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Geo-Temporal Analysis of Electricity Consumption Growth in Togo using Deep Learning

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DEDICATION

To my beloved Mother,

my beloved Father (in loving memory)

and

my Sisters.

"My Lord, have mercy upon them as they brought me up [when I was] small."

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ABSTRACT

Electrical energy plays a vital role in daily life. The developing world is making good progress in improving access to electricity toward UN sustainable Goal number 7 through better energy planning. Understanding energy consumption growth remains a fundamental aspect of energy planning. This study aimed to investigate the dynamic of electricity consumption growth in Togo and to build the most suitable deep learning model for predicting the yearly electricity consumption of the country's different regions. The analysis uses a data-driven approach to determining the relationship between average consumption and electrification rate. On the other hand, yearly electricity forecasting was modeled using multiple layer perceptron (MLP), convolutional neural network (CNN), and long short-term memory (LSTM) models, and evaluated using the mean absolute error metric. As a result of this research, the average consumption decreases as the electrification rate increases. It was also found that the multivariate and multi-steps LSTM model is the most suitable model for predicting yearly electricity consumption. However, the model accuracy can be increased when combining it with the CNN model. The former shows that low consumers can be aggregated on the same transformer because the average consumption is decreasing. The latter revealed the potential of deep learning techniques in predicting yearly residential electricity consumption. The CEET can use the LSTM model to right-size the residential electricity supply.

Key words: Electricity consumption; Growth; Prediction; Deep learning; Togo.

RESUMÉ

L'énergie électrique joue un rôle essentiel dans la vie quotidienne. Les pays en développement progressent bien dans l'amélioration de l'accès à l'électricité, en vue de la réalisation de l'objectif 7 des Nations Unies, grâce à une meilleure planification énergétique. Comprendre la croissance de la consommation d'énergie reste un aspect fondamental de la planification énergétique. Cette étude visait à étudier la dynamique de la consommation d'électricité au Togo et à dévélopper le modèle d'apprentissage profond le plus approprié pour prédire la consommation annuelle d'électricité des différentes régions du pays. L'analyse utilise une approche basée sur les données consummation pour déterminer la relation entre la consommation moyenne et le taux d'électrification. D'autre part, la prévision annuelle de l'électricité a été modélisée à l'aide des modèles MLP, CNN et LSTM, pu évaluée à l'aide de la métrique de l'erreur absolue moyenne. Le résultat de cette recherche montre que la consommation moyenne diminue lorsque le taux d'électrification augmente. Par ailleurs, le LSTM est le modèle le plus approprié pour prédire la consommation électrique annuelle des régions du Togo. Cependant, la précision du modèle peut être augmentée en le combinant avec le CNN. Le premier résultat montre que les faibles consommateurs peuvent être regroupés sur le même transformateur puisque la consommation moyenne est en baisse. Le second résultat a révélé le potentiel des techniques d'apprentissage profond dans la prédiction de la consommation électrique résidentielle annuelle. La CEET peut utiliser le modèle LSTM pour redimensionner l'offre d'électricité résidentielle.

Mots clés: Consommation d’électricité; Croissance; Prédiction; Apprentissage profond ; Togo.

ACRONYMS AND ABBREVIATIONS

AI : Artificial Intelligence

ANN : Artificial Neural Networks

AT2ER : Togolese Agency for Rural Electrification and Renewable Energies (Agence Togolaise d'électrification rurale et des énergies renouvelables)

BMBF : German Ministry of Education and Research.

CC : Climate Change

CEB : Electrical Community of Benin (Communauté d'Électricité du Bénin)

CEET : Togo Electricity Company (Compagnie Énergie Électrique du Togo)

CNN : Convolutional Neural Network

CREDS : The Centre for Research into Energy Demand Solutions

DL : Deep Learning

ED-ICC : École Doctorale Informatique pour le Changement Climatique

EE : Energy Efficiency

GHG : Greenhouse Gas

GRU : Gated Recurrent Unit

GSP : Graduate Study Program.

IEA : International Energy Agency

INSEED : Togo National Institute of Statistics (Institut National de la Statistique et des Études Économiques et Démographiques)

KWh : Kilo Watts hours

LSTM : Long Short Time Memory

LV : Low Voltage

MG : Mega Watts

ML : Machine Learning

MLP : Multi-Layer Perceptron

MV : Medium Voltage

NN : Neural Network

RNN : Recurrent Neural Network

SDGs : Sustainable Development Goals

SNPT **:** New Phosphates Company of Togo (Société nouvelle des phosphates du Togo)

WAPP **:** West African Power Pool

WASCAL **:** West African Science Service Centre on Climate Change and Adapted Land Use.

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INTRODUCTION

1. Background

Energy, in physics defined as the ability to do work, is a vital component of livelihood that has become an intrinsic part of our daily life. Every advanced economy can attribute its development and success to reliable access to modern energy (International Energy Agency, 2014). Since the adoption in 2015 of the new United Nations (UN) Sustainable Development Goals (SDGs), a lot of attention has been paid to the energy sector in particular. SDG number 7 aims to "ensure access to affordable, reliable, sustainable and modern energy for all" (Johnston, 2016). Moss (2021) defines the Modern Energy Minimum as a higher, more inclusive level of electricity consumption at 1,000 KWh per person per year, with at least 300 KWh at home and 700 KWh consumed in the wider economy. "Energy sector has been long recognized as essential for humanity to develop and thrive, it is also crucial to the achievement of many other SDGs, including those concern with gender equality, poverty reduction and improvements in health" (International Energy Agency, 2017). In contrast, according to Ritchie and Rosr (2020), about 73.2% of greenhouse gas (GHG) emissions come from energy production (electricity, heat, and transport). The concentrations of GHGs in the atmosphere due to humanity's increased use of fossil fuels to generate electricity are increasing the greenhouse effect and global warming. This greenhouse effect is the main driver of Climate Change (CC). GHGs were the main driver of tropospheric warming since 1997 and that human-caused stratospheric ozone depletion was the main driver of cooling of the lower stratosphere between 1979 and the mid-1990s (IPCC, 2021). Both warming and cooling of the stratosphere have a direct impact on electrical energy demand. For example, stratospheric warming requires electricity for cooling while stratospheric cooling requires electricity for heating purposes. Many studies conclude that demand for electricity will increase because of CC effects. Additionally, demand for electricity is set to increase further as a result of population growth, rising household incomes and growing demand for digital connected devices. Therefore, regarding environmental concerns, development aspects and increasing energy demand, it is important for policymakers to understand Energy Demand (ED) and how that ED will evolve with time.

ED designates the consumption of energy by human activities, which influences the total amount of energy used, the energy supply system, and the characteristics of the end-use technologies that consume energy (Bertelli, 2019). Regarding its influences, understanding ED is a key factor in energy policy and planning. Analysis of electricity consumption in a meaningful manner can yield useful information for understanding and forecasting demand. The ED analysis can give insights to policymakers regarding the decision-making of a country's energy sector, especially for developing countries where important decisions about how valuable public sector resources should be allocated to increase access to electricity are often made with little evidence, while new electrification technologies including solar home system and mini-grids, as well as traditional grid expansion reinvestments, are being explored to deliver electricity services in a sustainable manner (Fobi et al., 2018). For policymakers and energy planners, having a good understanding of electricity consumption patterns and factors affecting consumption growth is critical to making a good estimation of future demands. Additionally, forecasting consumption requires an understanding of present and previous consumption and how that consumption has evolved in the past even though the past is not a perfect indicator of the future. Indeed, future demands have direct impacts on World’s economic system and environment, especially in developing countries where reliably predicting energy demand is important to choose the most cost-efficient electrification solution mainly in off-grid areas, to ensure the best possible electrification economics.

West Africa, with a total population exceeding 391 million (United Nations, 2019) has one of the lowest rates of electricity consumption. Togo with a population estimated at 8 million in 2022 by the National Institute of Statistics is one of the most densely populated countries in West Africa (INSEED, 2015). Togo has the ambition to ensure universal access for all Togolese by 2030, with a 100% access rate. The electrification rate is still low in Togo, with significant differences between rural and urban areas. “At a country level, low electrification rates limit social and economic development that could lift millions out of poverty” (Nerini et al., 2016). The county’s energy sector does not effectively contribute to economic development because it is still largely dependent on traditional energy sources, the supply of which is under the combined pressure of population growth and climate change. According to World Bank Global Electrification Database, the rate of access to electrification in Togo is increasing from 30.7% in 2010 to 52.4 % in 2019, with 91% in the urban areas against 23% in the rural areas. Like most developing countries, Togo still has a majority of its population in rural areas (62.3% of the population). Togo is exploring a legal framework to promote renewable energy and a new off-grid rural electrification strategy. The Government is interested in increasing private sector investment in the power sector and attracting off-grid companies to increase access to electricity in rural areas. In 2016, Togo has established an agency to promote rural electrification. However, the electrical energy sector is monopolistic in Togo. Togo Electricity Company (CEET) is the utility having a monopoly on the distribution of electricity within the country. While CEET maintains some generation assets, it is mainly a distribution (of low and medium voltage) company purchasing its electricity from the Electricity Community of Benin (CEB) which is a binational entity for power generation and transmission co-own by Togo and Benin, and from Contour Global (a private generator). Most of the electricity produced domestically is based on hydropower (CEB) and fossil fuels. Since 2008, faced with the steadily growing gap between supply and demand, CEB became a net importer of energy from neighboring countries (Ghana, Niger, Nigeria, and Cote d'Ivoire). It is within this partnership framework that out of 1,286 GWh consumed in Togo in 2013, imports accounted for 74% (Ntagungira, 2015; Togo NDP, 2018). Table 1 summarizes CEET's energy purchase and production from 2014 to 2016.

Table 1: Energy purchase and production (CEET)

HEADINGS		2014	2015	2016	Evolution rate (%)	
		Energy (GWh)	Energy (GWh)	Energy (GWh)	2014-2015	2015-2016
Purchase (GWh)	CEB	944,70	744,66	486,18	-21,18	-34,71
	SNPT(*) Togo	0,86	0,29	0,21	-65,80	-28,94
CEET Gross production (GWh)		13,89	21,45	30,69	54,44	43,05
TOTAL CEET		**959,45**	**766,40**	**517,08**	**-20,12**	**-32,53**
Contour Global Gross production (GWh)		77,30	354,10	683,67	358,09	93,07

(*) The New Phosphates Company of Togo (SNTP) is an independent producer of energy

Source: CEET 2016 Annual Report

2. Problem statement

Achieving 100% of electrified households by 2030 would require the electrification of approximately 1,3 million households including 0,9 million non-electrified localities, with the majority in the rural areas (AT2ER, 2018). The electrification of remote localities requires extending grid connection as well as investment in the off-grid solution. Thus, it is necessary to estimate the energy demand for a better electrification strategy. In 2018, Togo established its electrification strategy. Several approaches and sources of information were used for the development of the electrification strategy. However, the strategy does not take into account the differences in consumption growth among and between newly connected and older customers. For instance, a better understanding of customers' electricity consumption behavior before deciding how to connect these customers can result in fewer underutilized grid connections that can be used to connect more customers (Fobi et al., 2018). Thus, the electrification strategy may miss estimating the likely near-term energy demand. "Uncertainty around electricity consumption and growth leads to inefficient resource allocation, high cost of energy, and poor planning" (N. Williams, 2020). In addition, Togo's population was projected to reach 14.2 million in 2050, based on 1960 to 2017 population data (Nyoni et al., 2019). Additional electrical energy will be needed to meet the country's growing population and the related development of this population growth. Indeed, an important part of the electricity supply in Togo is imported from neighboring countries. However, this importation is set to decrease because of the increasing domestic demand for electricity in these countries. Understanding energy demand can help to anticipate future demand. Particularly, knowing the relationship between customers' electricity consumption and electrification rate can assist the supplier (decision-makers), identify the most cost-effective technology (off-grid solutions or traditional grid extension) for improvement of electricity access. Furthermore, electricity consumption forecasting requires analyzing existing customer data (data-driven approach) to understand and predict the behavior of future consumption. This help to achieve universal access to modern energy both more quickly and in the most effective manner. With the rise of easier data collection and storage, there has been a transformation in the value chain of data usage. Raw consumption data coming from meters can mark a significant competitive advantage for utilities in their decision-making processes.

