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How Africa is Inventing Decentralized Electricity Networks: An Original Analysis Based on Machine and Deep Learning

Hugo Le Picard

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Hugo Le Picard. How Africa is Inventing Decentralized Electricity Networks: An Original Analysis Based on Machine and Deep Learning. Economics and Finance. Université Paris sciences et lettres, 2023. English. NNT: 2023UPSLD010 . tel-04217964

HAL Id: tel-04217964

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THÈSE DE DOCTORAT
DE L'UNIVERSITÉ PSL
Préparée à Université Paris-Dauphine

How Africa is Inventing Decentralized Electricity Networks
An Original Analysis Based on Machine and Deep Learning

Soutenue par

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Le 23 Janvier 2023

École doctorale n°543

Ecole doctorale SDOSE

Spécialité

Sciences économiques

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A ma famille,

Remerciements

J'exprime d'abord ma profonde reconnaissance à ma directrice de thèse, Sophie Meritet. Je la remercie d'avoir accepté de diriger mes recherches. Son soutien, son aide généreuse, ses encouragements et ses précieux conseils, tout au long de ces trois années ne m'ont jamais fait défaut et m'ont permis d'aller au bout de cette thèse de doctorat. Je tiens aussi à la remercier pour l'opportunité qu'elle m'a donnée d'enseigner la microéconomie à Dauphine, cela a été pour moi un atout important pour mon travail de thèse.

Je souhaite aussi exprimer toute ma gratitude à mon tuteur de thèse à l'IFRI, Marc-Antoine Eyl-Mazzega, qui m'a accueilli au sein de son Centre Energie & Climat. Ses enseignements auront été essentiels pour mes débuts professionnels et pour cette thèse réalisée en CIFRE. J'ai eu beaucoup de chance d'avoir pu bénéficier pendant ces trois années de son énergie et de son enthousiasme rares. J'ai beaucoup appris pendant ces années passées à ses côtés et je lui en suis particulièrement reconnaissant.

Je suis reconnaissant à tous deux de la confiance qu'ils m'ont accordée.

Tous mes remerciements vont également à mon jury de thèse, Arash Farnoosh, Pierre-Olivier Pineau, Anna Creti, Jean-François Jacques, Philippe Benoit et Fabrice Rossi.

J'exprime ma gratitude envers Arash Farnoosh et Pierre-Olivier Pineau pour avoir accepté d'être rapporteurs de cette thèse de doctorat. J'en suis très honoré. Je remercie en particulier Arash Farnoosh pour son implication dans ma pré-soutenance de thèse et pour ses précieux conseils. Mes remerciements s'adressent aussi à Anna Creti pour son suivi attentif de mon travail, son implication dans ma pré-soutenance et les avis si précieux qu'elle m'a régulièrement prodigués durant ces trois années de doctorat. Je tiens aussi à remercier vivement Philippe Benoit, qui, lui aussi, a suivi ma thèse depuis son origine. Les nombreuses discussions que nous avons eues au Café Maubert ont contribué à faire évoluer une problématique de thèse assez classique, vers un sujet beaucoup plus pertinent et original. Je le remercie profondément de l'attention qu'il a porté à mon travail. Je suis très reconnaissant également envers Jean-François Jacques, pour avoir accepté de faire partie de mon jury.

Enfin, je tiens aussi à exprimer ma gratitude envers Fabrice Rossi. C'est lui qui m'a initié au Machine Learning ainsi qu'au code. J'ai énormément appris à ses côtés et je suis très honoré d'avoir eu et d'avoir encore l'opportunité de travailler avec lui.

Que tous les membres du jury trouvent ici l'expression de mes remerciements les plus chaleureux. Je me réjouis par avance par avance des discussions que nous aurons à l'occasion de la soutenance.

Je tiens aussi à exprimer ma gratitude à Patrice Geoffron, pour l'intérêt qu'il a porté à ma thèse et son suivi attentif de celle-ci pendant ces trois années. Je le remercie aussi profondément pour toute l'aide et les conseils qu'il m'a apporté aux différentes étapes de celle-ci ainsi que pour la bienveillance et la confiance qu'il a exprimé à mon égard.

Je suis très reconnaissant également envers Nadia Ouedraogo, pour les échanges que nous avons eus au début de mon projet et qui ont été déterminants pour m'aiguiller vers les questions nouvelles soulevées par cette thèse.

Je remercie également Matthieu Toulemont, avec qui j'ai mené l'analyse du chapitre 2. J'ai énormément appris à ses côtés et j'ai pu, grâce à lui, bénéficier d'un enseignement particulièrement rapide en Deep Learning. Je tiens aussi à remercier Aurélien et Justus, pour leurs relectures attentives de différentes parties de ma thèse, ainsi que pour leurs conseils. Enfin, je remercie chaleureusement Serge Michailof pour les discussions que nous avons eues, qui m'ont fait bénéficier de son immense connaissance du continent Africain. Je tiens aussi à remercier Mélanie Rateau et Emmanuelle Guillou, chercheuses au laboratoire LATTS, qui m'ont fait bénéficier de leurs recherches de thèse au tout début de la mienne et qui ont contribué à façonner mon travail.

Je remercie aussi la direction de l'IFRI, Thomas Gomart ainsi que Valérie Genin, pour leur soutien et leurs encouragements pour que cette thèse soit finie dans les temps ! Je remercie aussi mes collègues du Centre Energie et Climat de l'IFRI : Carole et Cécile, pour leur gentillesse, leur bienveillance et leur amitié. Merci aussi aux équipes de l'IFRI, que j'ai eu la chance de côtoyer pendant ces trois années dans cette noble institution : Marc, Dimitri, Marc J, Laure, John, Norbert, Sharleen, Michael, Dimitri M, Céline, Anne, Barbara, Catherine, Aminata, Nathalie, Raphael, Yann, Dorothee, Alain, Sina, Elie, Corentin, Menah, Nicolas, Karine, Daniel et tous les autres...

Mes remerciements s'adressent également à toutes les équipes du LEDa et du CGEMP, notamment Marie Bessec pour les conseils d'économétrie qu'elle m'a prodigué, et pour m'avoir donné l'opportunité de donner un cours d'introduction à la vision informatique et au Deep Learning. Je remercie aussi mes camarades doctorants, Leopold, Cécile, Benoit, Aimée, Julien, pour tous les moments partagés ensemble.

Je suis reconnaissant envers mes amis, pour leur soutien pendant ces trois années, Leopold, Janieva, Lamine, Rayan, Elyes, Marco, Gregorio, Evan, Théo, Hector, Ed, Rob, Nicolas, Luc-Yaovi, Alexis, Camille et tous les autres...

Enfin, je remercie ma famille, à qui cette thèse est dédiée, mon père, pour son soutien constant, ma mère, pour ses relectures et surtout, mon frère Nessim, pour son appui et son concours décisifs.

Enfin, je suis extrêmement reconnaissant, à titre posthume, envers mon grand-père Rémi et ma tante Claudine, dont l'énergie et la bienveillance m'ont accompagné tout au long de cette thèse et m'accompagnent encore à ce jour.

How Africa is Inventing Decentralized Electricity Networks

An Original Analysis Based on Machine and
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Introduction

Despite the many natural riches present in Africa, the continent remains underdeveloped. Although sub-Saharan Africa has experienced yearly growth rates averaging 3.5% between 2009 and 2019 (World Bank, 2022a), the economies of individual countries in the region are fragile. Extreme poverty affects more than half of the population. According to most recent estimates, of the 700 million people living in extreme poverty worldwide (living on less than 1.9 dollar (USD) a day), more than half are in Africa (United Nations, 2015a). Furthermore, according to International Monetary Fund (IMF) projections, 20 million jobs will need to be created annually in sub-Saharan Africa over the next two decades to absorb the new entrants to the labor market (International Monetary Fund, 2018). Economic development is therefore a necessity to the resolution of the endemic poverty plaguing the region, which has increased in recent years due to the crises related to covid-19 and the invasion of Ukraine by Russia, but also to the employment of young people who are entering the labor market in greater numbers every year.

In the energy sector, this poverty translates into very little access to energy and in particular to electricity. The sub-Saharan electricity sector is among the least developed globally in terms of electrification rate, consumption, installed capacity, and reliability of electricity supply. Of the approximately 1 billion people in the world who do not have access to electricity, nearly 600 million are sub-Saharan Africans. While the continent accounts for almost 14% of the world's population, more than half (51.5%) of the sub-Saharan population still had no access to electricity services in 2020. In some countries, the electrification rate is less than 10% (World Bank, 2022a). The installed capacity in all of sub-Saharan Africa (excluding South Africa) amounted to about 80 Gigawatts (GW) in 2018, almost half that of France (130 GW), even though the region has 18 times as many inhabitants (International Energy Agency, 2019). The average individual consumption per year was about 170 kilowatt-hours (kWh) in 2020 (International Energy Agency, 2022a). This is barely enough to power a fan and two light bulbs for four hours daily. The consumption gap with industrialized countries is abysmal. As a comparison, the average annual consumption of a sub-Saharan is equivalent to one-twelfth of the consumption of a European and one-fourteenth of that of an individual in France (World Bank, 2022a).

To make things even worse, service interruptions are frequent, with an average of more than 51 hours of power cuts each month in the sub-Saharan region. This low reliability of electrical supply in electrified areas represents a major constraint for economic activity. It disrupts businesses and forces them to shut down their production lines during power outages, resulting in lost revenue from unrealized production. These power cuts also generate high additional costs for companies, such as those related to the costs of restarting production lines or replacing machines damaged by voltage drops or sudden

stoppages. According to the World Bank, the average losses of sub-Saharan companies due to power outages amount to 8.5 percent of their annual sales (World Bank, 2022b). At the macroeconomic level, the costs of power outages to the economy vary between 1 and 4 percent of national gross domestic product (GDP) depending on the country (Foster and Briceno-Garmendia, 2010). The poor development of electrical systems in sub-Saharan Africa is, therefore, a major constraint on the region's economic development.

In this context, many authors argue that developing the continent's power systems is essential because it enables economic development and directly promotes economic growth in sub-Saharan Africa (Akinlo, 2009; Cook, 2011; Iyke, 2015; Ouedraogo, 2013; Sarkodie and Adams, 2020). In developing countries, the academic literature shows that there are many gains for the population from access to electricity. For example, at the economic level, access to electricity is associated with productivity gains (Kirubi et al., 2009) and better employment opportunities (Dinkelman, 2011). It is also a more flexible energy carrier that allows for the efficient organization of activities in high-value-added sectors such as industry and manufacturing (Burke et al., 2018). At the social level, electricity allows better access to quality health care (Moner-Girona et al., 2021), a reduction in infant mortality rates (Mohammed and Akuoko, 2022) and an increase in literacy rates (Kanagawa and Nakata, 2008). In addition, electricity permits lighting after sunset and thus greatly increases the time available for productive activities, such as study time for children. Electricity also lets households access clean cooking facilities instead of using dangerous and polluting fuels such as coal or manure (Morrissey, 2017). While these are just a few examples, the academic literature is replete with research articles that demonstrate the socio-economic benefits of access to electricity. The extensive literature on the subject thus makes clear that developing electricity systems is a critical issue.

With the adoption of the Sustainable Development Goals (SDGs), the international community has committed to achieving universal access to electricity by 2030. SDG 7 aims to ensure universal access to reliable, sustainable, modern, and affordable energy services through the achievement of several sub-targets detailed in table 1. The governments of most developing countries emphasize the crucial role of access to electricity for human development (Parshall et al., 2009) and have made it a priority (Africa Progress Panel, 2015).

However, the goal of universal access to electricity for the African population by 2030 is unlikely to be achieved (Lucas et al., 2015). Sub-Saharan Africa is still struggling to develop its electricity sector and lags behind other regions. The continent appears to have idiosyncrasies that make it difficult to directly compare its power sector development with other regions of the world. For example, at first glance, the very low electrification of sub-Saharan Africa

Table 1: ODD7 - Ensure access to affordable, reliable, sustainable, and modern energy for all

Title of the target	Description of the target
Access to energy	7.1 By 2030, ensure universal access to affordable, reliable, and modern energy services
Renewable energy	7.2 Increase substantially the share of renewable energy in the global energy mix by 2030
Energy efficiency	7.3 double the global rate of improvement in energy efficiency by 2030
Research and investment	7.a By 2030, enhance international cooperation to facilitate access to clean energy research and technologies, including renewable energy, energy efficiency, and advanced and cleaner fossil fuel technologies, and promote investment in energy infrastructure and clean energy technologies
Energy supply	7.b By 2030, expand infrastructure and upgrade technology for supplying modern and sustainable energy services for all in developing countries, particularly LDCs and SIDS

Source : United Nations (2015b)

could be seen as one of the main consequences of the region's low level of economic development. Indeed, when comparing regions of the world, there is a clear correlation between the poverty gap and access to electricity. Thus, one might hypothesize that a high poverty gap, or in other words, a low level of development in a country, would directly impact the access to electricity of its population. However, if we compare the electrification levels of different low- and middle-income countries, controlling for the GDP per capita, we find that at relatively equal levels of wealth, electricity access rates are consistently lower in sub-Saharan Africa than in the comparator countries. Living in sub-Saharan Africa would, therefore, directly reduce the probability of a household having access to electricity, irrelative to the level of economic development (Trimble et al., 2016; Le Picard, 2019).

Although the continent cannot meet its population's current electricity consumption needs, the demand for electricity will continue to grow in the coming decades. In addition to the needs generated by economic development, Africa is experiencing significant urbanization, which goes hand in hand with strong demographic growth. Africa's population is expected to double to 2.1 billion by 2050 (United Nations, 2019). Moreover, by 2050, the proportion of the population in urban and rural areas will be reversed. In 30 years, 60% of the population is predicted to be urban and 40% rural (United Nations, 2018). In addition to electrification targets, the continent will therefore have to prepare the core networks³ of sub-Saharan Africa to accommodate nearly 1.2 billion urban dwellers by 2050 and provide them with electricity that is reliable, affordable, and sustainable.

Global warming could also augment the continent's electricity needs as the African continent will increasingly suffer the consequences of climate change. Temperatures are expected to rise more on the African continent than in other regions: up to one and a half times more than the global average. A study has shown that more than a third of Africa's urban population could be affected by extreme and even deadly heatwaves by 2090 (Rohat et al., 2019). This is even though the continent has very little responsibility for global warming. According to the International Energy Agency (IEA) statistics, in 2019, the entire continent emitted only 3.8% of global carbon dioxide (CO₂) emissions. As a result, the continent's urban population will have significant cooling needs, resulting in increased electricity consumption.

The IEA estimates that electricity demand in Africa will increase by 75% over the next decade (International Energy Agency, 2022a). How Africa will meet this growing energy demand is crucial. If sub-Saharan Africa followed a model of economic and energy development similar to other countries in the world,

³Throughout this thesis, the terms "network" and "grid" are used interchangeably and both refer to the central network unless clearly specified otherwise.

based on increased consumption of fossil fuels, this would seal the planet's climate future into a high carbon scenario (Le Picard, 2021).

Sub-Saharan Africa does, however, have at its disposal colossal solar electricity production potential, which should enable the region to meet its energy needs sustainably. But to date, it only exploits a small fraction of it, with solar representing only 2% of installed capacities of the central network (excluding South Africa)⁴ (International Energy Agency, 2019; IRENA, 2022).

Several factors suggest that the development of electricity sectors in sub-Saharan Africa will not follow the same path as in industrialized countries. Faced with the failures of the central networks, populations and companies can now use additional means of electricity production to satisfy their energy needs. In recent decades, decentralized power generation technologies, such as backup generators and decentralized solar systems, have been rapidly deployed on the continent. Africa is one of the world's biggest markets for auxiliary generators, as businesses across the continent invest massively in those systems to deal with grid deficiencies. More than half of sub-Saharan companies are equipped with or share a generator (World Bank, 2022b). At the continental level, auxiliary generators aggregated capacities are estimated to represent about 127 GW, almost the equivalent of total installed capacities on the region's central networks (International Energy Agency, 2019; Attia, 2022). Furthermore, the market for decentralized solar systems has constantly been growing in the past decade. 3.8 million units were sold in Africa in 2018, making sub-Saharan Africa the biggest market for these systems globally (Gogla, 2020).

The lack of electricity infrastructure is an attractive market for companies that trade in these systems and see sub-Saharan citizens without access to electricity as potential customers. Given the difficulties central grids have in meeting demand and providing reliable service, these technologies may also attract consumers connected to the central network. Several authors have already reported the use of such technologies by consumers connected to the grid, for economic reasons or to secure a more reliable supply of electricity (Jaglin, 2019; Barry and Creti, 2020). The market for decentralized systems could therefore represent the entire sub-Saharan population, or 1.1 billion potential customers today and 2.1 billion in 2050.

However, increased penetration of decentralized systems in network areas could have profound implications for the sector's development, which should be analyzed. Decentralized power generation systems offer grid-connected consumers

⁴These estimates do not consider the aggregated capacity of decentralized solar systems, which could be high in the region, and an alternative way to benefit from Africa's immense solar potential.

the opportunity to become less dependent on the grid for their electricity consumption. Given the significant increase in the urban population and the growing attractiveness of decentralized systems, the possibility that frail and inefficient centralized networks may become partly superfluous should not be disregarded.

This thesis therefore attempts to assess to what extent Africa's future electricity systems could be more decentralized than centralized. In this thesis, the validity of this hypothesis is explored and it is attempted to establish new key elements of analysis to understand the development of power systems in the region.

This thesis seeks to answer three main questions:

1. What can be the consequences of the deployment of decentralized technologies in the areas covered by network electricity on the organization and evolution of sub-Saharan electricity infrastructure?
2. How widespread are decentralized systems in urban grid-covered areas in Africa, and what types of consumers do they cater to?
3. What are the links between electricity supply and consumer empowerment, and how can an improvement in the electricity supply's reliability influence the use of decentralized systems by consumers connected to the grid?

As will become apparent, the academic literature on the development of power systems in sub-Saharan Africa has until very recently used an analytical framework that largely mirrors the evolution of power systems in industrialized countries. The issues raised by this thesis have thus far only been covered marginally. This thesis therefore takes a new angle on the academic literature that addresses topics related to the development of power systems in the region. This thesis focuses mainly on urban areas covered by the grid which seems all the more relevant as most of the population will be located in urban areas in the near future due to the region's urbanization.

This thesis is organized as follows.

The first chapter provides a general overview of the development of sub-Saharan electricity sectors. This overview allows us to better understand the main challenges faced by the centralized electricity sectors in the region and their capacity to address them. Given the problems related to electricity supply from the central grid, it is then explored whether decentralized technologies proposed by the private sector are also present in the areas covered by the grid. In other words : whether a consumer can use decentralized systems in

addition to the central grid to satisfy his electricity consumption needs. This thesis attempts to give a first assessment of this phenomenon. Based on these analyses, the consequences of increased penetration of decentralized systems in grid-covered areas is explored.

This first chapter presents a qualitative analysis that is the foundation of this thesis. It lays the groundwork for questions that are addressed with quantitative methods in this thesis's second and third chapters to complete the overall analysis. At the end of chapter 1, the first research question mentioned above will be answered. It will however become apparent that one of the limits of the analysis of the first chapter is that there is no database on the development of the decentralized solar market in African cities, although there are reasons to believe this market is developing in those areas. Some small parts of this chapter have been published in several Ifri publications, which are referenced throughout the chapter. The analysis of the chapter will be the subject of a future academic publication in an economics journal.

In the second chapter, the current extent of decentralized systems' adoption in grid-covered areas in sub-Saharan Africa is explored by analyzing the development of the decentralized solar market for the residential sector in African cities. As there is no database on this market segment, an original method that uses Deep Learning tools to analyze several million satellite images is implemented in chapter 2. This study is conducted in 14 cities in 13 African countries and covers more than 4 billion square meters of land. This initial analysis makes it possible to assess whether the market for decentralized solar systems is present in urban areas covered by the grid in sub-Saharan Africa. To understand the consequences of this market's development on the sector's finances, a subsequent econometric analysis helps assess what type of consumer these are aimed at. The econometric analysis facilitates the determination of which type of consumers this market caters to in terms of consumer revenues and reliability of electricity access from the central network. At the end of chapter 2, the second question and part of the third research question mentioned above will be answered. The Deep Learning analysis in this chapter was done in collaboration with Matthieu Toulemont, senior Machine Learning engineer at Photroom. A simplified version of the analysis presented in this chapter has already been published by Ifri and will be submitted to an academic journal in economics.

In the third chapter, how consumers use different decentralized technologies in addition to the central grid is explored. This question is addressed by analyzing the behavior of companies that are both connected to the grid and using auxiliary generators. As the first two chapters conduct a comparative analysis across multiple countries, a case study of a specific country is made in the third chapter. Nigeria was chosen as it is the country where the aggregated auxiliary

generator's capacities are the highest on the continent. A specific case study on this country will also make it possible to illustrate, with concrete examples, many of the points raised in the first chapters of this thesis and study in more detail the use of decentralized generators by consumers connected to the grid. This chapter is based on the analysis of an original database of hundreds of thousands of electricity consumption observations from auxiliary generators of grid-connected companies in Nigeria using Machine Learning algorithms. With regard to the questions asked by this thesis, it is determined whether there is a form of decorrelation between the use of generators and the reliability of electricity supplied by the network. In other words, to what extent an increase in the reliability of electricity supply by the network can curb the use of decentralized systems by consumers connected to the grid. At the end of chapter 3, it will be possible to answer the third research question mentioned above. The quantitative work in this chapter was done in collaboration with Fabrice Rossi, professor of data science at Paris-Dauphine University. This work will be submitted to an academic journal in economics.

It is important to underline that the second and third chapters are complementary and analyze the phenomena of consumer empowerment from the central network through three nexuses. The technology nexus: these two chapters study decentralized solar systems and backup generators, the region's two most widespread decentralized technologies. The consumer nexus: these two chapters study residential and commercial consumers, the two most important consumer categories for electricity systems in the region. And finally, the nexus between the use and adoption of these systems. The second chapter assesses the current extent of the adoption of decentralized systems in grid-covered areas in sub-Saharan Africa while the third chapter studies specifically the use of these systems.

The thesis uses original methodologies to collect data and study them. Data collection has been an integral part of the work of this thesis and is one of its main contributions. The data required for chapter 3 demanded an active research period of greater than six months, which allowed access to very accurate electricity consumption data (per minute) over several months from companies that have access to both the electricity grid and decentralized stand-alone power generation systems. We will see that accurate time-series consumption data is scarce in the region. Similarly, the second chapter of this thesis analyzes an even more original database on the development of decentralized solar systems in African cities. This database was collected directly for this thesis, using a method never used before to study the development of electrical systems in the region. The collection of this data was a colossal task, which took more than a year and a half. More than 2 million satellite images were downloaded and analyzed using artificial intelligence algorithms. This database, developed within the framework of this thesis, was then linked to

the latest geolocalized socio-economic database of Afrobarometer. Access to this database, which has not yet been made public, has been granted following submission of an application form. The use of this method, as the subject of the article, as well as the use of the latest Afrobarometer database, is therefore a first in the academic literature on the development of power systems in the region. It is important to note that in the second chapter, data was collected using an original method, given that the market segment of decentralized solar systems in urban areas had been entirely overlooked by the academic and grey literature on the subject. Data collection is an integral part of the research and answers many of the questions raised in this chapter on its own. Thus, this thesis presents three main originalities: the issues addressed with respect to the academic literature on the subject, the data used in the quantitative analyses, and the methodologies used in Machine Learning and Deep Learning to collect and analyze these data.

However, the thesis also has several limitations. First, due to the scarcity of research on electricity sectors in sub-Saharan Africa, it is challenging to find recent and reliable data in the region. In this thesis, cross-country analyses were essential for analyzing the trends transforming the region's power sector. However, sources that present comprehensive data and simultaneously cover several countries in the region are scarce. The few referent sources that exist were relied upon, but these, at times, dated back several years and can also present observations from different years depending on the countries covered.

The collection of original databases using original methods has partly responded to the problem of access to data in Africa. However, this was not effortless and took considerable time. For example, to find actionable data for Chapter 3, many formal calls and requests were made to local distribution companies. This was aimed at obtaining accurate consumption data. However, these are mostly not collected, even by professional actors in the field. Where recovered, they are usually confidential. A search of several months made it possible to find an institute that collected this type of data. Nevertheless, as will become apparent, this data are not perfect, at times had to be cleaned, and only a fraction of it could be used due to missing grid observations in some regions.

Thus, due to the difficulty of accessing data, this thesis does not provide a fully comprehensive and detailed overview of the various developments related to decentralized technologies that are taking place in sub-Saharan power sectors. Therefore, this thesis cannot provide definitive answers or solutions to these new challenges. Nevertheless, it still manages to show the emergence of these new dynamics in sub-Saharan Africa's electricity sectors, characterizes their main aspects, and explain why these will continue over the long term.

Within the framework of this thesis, a *Convention Industrielle de Formation par la Recherche* (CIFRE) was established and allowed the cooperation between the Dauphine Laboratory of Economics (LEDa), the energy and environment team of the Center of Geopolitics of Energy and Raw Materials (CGEMP) and the Energy and Climate Center of the French Institute of International Relations (IFRI). This CIFRE contractually delimited the time of the work of this thesis which lasted three years and took place from April 15, 2019, to April 15, 2022.

This cooperation has allowed the synergy of the expertise of both institutions. The energy team of LEDa-CGEMP indeed benefits from expertise in industrial economics applied to the energy sector. This team has provided vital support to set up an academic analysis framework to understand the development of electricity markets in sub-Saharan Africa. Thanks to the Paris-Dauphine University network, the author was able to train himself in the quantitative methods used in this thesis. He was able to study the use of artificial intelligence tools and, more particularly, Machine Learning and Deep Learning algorithms, which was essential to carry out this thesis work. The expertise in energy economics was complemented by the expertise on the energy sector of the Ifri's Energy and Climate Center. Ifri provided privileged access to an important network of professionals in the field. Thanks to this, it was possible to conduct a series of interviews with a large number of professionals in the field: international and regional energy experts from sub-Saharan Africa, senior officials in charge of activities related to the electricity sectors on the continent, and members of international development institutions. This allowed the definition of a thesis topic relevant to the empirical reality of the current development of sub-Saharan power systems. It has also led to the discovery of data used in the analysis of chapter 3. Finally, this thesis has allowed the opening of a work axis on electrification in sub-Saharan Africa within the Center for Energy and Climate, which has led to numerous publications and interventions at conferences and webinars. This thesis was therefore perfectly integrated into both the research activities of LEDa and the activities of the Center for Energy and Climate.

Chapter I

Greater autonomy from the national grid : a paradigm change for sub-Saharan Africa's electrification

1 Introduction

Considered natural monopolies, the electricity sectors of industrialized countries have been subject to a concentrated sectoral organization, accompanied by significant state involvement (Künneke, 1999). Electricity sectors have traditionally followed a "classic" development pattern throughout the world, primarily focused on extending the central network to the entire population. Several factors discussed in this chapter show that this classical approach to developing power systems that have shaped industrialized countries' electricity sectors is not directly transferable in sub-Saharan Africa. They suggest that sub-Saharan power sectors will follow their own development path, different from those experienced by industrialized countries.

Due to technological innovations and the falling cost of photovoltaic technology¹, decentralized technologies sold by private companies have become an attractive alternative to the national grid for providing electricity to populations. These technologies have the advantage of being relatively inexpensive in comparison to network expansion and quick to deploy in remote areas. Moreover, if these decentralized technologies can play an essential role in providing access to electricity in areas not covered by the network (International Energy Agency, 2019), they can also be used for electricity consumption by consumers already connected to the grid. Several authors have already reported the use of such technologies in grid-covered areas (Jaglin, 2019; Barry and Creti, 2020), where some consumers can use decentralized technologies in addition to the central network, for example, for economic reasons or to secure a more reliable supply of electricity.

Africa is all the while facing significant population growth and urbanization. In less than 30 years, the sub-Saharan population will almost double to reach 2.1 billion people by 2050, 58% of whom will be located in urban areas (United Nations, 2018, 2019). Meeting the electricity consumption needs of such a rapidly growing population in less than 30 years represents a significant challenge to frail and dysfunctional national grids. That said, it represents a potential opportunity for the decentralized systems market.

This combination of unprecedented trends may well lead to the growing appeal of decentralized technologies; undersized centralized grids and population growth could steer the development of the region's power systems in a different direction than those experienced by other countries in the world. Many analysts, however, endeavor to study the evolution of the region's power sectors as if they were following well-established patterns. As a result, they generally do not consider the emerging bottom-up developments made possible by

¹Solar photovoltaic systems global costs dropped by about 85% over the last decade (2010-2020) (IRENA, 2020).

the arrival of stand-alone power generation systems in areas covered by the grid (Jaglin, 2019). In the same vein, with the advent of mobile telephony in the mid-1990s, Africa, largely without pre-existing national fixed-line networks, made the leap directly to widespread mobile technology. Today, a key question is to what extent a similar dynamic could occur in African power systems with decentralized technologies. Africa's unprecedented, consumer-first approach to direct adoption of mobile technology could imply that access to electricity may also develop through market mechanisms and that the grid could coexist with decentralized systems on the continent, which would likewise be unprecedented.

This chapter analyzes the effects of decentralized technologies' deployment on the organization and evolution of sub-Saharan electricity networks and is organized as follows. Section 2 analyzes the organization of the region's centralized power sector, financial situation, and operational efficiency. Taking stock of the current difficulties the centralized power sectors face will facilitate the better understanding of their future challenges. Furthermore, this will allow the estimation of their ability to overcome these challenges. Section 3 then assesses how the academic literature approaches the issue of power systems development in sub-Saharan Africa as it relates to centralized and decentralized technologies. This examines how the academic literature has evolved on the subject over the past decades and to determine its current state-of-the-art. Section 4 is divided into two parts. The first part of Section 4 assesses whether consumers are turning away, partially or totally, from the centralized grid for decentralized systems. It assesses this new phenomenon and characterizes its different aspects for residential and commercial consumers. The second part of section 4 then proceeds to a prospective exercise and tries to determine the consequences of decentralized systems' deployment in the areas covered by the network. It explores this question in light of the electricity sector's challenges defined in Section 2. Finally, Section 5 concludes this chapter and lays the groundwork for the remaining research questions addressed in this thesis's second chapter.

The analysis of the chapter at hand relies on an extensive review of the academic and grey literature on the subject and the analysis of numerous interviews conducted by the author whilst at IFRI. These interviews were held with policymakers, regulators, academics, and professionals from NGOs, development institutions, and private companies working on electricity-related issues in the region. This should provide an assessment of, on the one hand, the state-of-the-art of the academic literature on the subject and, on the other, the "empirical reality" of the current development of power systems in sub-Saharan Africa. This will highlight the gaps in the current academic literature and attempt to bridge them.

2 Overview of electricity sectors in sub-Saharan Africa

2.1 Unfinished liberalization processes

The development of the power sectors and universal electrification in African countries was mainly seen as the responsibility of governments through state monopolies² (Scott and Seth, 2013). To develop power systems in Africa, governments focused first on expanding the national grid, as this was seen as an efficient way to benefit from economies of scale on electricity costs. The emphasis on central grid expansion, reflecting the electrification strategies of most industrialized countries, initially ignored off-grid alternatives (Pachauri et al., 2012).

In the 1990s, reforms were proposed in sub-Saharan Africa to increase the electrification rate and to address the chronic under-capacity and poor performance that were plaguing the development of the sector. They were inspired by the electricity sector liberalization reforms implemented in industrialized countries. These reforms consisted of a succession of steps aimed at bringing the vertically integrated public electricity sectors into greater competition. The main aim was to privatize parts of the sector and sometimes to corporatize its management into different companies, to move legislation towards "standard models", and to set up independent regulators. The ultimate goal was to unbundle the different segments of the sectors, sell the electricity generation and distribution assets to private companies in order to introduce competition (Bacon, 1999; Besant-Jones, 2006; Gratwick and Eberhard, 2008) and introduce more stringent regulatory oversight (Malgas and Eberhard, 2011).

²Even today, almost all of the installed power generation capacity in Africa has been financed by public institutions: the state or by development finance institutions (DFIs) through concessional loans (Meyer et al., 2018).

2. OVERVIEW OF ELECTRICITY SECTORS IN SUB-SAHARAN AFRICA 25

Box 1 : the "standard model" of power sector reforms

The electricity sectors were traditionally organized around vertically integrated natural monopolies controlled by the state. Sometimes the private sector managed these monopolies, but they were subject to significant control by public authorities (Joskow, 2008). However, factors such as high operating costs, construction cost overruns for new facilities, and high retail prices encouraged reform projects. These were aimed at optimizing infrastructure management while reducing electricity costs and retail prices to the end consumer (Joskow, 1998).

Reform models have therefore been put in place to create new institutional arrangements to achieve the above objectives. As a result, reform programs in most countries of the world have followed fairly closely a "standard model" described by (Joskow, 2008) as consisting of a succession of different steps: "privatization of state-owned enterprises, vertical and horizontal restructuring to facilitate competition and mitigate potential problems of self-exploitation and cross-subsidization, performance-based regulation (PBR) applied to transmission and distribution segments, wholesale market design facilitating effective competition among existing generators, competitive entry of new generators, and retail competition, at least for industrial customers."

The results of these reforms in industrialized countries have been mixed. Implementing reforms in the electricity sector is not easy, and there are risks that costly performance problems will emerge, particularly in the transformation phase of reforms or when they are implemented incompletely (Joskow, 2008).

In sub-Saharan Africa, reforms relatively similar to the "standard model" were proposed to promote power sectors development. However, the situation of the sub-Saharan power sectors was significantly different from that of the industrialized countries. They were not mature by comparison : african power sectors are plagued by significant institutional weaknesses: they have poor regulatory systems, a difficult access to finance, have poorly organised private actors and a lack of independence from political actors. For example, in 1996, less than one-third of the population had access to electricity in sub-Saharan Africa. Implementing sector liberalization reforms was like applying a same remedy to cure different ills: the implementation of power sector reforms in industrialized countries was driven by a logic of optimization (see box above for details); whereas in Africa, the objective of the reforms was supposed to accelerate the development of the electricity sectors to provide access to electricity for the entire population in order to promote economic growth in the region.

In many sub-Saharan countries, the generation subsector was first opened to competition. This was seen as an effective way to introduce competition into electricity markets while addressing chronic capacity shortages in the sector. One of the aims was to stimulate state-owned enterprises to improve their finances and management in the face of a private sector benchmark. This was seen as an efficient solution to make up for the decades lost by inefficient state-owned enterprises (SOEs) (Malgas and Eberhard, 2011). The message was all the more powerful as it was mainly conveyed by development finance institutions, even if though some cautious voices were already raised against these measures, doubting their immediate transferability to the African context (Gratwick and Eberhard, 2008).

In most countries, however, the main measure has been to facilitate the entry of independent power producers (IPPs) into the generation sub-sector. This was seen as an immediate solution to rapidly deploy new generation assets to address capacity shortfalls. Therefore, the priority was to enter into long-term power purchase agreements (PPAs) with IPPs. These long-term contracts provided firms with a legally enforceable agreement in an industry characterized by weak regulation (World Bank, 1993; Cordukes et al., 1994; Meyer et al., 2018). However, the PPAs between the state-owned power companies and the IPPs did not necessarily require further liberalization reforms or even the establishment of independent regulators. As a result, reforms stopped in most countries, leaving electricity markets in a state of hybrid competition. IPPs found themselves in markets where the level of competition was low and where SOEs retained significant control. In addition, SOEs often retained control of generation capacity in the generation sector, leaving IPPs to generate at the margin (Meyer et al., 2018; Woodhouse, 2005). The result has been a hybrid development of the region's partly private, partly public power sectors (Malgas and Eberhard, 2011).

Consequently, there are more than fifteen different organizational models of the sector in the region, ranging from complete nationalization to incomplete liberalization. The table I.1 shows the diversity of organizational models of the electricity sectors in the region. It is clear that competition has not been fully introduced in these sectors and that after two decades of reforms, the sub-Saharan power sectors have nowhere reached fully unbundled, privatized and competitive markets. Moreover, while one of the most important features of the reform was the introduction of independent regulators, barely more than half of African countries actually have a regulator (Malgas and Eberhard, 2011), with sometimes only limited responsibilities (Cussaguet, 2021). To date, capacity remains underdeveloped and utilities still lack financial resources. In light of this initial observation on the institutional organization of the region's electricity sectors, we now assess their current financial and operational status.

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Table I.1: Electricity sector structures in Sub-Saharan Africa (2016)

One vertically integrated state-owned utility	One main vertically integrated utility with generation companies	One main vertically integrated utility with other operators	Partial vertical unbundling	Full vertical unbundling
Benin	Republic of Congo (One main state owned utility and one state owned generation company)	South Africa (One main state owned utility with some IPPs and other public distributors)	Kenya (Integrated transport and distribution public utility along with one state owned generation and distribution company and some IPPs)	Ghana (Multiple IPPs and other public owned distributors)
Burkina Faso	Botswana (One main state owned utility and some IPPs)	Namibia (One main state owned utility and other public distributors)	Zimbabwe (One integrated transport and distribution utility and one state owned generation company)	Nigeria (State owned generation and transport companies, some IPPs and private owned distribution companies)
Burundi	Mali (One main state owned utility and some IPPs)	Tanzania (Two state owned utility with some IPPs)	Lesotho (One integrated transport and distribution utility and one state owned generation company)	Uganda (Public owned transport company, IPPs and private owned distribution company)
Congo (RDC)	Rwanda (One main state owned utility and some IPPs)	Mozambique (Two state owned utility, one generation and transport only, with some IPPs)		Sudan (Public owned generation companies, transport and distribution company)
Ethiopia	Senegal (One main state owned utility and some IPPs)	Zambia (One main state owned utility with some IPPs and one other public distributor)		
Malawi	Swaziland (One main state owned utility and some IPPs)	Angola (One main state owned utility with some IPPs and one other public distributor)		
Mauritania	Togo (One main state owned utility and some IPPs)	Niger (Two state owned utility)		
Central African Republic	Cape Verde (One main state owned utility and some IPPs)			
Chad	Guinea (One main state owned utility and some IPPs)			
Comoros	Madagascar (One main state owned utility and some IPPs)			
Equatorial Guinea	Mauritius (One main state owned utility and some IPPs)			
Eritrea	São Tomé and Príncipe (One main state owned utility and some IPPs)			
Gambia	Côte d'Ivoire (Main utility under private concession and some IPPs)			
Guinea-Bissau	Cameroon (Main utility under private concession and some IPPs)			
Liberia	Gabon (Main utility under private concession and some IPPs)			
Seychelles				
Sierra Leone				
Somalia				
South Sudan				

Source: Trimble et al. (2016)

2.2 The contours of a "vicious circle"

Electricity sectors have very little financial resources and cannot effectively invest in expansion. Most electricity sectors in sub-Saharan Africa are not financially viable and do not cover their operating or fixed costs (Trimble et al., 2016). The figure I.2 plots the revenue collected against the supply cost per kWh billed for several sub-Saharan countries for which data were available. Of a selection of 39 sub-Saharan countries made by the World Bank³, 19 were not recovering their operating costs⁴ and were facing short-term financial difficulties⁵. Of the 39 countries selected, only the Seychelles and Uganda manage to cover their total production costs. Uganda even achieves a profit of 6%. All other countries have deficits of more than 10% per kWh produced, amongst which 11 countries have deficits of more than 50 percent per kWh produced. The operating losses of all African power sectors would have exceeded 150 billion USD in 2020 (International Energy Agency, 2022a). The figures presented in the graph are shown in the table A.I.1 in the appendix.

The graph I.1 maps geographically the quasi-fiscal deficits of the electricity sectors as a percentage of GDP for selected African countries. The figures are available in the table A.I.3 in the appendix. Again, we see that only two sub-Saharan countries have a positive balance sheet and are financially viable. It is important to note that they are able to cover their operating costs but also their capital expenditures to cover the costs of maintaining and upgrading existing assets. However, these companies are not necessarily financially viable enough to cover future assets, for example following an expansion of the network to unconnected areas that requires funds to invest and maintain new generation or transmission capacity. In the context of network expansion, the tariff aspects must also be taken into account. For example, since the study by Trimble et al. (2016), Niger succeeded in reaching the grail of cost

³The report of Trimble et al. (2016) was produced by a team of more than 10 professionals from the World Bank, and benefited from the significant contributions of some fifty world bank specialists. The report is an in-depth study of the electricity sectors finances of more than 39 sub-Saharan countries. Trimble et al. (2016) and their teams have spent several years going through the annual reports, the financial statements of the national utilities as well as the power sector reports, tariffs studies and regulatory documents of the countries national electricity sectors. They also had access to data made available by World Bank teams in the field. To the best of my knowledge, it is the most recent and comprehensive document that exists on the financial state of the electricity sectors in the region.

⁴In countries where a large share of electricity is imported, or purchased from private producers, or where the utilities does not publish a financial statement in the generation sub-sector, the distinction between capital expenditure (CAPEX) and operating expenditure (OPEX) is an artefact that includes electricity purchases and taxes with the exception of refunded taxes such as Value Added Tax (VAT).

⁵These utilities operate at level 1 of the authors' taxonomy, which means that they require a constant injection of capital from the government to stay afloat. These capital injections can take the form of annual subsidies or major bailouts and/or debt restructuring and cancellation plans (Trimble et al., 2016).

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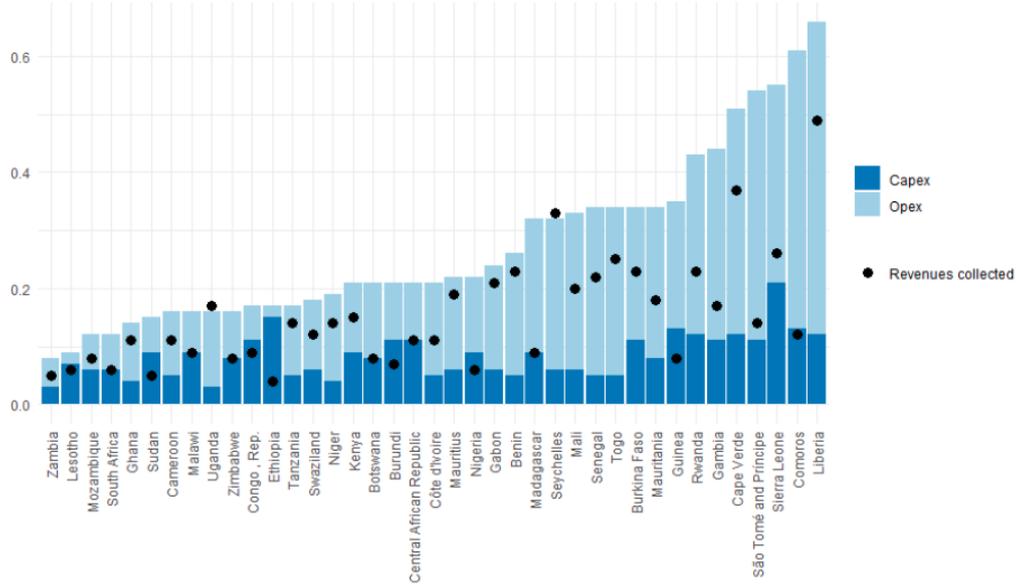
recovery tariffs after ambitious reforms and tariffs increases started in 2018. Those tariffs hikes allows Niger to ensure the financial viability of its electricity sector for the period 2018-2022⁶ (Cussaguet, 2021). It is important to note that these tariff hikes are not a silver bullet. The tariff revision in Niger, for example, accentuated cross-subsidies by favor of households benefiting from subsidized tariffs, while increasing the prices paid by other consumers through block pricing⁷. However, the planned expansion of networks to poor consumers in peri-urban and rural areas will increase the share of consumers benefiting from subsidized tariffs and may therefore affect the system's hard-won financial viability (Cussaguet, 2021).

The dire financial situation faced by almost all utilities in sub-Saharan Africa threatens the survival of the existing power infrastructures. Without improving their finances, utilities cannot afford to maintain system reliability at adequate levels and invest in expansion. Maintenance expenses are often the first to be cut, although it is nearly impossible to get reliable data on reductions in maintenance budgets because they do not necessarily show up in the financial statements of utilities (Trimble et al., 2016). As a result, sub-Saharan transmission and distribution networks are dilapidated and subject to line losses that increase the cost of electricity. Twenty-six countries have line losses of more than 20 percent, sometimes reaching more than 71 percent. In addition, there are non-technical losses such as theft of electricity through illegal connections and significant difficulties for utilities to collect payments for billed electricity. More than ten countries have uncollected electricity bills that amount to more than 20 percent. The annexed table A.I.4 presents technical and nontechnical losses for a selection of countries for which data were available. To this, we can

⁶However, these tariff hikes can be politically difficult to implement as they bring social unrest. Uganda also effectively increased its tariffs in the early 2000s. These were increased twice in 2006, by 41% and then by 35% (Meyer et al., 2018). For both countries, however, the tariff increase took place when electrification rates were low, 9% and 17.6% respectively for Uganda and Niger World Bank (2022a), which greatly limits the potential political risks associated with these tariffs increases.

⁷The most common pricing is block pricing, followed by volume pricing (Kojima et al., 2016). Block pricing means that electricity consumption is divided into several blocks with a different tariff schedule depending on the actual consumption of a household. For example, a first tariff block corresponds usually to a monthly consumption between 0 kWh and 50 kWh. For this first block the tariff can be subsidized, well below the production and transmission costs. This allows the households that consume little electricity, the poorest, to pay less. The electric utility company can then slightly overcharge the blocks that correspond to a higher consumption in order to recover the costs lost for this first block. This pricing has the advantage of making consumers pay for the electricity consumed per unit in each block. This is different in the case of volume pricing. This pricing also works by block of different tariffs but unlike the previous one, exceeding a consumption unit of the first block leads to the pricing of all consumption at the price of the second block.

Figure I.1: Electricity supply cost and revenue collected in USD per kWh billed (2014) for a selection of sub-Saharan countries



Source : Trimble et al., (2016) - graph by the author

also add overstaffing⁸ of public enterprises and low tariffs⁹. The breakdown of the sectors' deficits in different categories for a selection of countries are listed in the table A.I.5 in the appendix.

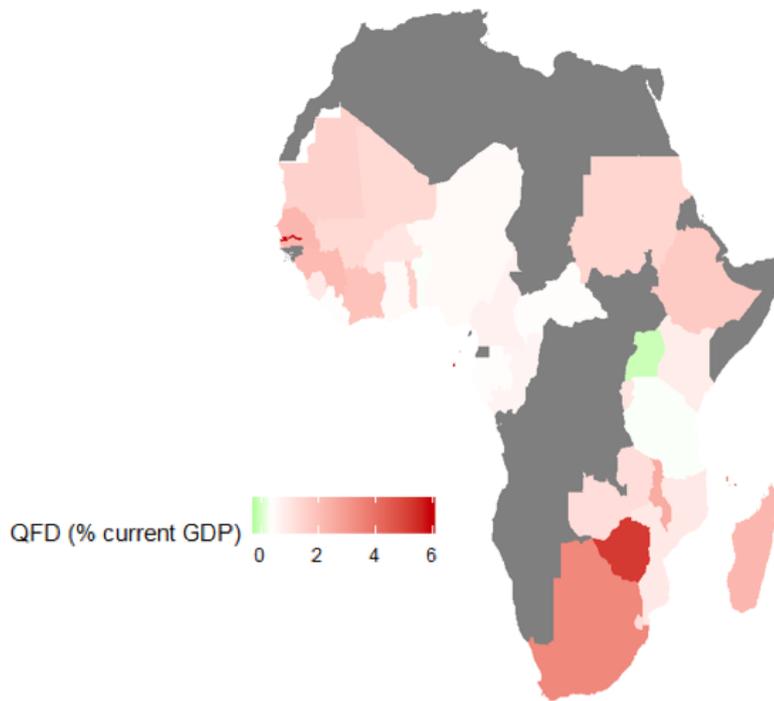
A vicious circle is therefore gradually taking hold. The main consequence of the poor financial situation of these companies is a decrease in investment in infrastructure maintenance. This contributes to maintaining the dilapidated state of the networks. As a result, the quality of services is deteriorating, and power cuts are chronic. Consequently, more and more users are refusing to pay for substandard service, further reducing the revenues of utilities who con-

⁸Several interviews revealed that if the utilities are overstaffed from an accounting point of view, in reality, it is not uncommon for a good number of employees not to appear in the organization chart of the companies.

⁹Although, these electricity tariffs can be higher than tariffs paid in other developing countries and even in developed countries. For example, the average prices paid by the residential sector in 2013 were around 200 USD/Megawatt-hour(MWh) for Kenya, Rwanda and Côte d'Ivoire and 150 USD/MWh for the Democratic Republic of Congo and between 130-140 USD/MWh on average for the region. In the industrial sector, average prices were 220 USD/MWh, 200 USD/MWh and 180 USD/MWh respectively for Rwanda, Cameroon and Côte d'Ivoire (IEA, 2014). Paradoxically, these tariffs do not allow sub-Saharan electricity companies to cover their total costs for all the countries mentioned above. This mainly due to the high costs generated by small economies of scale due to stunted centralized electricity sectors, high dependence on oil-fired or emergencies power plants with high costs or the important operational weakness of utilities (Trimble et al., 2016).

