

Norwegian University of Life Sciences

Master's Thesis 2024 30 ECTS

The Faculty of Environmental Sciences and Natural Resource Management (MINA) $% \left(\mathcal{M}_{1}^{2}\right) =0$

Energy System Analysis of Captive Solar PV systems in Kenya's Textile Industry

A case study

Acknowledgement

This thesis is a result of a partnership between the Norwegian University of Life Sciences and Moi University. I want to express my gratitude to the Norwegian Partnership Programme for Global Academic Cooperation (NORPART) for facilitating and funding my research.

I would like to give a special thanks to Professor Augustine B. Makokha, Doctor Stephen Talai and Professor Lucy Jepchoge Rono for supporting me both personally and professionally during my stay in Kenya. Furthermore, I am grateful to my supervisor, Professor Muyiwa Samuel Adaramola for guidance throughout the work of my thesis. Similarly, I would like to thank Eirik Ogner Jåstad for the helpful advice on energy system modelling.

Most of the data used in this thesis has been provided by staff at Rivatex East Africa Limited, and I would like to thank the staff for their good collaboration. Special thanks go to Caroline Mureithi, Enock Kiptoo Langat, Ezekiel Kigen, Christine Chebutey and Gideon Boit for providing data and information on the factory. Moreover, I would like to thank Abraham Kosgei for providing weather data.

I am happy to have shared coffee breaks and common suffering with my fellow students in the reading room. They have truly made the process of writing enjoyable. Last but not least, I want to thank Øyvind Lindberg Russwurm for bad jokes and good company during our stay in Kenya.

Karina Agerholm Arentsen Ås, 14.05.2024

Abstract

The textile industry is an energy-intensive industry that depends on reliable power supply for production. Meanwhile, the Kenyan national power grid experiences frequent outages, failing to deliver continuous supply. This thesis examines how the installation of solar PV, a battery and an electric boiler can address the challenge of an unreliable power grid in the textile industry. This is done through a case study of Rivatex East Africa Limited textile factory.

Using energy system analysis, this thesis shows that captive solar PV systems have great potential to reduce both dependency on the national power grid and system cost, even in the absence of governmental support. From analyses of four scenarios, it is shown that when a factory's energy consumption exceeds the energy production from solar PV, only the solar PV system decreases system cost and dependency on the power grid. However, in cases when solar PV production at times exceeds energy consumption, the flexibility offered by a battery system and an electric boiler improves the energy system of textile factories. Thus showcasing the synergistic benefits of combining the three technologies.

Due to the benefits of captive solar PV systems in the textile industry presented, this thesis initiates a discourse on the factors contributing to the limited adaption of solar PV in the Kenyan industries. The results show that the regulatory framework is not the main problem, whereas high investment costs seem like a more plausible explanation.

Sammendrag

Tekstilindustrien er en energiintensiv bransje som er avhengig av pålitelig energiforsyning for å sikre kontinuerlig produksjon. Hyppige strømavbrudd på det kenyanske kraftnettet hindrer imidlertid industrien i å opprettholde en stabil strømforsyning. Denne studien undersøker hvordan installasjon av solpaneler, et batterisystem og en elektrisk dampkjele kan møte utfordringene med upålitelig strømforsyning til tekstilindustrien. Dette gjøres gjennom en kasusstudie av fabrikken Rivatex East Africa Limited.

Gjennom en energisystemanalyse viser denne studien at solpaneler har potensial til å redusere både avhengigheten av det nasjonale kraftnettet og systemkostnadene, selv uten økonomisk støtte fra den kenyanske staten. Analyser av fire scenarier viser at hvis en fabrikk har et energiforbruk som overstiger produksjonen fra solpanelene, er det solpanelene alene som reduserer kostnadene og avhengigheten til kraftnettet. I motsetning til dette, i scenarier der produksjonen fra solpanelene til tider overstiger energiforbruket, vil fleksibiliteten som tilføres av en elektrisk kjele eller et batterisystem forbedre energisystemet til tekstilfabrikken. Dette resultatet viser fordelene med fleksibiliteten som oppnås gjennom samarbeidet mellom de tre teknologiene.

Basert på fordelene med solpanelsystemer i tekstilindustrien, som denne studien påpeker, åpnes det for en diskusjon om hvilke faktorer som har bidratt til den begrensede utbredelsen av solpanelsystemer i den kenyanske tekstilindustrien. Resultatene fra denne studien viser at det eksisterende lovverket ikke er hovedproblemet, mens høye investeringskostnader synes å være en mer sannsynlig forklaring.

Contents

1	Intr	oducti	on	9				
	1.1	Backg	round	10				
	1.2	Resear	ch question	12				
2	Lite	terature review 13						
	2.1	Captiv	ve solar PV systems in Kenya	13				
		2.1.1	FiT and net-metering in Kenya	14				
	2.2	Solar l	PV performance in Kenya	15				
3	Theoretical background 17							
	3.1	Energy	y system analysis	17				
		3.1.1	General procedure of energy system analysis	17				
		3.1.2	Optimisation objectives	17				
		3.1.3	Scenarios in energy system analysis	18				
	3.2	Linear	Programming	18				
	3.3	Electri	icity prices in Kenya	19				
	3.4	Curren	nt energy system at Rivatex	20				
4	Met	Method 22						
	4.1	Optim	isation with PuLP	23				
	4.2	Optim	isation scenarios	23				
	4.3	Model	ling and system constraints	25				
		4.3.1	Objective Functions	27				
		4.3.2	Modelling of solar PV system	28				
		4.3.3	Modelling of battery system	30				
		4.3.4	Modelling of steam boilers	32				
		4.3.5	Energy Demand	33				
	4.4	Financ	cial estimations	35				
		4.4.1	LCOE of solar PV system	36				
		4.4.2	Cost of battery system	37				
		4.4.3	Cost of electric boiler	38				
		4.4.4	Cost of steam production from firewood	38				
		4.4.5	Electricity prices	39				
5	Res	ults		41				
	5.1	Minim	uising system cost	42				
		5.1.1	High steam demand	42				
		5.1.2	Low steam demand	43				

	5.2	Minimisi	ng dependency on the national power grid $\ldots \ldots \ldots \ldots \ldots$	43	
		5.2.1 H	igh steam demand	44	
		5.2.2 L	ow steam demand	45	
	5.3	Sensitivit	y analysis	49	
		5.3.1 S	v stem cost minimisation $\ldots \ldots \ldots$	49	
		5.3.2 M	inimising dependency on the power grid	51	
6	Disc	cussion		53	
	6.1	Results a	nd findings	53	
		6.1.1 O	ptimal technology capacities when minimising system cost $\ . \ . \ .$	53	
		6.1.2 M	inimising dependency on the power grid $\ldots \ldots \ldots \ldots \ldots \ldots$	56	
	6.2	The pote	ntial of captive solar PV systems in Kenya	57	
7	Conclusion 59				
	7.1	Summary	of findings	59	
	7.2	Challenge	es and limitations of the study	60	
	7.3	Future re	search	60	
\mathbf{A}	Elec	ctricity co	onsumption groups at Rivatex	66	
A B	Eleo Eleo	ctricity co ctricity C	onsumption groups at Rivatex onsumption	66 67	
A B C	Elec Elec Moe	etricity co etricity C delling as	onsumption groups at Rivatex onsumption sumption	66 67 68	
A B C	Elec Elec Moc C.1	etricity co etricity C delling as Monthly	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex	66 67 68 68	
A B C	Elec Elec C.1 C.2	ctricity co ctricity C delling as Monthly Operatin	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex g hours	 66 67 68 68 68 68 	
A B C	Elec Elec C.1 C.2 C.3	ctricity co ctricity C delling as Monthly Operatin Choice of	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex g hours `mono-crystalline modules	 66 67 68 68 68 69 	
A B C	Elec Elec C.1 C.2 C.3 C.4	ctricity co ctricity C delling as Monthly Operatin Choice of Estimatio	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex g hours	 66 67 68 68 68 69 69 	
A B C D	Elec Elec C.1 C.2 C.3 C.4 Stea	ctricity contricity Contricity Contricity Contribution of the contributication of the	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex g hours	 66 67 68 68 68 69 69 70 	
A B C D	Elec Moo C.1 C.2 C.3 C.4 Stea Hist	etricity co etricity C delling as Monthly Operatin Choice of Estimation am Requi	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex g hours	 66 67 68 68 69 69 70 71 	
A B C D E F	Elec Moo C.1 C.2 C.3 C.4 Stea Hist	etricity co etricity C delling as Monthly Operatin Choice of Estimation am Requi corical electricity bi	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex g hours	 66 67 68 68 69 69 70 71 72 	
A B C D E F G	Elec Moo C.1 C.2 C.3 C.4 Stea Hist Elec Pyt	etricity co etricity C delling as Monthly Operatin Choice of Estimation am Requise corical electricity bise hon mod	onsumption groups at Rivatex onsumption sumption energy consumption from each transformer at Rivatex g hours g hours mono-crystalline modules on of electricity consumption per kWh of steam from firewood rement ectricity tariffs all December 2023	 66 67 68 68 69 69 70 71 72 73 	

List of Figures

1	Generation mix from June to December 2023	9
2	The current energy system at Rivatex	21
3	Simplified RES for scenario 1, 2 and 4	24
4	Simplified RES for scenario 3	24
5	RES for the energy system analysis of Rivatex textile factory	26
6	Scenario 1 & 2, Electricity production from solar PV and electricity demand in all	
	months of the analysis	42
7	Scenario 3 & 4, solar PV production, steam from el-boiler, charging of battery and	
	consumption from electricity demand groups when minimising system cost $\ . \ . \ .$	44
8	Scenario 3 & 4, Total energy throughout the time span of 20 years delivered to	
	the electricity demand groups from solar PV, the power grid and the battery	
	system	45
9	Scenario 3, Interaction between solar PV, battery and power from grid when min-	
	imising grid dependency \ldots	46
10	Scenario 4, Interaction between solar PV, battery and power from grid when min-	
	imising grid dependency \ldots	47
11	Scenario 4, interaction between solar PV, electric boiler and battery in the first two	
	years when minimising grid dependency	47
12	Scenario 3 & 4, Total electricity consumption from the power grid throughout the	
	time span of 20 years \ldots	48
13	Available hourly energy production from solar PV in January based on weather	
	data from Moi University	55
14	Average monthly load of each transformer at Rivatex textile factory	68
15	Historical energy tariffs from Shah (2024) adjusted for inflation (Inflation Tool, 2024)	71
16	Historical electricity levies from Shah (2024) adjusted for inflation (Inflation Tool,	
	2024)	71
17	Provided by electrical engineer Gideon Boit (personal communication, $27.03.2024$)	72

List of Tables

1	Decision variables in the LP model	27
2	Data for solar PV module	29
3	Consumption, and ratio of total consumption, of electricity from New Spinning and	
	Old Spinning	34
4	Calculation of solar PV system LCOE	37
5	Estimation of electricity tariffs applied to the model	39
6	Optimal technology capacities for each scenario and optimisation problem \ldots .	41
7	Scenario 1, Total Solar PV production, battery output and consumption from	
	the power grid throughout the time span of the analysis $\ldots \ldots \ldots \ldots$	45
8	Shadow prices and changes in optimal solution for the cost minimisation ob-	
	jective	50
9	Allowable increase of solar PV LCOE, allowable decrease of electricity tariffs from	
	the national power grid, and allowable decrease in battery investment cost in the	
	cost minimisation problem \ldots	51
10	Shadow prices and changes in optimal solution for the grid dependency min-	
	imisation objective	52
11	Description of consumption groups in Figure 2	66
12	Electricity consumption for all departments at Rivatex 2022 and 2023 (per-	
	sonal communication, electrical engineer, Ezekiel Kigen, 26.01.2024)	67
13	Steam demand from each machine (personal communication, Chief Engineer	
	Caroline Mureithi, 29.01.2024)	70

Abbreviations

Solar PV	Solar photovoltaic
kW	Kilo watt
kVA	Kilovolt-amperes
kWh	Kilo watt hours
MWh	Mega watt hours
GWh	Giga watt hours
h	Hours
m^2	Square meters
KES	Kenyan Shillings
MKES	Millon Kenyan Shillings
UN	United Nations
UNDP	United Nations Development Program
EPRA	Energy and Petroleum Regulatory Authority in Kenya
KPLC	Kenyan Power
LP	Linear programming
MGA	Modelling to Generate Alternatives

1 Introduction

In Europe, many countries are concerned about lowing their energy consumption and increasing the energy efficiency in order to meet the goals of the Paris Agreement (United Nations, n.d.). Meanwhile, over 1.1 billion people in developing countries are without access to electricity (Carvallo et al., 2017). Developing countries are thereby facing the dual challenge of increasing electricity supply and fighting climate change.

Kenya is an example of a developing country with significant growth in the electricity sector and in renewable resources. This is due to both growing demand, high access to renewable sources, and governmental initiatives (Keshavadasu, 2023). The Kenyan government has made an Energy Transition & Investment Plan aiming at achieving net-zero emission by 2050 while covering the expected growth in energy demand. To reach the net-zero goal, the government expects a higher degree of electrification in all sectors (Ministry of Energy and Petroleum, 2023).

The Kenyan electricity grid is currently characterized by a large share of renewable energy sources, covering more than 80% of the country's electricity supply, as illustrated in Figure 1. Furthermore, the government expects a large increase in renewable energy capacity towards 2050, with solar PV expected to account for the majority of the capacity according to Ministry of Energy and Petroleum (2023). Nonetheless, the country experiences frequent power outages, and a part of the population does not even have access to the national power grid (EPRA, 2021).





is Williamson Tea in Kericho, which has installed a grid-tied solar PV system of 1MW, covering 23-24 % of the factory's energy consumption (personal communication, Kipyegon Rotich, 08.02.2024).

The textile and garment industry is energy-intensive and therefore highly dependent on continuous power supply to avoid sales losses (UNEP et al., 2020). The high energy consumption also makes the industry one of the most polluting globally, accounting for approximately 10 % of global carbon emissions (European Environment Agency, 2023). At the same time, the textile industry in Kenya has the potential to employ 10 % of the population, playing an important role in a country with low human deployment estimated at 57 % (Mwangi and Mutabazi, 2023 Kamau, n.d.). The employment of renewable energy sources in the textile industry therefore serves three primary purposes: ensuring continuous power supply, reducing the industry's negative impact on the environment, and guaranteeing the future of the industry, which will ensure employment.

Especially solar PV systems have great potential in the Kenyan industries due to high solar irradiation. According to UNEP et al. (2020), there is a good market for captive PV in the manufacturing industry, captive solar PV is even financially competitive.

This thesis examines the techno-economic potential of a solar PV system in the Kenyan textile industry. This will be done through an energy system analysis of the textile factory Rivatex East Africa Limited.

1.1 Background

Using energy system optimisation models, particularly linear programming (LP) models, for captive energy systems has proven effective in energy management through many examples. Balcita et al. (2021) solved the optimisation problem of allocating renewable energy generation in the Philippines using several mathematical methods to confirm an LP model in MATLAB. The study showed that the result obtained from MATLAB corresponded to the results from other optimisation models, confirming the use of LP models for optimisation of generation allocation. This conclusion is supported by Polat and Gürtuna (2018), who investigated the different applications of LP in energy management. The research showed that LP is a popular tool used by policymakers, energy producers, and energy consumers. Within energy management, the application of LP covers the dispatching of generators, energy-efficient buildings, governmental planning, and introduction of renewable energy technologies. The application possibilities are many, and the study underlined that with an increasing energy demand and the implementation of new energy resources, the use of LP models will increase and find new application areas.

Within the textile industry, Kimutai et al. (2019) have shown that LP can be used to minimise the cost of production by optimising the number of units processed at each stage of the production. Another study by Perić et al. (2018) showed how LP combined with multi-criteria analysis can be used for production planning in the textile industry. The studies within textile industry focus on the allocation of resources and optimisation of production processes (Moussa, 2021) (Ferro et al., 2021). However, no research has been done on how the system cost of the textile industry can be reduced by introducing alternative energy resources. Similarly, the sustainability of the industry's energy system has not been investigated through energy system analysis. As the focus on renewable energy, carbon footprint, and CO2 emission rises, the interest in other optimisation criteria than costs and profit increases. Østergaard (2009) analysed some of the different optimisation criteria that one can apply to energy system optimisation. Amongst the optimisation criteria suggested are maximising the share of renewable energy, minimising carbon dioxide emissions, and minimising import/export of energy. The study concluded that different optimisation criteria render different results and suggested using multi-criteria analysis to compare results for decision making.

The study by Elbaz and Guneser (2021) used an algorithm to optimise a grid-connected PV-wind hybrid system. The algorithm maximised the REF while minimizing the cost of energy and the loss of likelihood of power supply. Malekpoor et al. (2018) optimised electricity generation by considering costs, independence from imported fuels, CO2 emissions, and social considerations. Thus, optimising energy systems based on several optimisation objectives have been applied in several previous studies, however, not within the textile industry.

1.2 Research question

The objective of this thesis is to examine the potential of solar PV and battery systems in the Kenyan textile industry through a case study. The analysis will be done through two optimisation objectives of four different energy system configurations of the textile factory Rivatex East Africa Limited. The current energy system at Rivatex consists of electricity supply from the national power grid along with firewood and oil consumption for thermal processing purposes. The optimisation model introduces an electric steam boiler, a solar PV system, and a battery system. The results of the optimisation will answer the following questions:

- How does the introduction of captive solar PV, a battery system, and an electric boiler affect the system cost of the textile factory's energy system?
- How does the introduction of captive solar PV, a battery system, and an electric boiler affect the dependency on the national power grid?
- Which technology capacities yield the lowest system cost and the minimal dependency on the national power grid, respectively?

The thesis analyses the energy system of one textile factory and interprets the results in the context of the current Kenyan energy policies and the energy system configurations suggested. Through the results, the potential and challenges of captive solar PV systems in Kenya's textile industry will be discussed.

2 Literature review

The literature review examines the potential of solar PV systems in Kenya through results from relevant literature. With a fokus on captive applications of solar PV, the challenges and changes in the regulatory framework highlighted by part of the literature is presented. Lastly, the performance of solar PV in Kenyan climate conditions from relevant research is presented.

