from 69 participants involved in PV power projects to determine the most pertinent risks in deploying the technology. As a result, the following relevant technology risks were identified:

- System actual performance vs system rated performance.
- The quality of the components (counterfeit equipment vs equipment from a reputable original equipment manufacturer (OEM)).
- The environment in which the plant operates.
- Know-how of the construction team for the technology.
- The level of confidence in the claimed yield is.
- Higher maintenance costs due to the novelty of the technology and faster degradation (Egli, 2020).

Gross *et al.* (2010) further highlight considerable differences in the technical risks of different technologies.

Economic and commercial risk

Economic risks are defined as risks that could influence the financial returns due to the construction cost (or total plant cost), operating costs, amortisation and interest payments (Lei *et al.*, 2020). The total plant cost (i.e. cost of equipment, construction and commissioning) significantly influences the investment returns. Higher capital costs will result in longer paybacks and higher interest costs. Various factors could affect the total plant cost:

- The technology used could impact the risk of build time, delayed commissioning, cost overruns, and risk of completion risks (Enzensberger *et al.*, 2003; Gross *et al.*, 2010). Therefore, selecting a technology that minimises the risks of delays is critical.
- Construction delays and project implementation risks are influenced by uncertainty about permits, planning, material and labour shortage, price inflation, rework, unexpected site conditions, and other unforeseen events (Love *et al.*, 2013; Surana & Anadon, 2015). In the project's planning phase, optimism bias can lead investors

to be over-optimistic about successes while ignoring the many potential unforeseen delays (Love *et al.*, 2013). Such optimism can reflect in over-optimistic timelines for construction and commissioning and over-optimism with implementing new technologies.

- Plant size plays an important role. Larger plants typically have better economies of scale, providing better yield for the investment due to higher efficiencies. Neto *et al.* (2018) show, for example, the effect of wind tower height on the NPV, highlighting that taller towers' better yield offsets the higher investment cost. Delivand *et al.* (2011) emphasised that the internal rate of return (IRR) and LCOE strongly depend on the plant size for rice husk-based power generation. Embedded generation for own consumption requires accurate matching of supply capacity and demand (see curtailment and utilisation risk). Therefore, oversizing the plant can result in higher costs and lower utilisation.

Operating cost uncertainty is also an economic risk (Lei *et al.*, 2020). Technology plays a role in the operational and operating costs' uncertainty levels (Gatzert & Kosub, 2016). During a project's feasibility phase, unfamiliar technology might require more estimation of the operating requirements. For established technology, the operational requirements can be obtained from historical values and suppliers who are familiar with the requirements.

Financial risk

Financial aspects influencing the investment risk include the cost of capital and capital structure (debt to equity ratio) (Enzensberger *et al.*, 2003). The cost of debt can fluctuate and is, therefore, a risk. In addition, large debt could result in liquidity problems if the project's cash flow is not as expected and can result in liquidity risks (Kayser, 2016).

The net cash flow from a project depends on all the risk factors included. The cash flow analysis based on all the risk factors will therefore indicate the financial risk posed to the project owner and investors. From the cash flow analysis of the project, the riskiness of the project can be evaluated. The risks will influence the investor's cost of capital as well as the debt-equity ratio.

In 2013, the cost of equity in South Africa for wind power projects was 15%, and the cost of debt was 7.5% (Waissbein *et al.*, 2013). The cost of equity is 6.5% higher than in the best-in-class country. The higher cost of equity is attributed to the power market risk (1.1%), counterparty risk (0.6%), financial sector risk (0.5%), and currency/macro-economic risk (1.2%), among others. Similar trends are observed for the increased cost of debt compared to best-in-class countries.

Policy, country, and regulatory risk

Policy risks are adverse outcomes due to the interaction of government institutions, regulations and the prevailing political climate (Kayser, 2016). An example of regulatory risk is the legislation regarding the maximum allowable embedded power generation without a licence. Similarly, possible changes in the air emissions act might influence the required emissions clean-up required in biomass combustion projects. The primary governance barriers to deploying renewable energy sources in the private sector are political commitment, transparency, corruption, late payment, and procurement regulations (Nel, 2015:54).

Country risks include economic development, legal stability and protection, currency, and macroeconomic risks (Enzensberger *et al.*, 2003; Kayser, 2016). These risks are difficult to quantify regarding their contribution to the total financial risk. Political risks specific to South Africa include social inequality and governance issues, which have moderate impacts on financing costs (Waissbein *et al.*, 2013)

2.5.2 Risk assessment and management

In addition to quantifying risks (i.e. the impact of a risk factor), it is crucial to consider the likelihood of a risk occurring. These two steps are known as risk assessment (Kristinsdottir, 2012:78). Follow the risk assessment step, risk management methodologies need to be considered. Methods include risk avoidance, control, acceptance or transfer (Kristinsdottir, 2012:78). Some risks have a high impact but can be easily mitigated. In contrast, others have a high impact but a low probability of occurring. The combination of risk impact, the likelihood of occurrence, and the measure of mitigation play a role in how the cost impact of risks can be lowered.

Risk assessment, control and mitigation are all good governance practices considered necessary in developing renewable energy projects. However, in a large-scale survey of stakeholders in the renewable energy industry (through questionnaires and interviews of stakeholders in South Africa), Nel (2015:60) found a perception in both the public and private sectors that there are gaps in these governance practices. In the survey, respondents also had to indicate the significance or impact of risks in IPP scale RE projects. Risks included political risks, corruption, human capacity risks, high cost of lending, technology risks, shareholder value, design risks, operational risks, construction risks, regulation risks, reputational risks, legislation risks, and institutional risks.

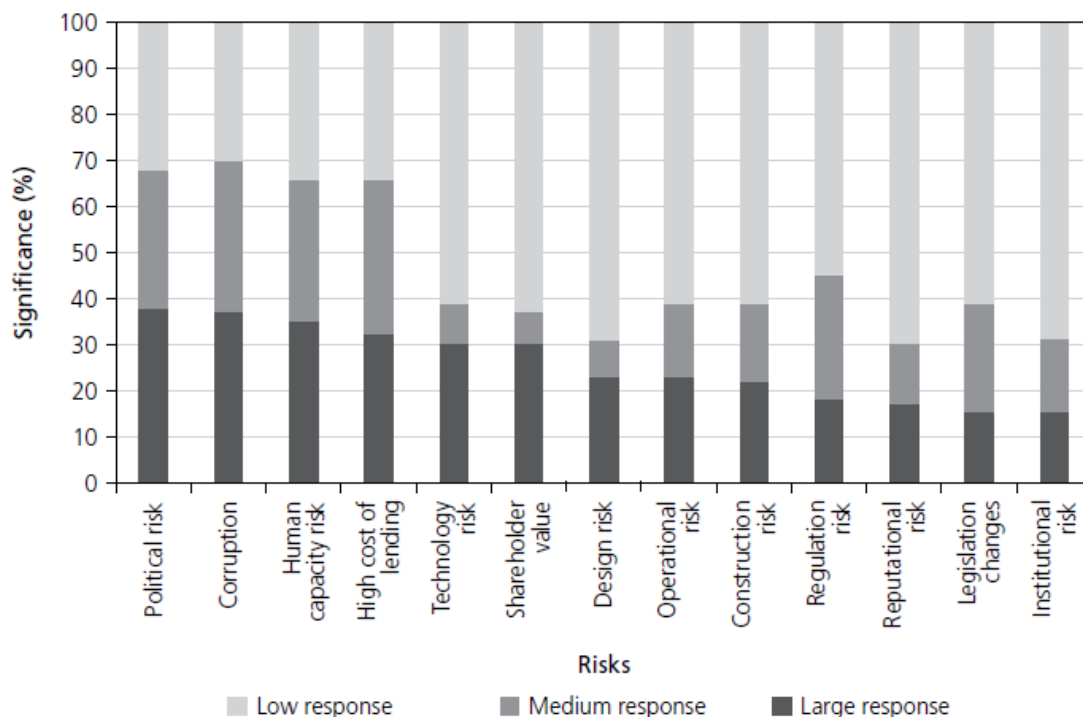


Figure 2-17: Ranking of the significance of risks as per stakeholder evaluation for IPP renewable energy projects

Source: Nel (2015:61)

The ranking of the risk significance is shown in Figure 2-17, while the likelihood of occurrence is provided in Figure 2-18 below. Aside from political and corruption risks, which are beyond the control of any small-scale renewable investors, human capacity risks, technology risks, and high cost of lending are all perceived to have significance

and the likelihood of occurrence. Although the risk analysis was performed for large-scale IPP projects, the same factors can be assumed to apply to small-scale power generation projects under investigation.

UNEP (2004) considers several risk management instruments in the form of insurance products for renewable energy projects. Insurance instruments include products to cover contractor's risks (e.g. defaulting) and property damage (e.g. risk of damage to large components during transport). Other factors include machinery breakdown (e.g. risk of component failure after supplier warranties have expired or due to integration issues), delays in start-up (e.g. due to project overrun) and design errors or omissions to allow for specific components/services (UNEP, 2004:21).

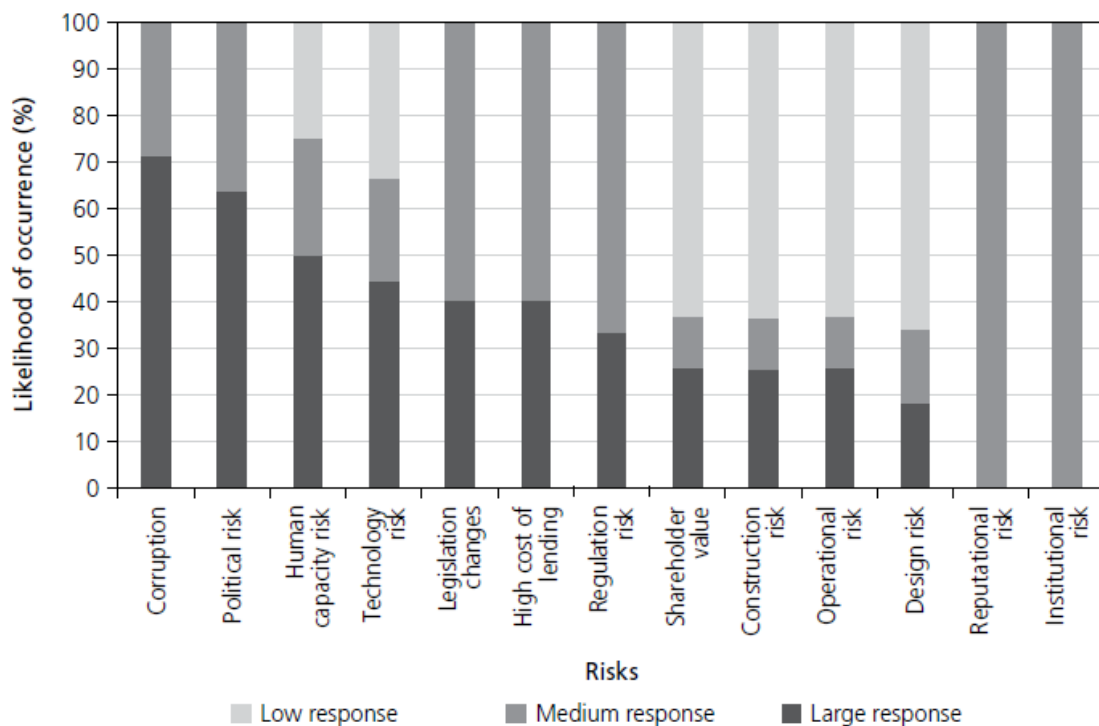


Figure 2-18: Ranking of the likelihood of occurrence of risks as per stakeholder evaluation for IPP renewable energy projects

Source: Nel (2015:62)

With insurance products, lending costs in RE projects can be lowered. Furthermore, under circumstances where events negatively influence the project, these products reduce pressure on liquidity (UNEP, 2004:21). It is, therefore, an important instrument,

especially when considering it with the risk of a high lending cost perceived by stakeholders as previously discussed. However, insurers require information and data concerning the likelihood and severity of insured events (UNEP, 2004:21). Most renewable energy projects do not have the necessary statistical data. The lack of data results in insurance being comparatively high, with small-scale projects (<USD15 million) having difficulty obtaining insurance (UNEP, 2004:21-22).

In Figure 2-19, a qualitative comparison is made of the insurance available for different renewable energy technologies and types of insurance. The data indicate that the traditional forms of insurance available for biomass technology are minimal.

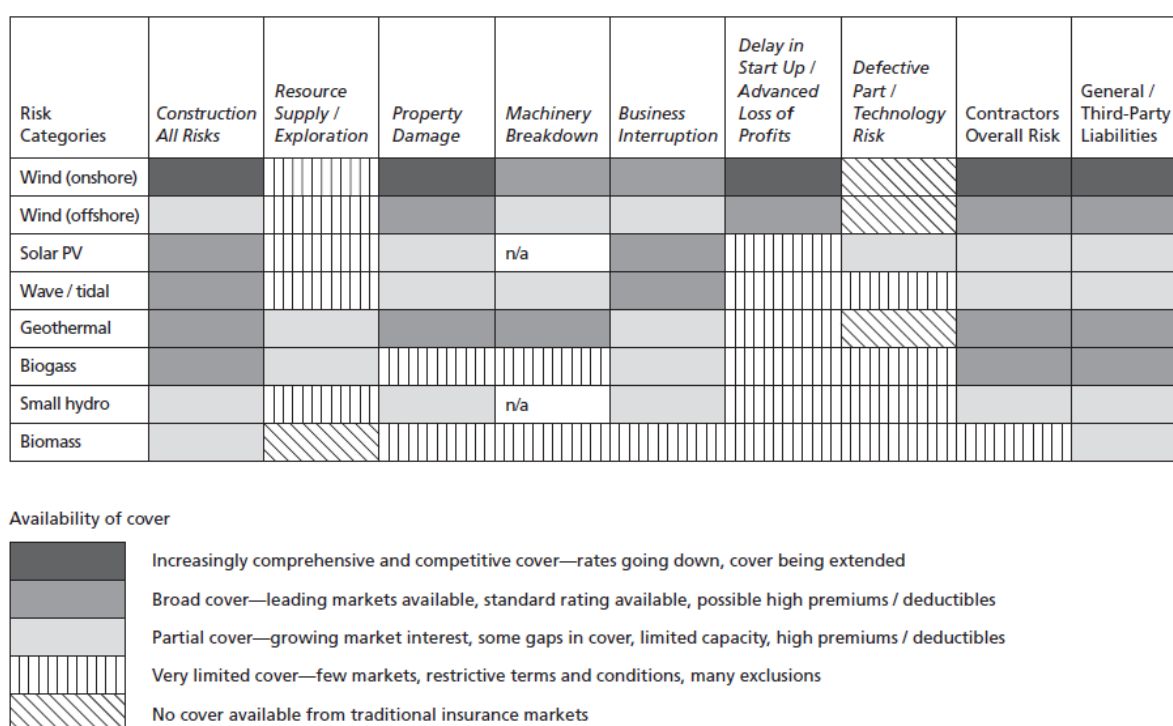


Figure 2-19: Renewable energy technology risk transfer map

Source: UNEP (2004:28)

Frisari *et al.* (2013) provide an overview of risk mitigation instruments for various risks for both developed and developing markets. They focused on green power infrastructure investment and broadly applied it to renewable technology. Gatzert and Kosub (2016) provided a comprehensive overview of the risks associated with onshore and offshore wind parks. They also provide an overview of how risks can be managed and broadly distinguish between risk mitigation, risk transfer, and risk avoidance

methods. Kristinsdottir (2012) discusses risk management methodologies. He emphasises risk transfer through an insurance instrument or third-party contractual mechanisms with, for example, contractors or lenders. Non-insurance transfer instruments are also discussed, such as hedging.

The focus of risk studies in the literature is primarily on large-scale projects. The risks identified in section 2.5.1 are summarised in Table 2-2 (p 38) in the following section. Table 2-2 also shows the associated risk assessment and management methodologies obtained from the literature.

2.5.3 Summary of risks

The risk classifications are graphically represented in Figure 2-20 below. The risks influence three crucial aspects – the investment size, the revenue generated, and the costs incurred. When combined, the resulting cash flow can be obtained. Various metrics can determine the investment or financial risk based on the cash flow. Some interdependencies between the risks are also shown, highlighting that risks can't be considered in isolation.

The risks are also summarised in Table 2-2, where the risk drivers, risk assessment and risk management tools are summarised. The risk assessment (likelihood of occurring and perceived impact) is rated as a low, medium, or high concern based on the literature reviewed. The purpose of this assessment of the risks is to assign relative importance to each risk. Risk management includes both risk mitigation and risk transfer tools. Reviews of investors' perceptions of risks are mainly focussed on wind turbines and solar PV. Some of these risks are common to all renewable sources. The analysis is not exhaustive but provides a high-level overview of which risks are considered more important than others. For small-scale power generation at a sunflower-crushing plant, many risks will be unique and are not covered in the literature. All the risk management tools will also not be applicable. The literature review provides a framework within which the risks identified in the following chapters can be classified. The methods typically used to manage the risks could be applied to the unique risks under consideration in this study.

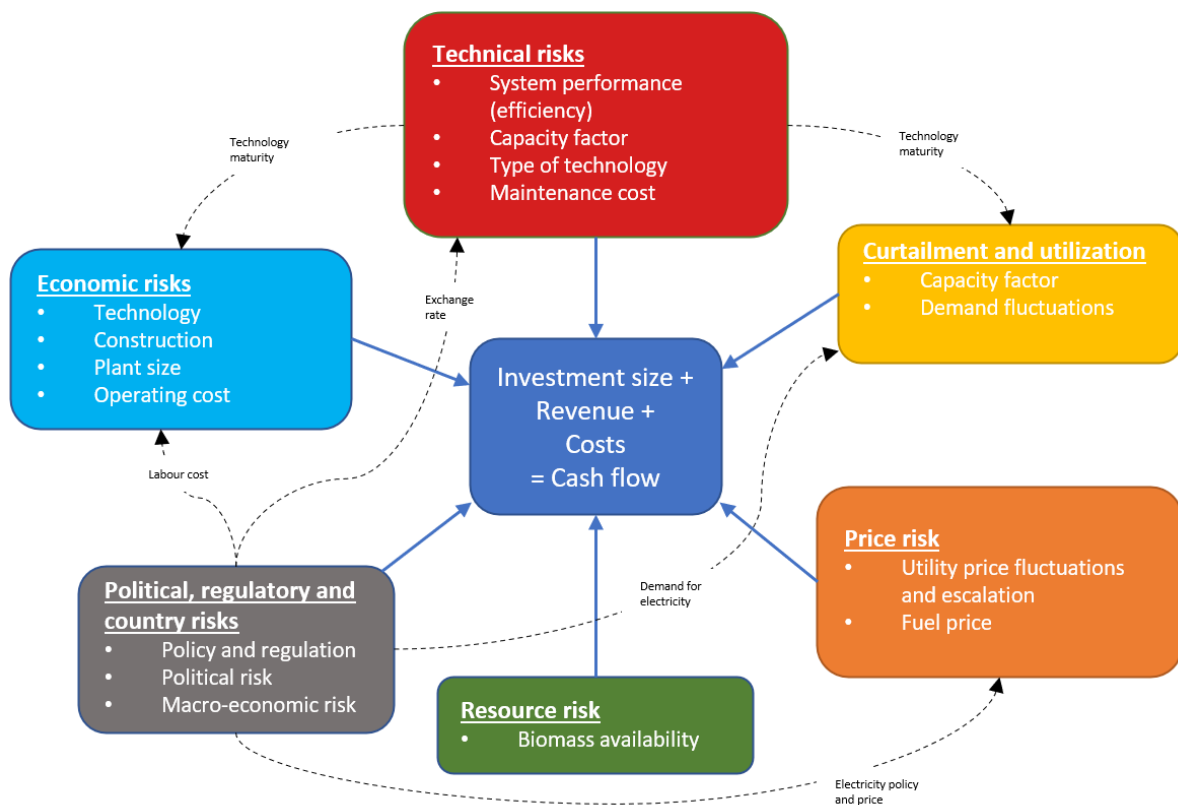


Figure 2-20: Summary of the risk classifications

Table 2-2: Summary of the risks, risk drives, risk probability and risk management.

Identified risk and classification	Risk driver	Risk assessment	Risk management methodology
Curtailment and utilisation risk			
Grid availability risk	Uncertainty in the future availability of the grid and its ability to accommodate the supply of electricity	Medium (Waissbein <i>et al.</i> , 2013)	Improved forecasting techniques (Gatzert & Kosub, 2016).
Demand/offtake risk, excess generation capacity	Uncertainty in the electricity demand for the embedded generator. The uncertainty depends on the off-taker's future production. It could also depend on the general market conditions and other external factors.		Sell reserve capacity on the spot market (Gatzert & Kosub, 2016).
Capacity factor risk	Uncertainty in the availability of the power generation plant, as well as the off-taker for embedded generation. Could be linked to the technology selected		Rely on proven technology (Gatzert & Kosub, 2016).
Price risk			
Electricity price risk	Uncertainty in utility future escalation. The political situation and general economic conditions.	High (Waissbein <i>et al.</i> , 2013)	Contracts and policy support (Frisari <i>et al.</i> , 2013). Energy derivatives, power purchase agreements, improved forecasting techniques, and sell reserve capacity on the spot market (Gatzert & Kosub, 2016).
Biomass price risk	Uncertainty of future value of biomass due to uncertainty in supply and demand		No instrument.

Resource risk

Biomass availability risk	Uncertainty in the availability of biomass	High (if biomass is not a by-product of the embedded generation) (Szabó <i>et al.</i> , 2010; UNEP, 2004)	Long-term contracts and resource modelling (Kristinsdottir, 2012) Indirect ways, such as site selection close to an abundant resource (Enzensberger <i>et al.</i> , 2003)
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Technology risk

Technology maturity during the initial planning phase	Lack of reference cases for the technology. Uncertainty in the claimed yield and system performance. Optimism bias in the use of new technology with claims of higher yield.	High (Nel, 2015)	Proven technology and suppliers (Gatzert & Kosub, 2016). Use proven technology and supplier (Kristinsdottir, 2012).
Technology maturity during construction and commissioning time	Uncertainty in the support provided by suppliers during construction and commissioning. Uncertainty in unforeseen implementation problems.	Low for biomass if mature technology is used (Szabó <i>et al.</i> , 2010) High (Nel, 2015)	Evaluate and understand risks based on industry data and previous lessons learned (Gatzert & Kosub, 2016).
Technology maturity during operations	Uncertainty in actual vs real maintenance costs. Uncertainty in the local know-how to operate and maintain technology	Low for biomass if mature technology is used (Szabó <i>et al.</i> , 2010)	Contracts (Frisari <i>et al.</i> , 2013)

Economic and commercial risk

Construction cost overrun risk	Uncertainty about planning, lack of planning, uncertainty in a labour shortage, and the uncertainty of technology	Medium (Nel, 2015) Low for biomass if mature technology is used (Szabó <i>et al.</i> , 2010)	Contracts and insurance for the delay in start-up, construction and transport (Frisari <i>et al.</i> , 2013; Gatzert & Kosub, 2016). Insurance is not available for biomass (UNEP, 2004). Full-service agreement for transport and construction (Gatzert & Kosub, 2016). Rely on proven technology (Gatzert & Kosub, 2016).
Operating and maintenance cost risks	Uncertainty of the actual operating cost, which could be influenced by technology. Uncertainty in labour costs, which the country's economic conditions could affect.	Medium (Nel, 2015)	Contracts (Frisari <i>et al.</i> , 2013). Full-service agreement for O&M (Gatzert & Kosub, 2016) Rely on proven technology (Gatzert & Kosub, 2016). Incentive based operations, experienced service provider (Kristinsdottir, 2012).
Incorrect plant size risks	Uncertainty in the demand of the off-taker in embedded generation. There is a risk if sizing is not adequately addressed during design.		Reduce risk through design, preventive maintenance, and available parts on standby (Gatzert & Kosub, 2016).

Financial risks

Cost of lending risk	Uncertainty in the future interest rate. The uncertainty depends on the country's economic conditions and international external factors.	Medium (Nel, 2015)	Interest rate SWAP (Kristinsdottir, 2012).
Cost of equity risk	Uncertainty in how all the factors influence the investment metrics and future cashflows. High cost of equity may make project unfeasible.	Medium to high in developing countries (Waissbein <i>et al.</i> , 2013)	No single risk instrument. All risks and uncertainties needs to the be reduced. Cost of equity increases to cover uncertainties (Frisari <i>et al.</i> , 2013).

Political, country, and regulatory risk

Policy and regulatory risks	Uncertainty changes of future legislation.	Medium (Nel, 2015)	Gaps in risk management (Frisari <i>et al.</i> , 2013).
Political risk	Risk of corruption, risk of political commitment, risk of procurement regulations.	High (Nel, 2015)	Contracts, political/institutional support (Frisari <i>et al.</i> , 2013).
Macroeconomic risks	Uncertainty in the country's economic conditions and prospects. Uncertainty in future currency exchange rate.	High (Waissbein <i>et al.</i> , 2013)	

2.6 Risk evaluation methods and metrics

From a stakeholder's perspective (investors, lenders, property/plant owners, among others), it is crucial to understand how certain risks impact the project's financial viability. Investment decisions are typically based on cash-flow analysis and forecasts, such as Net Present Value (NPV) (or discounted cash flows), Internal Rate of Return (IRR) analysis, Levelised Cost of Electricity (LCOE), cost-benefit analysis and real option (RO) theory (Liu *et al.*, 2021:94; O'Donnell *et al.*, 2002). However, uncertainty in the investment analysis is usually neglected in the standard method of determining LCOE, which is the most common method of comparing the costs of different technologies (Heck *et al.*, 2016; Ioannou *et al.*, 2017). It further neglects any endogenous effects, such as the correlation between fuel prices and the electricity process and critical terms, such as inflation, integration costs, and system costs (Geissman & Ponta, 2017; Sklar-Chik *et al.*, 2016).

The uncertainty associated with the investment parameters can be handled in various ways: best-case/worst-case scenarios, single-parameter sensitivity analysis, analytical error propagation, Monte-Carlo simulations (MCS) and decision trees (O'Donnell *et al.*, 2002:94).

Arnold and Yildiz (2015) used an MCS method to analyse the impact of risks on typical financial metrics such as ROI or NPV for a biomass project as an alternative to the usual sensitivity analysis and NPV estimation. Their results indicated that the risk-to-benefit ratio of an investment could be better quantified using the MCS method. The volatility of the investment yield could also be better determined. It was further indicated that if MCS methods are combined with financial analyses, the conceptual project design can be optimised and aid in raising capital and addressing risk division between stakeholders (Arnold & Yildiz, 2015:238). It is important to note that MCS doesn't necessarily address all the problems. For MCS implementation, distribution functions need to be selected, and the variables for the distribution functions need to be defined. Defining the distribution functions is not always easy since enough data for a specific variable is not always readily available. The outcomes of the MCS simulation are, therefore, dependent on the inputs. Arnold and Yildiz (2015) used a combination of MCS, scenario analysis, and sensitivity analysis to evaluate various combinations of variable information, such as fuel availability and price.

Liu *et al.* (2021) reviewed decision-making methodologies for comprehensively evaluating offshore wind power investments. As a result, they found 112 sources using MCS in investment analysis (Liu *et al.*, 2021:2). da Silva Pereira *et al.* (2014) used the MCS method in performing risk analysis in renewable energy generation. They concluded that the MCS method has considerable advantages over the traditional sensitivity analysis method and can take variables into account that do not have a purely deterministic pattern but change over the project's lifetime. These include risks in project implementation, market financial conditions, costs with O&M (operating and maintenance), and even policy issues (da Silva Pereira *et al.*, 2014:355).

Smith *et al.* (2019) found the MCS method helpful in visualising the parameters' influence on the LCOE of biomass co-firing in existing coal-fired power plants. They applied the MCS method to provide LCOE with reported standard deviations and skewness for various scenarios. Their analysis took the large variability associated with biomass material into account (Smith *et al.*, 2019:8). The variability included transport costs, raw feedstock costs, and O&M costs, among others (Smith *et al.*, 2019:10).

Neto *et al.* (2018) used MCS methods to evaluate the investment risk for wind power generation in Brazil. Their model incorporates predictive techniques for the electricity price variation and a stochastic model for wind volatility. Using the MCS method, they could estimate the probability distribution for the NPV. Based on these results, the Value at Risk (VaR) can be calculated at a 95% confidence interval, providing investors with a value of maximum loss exposure. In addition, variables such as technology selection (i.e. the height of the wind tower) were evaluated using sensitivity analysis.

Lei *et al.* (2020) used MCS methods to evaluate the investment risks for wind power generation in China. First, wind speeds and power density were modelled using a Weibull distribution. Other risk factors such as equipment cost, capacity factor, and operating and maintenance costs were modelled using triangular and normal distributions. Metrics used to evaluate the investment include NPV, IRR and payback time (PT).

Based on the literature reviewed, it is clear that the MCS method is a valuable instrument to analyse the influence of risk factors on investment, with the technique applied to a wide range of renewable energy sources. The MCS method is applicable where stochastic processes play a role. Sensitivity and scenario analysis is often used in combination with MCS methods. The metrics commonly used to evaluate the investment and quantify the risk are the NPV, LCOE, IRR, PT, and VaR.

2.7 Conclusion

This chapter provided an overview of the electricity generation situation in South Africa and the importance of RE sources. RE has dramatically increased over the last couple of years, both on the IPP scale and for SSEG. The impact of load-shedding and decreased coal-based power generation has been highlighted as a significant driver of the increased use of RE power in South Africa. The power situation in South Africa provides opportunities for embedded generation in the agro-processing industry, specifically in the sunflower value chain.

Secondly, an overview was provided of the sunflower industry and the factors contributing to the profitability of crushing plants. Several factors influence the annual sunflower seed production and the production levels of crushing plants in South Africa. Factors include international oilseed markets, sunflower seed quality, weather conditions, and exchange rates. It was also shown that the crushing margins of the South African sunflower-crushing industry are regularly under pressure, which emphasises the need to consider the uncertainties involved when investing in RE carefully. Finally, the lack of literature on power generation using sunflower husk and biomass in South Africa was highlighted, emphasising the need for further research.

Thirdly, an overview of the risks involved in RE projects was provided, with possible risk classification categories being:

- Curtailment and utilisation risk.
- Price risk.
- Resource risk.
- Technology risk.

- Economic and commercial risk.
- Financial risks; and
- Political, country, and regulatory risks.