2. OVERVIEW OF ELECTRICITY SECTORS IN SUB-SAHARAN AFRICA³¹

Figure I.2: Quasi-fiscal deficit (QFD) of electricity sectors in percent of GDP



Source : Trimble et al., (2016) - graph by the author

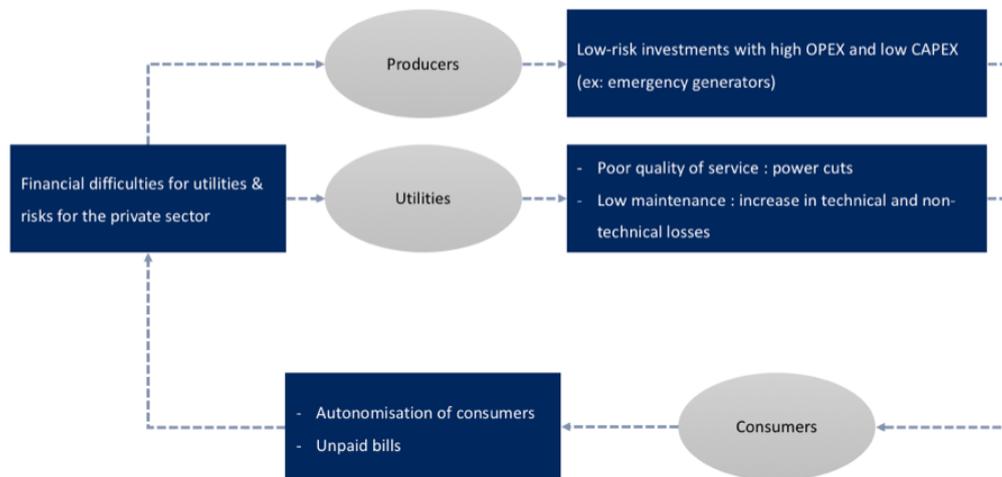
tinue to reduce the amount of funds allocated to the maintenance of facilities (Le Picard, 2020a).

This situation has three main consequences for central networks: power cuts are recurrent (1), installed capacities remain low (2), and network infrastructures are poorly developed (3).

1) Recurring power cuts

In areas covered by the network, power outages are frequent. For example, a typical sub-Saharan company suffers an average of 51.3 hours of outages per month. Nigeria is an extreme case: in 2014, the country recorded more than 32 power outages per month, each lasting about 12 hours. Each month, this amounted to 380 hours of outages or 16 full days without power. The annexed table A.I.6 shows the latest data made available by the World Bank on the average number of power outages for a business in a typical month, its average duration, and the average time without electricity by country each month. This reveals that the quality of electricity supply is low in the region.

Figure I.3: A vicious financial circle that constrains electricity sectors' development



Source : author

Box 2: Putting electricity access into context

It is important to outline several points relating electricity access in a general way. First, the electrification rate is a binary indicator, and does not mean that consumers have full access to electricity. This technical access to electricity, which does not take into account costs and consumers' ability to pay, depends on electrification technology. Even a grid connection may not mean full access to electricity. For example, in Nigeria, the electrification rates is around 55.4% at the national level and over 83.9% in urban areas (World Bank, 2022a). However, more than 25% of households report having access to electricity only occasionally.

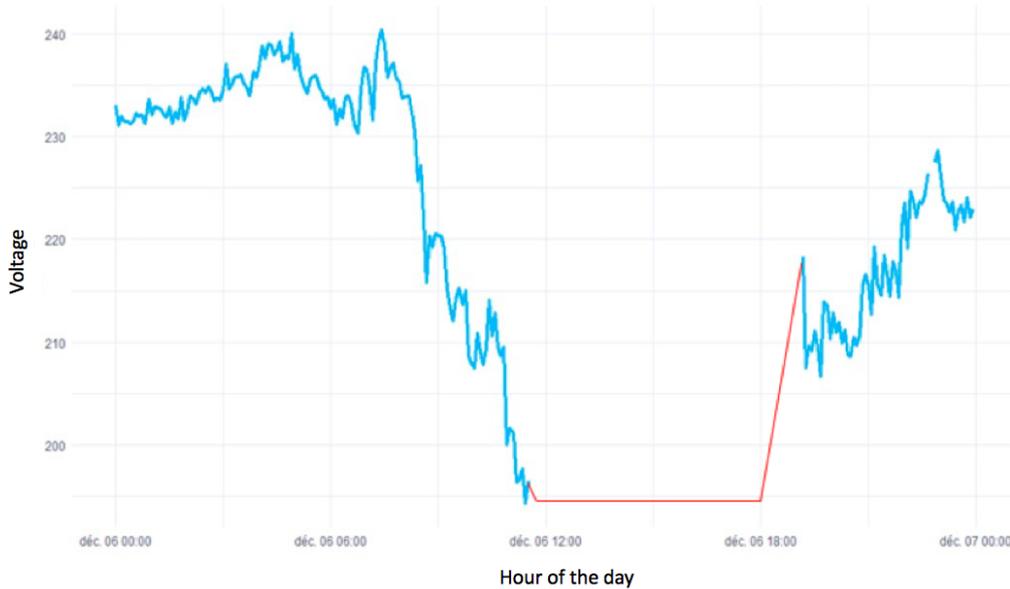
Similarly, when the network is operating, the voltage may be abnormally low on the central network. Blimpo et al. (2020) show during field investigation that the network can work but that the voltage can be barely sufficient to light up a low voltage bulb and insufficient for other electronic devices such as fans. The number and duration of power cuts are therefore also not exhaustive indicators of the quality of the electricity supplied. The graph I.4 from a database that will be analyzed in chapter 3 of this thesis illustrates this phenomenon. We can observe the voltage on the Nigerian grid on a typical day in 2019.

Finally, when households connect to the network, their consumption can also be particularly low due, for example, to their meager financial capacity to pay for the electricity consumed, but also to invest in electrical equipment that would allow them to use and therefore consume electricity (Lee et al., 2020).

It should be reminded that electricity access, which must take into account the reliability of electricity supply, costs and consumers' ability to pay, and access to a source of electricity, which just indicates whether or not a consumer is connected to a source of electricity, are distinct and the latter cannot be sufficient in itself.

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Figure I.4: Voltage on the central network a typical day in Nigeria



Source : A2EI (2020) - graph by the author

2) Low installed capacities

The sub-Saharan electricity sector is underdeveloped. In 2018, total installed capacity in sub-Saharan Africa (excluding South Africa) amounted to about 80 GW, just a few tens of GW more than South Africa's electricity fleet, or nearly half as much as France (130 GW) for 18 times as many inhabitants (International Energy Agency, 2019). Only eight countries, including South Africa, have a production capacity greater than 3 GW. Nigeria is second only to South Africa in having the most generating capacity: 11 GW of capacity in September 2019. Only a dozen countries have an intermediate level of installed capacity, ranging from 1,256 Megawatt (MW) for Uganda to 5,382 MW of installed capacity for Ghana. Some countries, such as Central Africa and Chad, have generating capacities of less than 100 MW. If demographics are taken into account, installed capacity is even lower in sub-Saharan Africa than in other countries. The average installed capacity per capita in the region (excluding South Africa) is about 0.1 kW. For comparison, it amounts to 0.98 kW for South Africa and 1.9 kW for France. For some countries, such as Burkina Faso, Burundi, Chad and Liberia, it is less than 0.04 kW per capita. The table A.I.8 in the appendix gives the total installed capacity by country in 2019 for a selection of countries for which data was available¹⁰. This table shows that

¹⁰It is important to note that the table A.I.8 indicates existing installed capacity in sub-Saharan countries but not necessarily the available capacity. For example, Nigeria has over 11 GW of installed generation capacity on the central grid. However, due to power plant maintenance issues as well as bottlenecks in power plant gas supply pipelines and transmission infrastructure, only between 3.7 and 4.1 GW was actually available/dispatchable in

installed capacity on the core grid is very low relative to a sub-Saharan population that has reached over 1.1 billion and is still growing. If installed capacity in sub-Saharan Africa has increased significantly over the past decades, from 68 GW in 2005¹¹ (Eberhard et al., 2011), to 94 GW in 2014 (Trimble et al., 2016), and to about 130 GW in 2018 (International Energy Agency, 2019), when comparing to demographics, the progression is less clear. Capacities per capita ranged from 0.09 kW to 0.097 kW to 0.12 kW in 2005, 2014, and 2018 respectively (Eberhard et al., 2011; Trimble et al., 2016; International Energy Agency, 2019; World Bank, 2022a).

3) Poorly developed network infrastructures

Finally, network infrastructures are also poorly developed. If we again exclude the special case of South Africa, sub-Saharan Africa has, on average, 229 kilometers (km) of transmission lines per million inhabitants (mh), compared to 800 km/mh for France (World Bank, 2017). At the same time, the population density is two and a half times higher in France. Nevertheless, investments in transmission lines are lacking in the region despite the needs. In 2018, for all of Africa, only 10 billion USD was invested in grid infrastructure, while the estimated need for the year is 60 billion USD (International Energy Agency, 2019). The table A.I.8 provides data on state-owned transmission and distribution lines in km with capacities greater than 1 kV for a selection of sub-Saharan countries for which data were available. We can conclude that sub-Saharan power transmission systems are also underdeveloped relative to population size.

The region's centralized power grids face an additional challenge: the region's significant population growth. Today, the continent is facing a considerable demographic increase. According to UN projections, the population of the sub-Saharan region will almost double in less than thirty years to reach 2.1 billion in 2050, compared to 1.1 billion today. Similarly, most of the population will be concentrated in cities, accounting for 58.1% of the population, or 1.2 billion inhabitants, by the middle of the century. Therefore, today's equivalent of the entire sub-Saharan population will be concentrated in cities in less than thirty years. Faced with the increase in the urban population, the electricity sector is facing difficulties developing at the same pace. The high concentration of African populations in urban areas does not necessarily facilitate access to electricity. Despite many new connections made each year, electricity coverage in urban areas in sub-Saharan Africa is struggling to develop; between 2019 and 2020, it even declined in some countries¹². This decline in electricity coverage

2018 (Arowolo and Perez, 2020).

¹¹Of which although 25 percent was not operational for different reasons, such as lack of maintenance (Eberhard et al., 2011).

¹²In Congo(RDC), Equatorial Guinea, Eritrea, Niger, Rwanda, Uganda (World Bank,

2. OVERVIEW OF ELECTRICITY SECTORS IN SUB-SAHARAN AFRICA³⁵

in urban areas partly reflects the difficulty of electricity supply companies in coping with the rapid increase in the number of city dwellers¹³.

Box 3: Electrification and population growth in Africa

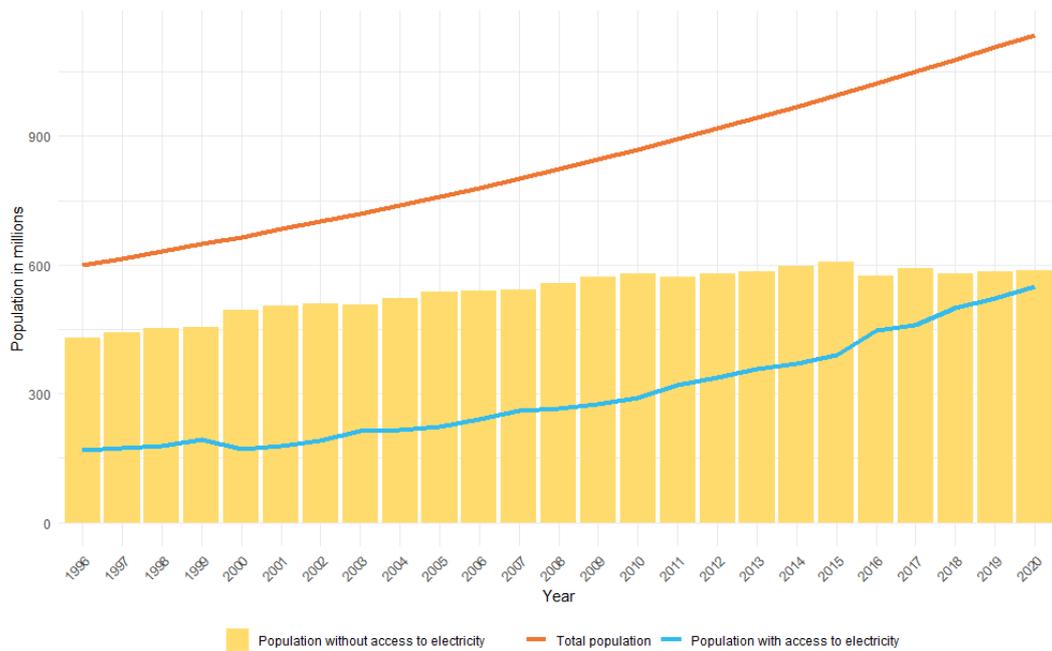
In the sub-Saharan electricity sector, the steady increase in the electrification rate is constantly challenged by population growth. A "mass demographic effect" persists, and the gradual increase in the number of people with access to electricity is paradoxically accompanied by an increase in the number of people without access to electricity. According to World Bank and UN data, the estimated number of people without access to electricity has increased from nearly 400 million in 1990 to just under 600 million in 2016. As illustrated in figure I.5, a catch-up in the curve of people having no access to electricity by the curve of people having access operates. It reflects that the electrification rate were higher than the population growth rate in the past years. In addition, an inflection point in both curves occurred in 2015 with a decrease in the number of people without access to electricity for the first time in two decades. This coincides with the development of the market of decentralized solar systems (Le Picard, 2020a). However, the IEA estimates that this number has gone up again in 2021 (International Energy Agency, 2022b).

There are several models of organization of the electricity sectors in sub-Saharan Africa, ranging from vertically integrated sectors controlled by the State to almost total liberalization. Moreover, the sub-Saharan networks are puny and not very functional. The networks are facing major problems, the poor financial situation of the electricity public service companies locks them into a vicious financial circle which reduces the quality of service, increases their costs and further fuels their financial difficulties. These problems limit their development potential. In view of the elements presented in this section, it is reasonable to think that we cannot hope for a significant improvement in the operation and development of centralized electricity networks in sub-Saharan Africa. This is further supported by the significant challenges that a doubling of the total population and almost a tripling of the urban population over the next thirty years represents.

2022a).

¹³Some megalopolises such as Lagos, Luanda, Kinshasa, Dar es Salaam or Nairobi have seen their population double in twenty years. These cities will continue to grow and some of them will see their population almost double again over the next fifteen years.

Figure I.5: Demographic growth, population with and without electricity in sub-Saharan Africa (in millions)



Source : World Bank (2022a) - graph by the author

3 The development of electricity systems in sub-Saharan Africa

In this section, we look at how the academic literature has addressed the development of the electricity sectors in the region through the issue of electrification planning. This will allow us to see how the academic literature has evolved on the subject over the last decades and to determine its current "state of the art."

3.1 A mutation of the traditional centralized model

Due to the high costs of extending the central grid in sub-Saharan Africa and the difficulty of the sector to develop, as early as the 2000s, the literature analyzed what were the best strategies for providing electricity access to the entire African population. Electrification rates are low in the region. Less than half of the population (48.4%) had access to electricity in 2020¹⁴, with a large gap between urban and rural areas. Sub-Saharan rural areas are the most under-served by electricity services in the world. Electricity access levels in the region were estimated at 78.3% in urban areas compared to only 28.7% in rural areas in 2020 (World Bank, 2022a).

However, electrification in rural areas via the central grid extension is very costly because it requires heavy investment in new electricity transmission and distribution infrastructure to electrify sparsely populated areas. For example, a rough estimation indicates that an electrification relying mainly on the extension of the network would cost 113 times more than an electrification achieved using mainly decentralized systems (Dagnachew et al., 2017). In addition, the households living in rural areas are essentially poor and using electricity mainly for needs requiring little energy, such as lighting. As a result, these rural households when connected to an electricity source consume less than 30 kWh per month (World Bank, 2012), 25% less than the region's average electricity consumption per capita which amounted to 40.6 kWh (per month) in 2014 (World Bank, 2022a). On the one hand, low population density means that few people share the costs of investments in transmission and distribution systems. On the other hand, consumers' low potential for electricity consumption makes them unprofitable customers for the network. In addition, tens of kilometers of high, medium, and low voltage lines require significant maintenance investments. Thus, the central grid extension to rural

¹⁴It is important to note that the electrification rate differs significantly between the different countries of sub-Saharan Africa. The countries most integrated into globalization generally have a significantly higher rate of access to electricity than the others, such as those in the Gulf of Guinea and the Horn of Africa and South Africa. Low electrification rates can also be explained in part by the importance of the rural world in sub-Saharan Africa.

areas leads to much higher investment costs per consumer and per kWh of electricity consumed, and present meager potential returns on investment (World Bank, 2012). In addition, more than 30 countries in sub-Saharan Africa have shortages of power generation capacity on the centralized grid (Foster and Briceno-Garmendia, 2010). This under-production must be addressed before extending the central network because network's extension in under-capacity situations does not allow new consumers to benefit from a satisfactory quality of service. However, it is difficult in practice due to the financial problems electricity sectors face, which were addressed in section II. Extending the central network in those conditions contributes to the creation of weak grid areas, where the quality of the electricity supply is deficient (where power cuts and voltage drops are common). In addition to these constraints, the extension of the network takes a long time to materialize. Thus, the extension of the network alone may not be able to quickly and sustainably meet the needs of achieving the objectives of universal and durable access to electricity in sub-Saharan Africa (Moner-Girona et al., 2016).

However, extending the central grid is not the only way to achieve universal access to electricity. The falling costs of solar technologies have led to a paradigm shift. This has allowed the development of stand-alone "decentralized" electricity generation systems which are not connected to the central grid. Generally speaking, they can be divided into two categories. First are "mini-grids," miniature grids that can electrify entire villages. Second are "autonomous systems," consisting, for example, of an individual solar panel, a battery, and some electronic devices¹⁵. The development of these decentralized systems has made the extension of the network one option among others for the continent's electrification (Debeugny et al., 2017).

The population density in a region is a critical factor in choosing the most relevant technology for giving access to electricity because it implies, depending on the technology chosen and the existing infrastructure, the economies of scale potentially achievable. For example, the network extension can be favored in urban and peri-urban areas closer to existing infrastructures and densely populated (Deichmann et al., 2011; van Ruijven et al., 2012). For decentralized areas located too far from the central grid for it to reach it in reasonable time and cost but with a high population density, mini-grid systems present an attractive alternative solution to the extension of the network. Finally, individual decentralized systems can be favored in remote rural areas, where the population is sparse (Cantoni et al., 2021).

Depending on several factors (existing grid infrastructure, availability of local resources, and population density), the electrification of Africa (as in other parts of the world that are not fully electrified) is seen as a combination of

¹⁵For example for the medium sized systems these comprise a radio, a fan and light bulbs.

these three main options:

- Network extension
- Mini-grids
- Autonomous systems

However, this involves choosing the most relevant technology for each non-electrified zone, concerning various objective criteria, the main ones:

- Economic criteria, linked to the costs relating to each technology.
- Socio-economic criteria, linked to the electrical consumption potential of each option¹⁶.
- Environmental criteria, each technology having different implications in terms of greenhouse gas emissions or local pollution.

The need to make "informed" choices based on the pros and cons of different electrification strategies has opened up a new field in research. Since the 2000s, electrification planning has attracted increased interest from academic researchers, made possible by the development of new quantitative and modeling methods. The study of electrification strategies in Africa has become a popular topic in the literature due to the challenge electrifying the entire African continent represent (Trotter et al., 2017).

Given the difficult financial situation in which most national electricity companies find themselves in, the investment cost related to the electrification strategy is often a determining factor (Dagnachew et al., 2017). Thus, in developing countries, choosing the appropriate means to provide access to electricity is still primarily determined by the investment costs, the kWh costs, and the maintenance needs associated with the different systems¹⁷ (Palit and Chaurey, 2013). Considering the electrification needs of the sub-Saharan region, researchers analyzed which electrification strategy would be the most relevant to achieving universal access to electricity in Africa from a cost perspective.

¹⁶For example, electrification via the central network does not provide the same access to electricity as a small solar home systems in terms of electricity services. The latter can constrain rapidly the consumption of a customer.

¹⁷Beyond the costs, some research articles take into account the objectives of mitigating global warming, but these remain marginal in the literature. For example, Dagnachew et al. (2018) analyze the synergies and contradictions between pursuing universal electricity access goals and global warming mitigation goals in sub-Saharan Africa.

The amount of investment needed to electrify sub-Saharan Africa directly depends on the levels of electricity consumption to be provided to the population, with regard to the World Bank’s “Tier” indicator¹⁸. In this regard, Dagnachew et al. (2017) use a multi-year bottom-up electrification model to estimate the development of sub-Saharan electricity sectors under different scenarios and determine the preferred electrification technology based on the least cost option¹⁹. They find that to reach a consumption level of Tier 5 according to the World Bank indicator, which is equivalent to full access, more than 95% of the sub-Saharan population must have access to electricity via the extension of the central network. However, Tier 1 electrification could be achieved mainly using decentralized systems. The investment costs directly depend on these objectives. The authors estimate that electrifying the region at Tier 1 would cost 22 billion USD and would cost over 2.5 trillion USD at Tier 5. By comparison, the IEA estimates that 120 billion USD per year - half of which for grid infrastructure - would be needed to achieve universal and full access to electricity over the next 20 years (International Energy Agency, 2019). The IEA’s estimation is roughly similar to the Tier 5 estimate by Dagnachew et al. (2017).

While the study by Dagnachew et al. (2017) analyzes the optimal electrification strategy at the level of the African continent, many authors have carried out more detailed analyzes at national levels. For example, Mentis et al. (2015) and Mentis et al. (2016) analyze the optimal electrification strategy in Ethiopia and Nigeria, considering many parameters such as population density, transmission networks, power plants (existing and planned), economic activity, electricity tariffs, as well as the costs of the different technologies (especially for mini-grid and off-grid systems which can include for example fuel costs for consumers). For electrification providing theoretical access to 170 kWh/inhabitant/year for rural areas and 350 kWh/inhabitant/year for urban areas, they conclude that electrification via the central grid extension would be optimal for the majority of inhabitants not electrified in these two countries. According to their analysis, grid extension is the least cost option for about 93% and 86% of the population of Ethiopia and Nigeria, respectively.

Gradually, the literature is refining these analyses by also considering the actual demand of consumers once connected to a source of electricity (and not just a consumption target per person as stated above) for their cost/benefit analyses linked to the different electrification technologies. For example, Zeyringer et al. (2015) estimate the least cost electrification strategy for Kenya by comparing grid extension to stand-alone photovoltaic systems. By using

¹⁸This indicator ranges from Tier 0, which corresponds to zero access, to Tier 5, which is equivalent to full access, similar to those enjoyed by industrialised countries. The detailed definition of the multi-tier framework for energy access is given in figure A.I.2 in annex.

¹⁹These technologies are grouped into three main families: access via the central network, mini-grids or autonomous (decentralized) systems.

national household survey data, they more realistically consider the latent electricity demand²⁰ of unconnected households. They find that decentralized photovoltaic systems can play an essential role in areas where demand is low and connection costs high. According to them, up to 17% of the population could be electrified by off-grid photovoltaic systems by 2020 in Kenya.

Subsequently, new studies continue to refine these analyzes by adding, in addition to latent consumer demand, factors related to consumers' ability to pay for their electricity consumption. Therefore, many studies have followed and concluded that due to the low ability of end-users to pay for electricity, the benefits they can derive from electricity are small compared to the associated high investment costs of central network's extension. At levels slightly above subsistence, Sievert and Steinbuks (2020) showed that the choice of small individual solar systems or even pico-solar systems is optimal, as they provide the greatest utility for households²¹. Lee et al. (2016b), in their study of rural Kenya using random price bids for electricity connection, conclude that the low ability of households to pay covers only a tiny part of the costs required for extending the central grid. Thus, electrification via the network would create a loss of social surplus. For the authors, the best way to achieve the goal of universal electrification is through electrification using mainly decentralized systems. This is also in line with the recommendations of Grimm et al. (2020) for Rwanda. However, Grimm et al. (2020) add that even with very low-cost technologies, universal access to electricity could only be achieved with subsidies to end consumers as consumers' willingness to pay do not cover electrification costs.

This literature review on electrification strategies in sub-Saharan Africa has shown that research articles mainly focused on the strategies that should enable the complete electrification of the African continent. In this context, due to the constraints on grid extension in the region, the use of decentralized systems has gradually gained more importance in electrification planning strategies.

3.2 Incomplete electrification in covered areas: a demand gap

In the research articles cited above, the cost/benefit analyzes that justify electrification via the centralized grid are often based on the strong assumption

²⁰The electricity that would be demanded by consumers if infrastructures to supply electricity were available.

²¹They assess households' willingness to pay for access to electricity for different technologies using survey data and a contingent valuation design featuring a dichotomous choice question followed by an action "game" among 1922 households in non-electrified rural areas in Senegal, Rwanda and Burkina Faso.

that the arrival of the central grid in non-electrified areas will automatically result in a connection of consumers to the network. However, this does not hold true in practice (Bos et al., 2018). Despite the presence of the central network, the connection to the central network by consumers cannot be taken for granted (Cantoni et al., 2021). To illustrate this, Chaplin et al. (2017) mention a rural electrification program in Tanzania that increased rural village coverage from 2.5% to 7% of the rural population from 2010 to 2013. However, in 2013, only about 3.8% rural households were actually connected to the grid, an increase of only 0.9% from 2007. In some cases, the connection to the network remains low more than five years after the network's arrival (Lee et al., 2016a). This reveals that even the possibility of a reduction in connection costs that would allow a significant extension of the network could not completely solve the problem of access to electricity in sub-Saharan Africa (Bos et al., 2018).

Living in an area covered by the central network does not necessarily mean being connected to it and having access to electricity. This difference reflects the fact that some individuals do not connect to the central network when it would technically be feasible to do so. The literature first attempted to explain this phenomenon by prohibitive costs sub-Saharan electricity utility companies charged to connect households to the central grid. Indeed, the costs of connection to the distribution network in sub-Saharan Africa can be extremely high in some countries. In 2014, these fixed charges for connection to the central network could amount to more than 155 USD in Burundi, 187 USD in Lesotho, 196 USD in Mali, or even 278 USD in Benin (Kojima et al., 2016). The table A.I.9 in the appendix shows the countries' average connection times and connection rates for which data were available. In addition to these official charges, corruption can also add additional costs to these network connection charges in bribes²².

In a research article, Blimpo et al. (2018) attempt to better understand what explains these prohibitive connection costs. Using a static utility model of the behavior of households and an electricity company, they estimate the causal link between a reduction in the price of electricity on the increase in the costs of connection to the network in Uganda. They use panel data from the first three waves of the Uganda National Panel Survey (2009–10, 2010–11, and 2011–12). They conclude that these high network connection costs are the consequence

²²The World Bank conducted household surveys in Nigeria and Malawi and asked whether households had to pay any "informal fees" to be connected to the network. In Malawi, more than 15% of the households surveyed answered in the affirmative compared to more than 50% of the households in Nigeria. In the West African country, informal fees were more common in urban areas than in rural areas and mainly for the wealthiest households than the poorest. This can be explained by the fact that households with a higher proportion paying these additional and informal fees were the most likely to be asked for bribes (Kojima et al., 2016).

of tariffs levels that does not cover the costs of producing and transporting electricity. By increasing grid connection fees, electricity companies reduce their number of clients and, therefore, reduce losses.

Subsequently, the literature continued to seek to understand the low electrification rates in the areas covered by the network. Blimpo et al. (2020) is a reference research article on the subject. They studied systematically and for more than 31 sub-Saharan countries the problems related to access to electricity in the areas covered by the network. Using mainly data from Afrobarometer's round 6 survey (2014-2015), they show significant variability between coverage rates and access rates between the different countries studied. Coverage rates vary between 21% in Burundi, up to more than 99% in Cape Verde, and the access rates (in the areas covered by the network) vary as 35% in Malawi against nearly 100% in South Africa.

According to the authors, demand-side issues cannot simply be reduced to affordability issues. By comparing several countries with relatively similar per capita GDP levels (2,818 USD for Kenya, 3,030 for Sao Tome and Principe, and 2,835 for Cameroon), they find that the connection rates in the areas covered by the network are much lower in Kenya (42%) compared to 85% and 91% in Sao Tome and Principe and Cameroon in 2014-2015. The authors using a regression model identify that several demand-side factors play a crucial role in connection choices, including household income levels, housing quality, and reliability of central grid electricity supply. In the areas covered by the network, beyond the connection costs and the possible strategies of the distribution companies to limit new connections, the questions related to the reliability of the network and the incomes of consumers, appears to play an essential role in explaining user behaviors.

This part has shown how the issue of electrification of Africa has evolved over the past decades. Due to significant constraints on grid extension in the region, decentralized systems have gradually gained prominence in electrification strategies. Thus, sub-Saharan electricity systems seem to be embarking on an electrification path that relies increasingly heavily on these decentralized systems. Apart from a few articles, the areas covered by the network and urban areas have so far been little covered by academic research. However, this literature comes back to this question with the recent article by Blimpo et al. (2020). Until then, the academic literature was based on the important implicit assumption that the arrival of the network automatically resulted in the connection of consumers, which is not always the case in practice. Continuing to return to urban areas for analysing the development of the power sectors seems particularly relevant today, as given the increase in the urban population, they will represent the bulk of the sub-Saharan population in less than thirty years.

However, this literature makes a clear distinction between centralized and decentralized systems in the areas covered. In other words, it relies on a second implicit assumption: a sub-Saharan consumer can access and consume electricity either through the central grid or through decentralized systems, but not both. It should be checked whether this assumption is valid in practice. Indeed, if a consumer can only access electricity via decentralized systems in areas not covered by the grid, due to the difficulties encountered by centralized electricity sectors, these decentralized technologies could also be attractive for consumers who are already connected to the central network, for economic or security of supply reasons.

4 Consumers empowerment in covered areas

In the continuity of the literature on the development of electrical systems in sub-Saharan Africa, presented in section 2, it is necessary to continue the analysis of the areas covered by the network because they have been the subject of very little research. Firstly, we see if the implicit assumption that there is a clear distinction between access to electricity through centralized or decentralized systems is verified in practice. We will also see if an alternative offer to the network exists in the areas covered. If this hypothesis were true, then the increased independence of consumers from central networks via decentralized means could have consequences for both the organization of systems and the financial viability of the centralized sector. We refer to the phenomenon of increased independence of consumers from central grids by decentralized means of electricity generation as consumer empowerment *vis-à-vis* the central grid. With the understanding that this consumer empowerment is only relative to the central grid. Secondly, we evaluate these consequences by taking into account the current state of the networks drawn up in section 2. This should enable us to evaluate the effects of technological, economic and demographic dynamics on the organization and development of sub-Saharan electricity systems.

4.1 Gathering evidences on consumer empowerment

In the areas covered by the central network, faced with the increase in the urban population and the difficulty of the sector to develop at the same pace, we are going to verify if it is common that populations and businesses use additional means of electricity production to meet their energy needs. These decentralized technologies, initially dedicated to rural areas, can indeed be used in urban areas to address the lack of grid reliability and optimize consumers' electricity expenditure. In urban and peri-urban areas, which are expanding rapidly due to the continent's significant urbanization, these decentralized means of production can be all the more attractive to meet user demand as the waiting times for connection to the network can be long and the connection tariff expensive, as can be seen in the table A.I.9 in the appendix. We will first detail the use of decentralized systems by residential consumers and then by commercial consumers.

4.1.1 Decentralized systems for residential consumers

Among the residential consumers who live in the areas covered by the network, various decentralized means of electricity production are developing to meet consumer demand.

In Nigeria, Rateau (2018, 2021) reports the rapid development of the storage battery market which are used by consumers to meet their electricity needs during power outages. The author identifies an offer of many different sizes of storage batteries, adapted to the needs and income of each consumers. In 2018 in Nigeria, the market already offered backup battery systems ranges from 1 kilo volt-ampere (kVa) and costing 185,000 Nairas (€441) to kits of several associated batteries that can go up to more than 10 kVa for a price of 1,550,000 Naira (3,694 €). The smallest kit can power a laptop, an LED television, several energy-saving bulbs, and a fan, while the second can power a refrigerator, more than a dozen bulbs as well as a television and an air conditioner. These kits are equipped with automated systems that take over during a power outage and can automatically turn off a certain number of devices that would damage the batteries (Rateau, 2021). Therefore, it is interesting to note that the use of electronic equipment may differ depending on the source of the electrical supply. Alongside the market for single batteries, the market for rechargeable electrical devices is also growing rapidly in Nigeria. Those devices are available at a wide variety of quality and price and are intended mainly for the most modest households — these range from flashlights to fans, or other small utility devices (Rateau, 2018). The table I.2, shows the use of battery systems for different residential consumers in the region. As we can see, battery systems can also be used at commercial and even utility scale. This underlines how scalable these decentralized systems are, and can be tailored to the needs of consumers.

According to the Mordor Intelligence agency, the West African battery market is developing rapidly and will grow strongly in the coming years. This market is driven mainly by the development of consumer electronics and backup power systems. If there was a drop in sales in the first quarter of 2020 due to the Covid-19 epidemic, the market should register a growth rate of more than 4% annually between 2022 and 2027 (Mordor Intelligence, 2022). Rateau (2021) argues that the fall in battery prices led to the growth of the rechargeable portable equipment market for the most modest households but also contributes to the development of emergency battery systems intended for the wealthiest households in the region.

Thanks to the development of new business models such as "Pay-as-you-go" (PAYG)²³ the market for solar kits has also grown rapidly in sub-Saharan

²³This system provides access to a solar kit under a leasing agreement that allows the use of a solar system while gradually repaying it through mobile money. Information technology is used to remotely and automatically lock the solar system if the consumer does not pay. This encourages the consumer to make regular payments to reimburse his solar system. In PAYG leasing, no collateral is required from the consumer, which makes the system more flexible than a micro-credit. Consumers are attracted to this flexibility because it allows them to cope with unforeseen financial events by having to make many small payments instead of paying the full upfront cost of the system.

Table I.2: Scalability of electricity storage systems in sub-Saharan Africa

	Before meter	Behind the meter
Grid level	<ul style="list-style-type: none"> • Integration of renewable energy sources • Load shift • Grid support • Frequency regulation • T&D service • Storage 	
Commercial and industrial level		<ul style="list-style-type: none"> • Self-consumption of solar generated electricity • Reduced fossil fuel consumption • Back-up • Smoothing • Energy price arbitration • Improved energy quality
Residential level		<ul style="list-style-type: none"> • Self-consumption of solar generated electricity • Mini-grid (Off-grid) • Reduced fossil fuel consumption • Back-up

Source : Mburu (2020)

Africa. The market is constantly growing. Sales of distributed solar systems²⁴ of all sizes reached more than 1.75 billion USD globally in 2019, with an increase in revenue generated by the sector of more than 30% per year between 2017 and 2019. More than 180 million solar products have been sold worldwide in a decade, including 150 million pico-solar products and around 30 million solar-home systems (Gogla, 2020). In 2018, 3.8 million units were sold in Africa, compared to 3.16 million in Asia, making the African continent the largest market for decentralized solar systems globally.

Until today, distributed solar system companies have mainly targeted rural areas not covered by the grid to give consumers first access to electricity. However, a new market segment is emerging today in areas covered by the grid but where it is unreliable and where decentralized solar systems are used to compensate for power outages. For example, the Global Off-Grid Lighting Association (Gogla), the leading organization for collecting data and information on the off-grid industry, estimates that 153 million potential customers have access to the main grid but face an unreliable network (Gogla, 2020). However, we will see that the number of potential customers of decentralized solar systems having access to the network advanced by Gogla is underesti-

²⁴For more information on the different definitions of distributed solar systems: www.gogla.org.

mated. Indeed, we will see in Chapter 2 that the decentralized solar market is also developing in areas where the network is reliable.

As with the storage battery market, the advantage of these decentralized solar technologies lies in their ability to be modulated and adapted as closely as possible to the electrical needs of consumers in terms of cost and consumption. Indeed, these decentralized solar systems are available in different product categories in terms of capacities, ranging from 1 watt peak (Wp) to 7000 Wp+. The smallest solar devices (1 – 20 Wp) range from a lamp providing basic lighting to small systems for charging a telephone. The medium-sized systems (100 Wp) can provide enough electricity to power a refrigerator or television. Finally, large-scale systems (7,000 Wp) can supply a household at levels of electricity consumption almost equivalent to the standards of industrialized countries.

We can thus confirm that an alternative offer to the network, via market mechanisms, is developing for residential consumers in the areas covered by the central network. The offer on the decentralized systems market for the residential sector is mainly composed of solar systems of all sizes, battery systems and battery-powered electronic equipment.

4.1.2 Decentralized systems for commercial consumers

The juxtaposition of electricity consumption systems mentioned by residential consumers is also observed among companies on the continent, mainly to deal with power cuts. The proportion of businesses experiencing outages is higher in Africa than in other world regions. In 25 of the 29 African countries covered by the study by Blimpo et al. (2020), less than a third of businesses had a reliable access to electricity. This weakness of the sub-Saharan electricity networks has a considerable negative effect on the economies, representing, on average and depending on the country, a cost typically ranging from 1 to 4% of the national GDPs (and sometimes up to 6%) (Foster and Briceno-Garmendia, 2010).

Businesses across the continent invest in backup generators to deal with grid deficiencies and to consume electricity when the grid is down. In sub-Saharan Africa, more than half of companies are equipped with or share a generator (53.5% on average) : around 80% in the Republic of Congo, and Angola, and around 70% in Sierra Leone, Chad, Angola, and South Sudan. The auxiliary generators are estimated to represent a capacity of 127 GW at the continental level, or almost the equivalent of the total centralized installed capacities on the central networks in sub-Saharan Africa, including South Africa (International Energy Agency, 2019; Attia, 2022). There are significant variations in the frequency and duration of power outages depending on the country, corre-

lated with the use of auxiliary generators. In 2014, these power cuts amounted to almost 190 days in Nigeria. The table I.3 shows the number of hours without electricity each month and the use of auxiliary generators in the region's countries. The complete table with also the number of power outages each month and the losses experienced by the firms is given in table A.I.6 in annex. The World Bank collects these data during national surveys conducted on an irregular basis by country. Therefore, data for some countries are unavailable while others figures may go back several years. However, to the best of my knowledge no other institution than the World Bank collects such data on a large scale.

In this context, Nigeria is an extreme case; the aggregate installed capacities of auxiliary generators in the country would be around 10 to 15 GW, i.e., two to three times more than the capacities available on the central network (Arik, 2019), which were below 5 GW in 2018 (Arowolo and Perez, 2020). In addition to the environmental and health problems that generators pose, they incur high costs. The variable cost of self-production of electricity via auxiliary generators would be around three times higher than that of the national grid.

In addition to auxiliary generators, new innovative solutions for autonomous electricity production are emerging, such as hybrid generators. These solutions combine an auxiliary generator, solar panels and eventually a storage system. This market is gaining traction today in Africa, especially among industries and businesses who want to insure themselves against the lack of reliability of the network while limiting their fuel consumption. With the growing cost-competitiveness of renewable energies, especially solar, large commercial consumers are turning to hybrid systems to meet their electricity needs at lower costs (IRENA, 2022). These systems can provide electricity 23-60% cheaper than using conventional generators, depending on the region (International Energy Agency, 2022a). This market is also developing with telecom companies that need continuous power for their telecommunication towers. These ranges from small installations to mini-power plants of up to 2 MW (Le Picard, 2020a). Although, to the best of the author's knowledge, no research article reports on the development of this market in the region, several qualitative interviews conducted as part of my work at IFRI, with chief commercial officers of three companies offering these solutions, showed that this market was booming. For example, one of the leading companies in the West African market raised more than 38 million USD in January 2021 to develop and benefited from direct financial support from Proparco and the European Union (Proparco, 2021). The market development is supported by different innovative enablers, summed in the table I.4.

Moreover, several recent academic articles have confirmed the attractiveness of such systems for businesses and industries. In Nigeria, (Adesanya and Schelly,

Table I.3: Power cuts and generator uses by enterprises (latest data available between 2009 and 2020)

Economy	Average duration without electricity each month (hours)	Percent of firms owning or sharing a generator
Angola	63.45	79
Benin	103.6	59.9
Botswana	11.07	34.5
Burkina Faso	32.34	28.3
Burundi	79.68	64.2
Cabo Verde	29.44	48.8
Cameroon	66.12	39.7
Central African Republic	234.9	81.4
Chad	38.25	67.7
Congo, Dem. Rep.	68.88	59.5
Congo, Rep.	737.45	81.8
Côte d'Ivoire	19.25	29.9
Eritrea	1.4	36.8
Eswatini	13.69	46.6
Ethiopia	47.56	49.1
Gabon	24.84	22.9
Gambia	122.38	55.7
Ghana	65.52	52.1
Guinea	14.4	56.8
Guinea-Bissau	93.08	68.4
Kenya	22.04	65.6
Lesotho	14.52	29.4
Liberia	37.35	73.2
Madagascar	12.73	19.3
Malawi	28.81	40.9
Mali	21.42	66.8
Mauritania	13.78	42.2
Mauritius	3.84	24.5
Mozambique	8.64	29
Namibia	3.48	18
Niger	114.4	69.4
Nigeria	380.48	70.7
Rwanda	2.4	33.8
Senegal	10.8	64.2
Sierra Leone	122.85	69.5
South Africa	17.71	63.3
South Sudan	7.05	73.3
Sudan	8.5	54.1
Tanzania	56.07	43
Togo	11.55	53.1
Uganda	63.63	52.2
Zambia	144.97	62.1
Zimbabwe	23.4	62.3

Source : World Bank (2022b)

Table I.4: Innovative enablers for the hybrid systems market

Business Model Innovation:	Transition across many industries towards outsourcing of power services, allowing businesses to enjoy the benefits of renewable energy systems without the upfront capital requirements.
System Price Innovation:	Significant reduction in renewable energy system costs, especially in the case of battery/storage systems.
Energy Storage Innovation:	Promising development of alternate storage technology, which can store more energy at lower costs, e.g., Solar + Hydrogen storage systems.
Energy Mix/ Hybrid Innovation:	Significant advancements in the combination of various renewable energy sources, e.g., Solar + Gas/Biogas, Solar + Hydrogen, Solar + auxiliary generator.
Digitalization Automation Innovation:	Rapidly growing digitalization of renewable energy systems now providing users with the ability to monitor, operate, and troubleshoot systems remotely

Source : Ezenwoko (2021)

2019) assessed the economic viability of solar PV-DG hybrid systems among private companies via an approach modeling their Levelized cost of energy (LCOE). Their findings indicate that core network reliability issues among Nigerian business consumers could be addressed with these systems. Three business case studies show that they could benefit from savings between €0.002 and €0.009/kWh. Furthermore, Mukisa et al. (2019) estimated the feasibility of grid-connected Ugandan industrial photovoltaic systems in Uganda. Their analysis reveals that the financial feasibility of the projects is robust, with an LCOE of 5.75 US cents/kWh, an internal rate of return of 7%, and a possible profit margin of 5.29 cents/kWh for each kWh supplied to the grid.

Therefore, an alternative offer to the network also appears to emerge progressively for commercial consumers in the areas covered by the network. This new offer is mainly composed of auxiliary generators. However, in recent years, a new market segment has been emerging. It offers hybrid generators that allow taking advantage of the benefits of each technology.

The last part showed an empirical phenomenon of juxtaposition of electrical uses among consumers connected to the network. In particular, we have seen that in areas covered by the network, it is common for consumers to use both decentralized means and the central network to consume electricity. Due to the difficulty of finding data in the region, this phenomenon can hardly be characterized and quantified with precision. Nevertheless, taking into account the quantitative and qualitative elements collected, it can be said that decentralized electricity production offers consumers connected to the grid the possibility of becoming less dependent on the central network. We have shown that the empowerment of consumers vis-à-vis the network can take place both

for economic reasons and for security of supply. This new phenomenon means that the supply of electricity in the areas covered by the network becomes less dependent on specific organizations in terms of centralized infrastructures. However, self-production via decentralized electricity systems does not necessarily imply the complete disconnection of consumers from the grid, which may still be necessary to guarantee security of supply or even serve budgetary interests.

4.2 The potential consequences of consumer empowerment for centralized networks

The juxtaposition of electricity consumption means among consumers connected to the network and its consequences have not been addressed in the economic literature on the development of sub-Saharan electricity systems. An increased penetration of decentralized systems in the areas covered by the network could have profound implications for the development of the sector and raise questions about the evolution of centralized networks in the region. Given the difficulties encountered by centralized electricity networks, exposed in part II of this chapter, the significant increase in the urban population and the growing attractiveness of decentralized systems, it is not excluded that the centralized network will become partly superfluous. It is therefore necessary to analyze the consequences of this empowerment, first on the financial viability of the sector, then on the electricity mix, and finally, on the socio-economic inequalities of access to electricity services in the region.

4.2.1 On the financial viability of the sector

The empowerment of consumers connected to the network could have profound implication for the development of centralized electricity sectors. It is a trend that risks reducing revenues from the sale of electricity by increasing payment defaults or by diverting consumers from the central grid. This is likely to aggravate the weak financial viability of electric utility companies (see section 2).

As we have seen, it is already difficult for companies to collect revenues from the sale of electricity. With the hybridization of networks, these problems are likely to be exacerbated. Pueyo (2018) discusses the complete empowerment of lucrative residential consumers with regard to expensive and unreliable electricity supplied by the central grid in Ghana. The most lucrative customers are turning away from the national grid and investing in self-production through auxiliary generators or photovoltaic systems. The Ghanaian regulatory agencies have even, according to the author, recommended a reduction in electricity tariffs to discourage the diversion of consumers from the network. Indeed, the

largest consumers are essential to ensure the system's sustainability because they pay higher tariffs, making it possible to subsidize the consumption of the poorest consumers. Consumer greater autonomy can deprive the network of its most lucrative clients and risks reinforcing the vicious circle described in section 2 of this chapter.

Furthermore, Oseni (2016) showed that wealthier households are the most likely to buy and use a generator in Nigeria. His analysis also reveals a partial decorrelation among some consumers between the possession of a generator and the network's reliability. In his study, nearly 16% of auxiliary generator owners do not wish to part with their auxiliary generators even in the event of a significant improvement in the quality of the electricity supply from the central network, despite the significant constraints related to the use of these systems for their users. The author suggests that improving the reliability of the electricity supply may not be enough to completely halt the use of backup generators in Nigeria. However, the author does not provide data for owners of photovoltaic systems, which do not have the disadvantages of auxiliary generators.

We can say that the sector's financial viability will be affected differently if wealthier or poorer consumers move away from the central grid. Therefore, a better knowledge of the types of consumers who tend to become autonomous, according to their level of income and the quality of the central network, is essential to better understand the development of networks. It appears also essential to analyze in more detail the effects of network reliability on consumer empowerment. This will allow us to verify whether an improvement in the quality of the electricity supply can influence the empowerment of consumers or the use of decentralized means.

4.2.2 On the electricity mix of the region

If the finances of the national purchasing companies are weakened due to the diversion of consumers from the grid, there is a risk of a slowdown in renewable technologies deployment on the central grid in the region. To be financed under favorable conditions, renewable projects require certainty of payment over the plant's entire life, i.e., for more than 25 years, because they have high investment costs and low operations costs. Such a time horizon involves many risks, which are higher when the national buying companies face significant financial problems. The risks of non-payment are significant and can compromise the stability of investors' income. These risks increase the cost of capital and can make projects non-bankable (Le Picard, 2020b).

Conversely, in the face of rapidly increasing energy demand and the financial difficulties of the sub-Saharan electricity sectors, "emergency" power plants

are becoming increasingly attractive. These solutions are mainly generators joined in containers to form power plants that can be installed in a months or even a few weeks. These are powered by coal or fuel oil and are rented at great expense from specialized companies. These power plants can be installed without collateral from national companies and can be withdrawn quickly in the event of cessation of payment (Le Picard, 2020a). However, these solutions are costly: they have electricity costs two to three times higher than conventional power plants. These emergency power plants mainly run on auxiliary or heavy fuel oil (HFO), the prices of which were estimated by Trimble et al. (2016) at around 0.30 and 0.40 USD per kWh during the period 2014-2016. Recent increases in fuel prices suggest much higher costs at the time of writing this chapter.

These plants tend to thrive in countries where power sector finances are in dire conditions. Contrary to their initial aims, they are often anchored in the long term in the national electricity markets, either by renewing rental contracts or by being bought by public companies. In 2007 there was about 750 MW of installed capacity of emergency power plants in sub-Saharan Africa. These capacities were estimated to have reached 2 GW in 2011. Estimates show that the power stations operated by the two main leaders in the emergency power station market in Africa alone, the British group Aggreko and the Turkish Karpowership, would represent capacities of more than 2.85 GW (Eberhard et al., 2011; Trimble et al., 2016; Le Picard, 2020a).

The growing use of emergency power plants on sub-Saharan grids reflects the various difficulties facing sub-Saharan power sectors. The more the electricity sectors are in financial difficulty, the more the investments are likely to be directed towards projects with high OPEX and low CAPEX, which run on fossil fuels. Conversely, only an improvement in the finances of the continent's electricity sectors will allow it to develop its immense renewable potential, with high CAPEX and low OPEX (Le Picard, 2020a).

The development of the market for decentralized solar systems in rural and urban areas of sub-Saharan Africa is also a parallel way to take advantage of the immense solar potential of the region and, therefore, increase the renewable capacities of the region. In Chapter 2, for a selection of 14 sub-Saharan cities in more than 13 African countries, it is estimated that the installed decentralized solar capacity is between 180 and 230 MW in fourteen African cities. IRENA (2021) estimates only about 1.7 GW of centralized solar capacity installed in sub-Saharan Africa, excluding South Africa. Our estimates based on Deep Learning and satellite imagery analysis in a selection of sub-Saharan cities show that decentralized solar systems represent nearly 10% of the centralized capacities installed in the region, which is not negligible. Therefore, there could be a dual effect of consumer empowerment on the development of solar in the

region. On the one hand, this could weaken utilities' finances and limit the potential development of centralized solar in the region. On the other hand, the empowerment of consumers through decentralized solar systems is *de facto* an additional means of increasing the installed solar capacities in the region. The net effect, however, remains unclear.