2.1 Captive solar PV systems in Kenya

In the literature, there is general agreement that solar PV systems have great potential in Kenya, both as grid connected, off-grid and captive systems. However, some literature points to challenges that might hinder the expansion of solar PV in Kenya.

The share of renewable energy in the energy mix of 2023 was approximately 85% as shown in Figure 1. According to EPRA Statistics Commitee (2024) 14.8% of the installed renewable energy capacity is solar PV of which almost half is captive capacity. Furthermore, the report noted that for captive energy systems, solar PV is the preferred technology accounting for 43.77% of the total captive capacity. The report attributed this preference to costeffectiveness, favorable solar insolation levels, and supportive government policies.

Unlike EPRA Statistics Commitee (2024), Keshavadasu (2023) highlighted policy inconsistency as one of the "critical areas of concern" (Keshavadasu, 2023, p.5) associated with solar PV projects. Along with tariff structure uncertainties, grid connection issues, land acquisition challenges and complex licensing processes, Keshavadasu (2023) argued that policy inconsistency is a hindrance to investments in solar PV projects. Hence the political framework is limiting the utilisation of the large solar PV potential in Kenya.

Nonetheless, EPRA Statistics Commitee (2024) showed how the energy generation from captive solar PV has increased since 2021, and according to Ministry of Energy and Petroleum (2023) solar PV will account for the majority of the energy capacity in the power generation mix in 2050. The report looked at different scenarios of demand and generation growth from 2020 to 2050, and in all scenarios, solar PV is expected as the technology with highest installed capacity by 2050 (Ministry of Energy and Petroleum, 2023).

In 2020, the United Nations Environment Program published a country report on Kenya's clean captive installations for industrial clients (UNEP et al., 2020). The report concluded that Kenya has a strong potential for clean captive energy and that the potential is strongest in the manufacturing sector. The textile industry is categorised as a manufacturing industry and is furthermore highlighted as one of the 12 industries with at least 20 enterprises exceeding a turnover of one million USD (UNEP et al., 2020, Table 20). According to the

report, the textile industry is one of the top 10 manufacturing sub-sectors for captive power in Kenya, with a medium potential. At the time the report was written, only two of the 139 textile enterprises had installed a captive power system and both of these were solar PV. In fact, 16 out of the 29 known captive systems in the top 10 subsectors for captive power were solar PV systems. The remaining 13 were bioenergy systems within the food production and paper production industries (UNEP et al., 2020, table 23). Thus, the report underlined the potential of solar PV for captive power systems.

Similarly to Keshavadasu (2023), UNEP et al. (2020) found uncertainty in Kenya's regulatory framework to be one of the key barriers to the development of clean captive systems. Yet, it should be noted that the report was published in 2020, and new regulatory framework was introduced in 2019 and updated in 2021 (Ministry of Energy, 2021a). Moreover, UNEP et al. (2020) stated the biggest barrier to be the financing of the captive systems.

2.1.1 FiT and net-metering in Kenya

The previous paragraph explained how several studies points to uncertainty in the regulatory framework as a hinder to investments in solar PV systems. The literature in this paragraph explains how the policy has changed since 2008, which UNEP et al. (2020) mentioned as a possible explanation for the uncertainty.

In 2008 the Kenyan government introduced a feed-in-tariff (FiT) policy to increase the attractiveness of investing in renewable energy. FiT is a set price per kWh produced from renewable energy sources and sold to the national grid. According to Ndiritu and Engola (2020) FiT policies have worked for many countries, however, did not prove to have great effect in Kenya where only 0.66% of the expected increase in renewable power generation was met. The study examined why the FiT policy in Kenya turned out ineffective. It states that a bad and ambiguous regulatory framework was the biggest challenge for the FiT policy. Apart from that, delays in decision-making and technical incompetence are mentioned as major causes of the low effect. Ndiritu and Engola (2020) recommended auctioning as an alternative to the FiT policy, and in 2021 that is exactly what the Ministry of Energy decided to do. In the 2021 FiT policy, the ministry excluded solar PV-generated power from the FiT policy and instead attained solar PV systems above 20 MW under the Renewable Energy Auction Policy (Ministry of Energy, 2021b). In addition, the Ministry of Energy published a proposal for including solar PV systems in the net-metering regulation. The proposal gives grid-tied prosumers a discount of 50% of the units exported to the national grid. The discount will be subtracted from the prosumer's monthly electricity bill making it more attractive to invest in captive renewable energy systems (Ministry of Energy, 2022). However, the proposal is not yet fully operational due to challenges with frequency stability of the national grid. In fact, only systems above 1 MW are currently allowed to tie to the grid (personal communication, Professor Augustine Makokha, 22/04/2024). Thus, the intended net-meting policy only applies for systems above 1 MW that have been allowed coupling to the national grid.

2.2 Solar PV performance in Kenya

The efficiency and power production of solar PV is affected by many weather and climate conditions. Research shows that increase in solar irradiation will increase power output, while dust accumulation and increase in cell temperature will decrease power output (Al-Badi, 2020; Arora et al., 2022; Ngure, 2022). A recent study on solar PV performance in Kenya also showed that increase in wind speed will increase the power output while increase in relative humidity decreases the power output (Ngure et al., 2023). By comparing their own results with other results from the literature, Ngure et al. (2023) concluded that the accuracy of the performance prediction models increase with the inclusion of more weather parameters. Nonetheless, accurate models will also require more data, hence the available data and its accuracy will also affect the accuracy of the energy output predictions. Furthermore, the model developed by Ngure et al. (2023) was a numerical model that cannot be directly transferred to other projects and other datasets.

Gopi et al. (2021) did research on weather impact on a utility-scale PV power plant in a tropical region. The study concluded that generation strictly follows the solar radiation pattern and that the temperature of the PV modules follows the ambient temperature in all seasons. This result highlights solar radiation as the most important weather parameter when estimating the power output from solar PV modules. However, results from Gopi et al. (2021) also showed that the performance ratio is highest in the rainy season due to lower temperature. This result is supported by Arora et al. (2022) who found highest performance ratio during the winter season in Northern India due to lower temperature.

A study on performance, degradation and reliability of PV modules in Kenya points to orientation, tilt angle, accumulation of dust and degradation of the panels as factors that influence the performance and power output from the PV system (Ngure, 2022). The study estimated a degradation rate of 1.15% and 0.99% for polycrystalline and monocrystalline modules respectively. Furthermore, the study showed that the degradation rate is highest the first five years before the degradation slows down. These degradation rates are higher than the once estimated by Danish Energy Agency (2016). In their report, they state that it is typical to use a degradation rate of 0.3 - 0.5% for the installed PV system. The difference might be explained by the fact that Danish Energy Agency (2016) used common assumptions

used globally, whereas Ngure (2022) used experimental data from Kenya.

Generally, studies on PV performance in Kenya show that increase in solar radiation and wind speed, increase the power output from solar PV, while high module temperature, accumulation of dust and increase in humidity decrease the power output. Ngure et al. (2023) showed that the accuracy of numerical models for performance prediction increases when more weather parameters are included. However, research from similar climates shows that solar radiation and module temperature have the highest influence on the power output and performance ratio of solar PV modules, and these weather parameters are therefore considered the most important for performance prediction. Moreover, other factors like tilt angle, orientation, degradation rate and the type of soil particles influence the performance of solar PV systems in Kenya (Ngure, 2022).

3 Theoretical background

This thesis primarily employs the theory and methodology of energy system analysis and linear programming, which are introduced in this section. In addition, the section introduces the Kenyan electricity tariff structure and the current energy system of the textile factory Rivatex as two key concepts.

3.1 Energy system analysis

The framework of energy system analysis is defined as "...the study of energy use, energy production and energy production in society." (Blok and Nieuwlaar, 2021, p.xxxi).

3.1.1 General procedure of energy system analysis

The analysis encompasses technical aspects that are based on thermodynamics. A simplified explanation of the first and second law of thermodynamics explains the key concepts of energy system analysis. The first law of thermodynamics states that energy cannot be lost, but can be converted from one form to another. The second law of thermodynamics states that conversion from one energy carrier to another is rarely 1:1, but often results in part of the energy being converted to heat (Blok & Nieuwlaar, 2021). These physical laws are the foundation of the energy balance resulting from the energy analysis of a given system. According to Blok and Nieuwlaar (2021, pp. 74–75) the analysis follows 5 steps

- 1. Determine the total energy use of all energy carriers in the system.
- 2. Register all energy-using and all energy conversion equipment along with its technical specifications.
- 3. When analysing space heating and cooling, register all building characteristics.
- 4. Additional measurements are made when the information in steps 2 and 3 is not sufficient.
- 5. Closing the energy balance by comparing the total energy inputs from step 1 to the total energy amount used and converted from step 2-4.

3.1.2 Optimisation objectives

Apart from the technical aspects, energy system analyses often contain financial aspects, environmental aspects or social science aspects depending on the aim of the analysis. These often serve as optimisation objectives that will either be minimised or maximised in the analysis.

When applying energy system analysis to captive systems to evaluate different energy technologies, one of the most important optimisation objectives is the economic cost (Blok & Nieuwlaar, 2021; Østergaard, 2009). However, there are many cost functions to consider such as the utility cost, the total system cost, or the societal costs (Østergaard, 2009). What cost to consider will depend on the purpose of the analysis. When the optimisation model is applied to captive systems, the enterprise will most likely be interested in the system cost. Analysing the economics of different technologies adds two steps to the general procedure. Namely evaluating the performance of the technologies, and evaluating the costs of the technologies. The costs include the investment and the operation and maintenance costs (O&M).

An energy system analysis can have many different aims, and apart from minimising costs, the aim can also be to minimise carbon dioxide emission, optimise the renewable energy fraction (REF), or minimising the unmet load fraction (Blok & Nieuwlaar, 2021; Malekpoor et al., 2018; Østergaard, 2009). The procedure of the analysis will be the same; identify the performance of the technologies, and evaluate the emissions, REF, or unmet load fraction associated with each technology.

3.1.3 Scenarios in energy system analysis

Energy system analyses can follow a scenario approach that assesses the outcomes of different scenarios. Since energy system analyses are often used to predict or evaluate future situations, using different scenarios will help decision-makers determine the consequences of their decisions. In the framework of energy system analysis, the decision-makers can be everything from policymakers to enterprises and non-governmental organisations.

The scenarios can either be descriptive or normative. Descriptive scenarios aim to describe the outcome of different future development paths, whereas normative scenarios describe how certain future situations can be achieved. Nonetheless, scenarios are often applied simply to contemplate the uncertainties associated with the analysis (Blok & Nieuwlaar, 2021).

3.2 Linear Programming

Linear programming is a simple mathematical model that can solve complex optimisation problems with hundreds of constraints (Bosch & Trick, 2014). The method is often used to solve energy system optimisation problems. An LP problem has an objective function that is a linear expression,

$$a_1x_1 + a_2x_2 + \dots + a_nx_n \{<=, =, >=\} b \tag{1}$$

where a_i and b are real coefficients and x_i are variables. In the case of the objective function, b is the objective value to be either minimised or maximised (Mitchell et al., 2009).

The solution to the problem gives the values of all decision variables that yield the optimal (minimal or maximal) objective value. The decision variables in a linear programming problem have real numerical values and are subject to several constraints. The constraints are, like the objective function, linear expressions that are often based on physical, financial, or social restrictions or requirements (Kimutai et al., 2019; Mitchell et al., 2009).

With its roots in linear programming, integer programming takes the same form as an LP problem, however, the decision variables are integers. Similarly, mixed-integer linear programming offers the possibility to solve problems containing both integer and non-integer decision variables. Common for linear programming, integer programming, and mixed-integer linear programming is the process of creating the model to solve the problem. The process is iterative and based on a defined problem. From the problem, the decision variables and their limitations are identified. The objective function and constraints are formulated and applied to a model in computer software. Through the software, the problem is solved, and the solution is evaluated. Based on the validity of the solution, one might need to modify the model until the solution gives reasonable results (Bosch & Trick, 2014; Mitchell et al., 2009).

3.3 Electricity prices in Kenya

The introduction of solar PV and battery systems in the industrial sectors serves as an alternative to buying power from the national power grid. To understand the financial impact of such a transition, one must understand the structure of the electricity tariffs in Kenya.

Kenya Power (KPLC) is the monopolist who sells power and sets the electricity prices in Kenya. They are, however, regulated by the Energy and Petroleum Regulatory Authority (EPRA) who is responsible for approving the tariff applications submitted by the KPLC. The latest retail electricity tariff review was released in 2023 and included an approved schedule for the electricity tariff until the year 2026 (EPRA, 2023).

The electricity tariffs are divided into two parts; the energy tariffs and the levies and adjustments. The energy tariffs include the consumption tariff, which is a price per kWh consumed, a fuel energy cost, which is a cost for electricity generated by thermal power plants, and a price for each kVA at the time of highest power consumption in a given month. In 2023 a time-of-use tariff (TOU) was introduced. This tariff only applies to some consumer groups and means a 50% reduction in the consumption tariff when consumption falls within the time frame of TOU. The levies and adjustment costs include adjustments for inflation and foreign exchange along with the WARMA levy, ERC levy, and REP levy that are passed to the Water Resource Management Authority, the Energy Regulatory Commission, and the Rural Electrification Authority respectively (Kenya Power, 2020). The WARMA levy varies each month depending on the share of energy produced from hydropower. The REP is fixed at 5% of the consumption charge (considering both regular consumption tariff and TOU) and the ERC is currently 0.08 KES per kWh. The ERC had been fixed at 0.03 for many years but was adjusted to 0.08 KES in 2023 (Shah, 2024).

The most recent tariff schedule showed a yearly reduction in the electricity consumption tariff for all consumer groups. However, historical data from 2014 shows fluctuating electricity tariffs that reached a peak in 2023 before the implementation of the new tariff scheme (Shah, 2024). Appendix E shows the historical prices of the consumption tariff, fuel energy cost, WARMA, and ERC.

3.4 Current energy system at Rivatex

The energy system at Rivatex uses electricity from the power grid for all machines at the factory along with general electrical purposes such as lighting and technical equipment. For the processing of textiles, the factory also uses firewood to create steam and oil for heat-treatment of the fabric.

According to the electrical technician Christine Chebutey (personal communication, 22.01.2024), Rivatex has divided the production of textiles into three main processes each supplied through its own transformer. A sketch of the energy system is shown in Figure 2. The first process is spinning, and this process is divided into "old spinning" and "new spinning". Old spinning is supplied through the first transformer (denoted T1) connected to the old main transformer. The new process is supplied through its own main transformer, that is the new main transformer. The second transformer (denoted T2) supplies the weaving process, while the third transformer (denoted T3) supplies the wet-processing which is the finishing process of the fabric. Rivatex also has a fourth transformer (denoted T4) that supplies the management system consists of automatic control of the steam production and fan motors that blow air into the oven to keep the production going (personal communication, Electrical Engineer, Ezekiel Kigen, 04.04.2024).

The factory regularly experiences power outages that last 5-15 min (personal communi-

cation, Christine Chebutey, 22.01.2024), however, there is no backup power system. Only a small UPS package of batteries for lighting is installed. According to Management Information System Administrator Enock Kiptoo Langat, wet processing is the process most sensitive to outages. Here, fabrics are treated with chemicals, and when an outage occurs, the fabrics will be kept in the chemical for too long which can affect the quality of the fabric.



Figure 2: The current energy system at Rivatex

The energy system can be divided into three subsystems; the electrical system, the steam system, and the thermal heat system. In the current energy system, these three subsystems do not interact, but act as separate systems. Each of the consumptions in Figure 2 represents a department or equipment at Rivatex, for which the electrical department has taken daily measurements of consumption. An explanation of these departments/equipments is found in appendix A. The monthly consumption of electricity for each department is shown in appendix B.

4 Method

The energy system model developed in this thesis introduced three new technologies to the existing energy system; a solar PV system, a battery system and an electrical steam boiler.

The intention of introducing a solar PV system is to increase the sustainability and feasibility of the textile factory, as well as decrease the dependency of the national power grid. The introduction of a battery system adds flexibility to the solar PV system and strengthens the independence from the power grid. Furthermore, it has the possibility to ensure continuous power supply to the factory when power outages occur on the national power grid. The model of the solar PV and battery system is grid-tied but without export capability, meaning that electricity can be imported from the national power grid, but excess generation from solar PV cannot be exported to the grid.

The introduction of an electric steam boiler serves several purposes. First of all, the current steam boilers do not meet the capacity requirements of the machines, as shown in appendix D. The current capacity is 12 tonnes/hour, however, the required capacity is 23.7 tonnes/hour. Thus installing a third boiler helps meet the demand for steam. Furthermore, the factory sometimes experiences a shortage of firewood, which increases the need for steam production from other energy sources (personal communication, Christine Chebytey, 22.01.2024). Secondly, the electric boiler couples the steam energy system with the electrical energy system of the factory. The electric steam boiler thereby increases the flexibility of the energy system because steam can be produced from electricity rather than firewood in times when the PV system produces a surplus of energy.

This thesis analysed two optimisation objectives. The first objective was to minimise the system cost with the purpose of increasing the feasibility of the enterprise. The second objective was to minimise the dependency on the grid because captive energy systems are considered a solution for the frequent power outages experienced on the national grid. In 2019, unreliable power supply, as reported by UNEP et al. (2020), contributed to 8.7% of sales losses in the textiles and garments sector.

Aside from examining the results of reducing system costs and decreasing reliance on the power grid, the analysis also employed a technique called Modelling to Generate Alternatives (MGA). The purpose of MGA was to ensure that the best solution for reducing grid dependency did not cause an unreasonably high increase in overall system costs. To achieve this, MGA introduced a constraint into the grid dependency minimisation problem. This constraint ensured that the total system cost did not exceed a 10% increase compared to the minimum cost solution of a given scenario. Essentially, MGA helped strike a balance between minimising grid dependency and keeping overall costs manageable (Price & Keppo,

2017).