The risks identified in the literature were summarised together with the risk assessment and management methodologies. The literature review provides a high-level framework of how RE project risks are typically considered. Based on this framework, the risks that will be unique in embedded generation for sunflower-crushing plants can be classified and assessed. After the categorisation, risk management methodologies can be proposed.

Finally, a literature review provided an overview of the tools typically used to evaluate the size of risks. The methods include MCS and sensitivity analysis. The standard metrics for reporting risks when performing a Monte-Carlo simulation are NPV, LCOE, IRR, PT, and VaR.

Chapter 3 will focus on the methodology used in this study to identify, classify, and assess the risks unique to embedded generation in sunflower-crushing plants.

Chapter 3

Methodology

3.1 Introduction

This study aims to assess the risks involved in developing embedded generation for sunflower-crushing plants using the husk by-product as a fuel source. The literature review has alluded to the lack of information on biomass power generation in South Africa. No known embedded generation projects for sunflower-crushing plants exist in South Africa. The risks must therefore be understood and quantified to perform a meaningful risk assessment. After the risks have been identified and assessed, suggestions can be made to manage these risks based on standard methodologies identified in the literature review.

This chapter will discuss the classification of the risks specific to embedded generation for sunflower-crushing plants. The process of quantifying (or assessing) the risks is split into stochastic methods and sensitivity analysis. The stochastic methods involve building statistical models that capture the variability in parameters that influence the risks. The chapter will also discuss the data collection, processing, and model verification steps.

The outline of the chapter is as follows:

Section 3.2 provides the broad methodology overview; 3.3 discuss how the risks that are identified are classified according to the classifications discussed in the literature review; 3.4 shows how the risks are quantified and the steps taken to ensure accuracy in the modelling process; and 3.5 discusses the method used to integrate the process of quantifying the risks into a final risk assessment and the methodology to classify the risks according to the risks management methodologies.

3.2 Methodology overview

Figure 3-1 describes the process that will be followed. The main objective of this study is to identify and quantify the unique risks. A second aim is to estimate and assign the

likelihood of occurrence to the risks. Combining the two objectives of quantifying the risks and assessing the possibility of the event enables a proper risk assessment.

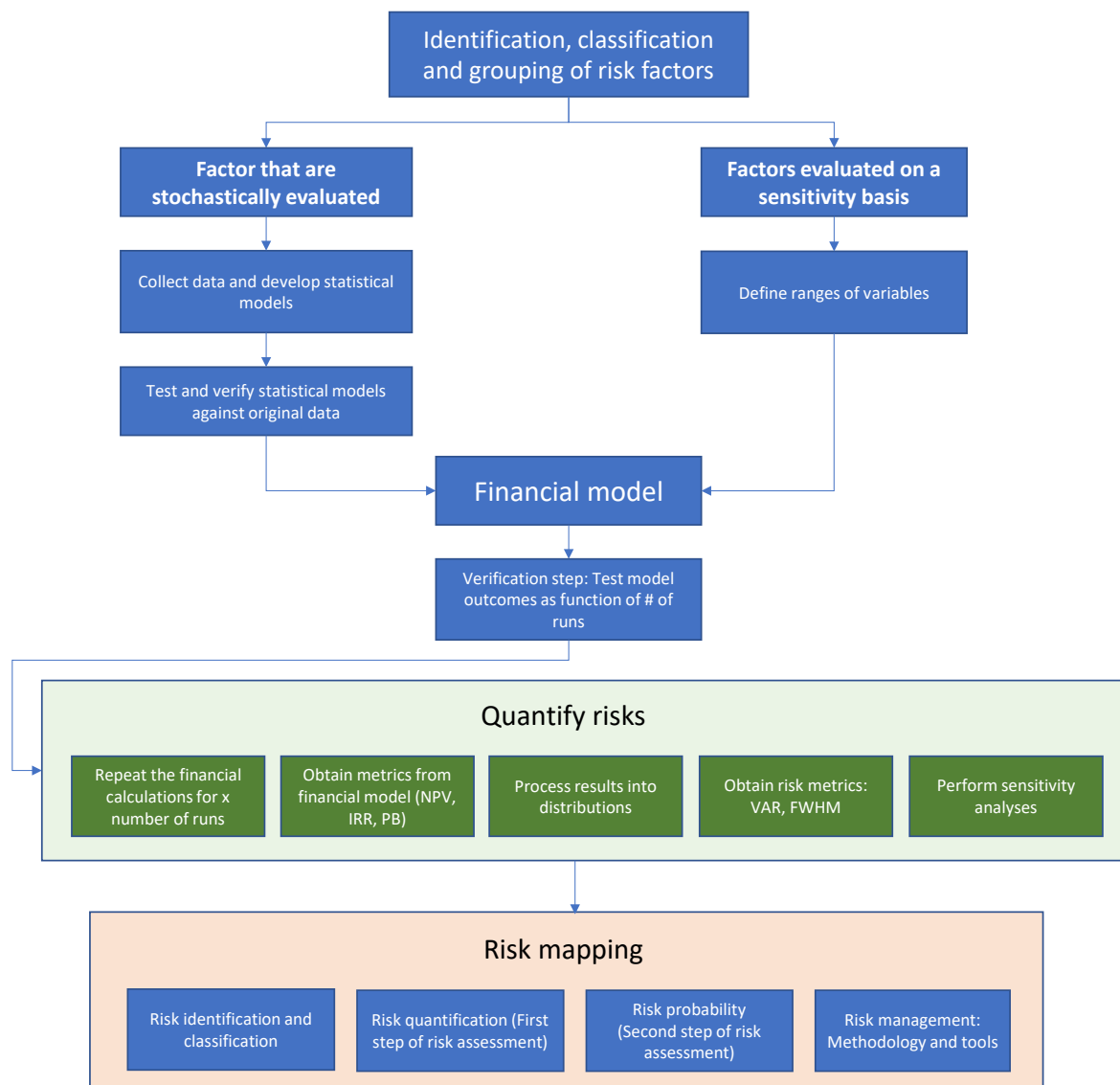


Figure 3-1: Overall methodology of the risk analysis

All risks are, however, not equally likely to occur. Some risks can be mitigated, while others are endogenous to the process and cannot be mitigated. Possible methods of managing the risks are therefore discussed. By assigning values to these three attributes of each risk (i.e. impact of the risk through quantifying it, likelihood of

occurrence, and level of mitigation), a basic framework can be developed to emphasise the key areas where risks need to be addressed to ensure a successful investment.

The detailed methods of the following aspects of the study are further discussed:

1. Classification of the risks.
2. Risk assessment methodology.
3. Proposing risk management methodologies.

3.3 Classification of the risks for the specific sector

The risks that will impact the investment of the particular type of power plant will be classified under the following types:

- Curtailment/utilisation risk
- Price/market risk
- Economic risk
- Financial risk
- Technology risk
- Policy risk.

Risks are quantified through two methods. First, a Monte Carlo Simulation (MCS) will quantify risks with a quantifiable stochastic nature. MCS will be done where enough data is available, and the stochastic nature can be converted into statistical models. Where the data underlying the risk is too complex or insufficient data exists, a sensitivity analysis will instead be used. A sensitivity analysis is preferred rather than making assumptions.

3.4 Risk assessment

Three of the large producers of unrefined sunflower oil were contacted with a request for data on actual production. However, due to the competitive nature of the crushing plants, there was a reluctance to provide plant-specific data. Data sources in the public domain were, therefore, primarily consulted. Data for the national production of sunflower seeds was used to quantify the variability in production rates of a typical

sunflower-crushing plant. This approach is justified by the fact that there is an overcapacity in crushing plants and competition in the market for sourcing sunflowers (van der Burgh *et al.*, 2015:39).

3.4.1 Risk quantification

Risks with a strong stochastic nature need to be evaluated by developing models to approximate their statistical behaviour. Where possible, a variable's statistical distribution is modelled through generally accepted continuous distribution functions. When the available distribution functions do not represent the distributions well, the variables are sampled from the distribution of the raw data. The verification step ensures that the underlying distribution is retained.

Each statistical model developed is qualitatively verified against the original data before implementation. It is therefore tested whether the results from the statistical model exhibit the same trends as the original data.

The statistical model for each parameter (such as production output per year) is used to create inputs for the financial model. Excel's random number generator is used to sample these variables from their distribution functions randomly. The process is repeated a large number of times, and each time the NPV and other metrics are calculated. Each repetition of the calculation of the cashflows represents a possible financial outcome for the investment into the power plant. The result is a distribution in NPV values and other metrics. Risks allocated under the sensitivity analysis grouping are fixed at nominal values. These variables are then independently varied over a range of values to investigate their impact on the NPV. The sensitivity of the NPV to changes in these variables then indicates the risk.

3.4.2 Test to determine the required number of simulations

The final distribution of the NPV (and other metrics such as LCOE and IRR) depends on the number of runs used in the Monte Carlo analysis. If too few runs are used, the final distribution of the data will not be accurate, and the risk cannot be analysed accurately. The model will be built in Excel due to the ease of programming and visualisation. There is, however, a limit to the number of runs that can be performed

in Excel before the simulations become unpractically long. A test is therefore committed to evaluating the impact of the number of runs on the final distribution. Other studies are also used to indicate the required number of runs to ensure accurate distributions.

3.4.3 Metrics used to quantify the risks

The risk is quantified by evaluating various metrics. The NPV of the cash flows from the financial model is calculated first. The distribution of the NPV based on the input parameters indicates the risks involved. If the spread is very narrow, there is a small risk that the input factors will result in an NPV that differs significantly from the nominal value. Various approaches can be followed to quantify the spread. If the NPV values are normally distributed, the standard deviation can be used as a metric. The final distribution of the NPV value could be very different from a normal distribution. Instead, the full width at half maximum (FWHM) is calculated. The FWHM gives the spread of the distribution at half the maximum likelihood. The value of the FWHM indicates the risk involved. The FWHM metric can be applied to the IRR distributions as well. The FWHM for IRR suggests how far off the returns might be from the most likely value. For example, if an IRR of 10% is sought, a large spread might prompt an investor to reject the investment opportunity, even if the most likely IRR is close to 10%. Alternatively, the investor might require a high nominal IRR to compensate for the large spread.

The second metric is the VaR at a 95% probability level. This metric states the NPV at the lowest 5% of cases (or 95% of the possible outcomes will result in a higher NPV). The VaR indicates the investor's maximum loss at a 95% confidence level. If this value is positive, there isn't a loss. Alternatively, the investor might argue that no loss is acceptable. The confidence level at zero NPV is therefore also reported.

Another metric that is reported is the payback period. The investment IRR can be high but with a long payback period. Over the plant's entire lifetime, the returns might be very high, but there might be significant risks in the short term.

3.4.4 Risk likelihood

The identified risks need to be ranked according to the likelihood of occurrence. The combination of quantifying the risks and assigning likelihoods assesses the risk. Where applicable, the probability of occurrence will be evaluated based on the literature review. In other cases, the likelihood of the risk will be argued based on the data available for the risk. The risks will be assigned a simple three-point scale of a low, medium and high level of likelihood.

3.5 Proposing risk management methodologies

The final step is to propose risk management methodologies for each risk by considering the methods provided in the literature. The risks can be accepted, transferred, avoided, or controlled. A simple scale will be used to assign the possible impact of risk management methodologies on the cost for investors. Risks that must be accepted will be ranked as high, while risks that can be controlled or transferred are rated as medium. Risks that can be avoided entirely are classified as low.

3.6 Conclusion

A methodology was presented whereby the critical aspects of risks are addressed, namely the identification of risks, the quantification, the likelihood, and the methods to manage these risks. When combined, these aspects can be used to provide investors with a map of which risks are critical. The map can enable investors to make informed decisions and help determine the required IRR and other investment requirements.

In Chapter 4, the risks specific to embedded generation for crushing plants will be identified. The process of collecting data and processing it will be discussed in depth.

Chapter 4

Risk identification, data collection and processing

4.1 Introduction

In the previous chapter, the methodology was outlined. This chapter discusses data collection and processing. Before collecting data, the risks applicable to this study need to be identified. The identification will be made by considering the risk classifications established in the literature review. Then, it is motivated why these risks are assessed and how they should be accounted for in the model.

The data sources and data processing are discussed in detail for each risk. The statistical models developed to simulate each risk are provided where applicable and compared to the original data.

The outline of the chapter is as follows:

- Section 4.2 discussed the risk identification according to the classifications previously defined and grouped each according to the methods used in the analysis.
- Section 4.3 discusses the data collection performed to allow the risk assessment in the following chapter.

Chapter 5 will then proceed to discuss the financial model parameters and nominal input values, as well as the results from the analysis. Next, applying the financial model will provide the risk quantification part of the risk assessment, after which mitigation strategies will be discussed.

4.2 Risk identification, classification, and grouping

The risk factors and classifications typically considered in renewable power generation were discussed in the literature review. The risks specific to embedded power generation using sunflower husk as a fuel source in South Africa will now be identified. The classifications specified in the literature survey will be used to identify risks.

Because the risks associated with small-scale projects are significantly different from large-scale projects, it can be expected that not all the risks identified will apply to this specific application (Kristinsdottir, 2012). The classifications, however, guide the identification of risks. The risks identified will also be divided into two groups: stochastic factors that can be modelled through the MCS method and characteristics that will be evaluated through a sensitivity analysis.

A particular risk that will be assumed to have been mitigated is the risk of using unknown technology. Such risks should be avoided since it would be difficult to establish the long-term risks involved with operations, maintenance, reliability, and capacity factors. Without quantifying this risk, it would be impossible to make an assessment and should instead be avoided.

The risks are motivated and summarised in Table 4-1.

Table 4-1: Identification, classification and grouping of risk factors

Uncertainty	Risk	Type of risk	Method of analysis and obtaining data	Risk Evaluation
Crushing plant production variation	The risk associated with sunflower seed production uncertainty and resulting power utilisation	Curtailment and utilisation risk	Curtailment risks are associated with grid instability and the availability of the grid. In this study, the crushing plant determines the demand. The grid will not influence the power plant supply, but the crushing plant power requirements will. Therefore, it is essential to consider this to determine the utilisation. Studies on wind farms' output due to wind variability provide a similar assessment (see section 2.5.1). The crushing plant's electricity demand is mainly influenced by the sunflower oil demand's macroeconomic factors. The literature study has indicated large fluctuations in sunflower oil demand (see section 2.4). Historical data for overall sunflower-crushing production in South Africa is modelled to consider this factor. Underlying factors such as the weather is accounted for in the production data. The data collection and model development are discussed in detail in section 4.3.1.	Stochastic evaluation
Crushing plant demand uncertainty risk	The risk associated with the uncertainty in the electrical consumption of crushing plant	Curtailment and utilisation risk	The specific energy consumption (kWh/ton) will determine the supply requirement of the power plant. Energy consumption can fluctuate over time and will influence the utilisation of the plant. The accuracy with which the power demand is determined will also affect the sizing of the power plant. There is a risk involved in estimating the exact requirements of the crushing plant. In the initial project evaluation phase, the information might not be readily available without detailed engineering studies. Initial incorrect assumptions can result in overoptimistic or pessimistic investment evaluation. In this study, the demand for a specific plant is unknown. The view is that an investor will rely on the best available data from the literature during the initial stages. Exact power requirements are unknown, and not all plants operate precisely the same way. Therefore, crude assumptions pose a risk to investment assessments. The energy requirements are based on literature values. The impact of the assumptions on the risk is illustrated through a sensitivity analysis. The data collection and model development are discussed in detail in section 4.3.2	Sensitivity evaluation

Uncertainty	Risk	Type of risk	Method of analysis and obtaining data	Risk Evaluation
Power plant sizing uncertainty risk	The risk associated with selecting non-optimal power plant capacity	Curtailement and utilisation risk	Once the crushing plant demand is known, a sizing recommendation must be made for the power plant. The power plant can be sized to provide the complete load, but it could also be sized only to give a portion of the electricity requirements. Since the crushing plant demand can vary significantly over time, depending on the annual crushing needs, it is essential to not oversize the power plant and under-utilise the capacity. The sizing of the power plant dramatically impacts the total investment cost and how well the capital is utilised. A sensitivity analysis is performed to show the impact. This uncertainty is closely associated with the uncertainty in the power requirements discussed previously. The two risks should be viewed together, and the management of the risks should be jointly addressed. The data collection and model development are discussed in detail in section 4.3.3.	Sensitivity evaluation
Electricity price uncertainty	The risk associated with the estimate in Eskom electricity price increase	Price risk	The selling price of electricity (or the value per unit produced) is equated to the price that would be paid to Eskom. The main driver of the price risk is Eskom's price increase. The historic data for price increases is limited and doesn't follow a clear pattern. Therefore, an average of the last ten years will be used, and the influence of possible future escalations will be evaluated on a sensitivity analysis basis. The data collection and calculations are discussed in section 4.3.12.	Sensitivity evaluation
Biomass price uncertainty	The risk associated with the uncertainty in the biomass value	Price risk	Although the powerplant feedstock comes from a waste product, it has a particular value. This value must be included in the plant's operating cost since the biomass could have been sold into the market to generate an income. Therefore, nominal values are used for the biomass selling price. Data is obtained by requesting prices from traders of husk. The data collection is discussed in section 4.3.9.	Sensitivity evaluation

Uncertainty	Risk	Type of risk	Method of analysis and obtaining data	Risk Evaluation
Production loss risk	The risk associated with uncertainty in Eskom's future load-shedding profile and the impact on production loss risk	Economic risk	Eskom load-shedding results in a risk for the crushing plant. The benefit of preventing the impact of load-shedding by generating power is considered through two factors. Firstly, the downtime due to load-shedding must be modelled, and secondly, the economic impact due to this downtime must be modelled. The data collection and model development are discussed in detail in section 4.3.4.	Stochastic evaluation
Investment cost (Total project cost) uncertainty	TPC cost uncertainty risk	Economic risk	Without a complete engineering study, the total investment cost is not known during the feasibility phase. Typically the main equipment costs can be obtained accurately from suppliers, but the balance-of-plant price can only be determined after basic design. These values must therefore be estimated. The cost of the power plant is obtained from literature-based values. The nominal value of the total plant cost is used, and the uncertainty is incorporated into the cost overrun risk. The data collection is discussed in detail in section 4.3.6.	See cost overrun risk
Economies of scale	The risk associated with the crushing plant size	Economic risk	The specific cost of the power plant depends on the size of the power plant. Therefore, there is a risk that the project will not be economically viable if the plant capacity is too small. Literature-based values are used, and a sensitivity analysis is used to indicate the impact on the risk. This risk is addressed in the investment cost and associated conversion efficiency uncertainty estimates.	Sensitivity evaluation
Cost overrun risk	The risk associated with a cost overrun of the total plant	Economic risk	There is a risk associated with cost overruns during the construction phase. Construction risks are modelled using literature-based distribution functions. The model used to account for this risk is discussed in section 4.3.10	Stochastic evaluation

Uncertainty	Risk	Type of risk	Method of analysis and obtaining data	Risk Evaluation
Debt interest	The risk associated with interest rate uncertainty during the feasibility phase	Financial risk	The debt rate at which the project will be financed is not necessarily known during the feasibility phase of the project. For instance, there is a risk that a debt rate is incorrectly assumed or a sudden increase in the prime lending rate due to macroeconomic factors. Therefore, this risk needs to be factored into the initial evaluation. Debt interest rates are based on historical values for the prime lending rate. A sensitivity analysis will evaluate how the debt rate influences investment risk. The data used for this evaluation is discussed in section 4.3.11	Sensitivity analysis
Inflation	The risk of higher-than-expected inflation	Financial risk	Some variables are adjusted with inflation, with O&M costs being mainly influenced. The sensitivity of the investment to inflation will be incorporated into the sensitivity analysis for the O&M costs. The data used for this evaluation is discussed in section 4.3.11	Sensitivity analysis
Exchange rate	The risk that the exchange rate would change after project initiation	Financial risk	Most of the equipment required for a power conversion plant will be imported. Therefore, there is a risk that the exchange rate will change from the evaluation date to the date of ordering equipment. If the exchange rate varies so significantly that the project is not feasible, then the project will not be considered. It is also difficult to quantify what portion of the TPC will be affected. The risk can be transferred using various instruments if a project is deemed feasible and the developer wants to proceed. In this study, it will be assumed that the risk is transferred.	Transfer risk
Technology selection risk	The risk that the technology selected will negatively impact the investment	Technology risk	There is a risk associated with selecting unfamiliar and unproven technologies in the country of use. Technologies without a track record for the specific application have less information on the operational aspect. This information is required to estimate the risks of conversion efficiency, O&M costs, and installation risks. As such, unproven technology must be avoided entirely. Technology will be selected that is considered mature. A discussion of the technology options is provided in section 4.3.5.	Avoid risk

Uncertainty	Risk	Type of risk	Method of analysis and obtaining data	Risk Evaluation
Conversion efficiency uncertainty	The risk of lower-than-expected conversion efficiency	Technology risk	The conversion efficiency must be estimated during the feasibility phase to determine the biomass required. There is, however, the uncertainty involved in the conversion efficiency estimate. Estimates are obtained from a literature review of similar technologies and plant sizes. The value of biomass is, therefore, the determining factor. The nominal efficiency will therefore be used, while the influence of the value of the biomass will be investigated. The data collected and the model used to determine the conversion efficiency are discussed in section 4.3.7.	Nominal value used
O&M cost uncertainty	The risk that the planned and actual O&M costs differ significantly	Technology risk	Operating and maintenance (O&M) costs must be known during the feasibility phase of a project. There is, however, uncertainty about the final O&M costs. Operating and maintenance costs are based on literature-reported values. A sensitivity analysis is used to analyse the impact of the O&M costs risks. The data used to account for this factor is discussed in section 4.3.8.	Sensitivity analysis

4.3 Data collection for the risk assessment model

4.3.1 Utilisation risk due to production variation

In the model used to evaluate the investment risks, it will be assumed that the power generated is only for the crushing plant's use. It is, therefore, essential to determine the plant demand and account for the variation in production. The production variation is estimated from the total production in South Africa, which is then scaled to the size of an individual plant. In a sunflower oilseed crushing plant, the biomass available as feedstock depends on the production of oilseed and cake. If there is no sunflower seed available in the market, then there is no oilseed and cake production, and no husk will be generated. There will also be no need for power generation since the production plant will not run. When considering the capital investment for the power generation plant as an independent project, it is essential to include the plant's utilisation in the analysis. If the plant is underutilised, the capital expenditure (CAPEX) per unit production (in kWh) will be very high. The availability of seed in the market becomes a determinant for the availability of biomass feedstock, as well as the utilisation of the plant.

Production figures were requested from several crushing plants in South Africa, but production managers were hesitant to share this confidential information. Therefore, a typical plant's monthly production figures and electricity consumption were not obtained. Instead, the total South African monthly production is used to estimate the volatility of the electricity consumption of a plant. This data was obtained from the South African Grain Information Service (SAGIS, 2022b) from 1997 to 2021, as shown in Figure 4-1 below. It is evident from the data that there is significant volatility in production. This volatility will also reflect in the power consumption of a production plant. Therefore, the average output would be used to analyse the most straightforward financial model. In a more complicated model, the standard deviation in the production rate could be used to indicate the sensitivity of the production rates. When considering the data in Figure 4-1, it will be noted that there could occur periods of up to two to three years of below-normal production (the red dashed line box indicates this). There are also seasonal lows far below the average (as indicated by the green dotted line boxes). The timing of such possible occurrences in the lifecycle of the power plant will also impact the return on investment: a long period of low

production may occur shortly after the plant is built. In such a scenario, the plant will be underutilised, while the CAPEX could have been invested in other projects, resulting in a decrease in profitability. Therefore, the time value of money should also be considered.

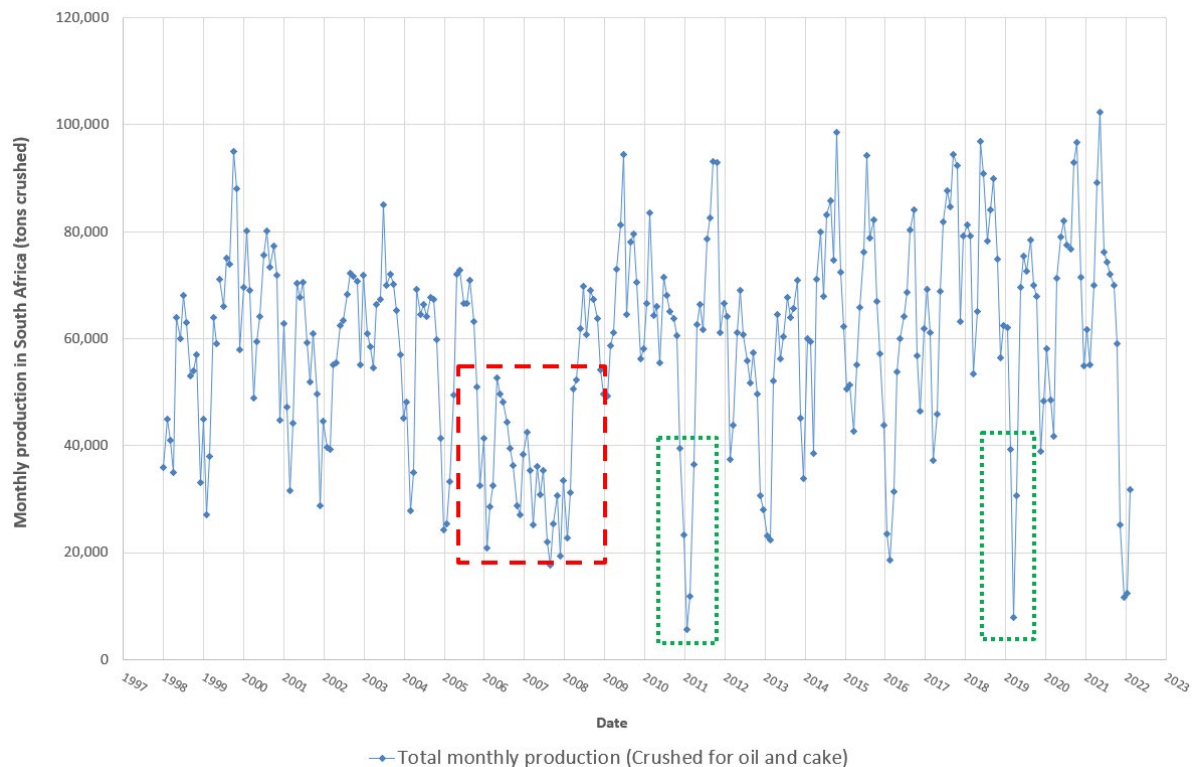


Figure 4-1: Monthly national production figures for sunflower

Data source: SAGIS (2022b)

A model was developed to describe the primary characteristics of the data through statistical analysis. Underlying the production rates are many of the macroeconomic forces discussed in the literature review (such as the seasonal rainfall, the local market conditions, and the international market conditions). Instead of modelling these effects independently and predicting the production rate, the historical production data is modelled.

Two crucial aspects are considered:

- The annual stochastic nature of the production rates;

- The seasonal variation in production rates.

The production rate model is based on the data for the total annual production of sunflower oil and cake in South Africa. The data was firstly arranged according to the production rates for each month of the year, as indicated in Figure 4-2. The average per month over the last 24 years suggests a seasonal trend – higher production rates are seen from May to November, after which the average production decreases from December to April.

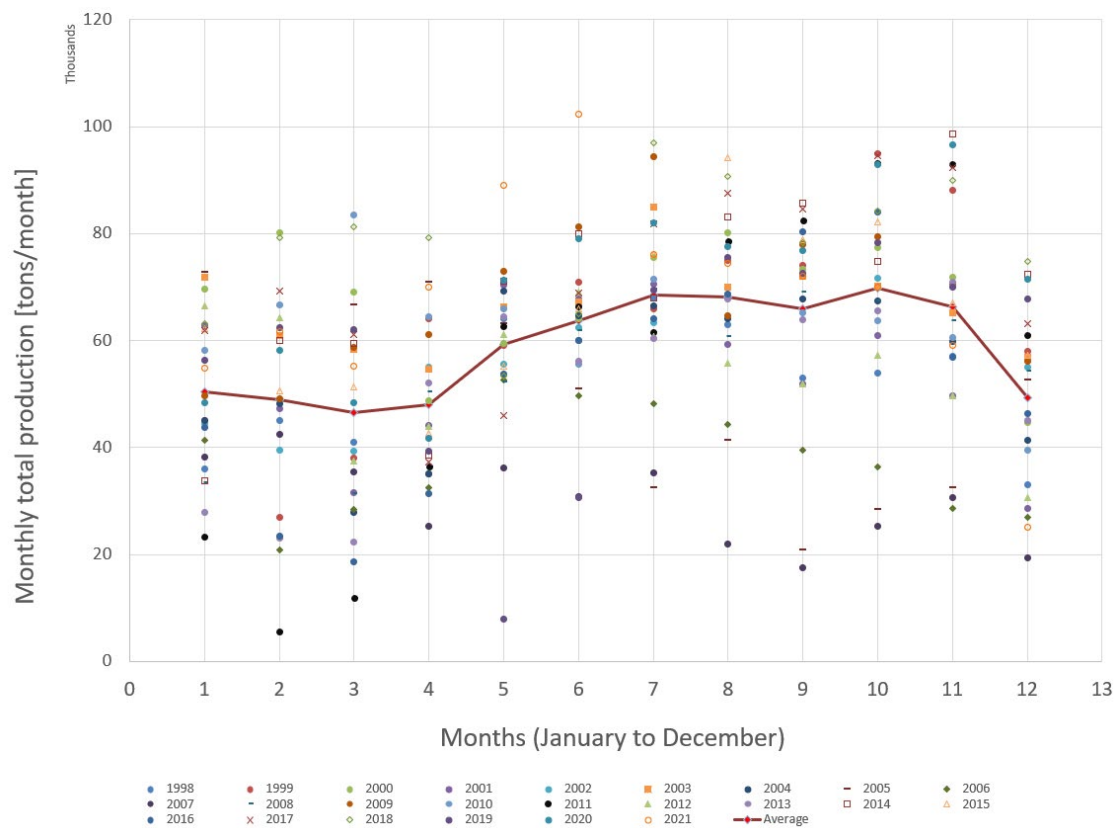


Figure 4-2: Monthly production rates for each month of the year

Source: SAGIS (2022b) & Author's simulations

The cyclic seasonal behaviour and fluctuations in the average monthly production rate can be described in the following equations:

$$p_i = \bar{p}_i + \mu_i$$

where $\bar{p}$ is the estimated average monthly production, μ is the fluctuation on the average, and i indicates the month of the year. The average monthly production is expressed as:

$$\bar{p}_i = f_i \bar{P}_a$$

Where $\bar{P}_a$ is the stochastically determined monthly average production rate for the year. f is the average ratio of the monthly production and the average annual production output for the last 24 years. It, therefore, relates the monthly fluctuations to the yearly average, and is defined by the following equation:

$$f_i = \sum_{j=1}^n \frac{\hat{p}_{ij}}{n \hat{P}_{aj}}$$

where $\hat{p}$ is the monthly production rate and $\hat{P}_a$ is the average annual production rate (from the historical data). The symbol j indicates the year and n the total number of years for which the information is available, i.e. 24. Figure 4-3 below provides a graph of the factor f per month. The data points are the ratio $\frac{\hat{p}_i}{\hat{P}_a}$.