4.2.3 On socio-economic inequalities

Consumers empowerment could contribute to increasing inequalities in access to electricity in sub-Saharan Africa, with only the wealthiest segments of the population having access to reliable and sustainable electricity. Decentralized systems which provide access to quality electricity that is clean in terms of noise pollution and emissions, such as decentralized solar systems, risk remaining out of reach for the poorest households. For example, in sub-Saharan Africa, the prices of a decentralized solar system of more than 100 Wp with electrical appliances vary between 780 and 1,760 USD (Gogla, 2020), or 49% to 112% of average annual GDP per capita in sub-Saharan Africa. Among consumers connected to the network, the electricity distribution companies are also encouraged to invest in the deployment of smart meters to offer them new services to keep them captive. However, they are only encouraged to do so for the wealthiest segments of the population, for whom the cost/benefit ratio is the highest. In poorer neighborhoods, distribution companies are encouraged to install less efficient technologies, such as simple prepaid meters, to ensure increased revenue collection (Le Picard, 2020a).

Therefore, there is a risk that in the urban areas of sub-Saharan African some consumers have access to modern electricity services, comparable to those of industrialized countries, while living next to slums where the inhabitants would only have access to small decentralized systems such as rechargeable devices.

Box 4: Smart Meters in sub-Saharan Africa

Smart meters allow multiple gains for the entire electricity sector in sub-Saharan Africa. The deployment of smart meters can be used to improve the quality of supply and develop new services and facilitate revenue collection by multiplying the payment mediums: payment via mobile, internet, relay point, automatic distractors, or even portable input terminals. This significantly improves the collection of electricity revenues by facilitating customer payment. Similarly, distribution companies can also benefit from savings related to the automation of readings. Thanks to automatic alert systems, these meters can also reduce non-technical losses such as electricity theft via meter traffic. However, installing these meters improves the collection of revenues, not the revenues themselves. Following the installation of meters, revenues can either increase, in the case where billing by estimate underestimated the actual consumption of a user, or decrease if this was, on the contrary, overestimated. Nevertheless, invoice disputes are reduced, and thus reduce the investigation costs incurred.

For the consumer, smart meters enable energy savings through continuous information on the user's electricity consumption and expenditure. Because a consumer can directly observe his electricity consumption and its associated cost, he is constantly aware of his use and expenses. It is the same principle for prepaid meters. Studies on prepaid meters have shown that they can double the energy savings (Faruqi et al., 2010).

With smart meters, pricing can be more easily scalable. By giving the consumer a price signal at all times concerning the electricity price, the latter could theoretically change according to the time of day, the season, and the local electricity mix. These meters would also theoretically allow the prepayment of electricity while maintaining the block pricing systems, which prevail in most sub-Saharan countries, and allow the poorest households to benefit from preferential rates, which was not possible with prepaid meters (Le Picard, 2020a).

Suppliers offering innovative goods and services have entered the electricity markets in sub-Saharan Africa over the last decade, particularly in areas covered by the network. The arrival of these new companies in the face of failing central networks shows that market mechanisms are at work and are helping to transform the centralized electricity landscape of the countries of the region by offering an alternative to the network. Residential or commercial consumers can thus use the various decentralized technologies in addition to the electricity supplied by the central network. Those decentralized technologies help consumers deal with the lack of reliability of the network but also to optimize their electricity costs. However, we have seen that this progressive empowerment of

consumers connected to the network can have profound implications for the development of centralized electricity sectors. This could have consequences for the financial viability of electricity companies, the region's electricity mix and socio-economic inequalities.

5 Conclusion: the need to develop a thorough analysis of consumer empowerment

In this chapter, it has become apparent that the centralized electricity sectors of the region are in financial dire straits. They are trapped in a vicious financial circle, which reduces service quality, increases costs, and further fuels their financial difficulties. After several decades of reforms, the situation has made little progress. Facing these empirical facts, the academic literature deals with the region's electricity sector's development mainly through the issue of electrification planning. This literature has mainly focused on strategies for the electrification of the African continent. However, it makes little mention of the emergence of a new phenomenon: the empowerment of consumers in the areas covered by the network.

Faced with the increase in the urban population, the sector's difficulty in developing at the same pace, and the poor reliability of the network, populations and businesses are encouraged to become more independent from the central network to meet their electricity consumption needs. Market mechanisms are at work to fill the gaps induced by the weakness of the central network. New markets are opening up for decentralized systems in areas covered by the network in sub-Saharan Africa. The fact that consumers are no longer captive to the centralized network makes the supply of electrical energy in the areas covered less dependent on specific organizations in terms of centralized infrastructure. If these trends continue, this could have profound implications for the sector's development and raise questions about the evolution and even, in some cases, the existence of centralized networks in the future. Therefore, this chapter has sketched the potential consequences of consumer empowerment in grid-covered areas and highlighted mechanisms that could transform the centralized electricity landscape of the region's countries. Indeed, the empowerment of consumers connected to the network could accentuate the financial difficulties of the sectors. As a result, this could influence the evolution of the electricity mix in the region and reinforce inequalities of access to electricity services in sub-Saharan Africa.

However, several questions remain unanswered. For example, depending on which consumers turn away from the central network, the financial consequences for the sector could differ. Therefore, it appears fundamental to develop a more detailed knowledge of consumers who become more autonomous from the grid, notably depending on their level of income and the quality of the electricity supply from the central network. It also appears essential to examine the extent that improvement in the quality of the electricity supply could influence this consumer empowerment or the use of decentralized systems. Answering these questions should allow the characterization of the dynamics of consumers' empowerment in the areas covered by the network.

Gogla (2020) estimated around 153 million potential customers for distributed solar systems with access to the main grid but who are facing an unreliable grid in sub-Saharan Africa²⁵. However, apart from this estimate, there is no database on the development of this market in areas covered by the network. Moreover, Gogla (2020) assumes that this market only caters to consumers with access to an unreliable network, which may not be the case in practice. Therefore, it is appropriate to verify whether the market for decentralized solar systems is developing in urban areas covered by the network in sub-Saharan Africa and to assess the extent of this development. Finally, if this market is developing in urban areas, it is essential to know what type of consumer it is aimed at. Finally, given the development of the decentralized market in urban areas, it is essential to know what demographic of consumers these systems are aimed at, notably in terms of revenue. Consumers pay different tariffs for electricity depending on their consumption, which is correlated to their revenue. Therefore, assessing which customers tend to become more independent from the grid is essential to determine the impact of consumer empowerment on the centralized sectors' finances.

The next chapter attempts to answer these questions in more than 13 African countries and 14 cities using an original method using Deep Learning algorithms to analyze 2.4 million satellite images representing a total surface covered of more than 4.6 billion square meters.

²⁵In comparison, the consumer market without access is estimated at around 588 million (Gogla, 2020).

Appendices

Table A.I.1: Cash collected versus costs in USD per kWh billed in electricity sectors of the region

Country	Cash collected	Opex	Capex	Total cost
Benin	0,23	0,21	0,05	0,26
Botswana	0,08	0,13	0,08	0,21
Burkina Faso	0,23	0,23	0,11	0,34
Burundi	0,07	0,1	0,11	0,21
Cameroon	0,11	0,11	0,05	0,16
Cape Verde	0,37	0,39	0,12	0,51
Central African Republic	0,11	0,1	0,11	0,21
Comoros	0,12	0,48	0,13	0,61
Congo , Rep.	0,09	0,06	0,11	0,17
Côte d'Ivoire	0,11	0,16	0,05	0,21
Ethiopia	0,04	0,02	0,15	0,17
Gabon	0,21	0,18	0,06	0,24
Gambia	0,17	0,33	0,11	0,44
Ghana	0,11	0,1	0,04	0,14
Guinea	0,08	0,22	0,13	0,35
Kenya	0,15	0,12	0,09	0,21
Lesotho	0,06	0,02	0,07	0,09
Liberia	0,49	0,54	0,12	0,66
Madagascar	0,09	0,23	0,09	0,32
Malawi	0,09	0,07	0,09	0,16
Mali	0,2	0,27	0,06	0,33
Mauritania	0,18	0,26	0,08	0,34
Mauritius	0,19	0,16	0,06	0,22
Mozambique	0,08	0,06	0,06	0,12
Niger	0,14	0,15	0,04	0,19
Nigeria	0,06	0,13	0,09	0,22
Rwanda	0,23	0,31	0,12	0,43
São Tomé and Príncipe	0,14	0,43	0,11	0,54
Senegal	0,22	0,29	0,05	0,34
Seychelles	0,33	0,26	0,06	0,32
Sierra Leone	0,26	0,34	0,21	0,55
South Africa	0,06	0,06	0,06	0,12
Sudan	0,05	0,06	0,09	0,15
Swaziland	0,12	0,12	0,06	0,18
Tanzania	0,14	0,12	0,05	0,17
Togo	0,25	0,29	0,05	0,34
Uganda	0,17	0,13	0,03	0,16
Zambia	0,05	0,05	0,03	0,08
Zimbabwe	0,08	0,08	0,08	0,16

Source: Trimble et al. (2016)

Table A.I.2: Multi-tier matrix for measuring access to household electricity supply

Attributes	1. Peak Capacity	Power capacity ratings (in W or daily Wh)	Tier 0	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5
		OR Services		Min 3 W Min 12 Wh	Min 50 W Min 200 Wh	Min 200 W Min 1.0 kWh	Min 800 W Min 3.4 kWh	Min 2 kW Min 8.2 kWh
2. Availability (Duration)	Hours per day		Min 4 hrs	Min 4 hrs	Min 8 hrs	Min 16 hrs	Min 23 hrs	
	Hours per evening		Min 1 hr	Min 2 hrs	Min 3 hrs	Min 4 hrs	Min 4 hrs	
3. Reliability						Max 14 disruptions per week	Max 3 disruptions per week of total duration <2 hrs	
4. Quality						Voltage problems do not affect the use of desired appliances		
5. Affordability						Cost of a standard consumption package of 365 kWh/year < 5% of household income		
6. Legality						Bill is paid to the utility, prepaid card seller, or authorized representative		
7. Health & Safety						Absence of past accidents and perception of high risk in the future		

Source : Bhatia and Angelou (2015)

Table A.I.3: Quasi-fiscal deficit of the electricity sectors in absolute and relative terms in electricity sectors of the region

Country	Absolute QFD (current USD million)	QFD (% current GDP)
Benin	\$26	0,3
Botswana	\$487	3,4
Burkina Faso	\$125	1
Burundi	\$29	1
Cameroon	\$214	0,7
Cape Verde	\$28	1,6
Central African Republic	\$7	0,4
Comoros	\$23	4,1
Congo, Rep.	\$76	0,6
Côte d'Ivoire	\$654	1,9
Ethiopia	\$636	1,7
Gabon	\$66	0,4
Gambia, The	\$52	5,8
Ghana	\$205	0,5
Guinea	\$129	2,1
Kenya	\$486	0,8
Lesotho	\$11	0,5
Liberia	\$7	0,4
Madagascar	\$229	2,2
Malawi	\$111	2,5
Mali	\$155	1,3
Mauritania	\$78	1,5
Mauritius	\$51	0,4
Mozambique	\$157	0,9
Niger	\$39	0,5
Nigeria	\$2,928	0,5
Rwanda	\$78	1
São Tomé and Príncipe	\$21	6,1
Senegal	\$325	2,2
Seychelles	-\$4	-0,3
Sierra Leone	\$33	0,9
South Africa	\$11,329	3,4
Sudan	\$1,024	1,4
Swaziland	\$52	1,2
Tanzania	\$193	0,3
Togo	\$70	1,6
Uganda	-\$19	-0,1
Zambia	\$317	1,2
Zimbabwe	\$643	5,2

Source: Trimble et al. (2016)

Table A.I.4: Technical and non-technical losses in sub-Saharan electricity sectors in 2014 (else stated otherwise)

Country	Electric power transmission and distribution losses (% of output) in 2014	Bill collection rate (2014)
Angola	11%	
Benin	61% (2008)	95%
Botswana	11%	99%
Burkina Faso	17%	98%
Burundi	28%	74%
Cabo Verde	32% (2012)	88%
Cameroon	11% or 28%	95%
Central African Republic	48%	78%
Comoros	40% (2012)	58%
Congo, Dem. Rep.	21%	
Congo, Rep.	45%	80%
Cote d'Ivoire	14% or 21%	82%
Eritrea	13%	
Eswatini		
Ethiopia	19%	87%
Gabon	28% or 24%	99%
Gambia, The	27%	73%
Ghana	23%	95%
Guinea	24% (2013)	70%
Kenya	18%	99%
Lesotho	9% (2010)	87%
Liberia	25%	94%
Madagascar	33%	60%
Malawi	24% (2013)	93%
Mali	23%	99%
Mauritania	23% (2013)	81%
Mauritius	6%	99%
Mozambique	15% or 22%	92%
Namibia	36%	
Niger	42% or 19%	86%
Nigeria	16% or 39%	66%
Rwanda	26% (2013)	95%
Sao Tome and Principe	43%	59%
Senegal	13%	93%
Seychelles	12%	99%
Sierra Leone	39% (2012)	79%
Somalia	7% (2011)	
South Africa	8% or 9%	98%
South Sudan	6%	
Sudan	14% or 15%	100%
Tanzania	18%	92%
Togo	71%	88%
Uganda	21%	99%
Zambia	15% or 12%	96%
Zimbabwe	16%	87%

Source: World Bank (2022a); Trimble et al. (2016)

Table A.I.5: Breakdown of costs (percentage of current GDP) in electricity sectors of the region

Country	Bill collection	TD losses	Over-staffing	Underpricing	Total costs
Benin	0.10	0.24	0.24	-0.30	0.28
Botswana	0.05	0.00	0.26	3.04	3.35
Burkina Faso	0.06	0.22	0.23	0.48	0.99
Burundi	0.32	0.13	0.06	0.44	0.95
Cameroon	0.08	0.39	0.23	-0.03	0.67
Cape Verde	0.53	1.40	0.00	-0.30	1.63
Central African Republic	0.09	0.26	0.16	-0.12	0.39
Comoros	1.36	1.62	0.32	0.83	4.13
Congo, Rep.	0.12	0.39	0.14	-0.10	0.56
Côte d'Ivoire	0.61	0.45	0.17	0.69	1.92
Ethiopia	0.23	0.34	0.05	1.07	1.69
Gabon	0.02	0.31	0.26	-0.22	0.36
Gambia, The	1.84	1.57	1.12	1.29	5.83
Ghana	0.10	0.31	0.20	-0.16	0.45
Guinea	0.65	0.39	0.13	0.92	2.10
Kenya	0.02	0.21	0.16	0.39	0.78
Lesotho	0.34	0.00		0.15	0.49
Liberia	0.06	0.21	0.08	0.00	0.36
Madagascar	0.89	0.75	0.16	0.42	2.21
Malawi	0.30	0.74	0.32	1.11	2.48
Mali	0.04	0.46	0.19	0.60	1.29
Mauritania	0.48	0.43	0.19	0.42	1.52
Mauritius	0.04	0.00	0.41	-0.02	0.43
Mozambique	0.17	0.31	0.33	0.11	0.92
Niger	0.20	0.16	0.21	-0.09	0.48
Nigeria	0.17	0.24		0.13	0.54
Rwanda	0.09	0.35	0.16	0.45	1.04
São Tomé and Príncipe	1.94	2.77	0.60	0.77	6.08
Senegal	0.35	0.45	0.38	1.00	2.18
Seychelles	0.06	0.18	0.35	-0.85	-0.26
Sierra Leone	0.21	0.47	0.08	0.10	0.87
South Africa	0.15	0.00	0.50	2.78	3.429
Sudan	0.00	0.10		1.32	1.41
Swaziland	0.04	0.04	0.43	0.73	1.24
Tanzania	0.13	0.14	0.07	-0.06	0.28
Togo	0.55	1.15	0.30	-0.40	1.60
Uganda	0.01	0.16	0.08	-0.32	-0.07
Zambia	0.12	0.09	0.23	0.79	1.23
Zimbabwe	1.26	0.58	0.75	2.59	5.19

Source : Trimble et al. (2016)

Table A.I.6: Relation between power cuts and generator uses by enterprises in sub-Saharan Africa (1/2)

Economy	Percent of firms experiencing electrical outages	Number of electrical outages in a typical month	If there were outages, average duration of a typical electrical outage (hours)
Angola	87,7	4,7	13,5
Benin	95,6	28	3,7
Botswana	92,4	4,1	2,7
Burkina Faso	91,9	9,8	3,3
Burundi	85,1	16,6	4,8
Cabo Verde	74	3,2	9,2
Cameroon	92,5	7,6	8,7
Central African Republic	89	29	8,1
Chad	70,2	4,5	8,5
Congo, Dem. Rep.	89,3	12,3	5,6
Congo, Rep.	89,7	21,5	34,3
Côte d'Ivoire	78,8	3,5	5,5
Eritrea	20,5	0,5	2,8
Eswatini	77,3	3,7	3,7
Ethiopia	80	8,2	5,8
Gabon	71,6	4,6	5,4
Gambia	93,2	21,1	5,8
Ghana	89,1	8,4	7,8
Guinea	84,2	4,5	3,2
Guinea-Bissau	57,1	5,2	17,9
Kenya	82,8	3,8	5,8
Lesotho	71,8	2,2	6,6
Liberia	44,3	4,5	8,3
Madagascar	86,9	6,7	1,9
Malawi	82,9	6,7	4,3
Mali	86,6	4,2	5,1
Mauritania	90,7	5,3	2,6
Mauritius	38,8	1,2	3,2
Mozambique	52,8	1,6	5,4
Namibia	26,9	0,6	5,8
Niger	78	22	5,2
Nigeria	77,6	32,8	11,6
Rwanda	39	2,4	1
Senegal	83,7	6	1,8
Sierra Leone	71,8	9,1	13,5
South Africa	92	7,7	2,3
South Sudan	15,3	1,5	4,7
Sudan	93,7	3,4	2,5
Tanzania	85,8	8,9	6,3
Togo	93,8	5,5	2,1
Uganda	81,5	6,3	10,1
Zambia	87,1	13,3	10,9
Zimbabwe	76,5	4,5	5,2

Source : World Bank (2022b)

Table A.I.7: Relation between power cuts and generator uses by enterprises in sub-Saharan Africa (2/2)

Economy	Average duration without electricity each month (hours)	If there were outages, average losses due to electrical outages (% of annual sales)	Percent of firms owning or sharing a generator	If a generator is used, average proportion of electricity from a generator (%)
Angola	63,45	12,6	79	27,3
Benin	103,6	9,4	59,9	37
Botswana	11,07	3,7	34,5	7,4
Burkina Faso	32,34	5,8	28,3	10,4
Burundi	79,68	3,4	64,2	17,5
Cabo Verde	29,44	5,5	48,8	24,4
Cameroon	66,12	9,9	39,7	16,6
Central African Republic	234,9	25,1	81,4	37,5
Chad	38,25	9,8	67,7	18,5
Congo, Dem. Rep.	68,88	7,8	59,5	37,2
Congo, Rep.	737,45	16,4	81,8	56,3
Côte d'Ivoire	19,25	4,9	29,9	27,3
Eritrea	1,4	0,2	36,8	3,4
Eswatini	13,69	7	46,6	29,2
Ethiopia	47,56	6,9	49,1	48,9
Gabon	24,84	1,7	22,9	9,6
Gambia	122,38	14,2	55,7	41,1
Ghana	65,52	15,8	52,1	21,5
Guinea	14,4	4,7	56,8	26,6
Guinea-Bissau	93,08	5,2	68,4	78,3
Kenya	22,04	5,4	65,6	17,8
Lesotho	14,52	2,5	29,4	25,7
Liberia	37,35	6,1	73,2	54,4
Madagascar	12,73	13,6	19,3	32,2
Malawi	28,81	7,2	40,9	27,3
Mali	21,42	8,8	66,8	15,6
Mauritania	13,78	2,4	42,2	17,2
Mauritius	3,84	2,2	24,5	3,4
Mozambique	8,64	3,2	29	16,8
Namibia	3,48	4,8	18	25,5
Niger	114,4	5,5	69,4	53,3
Nigeria	380,48	15,6	70,7	58,8
Rwanda	2,4	2,4	33,8	7,8
Senegal	10,8	2,8	64,2	9
Sierra Leone	122,85	15,8	69,5	45,9
South Africa	17,71	5,5	63,3	46,1
South Sudan	7,05	13,6	73,3	94,2
Sudan	8,5	1,2	54,1	7,2
Tanzania	56,07	15,1	43	24,5
Togo	11,55	3,7	53,1	11,8
Uganda	63,63	11,2	52,2	17,6
Zambia	144,97	18,8	62,1	30,1
Zimbabwe	23,4	6,1	62,3	19,3

Source : World Bank (2022b)

Table A.I.8: Installed capacities (MW), number of outages in a month and transmission lines in km in sub-Saharan Africa

Country	Total net installed capacity of electric power plants in MW, main activity autoproducer (2019)	Number of electrical outages in a typical month, latest data available	State owned transmission and distribution line data (km) above 1kV, latest data available
Angola	6156	4,7 (2010)	2832 (2011)
Benin	508	28 (2016)	3544 (2013)
Botswana	761	4,1 (2010)	3023 (2013)
Burkina Faso	390	9,8 (2009)	3923 (2014)
Burundi	87	16,6 (2014)	2101 (2014)
Cabo Verde	221	3,2 (2009)	859 (2012)
Cameroon	1669	7,6 (2016)	19017 (2014)
Central African Rep.	44	29 (2011)	225 (2014)
Chad	86	4,5 (2018)	
Comoros	35		588 (2012)
Congo	606	21,5 (2009)	2549 (2012)
Cote d'Ivoire	2233	3,5 (2016)	26400 (2014)
Dem. Rep. of the Congo	3190	5,6 (2013)	4513 (2013)
Equatorial Guinea	554		
Eritrea	226	0,5 (2009)	
Eswatini	193	3,7 (2016)	
Ethiopia	4300	8,2 (2015)	99059 (2012)
Gabon	784	4,6 (2009)	5461 (2014)
Gambia	137	21,1 (2018)	528 (2014)
Ghana	5382	8,4 (2013)	42569 (2013)
Guinea	621	4,5 (2016)	1378 (2013)
Guinea-Bissau	28	5,2 (2006)	458 (2014)
Kenya	3155	3,8 (2018)	59459 (2015)
Liberia	195	4,5 (2017)	87 (2014)
Madagascar	546	6,7 (2013)	3217 (2014)
Malawi	603	6,7 (2014)	14645 (2014)
Mali	1015	4,2 (2016)	3043 (2014)
Mauritania	608	5,3 (2014)	
Mauritius	844	1,2 (2009)	3736 (2013)
Mozambique	2814	1,6 (2018)	20629 (2014)
Niger	324	22 (2017)	4472 (2014)
Nigeria	11681	32,8 (2014)	137325 (2014)
Rwanda	228	2,4 (2019)	3379 (2013)
Sao Tome and Principe	29		149 (2014)
Senegal	1432	6 (2014)	8323 (2013)
Seychelles	157		330 (2014)
Sierra Leone	143	9,1 (2017)	205 (2012)
Somalia	91		
South Africa	58683	7,7 (2020)	79811 (2014)
South Sudan	131	1,5 (2014)	
Sudan	4138	3,4 (2014)	67146 (2014)
Tanzania		8,9 (2013)	27263 (2015)
Togo	230	5,5 (2016)	2722 (2013)
Uganda	1256	6,3 (2013)	13199 (2014)
Zambia	2981	13,3 (2019)	7922 (2014)
Zimbabwe	2346	4,5 (2016)	73239 (2012)

Source : United Nations (2021); World Bank (2022b); Trimble et al. (2016)

Table A.I.9: Connection time and tariffs to the network for consumers in sub-Saharan Africa

Country	Time to obtain an electrical connection (days), most recent year available	Upfront cost of grid connection for households in 2014 (USD)
Angola		52
Benin	193 (2016)	278
Botswana		679 (one-off payment) or 141 then 180 payments of 5 USD per month
Burkina Faso		270 in Ouagadougou and Bobo-Dioulasso or 70 in provinces
Burundi	25 (2014)	155
Cabo Verde		2
Cameroon	16 (2016)	50
Central African Republic	12 (2011)	
Chad	70 (2018)	
Comoros		181
Congo, Dem. Rep.	16 (2013)	
Congo, Rep.		
Cote d'Ivoire	40 (2016)	Depending on revenue level : 212, 308, 370 or 411
Equatorial Guinea		
Eritrea		
Eswatini	11 (2016)	
Ethiopia	194 (2015)	76
Gabon		114
Gambia, The	30 (2018)	169 in the Greater Banjul Area or 81 in provinces
Ghana	45 (2013)	87 if no extension needed or 436 if extension needed with 1 pole
Guinea	7 (2016)	
Guinea-Bissau		
Kenya	79 (2018)	171 if next to a facility with electricity or 370 if not
Lesotho	12 (2016)	187
Liberia	31 (2017)	54
Madagascar	24 (2013)	165 if no extension needed or 453 if extension needed with 1 pole
Malawi	50 (2014)	101
Mali	30 (2016)	196
Mauritania	16 (2014)	128 for 2 kilo-volt amperes or 168 for 6 kilo-volt ampere
Mauritius		31
Mozambique	18 (2018)	0 for social tariff, 4 for others
Namibia	20 (2014)	113 for urban else unknown
Niger	29 (2017)	19
Nigeria	9 (2014)	No connection fee but customers are charged for costs of materials
Rwanda	31 (2019)	82 within 35 meters of a pole else unknown
Sao Tome and Principe		52 single phase else 108 for three phase
Senegal	25 (2014)	Free if within 40 meters of a pole else unknown
Seychelles		Based on actual cost for the operator
Sierra Leone	22 (2017)	233 (one-off payment) or 118 and then 7 USD per month for 18 months
Somalia		
South Africa	12 (2020)	
South Sudan	10 (2014)	
Sudan	6 (2014)	
Tanzania	53 (2013)	197 in urban areas and 110 in rural areas
Togo	72 (2016)	244
Uganda	18 (2013)	101 if no extension needed or 244 if extension needed with 1 pole
Zambia	62 (2019)	125 in low-cost areas, 277 in medium-cost areas, 466 in high cost areas
Zimbabwe	22 (2016)	95 above ground, high-density areas or 185 above ground, low density areas

Source: World Bank (2022a); Kojima et al. (2016)

Chapter II

Decentralized solar systems in urban areas : a deep learning approach for satellite imagery analysis¹

¹The Deep Learning analysis in this chapter was done in collaboration with Matthieu Toulemont, senior machine learning engineer at Potoroom.

1 Introduction

In the last chapter, we saw that populations and businesses are driven to become more independent from the central network to meet their electricity needs. Market mechanisms are at work to fill the gap in the national grid, and new markets are now opening up for decentralized systems in grid-covered areas in the region. Therefore, consumers are no longer entirely dependent upon the centralized network, making electricity supply less dependent centralized infrastructure. If this trend continue, this could have profound implications for the sector's development and raise questions about the evolution of centralized networks in the region.

However, these consequences largely depend on the phenomenon's scale and the types of consumers who turn away from the network. In the first chapter of this thesis, Pueyo (2018) indicated that affluent residential consumers facing expensive and unreliable electricity supply from the grid in Ghana tend to become more autonomous from the grid. Consequently, Ghanaian regulatory agencies reportedly advocated lower electricity tariffs to discourage consumer diversion from the grid. The largest consumers are indeed essential to ensure the sustainability of the system. Furthermore, we saw that better-off households are the most likely to purchase and use decentralized systems in Nigeria. They were also likely to keep them even in the case of an improvement in supply reliability. Therefore, consumers' empowerment through decentralized systems could deprive the network of its most profitable customers and risk reinforcing the vicious circle exposed in chapter I.

At the same time, the market for solar home systems has been developing rapidly in sub-Saharan Africa in the past decades. The market is constantly growing. Today the African continent is the largest market for decentralized solar systems globally. It is now generally accepted that these decentralized solar systems are present in the continent's rural areas. In areas covered by the grid, the Global Off-Grid Lighting Association (Gogla) estimated that there could be about 153 million potential customers for decentralized solar systems who have access to the main grid but face an unreliable supply (Gogla, 2020). A few authors also mentioned that some sub-Saharan consumers invested in decentralized systems, mainly to cope with an unreliable network (Jaglin, 2019; Barry and Creti, 2020). However, these studies are based on very geographically localized case studies and do not consider areas where the network is reliable. No research article has sought to analyze the development of decentralized solar systems on a broad geographical scale in areas covered by the network. Given these elements, it is essential to assess whether the market for decentralized solar systems is developing in urban areas covered by the network in sub-Saharan Africa and the magnitude of this development. Then, given the financial consequences on the sector that consumer empowerment

can have, it is essential to understand which consumers invest in decentralized solar systems according to their income levels. Finally, as a result of the questions raised by this thesis, it is crucial to determine whether the centralized electricity sector can activate technical levers to curb consumers' greater autonomy, notably by assessing if consumer empowerment through decentralized solar systems correlates with the grid's reliability.

This chapter, therefore, assesses whether the market for solar systems in sub-Saharan Africa is also developing in urban areas. To do this, it establishes an original methodology based on Deep Learning and satellite imagery analysis, which, to the best of our knowledge, has never yet been applied to developing countries.

This chapter is organized as follows. Section 2 gives a contextual report on the development of decentralized solar technologies on the African continent. Section 3 reviews the literature on the adoption and usage of decentralized systems in sub-Saharan Africa. It also details the research questions that will be addressed as hypotheses to be tested. Section 4 develops the original methodology used in this chapter to gather the necessary evidence on the development of this market in urban areas. First, section 4.1 show how Deep Learning algorithms are used to analyze more than 2.4 million satellite images to assess and build an original dataset on the penetration of solar systems in sub-Saharan urban areas. Then, section 4.2 conducts a preliminary analysis of this original dataset, which allows answering part of our research questions. Subsequently, section 4.3 performs an econometric analysis on a complete dataset composed of our original solar data crossed with Afrobarometer's latest geolocated socio-economic survey. Finally, section 4.4 discusses the limits of the methodology used in this chapter. Section 5 then provides a general discussion of the results. Finally, section 6 concludes this chapter and lays the groundwork for the unanswered research questions, which will be addressed in the third chapter of this thesis.

2 Market context : the development of solar energy in Africa

In this part, we give a contextual report on the development of solar technologies on the African continent which has a long-lasting history in Africa that dates back to the second half of the 20th century. As early as the 1960s, technologies producing electricity from solar energy were deployed in several west African countries (Caille, 2017). The region benefits from significant solar radiation and is endowed with significant solar energy potential. Mugisha et al. (2021) have notably shown that Kenya and Rwanda, as well as other East African countries, benefited from advantageous geographic locations and enjoyed daily sunshine for more than 5 hours each day, even during rainy seasons. More generally, the region would have a theoretical capacity of 10 TW of solar energy (African Development Bank, 2017), or almost ten times the capacity installed in the United States in 2021 (Energy Information Administration, 2022).

However, as of today, sub-Saharan Africa only exploits a small part of its solar potential. In 2017, according to IEA statistics, 4.6 TWh of electricity from solar energy was produced in the region, less than 0,01% of its theoretical potential. Moreover, even regarding existing electricity production capacities in sub-Saharan Africa, solar amounted to 1.6 GW or 2% only of total installed capacities - excluding the particular case of South Africa² (IRENA, 2021).

While the deployment of centralized solar capacities is being rolled out gradually in sub-Saharan Africa as investment risks in solar are high for private developers³, the decentralized solar systems market has proliferated over the past decade. The first two companies to emerge in sub-Saharan Africa were M-Kopa, a Kenyan company founded in 2011, and Mobisol, a start-up founded in Berlin in 2010. In their early days, these two companies primarily operated in East Africa. They were notably the first to introduce flexible PAYG leasing schemes⁴ as early as 2009 (Rolffs et al., 2014). Gradually, they attracted

²South Africa's electricity sector is different from that of other sub-Saharan countries due to its more developed infrastructures, more significant investment in renewable energy sources and increased access to electricity. South Africa has the largest installed electricity capacity of all the sub-Saharan nations, with a total installed capacity of about 50 GW. For comparison, excluding South Africa, all sub-Saharan countries had 80 GW of installed capacity in 2018 (International Energy Agency, 2019). In addition, South Africa has a much higher electrification rate, with 84% of households having access to electricity in 2020, while the average electrification rate in the region was 48% (World Bank, 2022a).

³For more information on this subject see (Le Picard, 2020b).

⁴This system provides access to a solar kit under a leasing agreement that allows the use of a solar system while gradually repaying it through mobile money. Information technology can remotely and automatically lock the solar system if the consumer does not pay. This encourages the consumer to make regular payments to reimburse his solar system. See, for example, Barry and Creti (2020). In PAYG leasing, the consumer requires no collateral,

investors from the private sector and were thus able to develop rapidly in sub-Saharan Africa (Barry and Creti, 2020).

Subsequently, many more companies entered the decentralized solar market in the region. Today, Gogla, the referent organization for data and information gathering on the off-grid industry, accounts for more than 107 affiliated companies worldwide⁵, amongst which a significant number operates in Africa⁶. The market is growing: the sales amount of decentralized solar systems of all sizes⁷ globally reached over 1.75 billion USD in 2019 with an increase in revenues generated by the sector of more than 30% per year between 2017 and 2019. In total, in a decade, more than 180 million solar products have been sold worldwide, including 150 million pico-solar products and about 30 million solar home systems⁸ (Gogla, 2020).

In 2018, 3.8 million units were sold in Africa, against 3.16 million in Asia, making the African continent the biggest market for decentralized solar systems globally. The decentralized solar market has reportedly raised more than 2.3 billion USD in investments since 2010 in sub-Saharan Africa alone (Attia, 2022). The decentralized solar market follows different trends within Africa, depending on the region. For example, Barry and Creti (2020) discuss the fact that the PAYG solar home systems market has grown faster in East Africa than in West Africa, which represented only 12% of PAYG sales in Africa between 2013 and 2017. This is partly due to the slower penetration of mobile money in West Africa compared to East Africa. More generally for all Off-Grid Systems (OGS)⁹, in 2018 in sub-Saharan Africa, PAYG sales were still lower

making the system more flexible than a micro-credit. Consumers are attracted to this flexibility because it allows them to cope with unforeseen financial events by having to make many small payments instead of paying the full upfront cost of the system, see Moreno and Bareisaite (2015).

⁵These companies are businesses operating in the off-grid market affiliated to Gogla, IFC Lighting Global or Efficiency for Access Coalition which report sales information to Gogla. For more information see Gogla's website: <https://www.gogla.org/about-us>.

⁶Gogla reports do not indicate the number of affiliated companies that operate solely in Africa, in comparison to Asia. Also, affiliated members' market shares vary significantly from country to country in African countries. For example, it represents 97% in Rwanda but only 7% in Togo. This highlights that data presented by the report give general indications on the off-grid market's trends but cannot be considered as unyielding material.

⁷Decentralized solar systems can belong to different product categories in terms of capacities, which goes from 0 Wp to 100+Wp. The smallest solar appliances provide elemental lightning, while more important ones can supply enough electricity to power a fridge or television.

⁸Solar home systems' are defined as systems of 11Wp+ capacity which include both home lighting systems and appliances, while pico-solar product range typically from 0 to 11 Wp and only provide elemental lightning and eventually mobile phone charging.

⁹These include pico-solar systems, solar home systems as previously defined, and solar appliances which are powered by direct current and include household appliances (televisions or fridges) but also productive-use appliances (water pumps).

than cash sales in all regions, not by a significant amount, however. PAYG sales represented over 40% of sales in East Africa, 38% in West Africa, and around a third of sales in Central and South Africa (Gogla, 2020).

Even though the decentralized solar market is booming today, several factors hamper its development. These include, for example, the low capacity of people to pay for these systems, especially in remote and poor areas. In Eastern Africa, 70% of the population living in rural areas would only need solar systems to power small everyday appliances such as a radio or a mobile phone, limiting the market potential for medium to large systems. Since solar systems are almost exclusively imported from abroad, the price volatility of solar systems linked to currency fluctuations can also be a limiting factor¹⁰ (Mugisha et al., 2021).

Other factors must also be taken into account to understand the evolution of the market. Notably, on the offer's side, there need to be local capacities to distribute and ensure maintenance over an extended period of the systems in a locality. In particular, solar home systems require technical expertise to be designed, sized, installed, and maintained correctly (Friebe et al., 2013; Scott, 2017). Having access to maintenance for solar systems can be an important challenge for users if they bought them directly and not through a leasing scheme that could comprise dedicated maintenance services (Mapako, 2005).

At first, decentralized solar companies mainly targeted rural areas uncovered by the network. Thus, these systems were mainly used to provide first access to electricity. However, interviews conducted with sector professionals have shown that a new market segment is emerging today, in areas covered by the grid but where the network is unreliable and where decentralized solar systems are used to palliate power cuts. Gogla (2020) estimates that in sub-Saharan Africa, the market of people with access to the main network but dealing with unreliable electricity access could amount to 153 million potential customers or about 14% of the continent's population. In comparison, the market of consumers without any access is estimated to be around 588 million. Gogla (2020) notes that in comparison to uncovered areas, the market penetration is lower in areas where the network is unreliable, although without explicating clearly why it is so.

In this part, we have seen that the market for decentralized solar systems has developed rapidly in rural areas in recent years. Today, it is progressing towards the continent's cities already covered by the central network. However, apart from an overall estimate of the number of potential consumers for these

¹⁰Indeed, due to weak industrial sectors in sub-Saharan Africa, countries tend to rely heavily on imports for manufactured goods, which makes local currencies unable to compete with the USD.

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systems in unreliable network areas, no studies appear to have covered the subject.

3 Literature review and research questions

This section conducts a literature review regarding the adoption and usage of decentralized systems in sub-Saharan Africa. First, we review the specific literature on the dynamics surrounding technology adoption choices between centralized and decentralized systems in rural and peri-urban areas. Doing so, we analyze how the academic literature has so far studied the adoption of decentralized systems and in particular solar systems in the region, although, as we will see, most exclusively in rural areas. This should then allow us to lay out the relevant hypotheses to be tested with regard to this academic literature as well as the questions raised in this thesis.

3.1 Literature review on adoption choice between centralized and decentralized systems

Very scarce but interesting literature has developed recently on the technology chosen by a household to get access to electricity with regard to their socio-economic attributes when it is given a choice between decentralized or centralized solutions. Sievert and Steinbuks (2020) estimate that wealthy households in rural areas generally prefer central to decentralized access to electricity when they can, even if it is more expensive, as households derive more utility from a grid connection. They do so using a theoretical model of electricity technology choice in Rwanda, Senegal, and Burkina Faso and rely on 1922 observations from a socio-economic survey. This is in line with previous results in the literature, which shows that the proximity of the network to non-electrified residential consumers can be seen as an obstacle to the adoption of decentralized systems, as mentioned by Kizilcec and Parikh (2020) in a literature review, Azimoh et al. (2015) in their analysis of 88 households' interviews in South Africa and Dugoua and Urpelainen (2014) for a selection of five East African countries. Moreover, in areas uncovered by the grid, the proximity of a household to a solar system user directly increases the likelihood of adoption, income, and education. Lay et al. (2013) use a multinomial logit model on a socio-economic survey in Kenya to show that word of mouth and proximity of households to other decentralized solar users seems to be a critical factor in adopting these systems in rural areas.

Concerning auxiliary generators, if the grid is unreliable and the costs of purchasing and using an auxiliary generator are low enough, the latter system may become preferable for consumers (Sievert and Steinbuks, 2020). As we saw in chapter 1, auxiliary generator use is widespread across sub-Saharan Africa. However, it is essential to note that these palliative measures of electricity consumption from auxiliary generators are costly. In addition to the initial investment they represent, the variable cost of self-production of elec-

tricity via auxiliary generators would be about three times higher than that of the national grid due to the economies of scale made possible by the latter (Foster and Steinbuks, 2009; Oseni and Pollitt, 2015). This result indicates that choosing decentralized technology for electricity access over the centralized network appears to be closely linked to the quality of electricity provided by the grid.

However, very few research articles have analyzed decentralized technology adoption of consumers already connected to an unreliable grid. Indeed, users facing a failing grid can also choose to co-invest in a decentralized system to palliate power outages. Although, these investments in production capacity by businesses and households may be partial and cover part of their energy needs during power cuts. Even with autonomous means of production, households and businesses may still not fully meet their energy needs (Oseni and Pollitt, 2015). To this literature, we refer to Oseni (2016), and Oseni and Pollitt (2015)'s research articles focusing on Nigeria, which will be discussed in more detail in chapter 3. We also note the contribution of Barry and Creti (2020) who have shown that departments characterized by unreliable centralized electricity services in Benin have higher adoption rates for solar systems in PAYG. However, it is essential to note that this specific literature is very limited in time and geography, as it covers only two countries and, in each case, one specific period.

Several authors have shown that income is a crucial factor in explaining the adoption of decentralized solar systems in areas uncovered by the grid. Acker and Kammen (1996) analyze between 1980 and 1995 the Kenyan market for decentralized solar systems. They report the results of a survey conducted among forty solar home systems users questioned near urban centers, conducted in July and August 1994. Using descriptive analysis, they reveal that solar home systems are purchased mainly by wealthy households with above-average incomes living near the grid. However, the authors recognize a selection bias given that they conducted their household survey near urban centers and, therefore, close to the network. Jacobson (2007), also conducts a more in-depth descriptive analysis in the same country. This is based on two cross-sectional surveys among rural Kenyan households conducted in 2000 and 2001, including 1.512 and 1.755 observations, respectively. He also concludes that the decentralized solar market primarily targets the middle and upper classes, belonging to the top three wealth deciles.

Gradually, econometric tools have been used to refine the analyzes. Lay et al. (2013) and Guta (2018) study the determinants of a household's decision to adopt solar energy technology using logistic regression models. More specifically, Lay et al. (2013) study the determinants of household choices for lighting fuels in Kenya, particularly via solar home systems, using a multinomial logit

model. They use data from the Kenya Integrated Household Budget Survey (KIHBS) 2005/06 survey provided by the Kenya National Bureau of Statistics (KNBS), which includes a sample of 13,430 rural and urban households. Their data includes, in particular, socio-economic data such as income and level of education. They show that poor households use traditional lighting fuels but switch to kerosene as their income increases. It is only at high-income levels that households use decentralized solar systems for lighting. Guta (2018) also studies the determining factors of the decision to adopt a decentralized solar system by a household. His analysis is based on a sample of 195 rural Ethiopian households and uses a logit model. His analysis reveals that wealthier, more educated households are the most likely to adopt solar systems.

More recently, Aarakit et al. (2021) used a 2018 Uganda national electrification survey to analyze factors influencing the household choice of solar systems adoption. Their data come from the National Electrification Survey (NES) collected by the Uganda Bureau of Statistics (UBOS) between May and September 2018 and covers 5,231 randomly selected households. About 80% of households are rural, and 20% live in urban areas, of which 18% have access to the core network. They use a conditional mixed process model for their analysis, and they too find that income plays a crucial role in adoption. In addition, they find that access to the electricity grid is negative and statistically significant for adopting solar systems. However, the authors note that this result may have been affected by the considerable improvement of electricity supplied by the Ugandan grid in recent years.

This literature review has shown that income and education level appear to be key factors in explaining the adoption of decentralized solar systems. However, the literature on decentralized systems covering consumers already connected to the grid is particularly scarce. Articles also analyzing consumers connected to the grid are limited to three studies covering three countries only: Benin, Nigeria, and Uganda. Furthermore, two of these studies (Aarakit et al. (2021) and Barry and Creti (2020)) have only analyzed connected consumers marginally, as part of broader analyses also mainly comprising uncovered rural areas. Generally speaking, econometric tools used for analysis are not very sophisticated. The literature often uses simple regression models, as more sophisticated ones would require more comprehensive datasets over extended periods, which are unavailable in the region.

3.2 Research questions

As we have seen, the decentralized solar systems market has been studied primarily in rural and peri-urban areas. However, studies were limited in terms of data and geography each time. This chapter adds to the literature on the decentralized solar systems market's development and the hybrid electricity use of consumers connected to the network in sub-Saharan Africa.

In the literature review, we saw that wealthy households tend to favor solar system ownership in rural areas that are not covered by the central network. Although, when given a choice between a grid connection and a decentralized solar system, households tend to prefer the former. In urban areas where most people are already connected to the grid, the literature has not studied the choices related to adopting decentralized electricity production technologies. Indeed, in the context of the electricity sector's development in sub-Saharan Africa, the literature has mainly left urban areas unaddressed. Although they represent a growing part of the continent's population: it is expected that urban areas will represent the bulk of sub-Saharan's population in less than 30 years. According to the United Nations, urban areas will count more than 1.1 billion inhabitants in the region in 2050, or 60% of the region's total population (United Nations, 2018, 2019). Therefore, understanding new adoption choices of electricity technologies in urban areas covered by the network is vital to comprehending the development of electricity systems in sub-Saharan Africa.

First, it is essential to know whether the decentralized solar market is present today in areas covered by the grid, as Gogla suggests, and in particular, whether it is present in urban areas. Thus, we will first find out whether the following hypothesis holds:

Hypothesis I: Decentralised solar market penetration is significant in urban areas of sub-Saharan Africa, in the order of tens of MW, and represents at least one tenth of the solar capacity already installed on the grid.

Moreover, as we saw in the first chapter of this thesis, Pueyo (2018) reported that wealthy residential consumers facing an expensive and unreliable electricity supply from the grid in Ghana tend to become more autonomous from the grid. As we saw in the first chapter, if the most lucrative customers turn away from the grid and invest in self-generation, it could have significant consequences for the finances of the centralized sector. It has also been shown in the literature review that wealth was an important factor in determining technology choice. We will therefore seek to know if the following hypothesis holds :

Hypothesis II: the wealthiest residential consumers are the most likely to invest in decentralized solar systems in urban areas.

Finally, in the first chapter, we saw that consumers' independence is encouraged by the low reliability of the electricity supply, particularly for auxiliary generators. In the literature review section presented above, we have also seen that the electricity supply's reliability from the grid was an important factor for technology choice, although for a consumer not yet connected to the grid. If the first two hypotheses were verified, it would be essential to know whether consumers' becoming more independent for their electricity consumption with decentralized solar systems is correlated or not with the grid reliability. Thus, we will seek to know if the following hypothesis holds:

Hypothesis III: The reliability of electricity supply is not correlated to consumers' increased independence from the national grid through decentralized solar systems.

If these three hypotheses were verified, the sub-Saharan electricity sectors would face a significant challenge: the hybrid supply strategies of their most solvent customers.

4 Empirical analysis

To assess the market penetration of decentralized systems in African cities, we first use Deep Learning algorithms to analyze 2.4 million satellite images to assess overall volume of solar panels present in fourteen cities in the region. We thus build an original, geolocalized database of solar panels present in sub-Saharan cities comprising both their location and areas. Subsequently, we cross this database with the latest geolocalized socio-economic database from Afrobarometer (Round 7)¹¹. The crossing of these two databases makes it possible to analyze the socio-economic determinants of the decentralized solar systems' market development in the region's urban areas.

4.1 Gathering evidence from satellite imagery

First, we gather evidence of the deployment of decentralized solar systems in the region's cities by collecting satellite images and applying Deep Learning models to determine the localization of solar panels and the area they cover.

¹¹Afrobarometer is a "non-partisan, pan-African research institution conducting public attitude surveys on democracy, governance, the economy, and society in 30+ countries repeated on a regular cycle". It is notably known to provide high-quality data on democracy and governance issues and opinions of African citizens. The survey is presented in more detail later on in the chapter.

4.1.1 Collecting satellite images

Many satellite image providers exist, such as Airbus or Maxar Technologies. Satellite images can be purchased by ordering satellite activations to cover new areas or directly purchasing archive images. Depending on the specifics of the desired images in terms of resolution or spectral bands, a specific satellite and image types will be chosen. In our case, we wish to have images with three spectral bands "Red-Green-Blue" (RGB), a computer color-coding system used for ordinary images. An example of a panchromatic image (1 band) versus a multispectral (RGB) image is given in the figure II.1. However, we need to have access to the most satisfactory resolution images that exist on the market to make it possible to detect residential solar panels on the roofs of houses. We must access satellite images from the European "Pleiades" or American "Worldview" series¹². Therefore, we use Google's Static Map API to collect satellite images for budgetary and practical reasons, which allows us to retrieve geolocated satellite images at different resolutions through API calls. Google's Static Map API is not a satellite images provider *per se* but constructs orthomosaics which are large maps with high resolution constructed by combining smaller images from primary providers. Google only accepts its images to be used for research and non-lucrative purposes as it is not a primary satellite images provider. Although, API calls are not free and cost about 1.60 USD per 1000 API calls. For all our images, we used a zoom of 21 according to the Static Map API typology, which allows us to gather images at the most satisfactory resolution the API can provide: between 30 and 50 cm per pixel, depending on the region. An example of a 70 cm versus a 30-50 cm resolution image representing a white car on a similar road in Cape Town is given in the figure II.2. Each image is downloaded at a 640 by 640 pixels' resolution, corresponding to approximately 44.3 by 44.3 meters. The longitude and latitude associated with each picture correspond to the very center of the image.

To avoid gathering information that we cannot subsequently use in our econometric analysis, and due to budget limitations, we only downloaded images in a square area around geotagged points of Afrobarometer's socio-economic database, presented in the next section. We also previously verified that for each downloaded city, the quality of the satellite images was sufficient for our model to function¹³. We, therefore, had to restrict ourselves to fourteen cities for which the resolution was sufficient, as shown in figure II.2.