Many assumptions and modeling choices were made based on conversations, emails, and data received during several visits at Rivatex in January and February 2024. Among the most important sources are electrical engineers Gideon Boit and Ezekiel Kigen who provided the electricity consumption data (Appendix B), Chief Engineer Caroline Mureithi who provided steam capacity requirements (Appendix D) and information on the current system design, and electrical technician Christine Chebutey, who showed me around the factory. Furthermore, Management Information System Administrator, Enock Kiptoo Langat, provided an important overview of the factory and its energy system. In Addition to the data from Rivatex, weather data from Moi University Weather Station, which is located 23.5 km from Rivatex, was applied (Appendix H).

This section describes the method along with the constraints and assumptions made in the model.

4.1 Optimisation with PuLP

For the simulations and analyses in this thesis, a linear programming optimisation model was built in Python version 3.9. Appendix G shows the Python code. The model used the library PuLP v2.8.0 and the LpProblem class which creates a linear programming problem. To solve the problem, the default PULP_CBC_CMD solver version 2.10.3 is used. The model was run on a computer running Windows 11 Home operating system with an Intel Pentium Silver N5030 processor running at 1.10GHz.

The use of PuLP in Python offers a platform to implement the objective function, the decision variables, and the system constraints, that are then solved according to the chosen solver. The CBC solver is a mixed-integer linear programming (MILP) solver, that solves the optimisation problem iteratively.

All variables in the model are defined as continuous LpVariable with a lower bound of 0 which means that the solution cannot contain negative variable values.

4.2 **Optimisation scenarios**

This thesis analysed four descriptive scenarios, that clarify the effect of introducing solar PV, battery, and electric boiler to the energy system, while also addressing uncertainties in the model.

A simplified drawing of the reference energy system (RES) for scenario 1, 2 and 4 is shown in Figure 3, while Figure 4 shows the RES for scenario 3.



Figure 3: Simplified RES for scenario 1, 2 and 4



Figure 4: Simplified RES for scenario 3

In addition, the current energy system introduced in chapter 3.4 was used as a reference scenario in the analysis.

Scenario 1 (High Steam & Battery)

The first scenario introduced all three new technologies. The scenario implemented a high steam demand along with the requirement of 23.7 tonnes per hour steam capacity. Furthermore, the battery was required to have the capacity to supply Wet Processing during outages on the national grid because it is the most critical load.

This scenario represents the case where all new technologies are implemented, and where the introduction of an electric boiler and a minimum capacity of the battery ensures that all demands and requirements will be met. Demands and requirements are described in chapter 4.3.5.

Scenario 2 (High Steam & Free choice)

Scenario 2 was similar to scenario 1, however, ignoring the requirement of a minimum capacity of the battery. Thus, the model was free to choose the optimal battery capacity. This scenario implemented the high steam demand and the requirement of 23.7 tonnes/hour steam capacity.

Scenario 3 (Low Steam & Only Firewood)

The third scenario introduced the solar PV system and the battery system, however, excluded the electric boiler from the model. In the third scenario, the battery system was required to have the capacity to supply the Wet Processing, however, the steam demand was reduced to what can be provided by the two existing wood boilers. That is, a lower steam demand was implemented and the steam capacity requirement of 23.7 tonnes/hour was ignored.

Scenario 3 represents the case where no changes are made to the steam system, but only the electrical system is altered by introducing the PV system and battery system.

Scenario 4 (Low Steam & Free Choice)

The last scenario introduced the PV system, the battery system, and the electric boiler, but the demand and requirements were no different from the current system. Hence, the low steam demand was implemented, and there were no minimum capacity constraints for the battery and the steam boilers. Thus, the model was free to choose the optimal technology capacities.

The results of this scenario can be directly compared to the current system because only the available technologies and energy sources have changed.

4.3 Modelling and system constraints

The reference energy system (RES) in Figure 5 shows the introduction of a PV system, a battery system, and an electric boiler.

Comparing the current system in Figure 2 to the RES in Figure 5 the current electricity consumption groups have been divided into five electricity demand groups named ElGroup1, ElGroup2, ElGroup3, ElGroup4, and ElGroup5.

The green boxes in Figure 5 represent the new technologies introduced. The grey boxes represent the existing electrical system and the yellow boxes represent current thermal systems. The energy flows are expressed by the letter X and are treated as variables in the model. Table 1 describes all decision variables in the model.

In the model, the electric boiler is supplied through transformer T4 because this transformer is assumed to have spare capacity (see appendix C.1).

The time span of the analysis is 20 years, which is 5 years less than the typical economic lifetime of solar PV systems according to IRENA (2023). The choice of life span was based on the lifetime of batteries which is often shorter than the lifetime of solar panels. The



Figure 5: RES for the energy system analysis of Rivatex textile factory.

lifetime of batteries is difficult to estimate, but based on data from the Danish Energy Agency (2018) an estimate of 20 years was made. The 20 years were simulated in monthly time steps staring in January 2024. The choice of monthly time steps was based on the consumption data (see Appendix B). Even though electricity consumption at Rivatex is recorded every day in a notebook, only the monthly consumptions are recorded digitally. Thus, the monthly consumption was used in the model.

An operating time of 192.86 hours per month was assumed for modeling purposes as described in Appendix C.2.

Annotation	Description
X_{el1}	Energy in kWh from the grid through the transformer T1 (kWh)
X_{el2}	Energy in kWh from the grid through the transformer T2 (kWh)
X_{el3}	Energy in kWh from the grid through the transformer T3 (kWh)
X_{el4}	Energy in kWh from the grid through the transformer T4 (kWh)
X_{elnew}	Energy in kWh from the grid through the New Main Transformer (kWh)
X_{PV1}	Energy from solar PV to electricity demand group 1 (kWh)
X_{PV2}	Energy from solar PV to electricity demand group 2 (kWh)
X_{PV3}	Energy from solar PV to electricity demand group 3 (kWh)
X_{PV4}	Energy from solar PV to electricity demand group 4 and electric boiler(kWh)
X_{PV5}	Energy from solar PV to electricity demand group 5 (kWh)
X _{batin}	Energy from solar PV to the battery (kWh)
$X_{batout1}$	Energy from battery to demand group 1 (kWh)
$X_{batout2}$	Energy from battery to demand group 2 (kWh)
$X_{batout3}$	Energy from battery to demand group 3 (kWh)
$X_{batout4}$	Energy from battery to demand group 4 (kWh)
$X_{batout5}$	Energy from battery to demand group 5 (kWh)
X_{sw}	Energy in steam produced from firewood (kWh)
X_{se}	Energy in steam produced from electric boiler (kWh)
C_{bat}	Capacity of the battery (kWh)
C_{se}	Capacity of the electric boiler measured in tonnes of steam per hour
A	Area of solar PV (m^2)

Table 1: Decision variables in the LP model

4.3.1 Objective Functions

The objective of the analysis is to optimise the energy system of the textile factory Rivatex through two optimisation criteria; minimising the system cost and minimising the dependency on the national power grid.

Minimising system cost

The first objective of the analysis was to minimise the system cost measured in Kenyan Shilling (KES) through the following objective function,

Minimise:
$$Z_{cost} = \{ (X_{el1} + X_{el2} + X_{el3} + X_{el4} + X_{elnex}) \cdot a_{el} + (X_{PV1} + X_{PV2} + X_{PV3} + X_{PV4} + X_{PV5} + X_{batin}) \cdot a_{PV} + X_{sw} \cdot a_{sw} + (C_{bat} \cdot a_{bat} + C_{se} \cdot a_{se}) \cdot T \}$$

(2)

where all energy flows are represented by the letter X and capacities by the letter C (see Table 1). The costs are represented by the letter a. That is, a_{el} is the total electricity tariff

in KES/kWh, a_{PV} is the LCOE of the solar PV system in KES/kWh, a_{sw} is the price for each kWh of steam produced from firewood, a_{bat} is the discounted annual investment cost of the battery system and a_{se} is the discounted annual investment cost of the electric boiler. Lastly, T is the time span of 20 years. The objective function minimises the total system cost throughout the time span of 20 year. The solution provides the optimal capacity of each technology in order to achieve minimal system cost.

Minimising dependency on the national power grid

The second objective was to minimise the dependency on the national power grid. This was done by minimisation of the energy consumed from the national power grid though the following objective function,

Minimise:
$$Z_{grid} = \{X_{el1} + X_{el2} + X_{el3} + X_{el4} + X_{elnex}\}$$
 (3)

where X again refers to the energy flow measured in kWh as shown in table 1.

The objective function simply minimises the sum of energy from the power grid, thus, the solution provides the optimal technology capacities that minimise the energy from the power grid. Furthermore, the model calculates the system cost of the optimal solution which makes the results comparable to the results from the cost minimisation objective.

4.3.2 Modelling of solar PV system

For the LP model of this thesis, data from the Jinko Tiger Neo N-type 72HL4-575 panels were used since it is a monocrystalline model on the Kenyan market. The choice of monocrystalline panels is explained in appendix C.3. The data used in the model is given in Table 2 (Jinko Solar Co., 2021).

Since Kenya is located along the equator, it is discussed whether the solar panels should be oriented to the east and west or the south. Recent research on solar performance in Kenya shows that systems oriented to the south have a higher energy output than systems oriented to the east and west (Ngure et al., 2023). Thus, the area of the south-oriented roof at Rivatex factory in Eldoret has been measured using Google Earth and will be the upper limitation of the PV capacity at the factory (Google, n.d.). It was assumed that 90% of the area can be covered with PV modules. The remaining 10% was reserved for spacing between modules. The spacing allows wind to move between the modules and thereby cool the modules which increases the efficiency. The available area in (4) was applied as a constraint in the model.

$$A \le 8855.99m^2 \cdot 90\% \tag{4}$$

Rated power (W)	575
Hight of panel (mm)	2278
Width of panel (mm)	1134
Panel efficiency $(\%)$	22.26
Temperature Coefficient Pmax (%/ $^{\circ}$ C)	-0.30
NOCT $(\%/^{\circ}C)$	45 + / - 2
STC temperature $(\%/^{\circ}C)$	25
Maximum Power Current (A)	13.62
Maximum Power Voltage (V)	42.22
Short-circuit Current (A)	14.39
Open-circuit Voltage (V)	50.88

Datasheet for solar PV module AS545M

Table 2: Data for solar PV module

To estimate the energy output from solar PV panels, weather data from Moi University weather station was used. The data was provided by Abraham Kosgei who is in charge of the weather station (personal communication, 09.02.2024). The data covers hourly measurements of 10 different weather parameters in 2021, 2022 and 2023. Amongst these are radiation measured in W/m^2 and outdoor temperature measured in ^{o}C which were used for the estimation of energy output from PV panels in the model. These parameters were chosen based on their importance, as highlighted in the literature discussed in chapter 2.2. The average radiation and temperature for every hour of the year were calculated from the three years of data. Due to some technical issues at the weather station, there are some gaps in the measurements from 2022 and 2023. However, the missing measurements from the two years are never at the time of the year which means that the average values will always be based on at least two years of data. Graphs of the average temperature and radiation for each month are shown in Appendix H.

The calculation of energy production was based on the radiation, the efficiency of the PV module, inverter efficiency, and losses due to the high temperature of the module. The PV module cell temperature was estimated from the radiation and ambient temperature (Al-Badi, 2020),

$$T_c = T_a + \frac{NOCT - 20}{0.8} \cdot I \tag{5}$$

where T_a is the ambient temperature in degrees Celsius, NOCT is the nominal operating cell temperature from Table 2 and I is the solar radiation in W/m^2 . Once the module temperature has been determined, the energy output in kWh per square meter for every hour was calculated as follows (Ueda et al., 2009):

$$E_{PV,h} = \frac{I_h \cdot \eta_p \cdot \eta_{inv}}{1 + \alpha_t \cdot (T_{c,h} - T_n)} \tag{6}$$

where *h* denotes the hour, η_p is the solar PV panel efficiency, η_{inv} is the inverter efficiency, α_t is the temperature coefficient of the maximum power output of the PV module and T_n is the temperature in degrees Celsius during standard test condition. The inverter loss was estimated to be 1.6% which yields an inverter efficiency of 98.4%. The estimation is based on values from similar projects. Arora et al. (2022) used a value of 1.4% inverter losses, Al-Badi (2020) used 1.6% and (Ngure et al., 2023) uses 2%.

The power output from solar panels decreases with time due to degradation of the modules. Thus, the LP model included a yearly degradation rate of 0.99%, which is the result of the research by Ngure (2022). This rate is higher than the degradation rate of 0.40% from the data sheet from Jinko Solar Co. (2021), but the choice was based on the fact that the degradation rate of 0.99% stems from measured data in the Kenyan weather and climate, and is furthermore the most conservative estimate.

The monthly energy output in kWh from solar PV per square meter was calculated by summing the hourly energy output, and degrading the output each year. Equation (7) shows the calculation

$$E_{PV_{i,j}} = \sum_{h=1}^{t} E_{PV,h_{i,j}} \cdot (1 - r_{deg})^{i}$$
(7)

Here, *i* denoted the years, *j* denoted the months and *h* denotes the hours. *t* is the number of hours in a given month. r_{deg} is the degradation rate, and the equation ensures that the energy output in every month of the simulation is degraded by a rate related to the associated year.

The technology constraint for the solar PV system then becomes,

$$X_{PV1_{i,j}} + X_{PV2_{i,j}} + X_{PV3_{i,j}} + X_{PV4_{i,j}} + X_{PV5_{i,j}} + X_{batin_{i,j}} = E_{PV_{i,j}} \cdot A$$
(8)

4.3.3 Modelling of battery system

For this thesis, data for lithium-ion batteries will be used because it is the most common technology type for battery energy systems (Hannan et al., 2021).

According to the Danish Energy Agency (2018) lithium-ion batteries in 2020 have a round trip efficiency of 91% (η_{rt}), which also accounts for power losses in conversion. Additionally, batteries have an energy loss of 0.1% per day equivalent to 3.04% per month (Bøhren & Gjærum, 2016). In this thesis, these losses were accounted for in the state of charge (SOC). The SOC is measured in kWh and calculated as shown in equation (9).

$$SOC_{i,j} = SOC_{i,j-1} \cdot (1 - \eta_{batloss}) + X_{batin_{i,j}} - \frac{X_{batout_{i,j}}}{\eta_{rt}}$$
(9)

where *i* is each year while *j* is each month and $\eta_{batloss}$ is the monthly energy loss of 3.04%. X_{batin} and X_{batout} are the energy flows added to the battery from solar PV and supplied to the factory from the battery respectively. In this model, the SOC variable represents the stage of charge at the end of a period, that is, at the end of each month.

The SOC should always be within the capacity limits of the battery, assured by the constraint in (10). The model used the gross capacity, C_{bat} , which is the usable capacity adjusted for the allowable depth of discharge (DOD).

$$0 \le SOC_i \le C_{bat} \tag{10}$$

Furthermore, since batteries are meant to store energy for short time intervals, a constraint was added ensuring that the SOC at the beginning of a year was equal to the SOC at the end of that year (Danish Energy Agency, 2018, p. 172),

$$SOC_{i,0} - X_{batin_{i,0}} + \frac{X_{batout_{i,0}}}{\eta_{rt}} = SOC_{i,11}$$
 (11)

Here *i* denotes the year, $SOC_{i,0}$ is the SOC at the end of in the first month (January) of the i'th year, $SOC_{i,11}$ is the SOC at the end of December that same year. $X_{batin_{i,0}}$ and $X_{batout_{i,0}}$ are the energy flows to and from the battery in January in the i'th year. These are subtracted and added respectively in order to calculate the SOC in the beginning of January.

The battery capacity is a variable in the model and is determined by solving the optimisation problem. In scenarios 1 and 3 the battery had a minimum capacity constraint ensuring supply to wet processing during a power outage because it is the most critical production process (personal communication, Enock Kiptoo Langat, 22.01.2024). The power outages on the national grid typically last 5-15 minutes (personal communication, Christine Chebutey, 22.01.2024). Due to variations in both electricity demand and duration of the power outages, the battery was dimensioned to ensure energy supply for wet processing for one hour. From the consumption data of 2022 and 2023, the highest monthly power consumption for wet processing was 51900 kWh. Assuming 192.86 operating hours per month gives an hourly consumption of 269.11 kWh. The battery must be able to cover the consumption and the losses associated with discharging the battery and converting from DC to AC. The losses were calculated using the round-trip efficiency. Hence, the lower limit of the battery capacity in scenario 1 and 3 is given in equation (12).

$$C_{bat} >= 295.73 \text{ kWh}$$
 (12)

4.3.4 Modelling of steam boilers

The firewood steam boilers were modelled with an upper capacity constraint equivalent to the current boiler capacity at Rivatex, measured in tonnes per hour:

$$C_{sw} \ll 2 \cdot 6 \text{ tonnes/hour}$$
 (13)

The model added no capacity constraint on the electric boiler, however, in scenario 1 and 2, a constraint on the total steam capacity was implemented to ensure that the requirement in appendix D was met:

$$C_{sw} + C_{se} \ge 23.712 \text{ tonnes/hour}$$
(14)

Here, C_{se} is the capacity of the electric boiler.

The steam boilers were modelled with a technology constraint ensuring that they do not produce more steam than the capacity and operation time allows,

$$X_{sw_{i,j}} <= C_{sw} \cdot 192.86 \cdot E_{steam} \tag{15}$$

$$X_{se_{i,j}} <= C_{se} \cdot 192.86 \cdot E_{steam} \tag{16}$$

Where *i* represents each year and *j* represents each month. X_{sw} is the steam energy generated from firewood and X_{se} is the steam energy generated by the electric boiler, both measured in kWh. Lastly, E_{steam} is the energy measured in kWh contained in a tonne of steam, which is estimated in paragraph 4.3.5.

The electric boiler has an additional technology constraint coupling the steam production to the consumption of electricity:

$$X_{elb} \cdot \eta_{se} = X_{se} \tag{17}$$

where X_{elb} is the electricity consumption of the boiler and η_{se} is the efficiency of the electric boiler. According to Danish Energy Agency (2016) the efficiency of electric boilers is 99%, which was the value applied to the model.

4.3.5 Energy Demand

The demands for electricity and steam were estimated for every month in the 20-year life span of the analysis. The demand estimations were based on consumption data from 2022 and 2023.