Large amounts of data create enormous prospects for all activity sectors, and as a result, businesses are increasingly turning to Machine Learning (ML) tools as a way to tap into that potential. In the energy sector, ML is now well known. The work presented in (Narciso & Martins, 2020) emphasizes the application of ML tools for Energy Efficiency Analysis, Energy Management, Energy Production Forecast, Energy Consumption Optimization, and Energy Consumption Forecast. ML includes several tools for extracting important insights from raw data (e.g., class prediction, pattern recognition), which can then be utilized to help enterprises improve their operations and strategic decisions. ML is a subset of Artificial Intelligence (AI) aiming to give computers, the ability to learn without explicitly being programmed. Indeed, in classical programming computers are fed with a set of rules (computer program) and data as input. Then data are processed according to these rules to output answers. With the new paradigm of ML, computers are fed with data as well as expected answers from the data to output the rules. These rules can then be applied to new data to produce original answers. ML encompasses a wide range of tools including Deep Learning (DL). DL algorithms can automatically learn arbitrary complex mappings from inputs to outputs and support multiple inputs and outputs, offering opportunities for time series forecasting, especially on data with complex-nonlinear dependencies, multivariate inputs, and multi-step forecasting (Brownlee, 2021).

Understanding and predicting energy demand remains crucial in electricity access planning. For that purpose, this work presents a geo-temporal analysis of electricity consumption growth in Togo using deep learning. To the best of our knowledge, the scale and extent of such a longitudinal study have not yet been applied in the Republic of Togo. This work is the first attempt at geo-temporal analysis of CEET's energy demand. The analysis is built upon an agency-scale dataset on monthly electricity bills from residential electricity customers in Togo covering the period from 1990 to 2020.

3. Research questions

This study seeks to address two core research questions.

- Q1: How does average electricity consumption evolve and how does that relate to the electrification rate?
- Q2: What is the most effective DL model for predicting yearly residential electricity consumption?

4. Research hypotheses

The motivation behind this work assumes that:

- H1: Average electricity consumption is decreasing as the electrification rate increases.
- H2: Long short-term memory (LSTM) is the most effective DL model for predicting yearly residential electricity consumption.

5. Research objectives

The objectives of this work are:

- O1: To determine the relationship between average electricity consumption and electrification rate.
- O2: To build the most suitable DL model for predicting yearly residential electricity consumption.

6. Thesis structure

This thesis comprises a general introduction, followed by four chapters, and then the general conclusions of the study. The content is structured as follows:

- **The introduction** presents the overall context and justification of the study. Then problem statement is followed by research questions, research hypotheses, and research objectives.
- **Chapter 1: The literature review** presents the main results of related works.
- **Chapter 2: Study Area and Data** describe the Study Area and the Dataset that support this study.
- **Chapter 3: Descriptive Analysis**. This chapter presents an exploratory analysis of historical electricity consumption that addresses the first research question (Q1). The method used and the result obtained are presented.
- **Chapter 4: Predictive modeling.** A predictive analysis, the methods used as well as results are presented in this chapter. The predictive modeling addresses the second research question (Q2).
- **Conclusion and perspectives**. This last part concludes the thesis while recalling the objectives and how this work can be deepened.

CHAPTER 1: LITERATURE REVIEW

1.1 Introduction

This chapter presents previous studies related to this research. The chapter is composed of two parts. On the one hand, electricity access planning regarding the first objective of this work. On the other hand, electricity demand modeling concerns the second objective.

1.2 Residential electricity access planning

The International Energy Agency (IEA) defines energy access as “a household having reliable and affordable access to both clean cooking facilities and to electricity, which is enough to supply a basic bundle of energy services initially, and then an increasing level of electricity over time to reach the regional average” (IEA, 2020). This definition is used as a benchmark in the UN’s Sustainable Energy for All Initiative. The UN aims to achieve universal energy access by 2030. To date, many regions of the world have not yet achieved or are far from achieving universal access to electricity. South Asia and sub-Saharan Africa are the world regions with the lowest electricity access figures. According to 2019 IEA figures, nearly 572 million people of sub-Saharan’s total population are still without access to electricity. The lack of access to electricity in sub-Saharan Africa is even more dramatic in rural areas (Haanyika, 2006). Chattopadhyay et al. (2014) suggest that better electricity planning can improve the success rate of programs to expand access to electricity. Despite promising beginnings, electricity planning research has received less scholarly attention in developing Africa. Trotter et al. (2017), in their “electricity planning and implementation in sub-Saharan Africa: A systematic review (from 1977 through 2016)”, found that most sub-Saharan African countries have received little or no scholarly attention in terms of electricity planning. 306 scientific English language articles were found in their study, but less than 5 of them studied 36 of the 49 countries. There was no single article for 12 countries (Togo included). The adequate policy design, sufficient finance, securing social benefits, a favorable political situation, and community engagement were highlighted as some of the success factors for electrification. South Africa, Ghana, Kenya, Nigeria, Tanzania, and Ethiopia are the most notable countries that have studied electricity planning in detail. Furthermore, many studies pointed out sub-Saharan Africa’s electrification inequality between rural and urban areas. Trotter (2016), in his analyses on the topic, found that rural electrification is mostly driven by politicians’ actions. He also found that sub-Saharan states with more democratic institutions succeed more in rural electrification. On the other hand, there was a strong positive association between democracy and rural versus urban electrification inequality. Researchers are interested in technology choices for rural electrification. Leonard et al. (2016) have conducted a comparative study of mini-grid systems and solar home systems as a solution for rural electrification in South Africa. Previous studies in the country suggest that mini-grid projects are not feasible because of high electricity production costs. However, the South African solar home system program, the rural electrification program of the country, is yet to meet development objectives more than a decade after it was commissioned. They found that mini-grids are a better option than a solar home system and that the cost of electricity production can be reduced with proper planning. In addition, optimization of available resources could reduce the cost of electricity production. Similarly, mini-grid systems are widely adopted as a decentralized solution for rural electrification in East Africa mostly in Tanzania and Kenya (N. J. Williams et al., 2018). Recent studies conducted by Fobi et al. (2018) and Muhwezi et al. (2021) in Kenya reveal that new customers regardless of their residence area being rural or urban have low electricity consumption, and off-grid solutions (lowest-cost technology compared to grid power) could initially provide electricity access to them, at least until the demand grows significantly. With the creation of the West African Power Pool (WAPP) in 2000, an initiative for the integration of the electricity sector, West African countries are benefiting from efficient use of less expensive electricity generation facilities, and wider access to low-cost primary energy resources available in the region (Gnansounou et al., 2007). However, at the national level, access to electricity in remote areas remains a challenge. In 1998 the government of Senegal created an agency for rural electrification based on grid extension, local mini/micro photovoltaic, and diesel power plants. According to Diouf et al. (2013), the results targeted by this agency are not matching the expectation yet. They found that the agency faces difficult challenges when dealing with small, isolated villages. On the other hand, a study conducted by Ouedraogo et al. (2015) in Burkina Faso reveals that, hybrid photovoltaic /diesel power plant configuration is the optimum solution for off-grid rural electrification. Their work concludes that the abundance of solar resources in the country coupled with the projected decline of photovoltaic prices will undoubtedly lead to affordable electricity costs for the rural population if hybrid configurations are implemented. In Benin, Peters et al. (2009) found that accompanying rural electrification activities by general rural development activities will yield a successful rural electrification. These complementary services are crucial for ensuring relatively fast poverty impacts on the both local private and public sector. Furthermore, Peters et al. (2011), found that firms that existed before electrification perform no better than their non-electrified counterparts in their study in northern Benin. As a result, it is necessary to explore if grid extension is an appropriate solution for rural electrification.

The Togolese government has been implementing rural electrification measures since 1992. However, the "rural electrification program" was formally launched in 2012 and intends to connect rural areas to the grid. This program is a considerable improvement compared to past actions (Afo et al., 2013). Rural areas, on the other hand, which are home to more than 60% of the country's population, account only for 6% of total electricity consumption (SIE-Togo, 2009). Kwami Dorkenou (2014) did an earlier study of the program, which emphasized the program's challenges. His research reveals that in rural areas, residences are sparse and placed far apart, making traditional grid technical specifications economically unsuitable. Because of these technical problems, as well as the low levels of energy use in rural households, utilities are reticent to invest in rural electrification. Thus, the program has failed. In 2016, the Togolese Agency for Rural Electrification and Renewable Energies (AT2ER) has been created. AT2ER is a well-structured rural electrification program that involves the rural population, government, utilities as well as investors. It is based on traditional grid extension and off-grid solutions. According to 2019 World Bank database figures, the rural electrification rate is 23% against 6.3% in 2016. The Agency played a great role in this achievement (AT2ER, 2018). However, at the national level, the country still is a net energy importer from neighborhood countries. Etse et al. (2019) found that implementing hybrid photovoltaic/biodiesel in the northern rural region of Togo could decrease the country’s energy dependencies. In Togo, off-grids solutions are rural and remote area electrification oriented.

Unlike the previous works on electricity access planning, the research conducted by Fobi et al. (2018) and Muhwezi et al. (2021) based on data-driven approaches aims at understanding diverse Kenya Power (national utility) customer behavior to improve electricity access planning. This study takes a similar approach by conducting an exploratory analysis of the historical residential electricity consumption of Togo Electricity Company aiming to improve access to electricity planning.

1.3 Residential electricity demand modeling

Energy demand and supply forecasting has received a lot of attention in recent years due to the fluctuation of both variable generation and demand. Different techniques are used to forecast energy demand over different geographic extend, temporal resolutions, and horizons. Traditionally, these techniques are classified into: (i) Short-term energy consumption forecasting and (ii) long-term projections of national energy demand. The former is used to inform real-time electricity scheduling (hours up to a month) while the latter comes in longer-term system planning (at least one year ahead). Short-term forecasts can assist customers in more efficient use of energy. Thus, they can save money as well as proactively reduce energy use impacts on the environment. Better long-term energy forecasting can help utilities, governments, and investors determine where, when, and how to supply energy. Hence, forecasts with the high temporal and spatial resolution are important in energy demand modeling. In the literature, several techniques are used in energy demand modeling as summarized in Table 2. ML techniques such as artificial neural networks (ANNs) are the most forecasting technique used in residential electricity consumption modeling (Verwiebe et al., 2021). A review of electrical load forecasting models conducted by Kuster et al. (2017) confirmed the wide use of ANNs that can capture recurrent patterns. In their systematic review of electricity demand forecasting using ANNs-based machine learning algorithms, Román-Portabales et al. (2021) discovered that the Long Short Term Memory (LSTM) model, which is the most commonly used algorithm in the reviewed papers, has shown to achieve very good results in aggregated load forecasting, and that their predictions typically get more accurate as the number of electricity consumers grows. However, a mix of multiple ANN-based techniques could be used to create more accurate models at the tradeoff of increased complexity (Bashari & Rahimi-Kian, 2020).