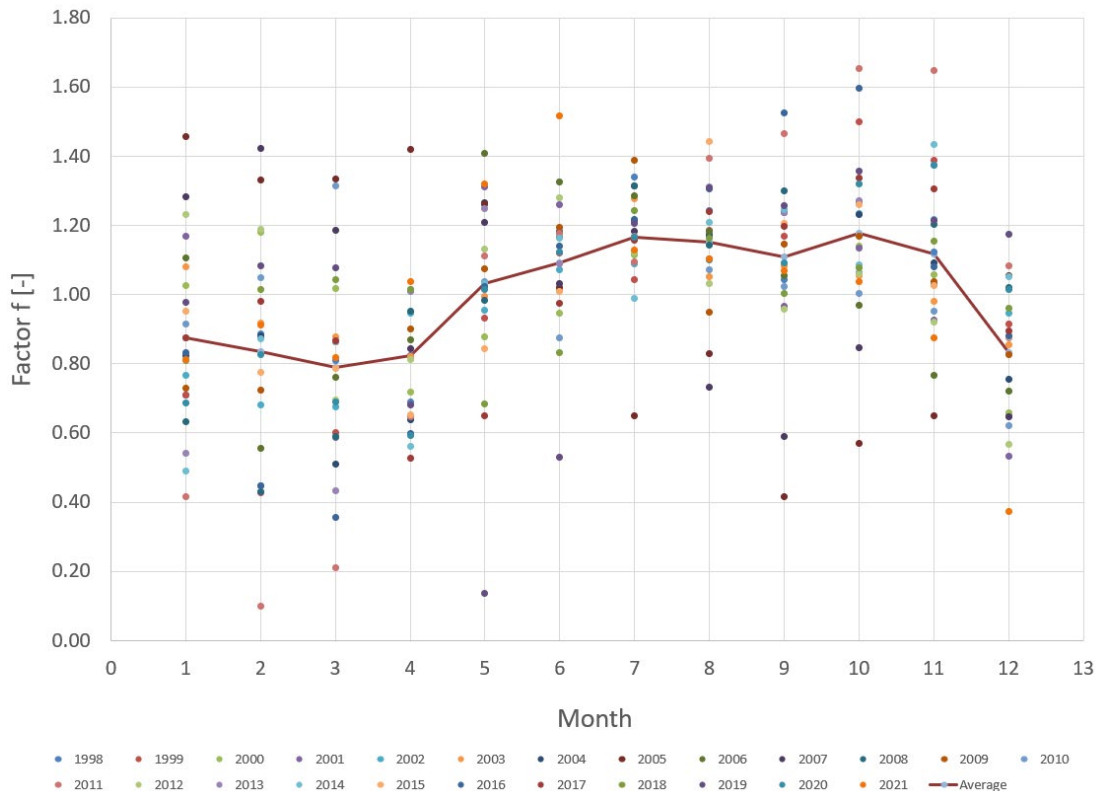


Figure 4-3: Normalising factor to determine the average monthly production

Source: SAGIS (2022b) & Author's simulations

The annual average monthly production rate, $\bar{P}_a$, is determined by randomly sampling from the historical data's cumulative distribution function (CDF). The CDF is indicated in Figure 4-4. In the model, for every year, a monthly average annual production rate will be obtained from the CDF, while the factor f is used to adjust the production rate for each month.

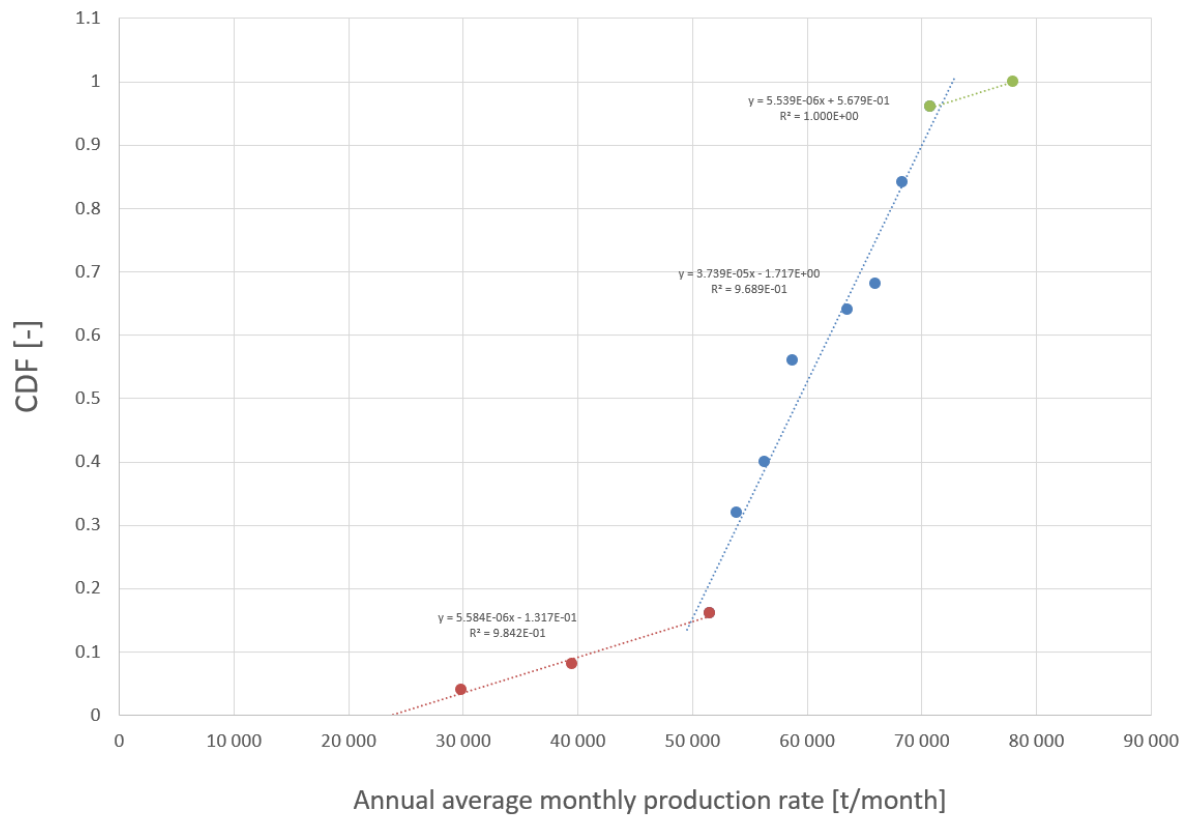


Figure 4-4: CDF for the average annual production data

Source: SAGIS (2022b) & Author's simulations

The deviation from the average monthly production, μ_i is calculated by first normalising the monthly deviations. Normalising is done as follows:

$$\tau_{ij} = \frac{\hat{p}_{ij} - \frac{\sum_{j=1}^n \hat{p}_{ij}}{n}}{\hat{p}_{a_j}}$$

The value provides a normalised deviation from the average monthly production. The average value of τ per month is calculated as follows:

$$\bar{\tau}_i = \frac{\sum_{j=1}^n \tau_{ij}}{n}$$

The standard deviation of τ_{ij} for each month is also calculated. The assumption is now made that the deviations in the monthly production rates are normally distributed around the average. This assumption allows the normalised deviation for each month, $\tau_{i,s}$ to be sampled from a normal distribution based on the average value $\bar{\tau}_i$ and the associated standard deviation. The absolute deviation μ_i , can then be determined:

$$\mu_i = \tau_{i,s} \cdot \bar{P}_a$$

The monthly production rate can therefore be expressed as:

$$\bar{p}_i = \bar{P}_a (f_i + \tau_{i,s})$$

In this formulation, the value of $\bar{P}_a$ makes provision for the annual fluctuations in production and is sampled from the CDF. f_i makes provision for the monthly variation in production rates, and $\tau_{i,s}$ for the random variation each month. In the simulation, the value of $\bar{P}_a$ is based on a random number selected between zero and one. For each year in the simulation, the value of $\bar{P}_a$ is constant. The value of $\tau_{i,s}$ is based on a random number between zero and one for each month in the simulation.

Several tests are performed to demonstrate that the model retains the underlying characteristics. First, the model is used to produce 1000 simulated annual total production values from which the simulated CDF for the yearly production was calculated. The simulation results are compared with the actual CDF from the data in Figure 4-5 below. It will be noted that the original data is reasonably well predicted and suggests that the distribution in the expected average production rate is well simulated.

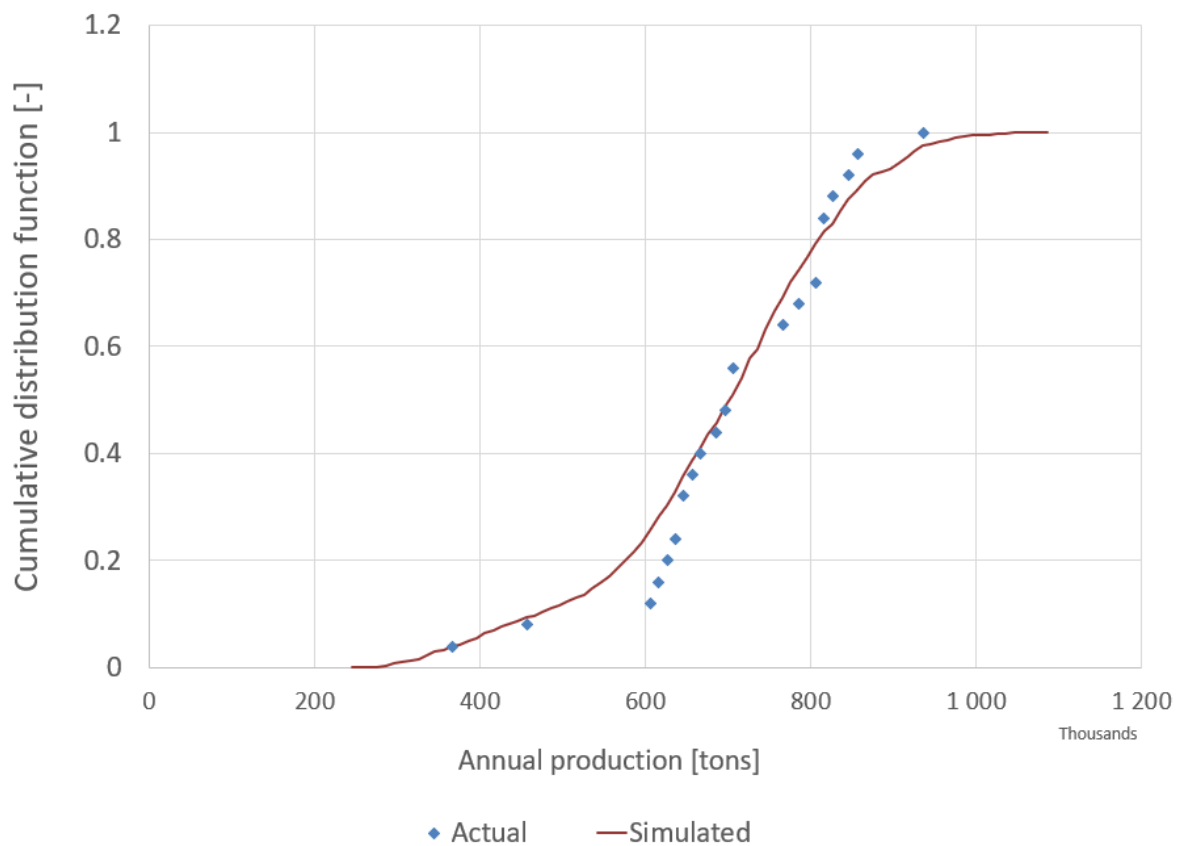


Figure 4-5: Comparison between the CDF for the annual production between the actual and simulated data

Source: SAGIS (2022b) & Author's simulations

Next, the annual variation in production is simulated. In this case, the value for $\bar{P}_a$ fixed on the historical data. The purpose is to show the influence of μ_i . The results are presented in Figure 4-6 below. It will be noted that the trends are very similar, with only fluctuations in the annual average.

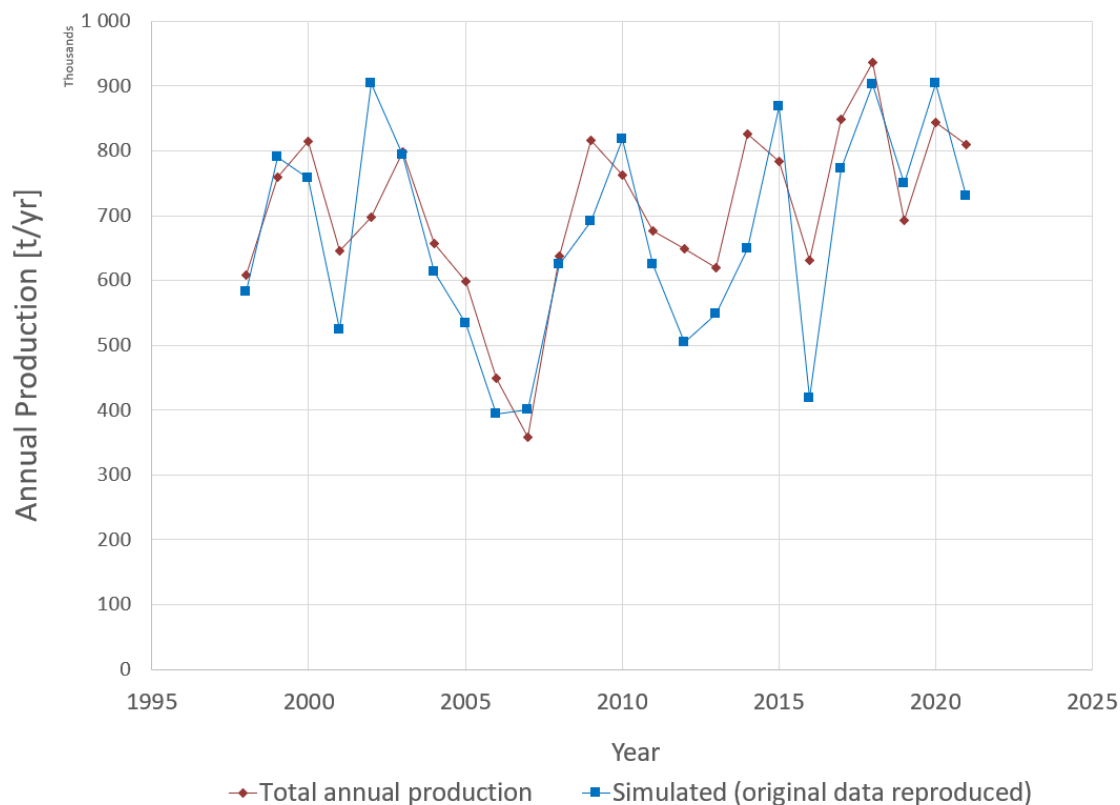


Figure 4-6: Comparison between simulated and actual annual data

Source: SAGIS (2022b) & Author's simulations

Finally, 1000 simulations were performed to obtain a 24-year average annual production. The simulation results are compared with the average annual production rate for the 24 years of data available, which is 704 993 tons/year. The distribution of the simulated results is shown in Figure 4-7, highlighting that the average from the distribution is close to 700 000 tons/year. The results of the 24-year annual average are normally distributed.

The annual production rates are stochastically sampled from the cumulative frequency distribution (CFD) function obtained from the production data. The seasonality of the production is obtained by modelling the monthly fluctuations of the average monthly production rates (for each month from January to December). It is important to note that the model doesn't take the historicity of the data into account and isn't autoregressive. The simplification is justified because the purpose of the model is not to make an accurate prediction of future production rates based on an initial condition but to capture the underlying annual and seasonal fluctuations.

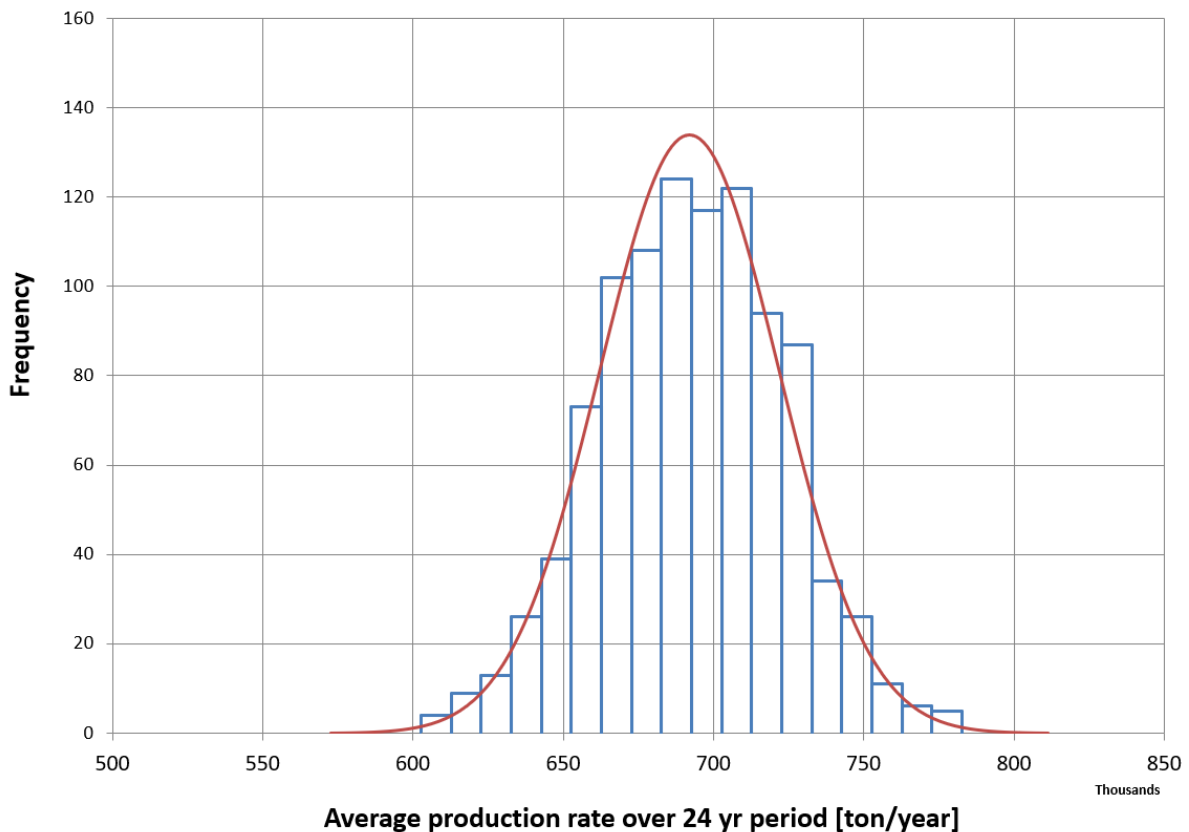


Figure 4-7: Distribution of the simulated 24-year average annual production rate

Figure 4-8 and Figure 4-9 below compare the historical annual and modelled production rates for two random simulations. Firstly, the red line (with diamonds) is compared with the blue line (with squares). This comparison is between the original data set and the stochastically modelled monthly production rates, where the average annual production is based on the original data set. The comparison illustrates that the monthly fluctuations can be modelled while maintaining the yearly trends. Next, the red line can be compared with the green line (with circles). The green line is the simulated data, where the annual production and the monthly fluctuations are stochastically modelled. Figure 4-8 and Figure 4-9 indicate how the simulated production rates over 24 years could change. Both graphs demonstrate that low production periods could occur over extended periods and at different stages of the power plant's lifetime.

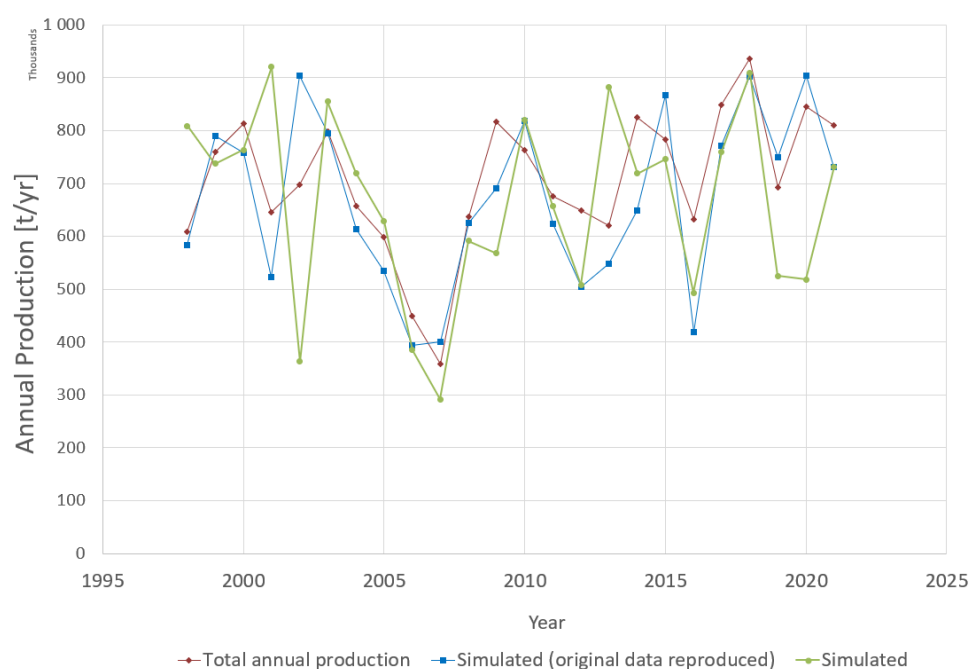


Figure 4-8: Original annual production rates compared with simulated production rate (1)

Source: SAGIS (2022b) & Author's simulations

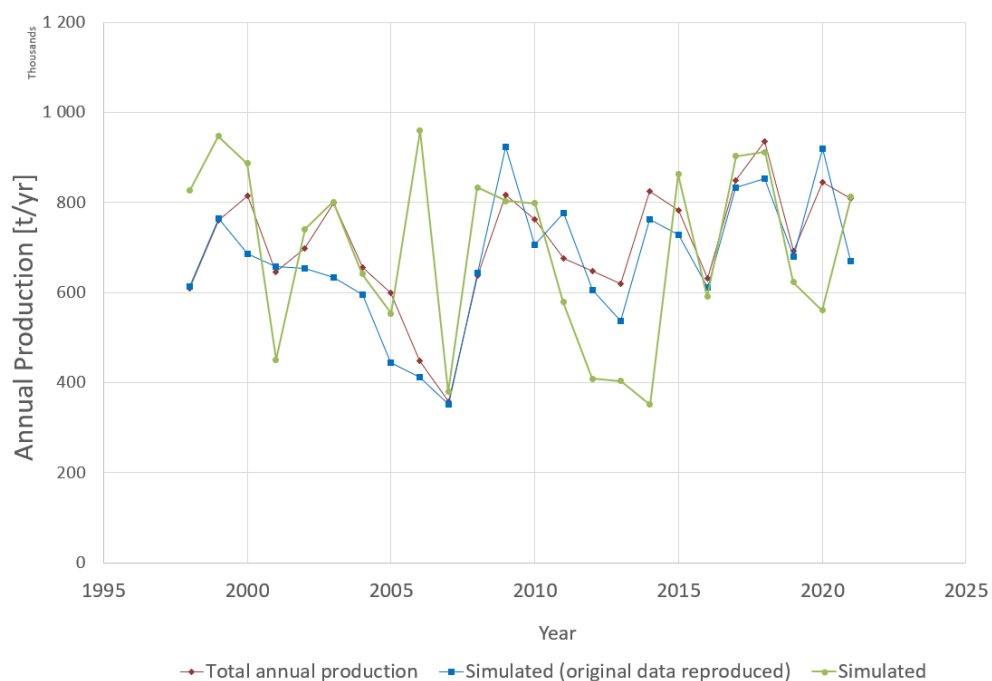


Figure 4-9: Original annual production rates compared with simulated production rate (2)

Source: SAGIS (2022b) & Author's simulations

It is now assumed that the national production data (as predicted) can be scaled to represent the crushing output of a typical plant. This scaling will be discussed in section 5.2.

4.3.2 Crushing plant electrical energy demand uncertainty

The total power demand of the crushing plant is critical in the financial analysis of the power plant. The power consumption of the crushing plant determines both the peak power required and the plant's total electrical energy (MWh electric). The peak power will influence the size of the power plant (i.e. the total installed capacity). The total electricity required impacts the amount spent on electricity. Data regarding the power requirements for an oil mill were obtained from the literature. Unfortunately, actual plant data were difficult to obtain, with none of the contacted oil mills willing to share operational data.

Maslikov (2012) analysed the energy consumption of twelve sunflower oilseed crushing plants in Ukraine. The twelve plants' specific electricity consumption (power per ton processed) is graphically presented in Figure 4-10 below. Most plants have an electricity consumption of between 100 and 150kWh/ton. No clear trend between production size and specific consumption is observed. The average specific electricity consumption is approximately 130kWh/ton. If the particular electricity consumption is production weighted, the average is approximately 122kWh/ton.

Nilsson *et al.* (2010) evaluated the production life cycle cost of margarine and butter in the UK, Germany and France. Sunflower oil is a base ingredient in margarine. Data on processing were obtained from Unilever, among others. Unilever is one of the world's leading fast-moving consumer goods suppliers Nilsson *et al.* (2010:919). The electricity consumption for sunflower oil was estimated at 200MJ/ton of crop input, or approximately 56kWh/ton.

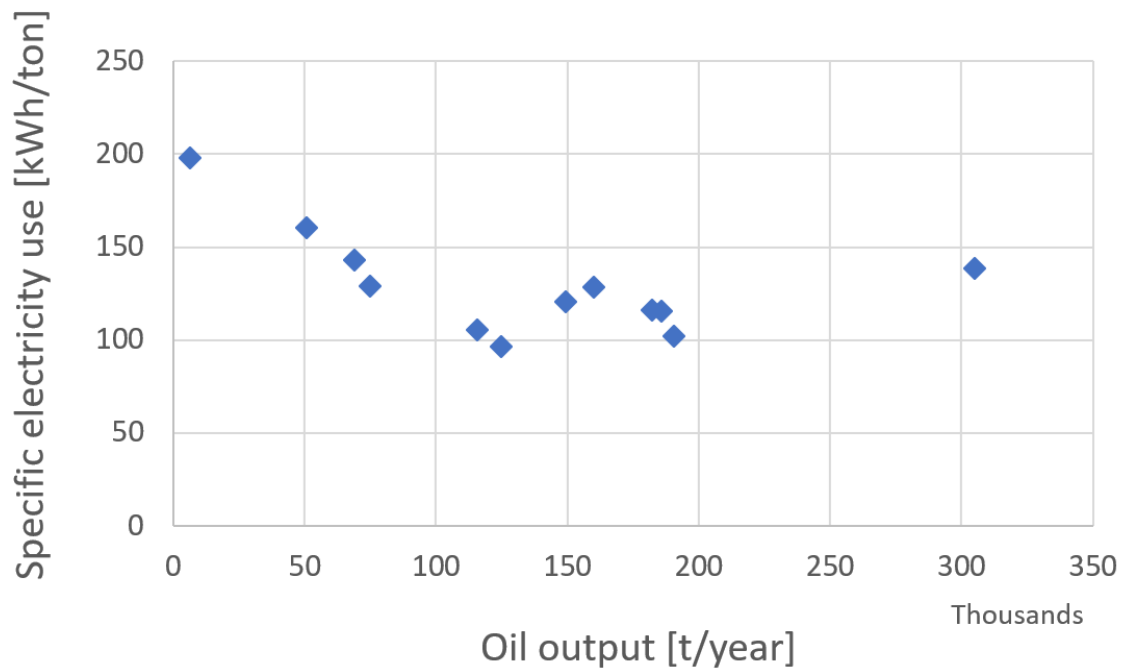


Figure 4-10: Specific electricity consumption of twelve sunflower-crushing plants

Source: Havrysh *et al.* (2020) & Maslikov (2012)

A comparison of the specific electricity consumption from the literature reveals a wide range. It is likely due to the difference in technology used in Europe versus in Ukraine, with Ukraine's sunflower oil industry being very energy intensive and higher than industry standards (Havrysh *et al.*, 2019; Havrysh *et al.*, 2020). For this study, the specific energy consumption is selected as the average value between the high and low consumption rates, namely at 93kWh/ton.

4.3.3 Power plant sizing uncertainty risk

The total plant cost (TPC) is based on the installed capacity. This capacity needs to be selected so that the power plant can supply the electricity needs of the crushing plant while not unnecessarily oversizing the power plant. Oversizing the power plant will result in underutilisation of the CAPEX and effectively higher power costs. Undersizing the power plant could, on the other hand, result in the power plant not being able to provide enough power. One approach to sizing the power plant would be to use the peak electrical requirements based on the maximum predicted production, as modelled in section 4.3.1. This approach is, however, not realistic since

most crushing plants have silos or storage bins. Storage helps to smooth out production. The peak predicted production rate would be lower than the model predictions as production is shifted between months. Since the actual plant power demand for a particular annual crushing capacity is unknown, an assumption must be made.

The production model (section 2.3.1) and the electricity consumption rates (section 2.3.2) were used to calculate the peak monthly power required to achieve the production rates for various crushing plant sizes. The production is estimated for each month using the model. Dividing the total output per month with the specific energy required gives the peak electricity based on a 24h per-day operation for 30 days per month. The results are shown in Figure 4-11 below as a cumulative distribution function of the peak power requirement. The y-axis represents the fraction of time (a fraction of the 240 months simulated in each case), and the x-axis is the peak power required. It is assumed that the peak power requirement needs to be satisfied 80% of the time. The other 20% of the time, the production will be spread between months to lower the peak requirement. From Figure 4-11 below, the 80% values can be obtained, as is summarised in Table 4-2 (p 72).