¹²The Pleiades and WorldView satellites have a higher resolution imaging capability than other satellites, allowing for more accurate mapping and imaging data. Compared to other Earth observation satellites, the Pleiades and WorldView satellites can capture images with resolutions as low as 30 centimeters per pixel. By comparison, Spots satellites provide images with resolutions ranging from 1.5 meters to 7 meters per pixel.

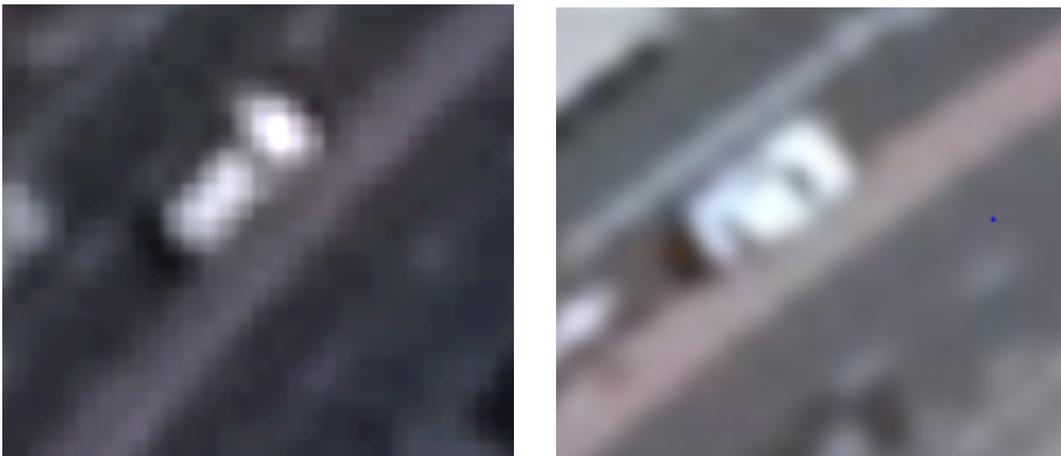
¹³We checked that the satellite images downloaded in each city had a sufficient resolution of less than 50 cm per pixel.

Figure II.1: Example of a panchromatic versus a multispectral (RGB) satellite image



Source : Ranchin (2005) (left hand side), Google Maps Static API (right hand side)

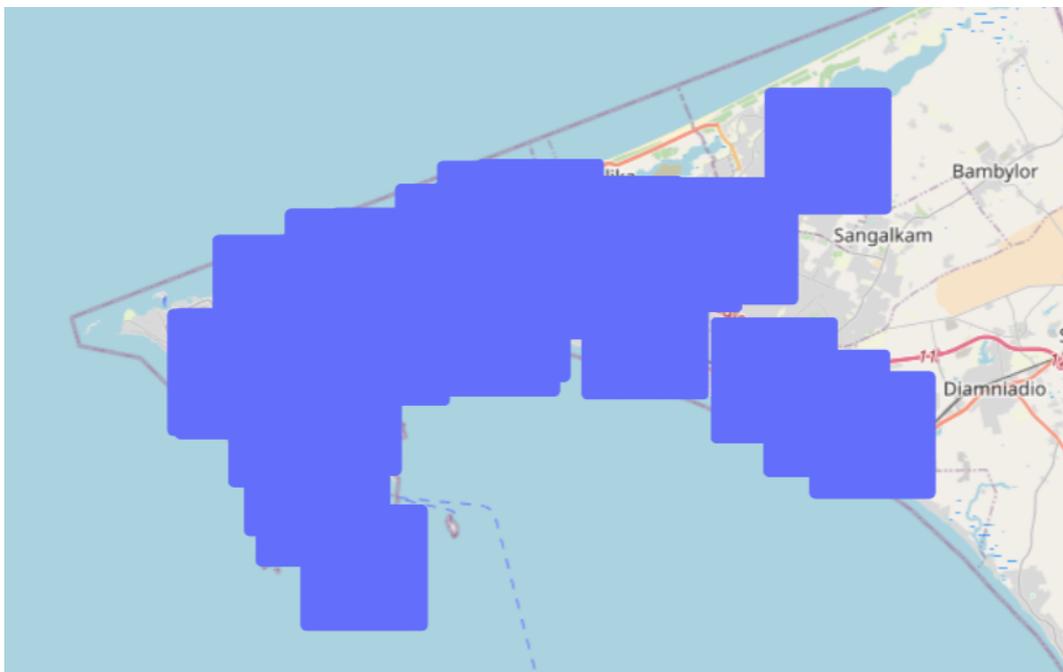
Figure II.2: Example of a 70 versus a 50 cm resolution satellite image in Cape Town, South Africa



Source : Courtesy of the CNES (left hand side), Google Maps Static API (right hand side)

Figure II.3 below shows an example of a zone download for the city of Dakar in Senegal. Three typical images of 640 by 640 are given for illustration in Figure II.4. The detail of the number of square meters covered and solar panel area detected by city is given in the appendix in table A.II.1. As the positions of the socio-economic data are not exact for confidentiality reasons, a relatively large field of 2.5 km was taken around each point to take these slight uncertainties into account. We downloaded more than 2.4 million images during the month of July 2021, representing a total area of approximately 4,710,000,000 square meters.

Figure II.3: Example of the area covered by our study for the city of Dakar



Source : authors, plotted with Plotly Express's python library

4.1.2 Classification model

We established a pipeline articulated around two different models to analyze our satellite images to determine solar panels' geolocalization and then extract areas covered by the panels. First, a classification model gives the probability that a panel is present in an image. It allows us to classify it using a probability threshold of 0.5. Then, we use a segmentation model to which we feed an image classified as having a solar panel and output a segmentation mask that can subsequently be used to retrieve the solar panel area in square meters.

In both cases, we use neural networks architectures, and in particular, convo-

from a pre-trained network on Imagenet¹⁶. The model is then fine-tuned¹⁷ on a specific database, in our case, images of solar panels. For the classifier, we used a ResNet-50 Dino as a pre-trained network, released recently by Facebook research teams and available on github¹⁸, as it has shown to work better than other pretrained models.

We proceeded using iteration to build our training database. First, we fine-tuned our model on the first series of two thousand hand-labelled images. The first trained model was then applied to all our images. We quickly expanded our training database and improved model performance by re-annotating the set of images predicted as positive using a high threshold and repeating the procedure. The training database now counts more than 23,957 images, of which 12,131 are positively labelled, and 11,826 are negatively labelled. The model was then thoroughly trained using Google Cloud virtual machines. We used an NVidia V100 graphics card with 16G of VRAM, thus allowing the model to be trained on images resized in 448 by 448, with varied batch sizes. After training, the classification model achieves an accuracy, recall, and precision of 92,6%. Subsequently, the trained model is applied to all images or more than 2.4 million satellite imagery to determine the probability of solar panels' presence in each. Figure II.6 below shows the panels' location predicted by the model in two of the fourteen sub-Saharan cities covered; points in yellow represent the locations of Afrobarometer's socio-economic data points.

4.1.3 Segmentation model

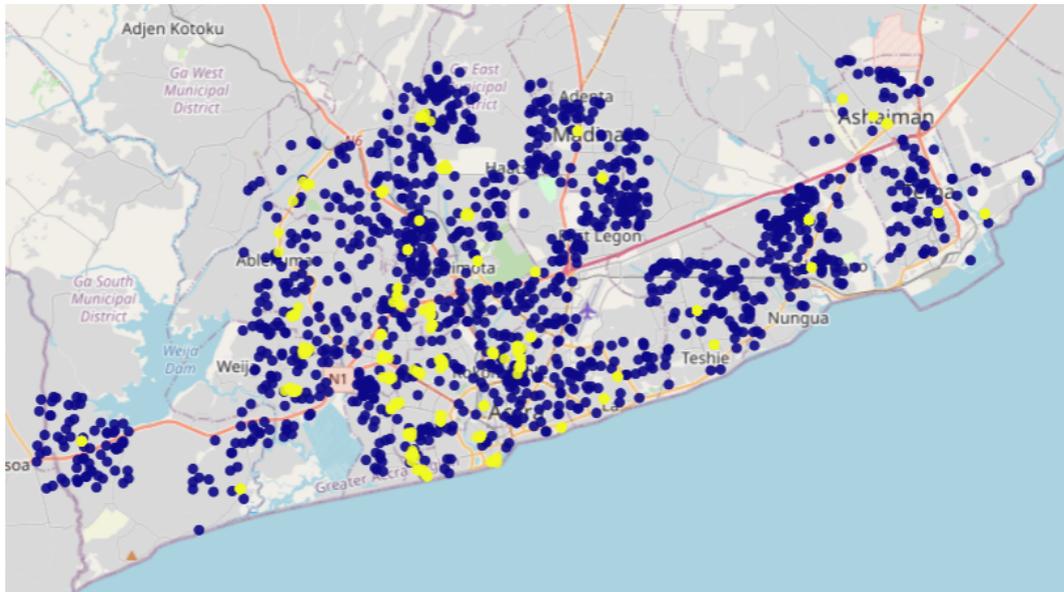
For the segmentation model, we used a U-Net architecture (Ronneberger et al., 2015). U-Net is a classic model architecture that has proven to perform particularly well for image segmentation. One of its peculiarities is that it does not necessarily require many training images to deliver good performance. Therefore, more than a thousand images have been labelled to constitute a dataset fit for segmentation training. We subsequently performed transformations on

¹⁶Transfer learning is a classic Deep Learning technique that involves using the weights of a network already trained. Imagenet pre-trained models have been trained on millions of different images over several hundred epochs. Therefore, these pre-trained networks have already learned general image features and can serve as generic models for computer vision tasks. For more information on transfer learning, see notably (He et al., 2015).

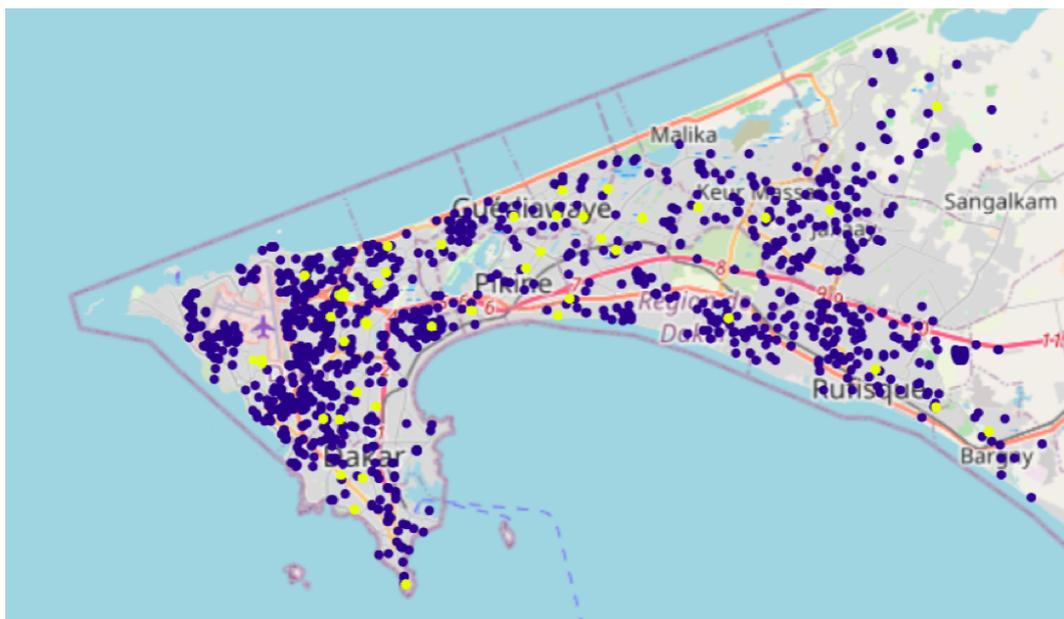
¹⁷At the early stages of training, only the model's head is trained, while the rest of the layers are frozen. This avoids adding hazards due to randomly initialized weights in the model's head, resulting in inadequate predictions and non-optimal training. After a few epochs, the rest of the model is unfrozen, and training can continue. The role of the backbone is to extract a feature map of the image that contains high-level semantic information. During fine-tuning, it can be shared between different classification tasks at first. The model head is the very last part of the network, responsible for the classification. The model head is inherent to the classification task and must be trained from scratch.

¹⁸For more information see Caron et al. (2021), Model weights are available at <https://github.com/facebookresearch/dino>.

Figure II.6: Example of solar panels detected by the classifier in two cities



(a) City of Accra (Ghana)



(b) City of Dakar (Senegal)

- Image characterized as having a solar panel
- Geolocalised data from Afrobarometer survey

Source : authors, plotted with Plotly Express's python library

labelled images to increase the training set's size. We notably used rotations and crops and resizing training images, neural networks being sensitive to this

type of transformations. After training, the model reaches a Dice score of 0.98¹⁹. The model is then applied four times to the same image that is flipped to improve performance for prediction. The model predictions are then averaged. Again, the computational power required to train this type of model required virtual machines. The figure II.7 shows an image classified as having a solar panel and our model's segmentation mask.

Figure II.7: Example of the segmentation model's results for two images classified as having a solar panel by the classifier



Source : Image : Google Static Map API ; segmentation mask : authors

¹⁹The Dice coefficient corresponds to two times the area of overlap between the segmentation results and the training mask divided by the total number of pixels in the two images.

4.2 Preliminary analysis of the satellite data

In this subsection, we first estimate the total capacity of decentralized solar panels installed in the areas covered by our analysis. Then, we show how we prepared the final database for the econometric analysis.

4.2.1 Decentralized solar panels capacities' estimations

Based on the classification and segmentation models' results, we can estimate the area of solar panels in downloaded areas. We can thus make a summary assessment of the installed capacity of decentralized solar panels in the various cities covered. The watt-peak (Wp) is used to define the power rating of a solar energy system under ideal theoretical conditions. To measure this power rating, solar panel manufacturers use standard test conditions (STC). These are conducted in an industrial laboratory and assume a solar cell temperature of 25°C, a solar irradiation of 1,000 watts per square meter and a sunlight incidence angle of 35° north latitude in summer. This standardised test is used to calculate the efficiency of a panel, which is defined as the ratio of the energy produced to the solar energy, or irradiance, incident on the panel. Panels with an efficiency of 19% produce approximately 190 Wp per square meter of panel area. The efficiency of residential solar panels typically ranges from a low average of 16% to a high average of 20% (Solar Learning Center, 2022). To calculate a rough estimate of solar panels capacity, we used the standard estimation of 1000 W per square meter multiplied by the two efficiency hypotheses. The table A.II.1 gives the number of square meters covered and solar panel area detected by city and the table II.1 summarizes the estimated installed capacity in the various sub-Saharan cities under the low assumption of 16% efficiency of photovoltaic cells and the high assumption of 20% efficiency²⁰. Since the downloaded areas only cover part of these cities, these are likely to be in the lower bound estimations.

We observe on this table that the wealthiest cities, in particular Windhoek, Nairobi, and Cape Town, are those which have the largest installed capacity of solar panels, respectively 23.7 MW, 21.7 MW, and 55.7 MW, at an efficiency of 16% and 29.6 MW, 27.1 MW and 69.6 MW at an efficiency of 20%. Poorer cities like Khartoum or Harare have much lower installed capacities, respectively 0.8 MW and 3.6 MW and 1 MW and 4.5 MW under the assumption of 16% and 20% efficiency.

The total estimate for all these cities of 184 MW to 231 MW under the two efficiency assumptions may appear marginal in view of European standards. However, it should be remembered that today in all of sub-Saharan Africa

²⁰To retrieve these figures, simply multiply the detected solar panel area in Table X by 1000 W times the efficiency assumption.

Table II.1: Decentralized solar panels capacities' estimations by city (MW)

City \ Efficiency	16%	20%
Ouagadougou	17.18	21.47
Accra	8.67	10.84
Bamako	17.64	22.05
Cape Town	55.72	69.64
Dakar	6.93	8.66
Harare	3.58	4.47
Ibadan	1.96	2.45
Kampala	3.17	3.96
Khartoum	0.84	1.05
Lagos	14.35	17.94
Lusaka	4.63	5.78
Nairobi	21.68	27.11
Niamey	4.89	6.11
Windhoek	23.70	29.62
Total	184.93	231.16

(excluding South Africa), there is only about 2 GW of centralized solar capacity installed. Decentralized solar systems therefore represents about 10% of this figure. In addition, we only covered thirteen sub-Saharan cities, which were only partially covered for obvious budgetary reasons. Therefore, this is likely to be a lower bound estimate of the totalled (decentralized) installed solar capacity. From the results of the Deep Learning models presented here, we can already conclude that Hypothesis I is verified: the penetration of the decentralized solar market is significant in urban areas in sub-Saharan Africa as it represents about 10% of the solar capacities already installed on the grid.

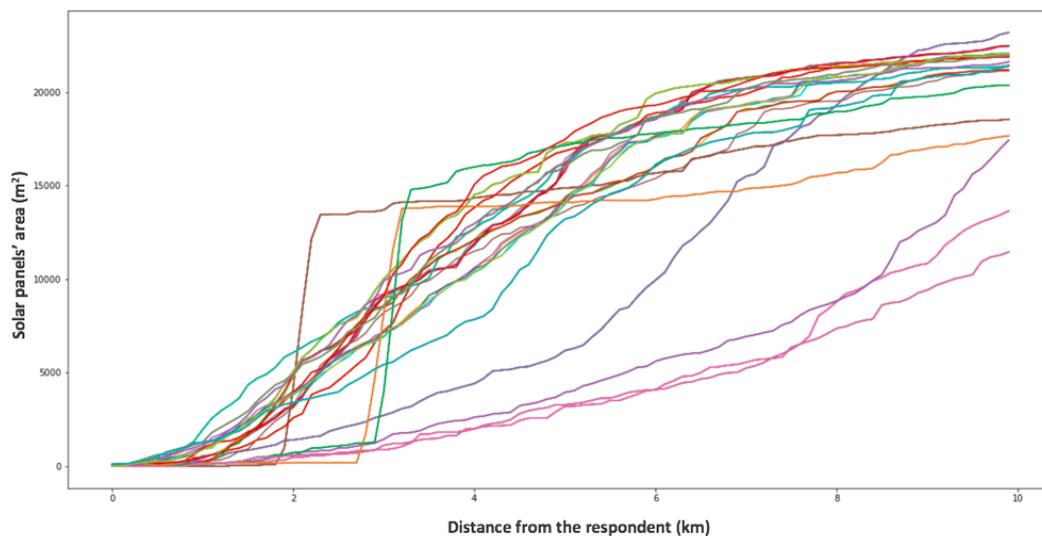
4.2.2 Solar data detailed analysis and final database preparation

In this part, we show how we prepared our database for the econometric analysis. In part (1) below, we explain how we separated residentials' from commercials' decentralized solar panels (more detail on this below). In part (2) we present the socio-economic survey with which our gathered database on decentralized solar systems has been crossed. Finally, in part (3) we present the final database, which comprise both solar and socio-economic data.

A limitation of our collected data from satellite imagery is that our model cannot differentiate between residential solar panels on the one hand and solar panels installed on commercial facilities on the other. This may subsequently introduce bias into our econometric analysis, as our socio-economic data relates

only to surveys of residential households. Disregarding this may distort the subsequent econometric analysis. Indeed, a household living in a commercial place with several mini-solar power plants would appear to have a large surface area of installed solar panels without these necessarily being residential solar panels. Therefore, this could bias our econometric analysis by giving more weight to observations that reside in commercial areas with a high prevalence of commercial solar panels. The figure II.8 shows the example of the area of solar panels installed in Dakar (Senegal) for a selection of respondents. The abscissa axis shows the distance from the respondent's location, and the ordinate axis shows the surface of installed PV panels around the respondent's location. We can clearly see the phenomenon previously stated on this graph with a step effect that corresponds to a mini-power plant installed in the city of Dakar. Some individuals are particularly close to this mini-power plant when the step is near the intersection point. For others, this power station is located further away from their location.

Figure II.8: Solar Panel Area (SPA) in square meters where each each line corresponds to a respondent of Afrobarometer survey for the city of Dakar and about 20 respondents

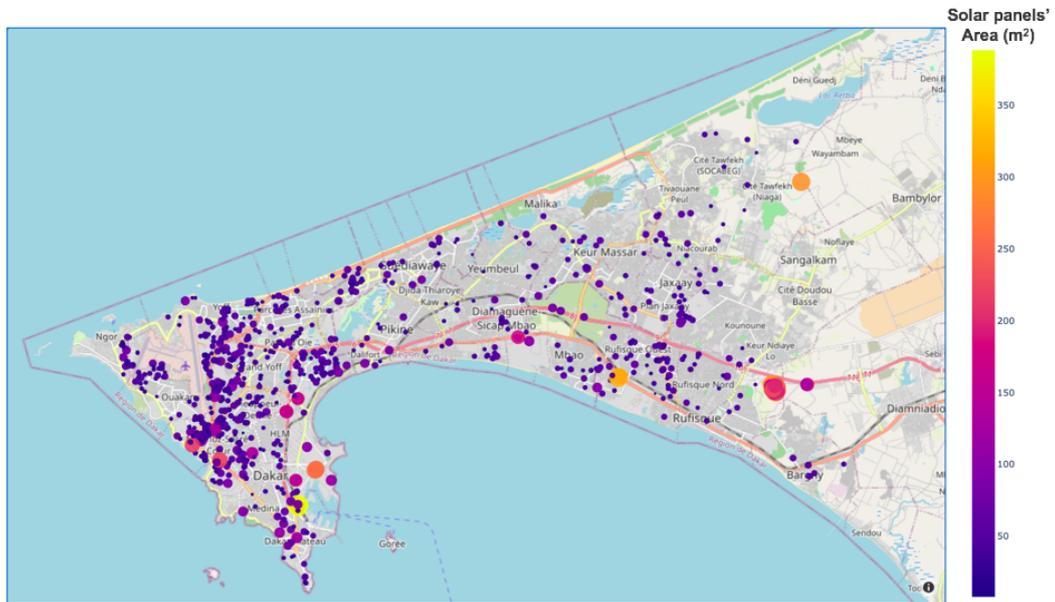


Source : authors

Figure II.9 below shows the location of Dakar's installed solar panels and their sizes (size of the bubble). As we can see, there are multiply mini-power plants in the city that can be either commercial or utility-scale.

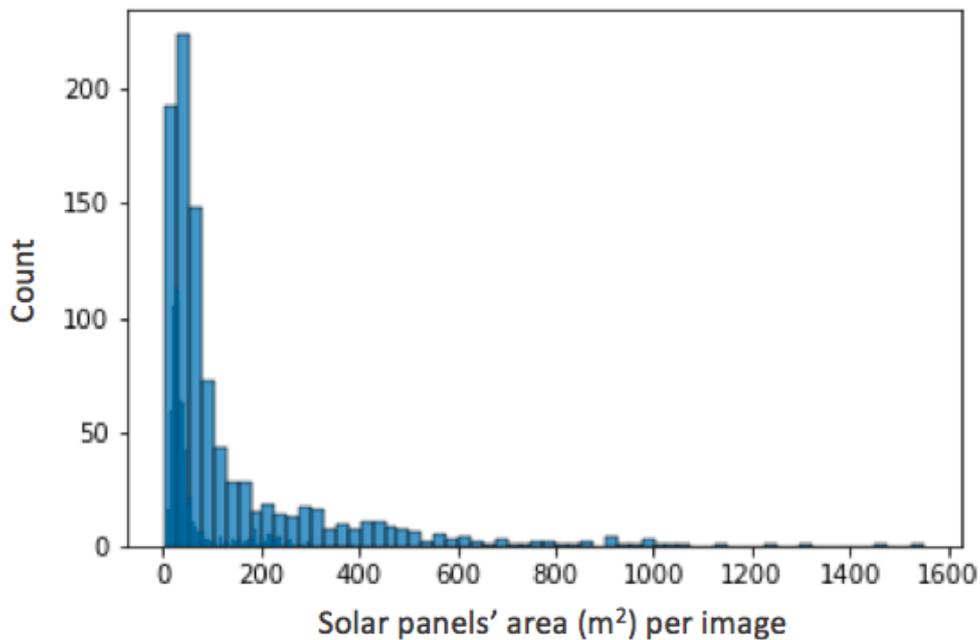
We, therefore, need to separate residential's from commercial's solar panels. Part (1) below explains how we used a Machine Learning algorithm to do so.

Figure II.9: Solar Panel Area (SPA)’s ”intensity” (surface installed per localization) for the city of Dakar



Source : authors, plotted with Plotly Express’s python library

Figure II.10: Solar Panel Area (SPA)’s distribution for the untransformed data



Source : authors

(1) Separation of residential from commercial data

In this part we explain how we used a Machine Learning algorithm in order to attempt to separate residential from commercial solar panels. First, part 1.a) presents the assumptions used in order to apply the Gaussian mixture model to separate the distributions of residential from commercial solar panels. Then, 1.b) derives the mixture model with two components and 1.c) presents the final algorithm. Finally, 1.d) presents the results of the mixture model.

1.a) Using Gaussian mixture model to separate the two distributions

To separate residential from commercial solar panels, we use a Gaussian mixture model. Indeed, when we take the logarithm of the distribution of installed solar panels' surfaces, we see what looks like a mixture of two Gaussian distributions. The figure II.10 shows the non-transformed distribution of installed solar panels' surfaces for our dataset, while the figure II.11 shows the mixture on the transformed data.

We make three (plausible) assumptions before setting up the mixture model. The **first assumption** is that there would only be two distributions of installed solar panels, one distribution corresponding to residential panels, the other for commercial panels. The **second assumption** is that commercial panels typically have a larger installed surface than residential panels since commercial activities require more electricity. Finally, the **third assumption** is that once passed in logarithm; these distributions follow a normal distribution, each determined by mean and variance parameters, which are still unknown.

1.b) The Gaussian mixture model with two components

We suppose that there are two distinct distributions representing a mixture of Gaussian distributions. They can be written as a linear superposition of two Gaussian of the form :

$$P(X_i = x) = \sum_{k=1}^{K=2} \pi_k N(x; \mu_k, \sigma_k^2)$$

where π_k is the mixing coefficient corresponding to the k 's distribution. Therefore, each observation is assigned to an unknown subset of the mixture distribution represented by K , and given by the latent variable Z_i (with values

$\{1, 2\}$), but which can also be written as a random binary vector with values in $\{0, 1\}^2$, such that $Z_i = l$ corresponds to $\forall k \neq l, Z_{ik} = 0$ and $Z_{il} = 1$. Z_i can be represented as follows with regards to the mixing coefficient π_k :

$$P(Z_i = 1) = \pi_k$$

where

$$\pi_k \geq 0$$

and

$$\sum_{k=1}^K \pi_k = 1$$

We define a random variable $\gamma(z_{ik})$ representing the conditional probability of z given x ($P(z_k|x)$). Using Bayes' theorem we can show :

$$\begin{aligned} \gamma(z_k) = P(z_k = 1|X) &= \frac{P(X|z_k = 1)P(z_k = 1)}{P(X)} \\ &= \frac{P(X|z_k = 1)P(z_k = 1)}{\sum_{j=1}^K P(X|z_j = 1)P(z_j = 1)} \\ &= \frac{\pi_k N(\mu_k, \sigma_k^2)}{\sum_{j=1}^K \pi_j N(\mu_j, \sigma_j^2)} \end{aligned}$$

As mentioned by Bishop (2006), π_k can be viewed as the prior probability of $k = 1$ and $\gamma(z_k)$ as the posterior probability once X as been observed.

We now derive the likelihood from the Gaussian mixture distribution :

$$L(\theta|X_1, \dots, X_n) = \prod_{n=1}^n \sum_{k=1}^K \pi_k N(x_n; \mu_k, \sigma_k^2)$$

so the log likelihood gives us:

$$\ell(\theta) = \sum_{n=1}^N \log \left(\sum_{k=1}^K \pi_k N(x_n; \mu_k, \sigma_k^2) \right)$$

where $\theta = \{\mu_1, \mu_2, \sigma_1, \sigma_2, \pi_1, \pi_2\}$

Maximizing under constraint the previous equations by taking the derivatives with respect to π_k , μ_k , and σ_k and setting to zero we get :

$$\mu_k = \frac{\sum_{n=1}^N \gamma(z_{nk}) x_i}{\sum_{n=1}^N \gamma(z_{nk})}$$

$$\sigma_k^2 = \frac{1}{\sum_{n=1}^N \gamma(z_{nk})} \sum_{n=1}^N \gamma(z_{nk}) (x_n - \mu_k)^2$$

and

$$\pi_k = \frac{\sum_{n=1}^N \gamma(z_{nk})}{N}$$

Although, those equations do not constitute a closed-form solution as they are linked together through $\gamma(z_{nk})$ which itself depends on the parameters estimated.

However, we can use an iterative scheme that corresponds to the Expectation-Maximisation (EM) algorithm for the specific case of Gaussian mixtures (Bishop, 2006).

1.c) Final algorithm

The EM algorithm in this case can be written as follows :

1. Initialisation step :

Initialize $\mu_k^{(0)}$, $\sigma_k^{(0)}$ and $\pi_k^{(0)}$ with the k-means algorithm and compute the log-likelihood.

Then for s from 1 to max :

2. Expectation step :

Evaluate the responsibilities $\forall k$:

$$\gamma(z_k)^{(s)} = \frac{\pi_k^{(s-1)} N(\mu_k^{(s-1)}, \sigma_k^{2(s-1)})}{\sum_{j=1}^K \pi_j^{(s-1)} N(\mu_j^{(s-1)}, \sigma_j^{2(s-1)})}$$

3. Maximisation step :

Evaluate the $\mu_k^{(s)}$, $\sigma_k^{(s)}$ and $\pi_k^{(s)} \forall k$:

$$\mu_k^{(s)} = \frac{\sum_{n=1}^N \gamma(z_{nk})^{(s)} x_n}{\sum_{n=1}^N \gamma(z_{nk})^{(s)}}$$

$$\sigma_k^{2(s)} = \frac{1}{\sum_{n=1}^N \gamma(z_{nk})^{(s)}} \sum_{n=1}^N \gamma(z_{nk})^{(s)} (x_n - \mu_k)^2$$

$$\pi_k^{(s)} = \frac{\sum_{n=1}^N \gamma(z_{nk})^{(s)}}{N}$$

4. Evaluate the log-likelihood :

$$\ell(\theta) = \sum_{n=1}^N \log \left(\sum_{k=1}^K \pi_k^{(s)} N(x_n; \mu_k^{(s)}, \sigma_k^{2(s)}) \right)$$

check for convergence and, if not achieved or if $s \neq \max$ return to the E step(2).

1.d) Results of the Gaussian mixture model

After implementing the EM algorithm, we find that the Gaussian distribution of residential panels is defined by the parameters and the surface distribution of commercial panels by the parameters. The graph below shows the mixture of our two distributions in solid lines, in front of the histogram of our observed data passed in logarithm. The vertical bar represents the threshold beyond which the probability that our installed solar panel surface belongs to a commercial system is greater than to a residential system. We subsequently use this threshold to separate solar panels belonging to commercial facilities from residential ones in our dataset.

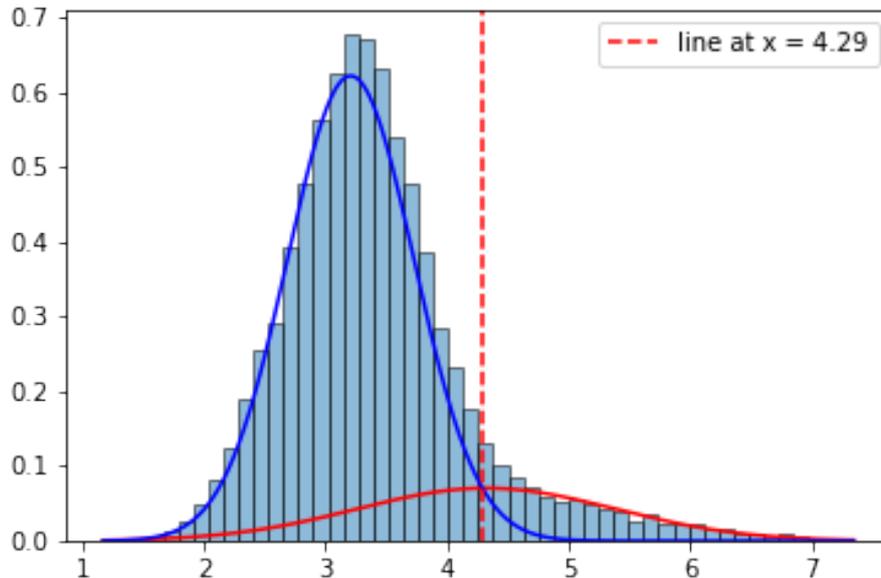
The results of the classification and segmentation models are then aggregated every hundred meters to two thousand meters around the locations of the Afrobarometer's survey's respondents. This database is then joined with Afrobarometer's full database on locations. Therefore, we have the installed solar panel area within a radius of 100 to 2000 meters for each respondent. The first rows of the final database are given in the appendix. In addition, we kept the radiuses of 500, 1000, and 1500 meters to conduct robustness checks during econometric analysis.

(2) Afrobarometer round 7 geolocated survey data

As previously mentioned, afrobarometer round 7 survey is used to analyze the results of our satellite imagery analysis. Afrobarometer surveys are part of the most exhaustive socio-economic databases found in sub-Saharan Africa. They cover more than 37 African countries for several rounds over two decades.

Each of these surveys provides information on democracy and governance issues and covers the opinions of over 200,000 African citizens. The surveys comprises direct interviews with 12,000 or 24,000 randomly selected respondents over 18 in multiple African countries. They stratify their samples by

Figure II.11: Graphical result of the Gaussian mixture model on the log-transformed SPA's distributions



Source : authors

government subunits: states, provinces, regions, and urban and rural areas. Their smallest unit for which geolocated socio-economic data is available is the Primary Sampling Units (PSU). Four or eight respondents are grouped in a cluster located by its longitude and latitude in these PSU (Afrobarometer, 2022). As previously mentioned, these clusters were used to determine areas from which satellite pictures were downloaded.

Afrobarometer has just started releasing for research on-demand only its round 7 of geolocated data conducted between 2016 and 2018. Therefore, we used this last round as it is the most recent survey and is the closest to our satellite imagery data, collected in the second half of 2021.

We have shown how we built an original database on surfaces of installed decentralized solar systems in sub-Saharan urban areas. We now join this original database with the latest geolocated socio-economic database from afrobarometer (Round 7), which has to date not yet been used in academic research on Africa's electrification. Using afrobarometers geolocated survey allows us to fully use the spatial granularity of our newly built solar database. It enables us to determine which socio-economic determinants can explain the further devel-

opment of the decentralized solar market we observe between African cities²¹.

(3) Final database preparation and descriptive statistics

We encode the dependent variable, the solar panels' area, as *log SPA*. It corresponds to the logarithm of the estimated installed decentralized residential solar panel area aggregated around a respondent. In order to check for the robustness of our results, we carry out our econometric analyses in three buffer zones corresponding to three different radius used in aggregating solar panel areas: 500m, 1000m, and 1500m. We therefore encode our variable as *log SPA 500*, *log SPA 1000* and *log SPA 1500*.

To estimate the effect of wealth on solar system adoption, we encode the variable *Wealth* using as a proxy the respondent's response concerning his perceived standard of living compared to the rest of the country's population. We create a binary variable that takes the value *Wealth 1* when the individual considers that his standard of living is much better than that of his fellow citizens and 0 otherwise. We also create another categorical variable used for robustness checks on the effect of our variable of interest. It takes the value *Wealth 1* when the individual considers that his standard of living is "much better" than that of his fellow citizens, *Wealth 3* when the latter considers that his standard of living is better, *Wealth 3* when the latter considers that his standard of living is similar, *Wealth 4* when the latter considers that his standard of living is worse, *Wealth 5* when the latter considers that his standard of living is much worse.

A set of control variables that could jointly influence the SPA and our independent variable of interest are selected to minimize potential problems from bias related to omitted variables.

When assessing the effects of a household's wealth level on the adoption of decentralized solar systems in sub-Saharan urban areas, we control for respondents' socioeconomic status. In particular, individuals' level of education is used as control, namely: whether a respondent has attained university education or not, referred to as *University education*. In addition, we also control if an individual is currently unemployed or not, defined by the variable *Unemployed*.

²¹The geolocalised survey is presented in more detail in the Afrobarometer round 7 geolocalised database section below. Afrobarometer is a "non-partisan, pan-African research institution conducting public attitude surveys on democracy, governance, the economy, and society in 30+ countries repeated on a regular cycle". It is notably known to provide high-quality data on democracy and governance issues and opinions of African citizens.

Neighborhood characteristics are also included in the model. More specifically, we look if the neighborhood benefits from sewage systems, which can be seen as a proxy factor representing the modernity of the neighborhood, and defined by the variable *Sewage present*. Sewage systems are mainly present in newly built districts in sub-Saharan Africa. We also include as a control variable the reliability of the household's access to electricity which is a crucial control variable with regard to the literature on hybrid energy uses mentioned above. As we saw previously, grid reliability plays a crucial role in adopting auxiliary generators in African urban areas. Likewise, Barry and Creti (2020) have also shown that this variable is also essential in peri-urban areas in Benin regarding the adoption of decentralized solar systems in PAYG. This will allow us to see if this factor also plays a role in adopting solar systems in urban areas. This variable is encoded as *Reliable electricity access* and corresponds to a level of electricity quality from the main grid, which functions "most of the time" and "always". The more granular variable *Grid reliability* will be used later to refine the results on the effects of grid reliability on decentralized solar systems' penetration. It has five levels, "Always", "Most", "Half", "Occasionally", "Never".

Two other control variables were added *Cities* and *Urban*. The former was added in order to control for cities' fixed effects. The second was added as although our data collection has mainly focused on the capitals, some observations are considered to be in rural areas. Indeed, the border between urban and rural areas can sometimes be unclear in sub-Saharan Africa.

Most of these variables were recoded to a binary indicator variable following a methodology similar to Blimpo et al. (2020) ; specific details on each variable are given in the table II.2.

4.3 Econometric analysis

To test our second and third hypotheses, we analyze whether households' wealth levels are essential for adopting such decentralized systems in African urban areas while also controlling for the reliability of electricity supplied from the main grid. To do so, we mainly aim to quantify the direction and the strength of the relationship between wealth and solar panel adoption while controlling for the network's reliability and other control variables. Simple OLS regression is therefore sufficient.

Therefore we aim to conduct a simple OLS estimate :

$$\log SPA_{ic} = \beta_0 + \beta_1 * Wealth_i + \beta_2 * \mathbf{X}_i + \xi_c + \epsilon_{ic}$$

Table II.2: Descriptive statistics

	Mean	Median	SD	Min	Max	N	NAs
<i>Solar data</i>							
SPA 500	116.30	43.61	195.22	0.00	1956.17	2423	0
SPA 1000	436.11	195.21	679.63	0.00	8741.65	2423	0
SPA 1500	960.40	459.10	1482.05	0.00	20102.24	2423	0
log SPA 500	3.65	3.87	1.68	1.45	7.58	2423	0
log SPA 1000	5.16	5.30	1.59	1.77	9.08	2423	0
log SPA 1500	6.01	6.15	1.53	2.15	9.91	2423	0
<i>Socio-economic data</i>							
Age	35.75	32.00	14.19	18.00	90.00	2423	0
Female	0.50	1.00	0.50	0.00	1.00	2423	0
<i>Wealth</i>							
Wealth 1	0.04	0.00	0.21	0.00	1.00	2423	101
Wealth 2	0.36	0.00	0.48	0.00	1.00	2423	101
Wealth 3	0.36	0.00	0.48	0.00	1.00	2423	101
Wealth 4	0.17	0.00	0.38	0.00	1.00	2423	101
Wealth 5	0.07	0.00	0.25	0.00	1.00	2423	101
Unemployed	0.53	1.00	0.50	0.00	1.00	2423	6.
University Education	0.10	0.00	0.30	0.00	1.00	2423	6
Sewage present	0.66	1.00	0.47	0.00	1.00	2423	32
<i>Grid reliability</i>							
Always	0.43	0.00	0.50	0.00	1.00	2423	278
Half	0.05	0.00	0.22	0.00	1.00	2423	278
Most	0.40	0.00	0.49	0.00	1.00	2423	278
Never	0.02	0.00	0.12	0.00	1.00	2423	278
Occasionally	0.10	0.00	0.30	0.00	1.00	2423	278
Reliable electricity access	0.74	1.00	0.44	0.00	1.00	2423	10
Grid access	0.89	1.00	0.31	0.00	1.00	2423	10
Urban	0.94	1.00	0.23	0.00	1.00	2423	0
<i>City</i>							
Accra	0.16	0.00	0.37	0.00	1.00	2423	0
Bamako	0.06	0.00	0.24	0.00	1.00	2423	0
Cape Town	0.05	0.00	0.23	0.00	1.00	2423	0
Dakar	0.13	0.00	0.34	0.00	1.00	2423	0
Harare	0.10	0.00	0.30	0.00	1.00	2423	0
Ibadan	0.01	0.00	0.10	0.00	1.00	2423	0
Kampala	0.05	0.00	0.22	0.00	1.00	2423	0
Khartoum	0.04	0.00	0.20	0.00	1.00	2423	0
Lagos	0.05	0.00	0.21	0.00	1.00	2423	0
Lusaka	0.06	0.00	0.24	0.00	1.00	2423	0
Nairobi	0.06	0.00	0.24	0.00	1.00	2423	0
Niamey	0.04	0.00	0.19	0.00	1.00	2423	0
Ouagadougou	0.08	0.00	0.26	0.00	1.00	2423	0
Windhoek	0.11	0.00	0.31	0.00	1.00	2423	0

for $i = 1, \dots, 2280$

Where $\log SPA_{ic}$ is the logarithm of the surface of installed solar systems around respondent i in city c . $Wealth_i$ indicates the wealth level of the respondent, where β_1 represents the leading coefficient of interest which estimates the association between wealth and solar system adoption. \mathbf{X}_i is a vector of control variables, notably comprising a variable for grid reliability and β_2 its corresponding vector of coefficients. ξ_c are the cities fixed effect, and ϵ_{ic} is an error term clustered on cities.

Then we would wish to refine the analysis by implementing a Spatial Autoregressive Model (SAR) to consider spatial proximity and dependency between our observations within cities.

We would thus carry out the evaluation of the following model:

$$\log SPA_{ic} = \rho.W.\log SPA_{ic} + \beta_1 * Wealth_i + \beta_2 * \mathbf{X}_i + \xi_c + \epsilon_{ic}$$

for $i = 1, \dots, 2280$

where W is an n by n spatial weight matrix and ρ is a scalar parameter and the other arguments are as previously defined.

4.3.1 OLS estimates on the socio-economic determinants of the decentralized solar market's development

Before conducting the econometric analysis, expectations are that more educated individuals will be better informed about the positive economic effects that solar systems can provide. Access to sewage systems will be positively linked with higher solar systems penetration in the area. Likewise, we expect unemployment and electricity supply reliability to be negatively linked with solar systems adoption. Regarding our *Urban* variable, expectations are less clear. Living in an urban area could facilitate solar system adoption through proximity to retailers. Conversely, living in rural areas makes access to electricity less likely and could encourage the adoption of solar systems.

The econometric approach consists in evaluating the equation:

$$\log SPA_{ic} = \beta_0 + \beta_1 * Wealth_i + \beta_2 * \mathbf{X}_i + \xi_c + \epsilon_{ic}$$

for $i = 1, \dots, 2280$

Where $\log SPA_{ic}$ is the logarithm of the surface of installed solar²² systems

²²To take into account 0 values, we used the colloquial method of adding half the minimum non-0 value : $\log(y + \min(y > 0])/2)$.

around respondent i in city c . $Wealth_i$ indicates the wealth level of the respondent, where β_1 represents the leading coefficient of interest which estimates the association between wealth and solar system adoption. \mathbf{X}_i is a vector of control variables, and β_2 is its corresponding vector of coefficients. Finally, ξ_c are the cities' fixed effects, and $\epsilon_{i,c}$ is an error term clustered on cities.

Table II.3 below shows the results of the model. We see that people with a higher standard of living are the most likely to adopt decentralized solar systems, with a positive and statistically significant coefficient at the 0.1 level in the three buffer zones. Interestingly, considering the living standards of the inhabitants, the reliability of the electricity supplied factor is not statistically significant in the three buffer zone, but its magnitude is relatively low compared to the other variables. This shows that the logic underlying the decentralized solar market's development in sub-Saharan Africa's urban areas is not the same as for the auxiliary generators market, which is mainly used to compensate for grid deficiencies. A particularly wealthy individual will be more likely to own a solar system regardless of the quality of the electricity supply from the centralized grid.

The effects of the control variables are relatively close to our expectations; the respondents who received a university education are more likely to live in an area where the decentralized solar market's penetration is high, with a significant coefficient at the 0.1% level. Likewise, the neighborhood's modernity factor, represented by the presence of a sewage system, is also significant at the 0.1% level with a magnitude similar to our variable of interest. It indicates that living in a modern neighborhood, well served by public services, tends to increase the likelihood of owning a decentralized solar system. This confirms the first result and indicates that the decentralized solar market's penetration in sub-Saharan Africa's urban areas is not necessarily directly linked to a deficiency in public services. As expected, being unemployed has a negative and significant effect on SPA. The coefficient linked to the Urban variable is significant at 0.1% and is high concerning the other coefficients. This tends to confirm the hypothesis that the importance of population density, proximity to other respondents with solar panels, and accessibility to retailers is an essential factors for adoption, although it would need to be verified more formally.

Table II.3: OLS estimates - binary variable of interest

	<i>Dependent variables</i>		
	log SPA 500 (1)	log SPA 1000 (2)	log SPA 1500 (3)
<i>Wealth 1</i>	0.618*** (0.139)	0.540*** (0.123)	0.465*** (0.114)
<i>University education</i>	0.243**	0.223**	0.252***

Table II.3, continued

	<i>Dependent variables</i>		
	log SPA 500 (1)	log SPA 1000 (2)	log SPA 1500 (3)
	(0.099)	(0.087)	(0.081)
<i>Unemployed</i>	-0.176*** (0.061)	-0.114** (0.053)	-0.103** (0.049)
<i>Sewage present</i>	0.617*** (0.069)	0.746*** (0.061)	0.672*** (0.057)
<i>Reliable electricity access</i>	-0.066 (0.086)	-0.047 (0.076)	-0.011 (0.070)
<i>Grid access</i>	0.369*** (0.123)	0.429*** (0.109)	0.292*** (0.101)
<i>Urban</i>	0.725*** (0.133)	1.499*** (0.117)	1.664*** (0.108)
City			
<i>Bamako</i>	2.033*** (0.137)	1.575*** (0.120)	1.507*** (0.111)
<i>Cape Town</i>	0.959*** (0.143)	0.554*** (0.126)	0.484*** (0.117)
<i>Dakar</i>	0.547*** (0.110)	0.205** (0.097)	0.117 (0.090)
<i>Harare</i>	-0.786*** (0.120)	-0.919*** (0.106)	-1.097*** (0.098)
<i>Ibadan</i>	-0.536* (0.289)	-0.838*** (0.255)	-0.857*** (0.236)
<i>Kampala</i>	0.142 (0.149)	-0.242* (0.131)	-0.687*** (0.122)
<i>Khartoum</i>	-0.614*** (0.162)	-1.742*** (0.143)	-1.957*** (0.133)
<i>Lagos</i>	0.836*** (0.158)	0.392*** (0.140)	0.107 (0.129)
<i>Lusaka</i>	-0.553*** (0.144)	-1.224*** (0.127)	-1.246*** (0.118)
<i>Nairobi</i>	-0.082 (0.143)	-0.220* (0.126)	-0.262** (0.116)
<i>Niamey</i>	2.025*** (0.168)	1.355*** (0.148)	1.167*** (0.137)
<i>Ouagadougou</i>	2.190*** (0.132)	1.547*** (0.117)	1.312*** (0.108)
<i>Windhoek</i>	0.698*** (0.119)	0.316*** (0.105)	0.240** (0.097)
Constant	1.836*** (0.158)	2.802*** (0.140)	3.761*** (0.129)

Table II.3, continued

	<i>Dependent variables</i>		
	log SPA 500 (1)	log SPA 1000 (2)	log SPA 1500 (3)
Observations	2,280	2,280	2,280
R ²	0.369	0.462	0.500
Adjusted R ²	0.364	0.457	0.496
Residual Std. Error (df = 2259)	1.347	1.188	1.100
F Statistic (df = 20; 2259)	66.192***	96.931***	112.932***

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table II.4: OLS estimates - categorical variable of interest

	<i>Dependent variables</i>		
	log SPA 500 (1)	log SPA 1000 (2)	log SPA 1500 (3)
<i>Wealth 1</i>	0.592*** (0.145)	0.458*** (0.128)	0.386*** (0.118)
<i>Wealth 2</i>	-0.043 (0.068)	-0.137** (0.060)	-0.129** (0.055)
<i>Wealth 4</i>	-0.084 (0.084)	-0.125* (0.074)	-0.113* (0.068)
<i>Wealth 5</i>	0.069 (0.122)	-0.059 (0.107)	-0.095 (0.099)
<i>University education</i>	0.241** (0.099)	0.222** (0.087)	0.250*** (0.081)
<i>Unemployed</i>	-0.177*** (0.061)	-0.116** (0.053)	-0.105** (0.049)
<i>Sewage present</i>	0.619*** (0.070)	0.746*** (0.061)	0.671*** (0.057)
<i>Reliable electricity access</i>	-0.067 (0.086)	-0.051 (0.076)	-0.016 (0.070)
<i>Grid access</i>	0.372*** (0.124)	0.433*** (0.109)	0.295*** (0.101)
<i>Urban</i>	0.724*** (0.133)	1.508*** (0.117)	1.674*** (0.108)
City			
<i>Bamako</i>	2.030*** (0.137)	1.570*** (0.121)	1.503*** (0.112)
<i>Cape town</i>	0.958*** (0.144)	0.569*** (0.127)	0.500*** (0.117)
<i>Dakar</i>	0.545*** (0.110)	0.198** (0.097)	0.111 (0.090)

Table II.4, continued

	<i>Dependent variables</i>		
	log SPA 500 (1)	log SPA 1000 (2)	log SPA 1500 (3)
<i>Harare</i>	-0.790*** (0.120)	-0.920*** (0.106)	-1.096*** (0.098)
<i>Ibadan</i>	-0.529* (0.289)	-0.827*** (0.255)	-0.847*** (0.236)
<i>Kampala</i>	0.156 (0.149)	-0.223* (0.132)	-0.671*** (0.122)
<i>Khartoum</i>	-0.630*** (0.163)	-1.770*** (0.144)	-1.981*** (0.133)
<i>Lagos</i>	0.839*** (0.159)	0.393*** (0.140)	0.107 (0.129)
<i>Lusaka</i>	-0.547*** (0.145)	-1.209*** (0.127)	-1.231*** (0.118)
<i>Nairobi</i>	-0.086 (0.143)	-0.231* (0.126)	-0.272** (0.116)
<i>Niamey</i>	2.027*** (0.168)	1.368*** (0.148)	1.180*** (0.137)
<i>Ouagadougou</i>	2.196*** (0.133)	1.556*** (0.117)	1.320*** (0.108)
<i>Windhoek</i>	0.695*** (0.119)	0.325*** (0.105)	0.251** (0.097)
Constant	1.861*** (0.162)	2.870*** (0.143)	3.827*** (0.132)
Observations	2,280	2,280	2,280
R ²	0.366	0.451	0.486
Adjusted R ²	0.359	0.445	0.480
Residual Std. Error (df = 2071)	1.345	1.191	1.104
F Statistic (df = 23; 2071)	52.080***	73.975***	85.080***

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

These results tend to go along the same lines as Oseni (2016) for auxiliary generator use in Nigeria. He found that the wealthiest households would keep their decentralized means of producing electricity in the event of a significant augmentation of the quality of electricity supplied. This confirms again that a particularly wealthy individual will be more likely to own a solar system regardless of the quality of the electricity from the centralized grid.