There are fewer studies on residential electricity demand modeling using ANNs in developing Africa. Several studies used a bottom-up approach to model electricity demand (Miketa & Merven, 2013; Castellano, 2015; Ouedraogo, 2017). Adeoye and Spataru (2019) modeled electricity demand for WAPP country members using multiple linear regression. Adjamagbo et al. (2011) used parametric models to model Togo's electricity demand. A recent study by Amega (2018) makes use of Stella (a system dynamic model software) to predict Lomé (Togo) residential electricity consumption. Unlike these studies, the present work model Togo residential electricity demand using ANNs.

Table 2: Energy demand modeling techniques

Techniques	Advantages	Disadvantages	Examples
Statistical techniques	Low implementation effort and reveal relations between independent and dependent variables.	limited when independent variables are correlated; Predicting extreme events and outliers is difficult; Less suitable for long-term forecasting.	Time Series Analysis Regression
Machine Learning	High predictive performance; Relatively low implementation effort; Can handle nonlinear relations; Many pre-set model configurations are available; Can be used without deeper knowledge of the technical system.	Black box character; Risk of overfitting; Sometime computationally expensive.	Clustering algorithms (Unsupervised Learning) Artificial neural networks (Supervised learning)
Meta-heuristic	Good at solving an optimization problem with an efficient search of solution space; Can be incorporated into other models.	No guarantee that the global maximum is attained; Requires additional knowledge and effort to implement in existing models;	Genetic algorithms
Engineering-based	Reveals detailed input-output relations; Can simulate energy demand in several scenarios	Knowledge-intensive; Prediction accuracy can be low due to simplifications	Particle swarm optimization
Stochastic	Can handle uncertainty; Allow estimating energy demand as well as demand variation.	High implementation effort and computationally expensive; Can be considered unsatisfying for decision-makers since model outputs are afflicted with probabilistic.	Fuzzy Grey

Source: "Modeling Energy Demand-A Systematic Literature Review" Verwiebe et al. (2021)

1.4 Conclusion

This chapter presents previous research related to this study. Regarding electricity access planning, previous works make use of diverse techniques aiming to improve access to electricity. Among these techniques, a recent work conducted in Kenya makes use of electricity data of historical consumption. The present work takes a similar approach by examining the historical electricity consumption of Togo Electricity Company residential customers. On the other hand, the literature reveals a wide use of ANNs in electricity demand forecasting. However, this technique has received less attention in developing Africa. The second objective of this work attempts to model Togo Electricity Company's yearly residential electricity demand using ANNs. The next chapter describes the Study Area as well as the Datasets that support this study.

CHAPTER 2: STUDY AREA AND DATA

2.1 Introduction

To attain objectives, verify the hypothesis and answer the research questions of the study, several materials and methods have been used. Figure 1 illustrates the conceptual framework of the study. First Togo country has been selected as a study area, then followed by the process of data collection and data analysis. The study ended with the development of a Web Application for data analytics (result visualization). This chapter presents the Study Area and Datasets that support the study.

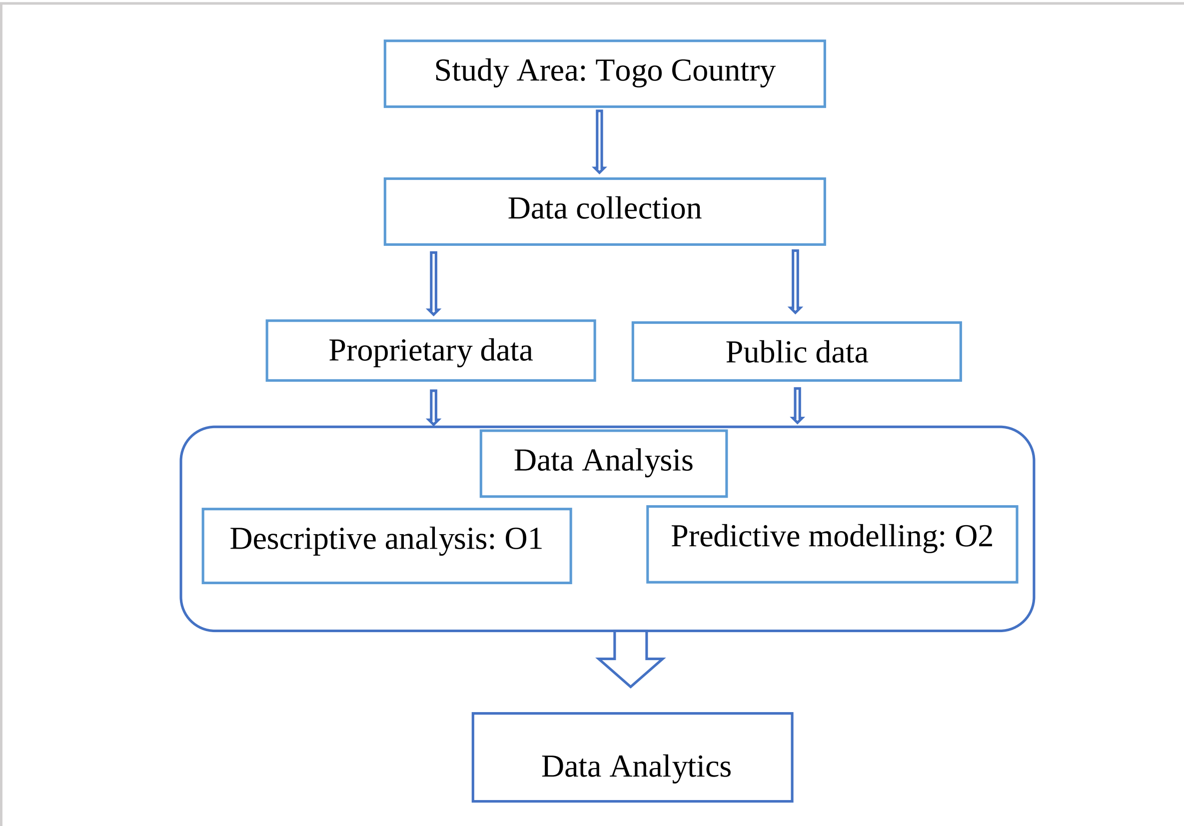


Figure 1: Conceptual Framework

2.2 Study Area

The study was conducted in Togo. The Republic is located in West Africa between latitudes 6^o and 11^o north and longitudes 0^o and 1^{o}40' east. Figure 2 shows a map of Togo with its main administrative subdivisions (regions). The country is divided into five (5) administrative regions namely (from South to North) Maritime, Plateaux, Centrale (Centre), Kara, and Savanes. The capital, most prominent port, and largest city is Lomé (6° 07' N, 1° 13' E) localized in the Maritime region. The country is drained by the two (2) main rivers. The Mono River and its tributaries in the south and the Oti River and its tributaries in the north. The following paragraphs give a brief description of the geography (Samuel Decalo, 2021) and climate of Togo country (Togo, 2015).

- **Geography**

Togo country is located on the Gulf of Guinea. It borders Burkina Faso to the north, Benin to the east, Ghana to the west, and the Atlantic Ocean to the south. The country covers almost 56 600 km². The plains in the north and south are dominated by savannah land, which makes up about 23% of the country's total area. About 16 % of the country is covered by tropical rainforests and savannah forests, about 33 % is used as meadows or grassland and about a quarter is used as agricultural land, especially for coffee, tea, cocoa, cotton, coconut and peanuts, cassava, rice, millet, and corn.

- **Climate**

Togo has a tropical climate influenced by two trade winds: The Harmattan (boreal trade wind), a hot, dry wind blowing from the northeast to the southwest; and the monsoon (southern trade wind), a hot, humid wind blowing from the southeast to the northeast. From the coast to 8° north, there is a sub-equatorial climate characterized by two dry seasons and two rainy seasons of unequal duration. Annual rainfall varies between 800 to 1400 mm distributed between the two rainy seasons: a large one from March/April to the end of July and a small one from the beginning of September to mid-November alternating with two dry seasons (a long one from November to March and a short one from July to September). The number of rainy days varies from 130 to 240 with a generally high relative humidity fluctuating around an average of 90% and an average annual temperature of 27°C. Beyond 10° North latitude reigns a Sudanese climate of semi-arid type, characterized by a rainy season of five months (May to October) for a rainfall of 900 to 1100 mm spread over 175 days. The temperatures vary between 17 and 41°C in the dry season and between 22 and 34°C in the rainy season with intense evaporation and relative humidity between 15 and 86%. Between these two climatic zones prevails a Guinean-Sudanese type of climate Sudanian type corresponding to a transition zone. In this zone, annual rainfall fluctuates between 1400 and 1500 mm with an average annual average temperature of 26.5°C (min: 15°C; max: 37°C). The average relative humidity varies between 60 and 80%.