Electricity Demand

Monthly electricity consumption for each department in 2022 and 2023 was used to estimate future demand. The data was provided by electrical engineer Ezekiel Kigen (personal communication, 26.01.2024) in many separate spreadsheets, some with consumption data for one month, others with data for several months, and some even contained daily data for one or two months. It should be noted, that different spreadsheets contained data for the same month, however, with different values. Hence, there was great inaccuracy in the data provided. The consumption data was gathered and represented in Appendix B.

According to Electrical Technician Christine Chebutey (personal communication, 22.01.2024), electricity consumption is highly dependent on the production each month, and there is little variation in the consumption from year to year. Furthermore, she expects no change in the consumption in the future. For that reason, the estimation of electricity demand is an average of the electricity consumption in 2022 and 2023.

Appendix B shows the sum of electricity consumption for new spinning and old spinning. However, these are two different departments supplied through two different transformers as illustrated in Figure 2. From the notebook with daily consumption readings, 14 random days were picked out, and the share of electricity consumption from each of the two departments was calculated. From the 14 days, an average ratio of electricity consumption from old and new spinning respectively was calculated, and the ratios were used to estimate consumption from each department. The consumption data and calculation of consumption ratios for the 14 days are shown in Table 3

From Figure 5 the electricity demand constraints were formulated in equations (18) - (22),

$$X_{elnew_{i,j}} + X_{PV5_{i,j}} + X_{batout5_{i,j}} = DM_{ElGroup5_j}$$

$$\tag{18}$$

$$X_{el1_{i,j}} + X_{PV1_{i,j}} + X_{batout1_{i,j}} = DM_{ElGroup1_j}$$

$$\tag{19}$$

$$X_{el2_{i,j}} + X_{PV2_{i,j}} + X_{batout2_{i,j}} = DM_{ElGroup2_j}$$

$$\tag{20}$$

$$X_{el3_{i,j}} + X_{PV3_{i,j}} + X_{batout3_{i,j}} = DM_{ElGroup3_j}$$

$$\tag{21}$$

17

$$X_{el4_{i,j}} + X_{PV4_{i,j}} + X_{batout4_{i,j}} = DM_{ElGroup4_j} + \frac{X_{se_{i,j}}}{\eta_{se}}$$
(22)

Date	New Spinning	Old Spinning	% New	% Old
01/04/2023	148	17	89.7	10.3
03/04/2023	812	27	96.8	3.2
04/04/2023	904	13	98.6	1.4
29/04/2023	1657	44	97.4	2.6
16/05/2023	3507	58	98.4	1.6
12/06/2023	0	15	0	100
01/08/2023	682	826	45.2	5.5
08/08/2023	529	20	96.4	3.6
05/09/2023	1448	33	97.8	2.2
15/09/2023	2989	3008	49.8	50.2
03/10/2023	2283	1437	61.4	38.6
03/11/2023	618	25	96.1	3.9
06/12/2023	813	24	97.1	2.9
22/01/2024	212	17	92.6	7.4
26/01/2024	452	21	95.6	4.4
		Average	80.9	19.1

Table 3: Consumption, and ratio of total consumption, of electricity from New Spinning and Old Spinning

where i denotes the year while j denotes the month.

It was assumed that the introduced electric boiler comes with its own control system and that no fan motors are necessary. Hence, the electricity consumption for steam control is purely related to the use of firewood boilers. In order to link the electricity consumption for steam control, to the steam production from firewood, an average electricity consumption per kWh of steam from firewood was calculated. Therefore, the demand for electricity from demand group 4 depends on the steam production from firewood. Appendix C.4 shows the calculation of electricity demand for steam control.

Steam demand and firewood consumption

Detailed monthly data regarding steam demand and consumption of firewood were not obtained. Furthermore, the absence of data sheets or technical documents for the firewood boilers leaves their efficiencies unknown. Through personal communication with the Store and Supply Chain Management (personal communication, 26.01.2024) it was, however, possible to receive monthly estimates which were used in the model. Due to the limited access to data, the steam demand estimations were made with high uncertainty, and the model therefore implemented two different steam demands.

According to Store and Supply Chain Management, each of the two wood boilers can produce six tonnes of steam per hour which is only half of the capacity required by the machines, as illustrated in appendix D. Therefore, it was assumed that the firewood boilers always operate at maximum capacity in the current system at Rivatex. Furthermore, it was assumed that steam is produced during normal working hours which is 192.86 hours per month (see Appendix C.2). The energy carried in steam depends on the temperature and pressure of steam (Kenki Dryer, 2020, Thunder Said Energy, n.d.). Appendix D shows that the average pressure required by the machines at Rivatex is 4.1 bar. According to Kenki Dryer (2020) the energy in saturated steam at 4 bar is 761 kWh per tonne. Hence, it was assumed that each tonne of steam carries 761 kWh and that the demand covers the energy extracted from steam so that the energy in water returning to the boilers does not need to be accounted for. Using these assumptions, the current monthly energy consumption from steam was estimated:

 $2\cdot 6$ tonnes/h \cdot 192.86 hours \cdot 761 kWh/tonne = 1, 761, 197.52 kWh

The lowest steam demand estimation was 1,761,190 kWh per month, which is slightly lower than the calculation of energy in the steam produced by the firewood boilers. A slightly lower estimation was chosen to ensure that the energy can be delivered by the firewood boilers alone despite inaccuracies and rounding of values in the model. However, because the boiler capacity does not meet the machine requirements, the introduction of an electric boiler was assumed to increase the demand for steam. Thus, the second estimation of steam demand is based on a capacity of 23.712 tonnes per hour and assumes 75% full load operating hours per month, which yields an energy demand from steam per month of

 $75\% \cdot 192.86~{\rm hour} \cdot 23.712~{\rm tonnes/h} \cdot 761~{\rm kWh/tonnes} = 2,610,094.72~{\rm kWh}$

The low steam demand was applied to scenario 1 and 2, while the high steam demand was applied to scenario 3 and 4.

4.4 Financial estimations

This section describes the estimations of prices applied to the model. The analysis assumed no export capacity to the national power grid. Consequently, potential financial benefits from exporting or selling electricity produced by the solar PV system were not included in the model. The decision to exclude export benefits was guided by literature pointing to regulatory uncertainty as a key challenge to the expansion of solar PV in Kenya (see chapter 2.1.1). By leaving out benefits, future changes in the regulatory framework will not reduce the feasibility or flexibility of the analysed energy system.
The total cost for any energy technology consists of an investment cost, operation and maintenance costs (O&M), fuel costs and decommissioning costs. The O&M includes both fixed and variable costs (Peake, 2018). This thesis did not include decommissioning costs, since the energy technologies are likely to be operational for longer than the time span of the analysis.

For investment costs, a weighted average cost of capital (WACC) of 7.5 % was applied since this is the standard value applied to all countries outside OECD (The Organisation for Economic Co-operation and Development) or China in 2020 (IRENA, 2023). From the WACC and the life span of 20 years, the annuity factor was calculated (Bøhren & Gjærum, 2016):

$$Af = \frac{0.075 \cdot (1 + 0.075)^{20}}{(1 + 0.075)^{20} - 1} = 0.09809$$

Furthermore, the model used real prices referring to the price level of 2024.

4.4.1 LCOE of solar PV system

The cost of generation units, including solar PV systems, are often modeled as levelised cost of energy form the following formula (IRENA, 2023):

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + M_t}{(1 + WACC)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1 + WACC)^t}}$$
(23)

 I_t is the annual investment cost, M_t is the annual operation and maintenance costs, E_t is the yearly energy production, and n is the lifetime of the system which in this thesis is 20 years. Note that solar energy does not have a fuel cost since the energy from the sun is free of charge.

Table 4 shows the cost components used to calculate the LCOE. All prices have been corrected for inflation and represent the 2024 value (Inflation Tool, 2024). Furthermore, the investment cost of solar PV systems from JKUAT Enterprise Limited (2022) depends on the installed capacity, which is one of the optimisation variables in the LP model. For that reason, the investment cost in Table 4 represents an inflation-adjusted average of the investment costs for systems above 100 kW, based on the assumption that the optimal capacity of the system will be above 100 kW. A system of 100 kW only covers 5.6% of the available roof area and can produce no more than 9.3% of the average yearly consumption at Rivatex, which explains why the assumed solar PV capacity is above 100 kW.

The calculated LCOE of 7.76 KES/kWh corresponds to a price of 0.058 \$/kWh, which is slightly higher than 0.049 \$/kWh presented in IRENA (2023), but lower than the lowest

	Value	Unit	Comments
Capacity per m^2	0.22259	kW/m^2	using dimensions from Table 2
			(Jinko Solar Co., 2021)
O&M	8.18	per kW	(IRENA, 2023)
	1090.38	KES/kW	Exchange rate 133.29 from Xe (2024)
Investment	921.91	\$ per kW	(JKUAT Enterprise Limited, 2022)
	$122,\!881.50$	KES/kW	Exchange 133.29 rate from Xe (2024)
Yearly production	377.18	kWh/m^2	Based on weather data from Moi University
			and neglecting degradation of the panels
LCOE	7.76	KES/kWh	Using a discount rate of 7.5%

Table 4: Calculation of solar PV system LCOE

predicted value of 0.06 \$/kWh in JKUAT Enterprise Limited (2022). It should be noted that both of these reports use data and price levels from 2022, and it is expected that the cost of solar PV systems have reduced since as a result of technological learning. The LCOE estimation is lower than the retail price of electricity in Kenya. As explained in chapter 3.3, the electricity bill consists of many tariffs, one of them being the consumption tariff. The consumption tariff alone was 12.52 KES/kWh in December 2023, and since 2014, the price has not been below 8 KES/kWh (see appendix E and F). Thus, from comparing the LCOE of solar PV and the consumption tariff, it is clear that solar PV is the most economically viable source of electricity.

4.4.2 Cost of battery system

The battery system is not a power-generating technology, and for that reason, the costs do not include fuel costs. The operation and maintenance costs (O&M) of the battery systems are considered to be neglectable because battery systems generally need little maintenance. O&M given in a report by Danish Energy Agency (2018) are insignificant compared to the investment cost and also vary depending on the system application. Furthermore, a similar study by Elbaz and Guneser (2021) ignores O&M for the battery system.

To estimate the investment cost of the battery system, numbers from the Danish Energy Agency (2018) were used.

The investment cost of batteries was calculated as an annual cost per kWh of capacity installed. It was assumed that all numbers in the report by Danish Energy Agency (2018) are based on the gross capacity of the battery and that the depth of discharge (DOD) limit has been accounted for. The investment cost for 2020 is estimated to be $1.042 \in /Wh$ in 2015 prices. With an average yearly inflation of the euro of 2.47% and an exchange rate of

143.87, this corresponds to an investment cost of 186.76 KES/Wh in 2024 prices (Inflation Tool, 2024; Xe, 2024). This cost covers the whole battery system including conversion, battery management systems, and installation. By multiplying with the annuity factor, the annual investment cost of a battery system applied to the model was estimated at 18319.80 KES/kWh.

4.4.3 Cost of electric boiler

To estimate the prices of the electric steam boiler, numbers from Danish Energy Agency (2016) were used. The O&M of the electric boiler given in the report is insignificant compared to the investment costs and is neglected in this thesis, like the O&M for the battery system.

The report, for which the financial data was updated in 2019, estimates an investment price of $0.15 \in \text{per W}$ in 2020 and $0.14 \in \text{per W}$ in 2030 for low-voltage electric boilers with a power rating of 1-5 MW. Since the power rating of the boiler for Rivatex must be above 1 MW to meet the steam capacity requirement listed in Appendix D, it falls within the category of the report (Danish Energy Agency, 2016).

The investment prices from the report include the price of a transformer and costs related to grid connection which do not apply to the project of this thesis. For that reason, the 2030 price estimation from Danish Energy Agency (2016) of $0.14 \in \text{per W}$ (corresponding to 20.14 KES per W (Xe, 2024)) was applied to the model.

The steam capacity requirement in Appendix D is given in tonnes/hour, thus, the investment cost was converted. To do so, data from Vapor Power International (n.d.) boiler models rated above 1 MW was used. An average power rating corresponding to one tonnes/h was found to be 646.13 kW, and from the following calculation, the investment cost is 13014.27 KES/tonnes/hour:

Inv. el-boiler = $20.1418 \text{ KES/W} \cdot 646.13 \text{ W/tonnes/h} = 13014.27 \text{ KES/tonnes/h}$

By multiplying with the annuity factor, an annual cost of 1276.60 KES/tonnes/h was determined.

Apart from the investment cost of an electric boiler, there will be a fuel cost associated with the consumption of electricity. This cost is calculated by multiplying the consumption of electricity with the electricity costs.

4.4.4 Cost of steam production from firewood

The firewood boilers are part of the current system, consequently, only fuel cost and O&M apply to the boiler. It was not possible to access data on the O&M, and the cost was

therefore excluded from the model. Hence, only the fuel cost was considered.

According to Store and Supply Chain Management (personal communication, 26.01.2024), the two firewood steam boilers consume approximately 364 tonnes of firewood per month at a price of 3000 - 3400 KES per tonne. When using the firewood boilers, the fuel cost is the cost of firewood. Since the number of operating hours per month and the efficiency of the boilers are unknown, the cost of steam production from firewood was based on the estimation of steam energy produced per month. This brings a cost of steam of

 $\text{Cost of steam from wood} = \frac{3200 \text{ KES/tonne wood} \cdot 364 \text{ tonne wood}}{1,761,197.52 \text{kWh}} = 0.66 \text{ KES/kWh}$

The estimate of 0.66 KES/kWh was applied to the model.

4.4.5 Electricity prices

To analyse the system cost, an estimation of electricity prices for the next 20 years was made. This estimation ignored adjustment costs because these historically contribute little to the total bill, they are highly fluctuating, and they even have negative values in some periods (Shah, 2024). Table 5 gives an overview of the assumptions regarding electricity prices.

Electricity tariff component	Assumption
Consumption tariff	Follows tariff schedule until 2026,
	and a replication of historical prices
TOU/Low Rate Consumption	50% of regular consumption tariff
	applies to 29.3% of consumption
FCC tariff	Follows tariff schedule until 2026,
	and a replication of historical prices
Maximum power demand tariff	Not included
WARMA Levy	0.01 KES/kWh
ERC Levy	0.08 KES/kWh
REP Levy	5% of consumption tariff
	considering both regular and TOU tariff
Adjustment costs	Not included
VAT	16% of total electricity bill

Table 5: Estimation of electricity tariffs applied to the model

Rivatex factory belongs to the consumer group CI3, which means that they currently pay a regular consumption tariff of 12.52 KES/kWh. To estimate the future consumption tariff, the planned prices until 2026 from EPRA (2023) have been applied. From 2026 and onwards, historical data on electricity costs in Kenya from 2014 to 2023 were used. These were made available online by Samir Shah (Shah, 2024) in nominal prices and were adjusted for inflation to represent the price level in 2024 (personal communication, Samir Shah, 18.03.2024). Appendix E shows the inflation-adjusted historical energy tariffs and levies.

An electricity bill for Rivatex for December 2023, (personal communication, Gideon Boit, 27.03.2024) shows that on average 29.3% of the consumption is low rate, that is, the TOU tariff applies (EPRA, 2023) (see Appendix F). For the purpose of this thesis, it was assumed that every month has an average of 29.3% low rate consumption.

The electricity bill also shows a maximum demand of 900 kVA in December 2023 for which the factory paid 333000 KES or 370 KES per kVA. This is a significant share of the total bill, however, since this thesis only looks at energy consumption and not power consumption, the demand charge was ignored in the model.

Since there is no clear trend in the change and fluctuations of the consumption and FCC tariffs (see Appendix E), it was assumed that the prices replicate themselves, as for the consumption tariff. That is, the electricity prices from 2014 to 2023 were used as the predicted prices for the second half of 2026 and onwards.

From Shah (2024) it shows that the WARMA levy has had a value of 0.02 or 0.01 without big fluctuations since 2017. The levy depends on the amount of electricity generated from hydropower in a given month, and based on the Kenya Energy Transition & Investment Plan, it is estimated that the share of generation from hydropower will decrease. The Kenyan Ministry of Energy and Petroleum expects a total increase in power generation from 3 GW in 2025 to 178 GW in 2045. Most of the capacity expansion is expected to come from solar PV while there will be almost no increase in power generation from hydropower (Ministry of Energy and Petroleum, 2023). For that reason, this model applied a WARMA levy of 0.01 KES/kWh.

As mentioned in 3.3, the ERC levy was adjusted to 0.08 KES per kWh in 2023, and it was assumed that the levy remained constant throughout the time span of the analysis. This assumption was based on the fact that the ERC levy had remained constant for at least 9 years before it was adjusted in 2021 (Shah, 2024).

Lastly, 16% VAT was applied to the total electricity cost, and the REP levy of 5% of the consumption tariff was implemented in the model.

5 Results

The results from all optimisation problems are represented in Table 6. The table shows the optimal capacities of solar PV, battery, and electric boiler along with the total system cost for the entire 20-year time span. As a reference, the table also shows an estimation of the current system cost based on the assumptions used in the model. It should be noted that the current system along with scenarios 1 and 2 applied the low steam demand, whereas scenarios 1 and 2 applied the high steam demand as explained in paragraph 4.3.5. The system costs outlined in Table 6 encompass the expenses related to grid electricity, firewood, and the technological components specified within the table for each scenario.

	System Cost (MKES)	Solar PV Cap. (kW)	Battery Cap. (kWh)	El Boiler Cap. (tonnes/h)
Current System	1217.89	-	-	-
Scenario 1 Cost	4443.26	1774.11	295.73	11.712
Scenario 1 Grid	4443.27	1774.11	295.73	11.712
Scenario 2 Cost	4334.91	1774.11	0	11.712
Scenario 2 Grid	4334.91	1774.11	0	11.712
Scenario 3 Cost	930.19	1283.00	295.73	-
Scenario 3 Grid	80,072.44	1720.99	216,744.84	-
Scenario 3 MGA	1024.21	1285.36	671.31	-
Scenario 4 Cost	771.46	1724.23	0	0.61
Scenario 4 Grid	$96,\!807.21$	1774.11	262,268.69	1.32
Scenario 4 MGA	848.61	1774.11	371.03	0.66

Table 6: Optimal technology capacities for each scenario and optimisation problem

Comparing the system cost from scenarios 1 and 2 versus the current system cost underscores the significant impact of steam demand estimates on the optimal solution. To meet increased steam capacity requirements, the addition of an electric boiler becomes necessary. However, the introduction of an electric boiler substantially increases system costs, evident in scenario 1 (4443.26 MKES) and scenario 2 (4334.91 MKES). Therefore, the analyse of the results will separate scenarios 1 and 2 (high steam demand) from scenarios 3 and 4 (low steam demand).