We test our model again with the more refined categorical variable on respondent wealth to check the results' robustness. Results are shown in table II.4. Overall, in terms of significance, the coefficients remain essentially similar. *Wealth 1* is still significant at the 0.1% level in the three buffer zones. Al-

though, *Wealth 2* becomes significant at the 5% level in the 1000m and 1500m buffer zones, but with a negative coefficient. This indicates further that the market for decentralized solar systems in urban areas is primarily aimed at the wealthiest segments of the population.

4.3.2 Spatial estimate on the socio-economic determinants of the decentralized solar market's development

When studying our linear model's residuals, they show heteroskedasticity. This leads us to doubt the reliability of our estimated p-values. Our geolocalized data can present spatial autocorrelations, which could partly explain our residuals' heteroskedasticity. This intuition is reinforced by the fact that having made area downloads around our respondents' localization; there may be overlaps between different zones. Thus, spatial autocorrelation would make the implicit independence assumption we made during our OLS estimation not verified in practice. The results of Breusch-Pagan tests performed on residuals are shown in table II.5 below.

Table II.5: p-values of Breusch-Pagan tests on residuals

Binarized <i>Wealth</i>			Categorical <i>Wealth</i>		
log SPA 500	log SPA 1000	log SPA 1500	log SPA 500	log SPA 1000	log SPA 1500
2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16

Therefore, we codify the neighborhood relationships between our observations by setting up a weight matrix that allows us to consider the spatial proximity of observations in the analysis. We thus set up a neighborhood weight matrix W based on a maximum distance between two individuals, fixed at 1 km. In other words, two observations will be considered neighbors when they are within 1 km of each other. This choice of 1 km distance allows us to consider the proximity between individuals while being close enough to limit the bias that could arise from afrobarometer's spatial anonymization method, i.e., limiting the risk of two non-neighbors being associated together through clustering. Likewise, we choose to use buffer zones of different SPA radius to test our results' robustness. We will not vary the distance for the coding of the weight matrix to avoid further bias in our geolocated data by crossing potential SPA and neighborhood biases.

We then perform the Moran Index test on our variable of interest, and on the residuals of our linear models, defined by Moran's I:

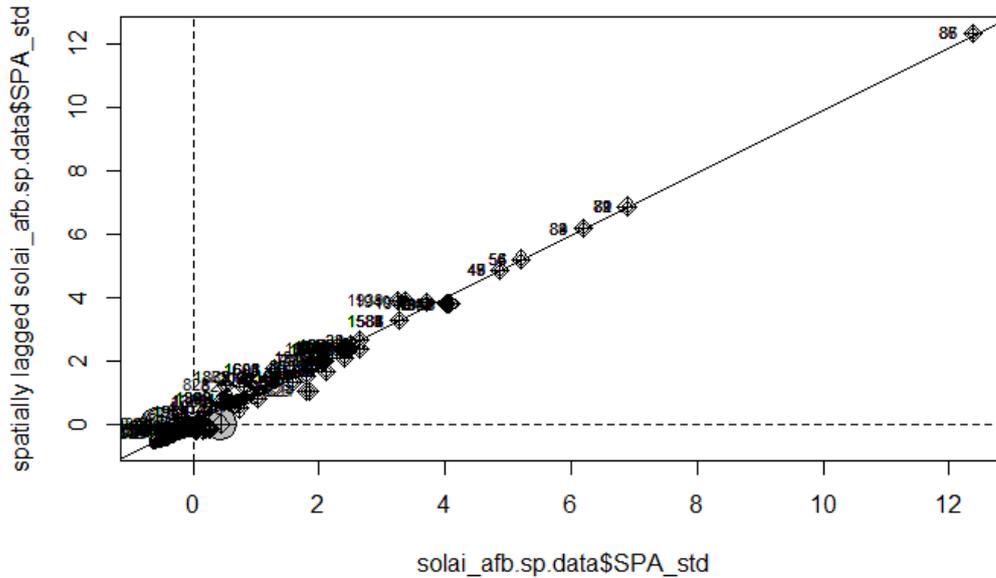
$$I_W = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (y_i - \hat{y})(y_j - \hat{y})}{\sum_j (y_i - \hat{y})^2} \quad i \neq j$$

In all cases, we reject the null hypothesis of non-covariance between neighbors in favor of the hypothesis of positive spatial autocorrelation. The p-values are given in the table II.6. Likewise, the Moran diagram on our normalized SPA variables plotted in the figure II.12, confirms the previous tests and clearly shows a strong spatial autocorrelation between our observations.

Table II.6: Results of Moran's I test on OLS estimates

Model	Moran's I statistics	p-value
OLS - Binary	89.25	1e-16
OLS - categorical	89.25	1e-16

Figure II.12: Moran plot for spatial auto-correlation in our geolocated database



Source : authors

We thus carry out the evaluation of the following model:

$$\log SPA_{ic} = \rho.W.\log SPA_{ic} + \beta_1 * Wealth_i + \beta_2 * \mathbf{X}_i + \xi_c + \epsilon_{ic}$$

for $i = 1, \dots, 2280$

where W is the n by n spatial weight matrix and ρ is a scalar parameter, and the other arguments are as previously defined in the OLS estimate.

In our model, a modification of the area of solar panels installed in a location can affect that of its neighbors and, in return, be affected by the area of solar

panels installed in its neighbors. Thus, in the presence of spatial interactions, the parameters of the explanatory variables cannot be interpreted as in a classical model. The explanatory variable has both a direct effect on the explained variable and an indirect effect by affecting through the explained variable that of its neighbors and, therefore, by feedback, affecting itself.

As a reminder a SAR model is typically defined as :

$$\begin{aligned} Y &= \rho.WY + X\beta + \epsilon \\ &= (1 - \rho W)^{-1}X\beta + (1 - \rho W)^{-1}\epsilon \\ &= \sum_{r=1}^k (1 - \rho W)^{-1}\beta_r X_r + (1 - \rho W)^{-1}\epsilon \\ &= \sum_{r=1}^k S_r(W)X_r + (1 - \rho W)^{-1}\epsilon \end{aligned}$$

where :

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix}, X = \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{pmatrix}, \text{ and } S_r(W) = \begin{pmatrix} S_r(W)_{11} & \cdots & S_r(W)_{1n} \\ \vdots & \ddots & \vdots \\ S_r(W)_{n1} & \cdots & S_r(W)_{nn} \end{pmatrix}$$

The direct mean effect is given by $\frac{1}{n}\text{trace}(S_r)$, the total mean effect is given by $\frac{1}{n}\sum_i[\sum_k S_r(W)_{ik}]$ and the indirect effect is given by the difference between the two.

We first perform the regression with our binarized variable of interest (upper or other). We evaluate our model with explained variable log SPA 1000, which corresponds to the same distance as our neighborhood matrix and then perform robustness tests using the explained variable log SPA 500 and log SPA 1500. We note that this approach allowed us to obtain homoscedastic residuals during the regressions on log SPA 1000 and log SPA 1500; however, our residuals remain heteroskedastic during the regression with as explained variable log SPA 500. The p-values of our Breusch-Pagan tests applied to the residuals of our spatial models are given in the last column of the table II.7, presenting the results of our analyzes. For clarity, the table for log SPA 500 and log SPA 1500 are given the appendix, see table A.II.2 and table A.II.3.

Table II.7: SAR estimates - binary variable of interest

	<i>Dependent variable (log SPA 1000)</i>		
	Direct	Indirect	Total
<i>Wealth 1</i>	0.159** [0.034:0.282]	0.634** [0.135:1.146]	0.793** [0.169:1.427]

Table II.7, continued

	<i>Dependent variable (log SPA 1000)</i>		
	Direct	Indirect	Total
<i>University education</i>	0.059 [-0.023:0.151]	0.236 [-0.093:0.607]	0.295 [-0.116:0.758]
<i>Unemployed</i>	-0.012 [-0.068:0.042]	-0.046 [-0.271:0.169]	-0.057 [-0.34:0.21]
<i>Sewage present</i>	0.205*** [0.138:0.266]	0.817*** [0.551:1.067]	1.022*** [0.689:1.339]
<i>Reliable electricity access</i>	-0.005 [-0.085:0.073]	-0.019 [-0.344:0.291]	-0.024 [-0.429:0.363]
<i>Grid access</i>	0.058 [-0.051:0.161]	0.230 [-0.199:0.647]	0.287 [-0.25:0.806]
<i>Urban</i>	0.219*** [0.101:0.337]	0.876*** [0.402:1.36]	1.095*** [0.502:1.698]
City			
<i>Bamako</i>	0.253*** [0.133:0.383]	1.008*** [0.528:1.514]	1.260*** [0.659:1.892]
<i>Cape Town</i>	0.036 [-0.095:0.164]	0.142 [-0.382:0.656]	0.178 [-0.478:0.817]
<i>Dakar</i>	-0.027 [-0.123:0.075]	-0.106 [-0.489:0.301]	-0.133 [-0.609:0.378]
<i>Harare</i>	-0.271*** [-0.378:-0.158]	-1.079*** [-1.494:-0.634]	-1.350*** [-1.865:-0.792]
<i>Ibadan</i>	-0.226* [-0.497:0.036]	-0.900* [-2.001:0.144]	-1.126* [-2.488:0.18]
<i>Kampala</i>	-0.111 [-0.245:0.023]	-0.441 [-0.997:0.094]	-0.552 [-1.242:0.116]
<i>Khartoum</i>	-0.420*** [-0.563:-0.285]	-1.677*** [-2.258:-1.138]	-2.097*** [-2.817:-1.423]
<i>Lagos</i>	0.006 [-0.135:0.148]	0.024 [-0.547:0.595]	0.030 [-0.679:0.739]
<i>Lusaka</i>	-0.229*** [-0.353:-0.098]	-0.913*** [-1.399:-0.389]	-1.142*** [-1.746:-0.487]
<i>Nairobi</i>	-0.102 [-0.222:0.021]	-0.407 [-0.87:0.085]	-0.509 [-1.094:0.106]
<i>Niamey</i>	0.228*** [0.079:0.382]	0.910*** [0.324:1.533]	1.138*** [0.403:1.913]
<i>Ouagadougou</i>	0.232*** [0.115:0.361]	0.926*** [0.455:1.461]	1.158*** [0.569:1.823]
<i>Windhoek</i>	-0.014 [-0.116:0.096]	-0.055 [-0.471:0.384]	-0.069 [-0.586:0.479]
Observations	2280		

Table II.7, continued

	<i>Dependent variable (log SPA 1000)</i>		
	Direct	Indirect	Total
AIC	2065.3		
Studentized Breusch-Pagan test	p-value = 0.0564		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Likewise, to check the robustness of our results, we perform the previous regressions again, with our variable of interest in its categorical form with the upper, medium-upper, medium, low, and very low classes (*Wealth 1-5*). Once again, our residuals are homoscedastic during the regressions on log SPA 1000 and log SPA 1500. Our residuals remain heteroskedastic during the regression on our variable log SPA 500. The table of impacts for log SPA 1000 is given II.8, the other two, for log SPA 500 and log SPA 1500 are given in the appendix, see table A.II.4 and table A.II.5.

In all cases, *Reliable electricity access* is not significant. These results confirm and provide evidence that wealthy individuals are more likely to own a solar system regardless of the quality of the electricity from the centralized grid. Therefore, Hypothesis II and III appear to be verified.

Table II.8: SAR estimates - categorical variable of interest

	<i>Dependent variables log SPA 1000</i>		
	Direct	Indirect	Total
<i>Wealth 1</i>	0.160** [0.028:0.293]	0.640** [0.109:1.192]	0.801** [0.137:1.484]
<i>Wealth 2</i>	0.001 [-0.058:0.059]	0.004 [-0.231:0.24]	0.005 [-0.289:0.298]
<i>Wealth 4</i>	-0.016 [-0.095:0.059]	-0.064 [-0.375:0.236]	-0.081 [-0.47:0.296]
<i>Wealth 5</i>	0.046 [-0.065:0.16]	0.185 [-0.26:0.642]	0.232 [-0.326:0.804]
<i>University education</i>	0.059 [-0.031:0.148]	0.234 [-0.122:0.587]	0.293 [-0.153:0.736]
<i>Unemployed</i>	-0.012 [-0.064:0.05]	-0.047 [-0.258:0.205]	-0.058 [-0.322:0.255]
<i>Sewage present</i>	0.206*** [0.141:0.271]	0.822*** [0.565:1.082]	1.029*** [0.706:1.353]
<i>Reliable electricity access</i>	-0.004 [-0.085:0.072]	-0.017 [-0.34:0.289]	-0.021 [-0.425:0.363]
<i>Grid access</i>	0.058	0.233	0.291

Table II.8, continued

	<i>Dependent variables log SPA 1000</i>		
	Direct	Indirect	Total
<i>Urban</i>	[-0.056:0.169] 0.218*** [0.104:0.334]	[-0.227:0.678] 0.868*** [0.418:1.338]	[-0.283:0.859] 1.085*** [0.522:1.665]
City			
<i>Bamako</i>	0.251*** [0.126:0.375]	1.003*** [0.516:1.484]	1.255*** [0.641:1.859]
<i>Cape town</i>	0.032 [-0.09:0.157]	0.130 [-0.36:0.628]	0.162 [-0.448:0.788]
<i>Dakar</i>	-0.027 [-0.124:0.068]	-0.107 [-0.503:0.273]	-0.134 [-0.623:0.341]
<i>Harare</i>	-0.272*** [-0.389:-0.167]	-1.087*** [-1.532:-0.654]	-1.360*** [-1.923:-0.823]
<i>Ibadan</i>	-0.225* [-0.461:0.002]	-0.896* [-1.875:0.009]	-1.121* [-2.342:0.011]
<i>Kampala</i>	-0.107 [-0.253:0.036]	-0.426 [-1.003:0.146]	-0.533 [-1.256:0.18]
<i>Khartoum</i>	-0.424*** [-0.579:-0.283]	-1.691*** [-2.304:-1.122]	-2.115*** [-2.876:-1.406]
<i>Lagos</i>	0.007 [-0.147:0.137]	0.029 [-0.589:0.555]	0.036 [-0.737:0.695]
<i>Lusaka</i>	-0.228*** [-0.358:-0.092]	-0.911*** [-1.428:-0.373]	-1.139*** [-1.79:-0.465]
<i>Nairobi</i>	-0.102 [-0.227:0.021]	-0.408 [-0.913:0.082]	-0.510 [-1.137:0.103]
<i>Niamey</i>	0.227*** [0.073:0.375]	0.905*** [0.292:1.492]	1.132*** [0.365:1.869]
<i>Ouagadougou</i>	0.234*** [0.111:0.344]	0.932*** [0.433:1.383]	1.166*** [0.545:1.722]
<i>Windhoek</i>	-0.017 [-0.131:0.089]	-0.068 [-0.518:0.359]	-0.085 [-0.652:0.448]
Observations	2280		
AIC	2070.2		
Studentized Breusch-Pagan test	p-value = 0.03943		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

4.3.3 Further results on the effect of the grid reliability

As we saw in chapter I, it is essential to understand better to what extent an improvement in the quality of the electricity supply could influence this empowerment of consumers or the use of decentralized systems. Unfortunately,

we do not have panel data which could allow us to estimate the causal effect of the improvement of the network reliability on consumers empowerment through decentralized solar systems.

However, we can further test the links between solar adoption and grid reliability, by conducting a new econometric analysis where our only explicating variable is the reliability of electricity supplied (although we control for cities' fixed effects). We use the more granular encoding of this variable as provided by afrobarometer's survey. Grid reliability, therefore, has five different values *Always* when the grid is always functioning, *Most* when the grid is working most of the time (about 75% of the time), *Half* when it is only working more than half of the time and finally *Occasionally* (25% of the time) and *Never*.

We fit a SAR model with only grid reliability as an independent variable and city as control.

We fit the regression on the three datasets for robustness check: the dataset comprising only residential solar panels, the dataset comprising only commercial panels, and the entire dataset comprising residential and commercial observations. As we can see, when the grid is reliable, the coefficient is always statistically significant in our three buffer zones. However, it is interesting to note that it is also the case when the grid is functioning most of the time and occasionally for both the dataset comprising both commercial and residential data, as can be seen in table II.9 and the one comprising residential data only, as can be seen in table A.II.6. For the dataset comprising only commercial data, the coefficient is only statistically significant for areas where the grid is always functioning and most of the time, which indicates that the logic surrounding commercial solar systems deployment in urban areas would be linked more to economic rather than security of supply issues. The table for commercial data can be found in the annex in table A.II.7 These results tend to confirm the results of the first model, although tempering them. It appears that residential consumers tend to move away from the grid, even though it is reliable.

Table II.9: SAR estimates - both residential and commercial data

	<i>Dependent variable (log SPA 1000)</i>		
	Direct	Indirect	Total
Grid reliability			
<i>Always</i>	0.217*** [0.127-0.301]	1.046*** [0.613-1.464]	1.262*** [0.738-1.759]
<i>Most</i>	0.171*** [0.085-0.258]	0.824*** [0.414-1.256]	0.995*** [0.498-1.514]

Table II.9, continued

	<i>Dependent variable (log SPA 1000)</i>		
	Direct	Indirect	Total
<i>Occasionally</i>	0.219*** [0.088-0.334]	1.055*** [0.434-1.614]	1.274*** [0.522-1.949]
<i>Never</i>	0.217 [-0.033-0.464]	1.049 [-0.163-2.231]	1.266 [-0.196-2.698]
City			
<i>Bamako</i>	0.262*** [0.131-0.397]	1.266*** [0.64-1.907]	1.528*** [0.772-2.304]
<i>Cape Town</i>	0.136 [-0.002-0.275]	0.657 [-0.008-1.329]	0.793 [-0.01-1.602]
<i>Dakar</i>	-0.013 [-0.108-0.088]	-0.063 [-0.519-0.422]	-0.077 [-0.622-0.51]
<i>Harare</i>	-0.230*** [-0.339-0.114]	-1.112*** [-1.639-0.558]	-1.342*** [-1.969-0.678]
<i>Ibadan</i>	0.162 [-0.129-0.471]	0.783 [-0.617-2.269]	0.945 [-0.742-2.742]
<i>Kampala</i>	-0.033 [-0.187-0.119]	-0.162 [-0.9-0.572]	-0.195 [-1.09-0.691]
<i>Khartoum</i>	-0.302*** [-0.456-0.152]	-1.456*** [-2.196-0.734]	-1.758*** [-2.651-0.887]
<i>Lagos</i>	0.098 [-0.062-0.242]	0.473 [-0.306-1.17]	0.571 [-0.368-1.407]
<i>Lusaka</i>	-0.145 [-0.279-0.006]	-0.697 [-1.322-0.029]	-0.842 [-1.601-0.035]
<i>Nairobi</i>	0.113 [-0.019-0.254]	0.547 [-0.091-1.232]	0.661 [-0.11-1.485]
<i>Niamey</i>	0.140 [-0.021-0.296]	0.676 [-0.104-1.418]	0.816 [-0.126-1.72]
<i>Ouagadougou</i>	0.254*** [0.134-0.373]	1.223*** [0.646-1.808]	1.477*** [0.78-2.18]
<i>Windhoek</i>	0.108 [-0.014-0.22]	0.522 [-0.07-1.06]	0.630 [-0.084-1.281]
Observations	2413		
AIC	1956		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

4.4 Limits of the empirical approach

The results provided are not without caveats. A potential concern with the results presented above is that our Deep Learning models can only detect and

segment panels with a minimum size of 1 to 2 square meters due to satellite images' relatively low resolution compared, for example, to aerial imagery. There is, therefore, a bias towards the detection of large panels, more likely to be in the wealthier neighborhoods. The model cannot detect smaller panels, particularly pico-solar systems, widespread in the region. In the future, access to better quality satellite images or aerial images with higher resolution will help us improve Deep Learning models' performances presented above. More sophisticated models such as Mask-RCNN could be trained to refine data collection. In the future, access to better resolution imagery might also let us expand the analysis to areas not covered by this chapter.

Another limitation of our data, which has been partly addressed, is separating residential data from business data. We used a Machine Learning method to separate the two distributions. However, there is an overlap between them. Therefore, there is room for improvement, and it might be necessary to refine this data separation in the future. A solution could be to use one of the Google Maps APIs to locate businesses in the covered cities and remove a defined area of solar panels installed around each of them. The socio-economic data used is also limited. For example, strictly speaking, we do not have the level of household income in monetary terms but the respondent's perception of their social level. In the future, it might be interesting to assess the feasibility of running a survey in cities of the region, with more specific questions on respondents' income streams. Furthermore, afrobarometer's data was collected between 2016 and 2018, while our satellite data were collected mainly in the middle of 2021. Although this is the last geolocalised data from Afrobarometer, still not made public at the time of writing, several years lag between our satellite and socioeconomic data.

It is also important to note that spatial econometric models are not particularly well suited to individual survey data. Only partial neighborhood relations are observed in survey data (only for the selected individuals), which requires making a strong enough hypothesis that the observations of uninvestigated neighbors do not affect the neighborhood effects for the individuals surveyed. Only direct effects can be truly estimated with survey data with low sampling rates and classic sampling designs, as stratified ones (De Bellefon et al., 2018).

However, this study offers room for future research. Due to Static Map API's limitations, we cannot retrieve past satellite imagery to evaluate the development of the solar market in time. In the future, however, a new collection of data could be implemented and cross-referenced with Afrobarometer's upcoming surveys. This could give a better idea of the decentralized solar market's temporal evolution in sub-Saharan Africa's urban areas and enrich the analysis. We could re-run download sessions on areas already covered in this chapter which could help us get closer to causal identification. As afrobarometer

is conducting new field works and releasing new surveys every 2-3 years, the following survey (round 8) conducted between 2019 and 2021 will be released in the next few years. Re-running download sessions on a regular basis will allow us to gather cross-sectional data (and not panel data as in this chapter). For example, we could use this to quantify the effect of public policies aimed at encouraging solar systems adoption through the introduction of fiscal tools such as a reduction in VAT or reduction in import tariffs on solar products. Those have been introduced in many countries in East Africa and are also starting to be introduced in West Africa.

The data presented in this analysis could also be used for other research. For example, the World Bank is regularly releasing "Enterprise Surveys" administered to businesses and managers of private sector enterprises. In addition, for many countries, geolocalised data are available. Joining those surveys with the original data presented in this chapter could be used to add up to the literature on firm performance in sub-Saharan Africa.

5 Discussion of results

The results discussed above provide evidence that the penetration of the decentralized solar market is significant in urban areas in sub-Saharan Africa, as in the areas we covered, it already represents about 10% of the solar capacities installed on the central network. Furthermore, we found that decentralized solar systems are primarily adopted by the better-off segments of the population in large sub-Saharan cities, regardless of the quality of the electricity distributed by the grid. These results in accordance with qualitative interviews conducted with professionals in the region.

These results are consistent with the literature that deals with the adoption of solar systems in rural areas. For example, Guta (2018) concludes that the wealthiest households are also the most likely to use solar systems, compared to the poorest households. This is also confirmed by Rahut et al. (2018) and Smith and Urpelainen (2014), who conclude that the probability of adoption of these systems increases with the level of households' wealth, which is also in line with the results of Acker and Kammen (1996), Jacobson (2007) and Lay et al. (2013). For Guta (2018) this result can be explained by the better financial capacity to pay for decentralized solar technologies of households for these systems as their income increases.

Authors have also argued that education positively affects the penetration of decentralized solar systems. As more educated consumers were more likely to be aware of the environmental and health benefits these systems could provide (Guta, 2018). However, other authors have argued that the environmental as-

pect related was a marginal factor for the use and adoption of distributed solar systems. Acker and Kammen (1996) explained that the environmental benefits associated with the use of these systems were among the last advantages noted by their owners. The most compelling factors related to decentralized solar systems were mainly economic. It is important to note however that the study by Acker and Kammen (1996) dates back more than two decades, and mentalities may have changed, in particular, due to major international campaigns to raise awareness on global warming. The authors agree, however, that the level of education can be a significant factor in the adoption of a solar system, only the underlying mechanism that links education and adoption is not clear.

The exact motivation for the adoption of solar systems in areas covered by the grid is therefore not completely understood. Economic benefits may take precedence over environmental benefits. One of the households in the study of Acker and Kammen (1996), for example, was connected to the grid and to a decentralized solar system. They clearly stated that they used both technologies to reduce their electricity bill. Unfortunately, our analysis does not allow us to shed light on this matter. But a few qualitative interviews conducted with consumers using decentralized solar systems while being connected to the grid indicated that the economic benefits were the principal reason for adoption.

Concerning the adoption of decentralized systems in rural areas close to the grid, we have seen in the literature review that it is believed that better-off households generally prefer central access when they can because households derive more utility from a connection to the network (Sievert and Steinbuks, 2020). Furthermore, the proximity of the network to non-electrified residential consumers could be considered an obstacle to the adoption (Kizilcec and Parikh, 2020; Azimoh et al., 2015; Dugoua and Urpelainen, 2014). However, Lay et al. (2013) found that the potential access to the grid did not significantly affect the choice of the household in the use of a solar system and that it could therefore be considered as a complementary source of electricity. We find results similar to those of Lay et al. (2013) in urban areas covered by the network as we show that people with a higher standard of living are the most likely to adopt decentralized solar systems without any clear effect of the electricity supplied reliability factor. This shows that the logic underlying the decentralized solar market's development in sub-Saharan Africa's urban areas is not the same as in rural areas (except for the results of Lay et al. (2013)). A particularly wealthy individual will be more likely to own a solar system regardless of the quality of the electricity supply from the centralized grid.

These results also tend to validate the hypothesis that these systems are primarily used for their economic benefits. This may be reinforced by the fact that wealthier and more educated consumers are also likely to be aware of the

significant financial difficulties utilities facing and that they are likely to face significant tariffs increases in the future to balance the finances of the sector. They can therefore be prone to use a decentralized system. In this context, solar systems become more attractive than auxiliary generators as the costs of solar systems are lower than for auxiliary generators and the latter is also subject to increases in fuel prices. A home with a distributed solar system can thus protect itself from fluctuations in fossil fuel prices (Acker and Kammen, 1996) and central grid electricity tariffs.

Finally, Jacobson (2007) and Lay et al. (2013) argue that solar systems are becoming more affordable for the middle classes in rural areas. This phenomenon is facilitated by the fall in the price of photovoltaic systems. We can hypothesize that the market in urban areas will follow a similar dynamic. The market is in its infancy and today aims at the wealthiest households, but it could gradually evolve towards the middle classes in a second phase of its development. An additional idea that emerged from these interviews is that there would be a "U-shaped" penetration of decentralized solar systems of all sizes depending on the standard of living of populations in urban areas. For the poorest populations living in slums, the connection to the grid is made inaccessible by their meager income; the only way to consume electricity would be through pico-solar systems like solar lamps and solar phone charging appliances. As incomes increase, these systems are abandoned by consumers for a connection to the grid, which has become more accessible. Therefore, the use of decentralized solar systems become marginal for the middle classes. Finally, solar technologies are reappearing in the form of large decentralized solar systems among the wealthiest segments of the population.

6 Conclusion

This chapter provided consistent evidence that the decentralized solar market's penetration is significant in sub-Saharan Africa urban areas. It was estimated that decentralized solar systems represent about 10% of the solar capacities already installed on the grid in the areas covered by this analysis. Furthermore, the econometric analysis has shown that decentralized solar systems are primarily adopted by the better-off segments of the population in large sub-Saharan cities, regardless of the grid's electricity quality. These results are consistent with the analysis of qualitative interviews conducted with regional professionals at Ifri.

This analysis shows that the gradual empowerment of consumers in parallel to the grid is a fundamental trend and cannot be countered simply by improving the management and reliability of the electricity supply. This confirms that, as shown in chapter 1, the gradual decentralization of power systems in sub-

Saharan Africa is underway and is being reinforced by the continent's rapid urbanization. In addition, it gradually decorrelates from the reliability of the network.

This empowerment of consumers could have negative consequences for the centralized sector. Considering the difficult financial situation in which almost all African power companies find themselves, losing their most lucrative customers (residential and commercial or small industrial) could severely negatively impact their profitability. In addition, the financial viability of strategies for extending the core grid to the poorest consumers in adjacent peri-urban and rural areas relies on cross-subsidies. Indeed, the largest consumers pay higher prices than the poorest, who consume less and thus benefit from subsidized tariffs. This system risks finding its limits quickly if the most profitable city customers turn away from the network. Consumer empowerment could therefore contribute to fragmenting centralized sub-Saharan networks.

In the first chapter, it was seen that populations and businesses are encouraged to become more independent from the central network to meet their electricity consumption needs. We saw that residential and commercial consumers use decentralized systems to tackle grid unreliability and optimize their electricity expenditure. The two main decentralized technologies used in the region were decentralized solar systems and auxiliary generators. The former technology was mainly used by residential consumers while the latter by commercial consumers.

In this second chapter, the adoption of decentralized solar systems by residential consumers connected to the grid was explored. To better understand the dynamics between consumers and technology, it seems appropriate to turn towards analyzing the use of backup generators by businesses connected to the grid. In the next chapter, an analysis of how commercial consumers use their auxiliary generators according to the network's reliability in Nigeria is presented. This will be done by studying an original database comprising time series of power consumption of businesses connected to the central network, using Machine Learning algorithms. With regard to the questions asked by this thesis, this seek to determine whether there is a form of decorrelation between the use of generators and the reliability of electricity supplied by the grid. Answering this question should grant a better understanding of this dynamic of consumer empowerment and its juxtaposition to grid electricity usage by consumers in the areas covered by the network.

Appendices

Table A.II.1: Areas covered and solar panel area detected (in thousands square meters)

City	Approximation of the area covered	Solar panel area
Ouagadougou	319 805	107
Accra	557 386	54
Bamako	281 327	110
Cape Town	788 468	348
Dakar	337 984	43
Harare	601 979	22
Ibadan	82 713	12
Kampala	258 130	19
Khartoum	213 529	5
Lagos	345 343	89
Lusaka	267 024	28
Nairobi	238 333	135
Niamey	190 901	30
Windhoek	238 596	148

Source : authors

Table A.II.2: SAR estimates - binary variable of interest

	<i>Dependent variable (log SPA 500)</i>		
	Direct	Indirect	Total
<i>Wealth 1</i>	0.232*** [0.06:0.407]	0.775*** [0.199:1.351]	1.007*** [0.258:1.757]
<i>University education</i>	0.075 [-0.05:0.191]	0.250 [-0.163:0.634]	0.325 [-0.213:0.826]
<i>Unemployed</i>	-0.035 [-0.109:0.043]	-0.115 [-0.365:0.145]	-0.150 [-0.472:0.188]
<i>Sewage present</i>	0.182*** [0.096:0.27]	0.608*** [0.321:0.903]	0.790*** [0.418:1.17]
<i>Reliable electricity access</i>	-0.025 [-0.133:0.089]	-0.082 [-0.451:0.296]	-0.107 [-0.584:0.384]
<i>Grid access</i>	0.078 [-0.071:0.228]	0.261 [-0.232:0.766]	0.339 [-0.303:0.995]
<i>Urban</i>	0.126 [-0.045:0.281]	0.421 [-0.149:0.939]	0.548 [-0.195:1.216]
City			
<i>Bamako</i>	0.427*** [0.249:0.594]	1.428*** [0.833:2.01]	1.855*** [1.093:2.602]
<i>Cape Town</i>	0.168*	0.563*	0.731*

Table A.II.2, continued

	<i>Dependent variable (log SPA 500)</i>		
	Direct	Indirect	Total
	[-0.002:0.346]	[-0.007:1.149]	[-0.009:1.495]
<i>Dakar</i>	0.068 [-0.064:0.211]	0.228 [-0.212:0.698]	0.296 [-0.276:0.91]
<i>Harare</i>	-0.235*** [-0.386:-0.084]	-0.785*** [-1.314:-0.279]	-1.020*** [-1.698:-0.364]
<i>Ibadan</i>	-0.172 [-0.526:0.163]	-0.576 [-1.748:0.53]	-0.748 [-2.265:0.698]
<i>Kampala</i>	-0.008 [-0.195:0.18]	-0.027 [-0.655:0.599]	-0.035 [-0.851:0.787]
<i>Khartoum</i>	-0.190* [-0.388:0.005]	-0.636* [-1.297:0.018]	-0.827* [-1.682:0.024]
<i>Lagos</i>	0.137 [-0.061:0.335]	0.459 [-0.213:1.123]	0.597 [-0.274:1.461]
<i>Lusaka</i>	-0.134 [-0.304:0.046]	-0.448 [-1.018:0.153]	-0.581 [-1.323:0.199]
<i>Nairobi</i>	-0.057 [-0.236:0.121]	-0.191 [-0.794:0.4]	-0.249 [-1.025:0.522]
<i>Niamey</i>	0.441*** [0.226:0.66]	1.475*** [0.757:2.2]	1.917*** [0.991:2.845]
<i>Ouagadougou</i>	0.457*** [0.288:0.613]	1.527*** [0.969:2.079]	1.984*** [1.256:2.689]
<i>Windhoek</i>	0.096 [-0.048:0.244]	0.322 [-0.162:0.815]	0.419 [-0.21:1.057]
Observations	2280		
AIC	4124		
Studentized Breusch-Pagan test	p-value < 2.2e-16		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.II.3: SAR estimates - binary variable of interest

	<i>Dependent variable (log SPA 1500)</i>		
	Direct	Indirect	Total
<i>Wealth 1</i>	0.179*** [0.07:0.292]	0.711*** [0.281:1.161]	0.890*** [0.351:1.456]
<i>University education</i>	0.069* [-0.007:0.16]	0.276* [-0.027:0.633]	0.345* [-0.034:0.792]
<i>Unemployed</i>	-0.024 [-0.072:0.022]	-0.095 [-0.283:0.087]	-0.118 [-0.353:0.11]
<i>Sewage present</i>	0.192*** [0.139:0.246]	0.765*** [0.551:0.985]	0.957*** [0.694:1.229]
<i>Reliable electricity access</i>	0.043 [-0.023:0.114]	0.172 [-0.093:0.458]	0.215 [-0.117:0.571]
<i>Grid access</i>	0.006 [-0.098:0.108]	0.023 [-0.388:0.432]	0.029 [-0.485:0.543]
<i>Urban</i>	0.231*** [0.126:0.336]	0.922*** [0.508:1.331]	1.153*** [0.634:1.661]
City			
<i>Bamako</i>	0.244*** [0.133:0.35]	0.971*** [0.534:1.384]	1.214*** [0.666:1.734]
<i>Cape Town</i>	0.021 [-0.093:0.137]	0.082 [-0.38:0.544]	0.103 [-0.477:0.68]
<i>Dakar</i>	-0.049 [-0.138:0.037]	-0.196 [-0.551:0.145]	-0.245 [-0.686:0.182]
<i>Harare</i>	-0.304*** [-0.402:-0.197]	-1.209*** [-1.58:-0.801]	-1.513*** [-1.985:-1.001]
<i>Ibadan</i>	-0.217* [-0.427:0.014]	-0.864* [-1.711:0.058]	-1.081* [-2.133:0.072]
<i>Kampala</i>	-0.194*** [-0.301:-0.073]	-0.774*** [-1.212:-0.288]	-0.969*** [-1.516:-0.361]
<i>Khartoum</i>	-0.458*** [-0.584:-0.331]	-1.824*** [-2.339:-1.327]	-2.282*** [-2.933:-1.669]
<i>Lagos</i>	-0.031 [-0.153:0.101]	-0.125 [-0.617:0.412]	-0.156 [-0.772:0.513]
<i>Lusaka</i>	-0.213*** [-0.322:-0.094]	-0.847*** [-1.314:-0.376]	-1.059*** [-1.635:-0.47]
<i>Nairobi</i>	-0.111* [-0.224:0.007]	-0.443* [-0.88:0.028]	-0.554* [-1.1:0.036]
<i>Niamey</i>	0.199*** [0.075:0.33]	0.791*** [0.3:1.336]	0.989*** [0.374:1.666]
<i>Ouagadougou</i>	0.189*** [0.087:0.297]	0.753*** [0.346:1.175]	0.942*** [0.433:1.472]
<i>Windhoek</i>	-0.047 [-0.139:0.049]	-0.188 [-0.549:0.19]	-0.235 [-0.688:0.239]

Table A.II.3, continued

	<i>Dependent variable (log SPA 1500)</i>		
	Direct	Indirect	Total
Observations	2280		
AIC	1478		
Studentized Breusch-Pagan test	p-value = 0.2687		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.II.4: SAR estimates - categorical variable of interest

	<i>Dependent variables log SPA 500</i>		
	Direct	Indirect	Total
<i>Wealth 1</i>	0.256*** [0.077:0.448]	0.857*** [0.253:1.511]	1.113*** [0.33:1.957]
<i>Wealth 2</i>	0.042 [-0.046:0.121]	0.142 [-0.154:0.392]	0.184 [-0.201:0.51]
<i>Wealth 4</i>	-0.008 [-0.115:0.087]	-0.025 [-0.39:0.292]	-0.033 [-0.506:0.38]
<i>Wealth 5</i>	0.100 [-0.042:0.249]	0.333 [-0.14:0.829]	0.433 [-0.183:1.07]
<i>University education</i>	0.074 [-0.042:0.198]	0.247 [-0.141:0.67]	0.321 [-0.183:0.864]
<i>Unemployed</i>	-0.034 [-0.111:0.035]	-0.114 [-0.38:0.12]	-0.148 [-0.493:0.155]
<i>Sewage present</i>	0.184*** [0.099:0.269]	0.616*** [0.337:0.897]	0.800*** [0.438:1.17]
<i>Reliable electricity access</i>	-0.023 [-0.125:0.088]	-0.076 [-0.427:0.297]	-0.098 [-0.55:0.385]
<i>Grid access</i>	0.077 [-0.067:0.226]	0.257 [-0.23:0.76]	0.334 [-0.295:0.988]
<i>Urban</i>	0.120 [-0.043:0.282]	0.402 [-0.141:0.959]	0.523 [-0.182:1.242]
City			
<i>Bamako</i>	0.428*** [0.27:0.603]	1.431*** [0.898:2.028]	1.859*** [1.167:2.63]
<i>Cape town</i>	0.158* [-0.016:0.336]	0.529* [-0.053:1.136]	0.687* [-0.069:1.472]
<i>Dakar</i>	0.070 [-0.061:0.212]	0.234 [-0.203:0.704]	0.304 [-0.265:0.914]
<i>Harare</i>	-0.238*** [-0.385:-0.089]	-0.795*** [-1.294:-0.305]	-1.032*** [-1.684:-0.394]
<i>Ibadan</i>	-0.173 [-0.524:0.183]	-0.577 [-1.747:0.616]	-0.750 [-2.283:0.803]
<i>Kampala</i>	-0.005 [-0.201:0.177]	-0.017 [-0.679:0.599]	-0.022 [-0.879:0.774]
<i>Khartoum</i>	-0.189* [-0.399:0.013]	-0.633* [-1.365:0.043]	-0.822* [-1.761:0.056]
<i>Lagos</i>	0.139 [-0.064:0.326]	0.466 [-0.219:1.072]	0.605 [-0.283:1.386]
<i>Lusaka</i>	-0.136 [-0.31:0.065]	-0.456 [-1.029:0.215]	-0.592 [-1.347:0.28]
<i>Nairobi</i>	-0.055	-0.183	-0.238

Table A.II.4, continued

	<i>Dependent variables log SPA 500</i>		
	Direct	Indirect	Total
<i>Niamey</i>	[-0.236:0.133] 0.434*** [0.237:0.65]	[-0.788:0.451] 1.453*** [0.8:2.176]	[-1.023:0.584] 1.887*** [1.035:2.833]
<i>Ouagadougou</i>	0.457*** [0.283:0.634]	1.528*** [0.969:2.094]	1.984*** [1.249:2.73]
<i>Windhoek</i>	0.088 [-0.067:0.24]	0.293 [-0.227:0.807]	0.381 [-0.293:1.046]
Observations	2280		
AIC	4127.4		
Studentized Breusch-Pagan test	p-value = 2.22e-16		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.II.5: SAR estimates - categorical variable of interest

	<i>Dependent variables log SPA 1500</i>		
	Direct	Indirect	Total
<i>Wealth 1</i>	0.177*** [0.067:0.294]	0.707*** [0.262:1.182]	0.884*** [0.328:1.476]
<i>Wealth 2</i>	0.014 [-0.038:0.07]	0.057 [-0.152:0.286]	0.071 [-0.189:0.358]
<i>Wealth 4</i>	-0.039 [-0.105:0.035]	-0.155 [-0.424:0.142]	-0.194 [-0.529:0.177]
<i>Wealth 5</i>	-0.014 [-0.114:0.094]	-0.055 [-0.449:0.368]	-0.069 [-0.563:0.462]
<i>University education</i>	0.067* [-0.011:0.15]	0.268* [-0.042:0.6]	0.335* [-0.052:0.751]
<i>Unemployed</i>	-0.022 [-0.07:0.025]	-0.088 [-0.28:0.103]	-0.110 [-0.349:0.128]
<i>Sewage present</i>	0.191*** [0.139:0.246]	0.760*** [0.562:0.982]	0.951*** [0.7:1.23]
<i>Reliable electricity access</i>	0.043 [-0.019:0.11]	0.170 [-0.073:0.435]	0.212 [-0.092:0.545]
<i>Grid access</i>	0.001 [-0.102:0.101]	0.004 [-0.402:0.401]	0.005 [-0.504:0.502]
<i>Urban</i>	0.232*** [0.13:0.326]	0.924*** [0.524:1.295]	1.156*** [0.653:1.623]
City			
<i>Bamako</i>	0.250*** [0.144:0.357]	0.994*** [0.579:1.426]	1.244*** [0.724:1.782]
<i>Cape town</i>	0.021 [-0.098:0.145]	0.082 [-0.387:0.58]	0.102 [-0.485:0.727]
<i>Dakar</i>	-0.048 [-0.137:0.044]	-0.191 [-0.544:0.178]	-0.240 [-0.684:0.221]
<i>Harare</i>	-0.301*** [-0.399:-0.199]	-1.200*** [-1.597:-0.807]	-1.501*** [-1.995:-1.008]
<i>Ibadan</i>	-0.214* [-0.45:0.013]	-0.854* [-1.788:0.05]	-1.069* [-2.238:0.062]
<i>Kampala</i>	-0.190*** [-0.316:-0.079]	-0.759*** [-1.25:-0.311]	-0.949*** [-1.567:-0.391]
<i>Khartoum</i>	-0.457*** [-0.594:-0.33]	-1.823*** [-2.363:-1.32]	-2.281*** [-2.946:-1.651]
<i>Lagos</i>	-0.033 [-0.151:0.09]	-0.130 [-0.605:0.352]	-0.162 [-0.754:0.441]
<i>Lusaka</i>	-0.210*** [-0.322:-0.095]	-0.838*** [-1.288:-0.378]	-1.048*** [-1.609:-0.472]
<i>Nairobi</i>	-0.112**	-0.445**	-0.557**

Table A.II.5, continued

	<i>Dependent variables log SPA 1500</i>		
	Direct	Indirect	Total
	[-0.224:-0.005]	[-0.893:-0.021]	[-1.115:-0.027]
<i>Niamey</i>	0.195*** [0.062:0.337]	0.777*** [0.244:1.349]	0.972*** [0.306:1.684]
<i>Ouagadougou</i>	0.188*** [0.078:0.298]	0.750*** [0.323:1.186]	0.938*** [0.401:1.485]
<i>Windhoek</i>	-0.049 [-0.149:0.052]	-0.195 [-0.592:0.209]	-0.244 [-0.745:0.261]
Observations	2280		
AIC	1481.5		
Studentized Breusch-Pagan test	p-value = 0.2759		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.II.6: SAR estimates - residential data only

	<i>Dependent variable (log SPA 1000)</i>		
	Direct	Indirect	Total
Grid reliability			
<i>Always</i>	0.177*** [0.099-0.257]	0.822*** [0.456-1.214]	0.999*** [0.555-1.474]
<i>Most</i>	0.144*** [0.058-0.225]	0.666*** [0.268-1.039]	0.810*** [0.326-1.268]
<i>Occasionally</i>	0.207*** [0.097-0.318]	0.960*** [0.446-1.473]	1.167*** [0.542-1.79]
<i>Never</i>	0.157 [-0.061-0.37]	0.726 [-0.282-1.712]	0.882 [-0.343-2.077]
City			
<i>Bamako</i>	0.245*** [0.126-0.365]	1.133*** [0.581-1.694]	1.378*** [0.705-2.054]
<i>Cape Town</i>	0.098 [-0.028-0.215]	0.454 [-0.129-0.995]	0.552 [-0.158-1.21]
<i>Dakar</i>	-0.003 [-0.09-0.092]	-0.013 [-0.417-0.432]	-0.016 [-0.508-0.525]
<i>Harare</i>	-0.224*** [-0.323-0.122]	-1.038*** [-1.482-0.563]	-1.262*** [-1.8-0.686]
<i>Ibadan</i>	-0.125 [-0.396-0.133]	-0.578 [-1.804-0.606]	-0.703 [-2.183-0.739]
<i>Kampala</i>	-0.035 [-0.176-0.098]	-0.163 [-0.825-0.449]	-0.198 [-1.001-0.547]
<i>Khartoum</i>	-0.314*** [-0.446-0.175]	-1.456*** [-2.081-0.82]	-1.771*** [-2.52-0.995]
<i>Lagos</i>	0.070 [-0.065-0.213]	0.325 [-0.313-0.975]	0.395 [-0.381-1.187]
<i>Lusaka</i>	-0.212*** [-0.325-0.094]	-0.983*** [-1.508-0.441]	-1.195*** [-1.833-0.538]
<i>Nairobi</i>	-0.039 [-0.161-0.085]	-0.181 [-0.747-0.4]	-0.220 [-0.908-0.485]
<i>Niamey</i>	0.135 [-0.003-0.285]	0.625 [-0.014-1.324]	0.759 [-0.017-1.611]
<i>Ouagadougou</i>	0.242*** [0.128-0.355]	1.119*** [0.593-1.635]	1.360*** [0.722-1.986]
<i>Windhoek</i>	0.051 [-0.059-0.146]	0.235 [-0.268-0.665]	0.286 [-0.327-0.809]
Observations	1893		
AIC	1758.6		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.II.7: SAR estimates - commercial data only

	<i>Dependent variable (log SPA 1000)</i>		
	Direct	Indirect	Total
Grid reliability			
<i>Always</i>	0.161*** [0.085-0.234]	0.740*** [0.392-1.083]	0.901*** [0.478-1.316]
<i>Most</i>	0.103*** [0.028-0.177]	0.474*** [0.127-0.819]	0.577*** [0.155-0.994]
<i>Occasionally</i>	0.055 [-0.043-0.16]	0.254 [-0.194-0.744]	0.309 [-0.237-0.905]
<i>Never</i>	0.174 [-0.019-0.377]	0.801 [-0.085-1.735]	0.975 [-0.104-2.115]
City			
<i>Bamako</i>	0.192*** [0.075-0.3]	0.880*** [0.344-1.395]	1.072*** [0.419-1.694]
<i>Cape Town</i>	0.156 [0.044-0.277]	0.716 [0.206-1.279]	0.872 [0.251-1.558]
<i>Dakar</i>	-0.056 [-0.14-0.029]	-0.257 [-0.652-0.132]	-0.312 [-0.791-0.16]
<i>Harare</i>	-0.084 [-0.187-0.015]	-0.385 [-0.867-0.068]	-0.468 [-1.055-0.083]
<i>Ibadan</i>	0.345*** [0.086-0.577]	1.586*** [0.387-2.665]	1.932*** [0.47-3.24]
<i>Kampala</i>	-0.045 [-0.164-0.076]	-0.207 [-0.755-0.351]	-0.252 [-0.921-0.427]
<i>Khartoum</i>	-0.062 [-0.207-0.068]	-0.285 [-0.946-0.321]	-0.347 [-1.154-0.389]
<i>Lagos</i>	0.170 [0.049-0.293]	0.781 [0.216-1.362]	0.951 [0.265-1.651]
<i>Lusaka</i>	0.039 [-0.075-0.143]	0.178 [-0.35-0.664]	0.216 [-0.428-0.81]
<i>Nairobi</i>	0.266*** [0.161-0.377]	1.219*** [0.732-1.733]	1.485*** [0.895-2.109]
<i>Niamey</i>	0.042 [-0.096-0.187]	0.193 [-0.432-0.868]	0.235 [-0.526-1.056]
<i>Ouagadougou</i>	0.136 [0.025-0.232]	0.623 [0.113-1.075]	0.759 [0.138-1.306]
<i>Windhoek</i>	0.186*** [0.09-0.276]	0.852*** [0.412-1.292]	1.037*** [0.5-1.572]
Observations	1893		
AIC	1295.6		

Note: Empirical confidence intervals (2.5% and 97.5% quantiles of 1000 MCMC simulations are shown in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Chapter III

Diesel generators in Nigeria: a mixture model for electricity consumption¹

¹The quantitative work in this chapter was done in collaboration with Fabrice Rossi, professor of data science at Paris-Dauphine University.