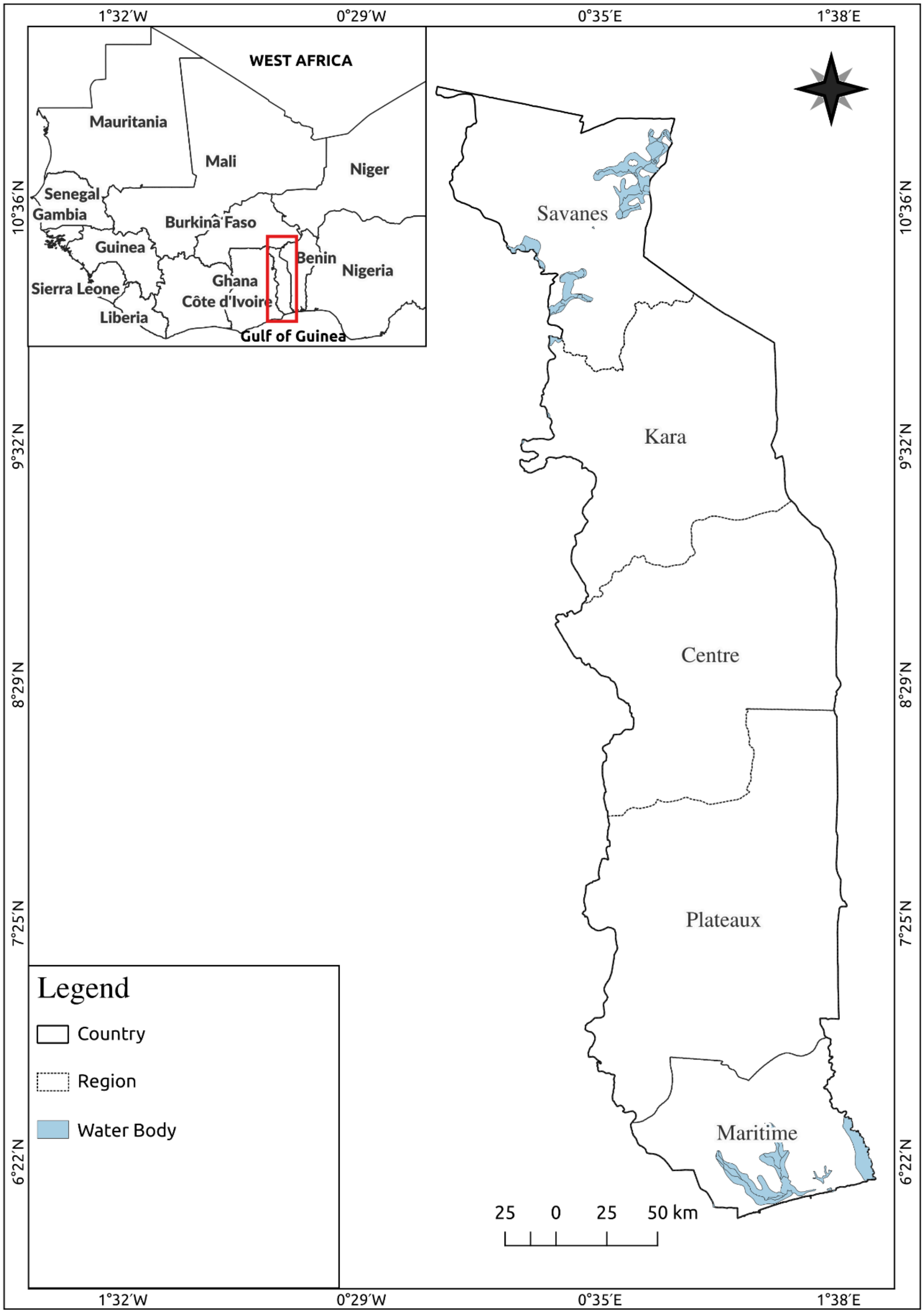


Figure 2: Map of the Study area (Design Author, source INSEED)

2.3 Data

2.3.1 Data Collection

The data supporting this study were collected from several sources. These data comprise a proprietary dataset provided by the CEET and a public dataset (available publicly). Table 3 summarizes the different datasets and data sources.

Table 3: Datasets and data sources

Data source	Dataset	Spatial resolution	Temporal resolution	Years
Togo National Institute of Statistics (INSEED)	Country boundary	Administrative subdivision	-	2010
	Population	Prefectural level	Yearly	1990-2020
		Urban/Rural split		2010-2020
Togo Electricity Company (CEET)	Postpaid Residential electricity consumption (KWh) Postpaid Residential number of customers	Agency scale	Monthly	1990-2020
		Urban/Rural split		2010-2020

2.3.1.1 Consumption Data

Togo Electricity Company operates on Medium Voltage (20 KV, 33 KV especially for interurban links, and 34.5 KV special network obtained on CEB's 161 KV line) and Low Voltage (230 V between phase and neutral and 400 V between phases). At CEET, except for medium/big enterprises and industries, the remaining clients are under LV power (from 2,2 KVA/10A to 13,2 KVA/60A). According to CEET 2016 annual report, more than 89,77% of LV power is consumed in households. LV power is also used in non-domestic power usage. This study is built upon a dataset of monthly electricity billing records from residential customers from LV power postpaid subscribers covering the period from 1990 to 2020. Postpaid electricity subscribers are charged monthly after power usage. Meters are at the center of this monthly billing service. The monthly consumption in KWh of a given client is collected by taking the difference of consecutive meter indices (current minus previous) at the end of each month. Most CEET clients are postpaid subscribers. CEET also provides prepaid electricity services called "LAFIA". LAFIA is a new service that started to emerge in late 2019. In contrast to postpaid service, prepaid is a credit-based service that allows the client to pay in advance for the energy to be used, similarly to what is done in “pay as you go” services.

Over the study period, residential electricity consumption has increased as shown in Figure 3. The number of residential customers of CEET in 1994 was 64944 against 5231719 in 2020. This increase is due to the implementation and reinforcement of grid connection extension-related projects.

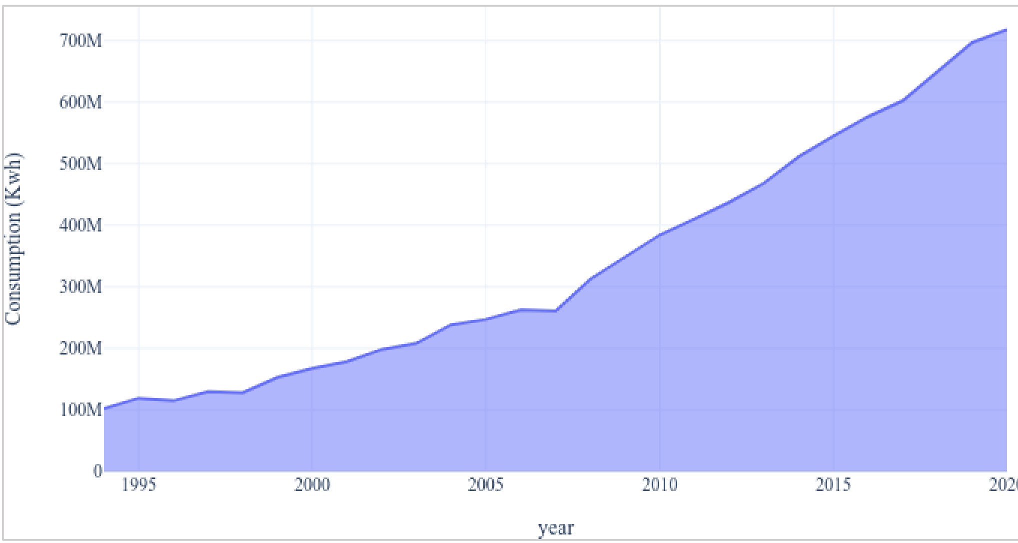


Figure 3: Residential electricity consumption over time

For simplification, in this study, the terms residential electricity consumption (respectively the residential number of customers) and electricity consumption (respectively the number of customers) are to be understood synonymously.

2.3.1.2 Population Data

population size datasets were provided by the National Institute of Statistics. These data were collected through Togo’s fourth census in 2010 **(**INSEED**,** 2011**)**. Before this fourth census, the last one was performed in 1981. From 1981 to 2010, the annual average growth rate was 3,18% for Savanes, 3,16% for Maritime, 2,58% for Plateaux, 2,18% for Centrale region, and 2,04% for Kara. In 2010 the rural population account for 62,3% of the country’s total population. The fourth census estimated the national annual average growth rate at 2,84%.

2.3.2 Data Preparation

The five (5) regions of the country are subdivided into 39 prefectures and their respective capitals. Each utility agency covers one or more prefecture(s) from the same region. Figure 5 illustrates the different agencies of Togo Electricity Company. The utility counts a total number of 31 operational agencies across the country. The raw data from the utility were available in Excel Open XML Spreadsheet (XLSX). After the data cleaning procedure, the raw data were transformed into Common Separated Values (CSV) format. The remaining raw data were available in CSV format except for the country boundary dataset which was in Shapefile format. Next to data transformation, filtering proceeded to discard incomplete records that cannot be used in the analysis. Finally, for analysis purposes, different datasets were aggregated at regional and rural/urban spatial resolution and yearly temporal resolution (from 1994 through 2020). Therefore, the analysis was built upon complete datasets instead of sampling of data, as it is done in some statistical approaches.

2.3.3 Data Analytics

Interactive dashboards and data applications were developed for data visualization and manipulation. This Web App was developed using the Dash framework (version 2.3.0).

Figure 4 shows the Dash framework's ecosystem (Dabbas, 2021). Dash uses Flask for the backend. For producing charts, it uses Plotly. React is used for handling all components, and actually, a Dash app is rendered as a single-page React app. Dash allows one to create fully interactive data, analytics, and web apps and interfaces using pure Python, without having to worry about HTML, CSS, and JavaScript.