Table 6 also shows that the optimal battery capacity varies from 0 kWh in scenario 2 (*High Steam & Free Choice*) to 262.37 MWh in scenario 4 (*Low Steam & Free Choice*) when minimising grid dependency. The optimal battery capacity is highly dependent on the electric boiler capacity and whether the model minimises system cost or grid dependency.

The following sections present the findings from each optimisation objective, detailing the optimal technology capacities in each scenario.

5.1 Minimising system cost

The system cost analyses of each scenario highlight a consistent trend: the implementation of a solar PV system reduces overall expenses. Specifically, when contrasting the current system cost of 1217.89 MKES with scenario 3 (930.19 MKES) and scenario 4 (771.46 MKES) aimed at minimising cost, the introduction of solar PV demonstrates a clear cost reduction.

The feasibility of a solar PV system is also evident from the optimal solutions of scenarios 1 and 2 which both utilises the full solar PV capacity potential.

5.1.1 High steam demand

The optimal solution of the two scenarios with high steam demand are rather similar. The scenarios both result in 1774.11 kW PV capacity and 11.712 tonnes/hour electric boiler capacity. However, scenario 1 is at minimum battery capacity in both cases, while scenario 2 had no capacity constraint for the battery, resulting in an optimal solution without a battery system. That is, the introduction of a battery increases system cost when the steam demand (and thus the electricity demand) is high. The result is evident in scenario 1 (*High Steam & Battery*) being 108.35 MKES higher than scenario 2 (*High Steam & Free Choice*).

Figure 6 shows how the yearly production from solar PV is far from enough to cover the factory's electricity demand. In fact, the electricity production from PV is only approximately 20% of the electricity demand. Hence, the installation of a battery does not decrease the dependency on the power grid. However, it does serve as backup power for the wet processing in scenario 1.



Figure 6: Scenario 1 & 2, Electricity production from solar PV and electricity demand in all months of the analysis

Figure 6 shows the production pattern for the solar PV system when the entire available roof area is utilised. The production pattern is repeated every year, however, owing to yearly degradation, its output diminishes annually.

The electric boiler capacity of 11.712 tonnes/hour is just enough to cover the requirement of a total boiler capacity of 23.712 tonnes/hour. Moreover, the steam demand was first and foremost covered by the firewood boilers that supplied 1,761,171 kWh of steam every month of the analysis and thereby utilising the firewood boilers' full capacity. This can be explained by the fact that steam from firewood has a cost of 0.66 KES/kWh, while the cost of steam production from the electric boiler is the cost of electricity which is more than ten times higher.

5.1.2 Low steam demand

Scenarios 3 and 4 are characterized by low steam demand. Scenario 3 only allowed the model to produce steam from firewood, and furthermore implemented a minimum capacity on the battery system. Scenario 4 allowed the model to optimize technology capacities without constraints, except for the upper limit on solar PV capacity. The results in Table 6 show that the system cost was significantly lower in scenario 4 (771.46 MKES) than in scenario 3 (930.19 MKES). Interestingly, scenario 4 had an electric boiler capacity of 0.61 tonnes/hour despite the steam demand being reduced to what the two firewood boilers can deliver. In fact, scenario 4 with the combination of 1774.11 kW solar PV, no battery, and an electric boiler of 0.61 tonnes per hour yields the lowest system cost of all scenarios analysed.

The optimal solution for both scenarios did not fully utilise the available area for solar PV, however, the optimal capacity was 441.23 kW higher in scenario 4 compared to scenario 3. Figure 7 illustrates how the battery and the electric steam boiler are utilised in scenarios 3 and 4 respectively.

The figure illustrates how the energy production from solar PV is higher in scenario 4 than scenario 3 due to the higher capacity. Furthermore, the figure shows that both the battery and the electric boiler are utilised in months when PV production exceeds the electricity demand.

5.2 Minimising dependency on the national power grid

Table 6 shows that minimising grid dependency causes the biggest variation in battery capacity, electric boiler capacity, and system cost across the four optimisation scenarios. The following paragraphs analyse and explain the differences in optimal solutions.



Figure 7: Scenario 3 & 4, solar PV production, steam from el-boiler, charging of battery and consumption from electricity demand groups when minimising system cost

5.2.1 High steam demand

The high steam demand makes the system highly dependent on electricity from the grid due to the big difference between electricity production on-site and electricity demand as illustrated in Figure 6. In scenario 2, where no battery was implemented, there was no difference between the optimal solution when minimising system cost and the optimal solution when minimising dependency on the grid. However, when looking at the results from scenario 1 (High Steam & Battery), Table 6 presents one difference between the two optimisation objectives, namely the system cost. The system cost is 10,000 KES lower when minimising cost rather than minimising grid dependency. This result can be ascribed to the battery input outlined in Table 7. When minimising the system cost, the input to the battery is higher than when minimising the dependency on the power grid. In both cases, the battery capacity is 295.73 kWh, which is the minimum capacity to supply wet processing during outages. Due to the electricity consumption being higher than the production from solar PV, the production from solar PV is consumed instantly. Consequently, the battery does not decrease dependency on the grid. Instead, the battery losses during storage and conversion actually increase the electricity consumption from the power grid. Moreover, as the cost of the battery system is solely an investment cost, which remains constant in both cases, utilizing the battery to shift consumption from times with high prices to times with low prices ultimately leads to the lowest system cost.

	Solar PV (MWh)	Grid (MWh)	Battery input (kWh)
Minimising Cost	54,793.22	203.356, 15	4883.03
Minimising Grid Dependency	54,793.22	203,355.19	0
Difference	0	0.96	4883,03

Table 7: Scenario 1, Total Solar PV production, battery output and consumption from the power grid throughout the time span of the analysis in the two optimisation objectives

5.2.2 Low steam demand

Implementing low steam demand enables the model to minimise the grid dependency. Figure 8 illustrates the energy delivered to the electricity demand groups from each technology throughout the time span of the analysis. It should be noted that the energy supplied by the battery initially stems from solar PV, and the PV bulk only includes the energy supplied directly to the demand groups. Hence, the total solar PV production is higher when minimising grid dependency than when minimising system cost.



Figure 8: Scenario 3 & 4, Total energy throughout the time span of 20 years delivered to the electricity demand groups from solar PV, the power grid and the battery system in both optimisation objectives.

Figure 8 shows that the electricity supplied by the national grid was almost eliminated by increasing the use of a battery system in both scenarios. The figure also shows that the electricity delivered by the grid was lower in scenario 4 where the electric boiler was utilised than in scenario 3, where the electric boiler was excluded from the model. In fact, the results from minimising grid dependency show that the total energy consumption from the power grid in scenario 4 was 638.10 MWh and 1361.18 MWh in scenario 3. This shows a reduction in the use of electricity from the grid of 53% in the optimal solution by introducing an electric boiler to the system. Nonetheless, even when minimising dependency on the grid, some electricity from the grid was still consumed in both scenarios. In scenario 3, consumption from the power grid was utilised in the last 11 years of the analysis. Figure 9 shows the interaction between solar PV production, consumption from the power grid, and the SOC of the battery.



Figure 9: Scenario 3, Interaction between solar PV, battery and power from grid when minimising grid dependency

In Figure 9 the green color represents the solar PV production that supplies the electricity demand groups directly, while the blue color represents the solar PV production that charges the battery. The black graph shows the development of the SOC of the battery. When the SOC increases, it increases with a value equivalent to the blue bulk. Furthermore, the orange bulk shows the total electricity demand in each month, while the grey bulk shows the electricity consumption from the grid.

Figure 9 shows that the electricity from the grid was used in September and December. September is a month with high electricity demand, however, December has relatively low demand. The supply of energy from the grid in December can be attributed to the constraint in equation (11) that ensures that SOC at the end of a year equals that at the beginning. The battery is thereby charged in December and discharged in January when the demand is high. Thus, the results showed a tendency for the model to utilise the power grid when the demand is high and in December when the battery must be charged.

A similar graph was made for scenario 4, and is illustrated in Figure 10.

The figure shows similar results as Figure 9, however, in scenario 4, the model utilises consumption from the grid in February, which has the third highest demand. Notably, Figure 10 shows that the electric boiler is not utilised in the last two years. In fact, the electric



Figure 10: Scenario 4, Interaction between solar PV, battery and power from grid when minimising grid dependency

boiler is only utilized in the first 13 years of the analysis, and similar to the results in scenario 3, the model only uses electricity from the grid in the last seven years.

Figure 11 shows the SOC, steam production from the electric boiler, and the PV production compared to the electricity demand from the demand groups in the first two years of the analysis.



Figure 11: Scenario 4, interaction between solar PV, electric boiler and battery in the first two years when minimising grid dependency

Figure 11 illustrates that the electric boiler is used in months where the battery is discharged and in December where electricity demand from production is low, but the solar PV production is high.

When minimising grid dependency the model introduced a battery with a capacity of 216,744.84 kWh in scenario 3 and 262,268.69 kWh in scenario 4. These are unrealistically high values and lead to system costs that are more than 100 times higher than the minimum. For that reason, MGA analysis was applied to scenarios 3 and 4.

MGA for scenario 3 and 4

Table 6 showed that minimising dependency on the national power grid comes with a high system cost due to the unrealistically high battery capacity. When using the Modelling to Generate Alternatives (MGA) method, the model increased grid dependency with the constraint that the total system cost cannot exceed 110% of the minimum system cost for both scenarios. That is, the system cost in scenario 3 MGA was limited to 930.19 \cdot 110% = 1024.21 MKES, while the system in scenario 4 MGA was limited to 771.46 \cdot 110% = 848.61 MKES

The optimal solutions show that when implementing an electric boiler of 0.66 tonnes/hour and a battery capacity of 371.03 kWh (scenario 4), the potential solar PV capacity was fully utilised. Without the electric boiler (scenario 3), the optimal battery capacity was 671.31 kWh and only 1285.36 kW solar PV was implemented. Hence, the available area of the roof was not fully utilised because it would require an increase in battery capacity which results in a higher system cost.

Figure 12 shows the total electricity consumption from the power grid when minimising grid dependency both with and without the limitation of a 10% increase in system cost compared to the minimal cost.



Figure 12: Scenario 3 & 4, Total electricity consumption from the power grid throughout the time span of 20 years

The figure illustrates that in both optimisation scenarios, scenario 4 relied less on energy from the grid than scenario 3. Furthermore, in the MGA analysis, scenario 4 achieved a lower overall system cost compared to scenario 3. In fact, the total system cost resulting from MGA in scenario 4 is even lower than the minimum system cost of scenario 3. This demonstrates how the overall system cost is reduced because the electric boiler, acting as a flexible load, enables the installation of higher solar PV capacity. The reduction in system cost enables investment in a battery capacity capable of meeting wet processing needs.

5.3 Sensitivity analysis

The sensitivity analysis explores the responsiveness of the optimal solution to variations in constraints and price estimations. Two analyses were made; one for the system cost minimisation problem, and one for the grid dependency minimisation problem.

5.3.1 System cost minimisation

For the system cost minimisation problem, the shadow prices of increasing the PV capacity constraint, battery capacity constraint, and total steam boiler capacity constraint with 5% are shown in Table 8. The table also shows how the increases in constraints change the optimal technology capacities. Furthermore Table 8 shows how 5% increases in LCOE of solar PV system, electric boiler investment cost, and battery investment cost affect the system cost and the optimal solution technology capacities. Values in the table are changes from the optimal solutions in Table 6, and negative values demonstrate a decrease while positive values demonstrate an increase.

In scenarios 1 and 2 with higher steam demand and thereby high electricity consumption, increasing the solar PV capacity by 5% reduces the total system cost by 27.51 MKES. This result confirms that electricity from solar PV is cheaper than electricity from the national power grid. However, in scenarios 3 and 4 with low steam demand, increasing the PV capacity limit does not alter the system cost or optimal solution, indicating that the PV capacity was not a binding constraint and the area for solar PV was not fully utilized

Table 8 confirms that increasing the battery capacity requirement and the total steam boiler capacity increases the system cost, but has no influence on the remaining technology capacities in the optimal solution. Similarly, increasing the estimated prices by 5% increases the total system cost. The system cost is especially sensitive to the LCOE of solar PV. Worth noticing is that the increase in LCOE of solar PV changes the optimal solution in scenario 4 (*Low Steam & Free Choice*). An increase of 5% LCOE, decreases the optimal PV capacity by 26.01 kW and the optimal electric boiler capacity by 0.03 tonnes/h.

The sensitivity analysis examined the allowable increase of LCOE of solar PV and allowable decrease of total electricity tariff for each scenario because the estimation of these

	$_{\rm PV}$	Battery	Total	\mathbf{PV}	El-boiler	Battery
	capacity	capacity	boiler	LCOE	investment	investment
			capacity			
System cost	(MKES)					
Scenario 1	-27.51	5.42	0.03	21.26	0.02	5.42
Scenario 2	-27.51	0.36^{*}	0.03	21.26	0.01	0
Scenario 3	0	5.39	-	15.38	-	5.42
Scenario 4	0	0.37^{*}	-	20.57	0^{**}	0
PV Capacit	y (kW)					
Scenario 1	88.71	0	0	0	0	0
Scenario 2	88.71	0	0	0	0	0
Scenario 3	0	0	-	0	-	0
Scenario 4	0	0	-	-26.01	0	0
Battery Ca	pacity (kW	h)				
Scenario 1	0	14.79	0	0	0	0
Scenario 2	0	1	0	0	0	0
Scenario 3	0	14.79	-	0	-	0
Scenario 4	0	1	-	0	0	0
El boiler Ca	apacity (to	nnes/h)				
Scenario 1	0	0	1.19	0	0	0
Scenario 2	0	0	1.19	0	0	0
Scenario 3	0	0	-	0	-	0
Scenario 4	0	0	-	-0.03	0	0

Table 8: Shadow prices and changes in optimal solution for the cost minimisation objective. *Minimum battery capacity changed from 0 kWh to 1 kWh

**Some increase in system cost was detected, however, of a value lover that 0.01 MKES

prices is defining for the optimal solutions. The results are shown in Table 9.

The findings indicate that in scenarios 1 and 2, the LCOE of solar PV can increase by 129% while the electricity tariff can decrease by 56% before the optimal solution shifts, and the optimal solar PV capacity starts decreasing. As previously stated, scenario 4 is responsive to the LCOE of solar PV. This sensitivity is evident in the allowable increase of LCOE of only 1.7% and allowable decrease of 1.9% in electricity tariff. Table 9 also shows that the battery investment must decrease by more than 99% in all scenarios before the optimal solution changes.

From the analysis it is clear, that investing in a battery system is not feasible. Furthermore, lower electricity demand makes the optimal solution more sensitive to changes in the LCOE of solar PV and electricity tariffs. This can be explained by the fact that a system with low demand and high solar PV production requires either a battery or an electric boiler to store or use the surplus energy in times with high PV production. That is, the inflexible energy supply requires a flexible energy demand. Consequently, the total system cost increases due to the investment in additional technology.

	Increase of	Decrease of	Decrease of		
	PV LCOE	electricity tariff	battery inv. cost		
Scenario 1	129%	56%	>99.9%		
Scenario 2	129%	56%	> 99.9%		
Scenario 3	112%	53%	99.4%		
Scenario 4	1.7%	1.9%	99.8%		

Table 9: Allowable increase of solar PV LCOE, allowable decrease of electricity tariffs from the national power grid, and allowable decrease in battery investment cost in the cost minimisation problem

The sensitivity analysis furthermore examined the allowable increase in electric boiler investment cost in scenario 4. The result showed that the investment cost can increase by 279% before the optimal solution changes, and more than 10,000 times the estimated value before for the boiler is no longer part of the optimal solution. Hence, the integration of solar PV and an electric boiler results in a cost-effective energy system.

5.3.2 Minimising dependency on the power grid

In the sensitivity analysis of the grid dependency minimisation problem, the shadow price represents a change in electricity from the national power grid. Since the battery only has a lower limit, increasing the constraint on battery capacity does not decrease the dependency on the grid. For that reason, the analysis only examines the shadow price of increasing the constraint on solar PV capacity by 5%. Additionally, the effect of changing the constraint on electric boiler capacity in scenario 3 from 0 to 1 tonnes/hour was investigated. The result from the analysis is shown in Table 10.

Table 10 shows that increasing the solar PV capacity by 5% reduces the electricity delivered by the power grid in scenarios 1, 2, and 4, whereas scenario 3 remains unaffected due to the non-binding constraint on PV capacity. The highest shadow price of -273.97 GWh occurs in scenarios 1 and 2 with high steam demand.

In scenario 4 (Low Steam & Free Choice) and its associated MGA, the increased solar PV capacity significantly impacts the optimal solution. When minimising grid dependency, both the battery capacity and the capacity of the electric boiler increase. Conversely, in the MGA the battery capacity is decreased by 2.58 kWh while the boiler capacity is increased by 0.10 tonnes/hour.