1 Introduction

Following Chapters 1 and 2 of this thesis, several questions remain. In the first chapter, it was discussed that consumer empowerment from the grid could negatively affect the sector's finances. Given the difficult financial situation the utility sector find themselves in, consumer empowerment in areas covered by the grid could significantly affect the sector's development. Sub-Saharan Africa has also seen widespread auxiliary generator adoption, especially among the continent's businesses. Indeed, it is common for African companies to invest in backup generators to continue their business activities during power outages. For example, the IEA estimates that more than 8% of the continent's total electricity generation was produced by backup generators in 2018, equivalent to more than 40 TWh of electricity consumed (International Energy Agency, 2019). In some countries, such as Nigeria or the Republic of Congo, more than 70 percent of businesses own or share a generator (World Bank, 2022b). In the second chapter, it was demonstrated that wealthy residential consumers tend to invest in decentralized solar systems, regardless of the quality of the power supply from the central grid.

In this third chapter, it seems appropriate to focus the analysis on auxiliary generators. This is a natural follow-up to the first chapters and will allow a better understanding of consumer empowerment by covering the two main types of consumers: residential and commercial, and the two leading decentralized technologies used in the region: solar systems and generators. Additionally, in the second chapter, consumer empowerment from the perspective of decentralized systems' adoption was explored. To complete this analysis, it now seems appropriate to study this issue from the perspective of usage². As part of the questions raised in this thesis, it is appropriate to ask whether there is a correlation between generator use and network electricity supply. In other words, if an enterprise connected to the grid can use its generator even if the grid is running, and under which conditions. The answer to this question should allow us to characterize consumer empowerment via decentralized systems.

The first two chapters analyzed trends at the continental level, which has proven helpful in understanding the general development dynamics of sub-Saharan power systems. However, it has sometimes been done at the cost of specificity. Therefore, in this third chapter, it seems important to make a case study of a specific country in the region. Chapter 3 makes a case study on Nigeria, as it is the African country with the highest aggregated auxiliary generator capacities. Furthermore, Nigeria combines many problems experienced by sub-Saharan electricity networks: incomplete liberalization of the sector,

²In the second chapter, the question of which type of consumers have decided to adopt a decentralized system is explored. This chapter will study how a consumer uses their decentralized system when connected to a deficient network.

maintenance problems with power plants and grid infrastructure, exceptionally high technical and non-technical losses, and regular and prolonged power outages - all against the backdrop of one of the highest population and urban growth rates on the continent. A specific case study on this country will also allow us to illustrate with concrete examples many of the points raised in the first chapters of this thesis and study in more detail the use of decentralized generators by consumers connected to the grid.

Furthermore, Nigeria is an interesting choice as the country is at a turning point. It is one of the main hydrocarbon-producing countries in Africa. However, the global energy transition is increasingly hindering African hydrocarbon-producing countries' traditional development prospects. These countries are suffering a double penalty. Firstly, they are greatly affected by the adverse effects of global warming, even if their contribution to climate change is marginal. Second, they are increasingly less able to use their natural resources to generate revenues to finance their economic development, notably in their electricity sectors, due to the progressive decrease in international funding for oil and gas projects (Auge, 2021).

With shrinking budgets, governments must now redouble their efforts to invest in their power sector to provide a growing population with access to reliable, affordable, and sustainable energy. In this context, Nigerian Vice President Yemi Osinbajio spoke in the United Kingdom in October 2021 at a UN-organized summit on energy transition in Africa. His speech, ahead of COP26, reflected the African region's concern and sense of injustice towards industrialized countries in the face of the global energy transition. In his speech, the Vice President stressed that it was essential that the climate agenda, coordinated mainly by industrialized countries, which are also the main emitters of greenhouse gases, be inclusive. In other words, this agenda must also consider the needs of Nigeria in terms of economic development and, more generally, of other African countries, which are still dependent on hydrocarbons for their energy consumption and national product. According to the Vice President, it is essential to prioritize the consumption needs of citizens because, if the central grid does not meet them, they will be met by particularly polluting means such as diesel, kerosene, and firewood.

In Nigeria, because the central grid supply is unreliable, electricity demand is mainly met by auxiliary generators. The country's residential and commercial sectors extensively use these decentralized systems to generate and consume electricity during power outages. The total installed capacity of backup generators in the country is estimated to be between 10 and 15 GW, two to three times more than the centralized installed capacity available on the national grid (Arik, 2019; Arowolo and Perez, 2020). However, these standby generators are imperfect solutions because they present health risks for their users

and the environment and are relatively expensive. Indeed, auxiliary generators emit fine particles and black carbon (World Bank, 2014b; Babajide and Brito, 2021). This pollution can cause respiratory diseases. For example, according to the estimates of Heft-Neal et al. (2018), exposure to fine particulate matter in sub-Saharan Africa resulted in 449,000 additional child deaths in 2015 – this accounts for 22% of all child deaths that occurred in the 30 countries of the region.

In this final chapter how commercial consumers use their backup generators relative to grid-supplied electricity in Nigeria is examined. To do so, time series of electricity consumption produced using Machine Learning algorithms will be analyzed. This should help provide a better understanding of consumer empowerment and the use of decentralized systems by consumers in grid-covered areas. Consistent with the academic literature on the topic, the aim is to understand how improved grid reliability can affect generator usage. Unlike solar energy, the use of backup generators negatively affects the environment and health of its users. It is therefore desirable to understand how their use can be reduced.

This chapter is organized as follows. Section 2 provides a background report on the Nigerian economy. It details its heavy dependence on oil and provides an overview of the state of its power sector. Section 3 first reviews the academic literature on backup generators used in the region by residential and commercial consumers facing an unreliable grid. However, as will become apparent, this literature is particularly scarce. Secondly, section 3 reports on relevant research hypotheses to be tested regarding the questions left unanswered by the first two chapters of this thesis and the academic literature. Section 4 then details the original database used in this article. How this database was cleaned and prepared for the empirical analysis will be shown. Section 5 includes the empirical analysis. In section 5.1, the Machine Learning model used to analyze the original database will be detailed and the model's results will be presented in section 5.2. Finally, sections 6 and 7 discuss the limitations of these results and conclude the chapter.

2 Nigeria country context : a colossus with feet of clay

2.1 Nigeria's economy : a heavy reliance on oil

Located in the western part of Africa, which borders the Gulf of Guinea, Nigeria is the most populous country on the continent, with an estimated population of over 206 million in 2020 (United Nations, 2019). Nigeria is the world's 26th largest economy by nominal GDP and the region's biggest economy. With a GDP of 432 billion USD in 2020, it is the first economy in Africa and represents most of the West African region's economy. In 2020, its GDP amounted to respectively 18% and 63% of the continent's and the Economic Community Of West African States (ECOWAS)'s GDP (World Bank, 2022a). The country is also the continent's leading oil producer and the third-largest gas producer, with around 1.8 million oil barrels per day on average and 49.4 bcm of natural gas production in 2020. Nigeria has the second-largest oil reserves on the continent after Libya, with about 37 billion barrels in 2020. Nigeria also has the largest gas reserves in Africa, 190 Tcf in 2020, almost twice as much as Algeria, the second-largest country in Africa (80.5 Tcf) (British Petroleum Company, 2022).

The Nigerian economy has experienced several economic growth and recession cycles in recent decades. After four continuous years of recession between 1981 and 1984 (-7.9 % of GDP growth on average) and five years of sustained growth between 1985 and 1989 (3.6% of GDP growth on average), Nigeria experienced a downturn in economic growth in the following decade (2.3 % on average between 1990 and 1999) due to decaying infrastructure (Olofin et al., 2014; World Bank, 2022a). With the emergence of democratic rule in 1999, Nigeria has improved and stabilized its economic growth for over 15 years. Between 2000 and 2014, Nigeria experienced a prolonged period of economic growth averaging over 7.15% annually. However, after 2014, the turmoil in global oil markets contributed to a slowdown of the country's economy and a return to periods of recession. Since then, economic growth has fluctuated between a mere 2.6% expansion in 2015 and a -1.8% recession in 2020 (Olofin et al., 2014; World Bank, 2022a). This volatile economic growth can be explained by Nigeria's economy mainly being driven by oil exploitation.

The petroleum sector has always played a significant role in Nigeria's modern and contemporary economic history. Before the end of independence in 1958, oil already accounted for 58% of the country's total exports. Since then, the oil sector has gradually seen its share increase in the national economy. Over the years, this development has condemned Nigeria to run an economy based on oil extraction and trade, and led to the gradual decline of other sectors (Iyke, 2015; Itaman and Awopogba, 2021).

For example, Nigeria was considered an agricultural powerhouse in the region, but by 1973, progress in the agricultural sector eroded, mirroring a shift in public policy towards the development of the oil sector (Walker, 2000; Itaman and Awopegba, 2021). Some flourishing sectors before the oil boom such as the Nigerian cocoa industry saw their working force migrate to oil rich urban center, further contributing to its decline (Walker, 2000). This deterioration of the agricultural sector in favor of the oil sector, against a backdrop of population growth, has had long-lasting and pervasive effects on Nigeria's food vulnerability. The country gradually became increasingly dependent on food imports for its domestic consumption. The share of food imports in the country's total imports almost doubled between 1971 and 2020, rising from 8.6% to 14.6%, while the population increased from 57 to 206 million inhabitants over the same period. This vulnerability to food imports was furthermore highlighted by the COVID-19 crisis, although the share of the population experiencing moderate to high food insecurity was already increasing before the crisis. It rose from 36.5% in 2014 to 57.7% in 2019 (World Bank, 2022a).

In other sectors, Itaman and Awopegba (2021) has shown that the decline of Nigerian industry, which began in the 1980s, was linked to the development of the oil sector. To promote its industrial development, the country adopted neoliberal policies in the 1980s with a withdrawal of the state with an increased transfer of control to the private sector. The promotion of foreign direct investment (FDI) that followed was supposed to bring fresh funds to the newly liberalized sector. However, it had only a moderate impact on the manufacturing industry, as FDI was mainly directed towards the lucrative extractive sectors and made the Nigerian economy even more dependent on oil. Rise in barrel prices between the mid-1980s and the 2000s, and positive trade balance, caused the Nigerian currency, the naira, to appreciate and led to the so called "Dutch disease", further reinforcing the above mentioned trends.

Today, the Nigerian economy is still structurally dependent on oil exploitation. This heavy dependence on oil means that its economy continually struggles to stay afloat when oil prices are below 100 USD (Adesanya and Schelly, 2019). With 87% of exports and nearly 36% of government revenues coming from oil activity (International Monetary Fund, 2022), support policies for non-oil economic sectors are vulnerable to highly volatile oil revenues (Iyke, 2015). For example, the Nigerian economy suffered a very steep economic recession due to the covid-19 crisis and the subsequent decline in activity and oil prices. In 2020, its economy contracted by -1.8%. In this context, the Nigerian Minister of Finance announced on the 27th of march 2020 on Nigerian television that the crisis significantly reduced the capacity to implement the budget at both state and federal levels. This forced to lower crude oil price estimates in the 2020 budget, from 57 USD a barrel, to 30 USD a barrel. Which further high-

lighted Nigeria's vulnerability and over-dependence on oil.

It appears imperative that Nigeria succeed in diversifying its economy away from oil. To ensure multidimensional growth and escape the Dutch disease, the development of infrastructure, particularly electricity, is considered key (Adesanya and Schelly, 2019; International Monetary Fund, 2022). The development of the Nigerian power sector, however, faces many challenges.

2.2 Nigeria's power sector: low capacities and unreliable electricity supply

Over the past five years, access to electricity for citizens in rural and urban areas has stagnated or even declined in Nigeria. This was partly due to the sector's difficulty coping with a rapidly growing population. Between 2014 and 2019, the urban population increased from 83 million to 103 million city dwellers, with an urban growth rate significantly higher in Nigeria than in the rest of the region³. The rural population increased from 93 million to 98 million inhabitants. Over the same period, electrification rates stagnated and even declined as they went from 28% to 25% and from 84% to 83.9% respectively for rural and urban areas (World Bank, 2022a).

Given a population of more than 200 million inhabitants, the sector's capacities also remain underdeveloped. The Nigerian electricity centralized fleet is comprised of only about twenty production plants, of which three are hydroelectric plants, while the rest is powered by natural gas. The power plants reached an aggregate capacity of about 8.4 GW for gas against 3.6 GW for hydroelectric power plants in 2016. However, many of these capacities are not fully operational (Adesanya and Schelly, 2019), due notably to a lack of adequate maintenance of existing facilities (Oseni, 2016).

Over the first three months of 2018, the genuinely functional capacities were between 7.4 GW and 8.2 GW. However, only half of this capacity was used over the same period, with peak production between 3.7 and 4.1 GW. Several factors can explain this situation: bottlenecks in electricity transmission capacity, gas supply problems at thermal power plants, water management problems for hydroelectric power plants (Arowolo and Perez, 2020). Furthermore, the gap between electricity generation capacity and transmission capacity is estimated at 8.6 GW (Adesanya and Schelly, 2019). As a result, the country's electricity supply represents less than a third of the demand (Babajide and Brito, 2021).

Faced with the chronic lack of investment in new electricity production and

³Over 2015-2020 there were of 4.23% per year on average for 3.98% for sub-Saharan Africa (United Nations, 2018).

transmission capacities and the maintenance of existing infrastructures, the operational viability of the sector is very low, and technical and non-technical losses are high. The technical losses, mainly related to the Joule effect during the routing of electricity in the electricity distribution cables and the loss related to the passage of electric current in the transformer stations, would amount to 16% in the country. At the same time, non-technical losses due to illegal connections, defective meters, false readings during meter readings, or estimation problems would amount to more than 30%. Thus, all technical and non-technical losses would represent nearly 46% of the electricity produced by the network (Edomah et al., 2021). Which are high, even compared to the region's average.

Due to depleted electricity infrastructures in Nigeria, power outages occur more than 45% of the time, most often in the middle of the day when economic activity is at its peak and businesses, and industries need power the most (Babajide and Brito, 2021). Similarly, an average Nigerian household would only benefit from an electricity supply for about five hours a day for both urban and rural city dwellers, according to the Nigerian National Bureau of Statistics (NBS) (NBS, 2012). However, there is considerable heterogeneity in the country's electricity supply reliability. Depending on the locality, the duration of power outages can vary from 1 hour to 15, with a power outage duration of 4 hour on average in the country (Babajide and Brito, 2021).

In addition to demand and supply unbalance, Oseni (2011) explains that the numerous power cuts are directly linked to a high defection rate of 11 kV/415 V transformers on the distribution networks. The lack of information systems on the load and the state of these transformers leads to overloads and low voltages at end consumers. These overloads pose significant risks for the equipment, and the absence of switching systems in the medium/low voltage distribution network makes it impossible to isolate specific areas and to cut them off when necessary to ensure system balance. The only remaining available option is at the level of the circuit breakers, further upstream, at the substations, which leads load shedding on a high number of consumers.

As a result, poor network reliability of electricity supply has significant economic consequences. The economic costs generated by power cuts are high for the Nigerian economy. According to the IMF, these would amount to more than 29 billion USD each year (International Monetary Fund, 2019). The electricity sector is estimated to contribute only 0.32% to the economic value-added and 0.22% to the country's economic growth (Oseni, 2011). Between 2000 and 2014, about 2,000 Nigerian factories were forced to close due to difficulties linked with energy supply (Adesanya and Schelly, 2019). Consequently, entrepreneurs avoid engaging in electricity-intensive business activities, and it is partly the quality of the electricity supply that influences the choice of

business location in the country (Adenikinju, 2003).

However, stirred up by economic development and population growth, electricity demand has grown in Nigeria. Demand is expected to reach almost 297 GW by 2030 (Adesanya and Schelly, 2019). The poor reliability of the Nigerian grid and its inability to meet consumer demand has resulted in the widespread use of backup generators in the country (Emodi and Boo, 2015; Edomah, 2019; Babajide and Brito, 2021). Nigeria is an important market for these generators, including large auxiliary units that power businesses and industries and small gasoline generators used by smaller residential or commercial consumers. These latter units have spread rapidly in recent decades in the country (Lam et al., 2019).

It is estimated that Nigeria imports more than 250 million USD a year in generator sets and spare parts, making the country one of the largest markets for generators⁴ in the world and the largest in Africa (Babajide and Brito, 2021). In Nigeria, the aggregated installed capacities of auxiliary generators would amount to around 10 to 15 GW (Arik, 2019), i.e., two to three times more than the capacities available on the central network.

As a consequence, more than 70.7% of businesses own or share a generator almost 20% more than the region's average (53.5%) (World Bank, 2022b). Additionally, a million households in Nigeria would rely solely on their generators as their sole source of electricity and thus wholly emancipate themselves from the central network (NBS, 2012; Oseni, 2016). This significant use of generators in the country means that Nigerian electricity production is heavily reliant on oil; the real Nigerian electricity mix would be more carbon-intensive than estimated. In fact, 40% of the total electricity consumed in the country would be generated by these oil-fired systems (International Energy Agency, 2022a).

However, the use of these generators is a second-order solution. The cost of electricity supplied by auxiliary generators can be three times that of grid electricity (Farquharson et al., 2018). Moreover, maintenance and operating costs of generators represent a burden for companies and a brake on their growth (Adesanya and Schelly, 2019). The cost to industries for operating these generators is estimated to be around 17 billion USD per year (Lam et al., 2019). However, it should be noted that even if the use of these generators is expensive, these costs are small compared to the losses avoided due to the inability to produce during power cuts (Oseni and Pollitt, 2013; Farquharson et al., 2018).

⁴However, in the gray or academic literature it is often not clear which exact type of generators are addressed, they are often called "auxiliary generators" or "diesel generators" even though many generators are gasoline generators.

Finally, beyond the economic costs, the pollution generated by auxiliary generators is significant and presents both a risk to the health of users as well as to the environment (World Bank, 2014a). Many small gasoline generators are two-stroke engines that burn a mixture of gasoline and lubricating oil and are particularly polluting (Lam et al., 2019). Generators also create substantial noise pollution (Babajide and Brito, 2021). Among the generators that can be used in Nigeria, in general, the smaller the generator, the higher its pollution per kWh (Adesanya and Schelly, 2019).

3 Literature review and research questions

This section conducts a literature review regarding the adoption and usage of auxiliary generators in sub-Saharan Africa. First, we review the literature on the use of backup generators by residential and commercial consumers facing an unreliable grid in the region. We will see that this literature is particularly scarce, notably due to the difficulty in finding reliable data. After this, we lay out the relevant hypotheses to be tested with regard to this literature review and the questions raised in this thesis.

3.1 Literature review on auxiliary generators ownership and use in Africa

As we saw, due to the unreliability of electricity supplied, consumers tend to use auxiliary generators to consume electricity during power cuts. Therefore, we will conduct a review of the very scarce literature that has analyzed the use of backup generators in the region by residential and commercial consumers who face an unreliable network. Andersen and Dalgaard (2013) looked at the links between the low reliability of electricity networks and economic growth in a selection of sub-Saharan countries. Their analysis estimates the total effect of power outages on the economic growth of countries in the sub-Saharan region over the period 1995 to 2007. They conclude that a 1% increase in power outages reduces long-term GDP per capita by 2.86%. If the other sub-Saharan countries of their selection had experienced the same quality of electricity supply as South Africa (over the period), the average annual growth rate of real GDP per capita on the continent could have been increased by two percentage points. Similarly, for Nigeria, Adenikinju (2003) analyzed power outages' economic costs. He estimated the marginal cost of power outages to be between 0.94 USD and 3.13 USD per kWh of electricity lost using business survey data. The low quality of the electricity supply entails costs to the economy.

Given the frequency of power cuts in countries of the region, one of the most common strategies companies adopt is to invest in self-production. Faced with the problem of the costs generated by the low reliability of the network and the pollution generated by the generators, three reference articles have studied the use of auxiliary generators in the region, two for a selection of countries in sub-Saharan Africa and one for Nigeria in particular.

Oseni and Pollitt (2015) studied the differential in economic losses due to power outages between companies that invest in backup generators and those that do not. Their analysis uses a sample of 2,665 businesses in eight sub-Saharan countries from the World Bank Enterprise Survey (WBES), collected in 2007. They first find that electricity consumption, business size, and whether a company is exporting or not directly influence investment in auxiliary generators when electricity from the national electricity grid is unreliable.

They then estimate unmitigated losses, i.e., losses related to investments in stand-alone capacities that do not cover all of the electricity needs of companies when the network is down. Indeed, companies that have invested in backup generators may still suffer losses from power cuts because these investments can be partial. Consequently, auxiliary electricity production capacities do not always make it possible to cover all consumers' needs during power cuts. Analyzing data from 12 African countries, Oseni and Pollitt (2013) show that 76-100% of companies that invested in an emergency generation capacity made only partial investments and therefore remained vulnerable to power outages. This under-investment could be explained by the high variable cost of using a generator, and therefore limited this investment to what is strictly necessary to safeguard critical appliances such as cooling, Information Technology (IT), or other sensitive devices (Oseni and Pollitt, 2015). Another reason could be linked to a financial constraint linked to the high initial investment the purchase of a generator represents (Jevgenijs, 2012).

The authors thus estimate that the losses for companies having invested in autonomous electricity production systems amount to between 2.01 and 23.92 USD per kWh. However, these companies would have suffered additional economic losses of 1 to 183% if they had not invested in auxiliary generators. In comparison, the losses of companies that decided not to engage in investments in self-generating capacity would be between 1.54 and 32.46 USD per kWh. If the latter had invested in a generator, they could have reduced their losses by 6 to 46%. The authors thus show that the economic costs linked to power cuts are significant despite investing in autonomous production capacities.

One of the limitations of this study is that the authors do not have a time series on the use of generators by companies connected to the central network. Access to data is indeed a limiting factor for research on this subject. However,

having this data would allow a better understanding of how auxiliary generators are used in the context of unreliable networks. In addition, since Oseni and Pollitt (2015) base their analysis on data from surveys in which companies declare losses due to power outages, the authors state that companies could be encouraged to overestimate their losses in these declarations, which could bias the aforementioned results.

Continuing from the previous study, Oseni (2016) then investigated the links between grid reliability and generator ownership by residential households in Nigeria based on an analysis of a 2013 survey of Nigerian households residing in Lagos and Osun states. The main objective of his study was to estimate to what extent consumers would be willing to part with their generator if the quality of service improved.

His preliminary analyzes show that a certain number of factors positively and significantly influence the adoption decision of an auxiliary generator by a household. These were: the level of income, the gender of the household's head, the size of the household, the fact of having a professional activity at home, and, to a lesser extent, the frequency and duration of breakdowns. In addition, the frequency of power outages seems to be a more important factor than the average duration of outages in the decision to use a generator. Therefore, according to the author, public authorities should prioritize increased attention to reducing the frequency of power outages rather than reducing their duration.

Oseni (2016) then shows that, on average, a fifth of generator users would be willing to part with them in exchange for improved service reliability. The willingness to stop self-generation increases as the service becomes more reliable: the share of users willing to part with their generators increases from 2% to 43% if the number of hours of power available during the day is increased by 2 to 12 additional hours. However, almost a sixth of users, the wealthiest consumers, want to keep their generator even if the quality of the network is significantly improved. Therefore, these results reveal that income increases the probability of owning and using a generator and conversely reduces the probability that a household will get rid of it even if the quality of electricity supplied improves. This, therefore, follows a logic similar to the results presented in the second chapter of this thesis.

However, the data used by the author in this study relate to only 2 of Nigeria's 36 states, which could make it difficult to generalize the results to other states, which, according to the author, may have significant cultural and economic differences. Also, like other articles on the use of auxiliary generators in Nigeria, the author does not have time series of electricity consumption from auxiliary generators as a function of grid conditions. Therefore, they also rely on surveys that could be biased.

More recently, Farquharson et al. (2018) used a Monte Carlo analysis framework to estimate greenhouse gas emissions, fossil energy consumption, and costs resulting from auxiliary generators in sub-Saharan Africa. They too use World Bank Enterprise Survey (WBES) data which includes the number and duration of outages per year on average for each business. The authors believe that increased grid reliability may not automatically lead to fewer backup generator owners. However, according to their analysis, an improvement in the network's reliability leads to a drop in the use of generators and therefore, a drop in pollution and associated costs.

According to the authors' estimates, the use of generators would increase fossil energy consumption by a factor of 1.5 to 1,000 compared to the consumption of the national grids. In addition, the surplus of aggregate costs of electricity production via auxiliary generators compared to the networks would be greater than one million USD in all the countries of their selection and could reach an average of 1.6 billion USD per year in Nigeria. However, again, one of the flaws of this study is that it does not have temporal data on the use of auxiliary generators compared to the grid. While the authors argue that not all of the unmet demand may have been replaced by generator use, which would lower their estimates, they omit entirely the possibility that generators can also operate in parallel with the network when it is functioning. As we saw in section II, many households in Nigeria rely solely on their generators, which means they run parallel to the grid. Moreover, the authors indicate that they also do not have detailed data on the exact time of the blackouts during the day. However, they believe that due to the low availability of data in the region, their estimate based on a Monte Carlo analysis corresponds to the best estimate to date.

To limit the economic costs linked to power cuts, companies mainly resort to auxiliary generators. These generators allow them to consume electricity during power cuts. This section has analyzed the results of recent literature that studied the use of backup generators in the region by residential and commercial consumers who face an unreliable network. Unfortunately, despite the scale of the problem of auxiliary generators, which are widespread in sub-Saharan Africa, this academic literature is scarce. This is notably due to the lack of data availability, which is an important constraint in the region.

3.2 Research questions

Following chapters 1 and 2 of this thesis, several questions remain. We saw in Chapter 1 that the empowerment of consumers vis-à-vis the network could negatively affect the finances of the sector and condition its development. In Chapter 2, we saw that wealthier residential consumers tended to invest in distributed solar systems, regardless of the quality of electricity access they have on the central grid. We have also seen that it is common for African companies to invest in auxiliary generators to be able to continue their economic activity during power cuts. However, in the literature review, we saw that no research article has yet been able to systematically study the consumption of electricity from generators according to the states of the network. Indeed, if the academic literature has studied the link between the reliability of the network and the possession of a generator, it has only done so via survey data. The limits of these surveys are that respondents could have an incentive to bias their answers. For example, companies could be encouraged to overestimate their losses due to power cuts. Therefore, it is essential to study the actual behavior of consumers facing an unreliable network using granular time series analysis. Additionally, in their analysis, Farquharson et al. (2018) make the implicit assumption that auxiliary generators only work when the grid is not working. However, this assumption may not be verified in practice. It appears appropriate to ask whether there is a form of decorrelation between the use of generators and the quality of the network electricity supply. In other words, test the following hypothesis:

Hypothesis I: Generators occasionally run while the grid is running.

If this hypothesis was verified, if auxiliary generators operated in parallel with the network, it would be necessary to know if a model would allow us to characterize these behaviors more finely. In particular, this would allow us to determine whether all generator users adopt the same behavior vis-à-vis the network. It would therefore be necessary to test the following hypothesis:

Hypothesis II: There are differences in behavior between different generator users, some being more sensitive to the reliability of the grid than others.

If this hypothesis was true, it would mean that not all generator users use their stand-alone power generation systems in the same way with respect to the state of the central grid. Therefore, we should try to characterize and group these different behaviors. Given the questions raised by this thesis and in the continuity of the academic literature on the use of auxiliary generators by productive companies, it would be interesting to assess to what extent an improvement in the quality of the electricity supplied by the network could drive down the use of these stand-alone systems. First, the following hypothesis could be tested :

Hypothesis III: An improvement in the quality of the electricity supply from the central network can significantly reduce the use of generators

It would be necessary to estimate the magnitude with which an improvement in the quality of electricity supply can reduce the use of auxiliary generators, considering the different types of behavior previously highlighted. As discussed in chapter 1, utilities are in dire financial situations and are often unable to cover their operating costs and their capital expenses to maintain existing assets. Maintenance expenditures are often the first to be cut, contributing to further deteriorating service quality and fueling the vicious circle exposed in chapter 1. If financially constrained utilities were to improve the quality of service via maintenance investments to increase their revenues and decrease auxiliary generators use in Nigeria, they should aim at the most sensitive consumers to the network's reliability. In other words, the consumers that, if the quality of service improves, are the most likely to decrease their generator use and consume their electricity from the grid.

4 An original dataset on generator uses

This section presents the original dataset used in this chapter. First, we present the complete database and detail how we cleaned it. Then, we show how we prepare a simplified dataset from the complete one, which will be used in our empirical analysis.

4.1 Database presentation

The data used in this chapter are time series of electricity consumption from auxiliary generators of Nigerian companies connected to a deficient grid. They come from 210 smart meters installed by the A2EI (Access to Energy Institute) on auxiliary generators (196 out of 210) and on-grid meters (14 out of 210) in various regions of Nigeria. These meters continuously measure, in intervals of one to six minutes: voltage (V); current (A); the power factor; frequency (Hz); power (kW); and cumulative consumption (kWh). Each meter has its own identifier and indicates with variable: the type (generator or grid), the capacity of the generator, the type of business with which the generator is associated with, and the region in which the meter is installed. Following discussions with the A2EI institute, we were also able to retrieve the GPS coordinates of the meters (longitude and latitude), which allowed their location to be further refined. However, for user privacy reasons, random noise of 5 to 10 meters has been added to each of them. Table III.1 details the temporal data variables available for generators and table III.2 for grid-connected meters. Table III.3

Table III.1: Temporal data variables for generators

Variable name	Value	Description
meter_number	ID	unique identifier of smart meter
record_time	YYYY-MM-DD HH:MM:SS (UTC)	timestamp of measurement
meter_count	kilowatt hours (kWh)	cumulative energy generated to date
a_voltage	volts (V)	active voltage at time of measurement
a_current	amperes (A)	active current at time of measurement
a_power	kilowatts (kW)	active real power at time of measurement
a_power_factor	ratio	apparent power / real power
frequency	herz (Hz)	frequency at time of measurement

Table III.2: Temporal data variables for grid connected meters

Variable name	Value	Description
meter_number	ID	unique identifier of smart meter
record_time	YYYY-MM-DD HH:MM:SS (UTC)	timestamp of measurement
a_voltage	volts (V)	active voltage at time of measurement
frequency	herz (Hz)	frequency at time of measurement

describes the variables available for the generators and grid-connected meters.

The raw database includes 2,348,980 observations and covers the period from June 1, 2019 at midnight (2019-06-01 00:00) to April 23, 2020 at 11:59 p.m. (2020-04-23 23:59). However, it should be noted that each generator only covers part of this period, depending on the date of their installation and whether they have been withdrawn or were malfunctioning.

This is, to our knowledge, the first time that such an extensive and granular database is used in academic research on electricity consumption by consumers connected to an unreliable network in sub-Saharan Africa. However, due to the nature of the terrain and the various technical issues in the region (for example, GPRS transmission), this database is not perfect and had to be cleaned. Furthermore, among the main limitations observed in the database are missing values among the variables. A lot of missing values for the meters are reported for : generator capacity, GPS data, and type of business, for example. The

Table III.3: Variables description table

Variable name	Value	Description
meter_number	ID	unique identifier of smart meter
meter_status	connected OR disconnected	whether meter is currently installed at listed account
connection_date	YYYY-MM-DD (UTC)	date meter was connected to listed account
disconnection_date	YYYY-MM-DD (UTC)	date meter was disconnected from listed account
type	generator OR grid	specifies what the smart meter is monitoring
generator_capacity	watts (W)	nominal power of generator (i.e. rated power)
type_of_business	-	describes the type of business
class_of_business	-	general grouping of some type of business
market	-	location
longitude	Decimal degree system	fine-grained geolocalized location
latitude	Decimal degree system	fine-grained geolocalized location

fact that a lot of meters have missing GPS data prevents us from using these specific meters later in the analysis.

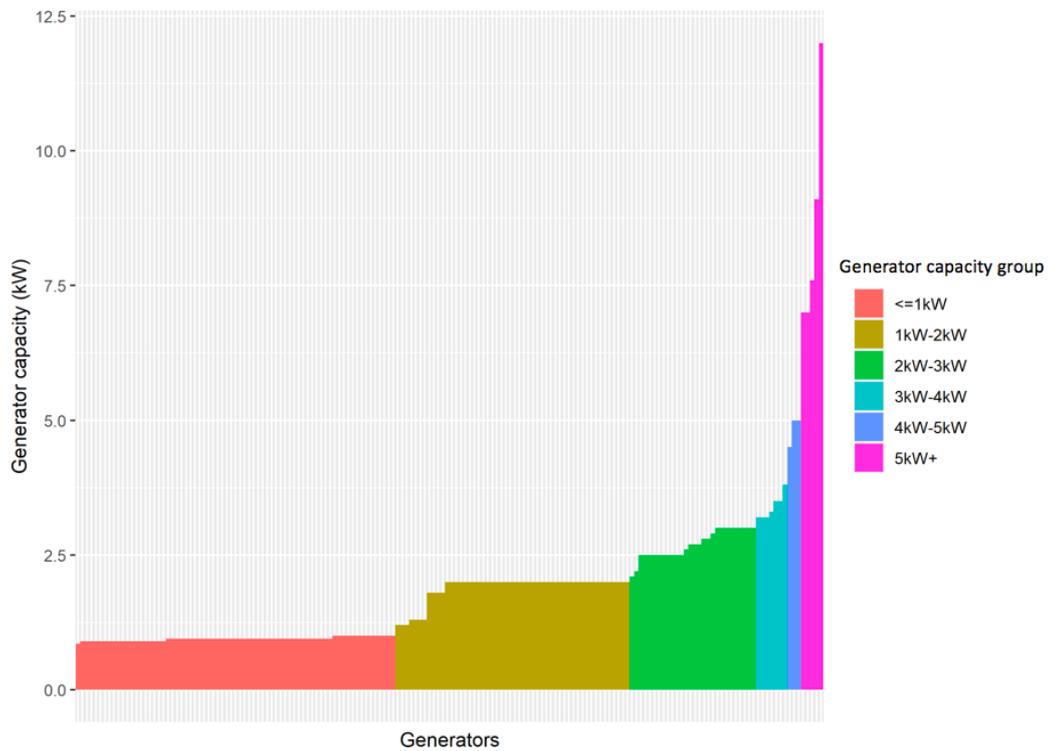
From the database, several variables have been added in order to facilitate the analysis: *generator_capacity_group*, which corresponds to the group in which a generator is according its capacity. We have classed our generators in 6 different groups depending on their available capacities, as shown in III.4 and figure III.1. These groups ranges from less than 1 kW to more than 5 kW. *geographical_cluster* is another constructed variable, which divides into 16 subgroups the location of the generators thanks to GPS data, the subgroups were made by regrouping all meters that were in a range of less than a kilometer from each other.

Data inconsistencies were found between the active power given by the raw database and the active power recalculated from the product of voltage and current (apparent power) and power factor. Following a discussion with the A2EI engineering teams, we were told that the most reliable variable was the power factor. So we decided to recalculate the active power using the product of the apparent power and the power factor and create the variable *calculated_a_power*. We also add a quality criterion for the electricity from the central network: low, normal or high, which corresponds to a deviation of less or more than 10% of the target value of 230 V.

Some series or parts have been deleted due to relocation issues. About fifteen generators have been relocated by A2EI teams on the ground to other businesses in the same locality. These relocations caused duplicates in the time series, which could not be separated automatically and therefore we were not able for these to distinguish between periods of use. In most cases, either the meter was not working correctly before the relocation, or it was working correctly and began to be non-functional after relocation. It was therefore decided to delete the part of the time series which was of lower quality before or after the relocation. In addition, four meters that were not working at all or very badly and were removed. With the GPS data, we could see that some of the meters had been incorrectly located, two had their types inverted, so we made the appropriate adjustments.

Interestingly, preliminary analysis of our generator shows that they are running much below their full capacity. On average, less than a fifth of the maximum power (18.16%) is needed when using the generators. The average load of a generator is much lower than their capacity, with a downward trend depending on the generator's capacity as shown in table III.5. Large generators seem to operate at a lower relative capacity than small generators, which are more used on average. A2EI notes that large generators are mainly used because of their longer lifespan than smaller ones. These observations are, however,

Figure III.1: Generator capacities per group (kW) in the full dataset



Source : A2EI (2019) - Graph by authors

Table III.4: Number of meters per generator capacity group

Generator capacity group	Number of generators
<=1kW	71
1kW-2kW	52
2kW-3kW	28
3kW-4kW	7
4kW-5kW	3
5kW+	5
NA	53
Total	219

Source : A2EI (2019) - Graph by authors

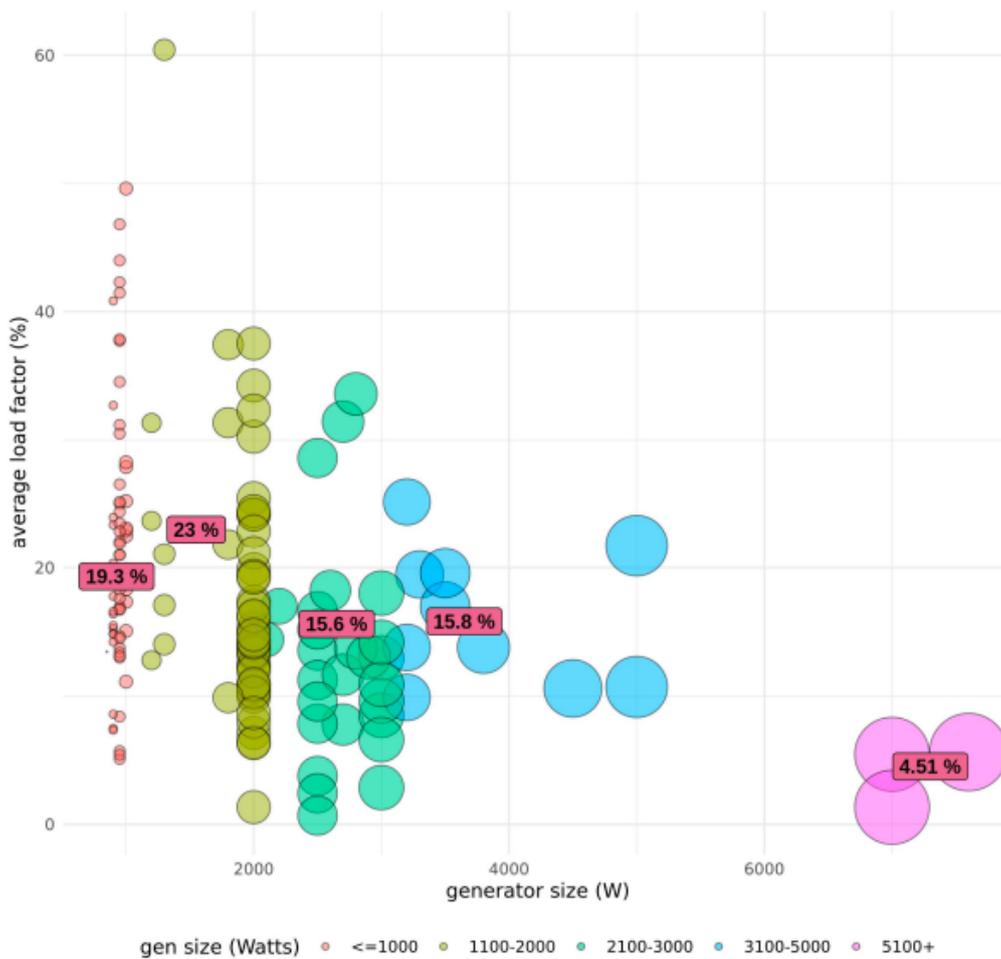
contrary to the ones of Oseni and Pollitt (2013), who noted that the companies which invested in auxiliary generators still suffered losses linked to power cuts because their investments in auxiliary generators were partial most of the time and did not fully cover their electricity consumption needs during power outages. Businesses were therefore still vulnerable to power outages. However, that does not seem to be the case for our sample here. However, it should be noted that the generators studied here are used by companies that

Table III.5: Load factor per generator capacity group (% of maximum capacity)

Generator capacity group	Load factor (% of capacity)
<=1kW	20.54
1kW-2kW	17.75
2kW-3kW	12.63
3kW-4kW	16.81
4kW-5kW	14.20
5kW+	5.61

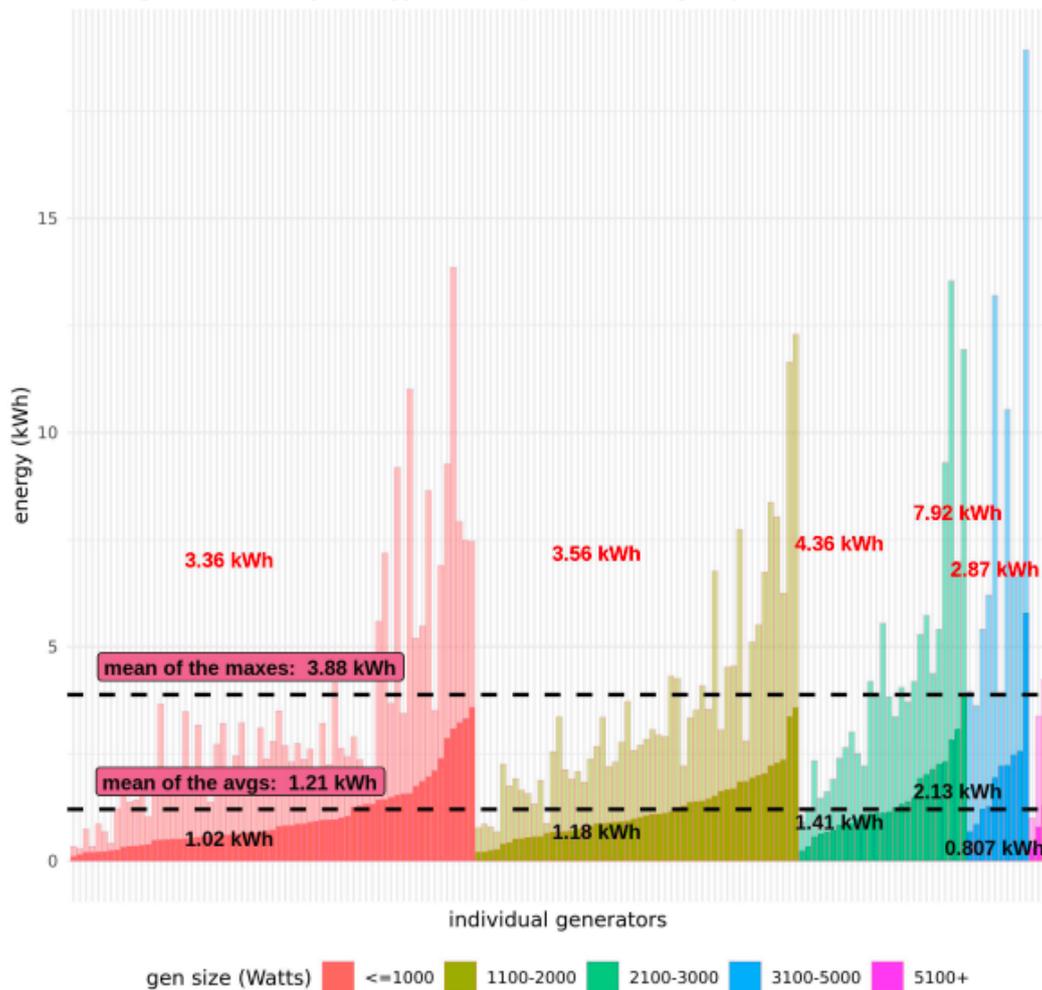
Source : A2EI (2019) - Graph by authors

Figure III.2: Average load factor by generator capacity (with group mean) in kWh



Source : Violand (2019)

Figure III.3: Average and maximum daily energy consumption served per generator (with group means)



Source : Violand (2019)

can be mainly related to commercial businesses and not companies producing goods. As a matter of fact, A2EI conducted a parallel field survey during the installation of meters on generators and studied the used devices found in stores or businesses. They observed that the electrical needs related to the use of generators were relatively low and were mainly limited to the use of equipment such as lighting, fans, televisions, etc. These relatively moderate uses of electricity required an average power of 230 W per company and could explain this oversizing of the generators. This is also confirmed by figures III.2 and III.3, provided by A2EI, which show the average load factor by generator capacity and the average and maximum daily energy consumption served per generator. An auxiliary generator's average electricity consumption in a day is 1.21 kWh, with, again on average, maximum electricity consumption of 3.88 kWh in a day. A2EI therefore noted that a solar system providing 350

We could therefore already replace more than 75% of generators in their dataset.

Finally, table A.III.1 and table A.III.2 in annex show the mean per market and per generator capacity group of the median daily use in minutes per generator. We see less variability in usage in minutes per generator capacity group than per market. Daily use in minutes goes from a minimum of 113 minutes for the 3kW-4kW generator capacity group to a maximum of 214 minutes for the 1kW capacity group. However, the minimum goes from 75 minutes of use in Banex to more than 300 minutes in Ap Plaza. We took the median of use per generator as the distribution of generator use appears to be heavily skewed, as shown in figure A.III.1 in annex. We can already conclude that there significant differences in generator uses. It appears at first glance that those differences are more important when grouping per market than per generator capacity group. This could indicate a more homogeneous use of generator use between generator capacity groups.

4.2 Data preparation

In this section we show how we prepared the final dataset for the empirical analysis. First, we show in section 4.2.1 how we simplified our database to focus on usage patterns of generators with regard to the grid's reliability. In other words, to study the use of generators with regards to the grid's states, we focus principally on the patterns of generators' ignition and extinction, depending on the state of the grid (whether the grid is functioning or not). More specifically, we focus on probabilities of ignition and extinction of both the central networks and the generators to conduct our analysis. We also conduct a simple preliminary analysis to familiarize the reader with the database. We seek which variables to consider to describe correctly the transition probabilities of extinction and ignition of generators in section 4.2.2. We then prepare the final database according so.

4.2.1 Data simplification

Many quantitative analyses could be performed on this database, as it is extremely rich in information. However, given the questions left unanswered by the first chapters of this thesis and academic literature, we only focus on generator usage patterns depending on centralized network states. Unfortunately, on-grid installed meters do not cover all areas where auxiliary generators meters are present. Because of the high heterogeneity in the reliability of power provided by the central grid, which exists between different localities in Nigeria as we have seen in the first parts of this chapter, we select the generators which are at a maximum distance of 1 km of a meter installed on the network. This should allow us to ensure that we are comparing the use of generators accord-

ing to the states of the related network. The heterogeneity in grid reliability mentioned above is illustrated in figure III.4, where we can see that there is important heterogeneity in the probabilities of the grid to be "on" depending on the time of the day per locality.

We, therefore, had to restrict our analysis to 67 generator meters in 5 sub-regional groups (called "geographical cluster") where we have both operational status data from the central network and auxiliary generator usage data. The geographical cluster corresponds to sub-groups where all generators and grid meters are within a maximum distance of 1 km from each other⁵. The full descriptive statistics for the final selection of grid meters are given in table A.III.4 and for generators meters in table A.III.5 in appendix. We then segment each day into 10-minute slices to homogenize our time series between them to make them comparable. As generators can send information on ignition at different time gap⁶. The 10-minute threshold was chosen to keep enough observations without risking "breaking" some time series, as some generators send information in longer time periods than the average. For example, if we had chosen a threshold of 5 minutes, a generator "on" all day but sending information every 6 minutes would have had a succession of phases "on" and phases "off" as time series. We also simplify our time series by making them binary. Thus, when a generator is "on", it takes the value 1 and when it is "off", it takes the value 0. We proceed in a similar way for the network data.