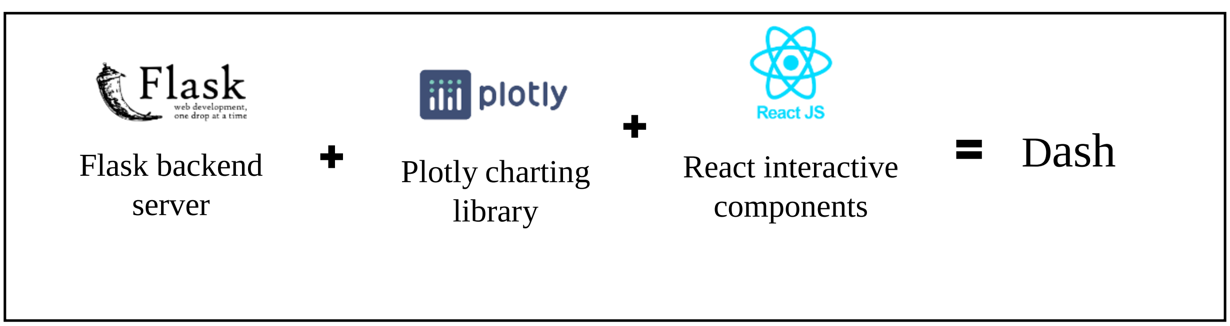


Figure 4: Dash ecosystem

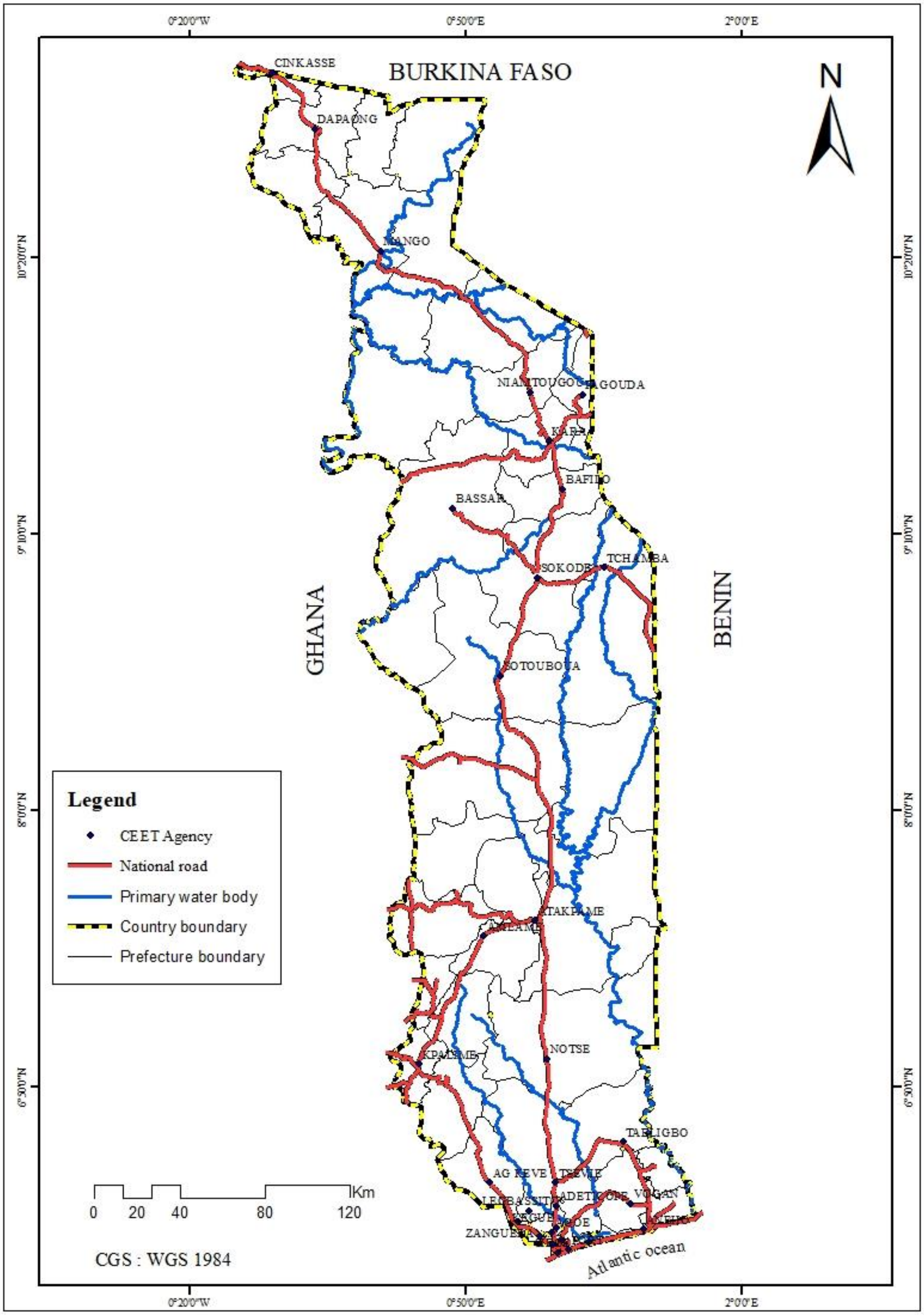


Figure 5: Togo Electricity Company Agencies (Design Author, source INSEED and CEET)

2.4 Conclusion

In this chapter, the Study Area and the Datasets were described. The Republic of Togo was selected as Study Area. On the other hand, electricity consumption records and population size were the datasets used to support this study. The next chapter presents the descriptive analysis aiming to verify the first motivation behind this study.

CHAPTER 3: DESCRIPTIVE ANALYSIS

3.1 Introduction

To verify the first hypothesis, an analysis aiming to understand the historical electricity consumption dataset was conducted. This chapter presents the method used as well as the finding of the analysis and the discussion of these results.

3.2 Method

The descriptive analyses were performed using the Python programming language (version 3.8.5) running on Jupyter Notebook (version 6.4.6) through the Anaconda environment (version 4.12.0). First, the average electricity consumption (consumption per connection) was computed followed by the electrification rate. Both were computed at regional (respectively at urban/rural) spatial resolution from 1994 through 2020 (respectively from 2010 to 2020). In Togo, urban/rural classification is based exclusively on the administrative definition of a town. Since Togo's fourth census in 2010, prefectural cities are considered urban areas as shown in Figure 6. The left figure shows different localities (as opposed to town a locality may be a village, hamlet, or farm) while the urban/rural localities [residential areas] are shown in the right figure). Finally, the descriptive analysis ended with hypothesis testing.

3.2.1 Average electricity consumption per connection

The average electricity consumption per connection was computed through the formula (1).

$$Avg_{Cons} = \frac{total\,consumption}{total\,number\,of\ customers} \tag{1}$$

The yearly average consumption per connection $\boldsymbol{Avg_{Cons}}$ equals ***total consumption*** divided by the ***number of customers***. Figure 7 (respectively Figure 8) shows the yearly number of customers and yearly total consumption of the different regions (respectively of urban/rural areas).

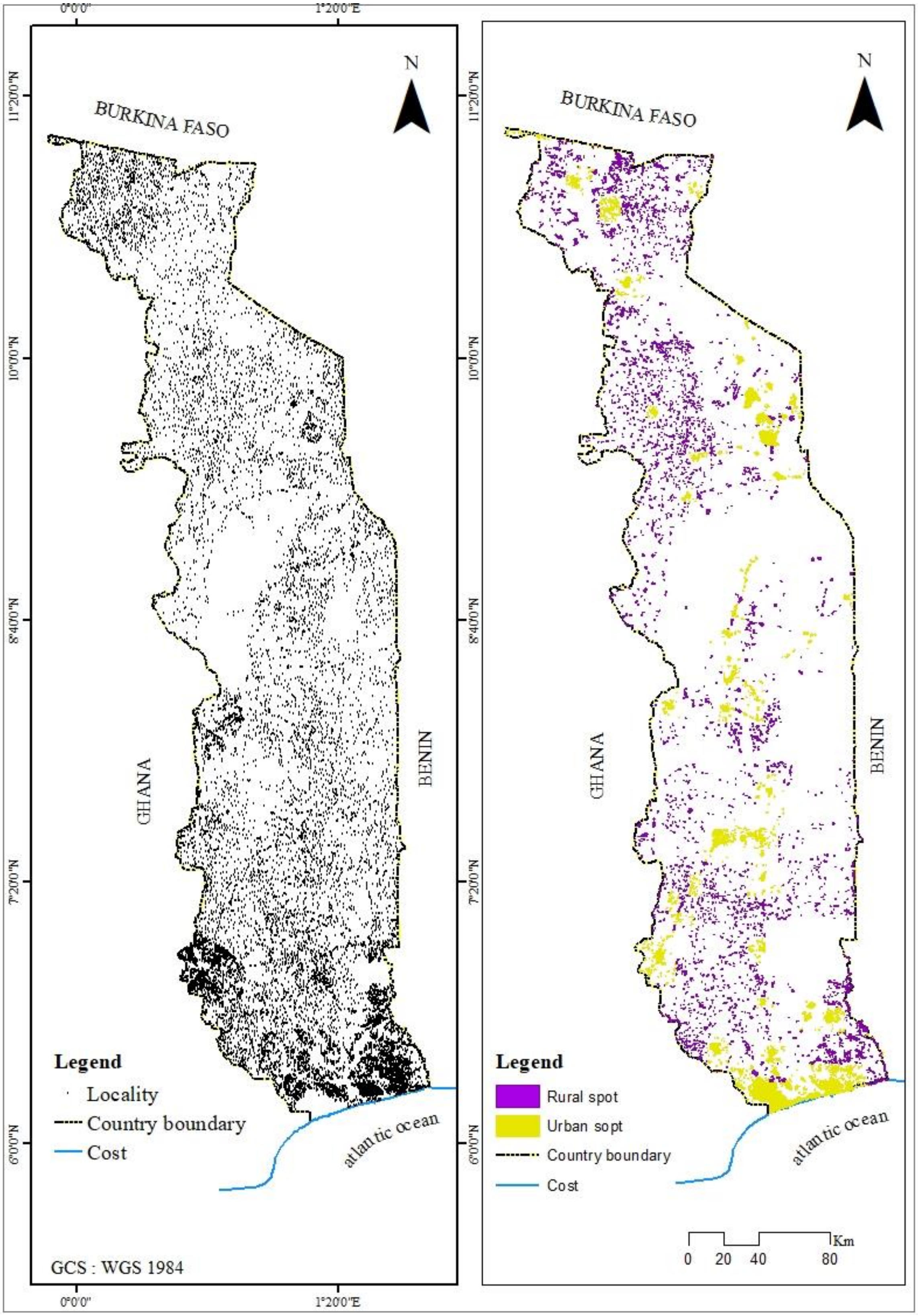


Figure 6: Lands' occupation in Togo (Design Author, Source INSEED 2010)

Figure 7: Regional electricity consumption and number of customers over time

3.2.2 Electrification rate

The electrification rate is computed as it is done at CEET (CEET, 2016). Electricity access rate or electrification rate (***El_{rate}***) is the ratio of the ***number of people with access to electricity*** to the ***total population*** as defined in formula (2).

$$El_{rate} = \frac{\begin{matrix} number\ of\ \ people\ \ with \\ access\ to\ electricity \end{matrix}}{total\ \ population} \times 100 \qquad (2)$$

Figure 9 shows the evolution of the total population in different regions as well as for urban/rural areas. The number of people with access to electricity (***P**_E*) equals the ***number of customers*** times the ***average household size*** as defined in formula (3)

$$p_E = number\ of\ customers \times household\ size \tag{3}$$

At CEET, the average household size is estimated at 7 in the Maritime region and 8 in other regions.

Figure 8: Evolution of Urban/Rural electricity consumption and number of customers

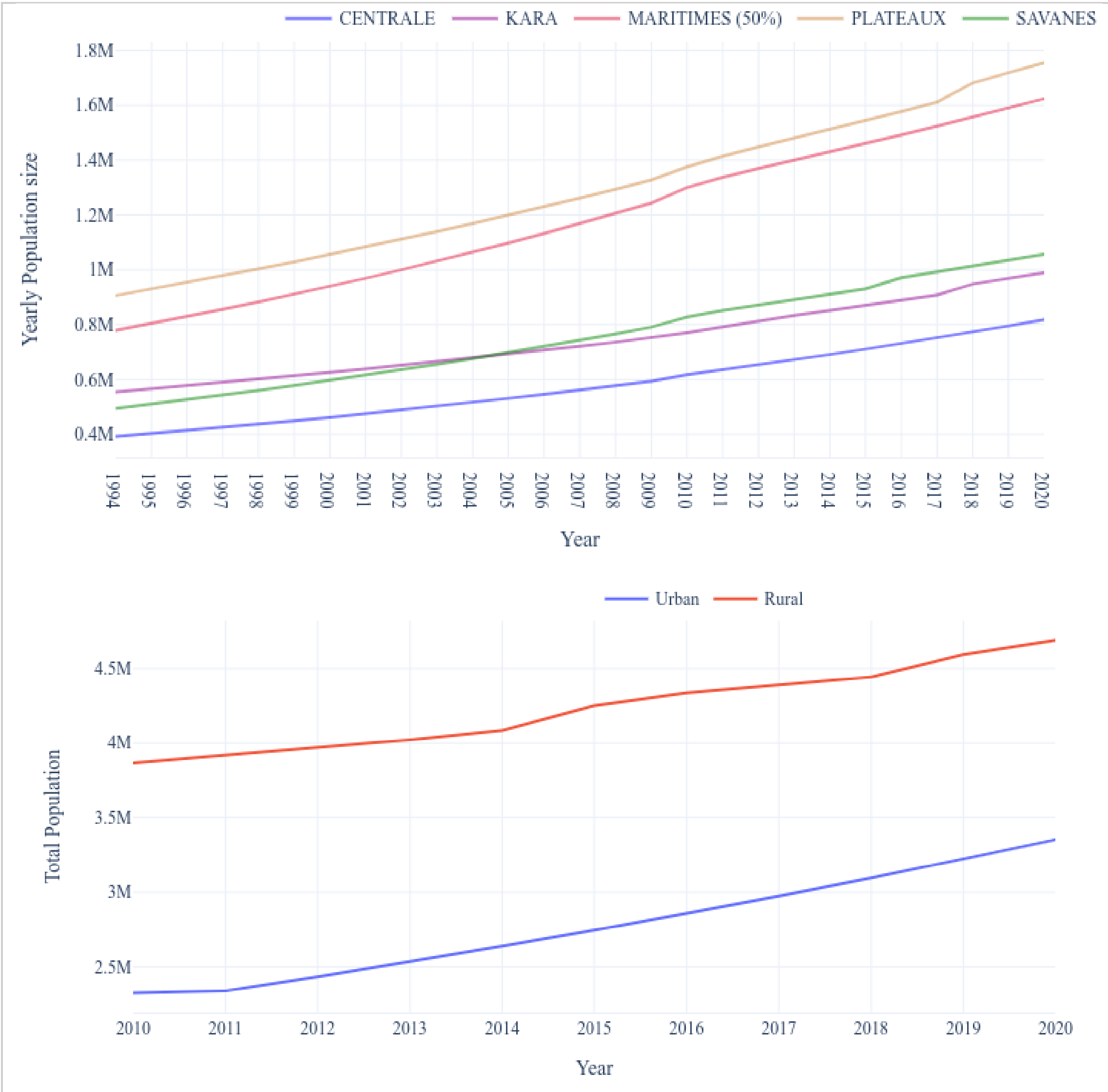


Figure 9: Evolution of the total population

Having the average electricity consumption per connection and the electrification rate, the first hypothesis was verified at regional spatial resolutions as well as at urban/rural spatial resolutions. The next section presents the findings.