Table 10 also shows that increasing the electric boiler capacity from 0 to 1 kWh in scenario 3 decreases the dependency on the grid. This is reflected in the optimal PV and battery capacity that both increase. Notably, when minimising grid dependency without considering system cost, the increase in PV capacity is less pronounced, while the increase in

	PV Capacity	El-boiler Capacity*
Energy from th	e grid (GWh)	
Scenario 1	-273.97	-
Scenario 2	-273.97	-
Scenario 3	0	-0.72
Scenario 3 MGA	0	-8.97
Scenario 4	-0.57	-
Scenario 4 MGA	-0.88	-
PV Capacity (k	W)	
Scenario 1	88.71	-
Scenario 2	88.71	-
Scenario 3	0	53.12
Scenario 3 MGA	0	488.75
Scenario 4	88.71	-
Scenario 4 MGA	88.71	-
Battery Capaci	ty (kWh)	
Scenario 1	0	-
Scenario 2	0	-
Scenario 3	0	$14,\!831.65$
Scenario 3 MGA	0	180.09
Scenario 4	72,928.84	-
Scenario 4 MGA	-2.58	-
El boiler Capac	ity (tonnes/h)	
Scenario 1	0	-
Scenario 2	0	-
Scenario 3	0	1
Scenario 3 MGA	0	1
Scenario 4	0.38	-
Scenario 4 MGA	0.10	-

Table 10: Shadow prices and changes in optimal solution for the grid dependency minimisation objective

*Boiler capacity increased from 0 to 1 tonnes/h in scenario 3

battery capacity is more substantial compared to the case where system cost is constrained. This result shows that increasing PV capacity is more cost-efficient than increasing battery capacity when minimising grid dependency.

Generally, the result confirms the result in Figure 12 illustrating that the introduction of an electric boiler decreases the energy delivered by the power grid.

6 Discussion

From an energy system analysis, this thesis examined the results of minimising system cost and minimising grid dependency of the textile factory Rivatex. The results showed that the optimal technology capacities are highly dependent on the steam demand of the textile factory because high steam demand leads to high electricity demand. The solutions' sensitivity to steam demand highlights that optimal capacities for captive systems within the textile industry fluctuate based on the balance between available solar PV production and electricity consumption. Consequently, reaching a singular conclusion applicable to all enterprises across the industry proves challenging. However, with the implementation of two different steam demands, the model analysed both high energy-demanding scenarios and lower energy-demanding scenarios. Thus, the analysis considers the sensitivity of demand and allows for the analysis of textile factories with differing energy demands.

6.1 Results and findings

The following sections discuss the results in relation to the assumptions and estimations in the model.

6.1.1 Optimal technology capacities when minimising system cost

Solar PV capacity

All four scenarios show that the system cost is reduced by introducing a solar PV system. Here, it should be noted that system costs in scenarios 1 and 2 are not comparable to the estimation of the current system cost since the steam demand is higher than the current steam consumption. The feasibility is enhanced by the fact that the *demand charge*, which is part of the electricity tariff, was excluded from the electricity price in the model. Excluding the *demand charge* gives an underestimation of the electricity tariff. However, the estimation favors the use of electricity from the grid, and adding the *demand charge* to the model would only increase the feasibility of solar PV. Nonetheless, the electricity bill in Appendix F shows that the *demand charge* is a large share of the electricity bill for the current system, and ignoring it leads to deviations in the model. With no data on Rivatex's historical power consumption, and the introduction of solar PV as a new power source, estimating the maximum power demand each month would cause high uncertainties in the model. Thus, whether included or not, the *demand charge* leads to inaccuracy of the model, however, excluding it renders the most conservative results.

The results unequivocally show that solar PV is more profitable than buying electricity

from the national grid. In fact, it is so profitable, that in every scenario analysed, the optimal solar PV capacity was above 1 MW, thus making the system eligible for the net-meting regulations (Ministry of Energy, 2022). This thesis did not allow the PV system to export energy to the grid, however, implementing the net-metering regulation to the model might change the optimal solutions presented in this thesis.

Battery capacity

The introduction of a battery system increases the system cost in all four scenarios. Hence, when aiming to minimise the system cost, opting for the minimum required battery capacity emerges as the optimal solution.

Initially introduced into the energy system to provide backup support for wet processing during national grid power outages, the battery's primary purpose was not cost reduction. However, it is important to note that power outages arguably lead to sales losses due to halted production. The model developed for this thesis did not consider the value of lost load (VOLL), overlooking the potential financial benefits that a battery system might entail. Furthermore, the battery system's capability to store surplus energy generated by PV during non-production periods was not considered. The use of monthly time steps ignores differences in solar PV production patterns and consumption patterns during the day, as well as the disparities between daily solar PV production and consumption patterns over the course of a month.

The boxplot in Figure 13 shows the distribution of energy from solar PV each hour across all days in January. Weather data from 2021-2023 was used along with equation (7). The orange lines show the median production each hour, the yellow box shows the range between the first and third quartiles, the whiskers extending from the box show the range of the data and the circles represent outliers.

Figure 13 shows that the energy production from solar PV is not evenly distributed over a day, but follows a pattern where it increases from 5 to 10 o'clock before it decreases until it reaches zero at 17 o'clock. Consequently, in scenarios 3 and 4, where the production from solar PV during some months is enough to cover the demand, the consumption pattern would need to mirror this trend. In this thesis, it was assumed that production follows regular working hours, that is 08-17 Monday to Friday and 09-15 Saturday (personal communication, Gideon Boit, 21.03.2024). Since solar PV produces energy from 05-16, no further analysis of consumption patterns is necessary to clarify the need for a battery system.

As mentioned earlier, the solar PV system is eligible for export to the national grid due to the capacity being above 1 MW. Exporting energy to the grid through the net-metering regulations eliminates the need to install a battery system since the surplus energy can be



Figure 13: Available hourly energy production from solar PV in January based on weather data from Moi University (personal communication, Abraham Kosgei, 09.02.2024)

exported. The question remaining would then be whether implementing a battery system or exporting energy to the grid through the net-metering regulations would render the overall minimum system cost.

Electric boiler capacity

The electric boiler capacity was introduced to the model in scenarios 1, 2, and 4. In scenarios 1 and 2 the electric boiler was necessary to meet the high steam demand, while in scenario 4, it proved advantageous over the firewood boiler in certain months. This highlights the economic advantages achieved through the interaction between a solar PV system and an electric boiler. However, the sensitivity analysis showed that scenario 4 demonstrates the highest sensitivity to increased LCOE of the solar PV system. Nevertheless, the solution was largely unaffected by increased investment cost for the electric boiler, enhancing the reliability of the results. The model used an investment cost from the Danish Energy Agency (2016), derived from estimations by the Danish company *Tjæreborg Industri*. It is questionable how well numbers from the Danish industry can be applied to the Kenyan industry as these are two very different countries and markets. Yet, even with a 279% increase in electric boiler investment costs, overall results remained unaffected. Thus, the price of electric boilers would have to be almost 3 times higher in Kenya than in Denmark to alter the results, which is considered unlikely. The same arguments apply to the battery investment cost, based on data from the Danish Energy Agency (2018). The sensitivity analysis showed that for the battery system to be financially viable, the investment cost must decrease by over 99%.

6.1.2 Minimising dependency on the power grid

Solar PV capacity

None of the scenarios analysed were able to gain complete independence from the national power grid. Furthermore, the results show that when minimising the dependency on the power grid, maximising the solar PV capacity is not always the optimal solution. Scenario 3 (*Low Steam & Only Firewood*) illustrates that the combination of solar PV and battery system cannot achieve independence from the grid. Furthermore, the optimal solution does not utilise the entire solar PV potential. The result might be explained by the modeling of solar PV degradation and limitations on battery storage time. The optimal solution does not use electricity from the power grid in the first years of the analysis. However, in later years, when the efficiency of solar PV has decreased, the system must use electricity from the grid.

In scenario 4 with low steam demand and the introduction of an electric boiler, the solar PV capacity is maximised. The sensitivity analysis furthermore shows, that increasing the solar PV capacity yields less energy consumption from the grid. Thus, increasing the PV capacity might enable this system configuration to operate disconnected from the grid.

Battery capacity

As previously mentioned, the battery was modelled with a constraint requiring the SOC at the beginning of a year to match that at the end of the year. This constraint merits discussion since Danish Energy Agency (2018, p. 172) states that storing energy in lithium-ion batteries for several months is unfeasible. Therefore, the model's allowance for storage across months might yield unrealistic results. The monthly time steps of the analysis hinder the examination of shorter storage duration. The results in Figure 9 and 11 show that energy is in fact stored in the battery for several months, implying a flexibility that may not be feasible in reality. Consequently, the actual system's reliance on the grid might exceed the findings of this thesis. However, the degradation rate of the solar PV modules applied in the model was higher than the typical values (Danish Energy Agency, 2016; Jinko Solar Co., 2021) and applying a lower degradation rate would increase the PV production in the last years of the analysis, and thereby reduce the need to use electricity from the power grid.

Electric boiler capacity

With the high steam demand in scenarios 1 and 2, an electric boiler is necessary to meet the demand. However, scenarios 3 and 4, characterised by a low steam demand, show that introducing a steam boiler decreases the dependency on the power grid. The results in Table 6 and Figure 12 show that the optimal solution when minimising grid dependency entails introducing a solar PV system, a battery system, and an electric boiler. Moreover, the sensitivity analysis showed that increasing the available solar PV capacity reduces grid dependency in scenarios 3 and 4 by increasing both battery and electric boiler capacities. Additionally, sensitivity analysis of scenarios 3 and 3 MGA (*Low Steam & Only Firewood*) indicates that increasing the electric boiler capacity decreases energy consumption from the grid. This result stems from the electric boiler serving as a flexible load, increasing electricity consumption when solar PV production peaks. The electric boiler is not essential to meet steam demand and is only utilized in certain months of the first years. The result demonstrates the importance of flexibility in consumption in an energy system with limited production flexibility due to weather dependency. Nevertheless, scenario 4 (*Low Steam & Free Choice*) implements the highest battery capacity of all scenarios, underlining the importance of energy storage in reducing dependency on the national power grid.

6.2 The potential of captive solar PV systems in Kenya

Despite the economic benefits of implementing captive solar PV systems in Kenya, only a few enterprises have invested in the technology. Research by Keshavadasu (2023) highlighted uncertainty in the regulatory framework as an obstacle to the development of solar PV projects in Kenya, a challenge also pointed out by UNEP et al. (2020). However, this thesis showed that even in the absence of FiT, net-metering regulations, or the ability to export energy to the grid, the installation of a solar PV system is financially viable. That is, the changing regulations and uncertainty in the regulatory framework alone cannot explain the low adaptation rate of solar PV, because captive solar PV systems in the Kenyan textile industry are feasible independent of governmental support or export benefits. The results from this thesis disprove that the regulatory framework is a hindrance to the deployment of solar PV systems in the textile industry, and the lack of dissemination must be caused by other factors.

UNEP et al. (2020) found raising capital to cover the investment cost to be the biggest challenge to employing captive energy systems in Kenya. The financial estimations presented in this thesis showed that the investment cost of solar PV systems is more than 100 times higher than the yearly O&M. Furthermore, the battery system and the electric boiler come with investment costs which further increase the capital needed to install the optimal system. Hence, the investment costs for the systems analysed in this thesis are rather high, and despite the system being financially viable over the course of 20 years, raising capital for investments might be challenging. Furthermore, the benefits of captive solar PV systems must be known to the industry, and individual enterprises need technical knowledge to support the implementation of solar PV. Information and technical abilities are challenges highlighted by Schäfer et al. (2011) as some of the biggest challenges for the development of decentralized power systems in developing countries. Thus, these challenges might be evident within the captive industry in Kenya as well.

7 Conclusion

The integration of captive solar PV, a battery system, and an electric boiler significantly impacts both the system cost and dependency on the national power grid within the energy system of a Kenyan textile factory. Through the energy system analysis conducted in this thesis, several key findings emerge, shedding light on the implications of these technologies and their capacities.

7.1 Summary of findings

Firstly, the introduction of captive solar PV proved to be a profitable investment, reducing costs in all scenarios. For factories where the electricity consumption exceeds solar PV production, investing in a battery system and an electric boiler only increases the system cost. However, for factories with lower electricity consumption, investing in an electric boiler reduces the system cost because it enables the installation of higher solar PV capacity. Nonetheless, a battery system was shown only to increase the system cost.

Secondly, the introduction of solar PV decreased the dependency on the national grid in all scenarios. For factories with excess consumption over PV production, introducing a battery and an electric boiler does not decrease grid dependency. However, for factories with lower consumption, both a battery system and an electric boiler increase the flexibility of the system and decrease the dependency on the grid.

The optimal technology capacities are highly dependent on the electricity demand of a given factory. When electricity demand is high, the case of Rivatex textile factory has the same optimal solution for both optimisation objectives, namely, 1774.11 kW solar PV and an electric boiler capacity of 11.7 tonnes per hour, which is just enough to meet the minimum requirement. With no battery capacity, this solution ignores the need to store energy generated outside operating hours and the wish for backup capacity. In the case of low electricity demand, the introduction of an electric boiler lowers both costs and dependency on the national grid, showcasing the synergistic benefits of the introduced technologies. However, the optimal battery capacity varies from 0 when minimising system cost to 262 MWh when minimising grid dependency. Therefore, it is recommended to employ a solar PV capacity of 1774.11 kW, a battery capacity of 371.03 kWh, and an electric boiler capacity of 0.66 tonnes per hour. This solution reduces both system cost and grid dependency compared to the current energy system at Rivatex.

In the context of current Kenyan energy policies and suggested energy system configurations, these findings offer valuable insights into the economic viability of captive solar PV systems in the Kenyan textile industry. Solar PV systems prove feasible over a longer time frame even in the absence of governmental support. By strategically leveraging captive solar PV, battery storage, and electric boiler technologies, textile factories can not only increase energy independence but also align with national objectives of sustainability and minimise costs. Nonetheless, raising capital to cover the investment costs of the proposed technologies might present a challenge for the industry.

7.2 Challenges and limitations of the study

Some of the key information and data used in this thesis are highly based on personal communication with staff at Rivatex. The model is based on electricity demand data from Rivatex with high uncertainty due to unstructured data management at the factory. Furthermore, assumptions on steam demand, operation time, and duration of power outages are based on conversations with staff and are rough estimates. The amount of personal communication and extent of assumptions made, question the reliability of the model. However, due to the analysis of several scenarios with different energy demands along with the sensitivity analysis, the thesis handles the uncertainty by analysing the impact of the key assumptions.

The model developed in this thesis did not account for physical limitations at Rivatex. The thesis aimed to analyse the potential of captive solar PV systems in the Kenyan textile industry by using Rivatex as a case study. Thus, the physical limitations such as suitable roof structures, possibilities of connecting the introduced technologies to the existing electrical system and steam system, along with optimal tilt angle of the PV modules were not considered in this research.

7.3 Future research

Addressing the physical limitations of the electrical system at Rivatex factory in the analysis would improve the recommendations for this specific case. By incorporating the existing limitations of the factory's electrical infrastructure into the model, such as constraints on the inverter, battery, and electric boiler connections, the recommendations can be tailored more precisely to Rivatex's unique circumstances. The model's ability to account for various electricity demand groups within the factory's current electrical system facilitates the implementation of these limitations, ensuring that the recommendations remain practical and relevant to Rivatex's operational context.

To broaden the analysis it is suggested to examine the VOLL within industry along with investigating the possible advantages of the net-metering regulation. Estimating the VOLL and applying it to the model might make the battery system more economically viable and thereby alter the optimal solution. Similarly, evaluating the implications of net-metering regulations within the model could offer insights into whether this regulatory framework presents a more viable alternative to investing in an electric boiler or a battery system Hence, integrating these financial considerations into the model would enrich the analysis.

Expanding the scope of research by conducting similar analyses on multiple textile factories across Kenya is advised for further investigation. Such comparative studies would improve the robustness of findings and the broader potential for captive systems within the industry.

The work of this thesis offers valuable information to both plant managers within the textile industry and policymakers. The findings of this thesis can help governments in supporting the deployment of solar PV systems. Furthermore, the numerous advantages of captive solar PV systems highlighted might expand to other industries or other African countries.

References

- Al-Badi, A. (2020). Performance assessment of 20.4 kw eco-house grid-connected pv plant in oman. International Journal of Sustainable Engineering, 13, 230–241. https://doi. org/10.1080/19397038.2019.1658824
- Arora, R., Arora, R., & Sridhara, S. N. (2022). Performance assessment of 186 kwp grid interactive solar photovoltaic plant in northern india. *International Journal of Ambient Energy*, 43, 128–141. https://doi.org/10.1080/01430750.2019.1630312
- Balcita, V. D. G., Bejar, A. T. A., Goy, T. P. P., Billones, R. K. C., & Dadios, E. P. (2021). Optimizing the allocation of renewable energy generation and energy consumption of power plants in the philippines using linear programming. 2021 IEEE 13th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management, HNICEM 2021. https://doi.org/10.1109/HNICEM54116.2021.9732024
- Blok, K., & Nieuwlaar, E. (2021). Introduction to energy analysis (3rd ed.). Routledge, Taylor & Francis Group.
- Bøhren, Ø., & Gjærum, P. I. (2016). Finans: Innføring i investering og finansiering (1st ed., Vol. 2). Fagbokforlaget.
- Bosch, R., & Trick, M. (2014, January). Integer programming. In Search methodologies: Introductory tutorials in optimization and decision support techniques (pp. 67–92). Springer US. https://doi.org/10.1007/978-1-4614-6940-7_3
- Carvallo, J. P., Shaw, B. J., Avila, N. I., & Kammen, D. M. (2017). Sustainable low-carbon expansion for the power sector of an emerging economy: The case of kenya. *Environmental Science and Technology*, 51, 10232–10242. https://doi.org/10.1021/acs.est. 7b00345
- Danish Energy Agency. (2016). Technology data-energy plants for electricity and district heating generation. http://www.ens.dk/teknologikatalog
- Danish Energy Agency. (2018). Technology data-energy storage. http://www.ens.dk/teknologikatalog
- Elbaz, A., & Guneser, M. T. (2021). Multi-objective optimization method for proper configuration of grid-connected pv-wind hybrid system in terms of ecological effects, outlay, and reliability. *Journal of Electrical Engineering and Technology*, 16, 771–782. https: //doi.org/10.1007/s42835-020-00635-y
- EPRA. (2021). Integrated annual report& financial statements. EPRA.
- EPRA. (2023). Retail electricity tariff review for the 2022/23-2025/26 4th tariff contril perios (tcp) effective 1st april 2023.