To recapitulate, we proceed to the following simplifications :

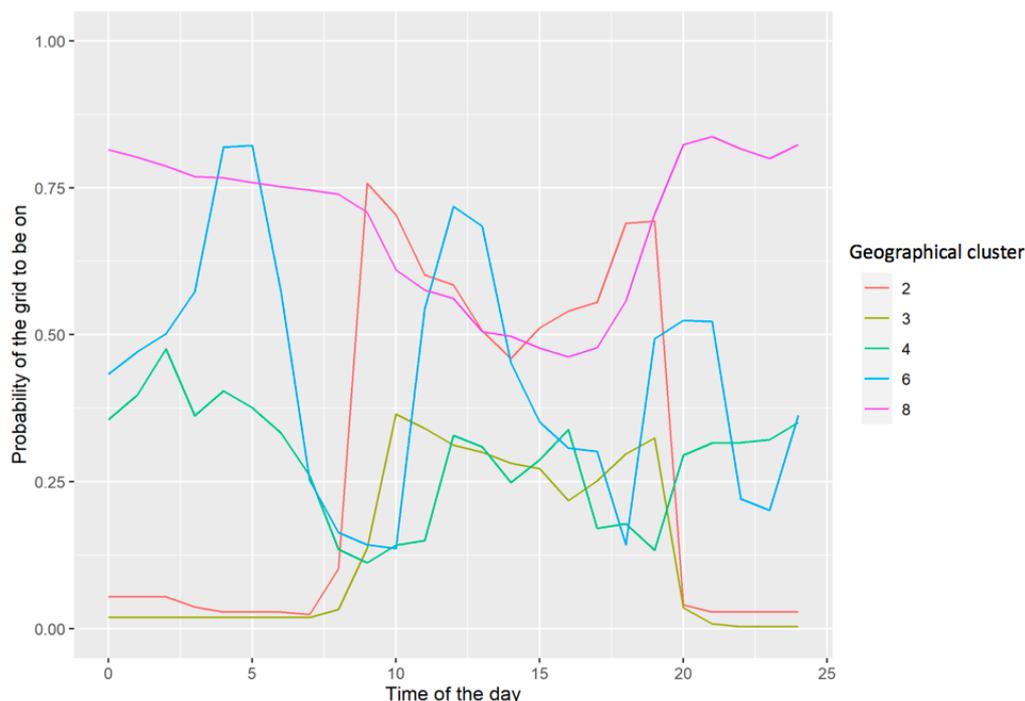
1. We group generator and grid meters in 8 geographical clusters where the maximum distance is 1,000 meters between two meters.
2. We segment each day into 10-minutes slices and take the average of the variables.
3. We simplify our time series by giving to a generator or to a grid meter the value 1 when it is "on" and 0 otherwise.

Due to lack of grid data for the geographical cluster number 1, 5 and 7 (no meters were installed by A2EI in those two areas), we will have to restrict the analysis to 5 geographical clusters : geographical cluster 2, 3, 4, 6 and 8. Preliminary analysis shows that during the day (between 7 a.m. and 12 p.m.), a generator is more likely to operate when the grid is "off" (probability of 0.289) than when the grid is "on" (probability of 0.139), which is close to our expectations. When we look at the generator ignition probabilities as a

⁵The geographical cluster 2 corresponds to a sub-group in Wuse, the geographical cluster 3 corresponds to Lagos, the geographical cluster 4 and 6 correspond to two sub-groups in Kano and the geographical cluster 8 corresponds to Kubwa.

⁶For example some generators send information every 2 minutes, while other every 3 or 6 minutes.

Figure III.4: Probabilities of the grid to be "on" depending on the time of the day in the five sub-regions covered (geographical cluster)



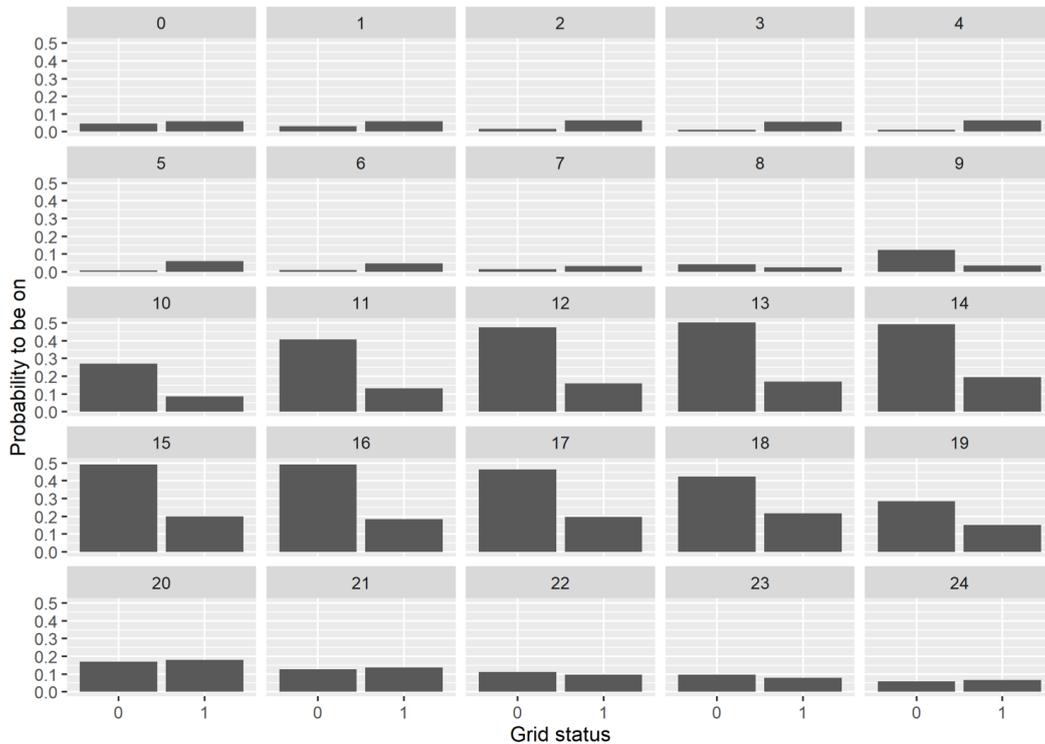
Source : A2EI (2019) - Graph by authors

function of grid states by the time of day, as depicted in figure III.5, we observe that generators are much more likely to be "on" between 9 a.m. and 9 p.m. Also, as expected, ignition probabilities are much higher when the grid is not working than when the grid is working. However, strangely, it seems that between midnight and 5 am, the probabilities of generator ignition, although low, are reversed. Indeed, generators running at this time slot seem to have a better chance of being ignited when the grid is running. This may seem counter-intuitive at first. However, in figure III.6 we see that the generators running during this time slot essentially belong to the "foods and drinks" class of business. For safety, therefore, facing an unreliable grid, we can imagine that these businesses will turn "on" their generators at night so as not to lose merchandise if the network ever goes down during the night.

4.2.2 Independence analysis

We seek which variables to consider to describe correctly the transition probabilities of extinction and ignition of generators. To do so we "unroll" the chain of use of our generators. We do so regarding the grid status (10 minutes ago) and the generators' status (10, 20, and 30 minutes ago). Those chains of use are represented in the tables III.6, III.7 and III.8. In each table, the probability

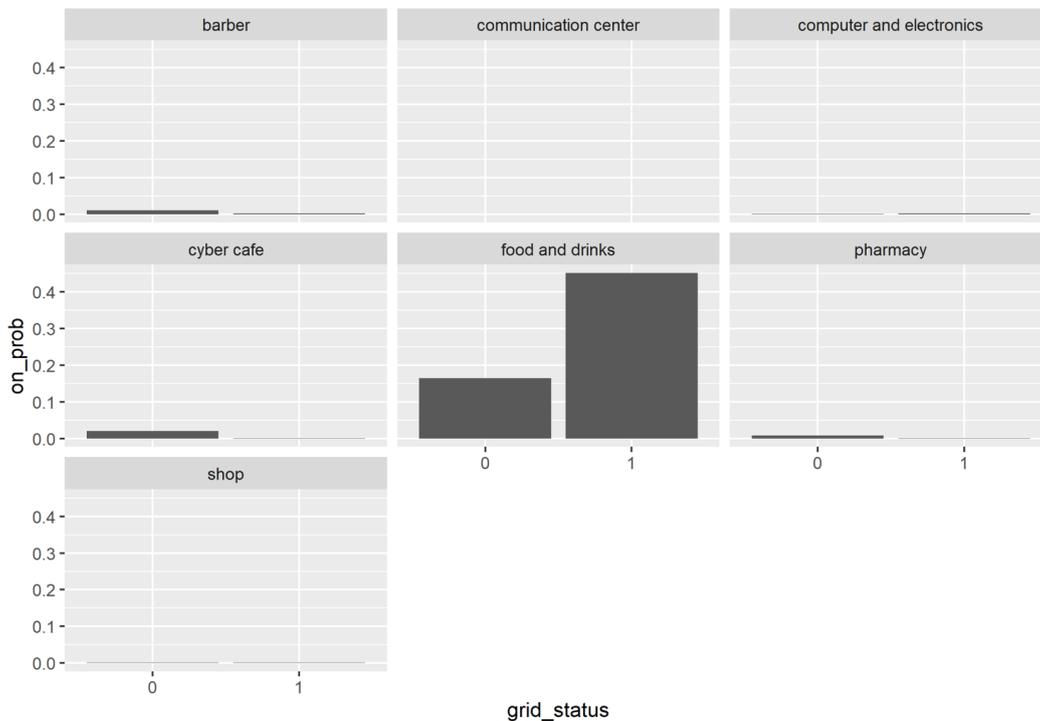
Figure III.5: Probabilities of all generators to be "on" depending on the time of the day and the grid activity (grid status = 0 means that the grid is down, grid status = 1 means that the grid is running)



Source : A2EI (2019) - Graph by authors

of observing a generator turned "on" is ranked from the highest to the lowest. In the table III.6 we always have a higher probability that the generator will be "on" controlling for the grid status. However, generator probability to be "on" seems to be much more sensitive to its own status one period ago. Indeed, if the grid is "on", the generator's probability to be "on" is much higher if the generator was "on" one period ago (0.835) than if it was "off" (0.025). If the grid is "off", the probability of a generator being "on" is much higher if it was "on" (0.904) than if it was "off" (0.046) 10 minutes ago. In table III.7 we added the generator status 20 minutes ago. Reordering by probability, we see again that the generator's probability of being "on" behaves as expected with regard to previous observations. The probability of a generator to be "on" controlling for its own status is always higher when the grid is "off". Similarly, the probability of the generator to be "on" controlling for the grid status is higher the longer the chain of use of the generator is. In table III.8, we add one more generator status (30 minutes ago). However, this extra information does not seem to add much. The generators' probabilities of being "on" are much less well defined than previously, and probability values can be very close to each other.

Figure III.6: Probabilities of the generators to be "on" at night (0 a.m. to 5 a.m.) depending on the grid status by class of business



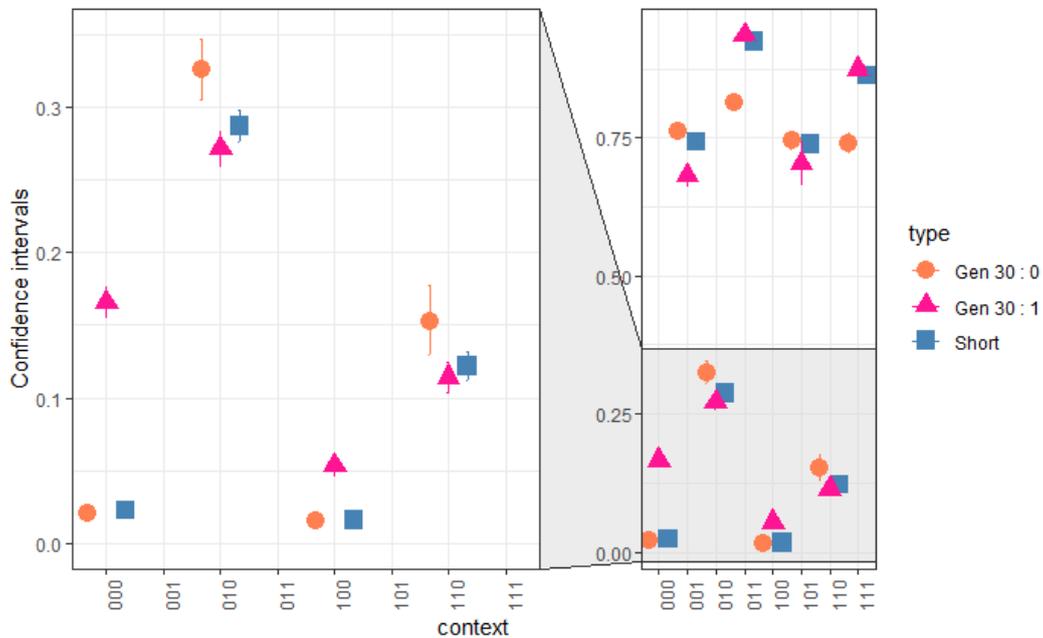
Source : A2EI (2019) - Graph by authors

We can also make an assessment of independence with the help of figures III.7, III.8 and III.9. The figures show the probabilities calculated with the whole set of generators along with their confidence intervals with regard to their specific context. The contexts are defined with regard to the past status of the grid and of the generators. The "short" context in the figures corresponds to the contexts in abscissa, where we take the past status of the grid (10 minutes ago) and two periods of time for the generators (10 and 20 minutes ago). For example, if the grid was "off" ten minutes ago but the generator was "on" ten and twenty minutes ago, the corresponding context would be "011". We then add up more contextual information. In figure III.7, we add the generator status 30 minutes ago, in figure III.8 the grid status 20 minutes ago and in figure III.9 both the generator status 30 minutes ago and the grid status 20 minutes ago. We then assess if probabilities along with their confidence intervals are significantly different between the short context and the extended ones which would give indication of dependence.

In all the three figures we can easily see that there are clear overlaps between most probabilities and their confidence intervals. It gives an indication that adding up extra temporal information does not enrich much our knowledge about the present generator's status. However, in some contexts, there

are distinct probabilities and confidence intervals between short and extended contexts, as for example in context "111" in figure III.7. Interestingly, in that case, we do not see a very significant difference in probabilities and confidence between the short context and the extended one when the generator status is "off" 30 minutes ago. However, there is a significant difference when the generator status is "on" 30 minutes ago. This would mean that adding the generator status if it was "on" 30 minutes ago would actually add valuable information.

Figure III.7: Probabilities and confidence intervals of the short contexts versus the shorts context and the generator status 30 minutes ago (the short context corresponds to the basic 3 dimensional K)



Source : A2EI (2019) - Graph by authors

In light of this, we make the assumption that controlling for the past status of the grid (10 minutes ago) and two periods of time for the generators (10 and 20 minutes ago) makes our observations independent between each other, controlling by generator. The conditional independence assumptions is summarized in the directed graph in figure III.10.

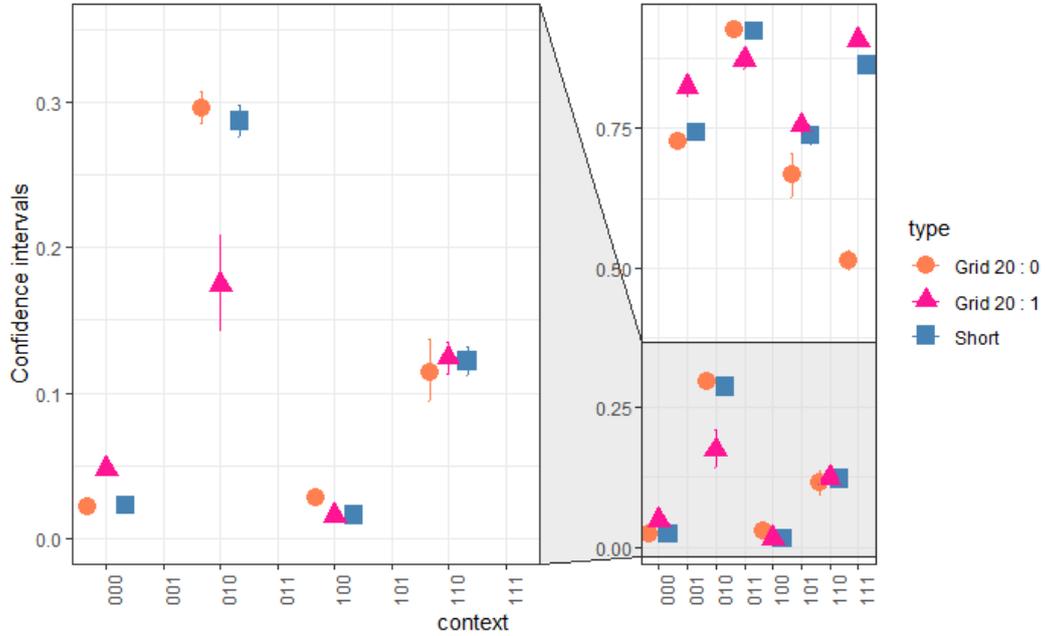
Table III.6: Probability of a generator to be "on" with regard to grid status and generator status, ten minutes before for the grid and 10 before for the generator (the short context corresponds to the basic 3 dimensional K)

grid_status_10_m	on_off_10_m	on_prob
0	1	0.9048853
1	1	0.8355585
0	0	0.0462447
1	0	0.0250168

Table III.7: Probability of a generator to be on with regard to grid status and generator status, ten minutes before for the grid and 10 and 20 minutes before for the generator

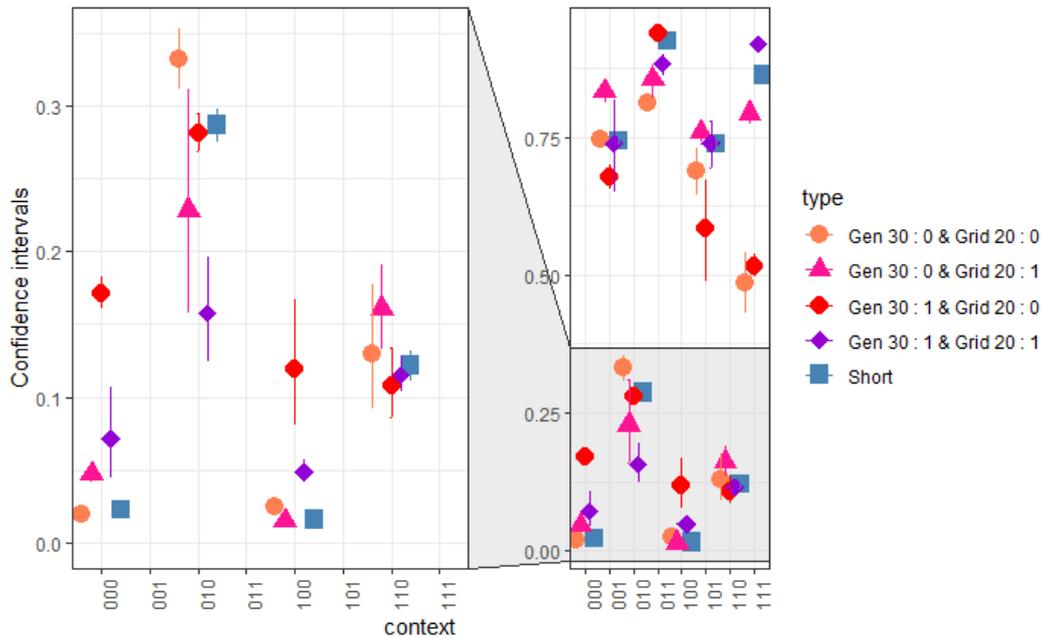
grid_status_10_m	on_off_20_m	on_off_10_m	on_prob
0	1	1	0.9248885
1	1	1	0.8496262
0	0	1	0.7414242
1	0	1	0.7334025
0	1	0	0.2949609
1	1	0	0.1229508
0	0	0	0.0370964
1	0	0	0.0221071

Figure III.8: Probabilities and confidence intervals of the short contexts versus the shorts context and the grid status 20 minutes ago (the short context corresponds to the basic 3 dimensional K)



Source : A2EI (2019) - Graph by authors

Figure III.9: Probabilities and confidence intervals of the short contexts versus the shorts context, the generator and the grid status 30 and 20 minutes ago (the short context corresponds to the basic 3 dimensional K)

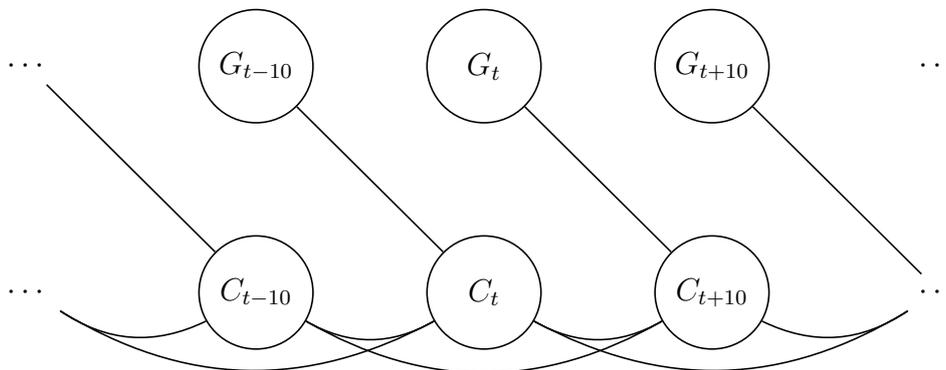


Source : A2EI (2019) - Graph by authors

Table III.8: Probability of a generator to be on with regard to grid status and generator status, ten minutes before for the grid and 10, 20 and 30 minutes before for the generator)

grid_status_10_m	on_off_30_m	on_off_20_m	on_off_10_m	on_prob
0	1	1	1	0.9364973
1	1	1	1	0.8610456
0	0	1	1	0.8143749
0	0	0	1	0.7600373
1	0	0	1	0.7392781
1	0	1	1	0.7367876
1	1	0	1	0.7076350
0	1	0	1	0.6824458
0	0	1	0	0.3265007
0	1	1	0	0.2816553
0	1	0	0	0.1719035
1	0	1	0	0.1530055
1	1	1	0	0.1150417
1	1	0	0	0.0537037
0	0	0	0	0.0334590
1	0	0	0	0.0212779

Figure III.10: Directed graph of the conditional independence assumptions



Source : Authors

5 Empirical analysis

To test these hypotheses and answer questions left unanswered by previous chapters as well as academic literature, we would like to use a custom unsupervised Machine Learning model that allows us to first group generators with similar behavior into clusters, then to determine the probabilities of ignition and extinguishing of the generators with regard to the states of the network. This should allow us to characterize better and understand the operation of generators vis-à-vis an unreliable central network.

We use an unsupervised Machine Learning model to analyze our data and answer our research questions while keeping the maximum granularity of our time series. However, as it is difficult to access electricity consumption data in Sub-Saharan Africa, it can also be complicated to analyze very granular datasets.

For example, in Nigeria, Adesanya and Schelly (2019) assessed the economic viability of solar PV-DG hybrid systems among private companies via an approach modeling their Levelized Cost of Energy (LCOE). They have conducted a survey to collect data from 150 Nigerian companies. However, they only received 40 responses. Of these 40 responses, only 28 companies provided data that could be used for their modeling exercise using HOMER Pro 3.9. However, they only perform an accurate quantitative analysis on three companies. This analysis shows the inherent difficulty of obtaining granular data in the region. Moreover, the fact that the authors confine themselves to the study of only three companies shows the difficulty of studying large granular datasets.

In our analysis, we use a very heterogeneous database, with, for example, observation periods that can be very different from one generator to another. To not have to simplify these data and thus lose information in our analysis, we need to set up a flexible model that can adapt to our data's heterogeneity and granularity. We address this difficulty by using unsupervised Machine Learning tools. The methodology used is detailed in the section 5.1 and the results in section 5.2.

5.1 A mixture model for electricity consumption

The goal of the model is to study a representation of the data in which each individual generator has a binary state (1 for "on", 0 for "off") which depends on its own binary state, 20 minutes and 10 minutes ago, along with the grid's state 10 minutes ago.

5.1.1 Principle

We observe N generators represented by a K dimensional array. Each k (where $k = 1, \dots, K$) represent a specific context of the grid status ($on = 1$ or $off = 0$) one period ago (10 minutes) along with a generator's past binary status two and one period ago (20 minutes and 10 minutes) for a generator i . For example, the context ($K = 001$) corresponds to a grid that was "off" ten minutes ago and a generator that was "off" 20 minutes ago and turned "on" ten minutes ago.

M_{ik} is the binary state of the generator i after having observed the context k .

We assume that there exists S subsets of generators. Each generator is associated to an unknown subset, given by the latent variable Z_i (with values $\{1, \dots, S\}$). The Z_i are assumed to be independent and identically distributed according to the categorical distribution characterised by $\pi \in [0 : 1]^S$, with $P(Z_i = s|\pi) = \pi_s$. We use the standard dual notation in witch Z_i denotes both a random variable with values in $\{1, \dots, S\}$ and a random binary vector with values in $\{0, 1\}^S$, such that $Z_i = s$ corresponds to $\forall h \neq s, Z_{ih} = 0$ and $Z_{is} = 1$.

We assume the M_i to be independent given the $(Z_i)_{1 \leq i \leq N}$.

But also, because we have made the assumption that within our generators, our observations were conditionally independent between each other while controlling for the grid's state 10 minutes ago and the generator status 20 and 10 minutes ago (as depicted by figure III.11), we can consider a set of K variables $M_k \in \{0, 1\}^K$ and quantities $M_{1k}, M_{0k} \in \mathbb{Z}$ which corresponds to the number of times we have observed a generator to be "on" and "off" after observing the context k . We can therefore finish to prepare our database according so. For each generator, we will prepare the quantities M_{1k}, M_{0k} . Each of the M_k are governed by a distribution with parameter λ_k , so that :

$$p((m_k)_{1 \leq k \leq K} | (\lambda_{sk})_{1 \leq s \leq S, 1 \leq k \leq K}, (\pi_s)_{1 \leq s \leq S}) = \sum_{s=1}^S \pi_s \prod_{k=1}^K \lambda_{sk}^{m_{1k}} (1 - \lambda_{sk})^{m_{0k}}$$

where parameter λ_{sk} corresponds to the probability that a generator which belong to the subset s is ignited, after having observed the context k . For example, $\lambda_{1-001} = 0.5$ means that a generator belonging to subset 1, has a 0.5 probability to be ignited after having observed the context 001 (the grid was "off" ten minutes ago and the generator was "off" twenty minutes ago then turned "on" ten minutes ago).

If we are given a dataset $M = m_1, \dots, m_N$ the log likelihood function for this model is given by :

$$\ln p((m_{ik})_{1 \leq i \leq N, 1 \leq k \leq K} | (\lambda_{sk})_{1 \leq s \leq S, 1 \leq k \leq K}, (\pi_s)_{1 \leq s \leq S}) = \sum_{i=1}^N \ln \left\{ \sum_{s=1}^S \pi_s \prod_{k=1}^K \lambda_{sk}^{m_{1ik}} (1 - \lambda_{sk})^{m_{0ik}} \right\}$$

We now have a summation inside our logarithm and therefore the maximum likelihood solution has no longer a closed form.

We therefore derive the EM algorithm for maximizing the likelihood function for the mixture distributions. We reintroduce our latent variable Z associated with our M_i .

We can rewrite the conditional distribution of M , given the latent variable as :

$$p((m_k)_{1 \leq k \leq K} | (z_s)_{1 \leq s \leq S}, (\lambda_{sk})_{1 \leq s \leq S, 1 \leq k \leq K}) = \prod_{s=1}^S \left(\prod_{k=1}^K \lambda_{sk}^{m_{1k}} (1 - \lambda_{sk})^{m_{0k}} \right)^{z_s}$$

the prior distribution for the latent variable is :

$$p((z_s)_{1 \leq s \leq S} | (\pi_s)_{1 \leq s \leq S}) = \prod_{s=1}^S \pi_s^{z_s}$$

the full data likelihood is given by :

$$p((m_{ik})_{1 \leq i \leq N, 1 \leq k \leq K}, (z_{is})_{1 \leq i \leq N, 1 \leq s \leq S} | (\lambda_{sk})_{1 \leq s \leq S, 1 \leq k \leq K}, (\pi_s)_{1 \leq s \leq S}) = \prod_{i=1}^N \prod_{s=1}^S \left(\pi_s \prod_{k=1}^K \lambda_{sk}^{m_{1ik}} (1 - \lambda_{sk})^{m_{0ik}} \right)^{z_{is}}$$

Therefore, the complete-data log likelihood gives us :

$$\ln p((m_{ik})_{1 \leq i \leq N, 1 \leq k \leq K}, (z_{is})_{1 \leq i \leq N, 1 \leq s \leq S} | (\lambda_{sk})_{1 \leq s \leq S, 1 \leq k \leq K}, (\pi_s)_{1 \leq s \leq S}) = \sum_{i=1}^N \sum_{s=1}^S z_{is} \left(\ln \pi_s + \sum_{k=1}^K m_{1ik} \ln \lambda_{sk} + m_{0ik} \ln(1 - \lambda_{sk}) \right)$$

5.1.2 EM algorithm

(1) Expectation phase

However we are not given this complete data M, Z but only the incomplete data M . The knowledge we have for Z is given only by the posterior distribution $p(Z|M, \lambda)$. Because we cannot use directly the complete data log likelihood, we consider instead its expected value under the posterior distribution of the latent variable.

$$\gamma(z_{is}) = E[z_{is} | m_{ik}, \pi_s, \lambda_{sk}] = P(z_{is} = 1 | m_{ik}, \pi_s, \lambda_{sk}) = \frac{P(m_{ik} | z_{is} = 1, \pi_s, \lambda_{sk}) P(z_{is} = 1 | \pi_s, \lambda_{sk})}{\sum_{s'}^S P(m_{ik} | z_{is'} = 1, \pi_{s'}, \lambda_{s'k}) P(z_{is'} = 1 | \pi_{s'}, \lambda_{s'k})} = \frac{\pi_s \prod_{k=1}^K \lambda_{sk}^{m_{1ik}} (1 - \lambda_{sk})^{m_{0ik}}}{\sum_{s'}^S \pi_{s'} \prod_{k=1}^K \lambda_{s'k}^{m_{1ik}} (1 - \lambda_{s'k})^{m_{0ik}}}$$

Therefore :

$$E_Z[\ln p((m_{ik})_{1 \leq i \leq N, 1 \leq k \leq K}, (z_{is})_{1 \leq i \leq N, 1 \leq s \leq S} | (\lambda_{sk})_{1 \leq s \leq S, 1 \leq k \leq K}, (\pi_s)_{1 \leq s \leq S})] = \sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is}) \left(\ln \pi_s + \sum_{k=1}^K m_{1ik} \ln \lambda_{sk} + m_{0ik} \ln(1 - \lambda_{sk}) \right)$$

(2) Maximisation phase

We need to maximise the above expression with respect to π_s and λ_{sk} .

$$\begin{aligned} \frac{\partial E_Z[\dots]}{\partial \lambda_{sk}} &= \sum_{i=1}^N \gamma(z_{is}) \left[\frac{m_{1ik}}{\lambda_{sk}} + \frac{m_{0ik}}{1 - \lambda_{sk}} \right] = 0 \\ \sum_{i=1}^N \gamma(z_{is}) [m_{1ik}(1 - \lambda_{sk}) + m_{0ik}\lambda_{sk}] &= 0 \\ \lambda_{sk} &= \frac{\sum_{i=1}^N m_{1ik} \gamma(z_{is})}{\sum_{i=1}^N (m_{1ik} + m_{0ik}) \gamma(z_{is})} \end{aligned}$$

For π_s we only need to maximize $\sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is}) \ln \pi_s$ since the rest is not a function of π .

To keep π as a distribution we require $\sum_{s=1}^S \pi_s = 1$. We set λ .

$$\begin{aligned} S(\pi, \lambda) &= - \sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is}) \ln \pi_s + \lambda \sum_{s=1}^S (\pi_s - 1) \\ \frac{\partial S(\pi, \lambda)}{\partial \pi_s} &= - \sum_{i=1}^N \frac{\gamma(z_{is})}{\pi_s} + \lambda = 0 \end{aligned}$$

$$\pi_s = \frac{\sum_{i=1}^N \gamma(z_{is})}{\lambda}$$

Now we solve for λ .

$$S(\lambda) = - \sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is}) (\ln \gamma(z_{is}) - \ln \lambda) + \left(\sum_{s=1}^S \gamma(z_{is}) - \lambda \right)$$

$$\frac{\partial S(\lambda)}{\partial \lambda} = \frac{1}{\lambda} \sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is}) - 1 = 0$$

$$\lambda = \sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is})$$

and so :

$$\pi_s = \frac{\sum_{i=1}^N \gamma(z_{is})}{\sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is})}$$

We can now proceed as follows : we choose initial values for our parameters $\lambda_{sk}^{(0)}$ and $\pi_s^{(0)}$ and we use these to calculate the responsibilities $\gamma(z_{is})^{(1)}$ (expectation phase). We then keep the responsibilities fixed and maximise the expected value of the complete likelihood with respect to π_s and λ_{sk} (maximisation phase). We then use those new found parameters' values $\lambda_{sk}^{(1)}$ and $\pi_s^{(1)}$ to calculate the new responsibilities $\gamma(z_{is})^{(2)}$ and iterate.

(3) Final algorithm

The EM algorithm in this case can be written as follows :

1. Initialisation step :

Initialise $\lambda_{sk}^{(0)}$ and $\pi_s^{(0)}$,

Then for j from 1 to max :

2. Expectation step :

Compute $\forall i$ and $\forall s$,

$$\gamma(z_{is})^{(j)} = \frac{\pi_s^{(j-1)} \prod_{k=1}^K \lambda_{sk}^{(j-1)m_{1ik}} (1 - \lambda_{sk}^{(j-1)})^{m_{0ik}}}{\sum_{s'}^S \pi_{s'}^{(j-1)} \prod_{k=1}^K \lambda_{s'k}^{(j-1)m_{1ik}} (1 - \lambda_{s'k}^{(j-1)})^{m_{0ik}}}$$

3. Maximisation step :

compute $\forall s$ and $\forall k$,

$$\lambda_{sk}^{(j)} = \frac{\sum_{i=1}^N m_{1ik} \gamma(z_{is})^{(j)}}{\sum_{i=1}^N (m_{1ik} + m_{0ik}) \gamma(z_{is})^{(j)}}$$

compute $\forall s$,

$$\pi_s^{(j)} = \frac{\sum_{i=1}^N \gamma(z_{is})^{(j)}}{\sum_{i=1}^N \sum_{s=1}^S \gamma(z_{is})^{(j)}}$$

4. Evaluate the log-likelihood :

$$\ln p((m_{ik})_{1 \leq i \leq N, 1 \leq k \leq K} | (\lambda_{sk}^{(j)})_{1 \leq s \leq S, 1 \leq k \leq K}, (\pi_s^{(j)})_{1 \leq s \leq S}) = \sum_{i=1}^N \ln \left\{ \sum_{s=1}^S \pi_s^{(j)} \prod_{k=1}^K \lambda_{sk}^{(j) m_{1ik}} (1 - \lambda_{sk}^{(j)})^{m_{0ik}} \right\}$$

check for convergence and, if not achieved or if $j \neq \max$ return to the E step(2).

(4) Addressing underflows with the log-sum-exp trick

We cannot calculate directly $\gamma(z_{is})$ due to numerical underflow. So we consider calculating $\ln \gamma(z_{is})$ instead, which gives:

$$\ln \gamma(z_{is}) = \ln \pi_s \prod_{k=1}^K \lambda_{sk}^{m_{1ik}} (1 - \lambda_{sk})^{m_{0ik}} - \ln \sum_{s'}^S \pi_{s'} \prod_{k=1}^K \lambda_{s'k}^{m_{1ik}} (1 - \lambda_{s'k})^{m_{0ik}}$$

the left hand side of the equation is computable but not the right hand side due again to numerical underflow so we rewrite the above :

$$\ln \gamma(z_{is}) = a_{is} - \ln \sum_{s'}^S e^{a_{is}}$$

where :

$$a_{is} = \ln \pi_s \prod_{k=1}^K \lambda_{sk}^{m_{1ik}} (1 - \lambda_{sk})^{m_{0ik}} = \ln \pi_s + \sum_{k=1}^K m_{1ik} \ln \lambda_{sk} + m_{0ik} \ln(1 - \lambda_{sk})$$

We then use the log-sum-exp trick on $\ln \sum_{s'}^S e^{a_{is}}$ to get :

$$\ln \sum_{s'}^S e^{a_{is}} = \ln \sum_{s'}^S e^{a_{is}} e^{A-A} = A + \ln \sum_{s'}^S e^{a_{is}-A}$$

where :

$$A = \max_{s \in [1, \dots, S]} a_{is}$$

5.2 Results of the model

The results of our preliminary analysis and the preparation of our data already show us that hypothesis I⁷ is verified. Indeed, it seems common for generators to operate in parallel with the network.

To verify the second hypothesis⁸, we need to determine the optimal number of clusters, or the number of components of the mixture, S . S simply represents the number of groups to which we will assign our different generators, regarding their behavior relative to the grid⁹.

The number of components of the mixture, S , is an hyperparameter of our model and is not directly determined by the algorithm. We therefore need a strategy to determine the "optimal" S . Increasing S always improves the fit of the model, by increasing its likelihood. However, this improvement is accompanied by an augmentation in the number of parameters. It is therefore necessary to compensate for the improvement in the likelihood of the model by the increase in its complexity due to the augmentation in the number of parameters. A criterion is necessary for model selection, which must allow us both to adjust the fit of our model to our data while balancing it with its complexity. We decided to use the Bayesian Information Criterion (BIC) (Schwarz, 1978) as an exploratory criterion to determine a suitable number of component for the mixture model S , as the BIC one of the most used criterion for model selection. The goal is to minimize the BIC defined by the formula:

$$BIC = S \ln(n) - 2 \ln(\hat{L})$$

where $\hat{L} = p((m_k)_{1 \leq k \leq K} | (\widehat{\lambda}_{sk})_{1 \leq s \leq S, 1 \leq k \leq K}, (\widehat{\pi}_s)_{1 \leq s \leq S})$ which is the maximized likelihood, S is the number of classes and n the number of observations.

Using an iterative process, we calculate the value of the BIC with S ranging from 1 to 20. Figure III.11 shows the evolution of the BIC as a function of S . We clearly see that the BIC reaches a minimum at $S = 10$ before stagnating and gradually rise again. In the light of these results we can therefore estimate that $S = 10$ is an adequate hyperparameter for our model. We will therefore specify our model by estimating ten general behaviors of generator use with respect to the states of the network. We can therefore already affirm that hypothesis II¹⁰ is verified.

⁷*Hypothesis I: Generators can run while the grid is running.*

⁸*Hypothesis II: There are differences in behavior between different generator users, some being more sensitive to the reliability of the grid than others.*

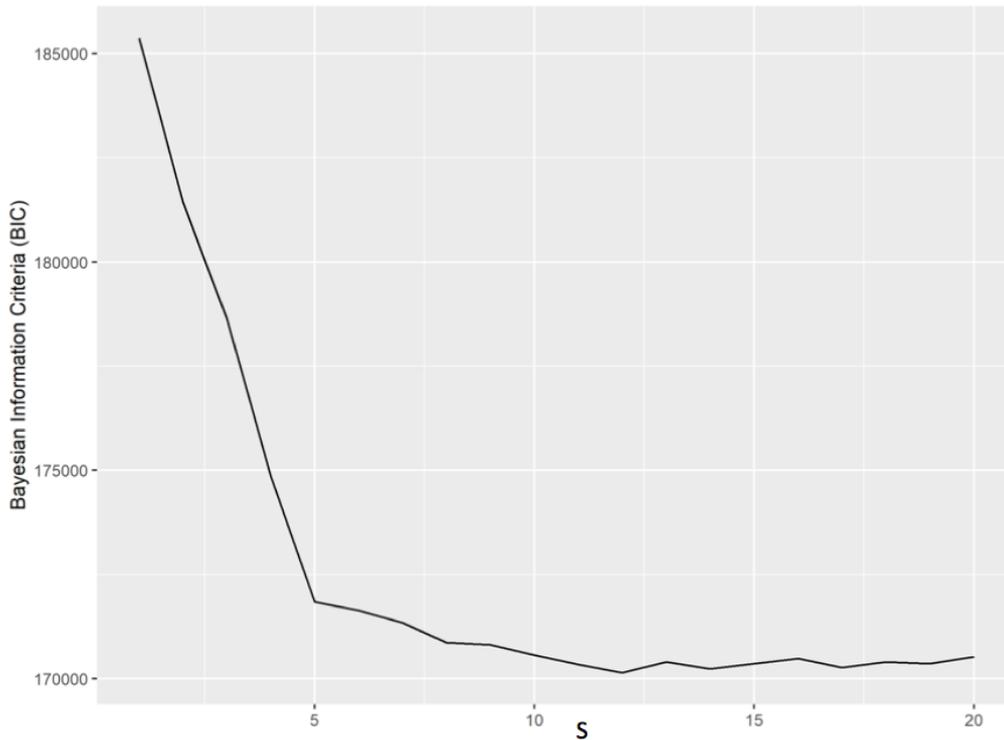
⁹For example, $S = 2$, simply means we having two main groups in which we can assign our generators.

¹⁰*Hypothesis II: There are differences in behavior between different generator users, some being more sensitive to the reliability of the grid than others.*

Table III.9: Pi per class for the full data

class	1	2	3	4	5	6	7	8	9	10
pi	0.015	0.164	0.226	0.03	0.162	0.132	0.09	0.105	0.015	0.062

Figure III.11: Bayesian Information Criteria for the model depending on the number of classes



Source : A2EI (2019) - Graph by authors

We then run the model with $S = 10$. The marginal distribution on s which is specified in terms of mixing coefficients π_s and which also corresponds to the prior probability of Z_{is} is given in table III.9. This prior probability can also be interpreted as the distribution of the number of generators assigned to the different classes. Thus, we see for example that the most important class in terms of generator number is the third one, in which 22.6% of our 67 generators are assigned, or 15 generators in total.

The results of the probabilities of the mixture model for each class as a function of K are given in table III.10. Table III.10 corresponds to the probability for each class that a generator turns "on" following the observation of the time series or context K . As a reminder, K corresponds to the state of the network

("on" or "off") 10 minutes ago and generator status ("on" or "off") 20 and 10 minutes ago. This table describes in detail the behavior of the different class. A graphical representation of these probabilities is given in figure III.13. In addition, figure III.12 shows an example of the central limit theorem applied to a generator (the generator number 541849) assigned to class 3. In this figure are represented the frequencies of the generator depending on each context K and the probabilities associated with the class. The horizontal bars represent the standard deviations, respectively for the frequency of the generator and for the class 3. With see that assigning generator number 541849 to class 3 improves our knowledge about the generator's behavior, due notably to the tightening of the standard deviations.

The interpretation of table III.10 is however not straightforward. To simplify its representation we construct table III.11 which is a simple transformation of table III.10 where the probabilities take the value "+" when these are greater than or equal to 0.5 (when the classes of generators are more likely to be "on") and take the value 0 when the probability is strictly less than 0.5 (when the classes of generators are more likely to be turned "off"). This representation allows us to see in a general way if there are significant difference in behaviors between classes. We see in table III.11 that each class behaves globally similarly to each other for all contexts K except for $K = 111$ and $K = 101$. In the first case ($K = 111$), class 3 has more chances of being extinguished with generator extinction probabilities of 0.857. This means that the generators belonging to this class are particularly sensitive to the network's states, more than to their own past status. $K = 111$ means that following a generator turned "on" during two subsequent periods, the fact that the network was "on" in the last period prompts the extinction of the generators for class 3. This, unlike the other classes where the probability of extinction is less than 0.5. Table III.9 also tells us that these two classes are not isolated behaviors because they represent about 22% of the generators studied. The second atypical behavior is given by class 9 where for $K = 101$, the generators have an extinction probability of 0.704. For this same class, even if the probability of extinction is less than 0.5 when $K = 111$, it is close 0.5 (0.471). This means that this class is also sensitive to network states. However, it represents only one generator.

We can already conclude that some classes seem to be much more sensitive to network states than others. In other words, generally speaking, when a generator turns "on" it has a tendency to stay "on", irrespective of the state of the grid. However, in the two classes mentioned above, and which represent almost a quarter of the generators studied, a return in grid operation augment the extinction probabilities of the generators.

Variables analysis shows that behavior in relation to the network (belonging to

Table III.10: Lambda for the full data per context per class

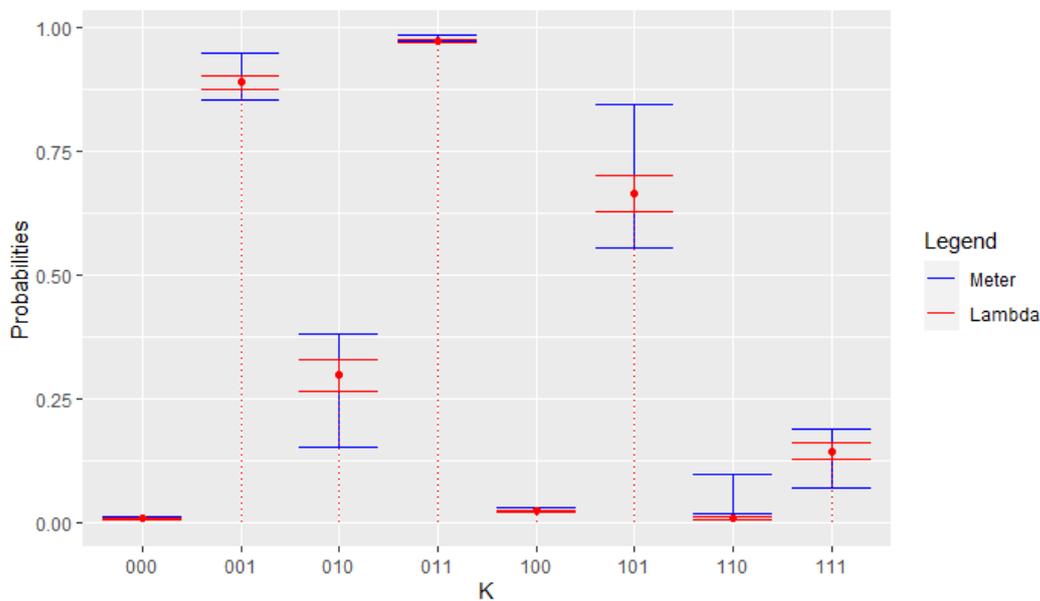
Class \ K	000	001	010	011	100	101	110	111
1	0.079	0.732	0.429	0.849	0.029	0.800	0.221	0.829
2	0.019	0.559	0.387	0.800	0.033	0.604	0.296	0.805
3	0.007	0.888	0.297	0.972	0.023	0.664	0.009	0.143
4	0.201	0.924	0.167	0.742	0.009	0.762	0.064	0.799
5	0.005	0.899	0.334	0.975	0.027	0.753	0.020	0.595
6	0.027	0.852	0.204	0.958	0.009	0.746	0.057	0.822
7	0.026	0.702	0.250	0.894	0.038	0.759	0.261	0.915
8	0.008	0.885	0.265	0.952	0.047	0.914	0.135	0.953
9	0.017	0.607	0.296	0.853	0.017	0.296	0.031	0.519
10	0.015	0.769	0.147	0.785	0.007	0.809	0.091	0.700

Table III.11: Lambda simplified over 0.5 for the full data per context per class

Class \ K	000	001	010	011	100	101	110	111
1	0	+	0	+	0	+	0	+
2	0	+	0	+	0	+	0	+
3	0	+	0	+	0	+	0	0
4	0	+	0	+	0	+	0	+
5	0	+	0	+	0	+	0	+
6	0	+	0	+	0	+	0	+
7	0	+	0	+	0	+	0	+
8	0	+	0	+	0	+	0	+
9	0	+	0	+	0	0	0	+
10	0	+	0	+	0	+	0	+

the different classes that we have characterized) seems to be linked to markets' locality. Table III.12 shows the distribution of generators by class according to the different markets. We observe that 50% of the generators of the Wuse market in Abudja belong to class 3 (the class defined as being the most sensitive to network's states). The second market to have generators that belong to classes 9 is Lagos, with 5.6% of its generators. Figure III.14 confirms this result in general and shows that classes are generally specific to markets. This high similarity in behavior by locality could suggest that there is a form of herding behavior in the use of generators.