3.3 Results and Discussion

3.3.1 Average electricity consumption per connection

Using the yearly number of customers and yearly consumption data, average consumption per connection was computed. Figure 10 shows the evolution of average consumption per connection in the different regions as well as in urban/rural areas.

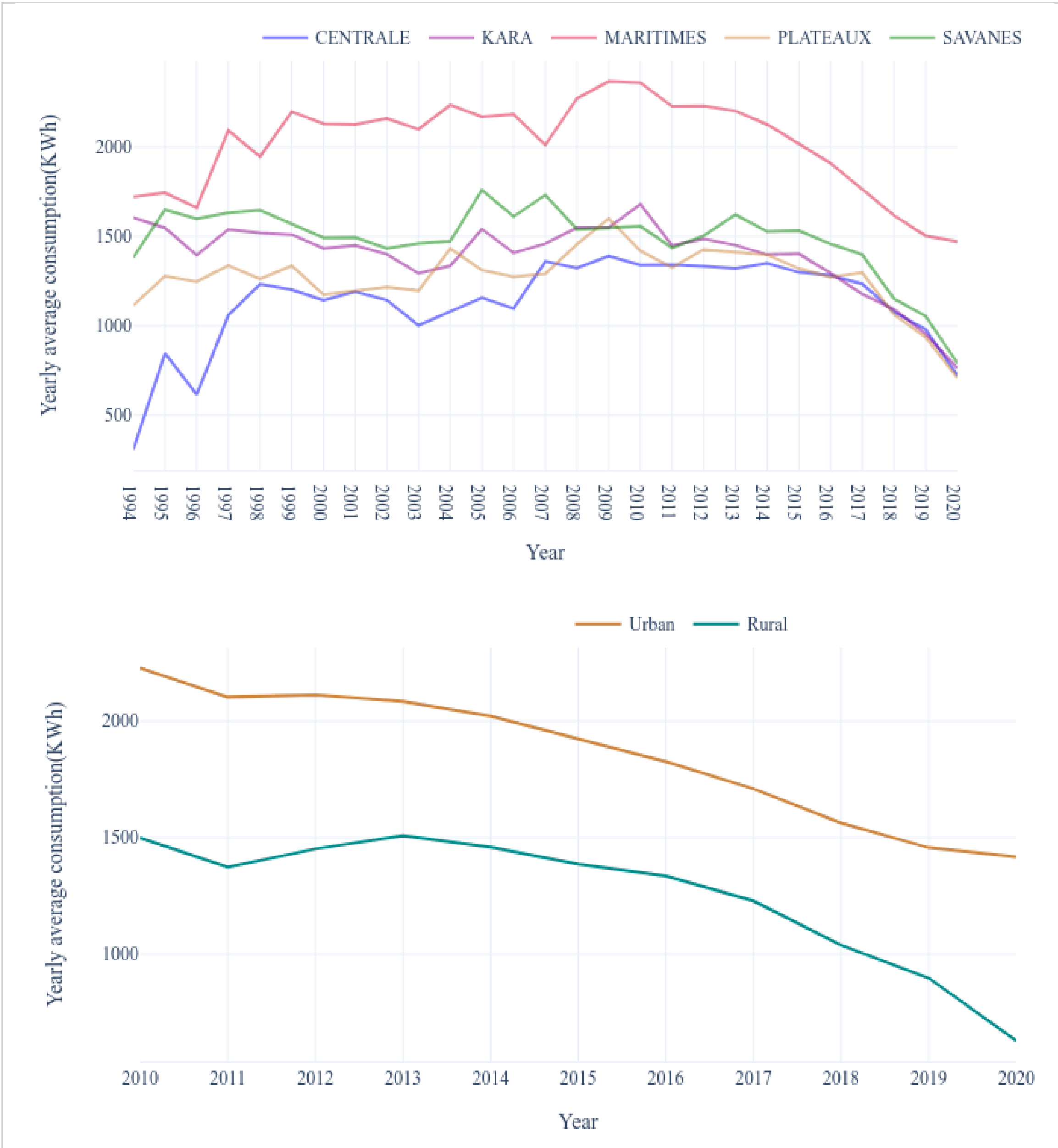


Figure 10: Evolution of average electricity consumption per connection

Regarding different regions, customers in the Savanes region reached their maximum average consumption per connection more quickly (2005) than customers in the Centrale region and Plateaux region (2009) followed by customers in the Maritimes region and Kara region (2010). All customers reached their steady state around 2013. Maritimes region is the region having the highest average electricity consumption per connection. This region is the most urbanized, containing the capital of the country. The Maritime region is also characterized by a high population density and large economic activities compared to other regions. The lowest average electricity consumption per connection is seen in the Centrale region. This region is the one having the lowest urbanization rate. The Central region is characterized by very low population density with poor economic activities. On the other hand, customers of urban areas have an average electricity consumption per connection higher than their rural areas counterparts (see Figure 11). Most of the newly-connected and unconnected households are in rural areas and these newly-connected customers have likely a low electricity consumption while urban areas have more customers with much greater consumption. Furthermore, beyond the stability period 2010-2013, the urban/rural average consumption per connection is decreasing from 2013 onwards. Several factors (or a combination of factors) may explain this decrease in electricity consumption. The reduction in consumption may be due to the energy efficiency of customers. This possible explanation is supported by the analysis conducted by Fobi et al. (2018) for 136k utility residential customers across Kenya from 2010 through 2015. In addition, Nadel and Young (2014) found that over the 2007-2012 periods, increased energy efficiency appear to be the most important contributor to decreased electricity growth rates in the United State. The decrease in electricity use may also be due to high electricity costs obliging customers to use less equipment, low revenue that cannot help customers to purchase new equipment as well as damaged equipment. However, understanding the reduction in consumption would require customer-level data to improve customer experiences.

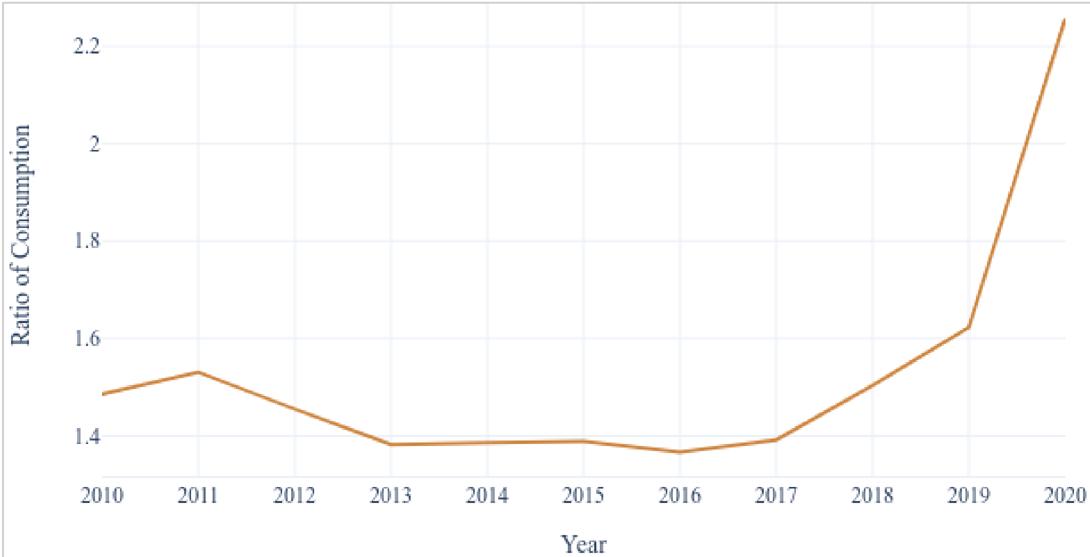


Figure 11: Ratio of urban to rural (average consumption per connection)

3.3.2 Electrification rate

The electrification rate is computed for each region (respectively for urban/rural areas) using formula (2). Figure 12 shows the evolution of the electrification rate in the different regions as well as in urban/rural areas. The electrification rate is increasing over the study period. However, the electrification rate increases more quickly in the Maritimes region (because of its high urbanization level) than in other regions. In all regions, a slight decrease in the rate of increase in the electrification rate can be observed from 2019 onwards. This is probably due to the Covid-19 effect. Since the appearance of the Covid-19 disease in 2019, countries around the World, particularly Togo country have taken significant measures aiming to slow the spread of the disease. Most of these measures have slowed down economic activities such as electrification processes. On the other hand, in both urban/rural areas, the electrification rate is increasing over the study period. The difference is due to political and economic reasons. It is cheaper and more beneficial for the utility to extend access to electricity in an urban area than in rural areas.

Figure 12: Evolution of electrification rate

3.3.3 Discussion

Figure 10 and Figure 12 show a decrease in average electricity consumption while an increase in electrification rate can be noticed. However, this opposite evolution is not seen over the entire study period. Figure 13 is a scatter plot of the electrification rate against average electricity consumption per connection. The negative correlation (opposite evolution) occurs over recent years. In the Maritimes region and Kara region, it occurs over the past ten years (from 2010). In the Centrale region, Savanes region, and Plateaux region it occurs more recently, from around 2013. Regarding urban/rural areas the same trend can be seen. The negative correlation occurs from 2010 onwards in urban areas while it occurs from 2013 onwards in rural areas. These results show that earlier electricity planning may be misleading. The CEET is probably increasing supply when the markets don't want it. However, these results can potentially assist the CEET (as a utility concerning the government's electrification plan) to achieve universal access to electricity both quickly and in the most effective manner. According to the 2018 Electrification Strategy, Togo has chosen to consider electrifying, a household with access to at least modern lighting and mobile phone charging, and the equivalent to this level of service in installed capacity is a minimum of 20W. Thus, the notion of access to electricity is redefined in terms of service level, for all technological solutions. Table 4 lists technological solutions of the strategy for achieving universal access by 2030. To achieve universal access by 2030, Togo will have to mobilize on average ~83 billion FCFA per year (4 times the historical average). Grid extension in particular will require an additional investment of 55 billion FCFA related to energy generation. With current trends of consumption rate per customer, recovering the investment may hinder the financial viability of the utility. However, an examination of grid-connected customers reveals that more customers can be added to the same transformer because of their low consumption. Thus, the CEET can densify existing networks with low-consuming customers as they can be accommodated on the same transformer. These results can help the CEET as well as the government to reduce the cost of providing electricity to households. On the customer side, the per-connection cost could be low. On the other hand, in all geographic areas the average electricity consumption per connection is below 1500 KWh in 2020 (see Figure 10). Thus, the CEET can supply households far from the existing network, with mini-grids. This analysis reveals that the Electrification Strategy of Togo can be improved and that the investment related to universal access may be lower.