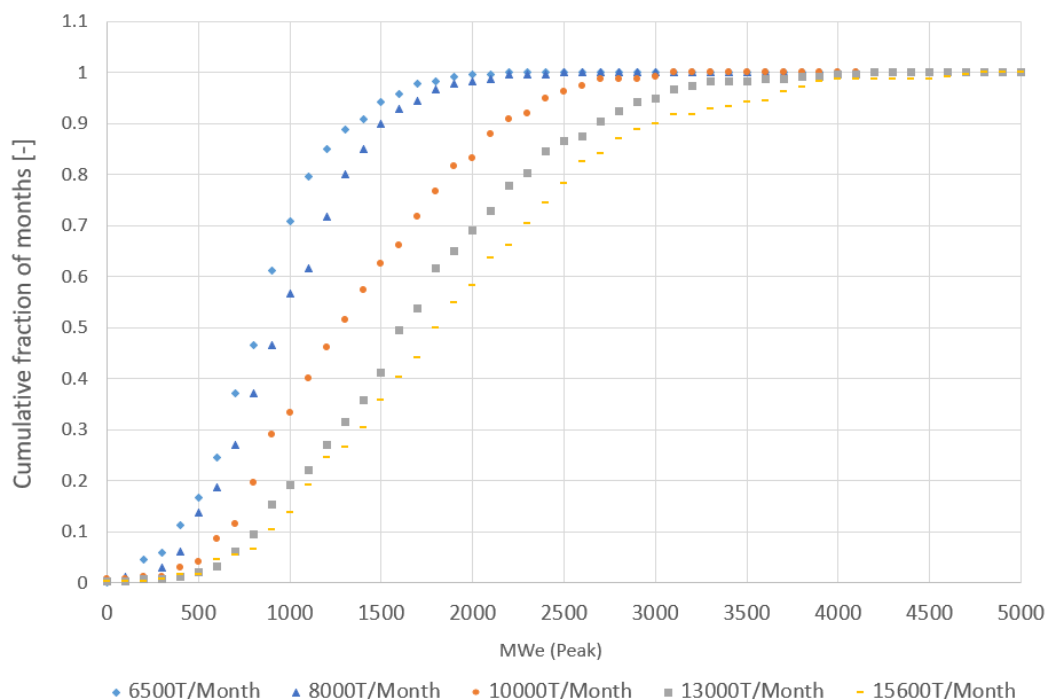


Figure 4-11: Peak power requirements for different crushing capacity plants

Based on the peak powers in Table 4-2, the total plant cost is estimated using the specific capital cost discussed in section 4.3.6. A sensitivity analysis can be used to investigate the peak power requirement assumption's influence on the financial metrics.

Table 4-2: Power plant peak capacity as a function of crushing plant production

Production Rate (Annual)	Power plant peak capacity	Average annual power requirement	Peak-to-average ratio
[t/month]	[MWe]	[MWe]	[-]
6500	1100	820	1.34
8000	1300	1000	1.3
10500	1850	1342	1.39
13000	2300	1680	1.37
15500	2550	2015	1.27

4.3.4 Production loss risk

The opportunity cost associated with the loss of production during load-shedding is discussed in this section. First, the hours lost in production due to load-shedding are estimated from the historical load-shedding data. Then, the crushing margins are calculated based on the sunflower seed's historical data and oilcake prices.

Load-shedding Data

Load-shedding (LS) significantly impacts the economy and manufacturers' ability to produce goods. Load-shedding results in lost production at a crushing-plant. Embedded generation can help to reduce the impact of load-shedding. To evaluate the benefit of eliminating the effect of load-shedding, it is required to develop a model that predicts future load-shedding events based on historical data.

Load-shedding data was obtained from Eskom through their data request form (Eskom, 2022b). Forced load reduction (i.e. load-shedding) data is available from 1 April 2018. In addition, hourly information is available, indicating the total load that was forcibly reduced. This data was processed to provide the following:

- The trend in the frequency of load-shedding
- The number of load-shedding events per month
- The probability of the duration of load-shedding, and
- The likelihood of the level of load-shedding (stages 1 to 8).

Figure 4-12 below indicates the trend in the cumulative number of load-shedding events over the past 51 months. A quadratic function is fit through this trend. The equation is differentiated to give the number of events per month:

$$n = 1.31 + 0.0397t$$

Where n is the number of events per month, and t is the number of months. Note that the constant, 0.0397, is the growth rate.

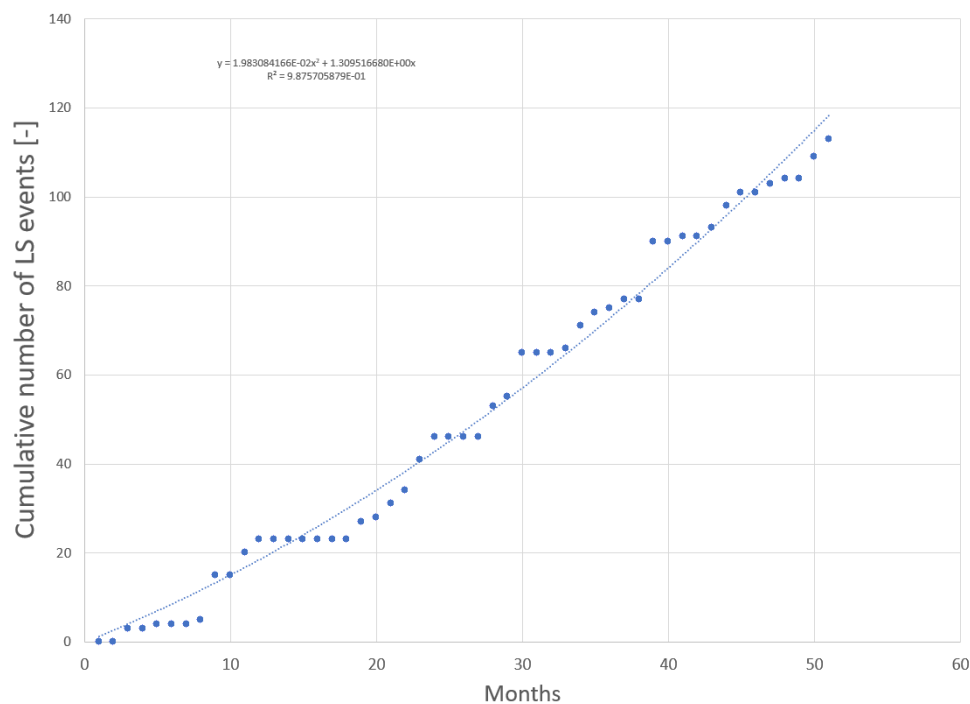


Figure 4-12: Trend in the cumulative number of load-shedding events

Source: Adapted from Eskom (2022b)

It will be assumed that this growth rate is constant beyond the period of data available. The value of n , therefore, serves as the average number of load-shedding events, irrespective of the duration. This approach evenly distributes the number of load-shedding events throughout the project. A discrete test for load-shedding events each month is therefore not performed.

Each load-shedding event has a duration. The durations can be presented in cumulative distribution function (CDF), as illustrated in Figure 4-13. Random sampling from the CDF is used to determine the duration of each event in the model.

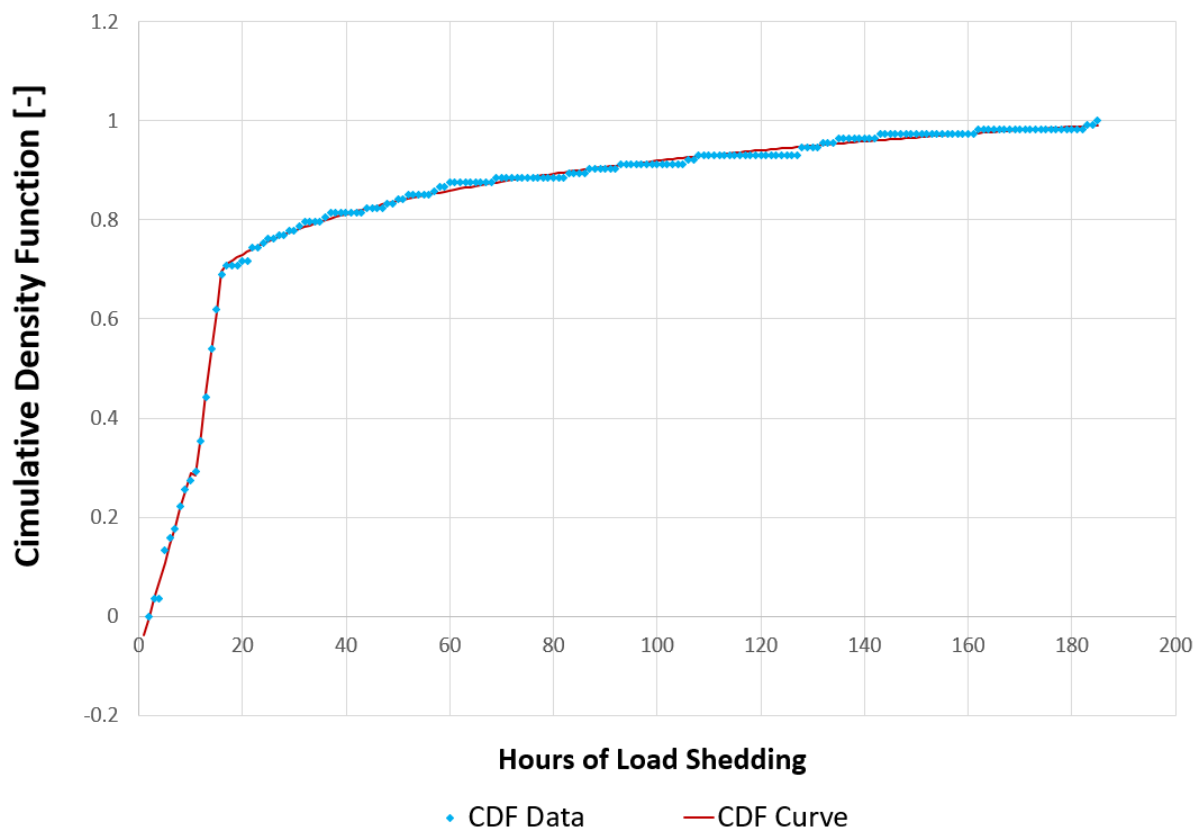


Figure 4-13: CDF for the duration of load-shedding events

Source: Eskom (2022b) & Author's calculations

The total monthly hours that load-shedding is enforced is calculated from the following equation:

$$h_{month} = n \cdot h_{event}$$

Where

- n is the number of events per month, and
- h_{event} is the duration of an event and is obtained from random sampling from the CDF.

It must be noted that several assumptions were made. Firstly, it is assumed that the frequency of load-shedding events and the duration of the events are uncorrelated. Secondly, it is assumed that the increase in load-shedding events will continue in the future beyond the five years of historical data.

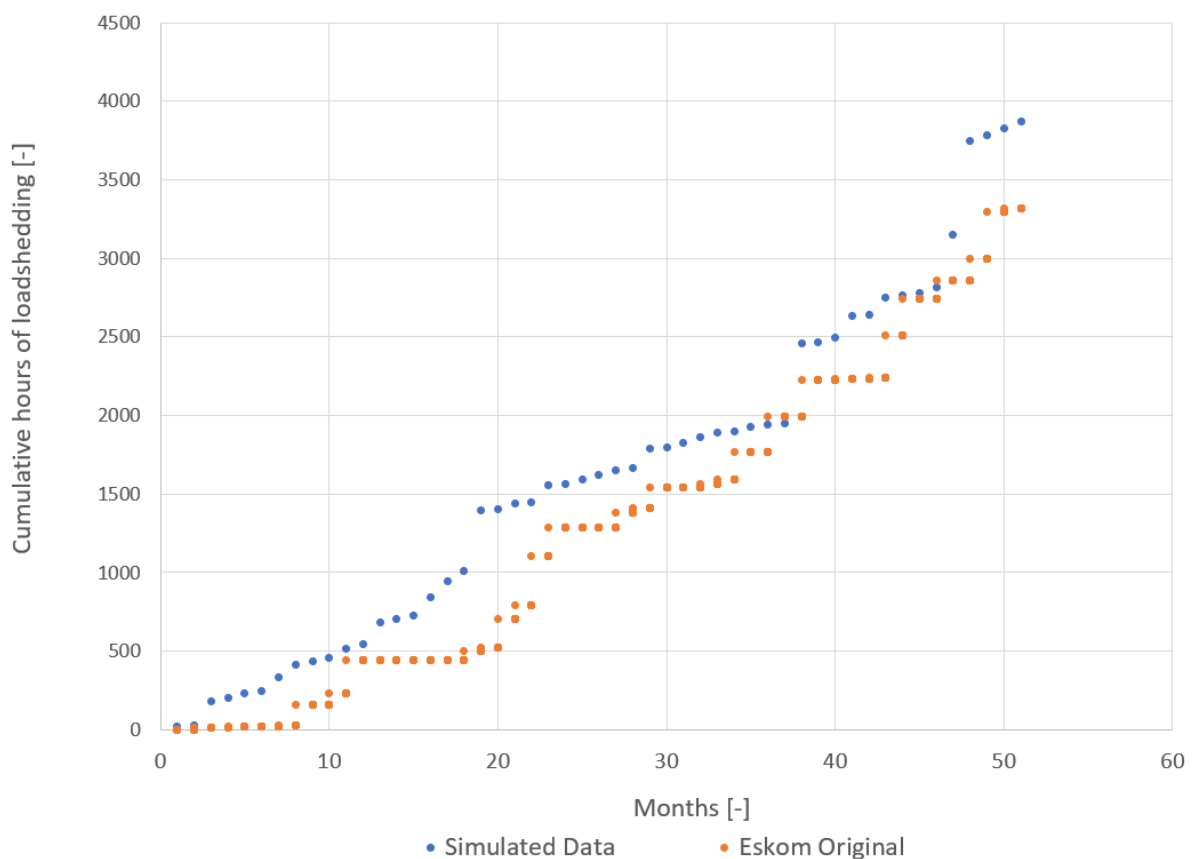


Figure 4-14: Cumulative number of load-shedding hours from the model and original data

Source: Eskom (2022b) & Author's simulations

The model is tested by simulating the cumulative load-shedding hours and comparing it to the original data. The result from a single simulation is provided in Figure 4-14 above.

Over the 51 months of available data, the total number of hours of load-shedding was 3292 hours. A thousand simulations were performed with the model for 51 months, and the total number of load-shedding hours was plotted (essentially, the graph in Figure 4-14 was reproduced 1000 times). The distribution of the total simulated hours of load-shedding is shown in Figure 4-15. The average value is around 3400 hours. The results are acceptable in comparison with the actual data.

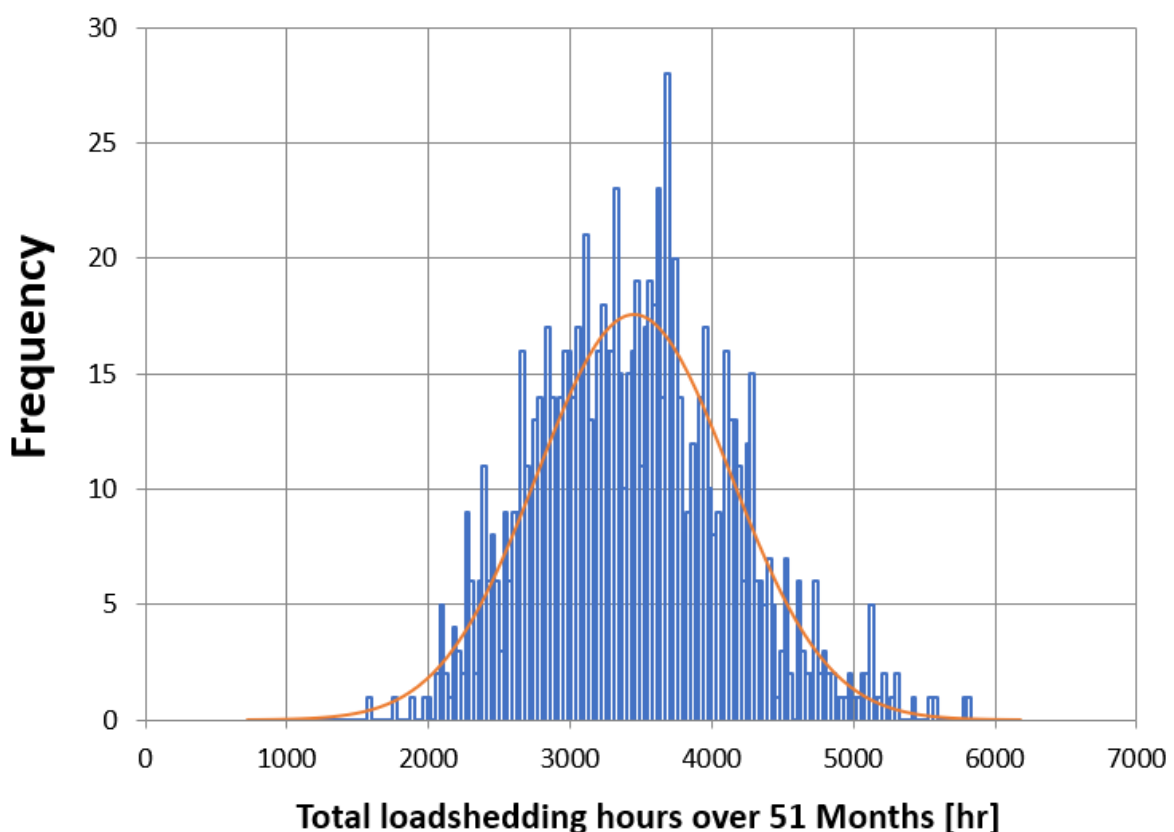


Figure 4-15: Distribution of the total simulated hours of load-shedding over 51 months

The final step in simulating the influence of load-shedding is to account for the stage of each event. The simulated hours of load-shedding do not account for the stage (total MW reduction in the grid) but only the duration of each event (i.e. from the time that

Eskom announced a specific stage of load-shedding until full power is restored). The stage of load-shedding will determine how many hours per day the power will be cut. Any uninterrupted forced load reduction above 1MW is defined as load-shedding. Each of the 114 forced load reduction events over 51 months, from March 2018 to May 2022, was analysed. The analysis found 84 load-shedding events during the period. The maximum forced load reduction was 8737MW, i.e. stage 8 load-shedding.

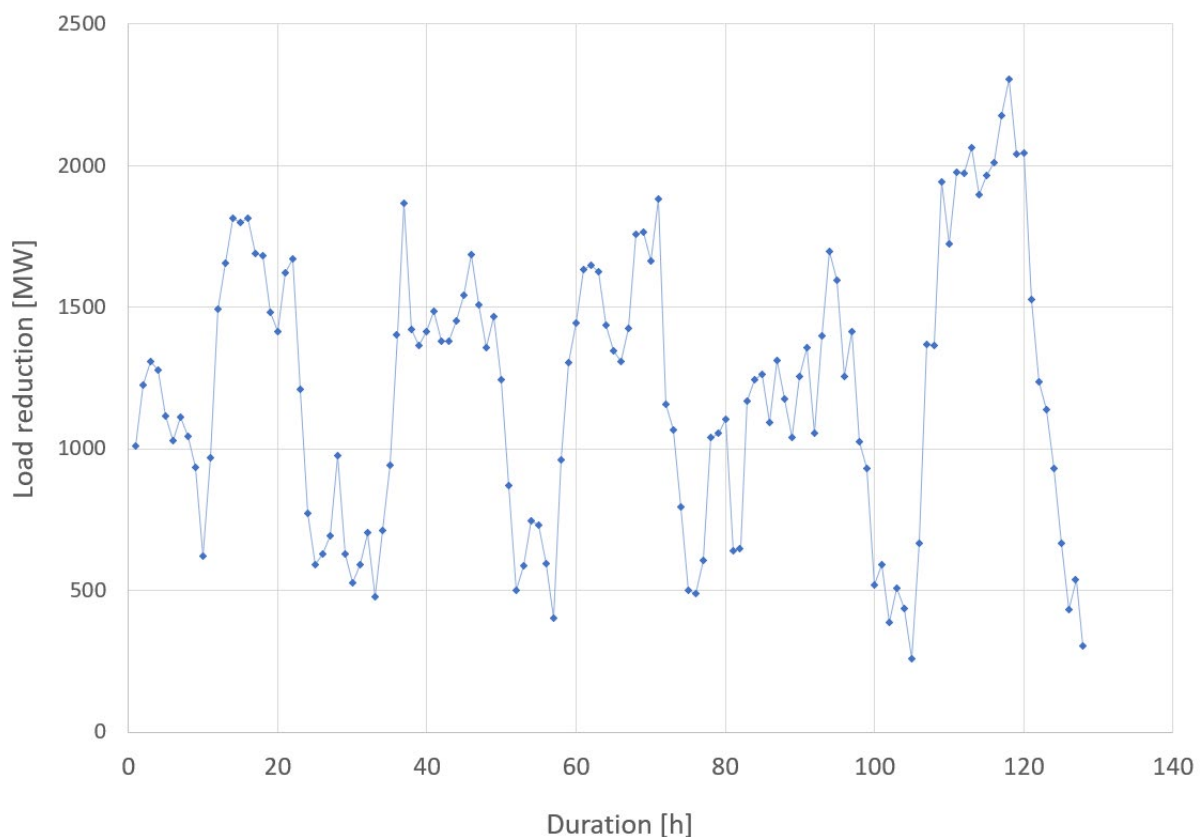


Figure 4-16: Example of a load reduction event

Source: Adapted from Eskom (2022b)

Figure 4-16 gives an example of the raw data. The stage of load-shedding may change during an event. For higher load-shedding stages, load-shedding typically starts at stage 1, increasing as the pressure on the grid increases. For each of the 84 load-shedding events, the average forced load reduction was calculated and used to determine the stage. The frequency of each load-shedding stage was then calculated, and a cumulative distribution function was calculated, shown in Figure 4-17 below. The load-shedding stage can be modelled by sampling from Figure 4-17. Although this

method of averaging does not allow for an event of the maximum load-shedding stage (i.e. stage 8), it does provide a means to incorporate the probability of different load-shedding stages.

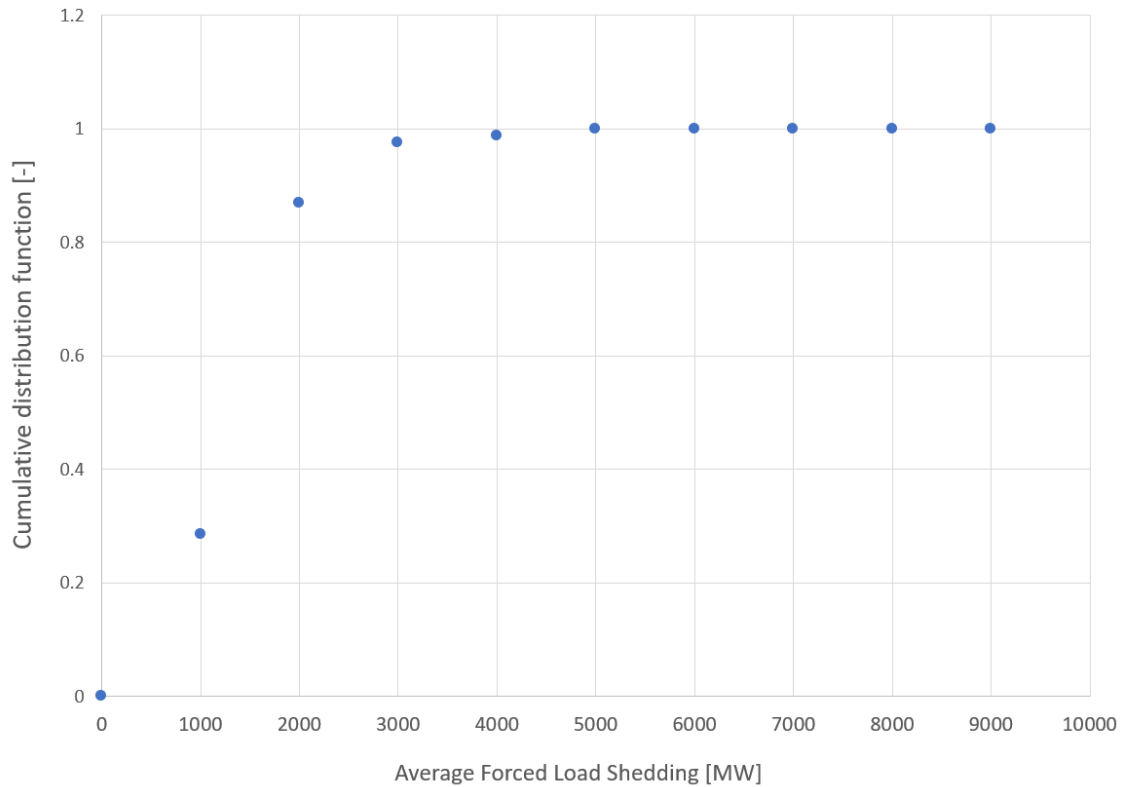


Figure 4-17: Cumulative distribution function for the average forced load-shedding per event

Source: Adapted from Eskom, 2022b

Finally, based on the load-shedding schedule, the number of lost production hours can be calculated. Figure 4-18 is an example of the load-shedding program. During stage 1, the power will be cut for approximately 23 hours per month, or roughly 3.2% of the month, in any given area if load-shedding continues for an entire month. For each stage, the total time per month without power will increase by around 23 hours. Therefore, the total production loss is calculated as follows:

$$h_{lost} = h_{month} \cdot LS_{stage} \cdot 3.2\%$$

Static monthly version . This schedule would apply each month. For 30 day month just drop day 31 and for Feb drop days 29 to 31.																																		
Day of the month			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	
	00:00	02:30	7									1	2	3	4		6	7	8	5								4	1	2	3		5	6
	02:00	04:30					1	2	3	4	5	6	7	8										4	1	2	3	8	5	6	7			
Province	04:00	06:30	1	2	3	4	5	6	7	8										4	1	2	3	8	5	6	7							
Free State	06:00	08:30	5	6	7	8														4	1	2	3	8	5	6	7					3	4	1
City/Munic	08:00	10:30										4	1	2	3	8	5	6	7									3	4	1	2	7	8	5
Naledi	10:00	12:30					4	1	2	3	8	5	6	7										3	4	1	2	7	8	5	6			
Suburb/Town	12:00	14:30	4	1	2	3	8	5	6	7										3	4	1	2	7	8	5	6							
Wepener	14:00	16:30	8	5	6	7										3	4	1	2	7	8	5	6									2	3	
	16:00	18:30										3	4	1	2	7	8	5	6									2	3	4	1	6	7	8
	18:00	20:30					3	4	1	2	7	8	5	6										2	3	4	1	6	7	8	5			
	20:00	22:30	3	4	1	2	7	8	5	6											2	3	4	1	6	7	8	5						
	22:00	00:30	7	8	5	6										2	3	4	1	6	7	8	5									1	2	

Figure 4-18: Example of a load-shedding schedule

Source: Eskom (2022a)

Sunflower seed, oil, and oilcake prices

An opportunity cost is involved when the plant is shut down due to load-shedding. The opportunity cost is quantified by making a few simplifying assumptions. Firstly, it is assumed that the plant is not in operation due to load-shedding and will always incur an opportunity cost. This assumption is not strictly valid since production could be shifted to periods without load-shedding. For example, the plant will not run at maximum capacity when the annual output is low. Production could be moved so that the impact of load-shedding is not so acute. In this study, however, it will be assumed that all load-shedding events result in a production opportunity cost.

Secondly, the opportunity cost will be quantified as the difference between the product selling price and raw material input price, or in other words, in terms of the crushing margin (van Zyl, 2010:69). Therefore, the opportunity cost per ton is calculated as

$$R_{opportunity} = R_{oil} + R_{oilcake} - R_{seed}$$

The loss in production is calculated as the lost hours due to load-shedding multiplied by the production rate. It is assumed that all other fixed costs for the production plant would be incurred, irrespective of whether there is load-shedding involved (such as personnel cost). Additional variable operating costs of production are not readily available in the literature and, therefore, are not included in the model.

The third assumption is that the seed price is unrelated to total national production. The price variation is likely correlated to national production, rainfall, and other factors. Correlating all these factors is, however, beyond the scope of this study. The aim is instead to model the general price trend and stochastically model the variation in price fluctuation around the average price.

Historical data for sunflower oil and oilcake prices were obtained from the Bureau of Agricultural Policy (BFAP) (BFAP, 2021), while data for sunflower seed producer prices were obtained from SAGIS (2021). The relationship between the sunflower seed price and oil and oilcake prices is shown in Figure 4-19 below. Both sunflower oil and oilcake prices are linearly correlated to sunflower seed prices. For this investigation, the relationship will be assumed to be linear.



Figure 4-19: Relationship between the producer price (sunflower seed) and the price of sunflower oil and oilcake

Source: Adapted from BFAP (2021) & SAGIS (2021)

The increase in sunflower seed prices of the simulated and raw data is compared in Figure 4-20 below. Only data from 1997 onward are shown. Before 1996, the oilseed board controlled the sunflower seed complex market (van Zyl, 2010). After the deregulation of the oilseed industry in 1996, sunflower oilseed has been traded on the South African Futures Exchange (SAFEX) (van Zyl, 2010:1). Oilseed producers and processors are therefore exposed to the foreign markets. For this reason, only the data from 1997 onward is used to evaluate seed price trends. The price increase is linear.