- EPRA Statistics Commitee. (2024). Bi annual energy and petroleum statistics report 2023. EPRA.
- European Environment Agency. (2023). The impact of textile production and waste on the environment (infographics). Retrieved February 10, 2024, from https://www.europarl.europa.eu/topics/en/article/20201208STO93327/the-impact-of-textile-production-and-waste-on-the-environment-infographics
- Ferro, R., Cordeiro, G. A., Ordóñez, R. E., Beydoun, G., & Shukla, N. (2021). An optimization tool for production planning: A case study in a textile industry. *Applied Sciences* (Switzerland), 11. https://doi.org/10.3390/app11188312
- Google. (n.d.). Google earth. Retrieved March 24, 2024, from https://earth.google.com/ web/@0.50015755,35.26812293,2107.59980166a,844.86271316d,35y,0h,0t,0r/data= OgMKATA
- Gopi, A., Sudhakar, K., Keng, N. W., Krishnan, A. R., & Priya, S. S. (2021). Performance modeling of the weather impact on a utility-scale pv power plant in a tropical region. *International Journal of Photoenergy*, 2021. https://doi.org/10.1155/2021/5551014
- Hannan, M. A., Wali, S. B., Ker, P. J., Rahman, M. S., Mansor, M., Ramachandaramurthy, V. K., Muttaqi, K. M., Mahlia, T. M., & Dong, Z. Y. (2021). Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues. *Journal of Energy Storage*, 42. https://doi.org/10.1016/j.est. 2021.103023
- Inflation Tool. (2024). Value of 2015 euro today. Retrieved March 22, 2024, from https://www.inflationtool.com/euro/2015-to-present-value?year2=2024&frequency=yearly
- IRENA. (2023). Renewable power generation costs in 2022. www.irena.org
- Jinko Solar Co. (2021). N-type mono-facial module positive power tolerance of 0 + 3% hot 2.0 technology. www.jinkosolar.com
- JKUAT Enterprise Limited. (2022). A study on the regulatory impact of net metering in kenya (NM RIA Study). EPRA.
- Kamau, A. (n.d.). Why the textiles and apparels sector? Retrieved February 10, 2024, from https://kam.co.ke/why-the-textiles-and-apparels-sector/
- Kenki Dryer. (2020). Energy amount conversion method of steam / sludge drying, slurry drying, waste drying. Retrieved April 8, 2024, from https://kenkidryer.com/2018/ 08/12/energy-amount-conversion-steam/
- Kenya Power. (2020). *Know you bill*. Retrieved March 14, 2024, from https://www.kplc.co. ke/knowyourbill/
- Keshavadasu, S. R. (2023). Regulatory and policy risks: Analyzing the uncertainties related to changes in government policies, regulations, and incentives affecting solar power

project development and operations in kenya. *Energy Policy*, 182. https://doi.org/ 10.1016/j.enpol.2023.113760

- Kimutai, I., Maina, P., & Makokha, A. (2019). Energy optimization model using linear programming for process industry: A case study of textile manufacturing plant in kenya. International Journal of Energy Engineering, 2019, 45–52. https://doi.org/ 10.5923/j.ijee.20190902.03
- Malekpoor, H., Chalvatzis, K., Mishra, N., Mehlawat, M. K., Zafirakis, D., & Song, M. (2018). Integrated grey relational analysis and multi objective grey linear programming for sustainable electricity generation planning. Annals of Operations Research, 269, 475– 503. https://doi.org/10.1007/s10479-017-2566-4
- Ministry of Energy. (2021a). Feed-in-tariffs policy on renewable energy resource generated electricity (small-hydro, biomass and biogas).
- Ministry of Energy. (2021b). Renewable energy auctions policy.
- Ministry of Energy. (2022). Energy (net-metering) regulations.
- Ministry of Energy and Petroleum. (2023). Kenya energy transition & investment plan.
- Mitchell, S., Kean, A., Manson, A., O'Sullivan, M., Phillips, A., & Peschiera, F. (2009). Optimization with pulp. Retrieved February 20, 2024, from https://coin-or.github. io/pulp/
- Moussa, A. (2021). Textile color formulation using linear programming based on kubelkamunk and duncan theories. Color Research and Application, 46, 1046–1056. https: //doi.org/10.1002/col.22626
- Mwangi, T. W., & Mutabazi, M. (2023). Analysis of human development of kenya. International Journal of Development and Economic Sustainability, 11, 45–73. https: //doi.org/10.37745/ijdes.13/vol11n44573
- Ndiritu, S. W., & Engola, M. K. (2020). The effectiveness of feed-in-tariff policy in promoting power generation from renewable energy in kenya. *Renewable Energy*, 161, 593–605. https://doi.org/10.1016/j.renene.2020.07.082
- Ngure, S. M., Makokha, A. B., Ataro, E. O., & Adaramola, M. S. (2023). Techno-economic performance analysis of grid-tied solar pv systems under tropical savanna climatic conditions in kenya. *International Journal of Ambient Energy*. https://doi.org/10. 1080/01430750.2023.2224329
- Ngure, S. M. (2022). Performance, degradation, and reliability of solar photovoltaic (pv) module under environmental field conditions [Doctoral dissertation, Moi University].
- Østergaard, P. A. (2009). Reviewing optimisation criteria for energy systems analyses of renewable energy integration. *Energy*, 34, 1236–1245. https://doi.org/10.1016/j. energy.2009.05.004

- Peake, S. (2018). *Renewable energy, power for a sustainable future* (4th ed.). Oxford University Press.
- Perić, T., Babić, Z., & Matejaš, J. (2018). Comparative analysis of application efficiency of two iterative multi objective linear programming methods (mp method and stem method). Central European Journal of Operations Research, 26, 565–583. https:// doi.org/10.1007/s10100-018-0543-x
- Polat, U., & Gürtuna, F. (2018). European journal of engineering and applied sciences a review of applications of linear programming and mixed integer linear programming in energy management: From policy makers/producers to consumers. *European J. Eng. App. Sci*, 1, 84–89.
- Price, J., & Keppo, I. (2017). Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models. Applied Energy, 195, 356–369. https://doi.org/10.1016/j.apenergy.2017.03.065
- Schäfer, M., Kebir, N., & Neumann, K. (2011). Research needs for meeting the challenge of decentralized energy supply in developing countries. *Energy for Sustainable Development*, 15, 324–329. https://doi.org/10.1016/j.esd.2011.07.001
- Shah, S. (2024). *Electricity cost in kenya*. Retrieved March 14, 2024, from https://www.stimatracker.com/
- Thunder Said Energy. (n.d.). Energy needed to produce steam: Enthalpy and entropy data? Retrieved April 8, 2024, from https://thundersaidenergy.com/downloads/energyneeded-to-produce-steam-enthalpy-and-entropy-data/
- Ueda, Y., Kurokawa, K., Kitamura, K., Yokota, M., Akanuma, K., & Sugihara, H. (2009). Performance analysis of various system configurations on grid-connected residential pv systems. Solar Energy Materials and Solar Cells, 93, 945–949. https://doi.org/10. 1016/j.solmat.2008.11.021
- UNEP, CICSA, & FS-UNEP. (2020). Clean captive installations for industrial clients in sub-sahara africa kenya country study. www.captiverenewables-africa.org
- United Nations. (n.d.). The 17 goals. Retrieved April 23, 2024, from https://sdgs.un.org/ goals#implementation
- Vapor Power International. (n.d.). Electric boilers resistance element type.
- Xe. (2024). Xe currancy converter. Retrieved March 20, 2024, from https://www.xe.com/ currencyconverter/convert/?Amount=1&From=EUR&To=KES

A Electricity consumption groups at Rivatex

Name	Description
AirComp1&2	Air compressors for high-pressured air for maschines
SpinningNew	New Spinning department
Administration	Administration building
SpinningOld	Old Spinning department
HumSpin	Supply humidity for the spinning process
Engineering	Engineering building
Tayloring	Tayloring department
AirComp3	Air compressors for high-pressured air for maschines
HumWeaving	Supply humidity for the weaving process
WetProcessing	Wet Processing department
Steam Control	Steam management system for firewood boilers
ETP	Effluent Treatment Plant for yarn processing

Table 11: Description of consumption groups in Figure 2 $\,$

B Electricity Consumption

2023	January	February	March	April	May	June	July	August	September	October	November	December
Air Compressor 1 and 2	37,931	5,338	5,338	8,463	9,295	4,565	4,206	8,723	7,852	7,549	8,506	1,280
Air compressor 3	11,297	8,312	7,603	17,499	10,778	2,314	6,215	23,797	24,049	9,062	8,308	15,163
Humidification weaving	2,267	2,122	1,506	2,337	2,866	412	354	1,709	3,164	2,502	1,621	771
Humidification spinning	19,601	7,004	5,049	10,936	19,895	2,456	8,704	24,483	28,675	5,170	11,681	9,859
Spinning (new and old)	119,330	54,949	37,558	104,085	65,902	36,117	56,350	118,306	159,420	65,669	83,936	44,996
Weaving	22,245	20,784	15,772	16,895	15,713	17,868	12,832	22,757	40,040	30,279	30,646	14,295
Processing	28,600	37,500	29,400	46,700	27,781	30,800	27,600	44,200	36,300	46,900	49,700	21,200
Steam boiler control	8,498	10,537	8,546	16,389	12,223	13,069	9,033	13,388	13,135	13,678	14,431	8,584
ETP	1,284	720	475	2,118	538	737	1,999	3,829	3,877	5,903	3,735	1,547
Administration	4,883	5,301	4,183	4,925	4,332	5,326	4,994	5,376	5,305	5,166	4,968	5,506
Engineering	2,102	2,067	1,525	1,650	1,411	1,858	1,786	1,752	1,769	1,767	1,708	2,004
Tailoring	2,414	2,077	1,679	2,102	3,038	2,054	2,038	2,895	2,145	2,114	2,174	1,669
Total units consumed (kWh)	260,452	156,711	118,634	234,099	173,772	117,576	136,111	271,215	325,731	195,759	221,414	126,874
2022	January	February	March	April	May	June	July	August	September	October	November	December
Air Compressor 1 and 2	January 20,071	February 18,482	March 38,431	April 11,446	May 14,832	June 18,053	July 28,457	August 19,392	September 48,635	October 17,878	November 26,644	December 19,668
Air Compressor 1 and 2 Air compressor 3	January 20,071 26,759	February 18,482 27,321	March 38,431 2,562	April 11,446 22,157	May 14,832 19,935	June 18,053 16,007	July 28,457 10,004	August 19,392 2,350	September 48,635 5	October 17,878 7,718	November 26,644 13,203	December 19,668 9,801
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving	January 20,071 26,759 4,445	February 18,482 27,321	March 38,431 2,562 1,469	April 11,446 22,157 846	May 14,832 19,935 -	June 18,053 16,007 175	July 28,457 10,004 1,401	August 19,392 2,350 30	September 48,635 5 1,992	October 17,878 7,718	November 26,644 13,203 1,535	December 19,668 9,801 2,526
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning	January 20,071 26,759 4,445 65,324	February 18,482 27,321 - 20,539	March 38,431 2,562 1,469 9,835	April 11,446 22,157 846 8,295	May 14,832 19,935 - 3,063	June 18,053 16,007 175 3,362	July 28,457 10,004 1,401 39	August 19,392 2,350 30 3,348	September 48,635 5 1,992 15,686	October 17,878 7,718 - 14,686	November 26,644 13,203 1,535 8,733	December 19,668 9,801 2,526 25,991
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old)	January 20,071 26,759 4,445 65,324 167,676	February 18,482 27,321 - 20,539 122,433	March 38,431 2,562 1,469 9,835 86,876	April 11,446 22,157 846 8,295 65,157	May 14,832 19,935 - 3,063 55,453	June 18,053 16,007 175 3,362 87,144	July 28,457 10,004 1,401 39 152,517	August 19,392 2,350 30 3,348 28,949	September 48,635 5 1,992 15,686 82,471	October 17,878 7,718 - 14,686 94,999	November 26,644 13,203 1,535 8,733 64,195	December 19,668 9,801 2,526 25,991 123,744
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old) Weaving	January 20,071 26,759 4,445 65,324 167,676 65,692	February 18,482 27,321 - 20,539 122,433 71,998	March 38,431 2,562 1,469 9,835 86,876 35,120	April 11,446 22,157 846 8,295 65,157 21,394	May 14,832 19,935 - 3,063 55,453 21,992	June 18,053 16,007 175 3,362 87,144 26,642	July 28,457 10,004 1,401 39 152,517 27,174	August 19,392 2,350 30 3,348 28,949 13,559	September 48,635 5 1,992 15,686 82,471 12,895	October 17,878 7,718 - 14,686 94,999 12,268	November 26,644 13,203 1,535 8,733 64,195 17,926	December 19,668 9,801 2,526 25,991 123,744 16,049
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old) Weaving Processing	January 20,071 26,759 4,445 65,324 167,676 65,692 51,900	February 18,482 27,321 - 20,539 122,433 71,998 33,794	March 38,431 2,562 1,469 9,835 86,876 35,120 46,200	April 11,446 22,157 846 8,295 65,157 21,394 37,800	May 14,832 19,935 - 3,063 55,453 21,992 48,101	June 18,053 16,007 175 3,362 87,144 26,642 47,500	July 28,457 10,004 1,401 399 152,517 27,174 40,400	August 19,392 2,350 30 3,348 28,949 13,559 34,668	September 48,635 5 1,992 15,686 82,471 12,895 35,000	October 17,878 7,718 - 14,686 94,999 12,268 25,300	November 26,644 13,203 1,535 8,733 64,195 17,926 19,400	December 19,668 9,801 2,526 25,991 123,744 16,049 25,400
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old) Weaving Processing Steam boiler control	January 20,071 26,759 4,445 65,324 167,676 65,692 51,900 11,344	February 18,482 27,321 - 20,539 122,433 71,998 33,794 9,740	March 38,431 2,562 1,469 9,835 86,876 35,120 46,200 12,773	April 11,446 22,157 846 8,295 65,157 21,394 37,800 9,529	May 14,832 19,935 - 3,063 55,453 21,992 48,101 12,562	June 18,053 16,007 175 3,362 87,144 26,642 47,500 11,421	July 28,457 10,004 1,401 39 152,517 27,174 40,400 11,728	August 19,392 2,350 30 3,348 28,949 13,559 34,668 12,915	September 48,635 5 1,992 15,686 82,471 12,895 35,000 16,001	October 17,878 7,718 - 14,686 94,999 12,268 25,300 9,351	November 26,644 13,203 1,535 8,733 64,195 17,926 19,400 6,527	December 19,668 9,801 2,526 25,991 123,744 16,049 25,400 7,161
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old) Weaving Processing Steam boiler control ETP	January 20,071 26,759 4,445 65,324 167,676 65,692 51,900 11,344 6,767	February 18,482 27,321 - 20,539 122,433 71,998 33,794 9,740 1,869	March 38,431 2,562 1,469 9,835 86,876 35,120 46,200 12,773 4,008	April 11,446 22,157 846 8,295 65,157 21,394 37,800 9,529 15,002	May 14,832 19,935 - 3,063 55,453 21,992 48,101 12,562 5,014	June 18,053 16,007 175 3,362 87,144 26,642 47,500 11,421 5,068	July 28,457 10,004 1,401 39 152,517 27,174 40,400 111,728 5,234	August 19,392 2,350 30 3,348 28,949 13,559 34,668 12,915 277	September 48,635 5 1,992 15,686 82,471 12,895 35,000 16,001 2,289	October 17,878 7,718 - 14,686 94,999 12,268 25,300 9,351 1,904	November 26,644 13,203 1,535 8,733 64,195 17,926 19,400 6,527 2,701	December 19,668 9,801 2,526 25,991 123,744 16,049 25,400 7,161 357
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old) Weaving Processing Steam boiler control ETP Administration	January 20,071 26,759 4,445 65,324 167,676 65,692 51,900 11,344 6,767 4,365	February 18,482 27,321 - 20,539 122,433 71,998 33,794 9,740 1,869 4,233	March 38,431 2,562 1,469 9,835 86,876 35,120 46,200 12,773 4,008 4,495	April 11,446 22,157 846 8,295 65,157 21,394 37,800 9,529 15,002 5,088	May 14,832 19,935 - 3,063 55,453 21,992 48,101 12,562 5,014 3,907	June 18,053 16,007 175 3,362 87,144 26,642 47,500 11,421 5,068 3,513	July 28,457 10,004 1,401 39 152,517 27,174 40,400 11,728 5,234 4,125	August 19,392 2,350 30 3,348 28,949 13,559 34,668 12,915 277 3,909	September 48,635 5 1,992 15,686 82,471 12,895 35,000 16,001 2,289 4,413	October 17,878 7,718 - 14,686 94,999 12,268 25,300 9,351 1,904 4,234	November 26,644 13,203 1,535 8,733 64,195 17,926 19,400 6,527 2,701 4,508	December 19,668 9,801 2,526 25,991 123,744 16,049 25,400 7,161 357 4,325
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old) Weaving Processing Steam boiler control ETP Administration Engineering	January 20,071 26,759 4,445 65,324 167,676 65,692 51,900 11,344 6,767 4,365 1,662	February 18,482 27,321 - 20,539 122,433 71,998 33,794 9,740 1,869 4,233 1,662	March 38,431 2,562 1,469 9,835 86,876 35,120 46,200 12,773 4,008 4,495 1,662	April 11,446 22,157 846 8,295 65,157 21,394 37,800 9,529 15,002 5,088 1,662	May 14,832 19,935 - 3,063 55,453 21,992 48,101 12,562 5,014 3,907 1,662	June 18,053 16,007 175 3,362 87,144 26,642 47,500 11,421 5,068 3,513 1,662	July 28,457 10,004 1,401 393 152,517 27,174 40,400 11,728 5,234 4,125 1,419	August 19,392 2,350 30 3,348 28,949 13,559 34,668 12,915 2777 3,909 1,507	September 48,635 5 1,992 15,686 82,471 12,895 35,000 16,001 2,289 4,413 1,703	October 17,878 7,718 - 14,686 94,999 12,268 25,300 9,351 1,904 4,234 1,807	November 26,644 13,203 1,535 8,733 64,195 17,926 19,400 6,527 2,701 4,508 1,810	December 19,668 9,801 2,526 25,991 123,744 16,049 25,400 7,161 357 4,325 1,723
2022 Air Compressor 1 and 2 Air compressor 3 Humidification weaving Humidification spinning Spinning (new and old) Weaving Processing Steam boiler control ETP Administration Engineering Tailoring	January 20,071 26,759 4,445 65,324 167,676 51,900 11,344 6,767 4,365 1,662	February 18,482 27,321 - 20,539 122,433 71,998 33,794 9,740 1,869 4,233 1,662 5,791	March 38,431 2,562 1,469 9,835 36,876 35,120 46,200 12,773 4,008 4,495 1,662 6,769	April 11,446 22,157 846 8,295 65,157 21,394 37,800 9,529 15,002 5,088 1,662 6,122	May 14,832 19,935 - 3,063 55,453 21,992 48,101 12,562 5,014 3,907 1,662 5,324	June 18,053 16,007 175 3,362 87,144 26,642 47,500 11,421 5,068 3,513 1,662 8,140	July 28,457 10,004 1,401 39 152,517 27,174 40,400 11,728 5,234 4,125 1,419 3,911	August 19,392 2,350 30 3,348 28,949 13,559 34,668 12,915 2777 3,909 1,507 4,908	September 48,635 5 1,992 15,686 82,471 12,895 35,000 16,001 2,289 4,413 1,703 6,361	October 17,878 7,718 - 14,686 94,999 12,268 25,300 9,351 1,904 4,234 1,807 5,925	November 26,644 13,203 1,535 8,733 64,195 17,926 19,400 6,527 2,701 4,508 1,810 2,470	December 19,668 9,801 2,526 25,991 123,744 16,049 25,400 7,161 357 4,325 1,723 1,945

Table 12: Electricity consumption for all departments at Rivatex 2022 and 2023 (personal communication, electrical engineer, Ezekiel Kigen, 26.01.2024)

C Modelling assumption

C.1 Monthly energy consumption from each transformer at Rivatex



Figure 14: Average monthly load of each transformer at Rivatex textile factory based on data in appendix B

Figure 14 shows the average electricity consumption from each transformer at Rivatex in the current system based on data from appendix B. From the figure it shows that least electricity is consumed from T4, thus it was assumed that this transformer has surplus capacity. Therefore, the electric boiler is supplied through this transformer in the energy system model.