Table 4: Electrification strategy of Togo for 100% by 2030

Minimum annual average consumption	4,32 KWh	72 KWh	360 KWh	1224 KWh	2952 KWh
Technological solution	Solar kits				
			Mini-Grids		
				Grid extension	

Source: Electrification Strategy of Togo (Togo, 2018)

Figure 13: Average electricity consumption per connection versus electrification rate

3.4 Conclusion

In this chapter, the descriptive analysis aiming at understanding historical residential electricity consumption is performed. The analysis reveals that average electricity consumption is decreasing as electrification increases. Some of the implications of these results are presented. For instance, The CEET may reduce costs related to grid extension by aggregating low consumers on the same transformer. In the long term, demand could be variable. Therefore, a long-term forecast of electricity consumption is essential for the CEET to formulate electricity supply. The next chapter presents yearly residential electricity consumption modeling.

CHAPTER 4: PREDICTIVE MODELLING

4.1 Introduction

One of the outcomes of the descriptive analysis is that annual average electricity consumption is decreasing. Thus, to formulate residential electricity supply policies, the CEET needs to rely on an accurate long-term forecast of residential electricity consumption. Reliably predicting electricity demand is essential to choosing the most efficient electrification solution that can ensure the best electrification economics. This chapter presents predictive modeling of CEET electricity demand in the residential sector. To the best of our knowledge, there is no a such system at the CEET that attempts to model residential electricity consumption. To date, at the CEET the interest is mainly focused on the future evolution of the number of customers. The objective of this predictive modeling is to build the most suitable DL model for predicting yearly residential electricity consumption. The prediction consists in forecasting one year in advance the electricity demand of the five (5) different regions of the country. The next sections present the method and the results of the predictive modeling.

4.2 Method

Earlier models (classical time-series modeling) focused on univariate datasets and applications. They can only work with a single feature. However, DL algorithms can automatically learn arbitrary complex mappings from inputs to outputs and support multiple inputs and outputs, offering opportunities for time series forecasting, especially on data with complex-nonlinear dependencies, multivariate inputs, and multi-step forecasting (Brownlee, 2021).

4.2.1 Deep learning overview

DL is a specific subset of ML that learn patterns from data using successive layers (stacked on top of each other) of increasingly meaningful representations of data. These representations are learned via ANNs. ANN is based on fundamental concepts that find their roots in the wiring between biological neurons that communicate chemically and electrically through neurites. "Although some of the central concepts in deep learning were developed in part by drawing inspiration from our understanding of the brain (in particular, the visual cortex), deep learning models are not models of the brain. There's no evidence that the brain implements anything like the learning mechanisms used in modern deep learning models"(Chollet, 2021). The basic function of neurons was formalized by Frank Rosenblatt in 1958 as the perceptron (see Figure 14), a model that contains the essentials of most modern deep learning. In the perceptron model, a neuron (network's node) receives input (any type of information) from other neurons. These inputs get integrated by summing them up. In this sum, each input from a neuron comes with its weight that marks its importance. The integrated input can then lead to a neural activation (as given by the neuron's activation function) that yields the output. This process is called feedforward propagation. In modern Neural Networks (NNs), activation functions are non-linear functions (sigmoid function, hyperbolic, rectified linear unit ...). The purpose of activation functions is to introduce non-linearity into the network. Linear activation functions produce linear decisions no matter the network size. In contrast, non-linearity allows for the approximation of arbitrarily complex functions.

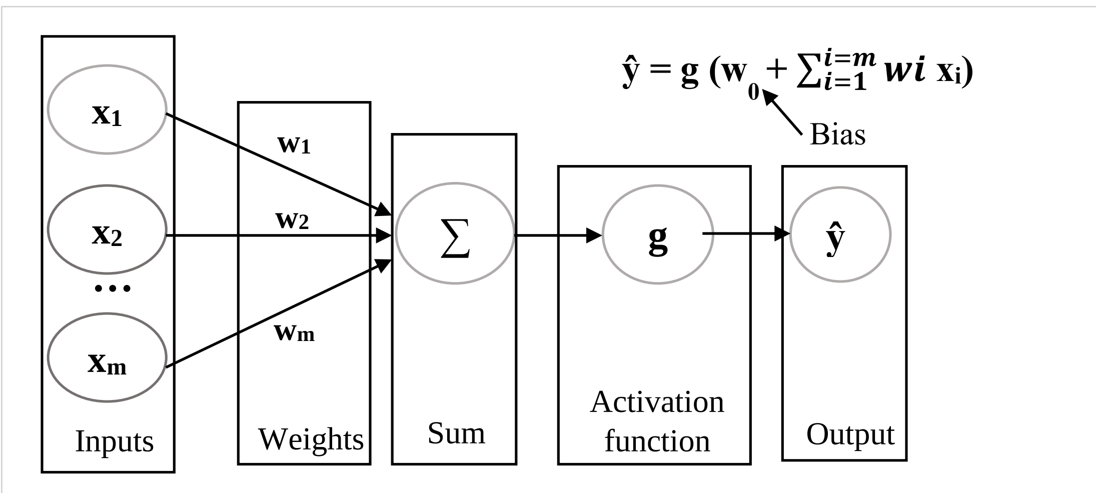


Figure 14: The perceptron model

A single-layer neural network comprises an inputs layer, a hidden layer (sum and activation function), and final output(s). Deep NNs, called Multi-Layer Perceptron (MLP) are NNs that contain multiple hidden layers. These NNs can be trained through a backpropagation algorithm. In backpropagation, outputs are compared to targets and the error derivative can be fed back through the network to calculate adjustments to the weights in the connections as illustrated in Figure 15. The early history of NNs started with the backpropagation algorithm in 1975. Since then many DL architectures were developed to solve complex real-world problems. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are the earliest and biggest success of deep learning.

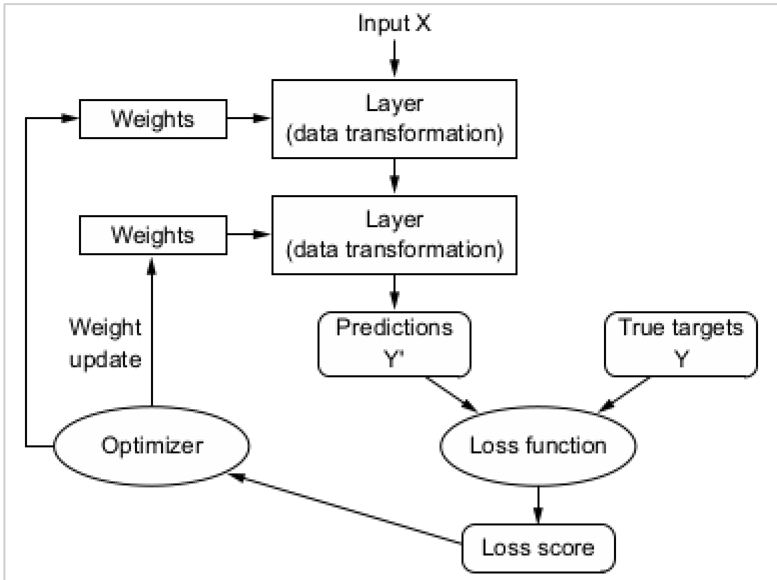


Figure 15: Backpropagation flowchart

4.2.2 Deep learning for time series

Recent years have seen a proliferation of DL applications in many domains. In forecasting, many DL algorithms have been applied more recently to time series, both with univariate and multivariate time series. DL algorithms applied to forecasting could overcome many of the challenges faced by classical approaches most importantly non-linear dynamics, usually neglected by traditional methods. These algorithms encompass CNNs and RNNs.

4.2.2.1 Convolutional Neural Networks

CNN is a type of deep model used in computer vision applications. Computer vision is the field of computer science that focuses on applying human vision complexity systems and enabling computers to identify and process objects in images and videos in the same manner that a human brain does. CNN models are applied in autonomous driving, robotics, object recognition, speech recognition, and natural language processing. The difference between densely connected layers and convolution layers is that the latter learn local patterns in their inputs feature space whereas the former learn global patterns. CNN can automatically extract features from high-dimensional raw data with a grid topology, such as the pixels of an image, without the need for any feature engineering. The model learns to extract meaningful features from the raw data using the convolutional operation, which is a sliding filter that creates feature maps and aims to capture repeated patterns at different regions of the data (local patterns). The patterns they learn are translation-invariant, which means that the features are extracted regardless of where they are in the data. Also, they can learn spatial hierarchies of patterns. A first convolution can learn small local patterns such as edges while a second convolution layer is learning larger patterns made of the features of the first layers, and so on (Figure 16). These characteristics make CNN suitable for dealing with one-dimensional data such as time series. Sequence data can be seen as a one-dimensional image from where the convolutional operation can extract features. A CNN model is usually composed of convolution layers, pooling layers (to reduce the spatial dimension of feature maps), and fully connected layers (to combine local features into global features). In a fully-connected layer, each neuron receives information from all neurons of the previous layer.

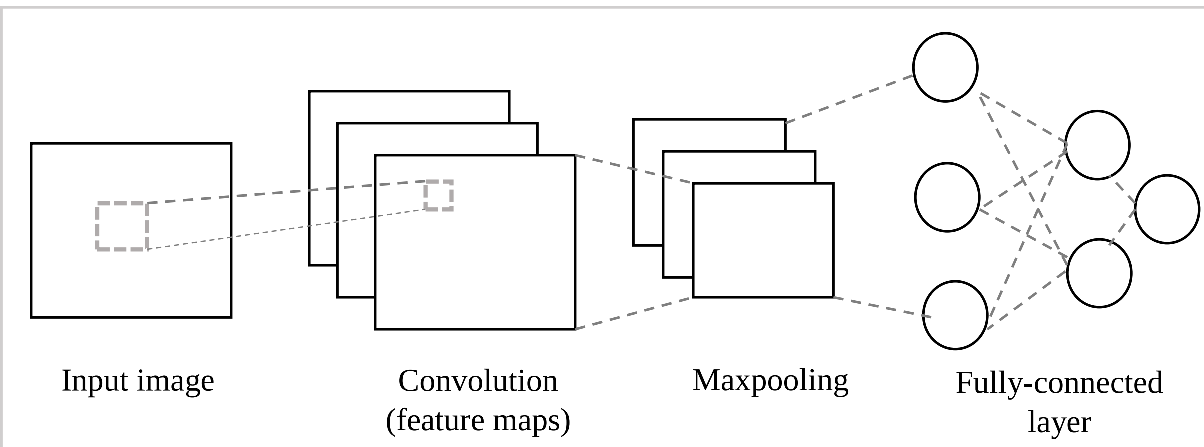


Figure 16: Convolutional Neural Network

4.2.2.2 Recurrent Neural Networks

Densely connected (fully connected) networks and convolutional networks are feedforward networks. Feedforward networks have no memory; each input is processed independently. To process temporal series of data points, these networks request the entire sequence at once. However, RNNs process sequences by iterating through the sequence elements and maintaining a state (h) that contains information relative to what it has seen so far (Figure 17). A data point is no longer processed in a single step, rather the network internally loops over sequence elements. RNNs are used in sequence modeling such as sequence prediction, sequence classification, sequence generation, and sequence-to-sequence prediction.