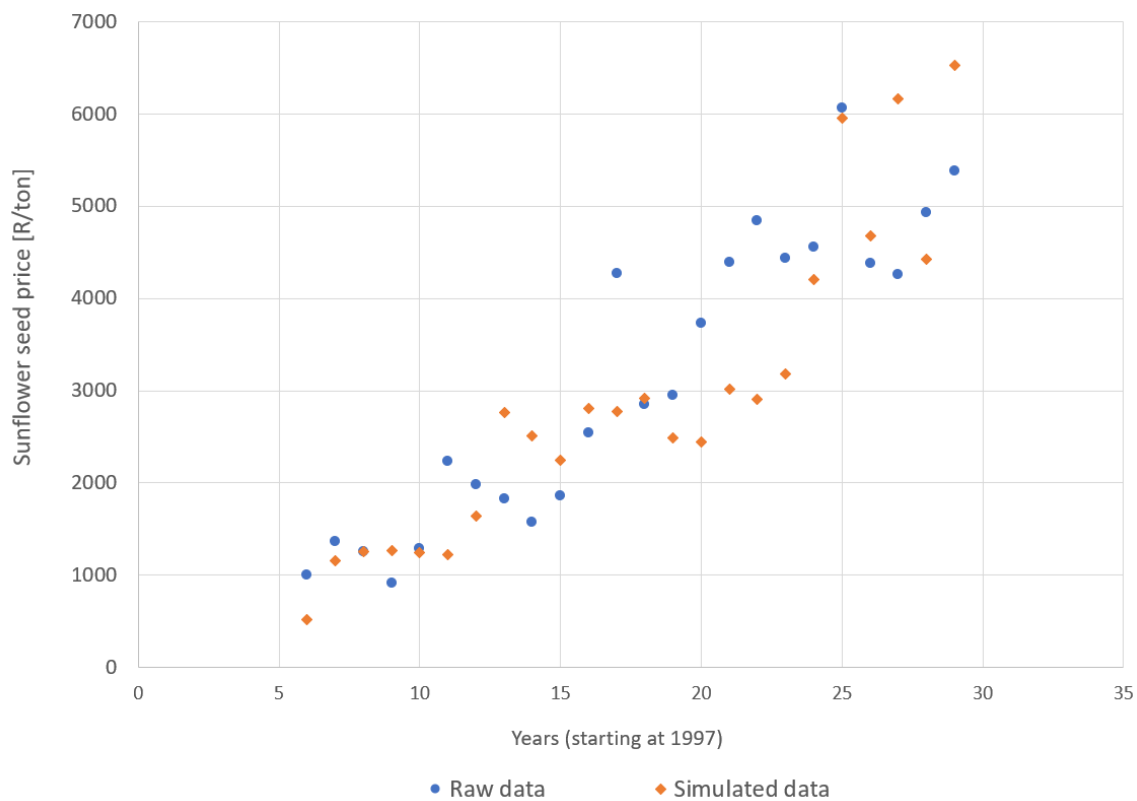


Figure 4-20: Sunflower seed producer price and simulated price

Source: BFAP (2021) & Author's simulation

The fluctuations around the average price were analysed by determining the distribution of the normalised difference between the actual and average price:

$$\delta_R = \frac{R_{seed,actual} - R_{seed,avg}}{R_{seed,avg}}$$

The values δ_R is very close to uniformly distributed around zero. The cumulative distribution function (CDF) for δ_R is shown in Figure 4-21 below. A straight line is fitted through the CDF, which can then be used to stochastically model the variation of the price fluctuation around the average price.

The price of seeds can then be determined using the following formula:

$$R_{seed} = R_{seed,avg} + \delta_R \cdot R_{seed,avg}$$

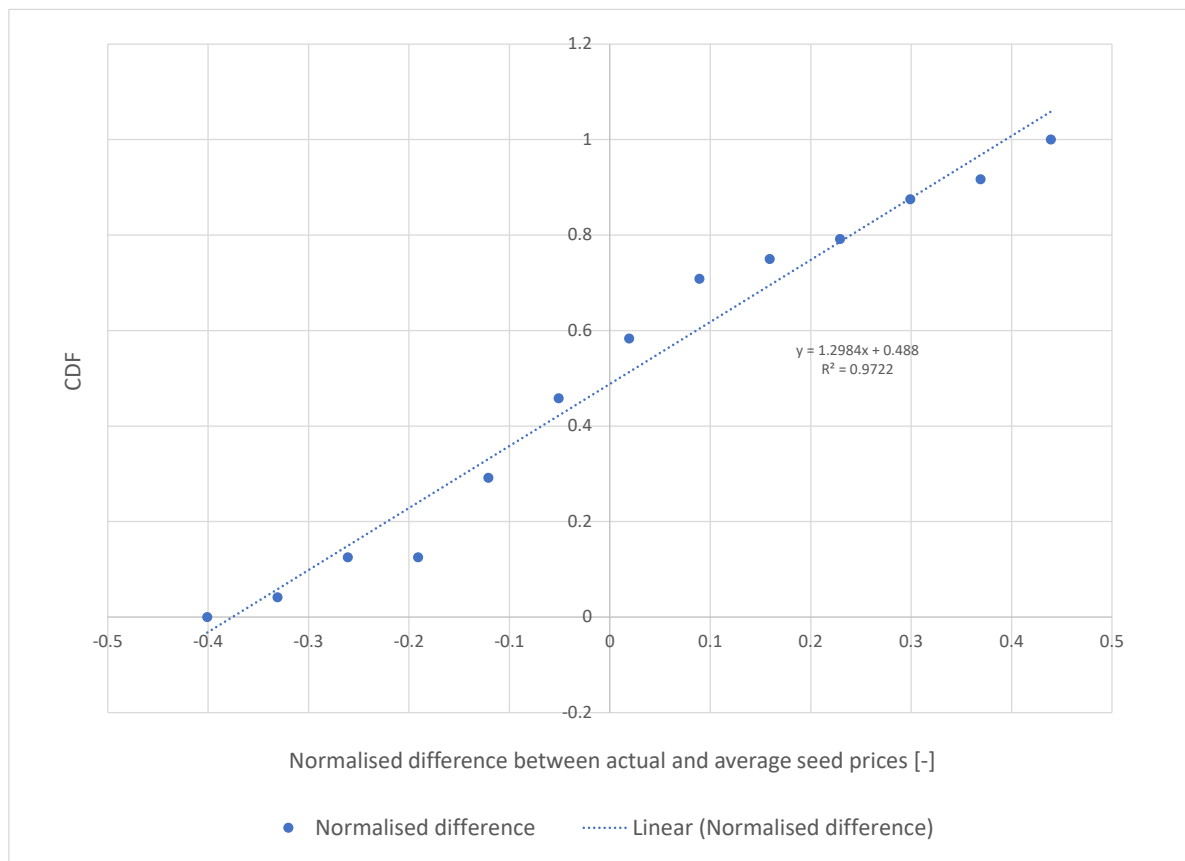


Figure 4-21: CDF for the normalised difference between actual and average sunflower seed prices

Figure 4-20 (p 81) demonstrates the seed price simulation results from 1997 onward. The prices of sunflower oil and oilcake are correlated to the seed price through the relationships provided in Figure 4-19 (p 80). The resulting simulated prices for

sunflower oil and oilcake since 1997 are shown in Figure 4-22 below. This model can determine the price for seed, oil and oilcake using the current price as the starting price. Since a uniform distribution is used for the seed price, the extreme value will not occur (e.g. price shocks due to the war in Ukraine will not be reflected in the model).

The fraction of oil and oilcake produced from the raw seed inputs are obtained from data published by SAGIS (SAGIS, 2022a). The average ratio between the manufactured oil and oil cake tonnages was obtained for 63 months. This ratio is 46% oil and 54% oilcake. This ratio is very close to the values reported by van Zyl (2010:10). Around 20% of the seed is husk (or hull) that can be used as fuel (van Zyl, 2010:83). Havrysh *et al.* (2020:365) put this value between 15.94% and 18.88%.

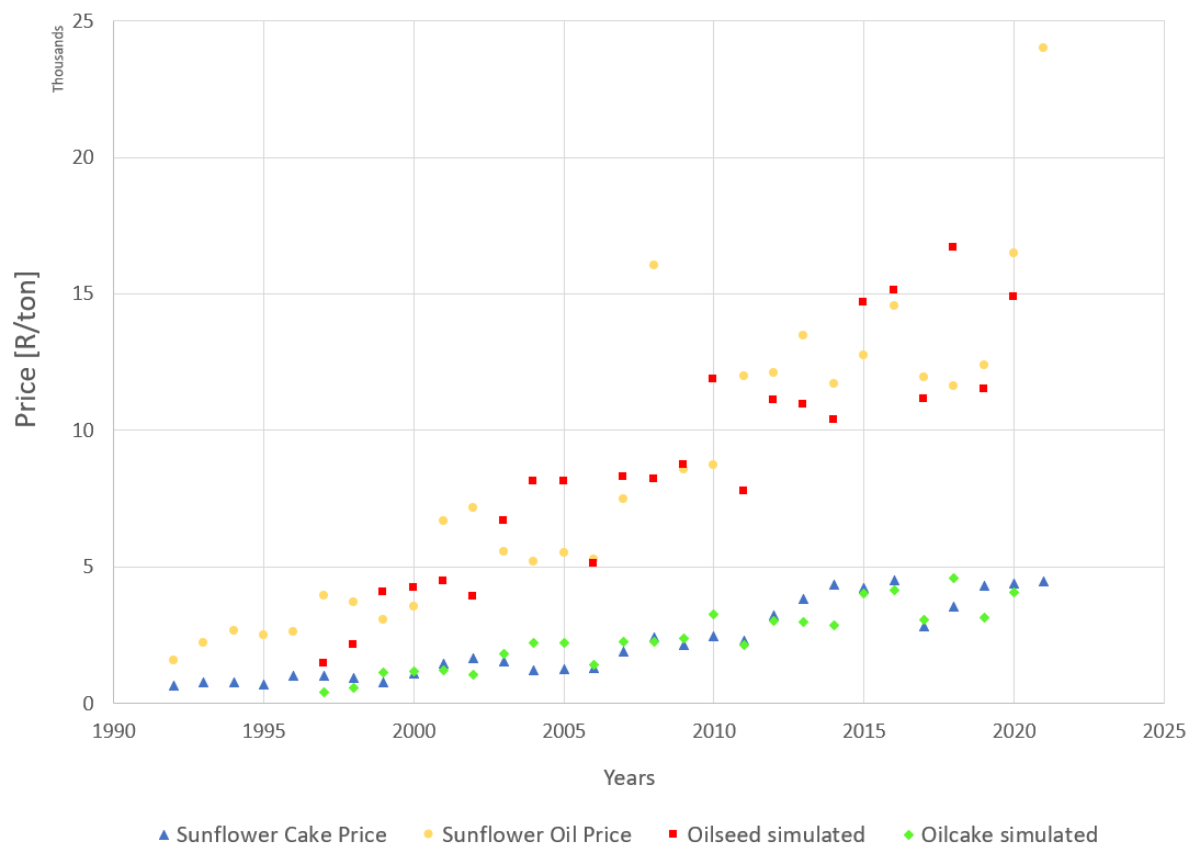


Figure 4-22: Actual and simulated sunflower oil and oilcake prices

Source: BFAP (2021) & Author's simulation

4.3.5 Technology selection risk

Glenting and Jakobsen (2017) provide a comprehensive overview of the technologies that can convert biomass into electricity. The primary technologies for husk include boiler-steam turbine technology, biomass gasification with internal combustion engine (ICE) technology, and thermal oil boilers with Organic Rankine cycle (ORC) technology. Boiler and steam turbines are the best proven commercial technology, with equipment and project cost estimates the most readily available (Glenting & Jakobsen, 2017:33). The focus of this study is not on the technical aspects of power generation or the selection and evaluation of various technologies. It will therefore be assumed that the best-proven technology will be used to avoid the risk of less familiar technologies. The technology combination of a boiler and steam turbine will be used.

The selection of technology will influence the uncertainty in the following factors:

- **The total project cost (TPC)** is the turnkey cost the owner would pay for the plant. It includes all the capital equipment, engineering, procurement and construction (EPC) costs, and commissioning.
- **The plant conversion efficiency** is the ratio of the net electrical energy available for the sunflower-crushing plant to the lower heating value (LHV) of the husks used during combustion. It is, therefore, the energy output in electricity per energy input in biomass.
- **Operational expenditure (OPEX)** is the power plant's operating cost. Typically, it includes (Boukis *et al.*, 2009; Delivand *et al.*, 2011):
 - Labour costs.
 - Operating and Maintenance (O&M) costs (direct material costs to maintain the plant).
 - Utility costs (chemicals, diesel, and others).
 - Fuel cost.
 - Waste disposal costs.

4.3.6 Investment cost (Total project cost) uncertainty

Technology costs and efficiencies are not directly available for biomass power plants using sunflower husks. Similar technologies have been employed for rice husk and

other biomass sources, such as wood. Figure 4-23 below demonstrates the capital-specific cost for power generation plants based on combustion technology in Thailand (Delivand *et al.*, 2011:3653). Note that the specific cost increases dramatically at the lower end. At 1MWe, the cost is estimated at \$4700/kWe. Boukis *et al.* (2009:367) estimate the cost for a 1MWe solution at approximately \$4600/kWe. The cost estimates need to be inflation-adjusted to obtain a present value estimate. Two approaches are followed. The first is to estimate the present value using two inflation rates, one for imported equipment and one for equipment procured in South Africa. Biomass boilers and turbines are typically imported from Europe, and their portion of the capital is therefore adjusted with an equivalent inflation rate for the European Union. The equivalent inflation rate from 2009 to 2020 is 1.28% (Macrotrends, 2022a). The other portion of the capital is adjusted using an equivalent inflation rate for the period from 2009 to 2020 for South Africa. This inflation rate is 5.17% (Statista, 2022). Boukis *et al.* (2009:369) estimate that boiler and turbine components make up around 62% of the total project cost (TPC), while Oliveira *et al.* (2012:1657) estimate it to be about 60%.

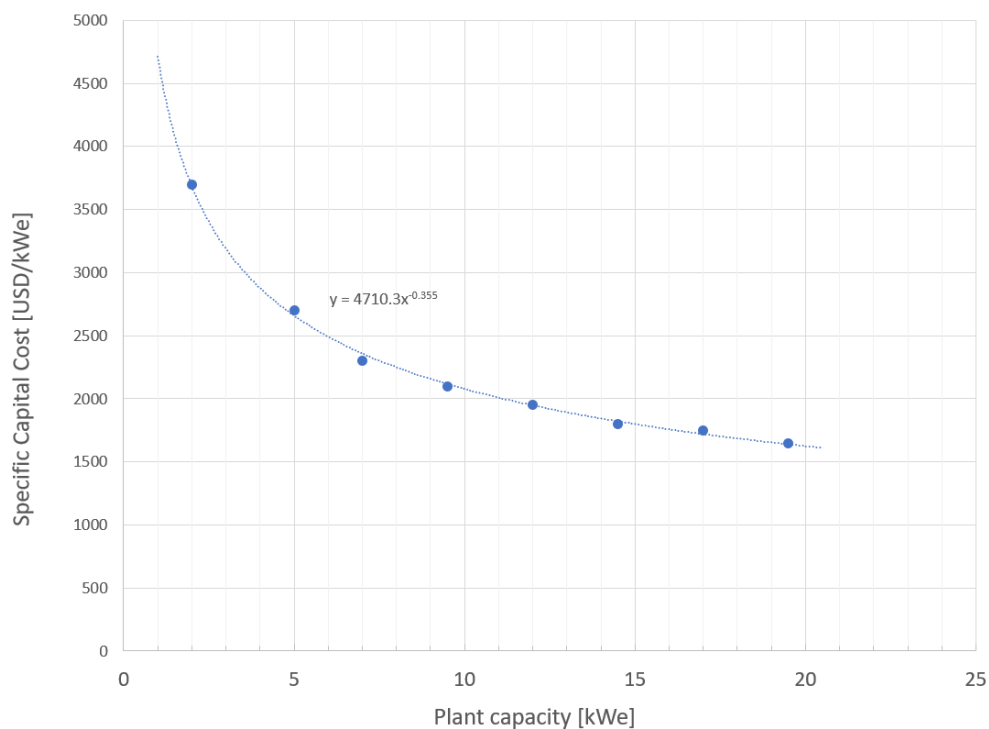


Figure 4-23: Specific capital cost for combustion power plants

Source: Adapted from Delivand *et al.* (2011)

The second approach is to escalate the specific cost with the equivalent world inflation rate over the same period. This rate is approximately 2.6% (Macrotrends, 2022b).

A nominal exchange rate of R16/\$ is used to estimate the total plant cost as a function of the plant capacity (electricity generating capacity), as indicated in Figure 4-24 below. Total CAPEX for a 1.25MW biomass power generation plant is expected to be between R122M and R128M.

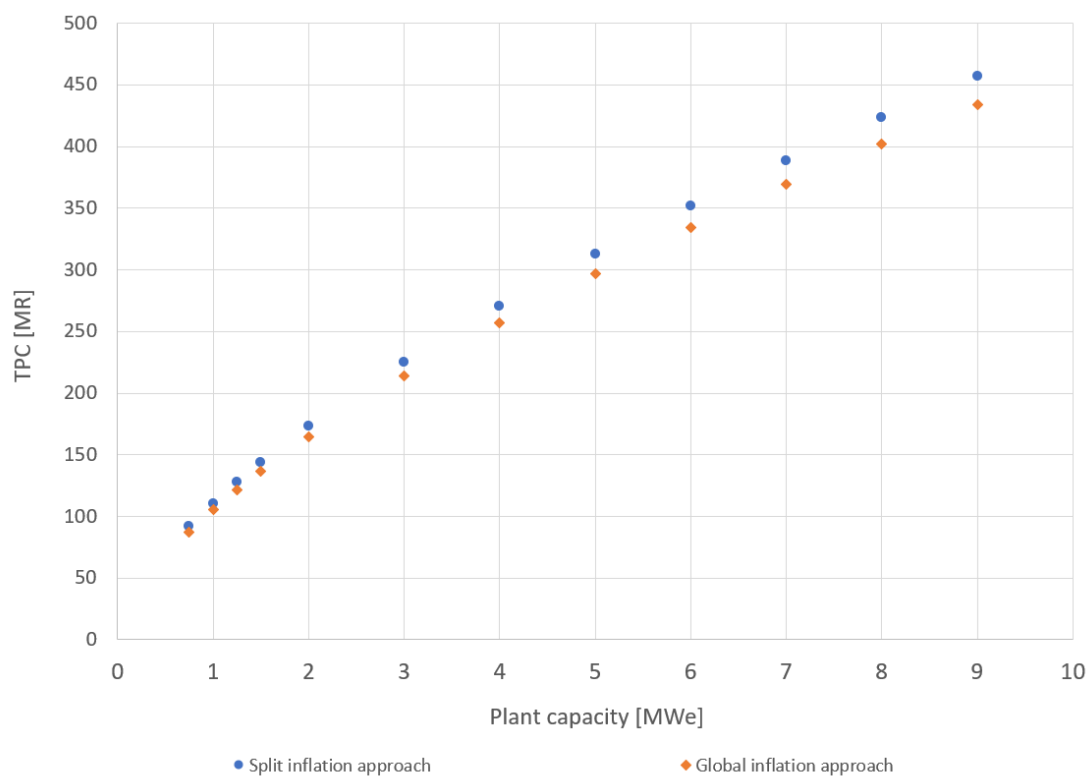


Figure 4-24: Total plant cost as a function of the plant capacity

4.3.7 Conversion efficiency uncertainty

Conversion efficiency data is not readily available from published literature. There is little information because there are few combined heat and power (CHP) plants for sunflower husks. The efficiency of CHP plants is typically reported with the inclusion of steam generation for the process (i.e. the efficiency is not reported separately for steam production and electricity generation). Data on cycle efficiencies are also

specific to each project and often considered confidential from a client's point of view. However, a conversion cycle efficiency analysis is beyond the scope of this study.

Literature for biomass combustion, in general, was consulted to obtain conversion efficiency data. Havrysh *et al.* (2019:247), Delivand *et al.* (2011:3653), and Boukis *et al.* (2009:367) report the efficiency to fall between 10% and 18% for the 1-2MWe capacity range. These efficiencies are based on industry norms reported in the literature. Solantausta (2000) performed an in-depth analysis of the conversion efficiencies of biomass combustion technology and compared the results with industry values. Figure 4-25 below shows the results for power plants from 3MWe to 27MWe. Data points for 1 and 2 MWe were extrapolated using a curve fit. This data is considered the most reliable and representative and will be used in this study.

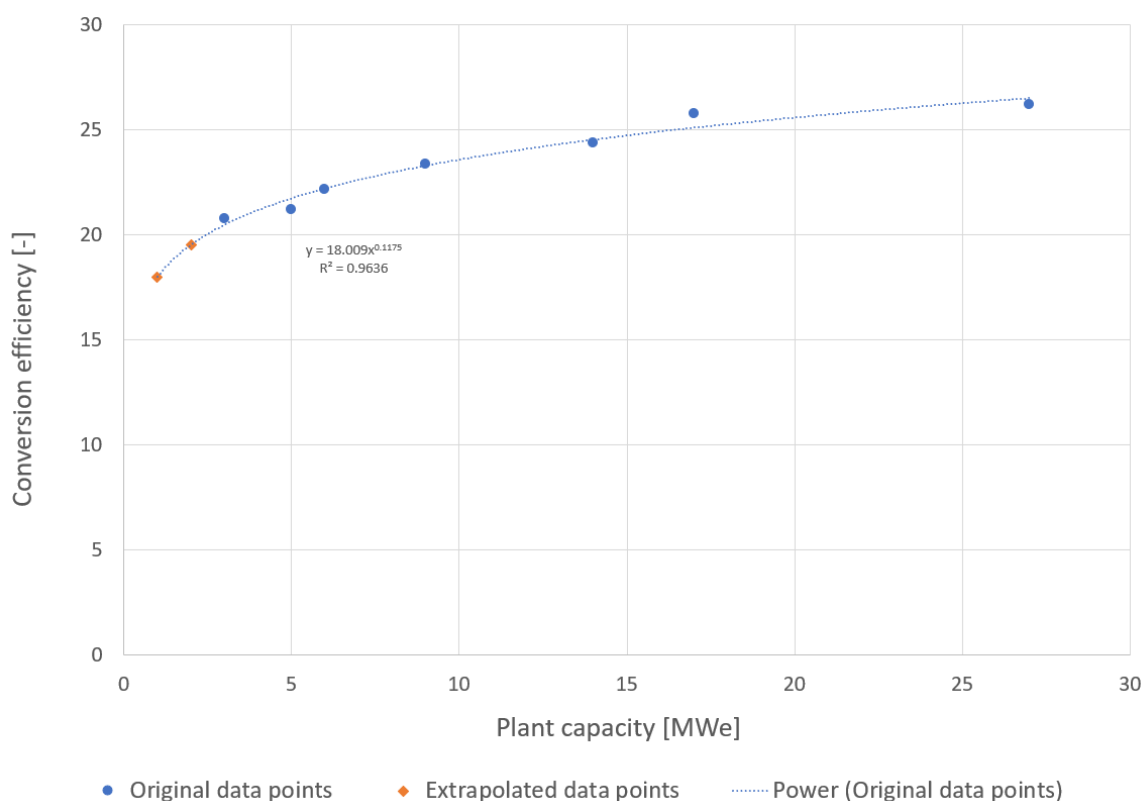


Figure 4-25: Conversion efficiency for biomass combustion power generation plants

Source: Adapted from Boukis *et al.* (2009)

4.3.8 Power plant O&M cost uncertainty

Biomass plant maintenance costs are estimated to be 1.5-4% of the total capital per annum (Boukis *et al.*, 2009; Delivand *et al.*, 2011). Therefore, for this investigation, it will be assumed that the maintenance cost is 2% of the TPC, similar to the values used by Boukis *et al.* (2009).

Labour costs are estimated to vary between 0.9-1.2% of the TPC for power plant capacities between 5-20MWe (Delivand *et al.*, 2011). Boukis *et al.* (2009:371) performed a detailed breakdown of personnel required for an 8MW and estimated the labour cost to be approximately 4.2% of the TPC per annum. In this study, it will be assumed that the personnel of the crushing plant will also operate the power plant installed on the same premises and that all administrative overheads will be carried by the staff employed at the crushing plant. Only additional personnel for operating the plant and maintenance will be required. The maintenance manager, mechanics and electricians will likely be shared between the plants. Therefore, labour costs are assumed to be at the lower end of the literature-based values. A value of 0.9% of the TPC per annum is used. Utility costs for the plant are assumed to be 1% of the TPC per annum, similar to values used in other studies (Boukis *et al.*, 2009:372).

The total O&M costs (maintenance, labour, and utilities) are expected to be 3.9% of the TPC per annum.

4.3.9 Biomass price uncertainty

The energy content of sunflower husks (or hulls) is crucial since it determines the amount that needs to be burned to produce electricity. It, therefore, also determines the total cost associated with the fuel used in the process as part of the OPEX costs.

The calorific value (CV) of sunflower husk, as calculated by (Maj *et al.*, 2017:80), is provided in Table 4-3. Parea-Moreno *et al.* (2018:3418) report an average CV of 16.5MJ/kg at a moisture content of 8.4%, while noting that the typical moisture content is usually below 10% when coming from sunflower extraction processes.

For this study, a conservative value of 16MJ/kg is used.

Table 4-3: Calorific value of husk

Moisture (%)	Average Calorific Value [MJ/kg]
32	13138 ± 292.72
16	16270 ± 135.62
9	18003 ± 206.45

Source: Maj *et al.* (2017:80)

The cost associated with biomass is difficult to establish since it is not traded on any official platform. However, a biomass trading company was contacted to confirm typical prices. The company's managing director indicated that the mills sell husk for between R650 and R700 per ton. A sensitivity analysis will be used to demonstrate the impact of biomass cost on profitability.

4.3.10 Construction risk

The probability of cost overruns has a critical impact on the profitability of a construction project. An increase in cost would result in longer pay back and lower NPV. The results from Love *et al.* (2013) were used to estimate the probability of cost overruns. In their analysis of 276 construction and engineering projects, 131 projects had a value between A1\$ and 10\$ million. The probability density function (PDF) for the cost overrun of this size project is provided in Figure 4-26 below. It is expected that the value of a small biomass power plant will fall within this value range. Although this analysis isn't specifically for power plants, it provides a reasonable basis for estimating the cost overrun probability. A Wakeby distribution was fitted through the data, with the inverse CDF (x) given as (Love *et al.*, 2013:328):

$$x(F) = \xi + \frac{\alpha}{\beta} \left(1 - (1 - F)^{\beta} \right) - \frac{\gamma}{\delta} \left(1 - (1 - F)^{-\delta} \right)$$

The constants of the distribution parameters are $\alpha = 1833.9$, $\beta = 42.444$, $\gamma = -10.698$, $\delta = 0.15$, and $\xi = -42.405$, and F is the random number between 0 and 1.

For each simulation of the financial model, this distribution will be used to calculate the factor with which to multiply the initial capital estimate.

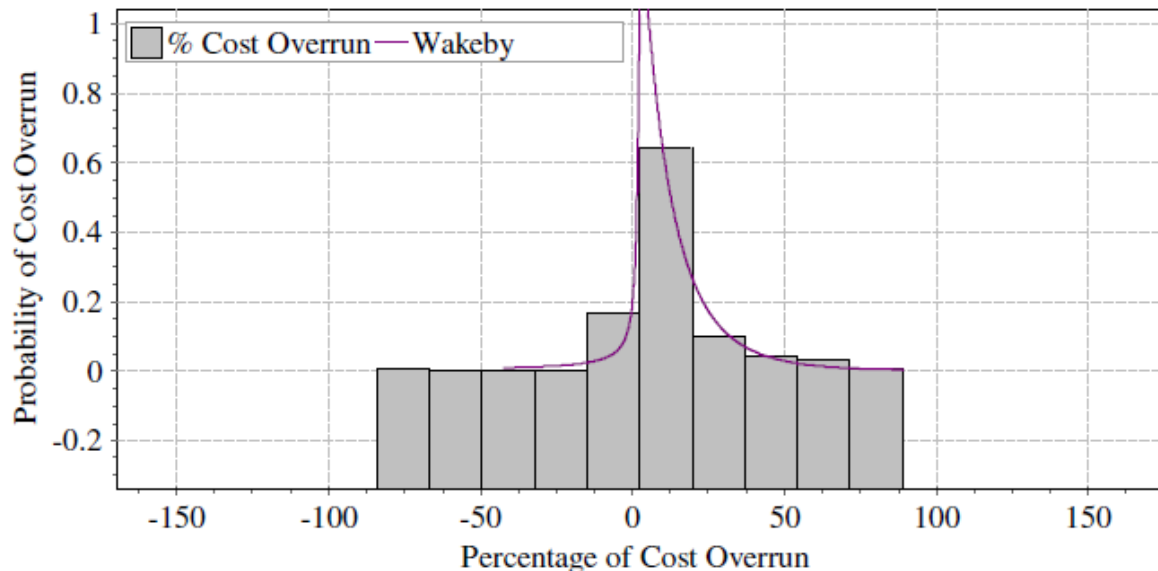


Figure 4-26: Probability of the percentage cost overrun for projects between A1\$ and \$10 million (R11M to R121M at R11/A\$)

Source: Love *et al.* (2013:327)

4.3.11 Lending and inflation rates

The historical prime lending rate data is provided in Figure 4-27 below. Note that there have been significant variations over the past 20 years. The fluctuations are dependent on macroeconomic forces. The modelling of such macroeconomic changes is beyond the scope of this study. A sensitivity analysis approach will instead be followed, where several lending rates will be used to show the effect of interest on the financial metrics.

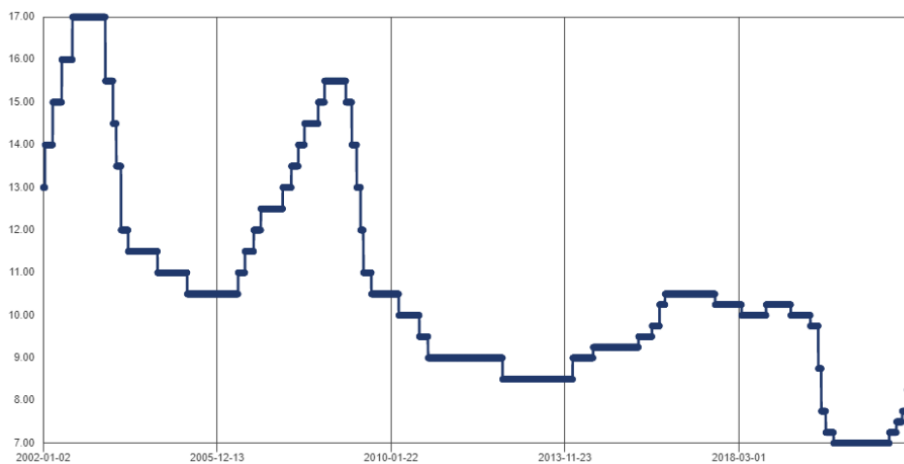


Figure 4-27: Historical interest rate data

Source: SARB (2022)

The inflation rate in South Africa will escalate certain costs, such as the O&M costs of the power plant. The inflation rate for the last 25 years is presented in Figure 4-28. As with the interest rate, simulating the inflation rate is beyond the scope of this study. The average inflation over the past ten years was approximately 5%. The nominal inflation rate will be assumed to be 5%.