C.2 Operating hours

For modelling the energy system, an assumption of monthly operating hours had to be made because the textile factory has no record of operation hours nor do they have a production log. It was therefore assumed that the operating hour of all machines follow the normal working hours. According to Gideon Boit, who is an electrical engineer at Rivatex, it is common to work 08-17 Monday to Friday and 09-15 Saturday. Including a one hour lunch break, this gives a 45 hour a week, which corresponds to 192,86 hour per month assuming 30 days in a month (personal communication, 21.03.2024). Thus, for the purpose of this thesis, an operating time of 192,86 hour/month was assumed.

C.3 Choice of mono-crystalline modules

For the solar PV system at Rivatex, mono-crystalline solar panels have been chosen. The study by Ngure (2022) showed that mono-crystalline modules have higher efficiency and lower annual degradation rate in tropical savanna climate compared to poly-crystalline modules. The mono-crystalline modules had a power degradation rate of 0.99% and a measured efficiency of 12.70%, while the poly-crystalline modules had a power degradation rate of 1.15% and a measured efficiency of 10.71%. However, it should be noted that the poly-crystalline solar panels are less affected by accumulation of dust than the mono-crystalline panels. Accumulation of dust caused power losses of 9% for poly-crystalline modules and 17% for mono-crystalline modules. Nonetheless, the effects of dust accumulation is estimated to be smaller than the effects of higher efficiency and lower degradation rate for mono-crystalline panels (Ngure, 2022).

C.4 Estimation of electricity consumption per kWh of steam from firewood

To estimate the steam control electricity consumption per kWh steam produced from the firewood boilers, and average of electricity consumption for steam control is first calculated. Based on the data in table 12 in appendix B an average of 11,356.79 kWh per month was calculated using the data from both 2023 and 2023. Using the estimation of steam energy from firewood calculated in chapter 4.3.5, the electricity consumption per kWh of steam is calculated kWh el per kWh steam = $\frac{11,356.79 kWhel}{1761190 kWhsteam} = 0.006448 kWh el/kWh steam$

D Steam Requirement

Machine	Steam Required (Kg/h)	Pressure (bar)
New Sizing and Cooker	2000	5
Old Sizing	0	0
Flat Bed Printer	500	4
Colour Kitchen	100	2
Old RD3 Printer	800	6
Steam Ager	1200	6
Singieng	200	2
Jigger	700	5
Washing Range	3720	4
Pad Steam	4032	4
Merceriser	2160	4
Raising	200	2
Sanforizer	400	3
Finishing Stenter	1200	6
Calendering	300	3
Cold Bleaching Range	3700	4
Yarn Dyeing	1000	6.5
Hot Flue	1000	6
Caustic Recovery Plant	500	5
Total steam Required	23712	

Table 13: Steam demand from each machine (personal communication, Chief Engineer Caroline Mureithi, 29.01.2024)

E Historical electricity tariffs



Figure 15: Historical energy tariffs from Shah (2024) adjusted for inflation (Inflation Tool, 2024)



Figure 16: Historical electricity levies from Shah (2024) adjusted for inflation (Inflation Tool, 2024)
F Electricity bill December 2023



Figure 17: Provided by electrical engineer Gideon Boit (personal communication, 27.03.2024)

G Python model

```
1
2 from pulp import *
3 import pandas as pd
4 import numpy as np
5 import Weather
8
    model = pulp.LpProblem( name: 'linear_programming', LpMinimize)
9
10 # get solver
11 s = pulp.PULP_CBC_CMD()
13 # average function
14 def avg_of_vec(vector1, vector2):
       #convert to numpy arrays
       array1 = np.array(vector1)
       array2 = np.array(vector2)
18
19
       # calculate average
       avg_vec = (array1 + array2)/2
20
        return avg_vec
24 months = 12
25 years = 20
    # define variables
28 X_elnew ={(i, j): LpVariable( name: f"X_elnew{i}_{j}", lowBound=0, cat='continuous')
29
            for i in range(years)
30
             for j in range(months)}
     X_el1 = {(i,j):LpVariable( name: f"X_el1{i}_{j}", lowBound=0, cat='continuous')
             for i in range(years)
33
             for j in range(months)}
     X_el2 = {(i,j):LpVariable( name: f"X_el2{i}_{j}", lowBound=0, cat='continuous')
34
             for i in range(years)
35
             for j in range(months)}
36
     X_el3 = {(i,j):LpVariable( name: f"X_el3{i}_{j}", lowBound=0, cat='continuous')
             for i in range(years)
38
39
             for j in range(months)}
     X_el4 = {(i,j):LpVariable( name: f"X_el4{i}_{j}", lowBound=0, cat='continuous')
40
41
             for i in range(years)
             for j in range(months)}
    X_sw = {(i,j):LpVariable( name: f"X_sw{i}_{j}", lowBound=0, cat='continuous')
43
            for i in range(years)
44
45
            for j in range(months)}
    X_se = {(i,j):LpVariable( name: f"X_se{i}_{j}", lowBound=0, cat='continuous')
46
            for i in range(years)
48
             for j in range(months)}
```

```
X_PV1 = {(i,j):LpVariable( name: f"X_PV1{i}_{j}", lowBound=0, cat='continuous')
50
             for i in range(years)
             for j in range(months)}
     X_PV2 = {(i,j):LpVariable( name: f"X_PV2{i}_{j}", lowBound=0, cat='continuous')
52
             for i in range(years)
54
             for j in range(months)}
     X_PV3 = {(i,j):LpVariable( name: f"X_PV3{i}_{j}", lowBound=0, cat='continuous')
             for i in range(years)
57
             for j in range(months)}
     X_PV4 = {(i,j):LpVariable( name: f"X_PV4{i}_{j}", lowBound=0, cat='continuous')
58
59
             for i in range(years)
             for j in range(months)}
61
     X_PV5 = {(i,j):LpVariable( name: f"X_PV5{i}_{j}", lowBound=0, cat='continuous')
             for i in range(years)
             for j in range(months)}
     X_batin = {(i,j):LpVariable( name: f"X_batin{i}_{j}", lowBound=0, cat='continuous')
            for i in range(years)
            for j in range(months)}
67
     X_batout = {(i,j):LpVariable( name: f"X_batout1{i}_{j}", lowBound=0, cat='continuous')
            for i in range(years)
69
            for j in range(months)}
70
     SOC = {(i,j):LpVariable( name: f"SOC{i}_{j}", lowBound=0, cat='continuous')
            for i in range(years)
            for j in range(months)}
     A = LpVariable( name: 'A', lowBound=0, cat='continuous')
     C_sw = LpVariable( name: 'C_sw', lowBound=0, cat='continuous')
75
     C_se = LpVariable( name: 'C_se', lowBound=0, cat='continuous')
     C_bat = LpVariable( name: 'C_bat', lowBound=0, cat='continuous')
78
79
     80
     # Demands
81
82
     ## Loading excel sheet
83
     PDM22 = pd.read_excel( io: "PowerDemand.xlsx", sheet_name: "2022")
     PDM23 = pd.read_excel( io: "PowerDemand.xlsx", sheet_name: "2023")
84
85
     ## Calculating average demand for each month for each of the processes
86
87
     DM_AirComp = avg_of_vec(list(PDM22.AIR_COMPRESSOR_ELGI), list(PDM23.AIR_COMPRESSOR_ELGI))
     DM_SpinningNew = avg_of_vec(list(PDM22.SPINNING_NEW), list(PDM23.SPINNING_NEW))
88
89
     DM_SpinningOld = avg_of_vec(list(PDM22.SPINNING_OLD), list(PDM23.SPINNING_OLD))
90
     DM_Admin = avg_of_vec(list(PDM22.ADMINISTRATION), list(PDM23.ADMINISTRATION))
     DM_HumSpin = avg_of_vec(list(PDM22.HUMIDIFICATION_SPINNING), list(PDM23.SPINNING_OLD))
     DM_Engineering = avg_of_vec(list(PDM22.ENGINEERING), list(PDM23.ENGINEERING))
92
     DM_Weaving = avg_of_vec(list(PDM22.WEAVING), list(PDM23.WEAVING))
93
94
     DM_AirComp3 = avg_of_vec(list(PDM22.AIR_COMPRESSOR_ELGI3), list(PDM23.AIR_COMPRESSOR_ELGI3))
    DM_WetP = avg_of_vec(list(PDM22.PROCESSING), list(PDM23.PROCESSING))
95
96
     DM_Tailoring = avg_of_vec(list(PDM22.TAILORING), list(PDM23.TAILORING))
     DM_ETP = avg_of_vec(list(PDM22.ETP), list(PDM23.ETP))
```

```
98 DM_HumWeaving = avg_of_vec(list(PDM22.HUMIDIFICATION_WEAVING), list(PDM23.HUMIDIFICATION_WEAVING))
```

```
E_steam = 761
                        # Energy in steam measured in kWh/tonne steam
     DM_steam = 2610094.72 #tonnes per month based on 141,43 full load hours per month (full load: 23,715 tonnes/h)
102
     # el consumption for steam control when using firewood (measured per kWh steam from fw):
104
     DM_SteamControl = lpSum(list(PDM22.STEAM_BOILER) + list(PDM23.STEAM_BOILER))/24/1761190
106
     # Costs
108
     selected_columns = ['year 0', 'year 1', 'year 2', 'year 3', 'year 4', 'year 5', 'year 6', 'year 7', 'year 8', 'year 9',
                       'year 10', 'year 11', 'year 12', 'year 13', 'year 14', 'year 15', 'year 16', 'year 17', 'year 18',
                       'year 19']
     ## Read specific columns from the Excel file into a pandas DataFrame
     a_con = pd.read_excel( io: "El_price_test.xlsx", sheet_name='consumption', usecols=selected_columns)
     a_FCC = pd.read_excel( io: "El_price_test.xlsx", sheet_name='FCC', usecols=selected_columns)
     a_WARMA = 0.01
     a ERC = 0.08
     a_REP = 0.05 * a_con*((1-0.293)+0.5*0.293)
118 VAT = 0.16
119
     a_dc = 900*370
120
     ## Convert DataFrame to a NumPy array (matrix)
     a_energy = (a_con*((1-0.293)+0.5*0.293)+a_FCC).values #matrix with energy related tariffs. OBS! months are first index
     a_levies = (a_WARMA+a_REP+a_ERC).values #matrix with levies. OBS! months are forst index
     a_el = a_energy*(1+VAT)+a_levies
    ## Other costs
127 a_sw = 0.66
                         #KES per tonnes steam when using firewood
128 a_PV = 7.76
                         #KES per kWh
129 a_bat = 18319.80
                         #KES for battery investment
130 a_se = 1276.60
                         #KES per year per installed capacity meastured in tonnes/year
133 # Technology constraints
135 ## Battery
136 eta_rt = 0.91 # AC round trip efficiency including inverter losses
137 eta_batloss = 0.0304 # Monthly losses in battery
138 C_batmin = 295.73 # kWh of capacity
    model += C_bat >= C_batmin, 'min_bat_cap'
139
    ## Steam boilers
    t_oper = 45*30/7
                                              #operating hours per month
     model += C_sw <= 2*6, 'SW_cap'</pre>
                                               #tonnes per hour for the two forewood boilers
     model += C_se + C_sw >= 23.712, 'min_steam_cap' #tonnes per hour
144
     eta_se = 0.99
     ## PV panels
                        #Potential solar PV production each month in kWh/m^2
148
     C_PV = Weather.Eavg
     model += A <= 8855.99*0.9, 'max_PV_area' # potential area in m^2 for solar PV..</pre>
```

99

```
### Calculation degradation of solar PV
      r_degPV = 0.0099
      C_PV_adj_matrix = []
      for i in range(years):
          C_PV_adj = [float(value) * (1 - r_degPV) ** i for value in C_PV]
         C_PV_adj_matrix.append(C_PV_adj)
      C_PV_adj_matrix = np.vstack(C_PV_adj_matrix)
      for i in range(years):
          model += (SOC[i, 0]*eta_rt - X_batin[i, 0]*eta_rt + X_batout[i, 0] == SOC[i, 11]*eta_rt)
          for i in range(months):
             model += (X_PV1[i, j] + X_PV2[i, j] + X_PV3[i, j] + X_PV4[i, j] + X_PV5[i, j] + X_batin[i, j] ==
                      C_PV_adj_matrix[i, j]*A)
             model += X_sw[i, j] <= C_sw*t_oper*E_steam</pre>
             model += X_se[i, j] <= C_se*t_oper*E_steam</pre>
             model += SOC[i, j] <= C_bat</pre>
             if j > 0:
                 model += SOC[i, j]*eta_rt == SOC[i, j-1]*eta_rt + X_batin[i, j]*eta_rt - X_batout[i, j]
             elif j == 0 and i > 0:
                 model += (SOC[i, j]*eta_rt == SOC[i-1, months-1]*(1-eta_batloss)*eta_rt +
                          X_batin[i, j]*eta_rt - X_batout[i, j])
     178
     # Demand constraints
     for i in range(years):
         for j in range(months):
             model += X_elnew[i, j] +X_PV5[i, j] == DM_AirComp[j] + DM_SpinningNew[j] + DM_Admin[j] # new main transformer
             model += X_el1[i, j] + X_PV1[i, j] == DM_SpinningOld[j] + DM_HumSpin[j] + DM_Engineering[j] # T1
             model += X_el2[i, j] + X_PV2[i, j] == DM_Weaving[j] + DM_AirComp3[j] + DM_HumWeaving[j]
                                                                                                      # T2
             model += X_el3[i, j] + X_PV3[i, j] + X_batout[i, j] == DM_WetP[j]
                                                                                                     # T3
             model += (X_el4[i, j]*eta_se + X_PV4[i, j]*eta_se ==
                      DM_Tailoring[j]*eta_se + DM_SteamControl*X_sw[i, j]*eta_se + DM_ETP[j]*eta_se + X_se[i, j])# T4
188
             model += X_sw[i, j] + X_se[i, j] >= DM_steam
                                                                                    # Steam demand assumed constant
     # Objective functions
     ## Cost minimisation
     model += (lpSum([X_el1[i, j]*a_el[j, i] for i in range(years) for j in range(months)] +
                    [X_el2[i, j]*a_el[j, i] for i in range(years) for j in range(months)] +
199
                    [X_el3[i, j]*a_el[j, i] for i in range(years) for j in range(months)] +
                    [X_el4[i, j]*a_el[j, i] for i in range(years) for j in range(months)] +
                    [X_elnew[i, j]*a_el[j, i] for i in range(years) for j in range(months)] +
                    [X_sw[i, j]*a_sw for i in range(years) for j in range(months)] +
                    [X_PV1[i, j]*a_PV for i in range(years) for j in range(months)] +
                    [X_PV2[i, j] * a_PV for i in range(years) for j in range(months)] +
                    [X_PV3[i, j] * a_PV for i in range(years) for j in range(months)] +
                    [X_PV4[i, j] * a_PV for i in range(years) for j in range(months)] +
                    [X_PV5[i, j] * a_PV for i in range(years) for j in range(months)] +
                    [X_batin[i, j] * a_PV for i in range(years) for j in range (months)] +
209
                    [C_bat * a_bat * years] +
                    [C_se * a_se * years]))
```

```
# Objective functions
193
    ## Minimise dependence on grid
194
    model += lpSum([X_el1[i, j]*100 for i in range(years) for j in range(months)] +
195
196
                [X_el2[i, j]*100 for i in range(years) for j in range(months)] +
                [X_el3[i, j]*100 for i in range(years) for j in range(months)] +
198
                [X_el4[i, j]*100 for i in range(years) for j in range(months)] +
199
                [X_elnew[i, j]*100 for i in range(years) for j in range(months)])
     # Solution
216
     results = model.solve(solver=s)
```

H Average weather data

The following figures show the average hourly irradiation and temperature calculated from measurements in 2021, 2022 and 2023 at Moi University Weather Station (personal communication, Abraham Kosgei, 09.02.2024).

















Norges miljø- og biovitenskapelige universitet Noregs miljø- og biovitskapelege universitet Norwegian University of Life Sciences Postboks 5003 NO-1432 Ås Norway