Figure III.12: Example of the Central Limit Theorem for meter number 541849 in class 3 per context for the meter data and the estimated lambda

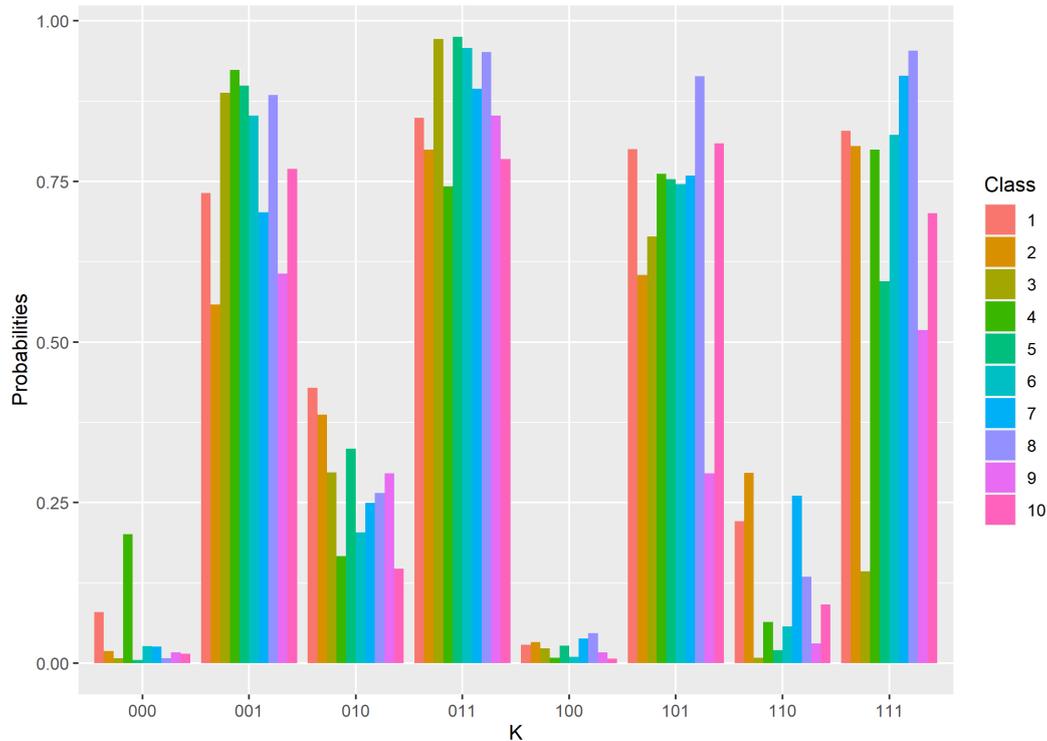


Source : A2EI (2019) - Graph by authors

It therefore appears that hypothesis III¹¹ is verified and that the improvement of the network reduces the use of generators, with a nuance however. In view of the model results, an improvement in the quality of central grid electricity supply reduces the use of generators, but with different scale depending on the region and on the sensitivity of users with regard to the grid's states. Indeed, for generators that do not belong to classes 3 and 9, being "on" 20 and 30 minutes ago, whether the network is working or not, makes it much more likely that the generator will remain "on" afterwards. This means that a long power outage would have the same effects as a short power outage by tricking a user

¹¹*Hypothesis III: An improvement in the quality of the electricity supply from the central network can significantly reduces the use of generators.*

Figure III.13: Estimated lambdas per class and per context



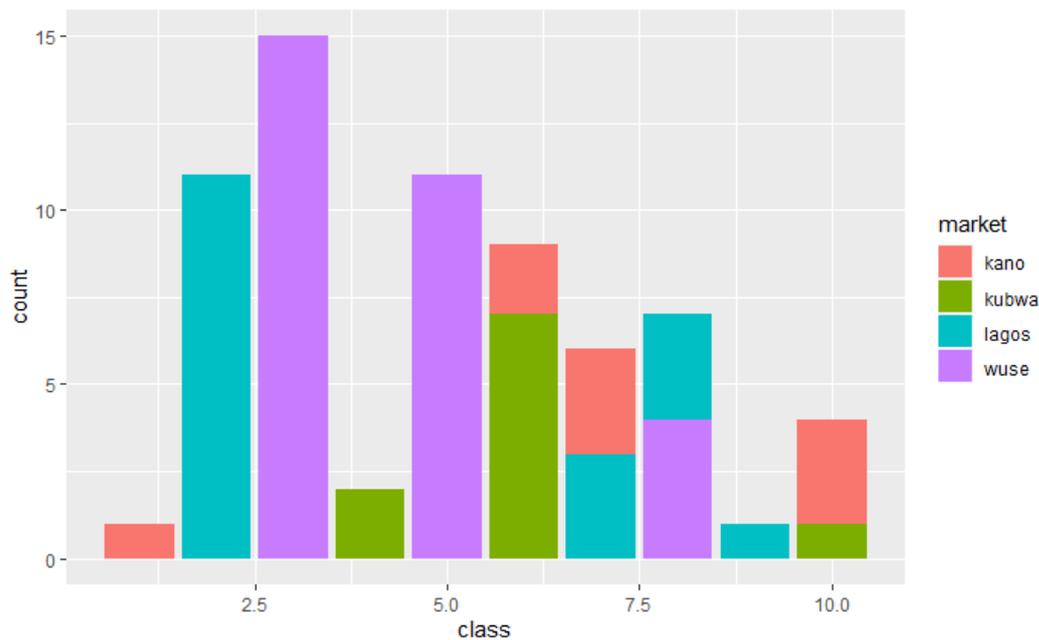
Source : A2EI (2019) - Graph by authors

into turning "on" a generator that is unlikely to be turned "off" afterwards, even with the return in operation of the network. This tend to go broadly in line with Oseni (2016)'s recommendation that public authorities should prioritize increased attention to reducing the frequency of power outages rather than reducing their duration.

Furthermore, the fact that classes allocation appears to be dependent on the market also mean that the doubts presented by Oseni (2016) would be founded. There appears to be forms of local, cultural and/or economic specificities in terms of generator use. Thus, a homogeneous improvement in the quality of the network in all Nigerian territories would have different effects in terms of reducing the use of generators depending on the geographical areas. This means that to reduce efficiently the use of generators in Nigeria at lower costs, priority should be to target areas where users of auxiliary generators are sensitive to the state of the network. Doing so should make it possible to obtain the best cost ratio for improving the network and effectively reducing the use of generators in the country.

The class of business could also be an important factor of class membership.

Figure III.14: Class (S) repartition per market



Source : A2EI (2019) - Graph by authors

Indeed, 48.3% of the "shop" generators belong to class 3. However, the majority of the generators used by shops are located in the Wuse market. It is therefore not possible to ensure that class membership is directly linked to the class of business. However, if it was, it could mean several things. The use of generators for "comfort" electricity may be more sensitive to grid conditions than for productive uses. Shops, for example, are more likely to use electricity for lighting, powering a radio or using a fan, and not directly for productive uses, where electricity would be used above all as energy carrier to produce, store a good or a service (e.g. barber, food and drink shop). As a power outage or drop in voltage can damage productive equipment, it could explain why some consumers are more sensitive than others to network's status. Low reliability of the network may encourage companies to turn "on" their generators directly after a power outage, not turning it "off" directly when the electricity from the network returns, fearing the occurrence of a drop in voltage or another power outage that would damage their equipment. However, apart from the locality and the class of business for classes 3 and 9, the reasons for generators assignment to the other classes cannot be explained by those variables, as can be seen on the tables III.13 and III.14.

Therefore, in the short term, the priority should be to improve the quality of the electricity supply in the Wuse market, which, as we saw, will have the greatest efficiency in reducing the use of auxiliary generators. Indeed, we saw that the use of backup generators was more sensitive to the grid's status in

Table III.12: Percentage of markets assigned to each class (S) for the full data

class	Kano	Lagos	Wuse	Kubwa
1	11.1	0.0	0.0	0
2	0.0	61.1	0.0	0
3	0.0	0.0	50.0	0
4	0.0	0.0	0.0	20
5	0.0	0.0	36.7	0
6	22.2	0.0	0.0	70
7	33.3	16.7	0.0	0
8	0.0	16.7	13.3	0
9	0.0	5.6	0.0	0
10	33.3	0.0	0.0	10

Table III.13: Percentage of class of business assigned to each class (S) for the full data

class	barber	computer and electronics	shop	communication center	cyber cafe	food and drinks	pharmacy
1	25	0	0.0	0	0	0.0	0
2	0	44	0.0	0	0	0.0	0
3	0	4	48.3	0	0	0.0	0
4	25	4	0.0	0	0	0.0	0
5	0	12	27.6	0	0	0.0	0
6	0	4	6.9	50	100	33.3	100
7	25	12	0.0	0	0	66.7	0
8	0	16	10.3	0	0	0.0	0
9	0	4	0.0	0	0	0.0	0
10	25	0	6.9	50	0	0.0	0

Table III.14: Percentage of generator capacity groups assigned to each class (S) for the full data

class	<=1kW	1kW-2kW	2kW-3kW	5kW+	3kW-4kW	4kW-5kW	NA
1	5.9	0.0	0.0	0	0	0	0
2	0.0	0.0	0.0	0	0	0	55
3	17.6	47.6	16.7	100	0	0	0
4	5.9	0.0	0.0	0	0	0	5
5	11.8	14.3	66.7	0	100	0	5
6	17.6	19.0	16.7	0	0	100	0
7	17.6	0.0	0.0	0	0	0	15
8	11.8	9.5	0.0	0	0	0	15
9	0.0	0.0	0.0	0	0	0	5
10	11.8	9.5	0.0	0	0	0	0

Wuse than in the other markets covered in this study. More broadly, this also means that in view of the difficulty of improving the electricity supply in a homogeneous manner throughout the Nigerian territory, it is necessary to prioritize the grid's reliability of areas where auxiliary generator users are sensitive to the network's status. Despite the difficulty to refine our analysis due to lack of data, we have however seen that stores prevailed in the Wuse market. This could mean that to benefit from a greater decline in generators use, increase in network reliability in markets where shops prevail could be prioritized.

Finally, our results show that the assumptions made by the literature today, in particular on the uses of generators could be partly false. The partial decorrelation between the use of auxiliary generators and the states of the network shows us that the hypothesis of Farquharson et al. (2018), which makes the implicit assumption that generators only work when the network is not working, could be false. If it was, it could actually mean that their estimates would be a lower bound estimate, and not an upper bound as the authors argue.

6 Limitations of the analysis

The analysis presented in the chapter has two main limitations, one related to the data, the other on the independence assumption used for the empirical analysis. The two subsections below present these two main limitations in more detail and elaborate on promising solutions to address them.

6.1 Data related limitations

Two factor would significantly improve the analysis presented in this chapter. The first would be to have more data and variables about the auxiliary generators studied in this chapter. Indeed, the lack of data such as missing data in our longitude and latitude data or variables related to the turnover of the companies that are completely absent from our database is an important limiting factor in our analysis. However, it is particularly common in quantitative studies of the region's electricity systems. The second limiting factor is having network data for only 67 of the 196 generators installed. Having these missing data would allow us to refine and generalize our analysis' results by applying our mixture model to more generators. In theory, however, it could be possible to estimate the unknown network states for the other generators using a maximum likelihood method, such as the following algorithm.

C_i^p represent meter p at time i and S^p the class of meter p (which is unknown).

1. Initialisation :

$\forall i$ we determine $g_i^{p,s}$ which is the "optimal" grid state for C_i^p if $S^p = s$

$$g^{p,s} = \arg \max_g \prod_{i=3}^N P(C_i^p | C_{i-1}^p, C_{i-2}^p, S^p = s, g_{i-1}^p)$$

$$V^{p,s} = \max_g \prod_{i=3}^N P(C_i^p | C_{i-1}^p, C_{i-2}^p, S^p = s, g_{i-1}^p)$$

we would then keep g^p which would equal $g^{p,s}$ with the highest $V^{p,s}$

2. Determine the probability the grid is on g^r for region r :

We evaluate $P(g_i^r = 1)$ where :

$$P(g_i^r = 1) = \frac{\#(g_i = 1 | p \in r)}{\#(p \in r)}$$

3. Determine the class s for meter p which maximises :

$$V^{p,s} = \max_s \prod_{i=3}^N \left(P(C_i^p | C_{i-1}^p, C_{i-2}^p, S^p = s, g_{i-1}^r = 0) \times P(g_{i-1}^r = 0) + P(C_i^p | C_{i-1}^p, C_{i-2}^p, S^p = s, g_{i-1}^r = 1) \times P(g_{i-1}^r = 1) \right)$$

4. Determine the optimal grid q^p with regard to previously defined class in 3.

$$g^{p,S=s} = \arg \max_g \prod_{i=3}^N P(C_i^p | C_{i-1}^p, C_{i-2}^p, S^p = s, g_{i-1}^p)$$

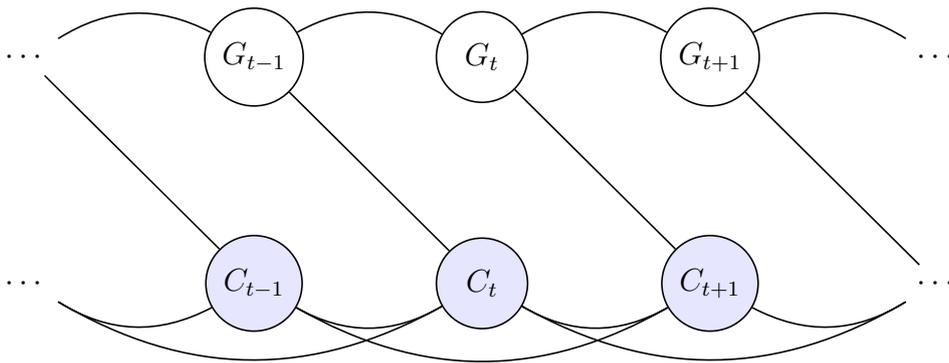
5. Check for convergence and if not achieved go back to 2.

Preliminary trials on our known 67 meters subset were encouraging, showing it could be possible to have decent estimates for the grid's states. However, our model's results have shown that location played an important role in class defining. Therefore, the class determined in our analysis would be specific to the meters in the locations studied and could not be transposed directly to other locations. If we would try to retrieve the networks' states in other locations with the methodology presented above, we would have serious reasons to doubt our estimates.

Another promising lead to recover unknown grid states in other regions would be to use a Double Chain Markov Model¹²(DCMM) with possibly higher order in the latent and observed time series. A typical model with regard to our data could be a discrete time process $\{G_t, C_t\}$ where $\{C_t\}$ denotes the observed meter status at time t with values in $\{0, 1\}$ and $G_t \in \{0, 1\}$ represents the latent grid status at time t . With regard to our preliminary analysis and model results, the conditional independence assumptions could be summarize by the directed graph presented in figure III.15. However, due to time and financing limitations, we will not have the opportunity to explore this lead further.

¹²For more information on DCMM of order one and higher see Berchtold (1999) and Berchtold (2002).

Figure III.15: Directed graph of the conditional independence assumptions for a Double Chain Markov Model



Source : Authors

6.2 Conditional independence assumption related limitations

For the empirical analysis, we made the assumption that controlling for the past status of the grid (10 minutes ago) and two periods of time for the generators (10 and 20 minutes ago) made our observations independent between each other, controlling by generator.

This assumption allowed us to perform our analysis. However, it assumes that the order of the Markov Chains (or the memory of the process) of all the generators with respect to their past states and that of the network is similar between the different contexts and the different generators. However, this may not always be the case in practice, and taking better account of this disparity in the Markov processes should allow us to refine the analysis even further.

In this context, an innovative model has been developed, which allows a Markov Chain to have a variable length depending on its past states. This model mainly solves the problem of the curse of dimensionality that appears in the estimation of complete Markov Chains. Indeed, when estimating complete models, the number of parameters increases exponentially with the order of the Markov Chain. This makes the estimation difficult by leading to estimates that can be very variable in the sparsest contexts (Buhlmann and Wyner, 1999). The estimation of such contexts, moreover, may not be relevant.

The Variable Length Markov Chain (VLMC) solves this problem by allowing contexts of different lengths sufficient to predict the next values of the Markov Chain. In other words, the memory of the Markov process can be of different lengths depending on its past states. The estimated VLMC can be represented simply as a simple node tree (Zanin Zambom et al., 2022).

A first version of the VLMC was proposed by Rissanen (1983) and refined by Buhlmann and Wyner (1999). However, these classical VLMC estimation methods did not include the possibility of introducing exogenous covariates to the process. In the data presented in this chapter, it is clear, for example, that network states affect generator use. Failure to account for this fact when estimating a VLMC would lead to incorrect estimation of the contexts and their parameters.

To address this problem, the Zanin Zambom et al. (2022) research paper has recently introduced an algorithm that estimates the relevant contexts of the Markov process and their parameters along with the significant covariates and their coefficients. These covariates can furthermore be of an order greater than 1. The implementation of Zanin Zambom et al. (2022)'s procedure is offering promising leads to refine the analysis presented in this chapter.

7 Conclusion

In this third chapter, the use of backup generators by grid-connected businesses in Nigeria was reviewed. Due to the frailty of the Nigerian centralized power sector and its inability to meet the demand of commercial and residential consumers, the use of backup generators is widespread in the country.

Contrary to the decentralized solar systems presented in chapter 2, even if auxiliary generators allowed companies to maintain production during power cuts and thus limit their losses, their use presents many disadvantages. The pollution generated by these systems is important and presents a risk to the health of the users and the environment. It is therefore desirable to reduce their use, particularly by improving the reliability of electricity electrical supplied.

In the first chapter of this thesis, the fact that electricity companies are in difficult financial situations was pointed out. It is challenging for the region's centralized power sectors to cover their operating costs and capital expenditures to maintain existing assets. Maintenance expenses are often the first to be cut, contributing to further deterioration in service quality and thus potentially increasing the use of backup generators to compensate for power outages.

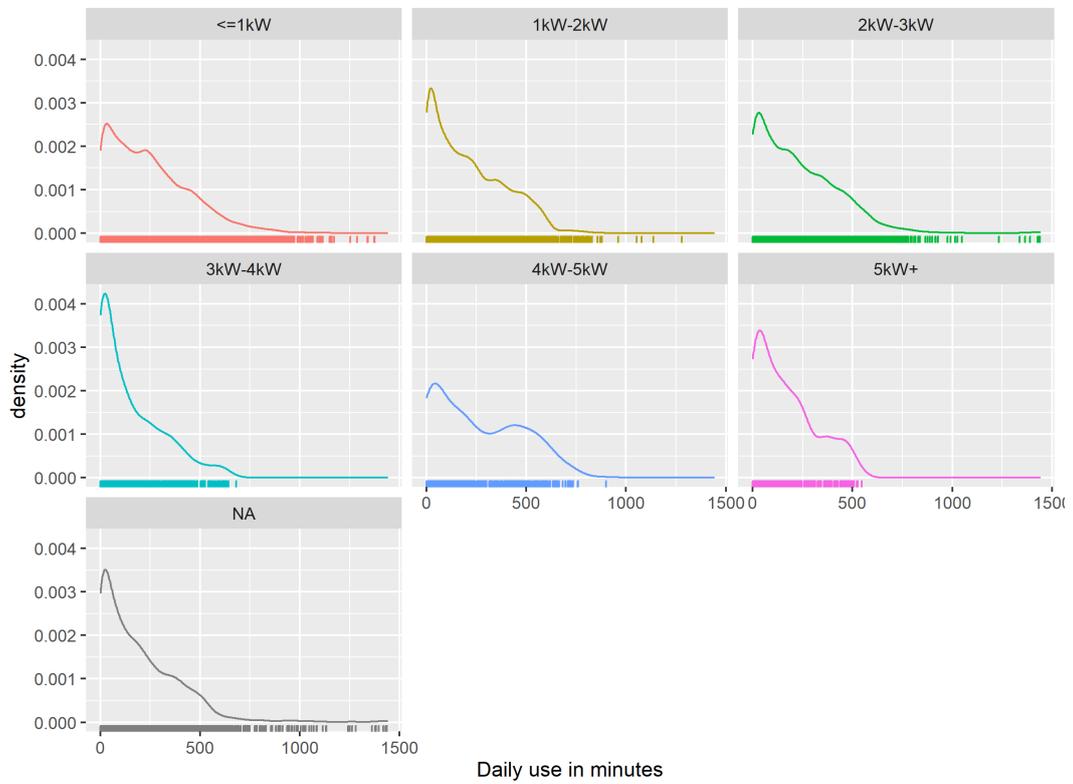
With limited budgets to invest in improving the operational efficiency of the central network, it is essential to understand the use of these generators with regard to the grid's reliability. If financially distressed utilities were to improve service quality through maintenance investments to reduce the use of generators in Nigeria, they would have to target the consumers most sensitive to the reliability of electricity supplied by the grid. In other words, consumers who, if service quality improves, are likely to reduce their generator use and consume their electricity from the grid.

In this chapter, both the questions left open by our first two thesis chapters and the questions left open by the academic literature have been answered. Consistent evidence that there are several types of auxiliary generator usage behavior with respect to the network's reliability of electricity supplied has been presented. That improvement in the quality of the central grid power supply reduces generator usage, but with different magnitudes depending on the sensitivity of users to the network's reliability, has been highlighted. The analysis conducted in this chapter indicates that in the short term, to reduce backup generator use efficiently, the priority should be to improve the quality of power supply in the Wuse market. Indeed, in this market, auxiliary generators are very sensitive to the reliability of electricity supplied from the grid. A grid reliability improvement would more significantly reduce generator use in Wuse than in the other regions covered in this chapter.

More generally, these results indicate that to reduce the use of backup generators in Nigeria, it is necessary to prioritize improvements in grid reliability in areas where generator users are sensitive to the reliability of electricity supply. Replicating this analysis with a large-scale generator usage data collection in Nigeria would help determine which areas are more likely to experience a significant decrease in generator usage due to improved power supply.

Appendices

Figure A.III.1: Density plot of generator daily use in minutes per generator capacity group



Source : A2EI (2019) - Graph by authors

Table A.III.1: Daily use of generator in minutes per market

Market	Mean of the median daily use (mins)
Ap Plaza	300
Banex	75
Kano	216
Kubwa	164
Lagos	96
Mpape	97
Nga	209
Wuse	202

Table A.III.2: Daily use of generator in minutes per generator group

Generator capacity group	Mean of the median daily use (mins)
$\leq 1\text{kW}$	214
1kW-2kW	169
2kW-3kW	164
3kW-4kW	113
4kW-5kW	208
5kW+	125
NA	155

Table A.III.3: Class of business and type of business

Class of business	Type of business
barber	barber
communication center	communications center
computer and electronics	computer accessories
	computer games
	computer hardware
	computer hardware; accessories
	computer hardware; software
	computer software; accessories
	console games
	electronic accessories
	ict components
	ict; software
	laptops; computer accessories
	network gadgets
	phone accessories
	phone repair
printers; computer accessories	
travel agency; computer software	
cyber cafe	cyber cafe
food and drinks	provisions
	soft drinks
pharmacy	pharmacy
shop	babywear
	bedding
	boutique
	cosmetics
	fancy beads
	fashion design
	fashion design; tailoring
	footwear
	laces wrappers
	ladies wear
	materials
	menswear
	native materials
	office equipment
	textiles
undergarments	

Table A.III.4: Descriptive statistics for grids

	Mean	Median	SD	Min	Max	N
Wuse (geographical cluster 2)						
Date				2019-11-14	2020-01-09	52
Grid status (On / Off)	0.297	0	0.457	0	1	144720
Apparent voltage	66.126	0	101.83	0	247.65	144720
<i>Grid quality</i>						
Down	0.703	1	0.457	0	1	144720
Low	0.003	0	0.053	0	1	144720
Normal	0.294	0	0.456	0	1	144720
Lagos (geographical cluster 3)						
Date				2019-11-14	2020-03-25	98
Grid status (On / Off)	0.139	0	0.346	0	1	164304
Apparent voltage	29.355	0	73.22	0	236.2	164304
<i>Grid quality</i>						
Down	0.861	1	0.346	0	1	164304
Low	0.036	0	0.186	0	1	164304
Normal	0.103	0	0.303	0	1	164304
Kano (geographical cluster 4)						
Date				2019-11-14	2020-04-23	147
Grid status (On / Off)	0.281	0	0.45	0	1	99216
Apparent voltage	54.331	0	87.342	0	234.05	99216
<i>Grid quality</i>						
Down	0.719	1	0.45	0	1	99216
Low	0.214	0	0.41	0	1	99216
Normal	0.067	0	0.251	0	1	99216
Kano (geographical cluster 6)						
Date				2019-11-14	2020-04-23	161
Grid status (On / Off)	0.429	0	0.495	0	1	36576
Apparent voltage	89.9	0	104.011	0	238.85	36576
<i>Grid quality</i>						
Down	0.571	1	0.495	0	1	36576
Low	0.177	0	0.382	0	1	36576
Normal	0.251	0	0.434	0	1	36576
Kubwa (geographical cluster 8)						
Date				2019-06-27	2020-04-23	250
Grid status (On / Off)	0.68	1	0.466	0	1	193626
Apparent voltage	148.533	209.067	102.995	0	272.4	193626
<i>Grid quality</i>						
Down	0.32	0	0.466	0	1	193626
High	0	0	0.015	0	1	193626
Low	0.164	0	0.37	0	1	193626
Normal	0.517	1	0.5	0	1	193626

Table A.III.5: Descriptive statistics for generators

	Mean	Median	SD	Min	Max	N
Wuse (geographical cluster 2)						
Date				2019-11-14	2020-01-09	52
On / Off	0.189	0	0.392	0	1	144720
Calculated apparent power	44.424	0	110.081	0	1731.30986	144720
Power factor	0.17	0	0.353	0	1	144720
Apparent current	0.232	0	0.583	0	9.07	144720
<i>Generator capacity group</i>						
<=1kW	0.246	0	0.431	0	1	144720
NA	0.035	0	0.183	0	1	144720
1kW-2kW	0.496	0	0.5	0	1	144720
2kW-3kW	0.159	0	0.366	0	1	144720
3kW-4kW	0.029	0	0.167	0	1	144720
5kW+	0.036	0	0.186	0	1	144720
<i>Class of business</i>						
computer and electronics	0.148	0	0.355	0	1	144720
shop	0.852	1	0.355	0	1	144720
Lagos (geographical cluster 3)						
Date				2019-11-14	2020-03-25	98
On / Off	0.134	0	0.34	0	1	164304
Calculated apparent power	32.455	0	102.141	0	899.99644	164304
Power factor	0.12	0	0.306	0	1	164304
Apparent current	0.163	0	0.511	0	4.3	164304
<i>Generator capacity group</i>						
NA	1	1	0	1	1	164304
<i>Class of business</i>						
computer and electronics	1	1	0	1	1	164304
Kano (geographical cluster 4)						
Date				2019-11-14	2020-04-23	147
On / Off	0.193	0	0.394	0	1	99216
Calculated apparent power	27.692	0	68.413	0	1157.26	99216
Power factor	0.173	0	0.356	0	1	99216
Apparent current	0.152	0	0.368	0	5.585	99216
<i>Generator capacity group</i>						
<=1kW	0.943	1	0.231	0	1	99216
1kW-2kW	0.057	0	0.231	0	1	99216
<i>Class of business</i>						
barber	0.295	0	0.456	0	1	99216
communication center	0.104	0	0.306	0	1	99216
food and drinks	0.415	0	0.493	0	1	99216
shop	0.186	0	0.389	0	1	99216
Kano (geographical cluster 6)						
Date				2019-11-14	2020-04-23	161
On / Off	0.195	0	0.396	0	1	36576
Calculated apparent power	20.938	0	57.687	0	434.057	36576
Power factor	0.171	0	0.352	0	1	36576
Apparent current	0.115	0	0.308	0	2.005	36576
<i>Generator capacity group</i>						
<=1kW	1	1	0	1	1	36576
<i>Class of business</i>						
communication center	0.429	0	0.495	0	1	36576
food and drinks	0.571	1	0.495	0	1	36576
Kubwa (geographical cluster 8)						
Date				2019-06-27	2020-04-23	250

On / Off	0.169	0	0.375	0	1	193626
Calculated apparent power	107.789	0	280.924	0	4572.21996	193626
Power factor	0.152	0	0.338	0	1	193626
Apparent current	0.571	0	1.494	0	22.14	193626
<i>Generator capacity group</i>						
<=1kW	0.152	0	0.359	0	1	193626
NA	0.055	0	0.228	0	1	193626
1kW-2kW	0.491	0	0.5	0	1	193626
2kW-3kW	0.157	0	0.364	0	1	193626
4kW-5kW	0.145	0	0.352	0	1	193626
<i>Class of business</i>						
barber	0.184	0	0.387	0	1	193626
computer and electronics	0.124	0	0.329	0	1	193626
cyber cafe	0.436	0	0.496	0	1	193626
pharmacy	0.106	0	0.307	0	1	193626
shop	0.151	0	0.358	0	1	193626

Table A.III.6: Responsibilities (gamma) for the full data

Meter number \ Class	1	2	3	4	5	6	7	8	9	10
541821	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000
541822	0	0.000	0.000	0	0.000	0.00	0.000	1.000	0.000	0.000
541823	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541826	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541827	0	0.994	0.000	0	0.000	0.00	0.001	0.000	0.000	0.005
541838	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541839	0	0.000	0.001	0	0.999	0.00	0.000	0.000	0.000	0.000
541842	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541844	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541845	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541848	0	0.000	0.964	0	0.000	0.00	0.000	0.000	0.036	0.000
541849	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541850	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541851	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541853	0	0.000	0.000	1	0.000	0.00	0.000	0.000	0.000	0.000
541857	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000
541861	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541865	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541866	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541871	0	0.000	0.000	0	0.000	0.00	0.000	0.000	0.000	1.000
541874	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541875	0	0.000	0.000	0	0.000	0.00	1.000	0.000	0.000	0.000
541878	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541881	0	0.000	0.000	0	0.000	0.00	0.000	1.000	0.000	0.000
541882	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541887	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541888	0	0.000	0.000	0	0.000	0.00	0.998	0.002	0.000	0.000
541889	0	0.000	0.000	0	0.000	0.00	1.000	0.000	0.000	0.000
541890	0	0.000	0.000	0	0.000	0.00	1.000	0.000	0.000	0.000
541893	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541894	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541901	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000
541905	0	0.000	0.000	0	0.000	0.00	0.000	0.000	0.000	1.000
541907	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000
541918	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541921	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000
541931	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541934	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541939	0	0.000	0.000	1	0.000	0.00	0.000	0.000	0.000	0.000
541941	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541942	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000

541945	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541949	0	0.000	0.000	0	0.000	0.00	0.000	0.000	1.000	0.000
541952	0	0.000	0.174	0	0.826	0.00	0.000	0.000	0.000	0.000
541953	0	0.000	0.000	0	0.000	0.87	0.000	0.000	0.000	0.130
541959	0	0.000	0.000	0	0.000	0.00	0.000	0.000	0.000	1.000
541960	0	0.000	0.000	0	0.000	0.00	0.000	1.000	0.000	0.000
541961	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541963	0	0.000	0.000	0	0.000	0.00	0.000	1.000	0.000	0.000
541964	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541965	0	0.000	0.000	0	0.000	0.00	0.000	1.000	0.000	0.000
541967	0	0.000	0.000	0	0.000	0.00	1.000	0.000	0.000	0.000
541968	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541969	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541971	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541974	0	0.000	0.000	0	0.000	0.00	0.000	0.000	0.000	1.000
541975	0	0.000	0.000	0	0.000	0.00	0.000	1.000	0.000	0.000
541978	0	1.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541987	0	0.000	0.000	0	0.000	1.00	0.000	0.000	0.000	0.000
541988	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000
541989	0	0.000	0.000	0	0.000	0.00	1.000	0.000	0.000	0.000
541993	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541994	1	0.000	0.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541996	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000
541997	0	0.000	0.000	0	0.000	0.00	0.000	1.000	0.000	0.000
541998	0	0.000	1.000	0	0.000	0.00	0.000	0.000	0.000	0.000
541999	0	0.000	0.000	0	1.000	0.00	0.000	0.000	0.000	0.000

Conclusion

After several decades of reforms, the situation of the centralized power sectors has changed little. The sub-Saharan electricity sectors remain underdeveloped in terms of electrification, consumption, and installed capacity. In addition, the power sectors are currently facing significant financial difficulties. Faced with these challenges and the demographic and urban growth of the region, the centralized networks cannot fully meet the electricity needs of the populations, even in areas already covered by the central network. As a result, individuals and businesses are encouraged to become more independent of the central grid to meet their electricity consumption needs.

Market mechanisms are at work to fill the gaps created by the weakness of the central grid: companies marketing decentralized power generation systems are taking advantage of this. As a result, the market for decentralized systems is growing rapidly in the region. Its potential is enormous: the 600 million sub-Saharanans without access to electricity are now joined by 500 million sub-Saharanans who do have access but face an unreliable or expensive grid. The actual market for these systems could therefore represent 1.1 billion potential customers today or 2.1 billion in 30 years. At the continental level, it would represent an opportunity worth more than 350 billion USD as early as 2030 (Attia, 2022).

The phenomenon of early decentralization of services under the pressure of demand and a proactive private sector are not new in sub-Saharan Africa. It is worth recalling that with the advent of mobile in the mid-1990s, Africa made a "leap" from the difficult development of national fixed networks directly to mobile telephony. However, many analysts today study the evolution of the electricity sector as if it followed well-established patterns. This fails to consider the emerging bottom-up developments made possible by the arrival in areas covered by the grid of novel, autonomous means of electricity production (Jaglin, 2019). This new dynamic, which is still relatively unresearched, has only been partially covered by academic research and was the subject of this economics thesis.

This thesis, therefore, set out to study this new dynamic of consumer empowerment in areas covered by the central network. Because of the new angle adopted in the analysis and the methodology implemented, the contributions of this thesis are multiple.

The literature review conducted throughout this thesis has shown that the existing academic literature has often been limited to studying the development of power systems in Africa *ceteris paribus*: "all other things being equal." African demography is among the clearest examples of this. The doubling of Africa's population in less than thirty years is often seen in the literature as an external factor that mainly serves to illustrate the magnitude of the challenge

that represents the continent's universal electrification. This approach fails to integrate the significant population growth in the region as a structuring factor, which also helps shape how the region's networks develop. The academic literature has a record of taking little account of the underlying trends actively involved in transforming African power systems. This thesis responds to this gap by focusing on several trends that the author believes are fundamental to understanding sub-Saharan electricity networks development dynamics. These trends include the historical development of centralized power systems, demographic and urban population growth, and recent technological developments related to the development of mobile telephony and solar systems.

The first chapter explored the implications of the increased penetration of decentralized systems in grid areas on the organization and evolution of sub-Saharan power systems. These issues had been neglected by academic research. Indeed, the academic literature analyzes the development of the region's electricity sectors almost exclusively in the context of electrification planning. Except for a few articles, the areas covered by the grid and the urban areas have been infrequently addressed. This first chapter has shown that many preconceived notions in the literature concerning electrification in Africa are gradually being challenged. Until now, for example, the academic literature was based on the implicit assumption that the arrival of the grid automatically led to consumers connecting to the central grid. The article by Blimpo et al. (2020) showed that this was not the case in practice, as new connections by consumers in grid-covered areas are not systematic. We have also seen that the literature has paid little attention to areas covered by the grid. It has focused instead on the electrification of consumers with no access to electricity, mostly in rural areas.

The first chapter showed a gap in the existing literature which makes a second implicit assumption: that a sub-Saharan consumer can access and consume electricity through the central grid or decentralized systems, but not both. The first chapter filled this gap by showing that this assumption was not always verified in practice. Because of the difficulties encountered by the centralized electricity sectors, decentralized technologies are also used by consumers already connected to the central grid for economic or security of supply reasons. The first chapter has thus complemented the existing literature by evaluating this new phenomenon and characterizing its benefits and downsides for residential and commercial consumers.

After highlighting this new phenomenon, the first chapter goes further by doing a prospective exercise. It determines the consequences of the deployment of decentralized systems in the areas covered by the network. The analysis presented in the chapter explores this issue in light of challenges the electricity sector faces, as identified in the earlier parts of the chapter. It shows how con-

sumer empowerment could influence the evolution of the electricity mix in the region and reinforce inequalities in access to electricity services in sub-Saharan Africa.

The recommendations that stem from the first chapter's analysis are addressed primarily to academia. From the evidence presented, it is clear that consumer empowerment will significantly impact the development of the region's electricity systems. It is therefore necessary to better understand these new uses. Several questions remained unanswered in the first chapter. Depending on which consumers turn away from the central grid, the financial consequences for the sector could be different. Therefore, the first chapter raises two fundamental questions that the author believes should be the subject of further research. First, it seems essential to understand which types of consumer are becoming more autonomous with respect to the network, in particular as relating to their income level. Second, it is crucial to examine to what extent the improvement of the quality of the electricity supply could influence consumers' autonomy through the use of decentralized systems.

In its second chapter, this thesis determines the extent of the development of decentralized systems in urban areas covered by the grid. This analysis addresses the research questions left open by the first chapter. The literature review has uncovered almost no mention of the decentralized solar systems market in rural off-grid areas. A few rare articles mention the presence of decentralized solar systems in grid-covered areas, but in an approximate way and only in peri-urban areas where the grid is unreliable. Thus, academic research seems to have completely overlooked the possibility that the market for decentralized systems could also develop on a large scale in areas covered by the grid but where electricity supply is reliable.

The second chapter fills this important gap in the current academic literature. It does so using a method never before used to study the development of power systems in the region. Over 2 million satellite images were downloaded and analyzed using artificial intelligence algorithms, searching for photovoltaic panels. This made it possible to demonstrate that the decentralized solar market is actively developing in African urban centers, a phenomenon that had been completely neglected by academic research on the development of electrical systems in sub-Saharan Africa.

The second chapter then expands upon the analysis by crossing this original database with a geo-localized socio-economic survey database. The subsequent econometric analysis showed that the market for decentralized solar systems in large cities is primarily for the most affluent, grid-connected residential consumers, regardless of the quality of the electricity supply. Thus, this chapter addresses a gap in the academic literature as it both discovers and character-

izes a new phenomenon that had been, to date, unrecognized.

The results show that consumer empowerment through decentralized solar systems can reinforce the financial difficulties of central grids and that the grid cannot hamper consumer empowerment simply by improving the reliability of the electricity supply. In light of the results of the first chapter, this analysis shows that implementing cost-reflective tariffs at any cost may be counterproductive. This is because the most lucrative customers turn away from the national grid and invest in self-generation through photovoltaic systems. Tariff increases, mainly imposed on the largest consumers, will further encourage them to become self-sufficient through decentralized production systems. Alternatives must be found to integrate these new uses into the proper functioning of the network.

In its third chapter, this thesis investigates the use of the second most common decentralized technology in sub-Saharan Africa: backup generators. This analysis explored the links between consumer empowerment and poor grid reliability by analysing how improving the electricity supply's reliability can influence grid-connected consumers' use of decentralized systems. This chapter answers these questions through a case study of Nigeria, the African country with the most widespread use of backup generators.

The analysis in this chapter has filled an important gap in the literature, which had never studied the actual use of generators, but only their adoption. Despite the magnitude of backup generator prevalence, which is widespread in sub-Saharan Africa, chapter 3 revealed that academic literature is scarce on the subject. One reason for this is data availability, which is a significant constraint. As a result, research papers have had to rely on survey data or strong assumptions that may have biased their results. Several research papers based their analysis on the strong assumption that there was a perfect negative correlation between auxiliary generator use and grid condition. This chapter has shown that the aforementioned assumption is unfounded in the context of our data.

This chapter also supported the analysis by providing consistent evidence that there are several distinct usage patterns of auxiliary generators, relative to the central grid's reliability. It found that an improvement in the quality of central system supply reduces generator usage, but with different magnitudes depending on the region and the sensitivity of users to the grid's reliability.

In light of the financial challenges facing central networks, as discussed in the first chapter of this thesis, the main recommendation of chapter 3 is that it is essential to target priority regions where improving grid reliability will have the most significant impact on generator use. The methodology presented in

this chapter is remarkably flexible and can easily be used for such purposes. Chapter 3, therefore, completes the analysis of chapters 1 and 2, fills a gap in the academic literature on backup generators in sub-Saharan Africa, and provides a simple tool directly actionable by policymakers.

This thesis has several general limitations in addition to the limitations of the quantitative analyses detailed at the end of each chapter. Due to the scope of the task, this thesis cannot provide a comprehensive and detailed overview of the various developments related to decentralized technologies that are taking place in the sub-Saharan power sectors. Nor can it provide definitive answers or solutions to these emerging issues. Thus, several important questions remain unanswered. In particular, due to the difficulty in finding reliable and accurate data, a precise study of the underlying reasons for the behaviour of the users of these systems could not be conducted. This is, however, fundamental as it could lead, for example, to a better understanding of these systems' use on economic development. It would be interesting to understand what the effects of mixed development of both decentralized and centralized electricity systems could be on the development of sub-Saharan economies and, more specifically, for example, on their industrial sectors. Further, this thesis does not develop upon the issues related to the informal economy, which is essential for a better understanding of the decentralized systems market. Indeed, in African economies, a large part of the market for decentralized systems is driven by the informal sector. However, it was impossible to elaborate on this subject due to the very nature of this sector and the conditions under which this thesis was carried out during the Covid-19 pandemic. Finally, the regulatory solutions that would make it possible to accompany the new trends transforming sub-Saharan electricity systems have been left relatively unaddressed. It is the belief of the author that any recommendations on regulation regarding novel uses of decentralized systems in areas covered already by the network are a distinct topic that must be the subject of separate work. In this context, the extensive literature that exists on the death spiral of utilities in industrialized countries is a good starting point, although it needs to be adapted to the specificities of the African context.

The evidence gathered in this thesis demonstrate that African power sectors are embarking on a development path of their own, different from that experienced by power systems in other regions of the world. This thesis shows that the gradual empowerment of consumers from the grid is an underlying trend and cannot be countered simply by improving the management and reliability of power supply. The progressive decentralization of power systems in sub-Saharan Africa is thus underway and is reinforced by the continent's rapid urbanization. Moreover, it is progressively becoming less correlated with the grid's reliability.

If these new uses are thought out and integrated into the development policies of electrical systems, they could represent opportunities.

These systems can provide faster access to electricity than the central network for populations that are deprived of it. The high scalability of these systems allows consumers who already have access to electricity to move up the energy ladder, allowing them to access new electricity services according to their budget and needs.

Lowering the cost of decentralized renewable systems could also lower the price of electricity for commercial and industrial consumers, thereby promoting their economic competitiveness and the penetration of renewable technologies on the continent. Auxiliary generators could be replaced by decentralized solar systems, increasing total solar capacity. To date, Africa accounts for only 1% of the world's installed centralized solar capacity, while it hosts 60% of the world's solar resources (International Energy Agency, 2022a). Auxiliary generators, on the other hand, are estimated to represent a capacity of 127 GW on the continent, 13 times more than the centralized photovoltaic capacity currently installed in the same area (Attia, 2022; IRENA, 2021).

Decentralization of generation capacity could also increase the resilience of networks to events that could damage them, by making consumers less dependent on centralized infrastructure. For example, last January, Kenya experienced a nationwide power outage after the collapse of electricity towers. This directly affected residential and commercial consumers as well as critical infrastructure such as hospitals for over 24 hours. Consumers using decentralized systems, on the other hand, were able to continue to receive power during this time (Roussi, 2022).

Finally, in the longer term, if electricity is generated primarily where it is consumed, it does not need to transit through transmission lines. This would thus prevent electricity from being subject to line losses, which are high in many countries in the region: 24 countries have losses that are above 20% and sometimes reach over 48% (Trimble et al., 2016). This would also limit the need for colossal investments in network infrastructure, for which it is challenging to mobilize private funds, and where the IEA estimates the needs at 40 billion per year on average in the coming years (International Energy Agency, 2022a).

However, if not considered in the sector's development policies, this empowerment of consumers could also have negative consequences for the centralized sector. Given the difficult financial situation in which almost all African utilities find themselves, the partial short-term loss of their best customers (residential as well as commercial or small industrial) would be a significant blow to their finances. Moreover, the financial viability of strategies to extend the

central grid to the poorest consumers in adjacent peri-urban and rural areas relies on cross-subsidies. This is because the largest consumers pay higher tariffs than the poorest, who consume less and thus benefit from subsidized tariffs. This system is likely to reach its limits even more quickly if the most profitable customers in the cities leave the system. The empowerment of consumers could contribute to the fragmentation of centralized sub-Saharan networks.

This new trend will profoundly impact the necessary access of African populations to electricity and the financial health of the region's centralized networks. While these impacts are still difficult to assess, the phenomenon of consumer autonomy vis-à-vis the centralized network offers avenues for research to develop future public policies and conceive a regulatory framework tailored to the specificities of African electricity systems. Unfortunately, while awareness is growing among professionals, these trends have been covered only marginally in the academic literature. Therefore, more research on these issues is needed to continue working toward adequately developing Africa's power systems.

To conclude, this thesis has therefore set out to demonstrate the emergence of new consumer empowerment dynamics in the areas covered by the networks in sub-Saharan Africa and to explain why these are likely to continue over time. In light of these developments, one may earnestly wonder whether the sub-Saharan electricity market will continue to be built around centralized infrastructure driven by the public sector, or whether the vibrant entrepreneurial ecosystem, which is exploding in Africa today in the tech, e-commerce, and mobile finance sectors, will largely take over the power sector, and what the consequences for the region's economic development could be.

As the last lines of this thesis are written, in the summer of 2022, major energy and economic crisis threatens to engulf the world's economies. The sanitary and economic crisis of covid-19 had already considerably weakened sub-Saharan economies. With limited financial capacity, African governments had to mobilize their resources to the health sector to deal with the health crisis, thus reducing their ability to implement economic development projects. The covid-19 crisis also added to the financial difficulties of the electricity sectors. The drop in activity due to the lockdowns and the slowdown in the global economy led to a temporary drop in electricity consumption. Many countries that had signed PPAs with IPPs had to honor their take-or-pay clauses and most governments have also sought to protect vulnerable consumers by increasing electricity subsidies for the poorer population segments, but this has further widened the sector's deficit.

Today, rising fuel prices resultant of Russia's invasion of Ukraine, inflation, and the subsequent rise in policy rates are likely to affect the region's power

sectors by discouraging new investment and limiting governments' ability to implement their budgets. Moreover, countries with a significant portion of their electricity mix composed of hydrocarbons will see their financial resources dwindle in the context of a sharp increase in oil and gas prices. It is, therefore, unlikely that the region's power sectors will be able to mobilize additional financial resources and meet the vast needs of their power systems to expand. As a result, in the face of the difficulties facing the region's centralized power sectors, which will be exacerbated by the crisis, the trend toward consumer empowerment will likely increase in the years to come.

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RÉSUMÉ

Après plusieurs décennies d'efforts, force est de constater que les secteurs électriques d'Afrique sub-saharienne restent peu développés. Plus de 600 millions de subsahariens n'ont toujours aucun accès aux services électriques, un chiffre qui a augmenté ces dernières années du fait de l'important accroissement démographique que connaît la région.

Cette thèse montre que les secteurs électriques d'Afrique subsaharienne s'engagent aujourd'hui sur un chemin de développement différent de celui emprunté par les pays industrialisés. Dans les zones couvertes par le réseau, face aux faiblesses des secteurs électriques centralisés, les particuliers et les entreprises ont tendance à s'autonomiser du réseau central en investissant dans des systèmes décentralisés. Cela, pour des raisons économiques ou encore pour des raisons de sécurité d'approvisionnement électrique.

Ces phénomènes d'autonomisation des consommateurs vis-à-vis du réseau central et leurs conséquences n'ont été couverts que de façon marginale par la recherche académique. En utilisant des méthodes originales de Machine Learning pour récolter et analyser des données inédites, cette thèse étudie les dynamiques à l'œuvre dans les secteurs électriques subsahariens et les effets du déploiement des technologies décentralisées sur l'organisation des réseaux centralisés de la région.

Ainsi, à l'aide d'outils de Deep Learning cette thèse analyse plusieurs millions d'images satellites, et montre que le déploiement des technologies solaires décentralisées dans les grandes villes africaines est significatif et que ces systèmes sont adoptés principalement par les consommateurs appartenant aux franges les plus aisées de la population. Cette thèse analyse aussi grâce à des algorithmes de Machine Learning une base de données originale de plusieurs centaines de milliers d'observations de consommation d'électricité d'entreprises nigériennes connectées au réseau et utilisant des générateurs auxiliaires en parallèle. Cette analyse révèle qu'il existe plusieurs types de comportement d'utilisation de ces systèmes décentralisés vis-à-vis du réseau. Enfin, cette thèse montre que ces phénomènes d'autonomisation des consommateurs vis-à-vis du réseau central vont très probablement s'accroître ces prochaines décennies et affecter de façon significative le développement du secteur tout entier.

Les secteurs électriques de la région évoluent ainsi vers des systèmes hybrides où dans les zones couvertes par le réseau, les technologies décentralisées se mêlent en nombre à un réseau national peu fiable. Le continent Africain invente ainsi le "réseau électrique décentralisé", avec ses avantages et ses inconvénients.

MOTS CLÉS

électrification, Afrique, deep learning, machine learning, analyse d'images satellites, énergie solaire, générateurs diesels.

ABSTRACT

After several decades of effort, electricity sectors in Sub-Saharan Africa remain underdeveloped. More than 600 million sub-Saharan Africans still have no access to electricity services, a figure that has increased in recent years due to the region's significant population growth.

This thesis shows that the electricity sectors in Sub-Saharan Africa are now embarking on a development path of their own, different to that of the industrialized countries. In grid-covered areas, faced with the weaknesses of the centralized power sectors, individuals and businesses are tending to become independent of the central grid by investing in decentralized systems, for economic reasons or for security of supply.

These phenomena of consumer autonomy from the central grid and their consequences have been covered only marginally by academic research. Using original Machine Learning methods to collect and analyze novel data, this thesis studies the dynamics at work in the sub-Saharan electricity sectors and the effects of the deployment of decentralized technologies on the organization of centralized networks in the region.

Using Deep Learning tools, this thesis has analyzed several million satellite images, and shows that the deployment of decentralized solar technologies in large African cities is significant and that these systems are mainly adopted by consumers belonging to the most affluent segments of the population. This thesis has also used Machine Learning algorithms to analyze an original database of several hundred thousand electricity consumption observations of grid-connected Nigerian businesses using auxiliary generators in parallel. This analysis reveals that there are several types of usage behaviors of these decentralized systems with respect to the grid. Finally, this thesis shows that these phenomena of consumer autonomy from the central grid are likely to increase in the next decade and significantly affect the development of the entire sector.

The region's electricity sectors are thus evolving towards hybrid systems where, in the areas covered by the grid, decentralized technologies are mixed in number with an unreliable national grid. The African continent is thus inventing the "decentralized electricity network", with its advantages and disadvantages.

KEYWORDS

electrification, Africa, deep learning, machine learning, satellite imagery analysis, solar energy, diesel generators.