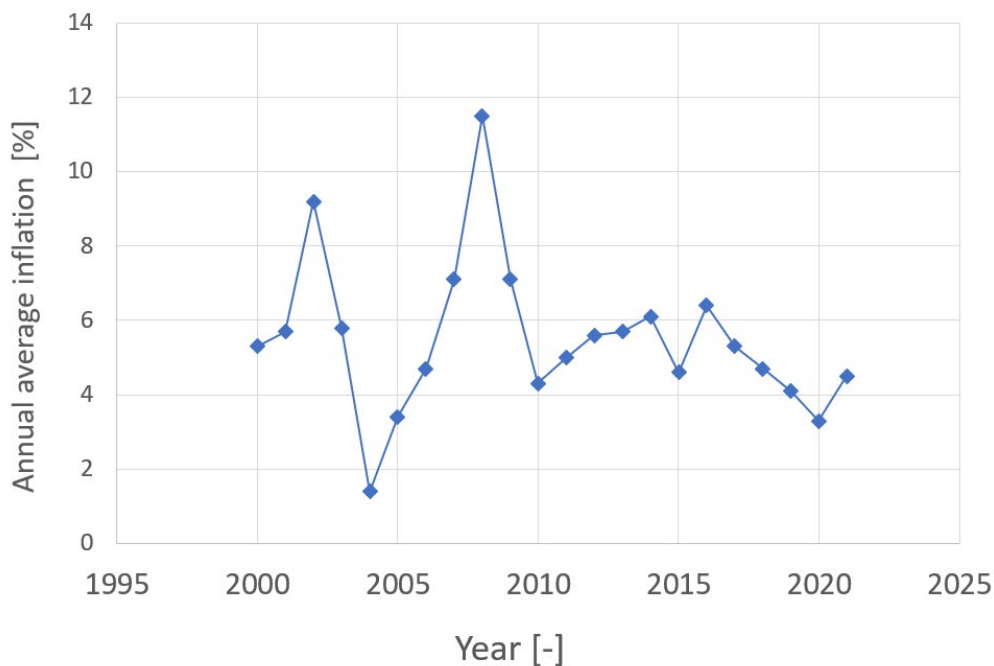


Figure 4-28: Inflation rate for the past 25 years

Source: Statistics South Africa (2022)

4.3.12 Eskom tariffs and tariff increase

Eskom tariffs for electricity were calculated from the official tariffs and charges booklet for the 2021/2022 year (Eskom, 2021). The electricity energy use charge was estimated based on the Nightsave Urban Large tariff structure (non-local authority basis). Costs associated with transmission and distribution were not included, but ancillary service and rural electrification subsidy charges were. The average cost for high- and low-demand seasons is around R1.46/kWh. Therefore, an initial price of R1.50/kWh will be used in the model.

The annual increase of tariffs since 2005 is compared in Figure 4-29. The fluctuations over a long period are significant. It is further difficult to model any future volatility. Over the last ten years, the average annual increase was approximately 9.3%. For the model, the influence of increase will be evaluated on a sensitivity basis. A base increase of 10% per year will be used.

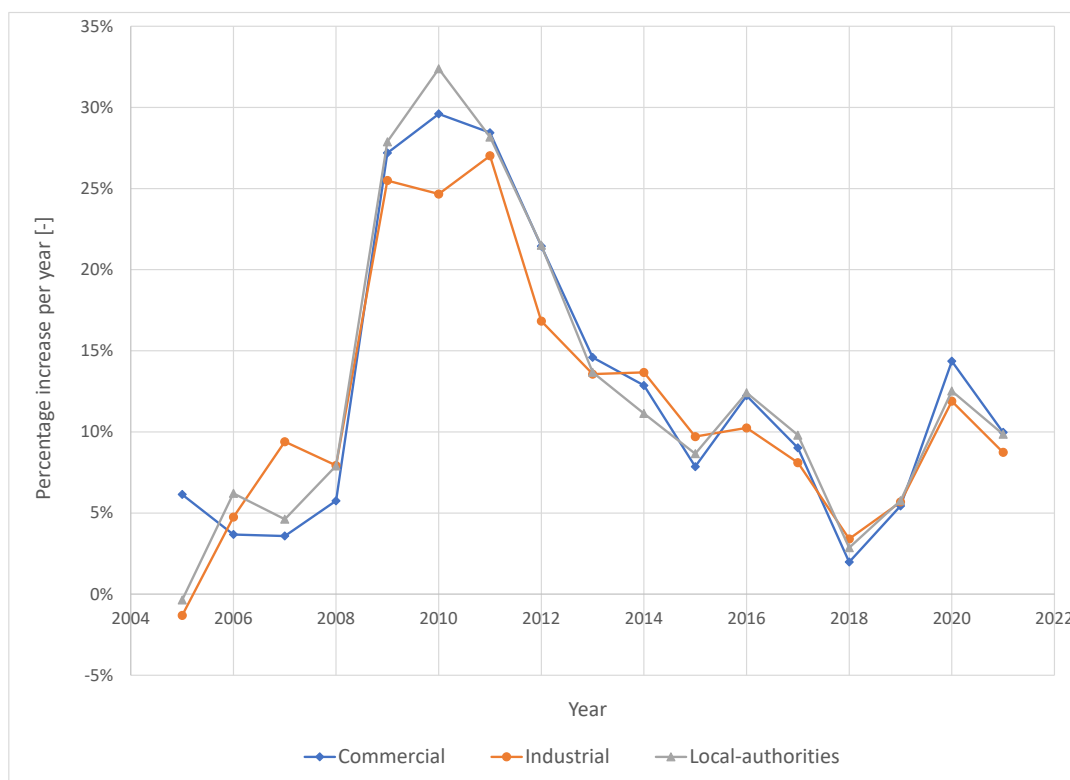


Figure 4-29: Annual increase in commercial and industrial tariffs

Source: Adapted from ESKOM (2021)

4.3.13 Exchange rate risk

Exchange rate risks are common to many businesses, and various hedging instruments are available to manage this risk. Instruments include over-the-counter (OTC) products such as currency forwards, cross-currency swaps, and exchange-traded products (Papaioounnou, 2006). Exchange-traded contracts include currency options and currency futures. A discussion of the various options and their respective advantages and disadvantages are not the focus of this study. Instead, it will be assumed that a suitable instrument will be used to transfer this risk.

4.4 Conclusion

Chapter 4 identified the risks related explicitly to embedded generation projects using husk. First, the risks were determined according to the classifications identified in the literature study. The risks were then grouped according to the method used to evaluate each risk. Finally, data collection and processing were discussed, together with the models developed to analyse the risks in the financial model.

In Chapter 5, the financial model will be discussed. First, the assumptions and nominal values will be highlighted. The model results will then be shown, providing the risk quantification part of the risk assessment.

Chapter 5

Financial model and results

5.1 Introduction

In the previous chapter, the specific risks relevant to the investment in power generation for a crushing plant were identified and discussed. The identification was made by considering the risk classifications specified in the literature review. The methods of incorporating each risk into the financial model through stochastic models or sensitivity analysis were also discussed and motivated. The data collection and processing for each risk factor were then discussed, and models were developed to implement each risk factor into the financial model.

In this chapter, the financial model and results will be discussed. The identified risks and developed models must be integrated into a financial model. The risk evaluation methods were divided into Monte Carlo simulations and sensitivity analysis. This chapter, therefore, provides the implementation framework that will be used to produce the results. The results are then discussed and summarised to provide insight into each risk.

The outline of the chapter is as follows: Section 5.2 provides the financial model description and the assumptions, section 5.3 discusses the analysis scenarios that will be used to evaluate the risks, section 5.4 presents the results for each of the scenarios, section 5.5 summarises the results and discusses which risk mitigation strategies could be used, and section 5.6 concludes the chapter and highlights the managerial implications.

5.2 Model description and assumptions

A financial model was built in Microsoft® Excel® for Microsoft 365 MSO (Version 2202 Build 16.0.1491.20704). The data table function was used to perform the Monte Carlo simulations. The random numbers for the various distribution functions were generated using Excel's built-in random number generator.

An overview of the financial model is provided in Figure 5-1, while the assumptions and inputs for the nominal model are provided in Table 5-1. The values presented will be used unless otherwise stated for the specific scenario analysis.

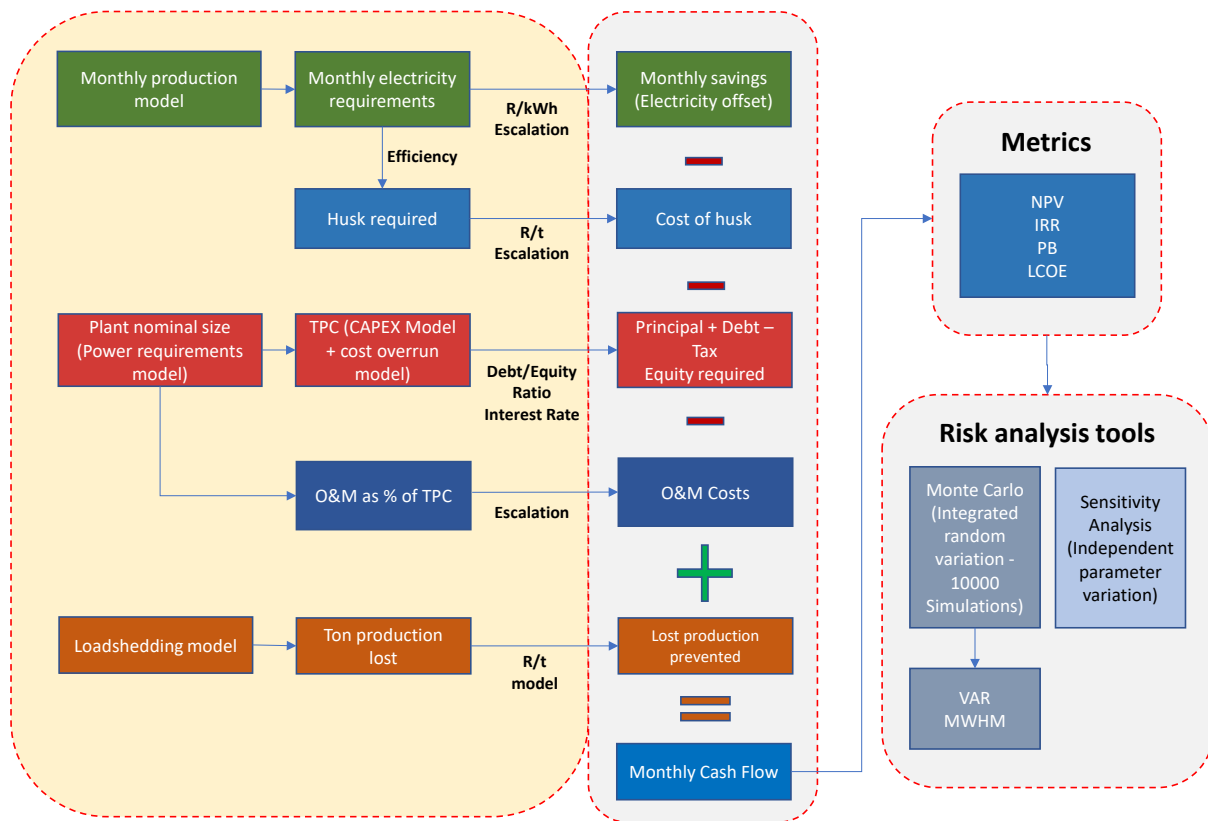


Figure 5-1: Overview of the financial model

A fundamental assumption in the model is that the input variables are uncorrelated. The operating and maintenance costs are assumed to be uncorrelated with the production demand. The biomass price is also considered to be independent of the production rates. In reality, there might be a correlation between these variables as over or undersupply in sunflower seed would directly influence the availability of excess biomass and the price. It is assumed that there is no correlation between sunflower oil and oilcake prices and the production levels (overall national production). In reality, the prices would be correlated through supply and demand. The sensitivity analysis assumes that each risk is independent but that the risks of production, loadshedding and cost overruns are all present.

It was assumed that the annual production level could be scaled down by a factor to represent the fluctuation in the production of an individual plant. It is further assumed that the interest on the debt is tax deductible.

A discount rate of 10% was used, which is in line with the lower-end IRR requirements for biomass projects in the demonstration stage of maturity (Kristinsdottir, 2012).

Table 5-1: Model nominal assumptions and inputs

Variable	Value
Financial inputs	
Debt rate	80%
Interest on debt	8%
Debt term	20%
Tax rate	28%
Depreciation	5 yrs straight line
Nominal discount rate	10%
Inflation rate (for escalation)	5%
Time period	1 month increments
Plant nominal inputs	
Husk energy content	16 MJ/kg
Production electrical consumption	93 kWe/ton
Conversion efficiency	See Figure 4-25 (p 87)
Power plant installed capacity	See Table 4-2 (p 72)
Husk yield as a fraction of total production	20%
Production losses	3%

Variable	Value
The capital cost of the plant	From Table 4-2 (p 72) & Figure 4-24 (p 86)
Oil fraction of output	46%
Oilcake fraction of output	54%
OPEX	3.9% of TPC/year
OPEX inflation	Inflation
Electricity cost assumptions	
Eskom electricity price	R1.5/kWh
Eskom electricity price escalation	10%/year

5.3 Analysis scenarios

The analysis scenarios are summarised in Table 5-2 below. The left-hand column provides the scenario grouping of the analyses, while the second column gives the number of each analysis as a reference. A nominal crushing plant capacity of 10500t/month was selected for the baseline scenario. In the first grouping, the influence of production rate, load-shedding and cost overruns are compared. Analysis number 1a gives the baseline scenario where all the factors are included. In analysis 1b, only the opportunity cost is included to show the effect of only accounting for load-shedding while assuming a constant production demand. In study 1c, the lost production due to load-shedding prevented through embedded generation and production demand uncertainties are included, but the cost overrun risk is not. The first group of analyses provides an overview of the influence of the factors with the most significant underlying uncertainty and possible fluctuation. The rest of the scenarios focus on the parameters that will influence the investment through a sensitivity analysis approach. Case 1d is provided to show the difference between investing in embedded generation when there is no future loadshedding versus the predicted levels of loadshedding.

In the second scenario, the baseline analysis (analysis 1a) is compared with crushing plant capacities with higher and lower production capacities. The purpose is to investigate how economies of scale influence risk.

Table 5-2: Analysis scenarios

Analysis scenario	Risk evaluated	Analysis number	Variable
1: Influence of production rate, opportunity cost and Cost overrun	Nominal production rate of 10500t/month		
	The risk associated with sunflower seed production uncertainty	1a	10500t/month nominal case
	The risk associated with uncertainty in Eskom's future load-shedding profile and the impact on production loss risk	1b	Only load-shedding prediction included
	The risk associated with a cost overrun of the total plant	1c	Only load-shedding and production demands included
	The scenario where no loadshedding occurs	1d	No loadshedding, and no cost overruns
2: Comparison between plant capacities	Nominal production rates per month		
	Risks associated with the crushing plant size	2a	6500 t/month
		2b	8000 t/month
		1a	10500 t/month
		2c	13000 t/month
		2d	15500 t/month
3: Crushing plant energy consumption	Production rate: 10500t/month.		
		3a	62 kWh.t

Analysis scenario	Risk evaluated	Analysis number	Variable
	The risk associated with the uncertainty in the electrical consumption of crushing plant	3b	70 kWh/t
		3c	77.5 kWh/t
		3d	85 kWh/t
		1a	93 kWh/t (Nominal)
		3e	102.3 kWh/t
		3f	108.5 kWh/t
		3g	121 kWh/t
4. Power plant capacity assumptions	Production rate: 10500t/month.		
	The risk associated with selecting non-optimal power plant capacity	4a	1610kWe (15% below nominal)
		1a	1850kWe
		4b	2130kWe (15% above nominal)
5: Fuel value assumption	Production rate: 10500t/month.		
	The risk associated with the uncertainty in the biomass value and use	5a	R500 / ton
		1a	R650 / ton
		5b	R800 / ton
6. Debt rate	Production rate: 10500t/month.		
	The risk associated with interest rate uncertainty during the feasibility stage	6a	8%
		1a	10%
		6b	12%
7. Eskom escalation	Production rate: 10500t/month.		
		7a	8%

Analysis scenario	Risk evaluated	Analysis number	Variable
	The risk associated with the estimate in Eskom electricity price increase	1a	10%
		7b	12%
8. Operating and maintenance costs	Production rate: 10500t/month.		
	The risk associated with the uncertainty in O&M costs during the feasibility stage	8a	3%
		1a	3.9%
		8b	4.8%

In the third scenario, the risk associated with the uncertainty in the assumption of the crushing plant energy consumption is evaluated. The evaluation is done through a sensitivity analysis. A more energy-intensive process will provide a better opportunity for electricity savings, resulting in a better investment opportunity. On the other hand, if the crushing process is very efficient, the benefit of offsetting the electricity bought from the grid might not be worthwhile. Scenario four focuses on the influence of the power plant capacity assumptions. It is presented with the third scenario. The assumption influences the total power generation and TPC in both groupings. A low, nominal, and high value is assumed for the plant capacity. The high value corresponds to a plant capacity that will satisfy the lower 90% of the monthly output in Figure 4-11 (p 71). The low power plant capacity meets the lower 60% of the monthly production in Figure 4-11. It is assumed that production above these values is avoided by smoothing the higher output over time by storing the seeds. Storage could lower the peak demand for electricity and the generation capacity required. However, the total annual electrical energy demand is still satisfied (i.e. it is assumed that the total electricity demand is met through embedded generation).

In scenario five, the impact of the fuel cost is evaluated. High and low values for the husk are assumed. The values are arbitrarily chosen so that the trend can be assessed. In scenario six, the impact of the debt rate is evaluated. The high and low

values are once again arbitrarily chosen so that the trend can be assessed. Scenario seven looks at the impact of various Eskom price increases. It is assumed that the percentage price increase applies every year over the plant's lifetime. Finally, scenario eight investigates the impact of the operating and maintenance costs assumptions.

A test was done to evaluate whether the number of simulations in the Monte-Carlo analysis was sufficient to provide a smooth distribution function. Performing MC simulations in Excel is time-consuming, and a trade-off between time and accuracy is required. Figure 5-2 below compares the distribution of NPV values between 1000 and 10000 simulations. The two simulations showed differences between the most likely value and the frequency of the most likely value. Therefore, 10000 simulations were performed in all the MCS analyses. The number of simulations aligns with the approach followed by Arnold and Yildiz (2015:236).

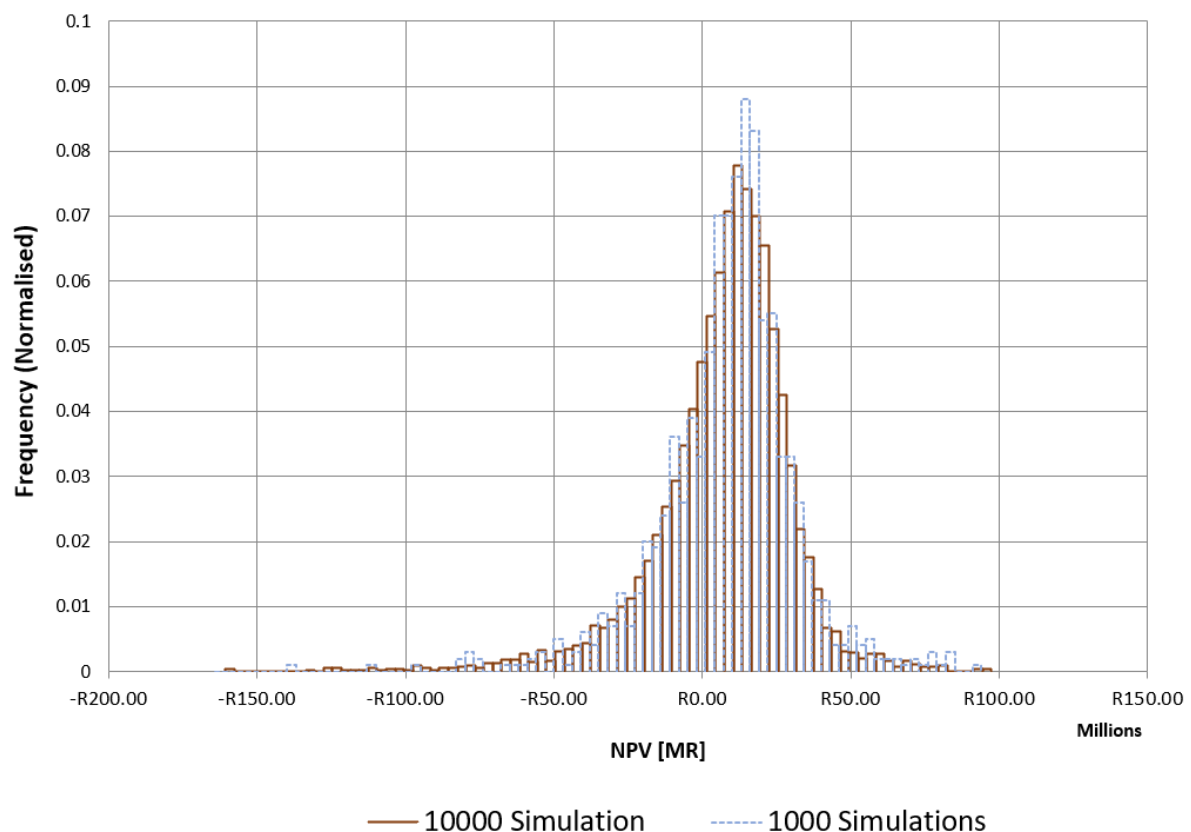


Figure 5-2: Comparison between the results obtained from 1000 and 10000 simulations

5.4 Results

5.4.1 Introduction to the interpretation of the results

The results need interpretation to evaluate the impact, likelihood, and mitigation options. Each risk's impact, likelihood and mitigation options will be ranked low, medium, or high. This will enable a final ranking of the risks to highlight where attention is required.

When interpreting the results, it is crucial to keep the scope of the study in mind, i.e., that the analysis is performed from the perspective of an investor or company who would consider embedded generation in this specific industrial context before any engineering or other specialist studies. The purpose of the results is to inform the decision-makers on the key things they need to consider to minimize or control the risks. Risks that need to be accepted should also be highlighted.

The results are summarised at the end of this section in Table 5-6, together with the underlying drivers. Some of these factors are unique to the investment under consideration, while others correspond to risks identified in the literature study (such as political risks). The calculated VaR is used to consider the impact of the risk. A high-impact risk significantly increases the VaR. The FWHM is also used to assess the impact. If the risk factor increases the FWHM, then the risk is increased. Where sensitivity analysis is used, the sensitivity of the VaR to the change in a factor is used instead of the VaR self.

Additionally, the uncertainty in the evaluated factor also influences the risk impact. If the VaR associated with the factor is sensitive to a change in the factor, and there is high uncertainty in the factor, then the risk can also be considered high. Arguments will be made based on the sensitivity and uncertainty to designate the impact of the risk as low, medium, or high. The designations are provided in Table 5-3 below for the evaluation methods.

Table 5-3: Risk impact assessment from the results

Risk impact evaluation methods	Low impact	Medium impact	High impact
VaR	↓	→	↑
FWHM	Narrow	Moderate width	Wide
$\frac{\Delta VaR}{\Delta Factor} \times u(factor)$	↓ × ↓ → × ↓ ↓ × →	→ × → ↑ × ↓ ↓ × ↑	↑ × ↑ → × ↑ ↑ × →

The risk likelihood is also argued from the results. Risks inherent to the project are assigned a high probability of occurrence, such as load-shedding. However, risk mitigation strategies could lower the likelihood of risks, and this will be indicated. Unless otherwise specified, the VaR is for a 95% probability (5% probability of occurring).

Table 5-4: Basis on which risk likelihood, impact and mitigation are evaluated

	Risk likelihood	Risk impact	Risk mitigation
Low	Risk will not likely happen Risk can be avoided entirely	Small VaR compared to the other risks A small change in VaR due to a change in factor in the sensitivity analysis	Risk can be completely mitigated

	Risk likelihood	Risk impact	Risk mitigation
Medium	Risk is likely to happen, but mitigation to avoid/control/transfer it is possible	Medium VaR compared to the other risks. VaR is moderately sensitive to changes in the factor in the sensitivity analysis	Risk can be mitigated, but not completely
High	Risk is inherent or can't be avoided or controlled. Risk must be accepted	Large VaR compared to the other risks. VaR highly sensitive to changes in the factor in the sensitivity analysis	Risk can't be mitigated at all

5.4.2 Scenario 1: Analyses 1a to 1c

The results from analyses 1a to 1c provide insight into the significant underlying uncertainties that will influence the overall risk. The distribution results for the NPV simulations from calculations 1b and 1c are first compared. Analysis 1b simulates the scenario when only the lost production due to load-shedding is prevented through the implementation of embedded generation. Analysis 1c includes both the influence of load-shedding and the production demand fluctuation. The results for analyses 1a to 1c are compared in Table 5-5. The metrics presented are the net present value of the initial investment and future cashflows (NPV), the internal rate of return (IRR), the levelised cost of electricity (LCOE), and the payback period (PB). The median (top value) and most likely value (bottom value) are provided in each case. In scenario 1a, which includes all the uncertainties, the results indicate a significant difference between the median and the most likely value. This difference is attributed to the

skewness of the results. The most notable difference is observed in the NPV. The most probable value will be reported for the rest of the results.

The results also provide the VaR for two confidence levels, namely 95% and 90%. A negative value (in brackets) indicates a loss at the confidence level, while N/A suggests that a loss will not be made at the confidence level. The column furthest to the right is the confidence level at the position where the VaR is zero. This value indicates the confidence level that no loss will be incurred.

Table 5-5: Results for analyses 1a to 1c

#	Crushing plant capacity	CAPEX (Median)	NPV	IRR	LCOE	PB	VaR 95%	VaR 90%	% @ 0 VaR
1a	10500	R176 719 390	R18 945 638	12.1%	R2.63	154	(R24 990 066)	(R10 510 225)	82.4%
			R28 089 165	12.3%	R2.62	152			
1b	10500	R156 467 470	R33 020 003	13.9%	R2.52	143	N/A	N/A	100%
			R32 460 756	13.9%	R2.53	140			
1c	10500	R156 467 470	R32 540 954	13.8%	R2.52	142	N/A	N/A	100%
			R33 156 403	14.0 %	R2.50	139			
1d	10500	R156 467 470	(R8 175 757)	8.94%	R2.93	178	(R24 655 746)	(20 155 746)	81%
			(R9 053 580)	8.93%	R2.91	175			

The results in Figure 5-3 below indicate that the most probable NPV values of analyses 1b and 1c are very close. One can expect this since the average production demand for both cases is the same. The influence of load-shedding alone results in a narrow spread around the most likely NPV. Adding the demand fluctuation due to the uncertainty in the monthly production rates results in a significantly larger spread. A normal distribution well approximates both curves. The median NPV and most likely NPV values are, therefore, more or less the same.

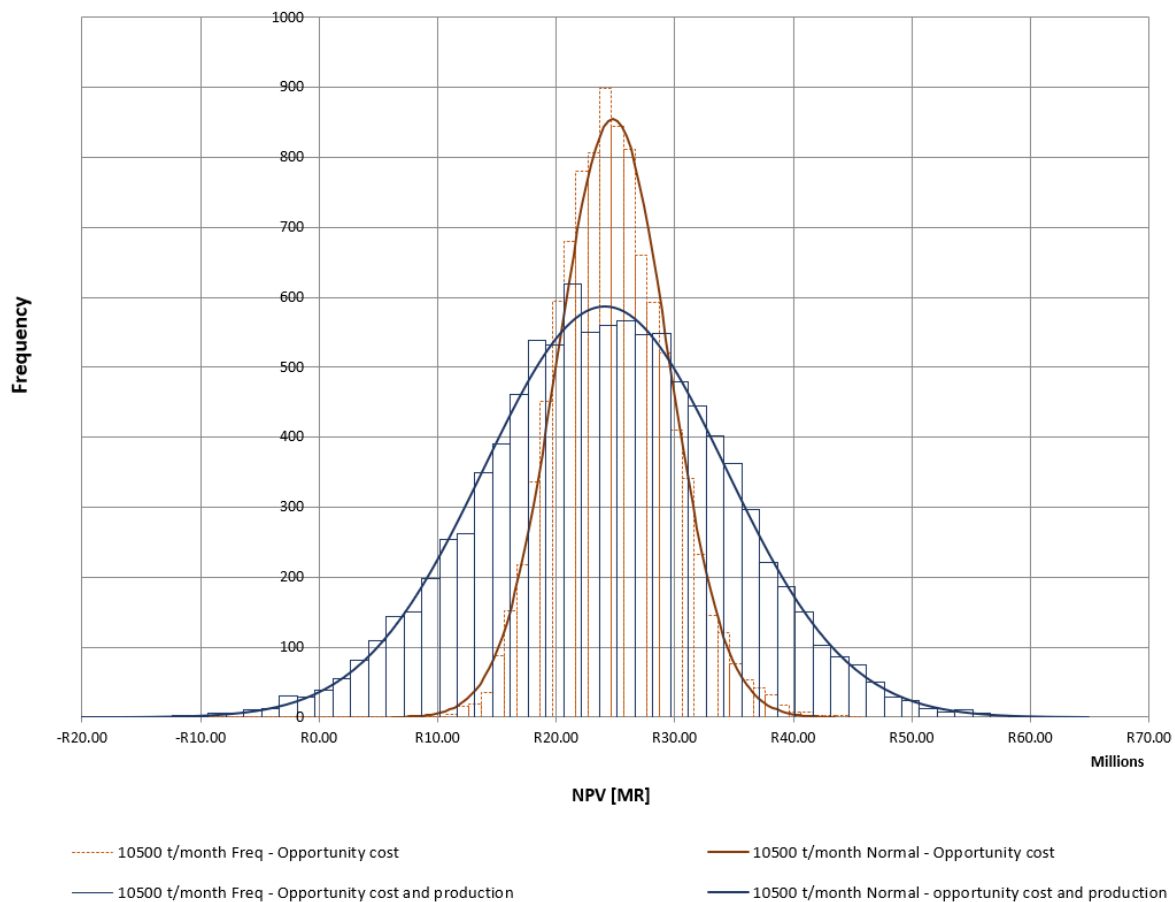


Figure 5-3: Comparison between the NPV for analyses 1b and 1c

Figure 5-4 below compares the estimated NPVs between analyses 1a and 1c. Analysis 1a includes all the factors, namely the demand variation, the load-shedding and the cost overrun uncertainty. Analysis 1c only consists of the demand variation and influence of load-shedding. Comparing the two cases highlights the impact of accounting for possible cost overruns. It will be noted that the inclusion of potential cost overruns results in a skewed distribution, with a long tail to the lower NPV values. Since the distribution is not symmetric, the median NPV and most likely NPV differs. The most likely NPV shifts from R33M (in analysis 1c) to R28M (in analysis 1a). The shift is due to the cost overrun model predicting a most likely cost overrun of 8.1% of the TPC (see section 4.3.10). Applying the cost overruns model will shift the most likely NPV to a lower value. Even more significant than this shift is the change in the VaR.

Because of the long tails in the NPV distribution, the VaR significantly increases when considering the possibility of cost overruns.

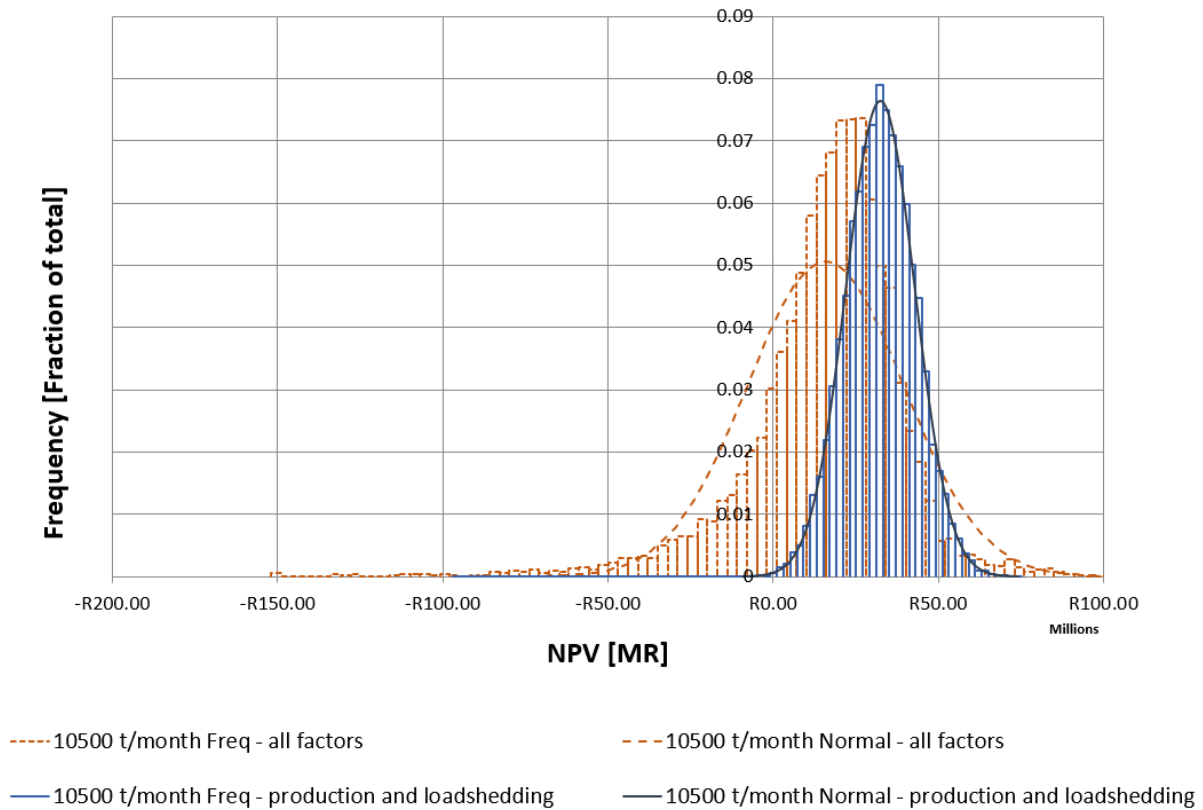


Figure 5-4: Comparison between estimated returns for analyses 3 and 8

Figure 5-5 below provides an example of the cash position throughout the plant's life. The results are for 15 simulations compared to the nominal value, showing significant variations in the breakeven time and final NPV. The possibility exists that a project can become cash-positive and again cash-negative due to unforeseen circumstances (such as deficient production for a couple of years).

Comparing the results of case 1c and case 1d reveals that the predicted future load-shedding benefits the investment. If there had been no load-shedding, the investment might not have been worthwhile. But, with the expected load-shedding taken into account, there is an R40M increase in the NPV of the investment. This highlights the decision for embedded generation due to loadshedding. It must, however, be noted that the FWHM of the distribution of NPV values when only considering load-shedding

(case 1b) is approximately R10.5M. Therefore, there is still considerable uncertainty about the precise impact of load-shedding.

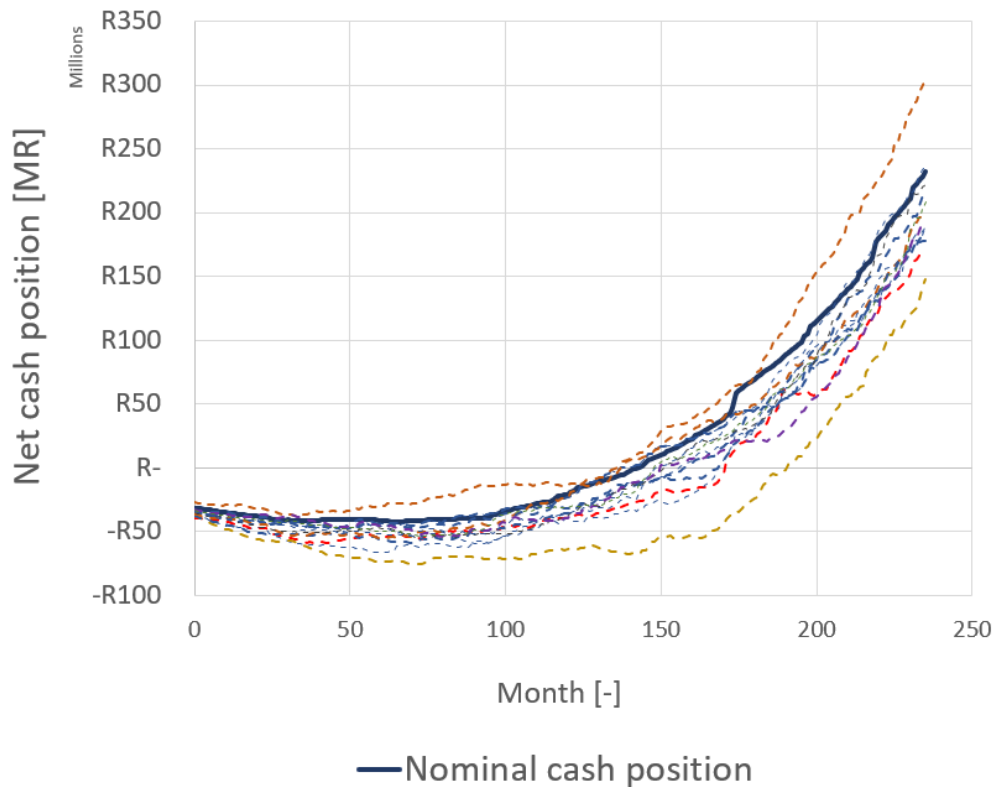


Figure 5-5: Examples of cash flows

Key findings for Scenario 1

The key findings are the following:

- The uncertainty in the fluctuations in future load-shedding events results in uncertainty in the NPV of the investment. The uncertainty is an inherent risk. Implementing embedded generation helps address the production loss of the crushing plant, but the uncertainty in how much the saving would be is innate and cannot be mitigated. The risk impact can be considered medium since the FWHM for this factor is less than the FWHM due to the production variation. Load-shedding is one of the drivers for embedded generation, and the trend does not predict a decrease in the number and duration of events. However, the results

demonstrate that there is a medium level of uncertainty in how much will be saved by off-setting load-shedding.

- The uncertainty in the production fluctuations results in an inherent uncertainty in the profitability of the investment. Both the VaR and FWHM increase due to this uncertainty. Very little can be done to mitigate this risk since the factors are almost exclusively external. The risk associated with this uncertainty can be considered medium. Nevertheless, it is a real risk and should be considered.
- The uncertainty in the TPC due to cost overrun significantly impacts the uncertainty of the investment and poses a severe risk. The VaR increases considerably due to this risk. This risk can, however, be mitigated. Mitigation can be achieved through careful planning, selecting less risky technology, using suppliers with a good track record, and following a systems engineering approach to managing the risk at each stage of development (Frisari *et al.*, 2013; Gatzert & Kosub, 2016). This risk is highly likely because the distribution curve is highly skewed towards a cost increase compared to the planned cost (see Figure 4-26).
- The impact of load-shedding results in embedded generation being much more feasible and serves as a driver to become more independent from Eskom. However, there is still considerable uncertainty about the exact financial benefit of embedded generation.

5.4.3 Analyses 2a to 2d

The results of analysis scenario 2 highlight the impact of plant capacity on the risk and feasibility of implementing embedded generation. The results are shown in a series of graphs. The first set presents and discusses the variation of the metrics as a function of the plant capacity. The second set of graphs shows the distribution of the results for the smallest and largest capacity plants to elucidate the details of the distribution.

Figure 5-6 below presents the NPV as a function of the crushing plant capacity. The FWHM is indicated as bars on the NPV graph, showing the spread's size in the distribution. The NPV increases as the plant capacity increases. The VaR decreases as the plant capacity increases (i.e. the value becomes more positive). The probability value for zero VaR further highlights this. The probability of incurring a loss decreases as the plant capacity increases.

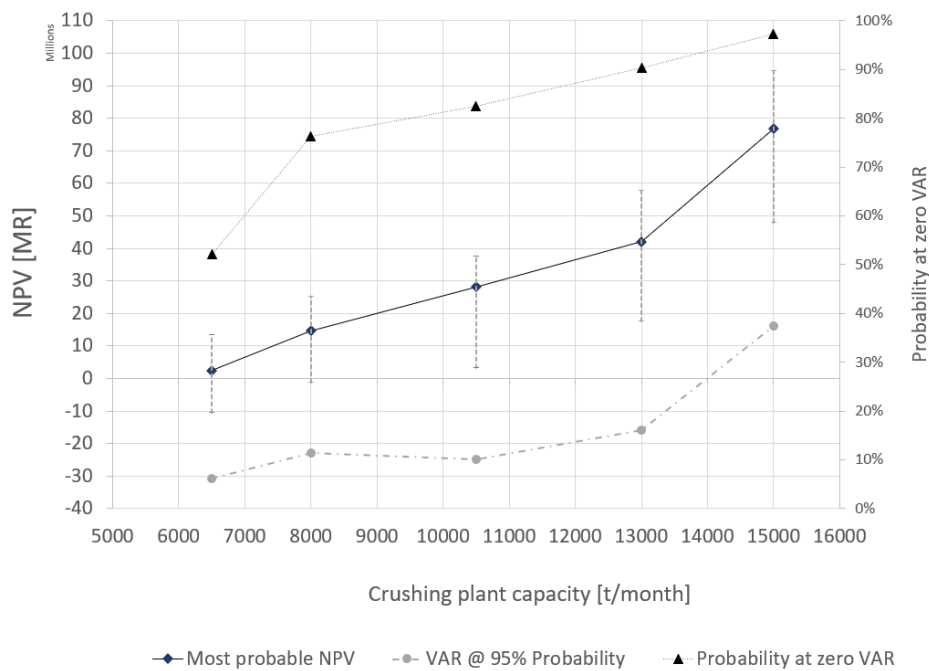


Figure 5-6: Most likely NPV as a function of crushing plant capacity, with FWHM and VaR

In Figure 5-7, the IRR increases with increasing plant size while the LCOE and payback period decreases. This result is due to the economies of scale since the specific capital costs decrease with an increase in size, as shown in Figure 4-23 (p 85).

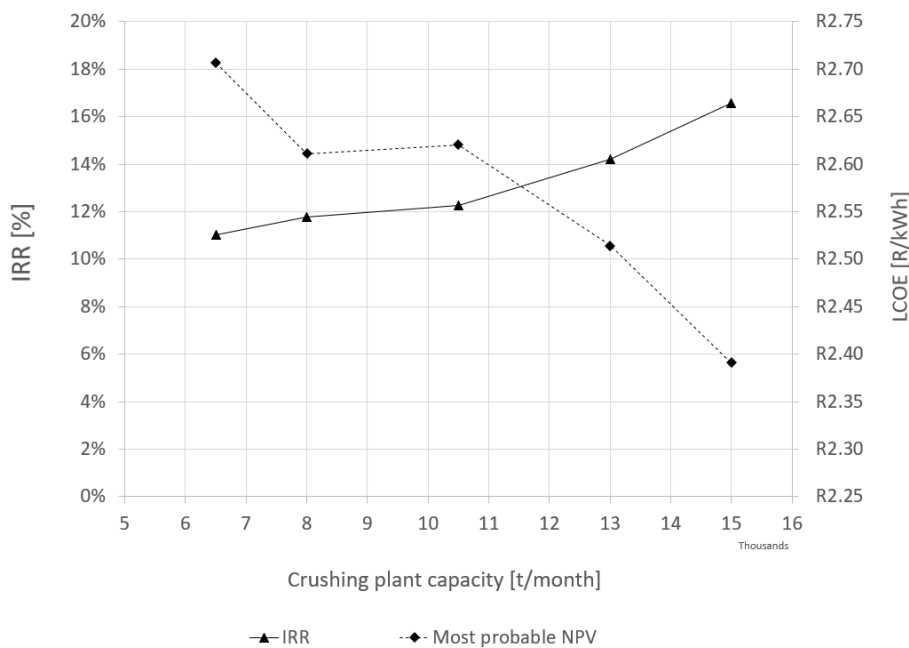


Figure 5-7: IRR and LCOE as a function of crushing plant capacity

The results provide further insight into the risks associated with the investment. For example, for a crushing plant size of 13000t/month, the most likely NPV is around R30M. An analysis performed based on the assumption of average values for all factors (i.e. power demand, Eskom load-shedding, and zero cost overrun risk), the investment decision would be based on the NPV value of R30M and an expected IRR of 12%. Sensitivity analysis would be able to provide best- and worst-case results but would not demonstrate the risk. The risk is estimated using the MCS, showing an 18% likelihood of making a loss. The NPV might be sufficient for investors, but possibly not the risk.

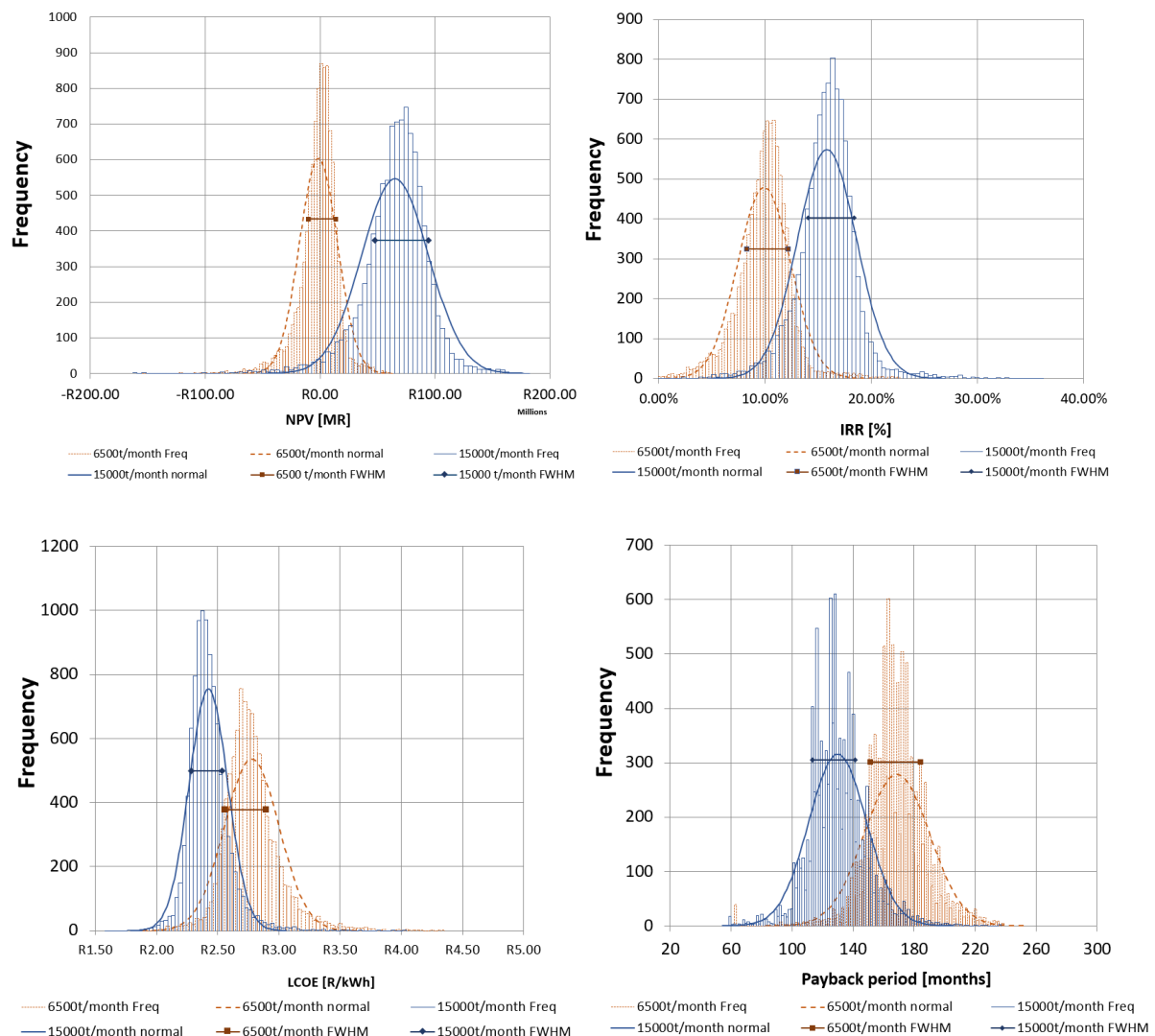


Figure 5-8: NPV, IRR, LCOE and PB of the smallest and largest crushing plants (Analyses 2a and 2d)

Figure 5-8 above presents the distributions in the metrics for the smallest and largest crushing plants (6500t/month and 15000t/month). Note that the NPV for the smaller crushing plant is more narrowly distributed than for the larger one. This is because the FWMH results assume that the production output can be scaled from the total national production. Therefore, the production variation distribution in a large crushing plant would be more prominent in absolute terms than for a smaller crushing plant. The cost overrun risk is also scaled to the total investment cost; therefore, the distribution in outcomes will similarly be more significant in absolute terms for the large crushing plant.

Key findings for Scenario 2

Figure 5-6 and Figure 5-7 suggest that the relationships between plant capacity and the results are not linear. The results highlight the complex impact of the underlying assumptions on the results. The primary finding from this analysis is the following:

- The plant capacity has a significant impact on the expected NPV of the project as well as the risk.
- Larger crushing plants have a lower risk due to the economies of scale and higher efficiency.
- Smaller plants run a higher risk of not being profitable and present a higher risk of investment.

5.4.4 Scenarios 3 and 4

Scenario 3 tests the influence of the assumption of the crushing plant's electrical requirements by changing the electrical power requirements per ton of crushed sunflower seed. Scenario 4 evaluates how selecting a suitable power plant size to match the demand influences the risk. The production of seeds fluctuates significantly. If a crushing plant has storage facilities, these fluctuations can be smoothed out so that the crushing plant runs close to full production most of the time. However, storage facilities do not protect the crushing plant from the seasonal low points where there is possibly no sunflower seed available in the market. Therefore, the power demand will also fluctuate. Following the arguments in 4.3.3, an assumption for the power plant capacity must be made since the historical production demand of a plant is not

available. A sensitivity analysis is performed where the power plant satisfies the peak monthly production demand 60% (analysis 4a), 80% (analysis 1a) and 90% (analysis 4b) of the time. Essentially, these assumptions imply that storage facilities at the crushing plant have to smooth out production. A 100% value would mean that the plant is sized to handle the maximum fluctuations that could occur if there was no seed storage. The power plant sizes for each analysis are provided in Table 5-2 below.

Figure 5-9 shows the variation in NPV as a function of the specific electricity consumption. It is based on a crushing plant capacity of 10500t/month. The more power intensive the crushing plant, the more profitable it will be to invest in power generation. The risk also decreases as the specific electricity consumption increase.

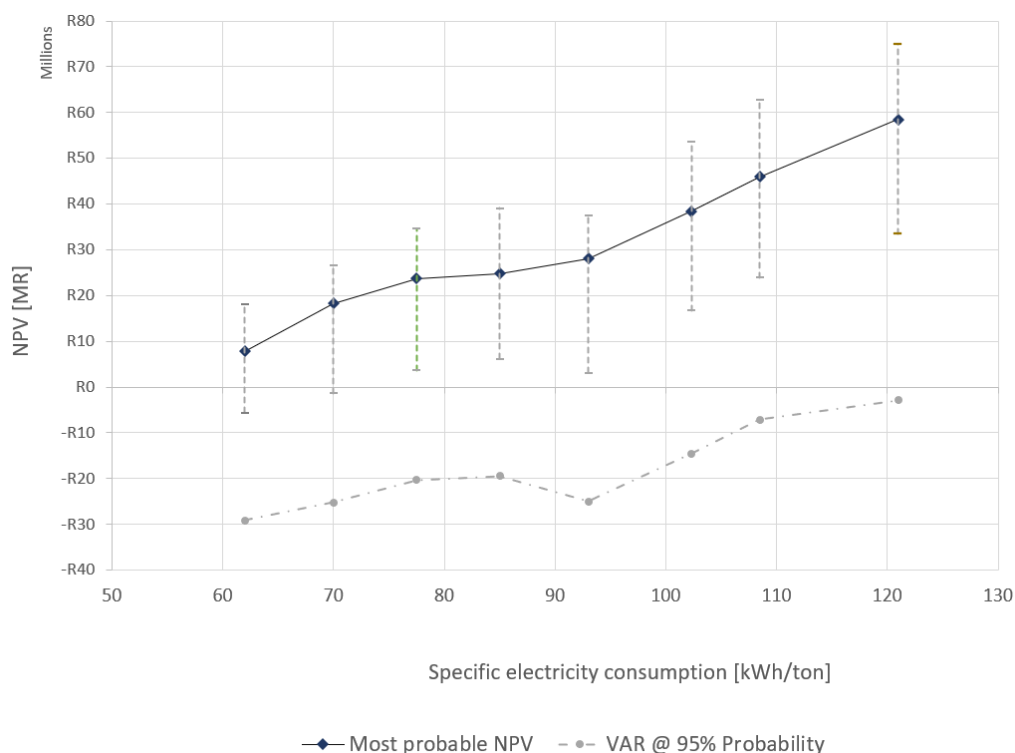


Figure 5-9: NPV and VaR for various specific energy consumptions at the nominal crushing capacity

Figure 5-10 below compares the NPV and VaR for analyses 4a, 1a, and 4b. The selected power plant capacity significantly impacts the NPV and is directly linked to

the extent to which production can be distributed over time through storage. The VaR is also considerably decreased if the output can be distributed, enabling the use of a smaller power plant. The results indicate that careful planning is necessary to optimise the plant size and minimize the risk.

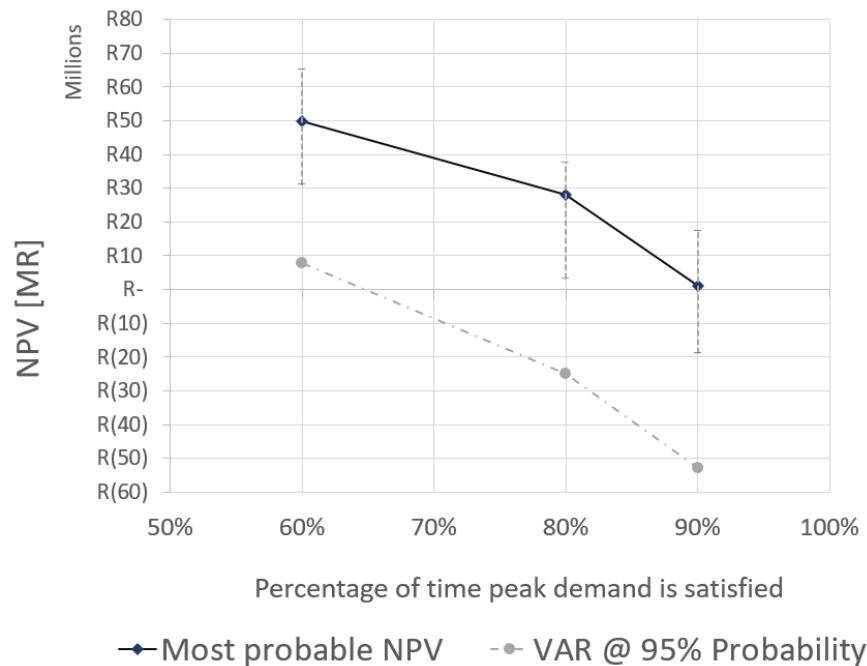


Figure 5-10: NPV and VaR for various power plant capacities at the nominal crushing capacity

Key findings from Scenarios 3 and 4

The key findings from the two scenarios are the following:

- Crushing plants with lower energy efficiency (in terms of electricity) provide an opportunity for greater returns using embedded generation. It is, however, advisable to optimise electricity consumption since it would decrease the required investment.
- The sensitivity of VaR for errors in specific energy consumption is moderate (i.e. the slope is relatively flat). Therefore, uncertainty in the specific energy consumption poses a moderate impact and is classified as medium risk. However,

the risk can be mitigated by performing a proper energy audit, reducing the probability to low.

- The power plant sizing has a significant influence on the risk. Oversizing the plant with 200-300kW can significantly increase the VaR and lower the NPV. The importance of distributing the production of the crushing plant through storage is emphasised. The impact of the risk is considered high, but it can be mitigated through careful planning. Without proper analysis, the probability of this occurring in the feasibility phase is high – it is only through detailed studies that the risk can be quantified.

5.4.5 Scenario 5

Scenario five investigates the impact of biomass price variations. The results of the sensitivity study are provided in Figure 5-11. The results show that the NPV and risk are highly sensitive towards changes in biomass price. Since the crushing plant produces its own biomass for power generation, this cost is hidden and can easily be considered irrelevant. However, the loss of income from the sale of biomass can be considerable.

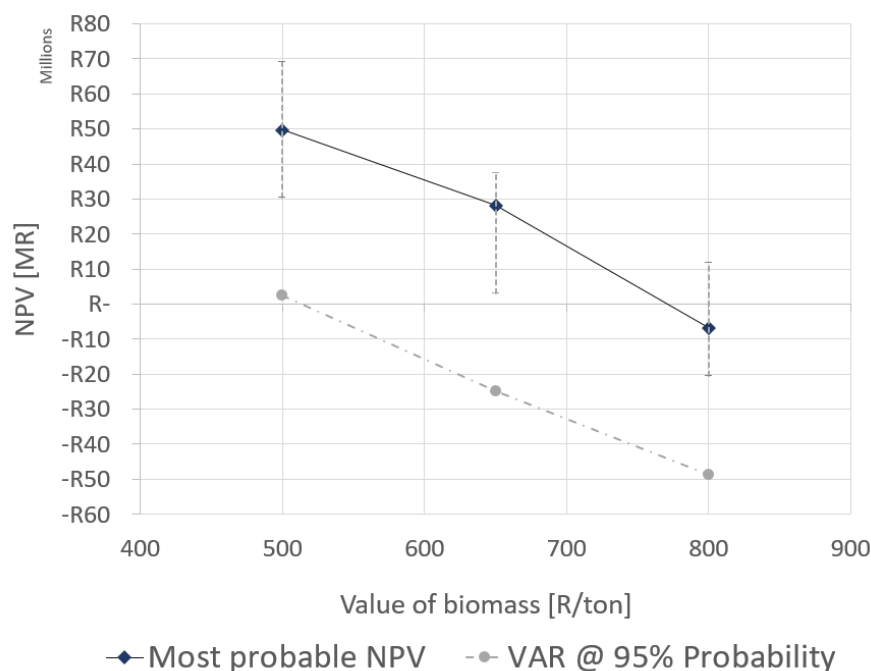


Figure 5-11: Sensitivity of the NPV and VaR to changes in the biomass price

Biomass as an energy source has increasing value as other energy source increase in price, such as coal. Husks can be burned in a boiler and traded as commodities. It is also sold as bedding for hatcheries. If the biomass has considerable value, it might be worthwhile investing in other RE technologies for power generation and selling the biomass or even considering a mixture of electricity sources that optimise the use of the biomass.

The actual value of the husks depends on the specific crushing plant, its proximity to industries, and possible offtakes for the husks. Although the impact of the price is high, a crushing plant should have historical financial data on the sales of biomass. Financial information is generally readily available, and no specialist studies are required to determine the value of the husk for the specific crushing plant. The probability of the risk can therefore be minimized.

Key findings from scenario 5

The key findings are that the uncertainty in the husk price fluctuation significantly impacts the investment risk. However, the risk can be minimised using historical financial data to determine the actual value.

5.4.6 Scenario 6

Scenario six evaluates the impact of interest rate changes. The results of the sensitivity analysis are presented in Figure 5-12 below. The results indicate a slight change in the NPV as the interest rate increases, but the VaR change is more significant. An uncertainty in interest rate fluctuations, therefore, poses a real risk. Fluctuations in the interest rate are due to external factors. A difference between the interest rate used during the feasibility study and the final interest rate on the debt will result in a change in the risk profile.

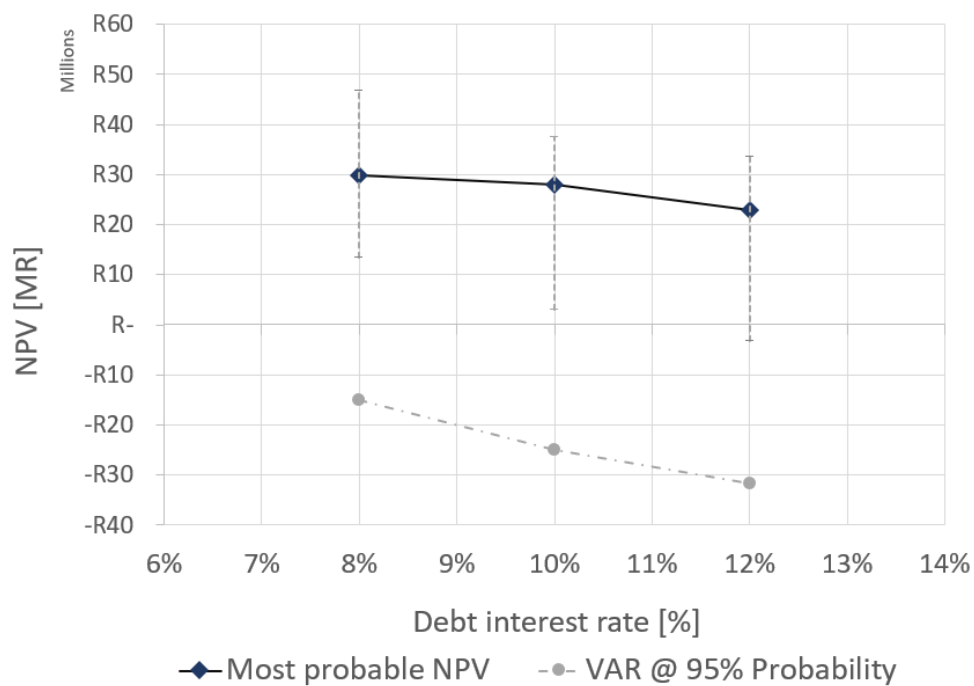


Figure 5-12: Impact of interest rate on NPV and VaR

Key findings for scenario 6

The critical finding for scenario 6 is the following:

- The debt interest rate has a minimal impact on the NPV. However, the VaR is more significantly influenced, which poses a medium risk level to the investor.

5.4.7 Scenario 7

Scenario seven evaluates the impact of the escalation in Eskom's electricity price. The results are presented in Figure 5-13 below and indicate that the investment return and VaR are highly sensitive to the expected increase in Eskom electricity price. The uncertainty associated with this factor, therefore, has a significant impact. An investor can only look at the historic price escalation and consider the current state of affairs to evaluate the possible future escalation. Furthermore, a fixed annual escalation over the plant's lifetime is assumed. Therefore, a long-term escalation prediction is impossible, adding to the uncertainty.

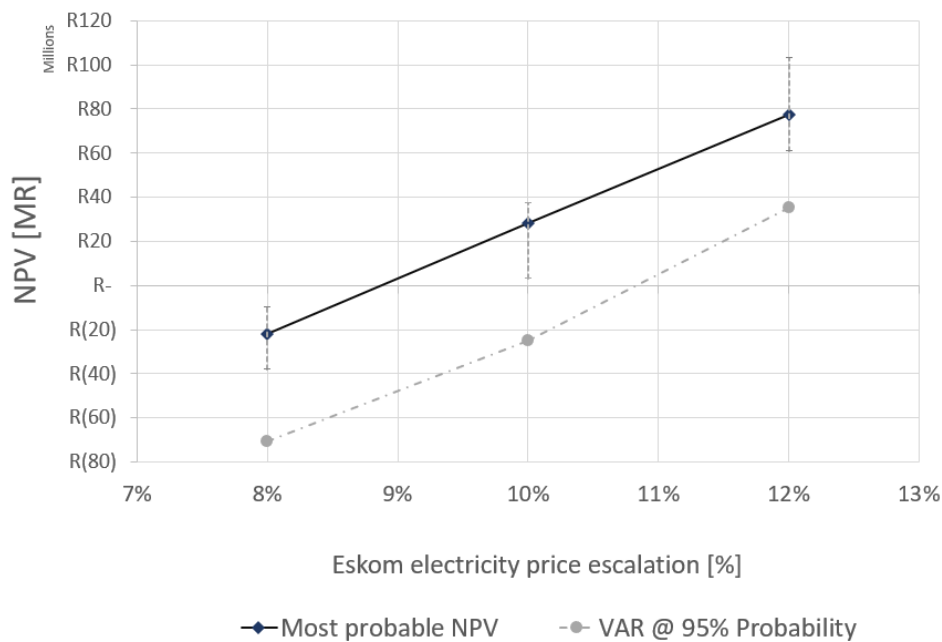


Figure 5-13: Impact of Eskom electricity price on NPV and VaR

Key findings from scenario 7

The key findings are the following:

- The electricity price escalation assumption significantly impacts the profitability and investment risk. The impact of the risk associated with this uncertainty is, therefore, high. Under certain assumptions, the investment looks very profitable and the risk low. However, the results indicate that an error in the assumption will have a significant impact. There is furthermore very little that can be done to mitigate this risk.

5.4.8 Scenario 8

Scenario 8 investigates the impact of the O&M costs with the results presented in Figure 5-14 below. The O&M cost is expressed as a percentage of the TPC. (For this calculation, the TPC is the cost without taking any cost overruns into account). For the range presented in Figure 5-14, the O&M costs vary between R4.6M/year and R7.5M/year (from minimum to maximum). The NPV, as well as the VaR, is highly sensitive to changes in the O&M costs. A significant difference between the actual and

budgeted costs will significantly change the risk. Uncertainty in the O&M costs, therefore, poses a high risk.

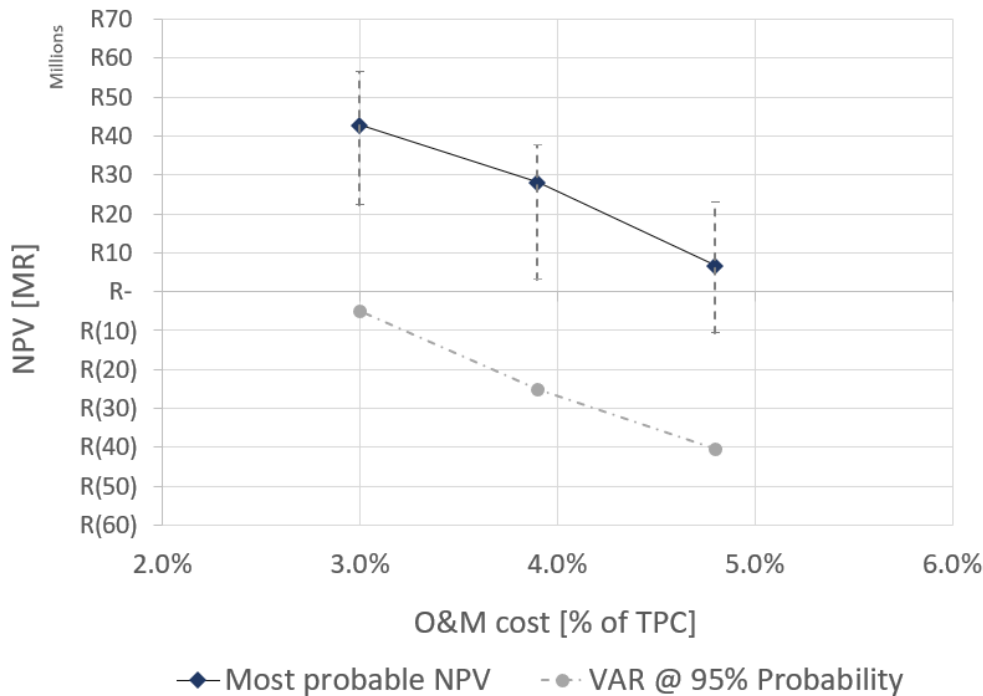


Figure 5-14: Impact of O&M costs on the NPV and VaR

A difference between the expected and actual O&M costs can result from various reasons. First, technology plays an important role. Due to the proven track record, the maintenance costs for standard technology can be much better predicted. The quality of the equipment will also be a factor. Buying from a reputable supplier will ensure fewer defects and the replacement of components.

Furthermore, correct installation and commissioning are also necessary. A properly commissioned plant will ensure optimal operation from the beginning, resulting in less downtime and breakages. Contractual agreements between the OEM and plant owner are also critical. Finally, the management of a power plant will play a crucial role. A lack of planned maintenance will result in more unplanned downtime in the long run.

It must be emphasised that production loss due to maintenance downtime is not modelled. Unplanned downtime could have a significant impact on the NPV and VaR.

It is also important to note that O&M costs are assumed to be independent of production. This assumption is not entirely accurate since higher production will result in more ash as waste, more chemical use, and higher water consumption. All this will influence the running cost of the power plant. The scenarios presented are a lumped approach where various factors are combined, and the sensitivity to errors in the O&M costs is evaluated.

Key findings from scenario 8

The key findings from this scenario are the following:

- The NPV and VaR are sensitive to changes in the O&M costs. The risk associated with underestimating the O&M costs can be considered high.
- Without careful planning, the O&M can be under or overestimated. However, it is a risk that can be mitigated in several ways.

5.5 Results summary

The results are summarised in Table 5-6 (p 122). The purpose of the summary is to provide an overview of the risks to inform decision-making and highlight risk mitigation strategies.

The risks are also summarised as a risk map in Figure 5-15 below. This map indicates the risk likelihood and the risk impact combination. The size of the bubble represents the level of mitigation possible. Bubbles that are full colour are risks that need to be accepted. Diagonally hashed Bubbles are risks that can be mitigated through engineering studies in the feasibility and EPC phases and contracts. Horizontally hashed bubbles are those that can be mitigated through financial planning. Bubbles in the red areas present the risks that must be most carefully considered.

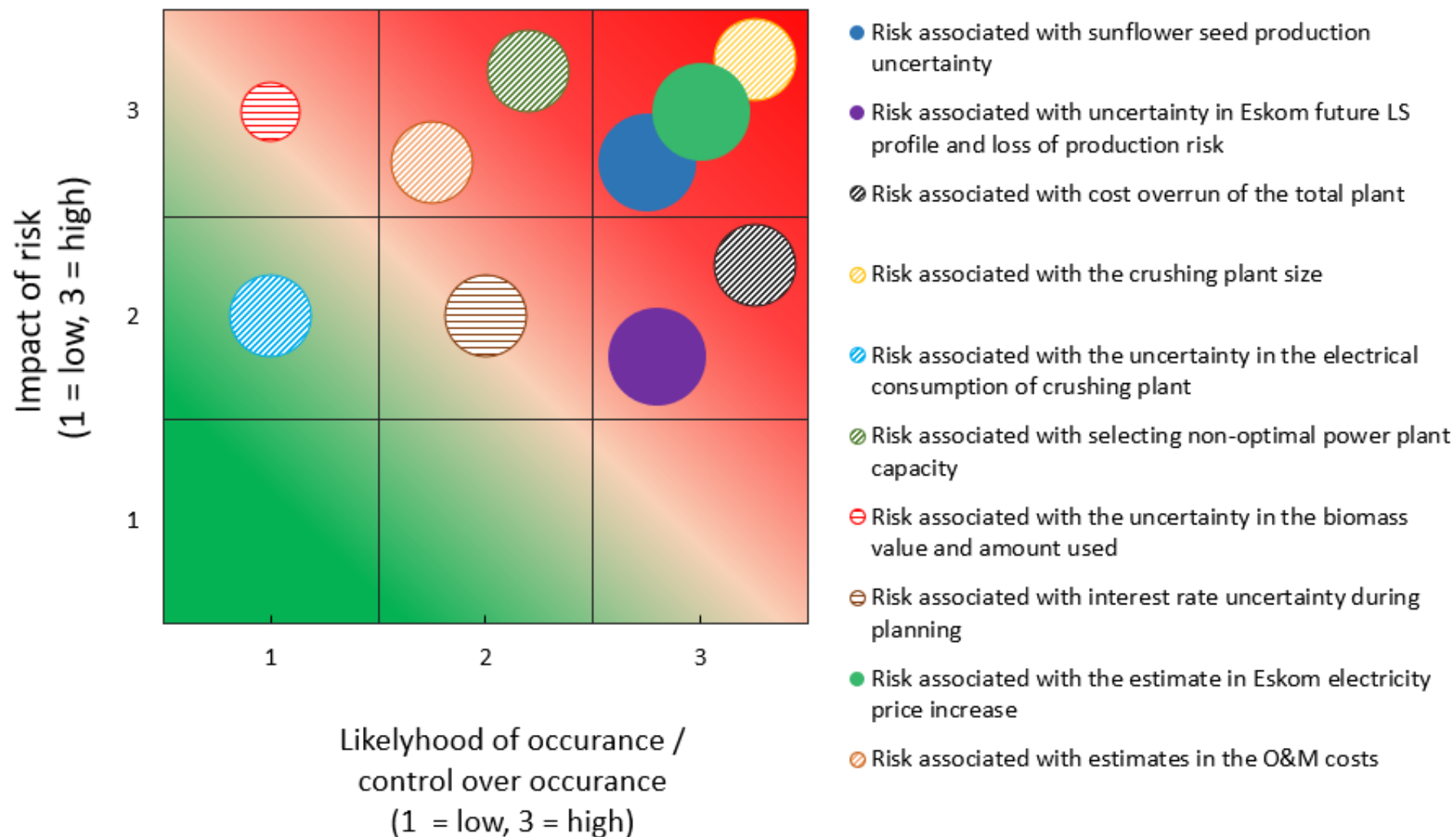


Figure 5-15: Risk map

Table 5-6: Summary of the impact of the risk factors

Scenario	Risks evaluated	Factors resulting in risk/uncertainty	Risk impact	Risk likelihood	Risk mitigation options
1	The risk associated with sunflower seed production uncertainty.	Rainfall, global markets, macroeconomic factors and demand for other oilseed products.	High: large VaR	High (Inherent)	Long term: None – accept the risk Short term: Storage facilities for seed
	The risk associated with uncertainty in Eskom's future load-shedding profile and the impact on production loss risk	Political risks, macro-economic risks. Government failure Uncertainty in the opportunity cost (margin uncertainty in oil and oilcake sales). Demand for sunflower oil and other oilseed products.	Medium: Medium VaR compared to other risks	High (Inherent)	None – accept the risk
	The risk associated with a cost overrun of the total plant	Construction risk, poor planning, use of unproven technology, poor	High: large VaR	Medium (Can be mitigated)	Contracts and insurance – transfer the risk

Scenario	Risks evaluated	Factors resulting in risk/uncertainty	Risk impact	Risk likelihood	Risk mitigation options
		supplier evaluation, lack of systems engineering process.			Rely on proven technology – control the risk
2	The risk associated with the crushing plant size	Economies of scale (specific cost of equipment). Plant efficiency and uncertainty	High for small plants. Lower for larger plants	High for small plants (Inherent)	The decision to not invest in small plants – avoid the risk Accept the risk for medium to large plants
3	The risk associated with the uncertainty in the electrical consumption of crushing plant	Inability to determine the exact requirements. Poor measurement of power consumption.	Medium: Moderate change in the VaR for uncertainty in factor	Low (can be mitigated)	Engineering study on the energy requirements before investment – control/avoid the risk
4	The risk associated with selecting non-optimal power plant capacity	Uncertainty in the production variation.	High: VaR very sensitive to changes in the factor	Medium (can be mitigated)	Detail engineering studies and improved forecasting techniques – control the risk

Scenario	Risks evaluated	Factors resulting in risk/uncertainty	Risk impact	Risk likelihood	Risk mitigation options
5	The risk associated with the uncertainty in the biomass value and consumption	External factors such as coal price variation. Location of plant Demand for husk as bedding Conversion efficiency	High: VaR very sensitive to changes in the factor	Low (can be mitigated)	Use historical sales of husk to determine value – avoid the risk
6	The risk associated with interest rate uncertainty during the feasibility phase	Political risks, macroeconomic risks	Medium	Medium (Can be mitigated)	During planning – be conservative in the interest rate selected – avoid the risk Conservative assumption in the interest rate during feasibility

Scenario	Risks evaluated	Factors resulting in risk/uncertainty	Risk impact	Risk likelihood	Risk mitigation options
7	The risk associated with the estimate in Eskom electricity price increase	Political risks, risk of corruption, macro-economic risks	High	High	None – accept the risk
8	The risk associated with estimates in the O&M costs	Supplier and technology Construction and commissioning Contractual agreements Level of skilled labour	High	Medium	Supplier and technology evaluation during the feasibility phase. Use of a reputable EPC partner for construction and commissioning. Contractual agreements with OEM on equipment warranties

5.6 Discussion and implications for investors and decision-makers

The risks that need to be accepted are discussed below:

- **The risk associated with the estimated increase in Eskom electricity price.** The only way to deal with this risk in the planning phase is to be conservative in future estimates. It is prudent as an investor to work on the lower expected price increase than to be biased towards higher prices and, therefore, higher yield.
- **The risk associated with sunflower seed production uncertainty and the implicated uncertainty in utilising the asset.** This uncertainty is likely the most problematic risk for the investor. This risk is due to the inherent uncertainty in the industry, and it significantly impacts the VaR. This risk must be carefully considered in light of the economies of scale. The investment risk might be too high for a small crushing plant. A crushing plant considering the implementation of a power project should model its historical production data to provide a more accurate view of the possible returns.
- **The future impact of load-shedding on the loss of production plays a crucial role in decision-making.** The model has provided a way to inform decision-making better. The uncertainty associated with this factor is lower than the production uncertainty, and factoring this into the investment presents a lower risk than the production uncertainty (based on the assumption that load-shedding will increase with the modelled trajectory).

Several risks can be mitigated by performing proper engineering studies beforehand. These include the following:

- The most significant risks are that the power plant size is not optimally selected or the crushing plant doesn't have the economies of scale necessary to ensure a feasible project. The risks highlight the need for detailed engineering feasibility studies, where factors such as matching the power plant with the demand of the crushing plant are carefully considered. The results emphasise that there is no one-size-fits-all approach to complex power generation projects such as biomass.

- The electrical consumption of the crushing plant needs to be confirmed. Although this factor doesn't change the risk significantly, it influences the NPV. It must therefore be determined beforehand and not based on assumptions.
- Technology selection also falls into this category, and partly the risk of cost overruns. This study did not evaluate the impact of different technologies, and it was assumed that a proven technology was selected. Other technologies exist, but careful consideration must be given to the possible effects on the risk. Other technologies might seem cheaper on paper, but as shown by the cost overrun risk, the impact of not keeping to the budget has significant implications for the investment.
- Operating and maintenance costs possibly have a sizeable impact on the risk. Technology is once again a key factor, as well as supplier evaluation and selection. It is possible for an investor to mistakenly only look at the capital cost of equipment during the feasibility phase and prefer a lower initial investment cost while not taking the O&M costs into account or the risk that the O&M might be optimistic. Due diligence concerning supplier selection is essential. It would be prudent to request proof of O&M costs from existing plants. The choice of an EPC contractor is also vital to ensure that installation and commissioning are performed according to supplier requirements. Personnel will also play a critical role during operation. It would be prudent to budget for better-skilled maintenance teams that will help ensure less unplanned maintenance.
- The key implication is that investors must realise that some costs must be incurred before an accurate decision can be made for this type of project. It is easy to recognise the opportunity in embedded generation without realising the intricacies of correctly selecting and sizing the technology. Investors must view this investment differently from other RE technologies, such as solar PV. Even with the increased impact of load-shedding and electricity insecurity faced by the industry, risks should be carefully considered. Risks can only be reduced by being willing to pay for the studies upfront. Investors must realise that cutting costs during the feasibility phase could lead to considerable exposure to otherwise manageable risks. Additionally, any third-party investor would be advised to perform proper due diligence and independent analysis to address risks adequately.

The following risks can be reduced through contracts and insurance:

- Cost overrun risks can be reduced through contracts providing for unforeseen circumstances. Delayed delivery will influence the interest paid during construction, and penalties should be considered. Terms of delivery and commissioning of equipment are also relevant. A pandemic such as COVID-19 could prove disastrous if the equipment is imported but can't be commissioned by the supplier due to travel bans, and it could also impact warranties. Integration between equipment is a critical risk. The role of the EPC contractor is paramount to the project's success. Before contracting, proper due diligence on both the suppliers and the EPC contractor is required. Contracts can help reduce the risks, but the decision of the suppliers and EPC contractors will largely determine whether the agreements will be beneficial. Insurance is essential during procurement and construction to protect against unforeseen incidents, such as theft or damage during transport.
- The main implication of the results discussed in this section is that the investor must take cognisance of the cost overrun risk involved when deciding to start the EPC process. Knowing the risk size can help overcome the optimism bias and result in more realistic planning and timelines. Highlighting the risks should also inform the investor's decision to allow more time to evaluate the main contractors and suppliers critically. Risk reduction requires incurring costs during the engineering and procurement processes, where legal expertise is needed. Knowing the extent of the risk should also help counter the investor's bias toward selecting the lowest bidder instead of the most reputable bidder. It is also suggested that an investor appoints an owner's engineer to look after the investor's interest. This would help to evaluate proposals by both contractors and suppliers critically.

Investors must be conservative during the feasibility phase of the project in selecting parameters. The debt interest rate is one. There could be a significant difference between the interest rate used during the feasibility study and the interest rate approved based on the project risk profile. Therefore, it is prudent to be conservative in selecting the initial interest rate to evaluate the feasibility. The interest significantly influences the risk, while the same sensitivity does not apply to the NPV. The investor must consider the risk appetite of the high-risk value rather than the low-risk. The influence of the biomass value

must be accurately determined and based on historical prices. If only recent, high values are used, then the project might seem more profitable than it truly is. A critical assessment of the value of the biomass and the factors that will influence it must be undertaken.

5.7 Summary and conclusion

This chapter discussed the financial model used to evaluate the risk factors. Then, the assumptions for the model were provided together with the nominal values selected as inputs to the model. Scenarios were defined to investigate the various factors that investigate the risks.

The results were summarised in a table that provides the impact of each risk, the likelihood of the risk, and the mitigation strategies that can be used to address each risk. In addition, the presentation of the risks in a map provides a graphical way to highlight where the focus of risk mitigation strategies should be and which risks must be accepted as inherent to the industry. Finally, the implications of the results for investors and decision-makers were discussed, together with recommendations for lowering risk exposure.

Chapter 6 is the conclusion and recommendations. The purpose of the chapter is to consolidate the results and implications and highlight what investors should be aware of when considering an investment in biomass power generation for sunflower-crushing plants. Suggestions for future research will also be made.

Chapter 6

Conclusions, recommendations, and future research

6.1 Introduction

In this chapter, a brief overview of the previous chapters is provided. Firstly, the need for the study is highlighted, accompanied by the objectives that endeavoured to answer the research questions. Next, the pertinent findings are emphasised, after which recommendations are made to investors and crushing plant owners based on the insights obtained from the study. Finally, the study's limitations are related to possible future research, after which it is explained how this study has contributed to the field of research.

6.2 Summary of the study and main findings

The power generation situation in South Africa is dire, with rising energy costs and a significant increase in the frequency of load-shedding events. This situation has severely impacted the commercial and industrial sectors and has led to an increase in embedded generation. Embedded generation in South Africa consists almost exclusively of solar PV. Sunflower-crushing plants are also affected by the power situation. These crushing plants are, however, uniquely positioned to produce power by utilising the husks that are available as a by-product of the crushing operation. Unfortunately, the lack of available literature on the topic and the lack of reference projects in South Africa leave investors without a basis to evaluate the risks associated with this opportunity.

This has led to the primary objective of this study, which is to identify and quantify the factors that will influence the LCOE of power generation for a crushing plant when using sunflower husk as a fuel source. Through risk identification and assessment, a framework can be developed for better decision-making and comparing investment alternatives.

The specific objectives of this study were the following:

- Identify the factors influencing the uncertainty and risks in the investment returns.
- To quantify these uncertainties and risks.

- To develop a financial model that can incorporate all the risks in such a way that it can be used to analyse the influence on decision-making during the feasibility phase.
- To analyse the impact of risks and whether there are ways to mitigate these risks.
- To use the analysis to inform the implications for decision-making before investment in the power generation project.

A further objective of this study is to contribute to the available literature concerning biomass power generation in South Africa, specifically to power generation using sunflower husk.

In chapter two, an overview was provided regarding the power generation and renewable energy situation in South Africa. The factors that specifically influence the sunflower industry were highlighted, providing a background for identifying the risks involved in SSEG for sunflower-crushing plants. A literature review identified the typical risks and risk drivers for renewable power projects. The standard methods used to quantify the risks and the metrics used to report risks were also discussed. Chapter three outlined the methodology used in the study to identify the critical risks and the methods applied for risk assessment. Chapter four discussed risk identification, data collection and processing, and the statistical models developed to enable the use of the data in a financial model. In chapter five, the financial model and assumptions were discussed, while the scenarios used to demonstrate the impact of each risk were motivated. The results from the Monte-Carlo simulations and sensitivity analyses were presented as the basis for the risk assessment. The risks were summarised according to impact, likelihood, and level of mitigation that can be taken to manage each risk. The results were presented in a graphical format to enable a visual representation that highlights the most pertinent risks.

The analyses have provided insight into various risks that need to be considered. First, fluctuating sunflower production in South Africa and the associated availability of seed for crushing is an inherent risk that needs to be considered. By including this risk, the VaR of the investment could be estimated purely based on seed availability. Without considering this risk, the investment return could be overoptimistically calculated. The influence of load-shedding was shown to be significant. There is uncertainty in the exact

benefit of reducing the impact of load-shedding with embedded generation, as indicated by the spread in the NPV predicted from the MCS. The risk of cost overruns in a project dramatically influences the VaR, highlighting a negative shift in the NPV and VaR if a project cost overruns. The most probable NPV is much lower when considering this risk and provides insight into how over-optimism can result in a significant disparity between expected and actual returns.

The size of the crushing plant under consideration has a very large impact on investment returns and risk. Small crushing plants require smaller power plants and are negatively influenced by the economies of scale of power generation and lower efficiencies of smaller power plants. On the other hand, if the power plant is oversized to be conservative in ensuring sufficient power supply, the investment risk increases significantly. This result emphasises the need to carefully plan the power plant capacity and match it with the crushing plant demand.

The investment returns are driven by replacing Eskom as the electricity source. As such, the price of Eskom electricity, with the assumption of future price escalations, significantly impacts the returns. However, as highlighted by the sensitivity study, future electricity price escalation is one of the most significant and unknown factors. Therefore, investors should be wary of being too optimistic about price increases (i.e. assuming significant escalations). In addition, the selected technology could be fundamental to the risk profile. The possible impact of technology is reflected in the considerable variation in the VaR attributed to O&M costs uncertainty, as well as the potential impact of unfamiliar technology on project cost overrun and longer commissioning times.

The study has highlighted several risk mitigation options. Emphasis is placed on making informed decisions, which can only be done by understanding the factors that drive the risks. The importance of engineering and other specialist studies was highlighted to mitigate the risks. The use of mature technology, reputable suppliers and EPC partners, and dependable contractual agreement are some crucial things to consider.

6.3 Recommendations for managing investment risks

This study has identified uncertainties and risks influencing the investment returns from embedded power generation for a sunflower-crushing plant. The investigation also provided insights into possible risk mitigation strategies and the area on which the investor and plant owner should focus before considering such an investment. As a result, several recommendations are now made to investors or crushing plant owners who consider implementing embedded generation using sunflower husk as a fuel source.

- The results have emphasised the need for a proper risk analysis when considering a complex project such as a biomass power plant. The power generation situation in South Africa provides numerous challenges and opportunities. It might seem logical to invest in technology to utilise the husks for this purpose. However, the study has shown that various factors play a role in the investment returns and the associated risks. Only through quantifying the risks can possible optimism bias be countered. The necessity to counter optimism bias is especially true when considering the impact of cost overruns typically associated with complex engineering projects. Estimating the risk has value since it makes the investor aware of the pitfalls and prompts vigilance and proper planning. It also counters the inclination to make optimistic assumptions that support the investment decision favourably. Therefore, an appropriate risk analysis is highly recommended to be performed specifically for the crushing plant under consideration.
- The uncertainties and risks associated with production variation and load-shedding should be accepted. National low production and seasonal fluctuations are inevitable. The investor should be aware of this but accept the risk. The uncertainty in the exact influence of load-shedding is similarly unavoidable, and investors should be aware that there exist scenarios where the benefit of avoiding load-shedding with embedded generation can be lower than expected.
- In addition to the risk analysis, various engineering and specialist studies are required. The results have shown that such studies should be budgeted for and conducted. It is recommended that investors and plant owners spend more time and money on studies in the feasibility phase. It is also advised that the plant owner or investor appoint an owner's engineer with experience in this specific field and not only rely on third parties

or suppliers who do not necessarily have the investors' interest at heart. The selection of technology was pointed out as playing an important role. Even in the early stages, a detailed evaluation of technology should be considered. Such an evaluation should include the total plant cost, operating and maintenance costs, conversion efficiency, and support for the technology in South Africa. Relying on high-level figures for expenses could result in a significant disparity between expected and final investment returns.

6.4 Contribution of the field of study

This study contributes to the literature on renewable energy in South Africa, primarily due to the lack of information on the use of biomass for embedded generation in industrial applications. To the author's knowledge, no study exists in the public domain investigating the opportunities for embedded generation at sunflower-crushing plants using husks in the South African context. The study, therefore, sheds light on the unique factors that could influence such an investment and provides crushing plant owners and possible investors with a theoretical basis from which to evaluate this opportunity. Furthermore, to the author's knowledge, there does not exist academic literature that assesses the impact of load-shedding using MCS. The study also broadens the general literature on renewable energy in South Africa beyond the mainstream electricity sources of solar PV and wind.

The study further contributes to the literature on risk evaluation and management in renewable power generation. In addition, the study provides a strong motivation for why engineering and specialist studies are essential and why these studies should not be downplayed in the initial stages of power generation projects in South Africa.

6.5 Areas of further research

6.5.1 Improvements to the risk assessment method

Several assumptions were made in this investigation. However, the following assumptions should be reconsidered and improved upon:

- It was assumed that there is no correlation between the annual sunflower production variation and the cost of sunflower oil and cake. This correlation should be investigated and included in the model.
- It was assumed that the technology selected is mature and has lower risks. The risk profile of different technologies should be evaluated, providing further insight into how the technologies might impact decision-making.
- The assumption that the national production levels can be scaled to represent the production fluctuations of a crushing plant needs to be verified with data from an actual crushing plant.
- Alternative renewable energy should also be investigated. It is proposed that combinations of biomass and solar be evaluated to provide an optimum mix of electricity to the crushing plant. The possibility of wheeling power over the grid to other users should also be investigated.

6.5.2 Application of the risk assessment method

The risk assessment method applied in this investigation provides a basis for developing a framework within which crushing plants can evaluate the investment risk for embedded generation. It is proposed that this framework be used to assess how investors view the risks for embedded generation at crushing plants. Therefore, research can be conducted using this framework to evaluate the perceived risks' influence on investors' decision-making.

6.6 Concluding remarks

The research conducted in this study endeavoured to identify and assess the risks associated with embedded generation at sunflower-crushing plants, providing investors and crushing-plant owners with a risk map that can be used to improve decision-making.

The study has shown that a risk assessment can be conducted using Monte-Carlo simulations and sensitivity analysis while using the metrics such as VaR to report the risks. The study concluded that several factors could significantly impact the risk profile of the investment, many of which are unique to South Africa. The inherent risks include the uncertainty in national sunflower production levels and future load-shedding events.

Other factors of paramount importance for the NPV and risk of the project are the technology used, the projections of Eskom electricity price escalations, and the optimum plant size selection.

Risk analysis should form a critical part of the planning of any complex engineering project, including renewable energy projects using biomass. Risk analysis can inform the areas on which to focus and the required specialist studies. Engineering and other specialist studies are essential in managing risks by selecting and sizing the technology employed.

The power generation situation in South Africa presents an opportunity for crushing-plant owners to implement embedded power generation using sunflower husks as the fuel source. This investigation could help them make more informed decisions and make fewer assumptions that could result in unwanted risks.

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