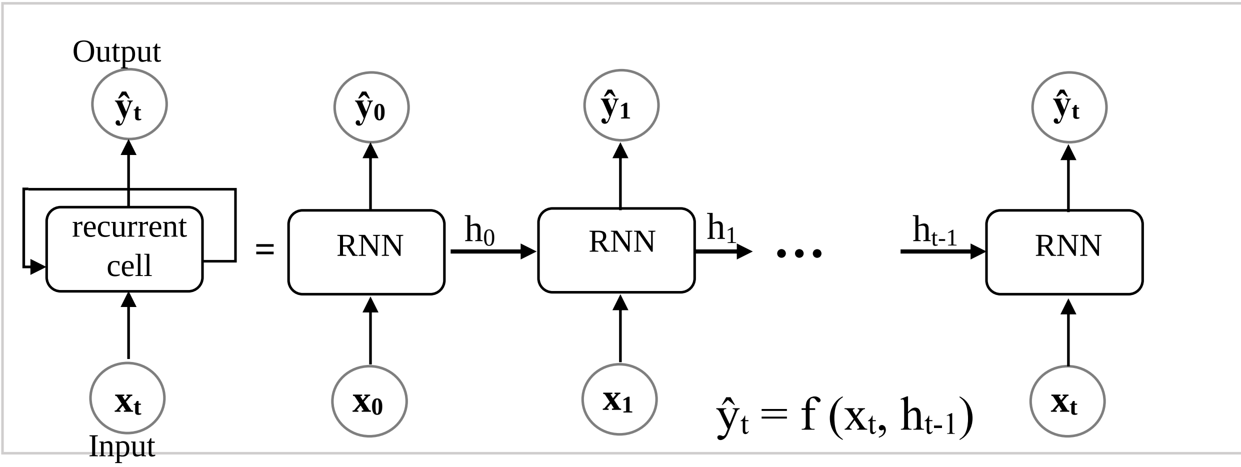


Figure 17: Recurrent Neural Network

Sequence modeling requires the handling of variable-length sequences, tracking of long-term dependencies and information about the order, and parameters sharing across the sequence. RNNs do take these requirements into account. However, long-term dependencies are impossible to learn in practice. This is due to vanishing gradient and exploding gradient problems during backpropagation. Vanishing gradient (respectively exploding gradient) occurs when backpropagation error signals tend to shrink (respectively grow) due to the multiplication of many small numbers (respectively, due to the multiplication of many big numbers) with every time step. To address this issue, LSTM and Gated Recurrent Unit (GRU) were designed. LSTM is a family of RNNs that saves information for later, preventing older signals from gradually vanishing during processing. LSTM cells can track information through many time steps. Figure 18 illustrates a comparison between the RNN cell and the LSTM cell (tanh and σ are respectively hyperbolic and sigmoid activation functions). GRU is very similar to LSTM. GRU is a slightly simpler, streamlined version of the LSTM architecture. It was introduced in 2014 when RNNs were just starting to gain interest anew in the then-tiny research community. LSTMs have been applied a lot to multivariate electricity consumption forecasting as the state of the art which can be seen in the M4 competition (Makridakis et al., 2020).

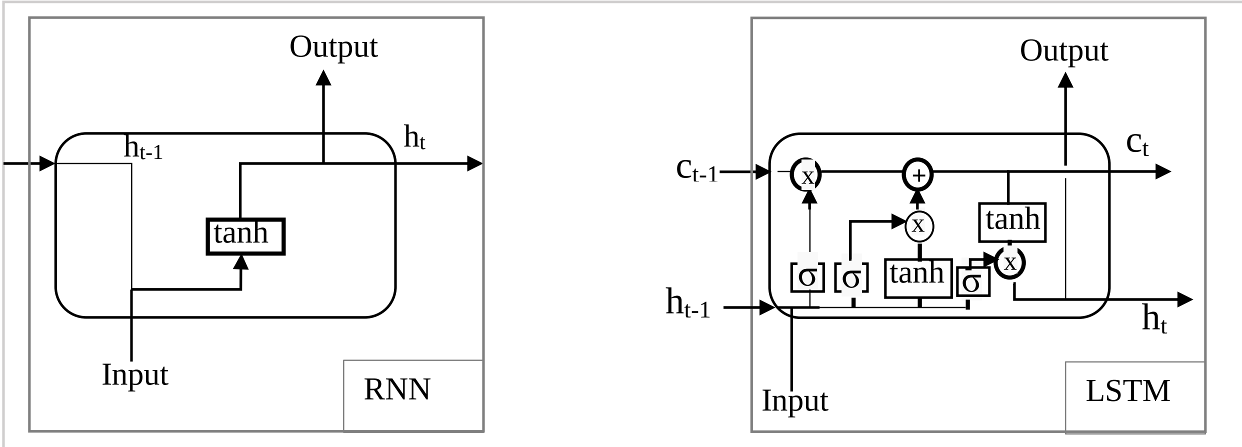


Figure 18:Anatomy of RNN cell versus anatomy of LSTM cell

4.2.3 Electricity consumption modeling

4.2.3.1 Problem framing

The problem to be modeled can be expressed as follows: given five (5) devices measuring the yearly residential energy consumption of the different regions, build a model to forecast the next residential energy consumption of each region. This corresponds to forecasting the next multiple time steps. In addition, a set of features were used as ingredients for consumption growth, making the prediction to be multi-variate forecasting. Thus, the modeling can be performed as Multivariate and Multistep forecasting.

The multivariate and multistep residential electricity consumption forecasting was performed using Tensorflow version 2.8.0. Tensorflow is a python end-to-end open-source package designed for machine learning (deep learning).

4.2.3.2 Understanding variables

A set of variables were selected to perform the multivariate time series forecasting task. These variables are:

- Residential consumption data (KWh);
- Residential number of customers;
- Total population;
- Electrification rate (%);
- Medium voltage consumption data (KWh);

- Medium voltage number of customers.

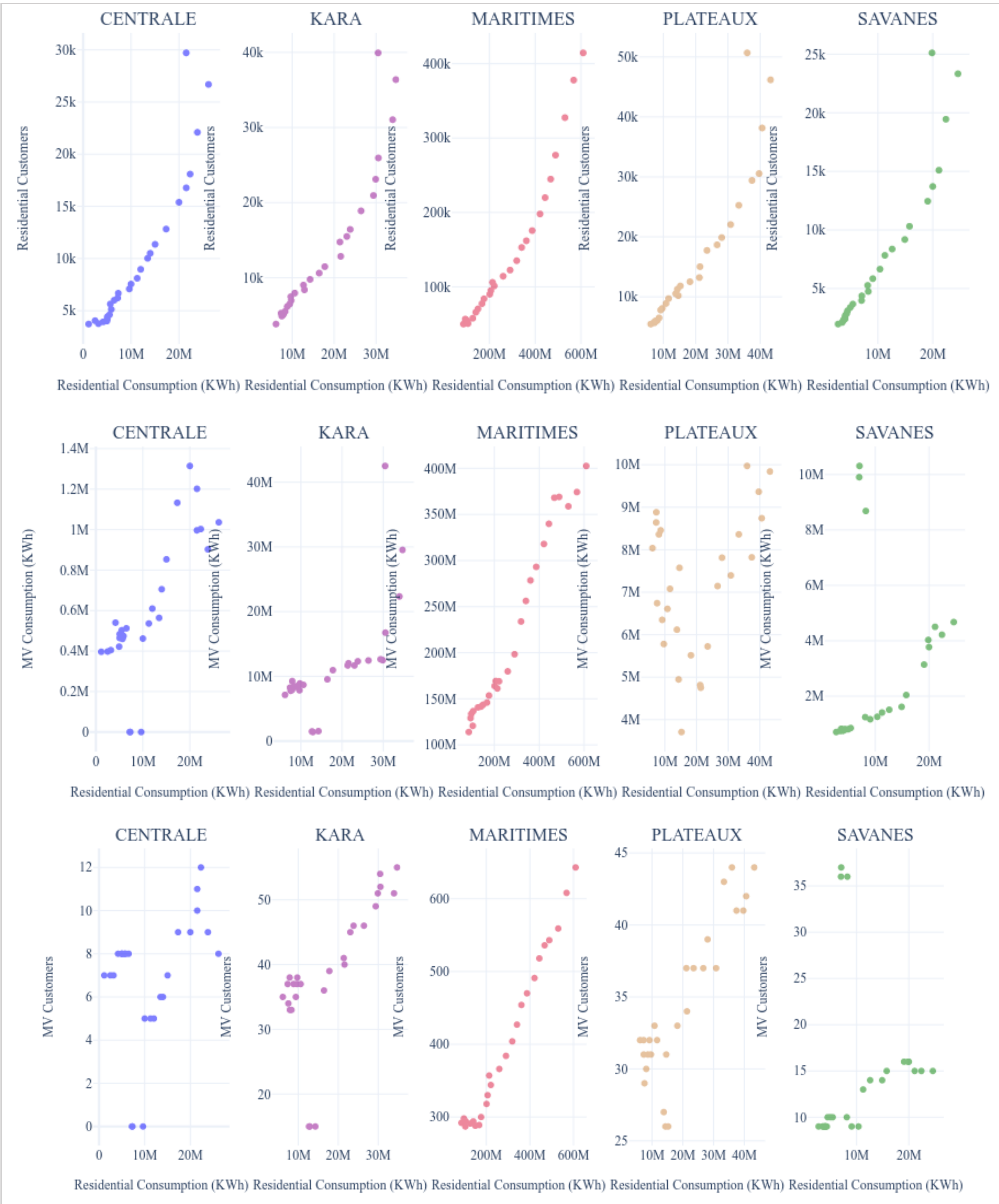
Residential consumption data is the dependent variable (predictor). Medium voltage consumption and the number of customers are used as economic factors. The variables were selected through Pearson correlation between variables (see Table 5). In multivariate time series, each dependent variable does not only depend on its past values but also potentially on other past values of other variables. This introduces complexity such as collinearity. A coefficient value of 1 means both variables are 100% correlated. In contrast, a coefficient value of 0 means both variables are not correlated at all.

Table 5: Pearson correlation coefficients

	Residential consumption data (KWh)	Residential number of customers	Total population	Electrification rate (%)	Medium voltage consumption data (KWh)	Medium voltage number of customers
Residential consumption data (KWh)	**1**	**0.98**	**0.99**	**0.96**	**0.91**	**0.94**
Residential number of customers	**0.98**	**1**	**0.95**	**0.92**	**0.88**	**0.96**
Total population	**0.99**	**0.95**	**1**	**0.99**	**0.91**	**0.92**
Electrification rate (%)	**0.96**	**0.92**	**0.99**	**1**	**0.93**	**0.89**
Medium voltage consumption data (KWh)	**0.91**	**0.88**	**0.91**	**0.93**	**1**	**0.86**
Medium voltage number of customers	**0.94**	**0.96**	**0.92**	**0.89**	**0.86**	**1**

4.2.3.3 Uncovering the relationship between variable

A scatter plot between the independent and dependent variables was plotted for a visual evaluation of the correlation between variables across the different regions as shown in Figure 19.



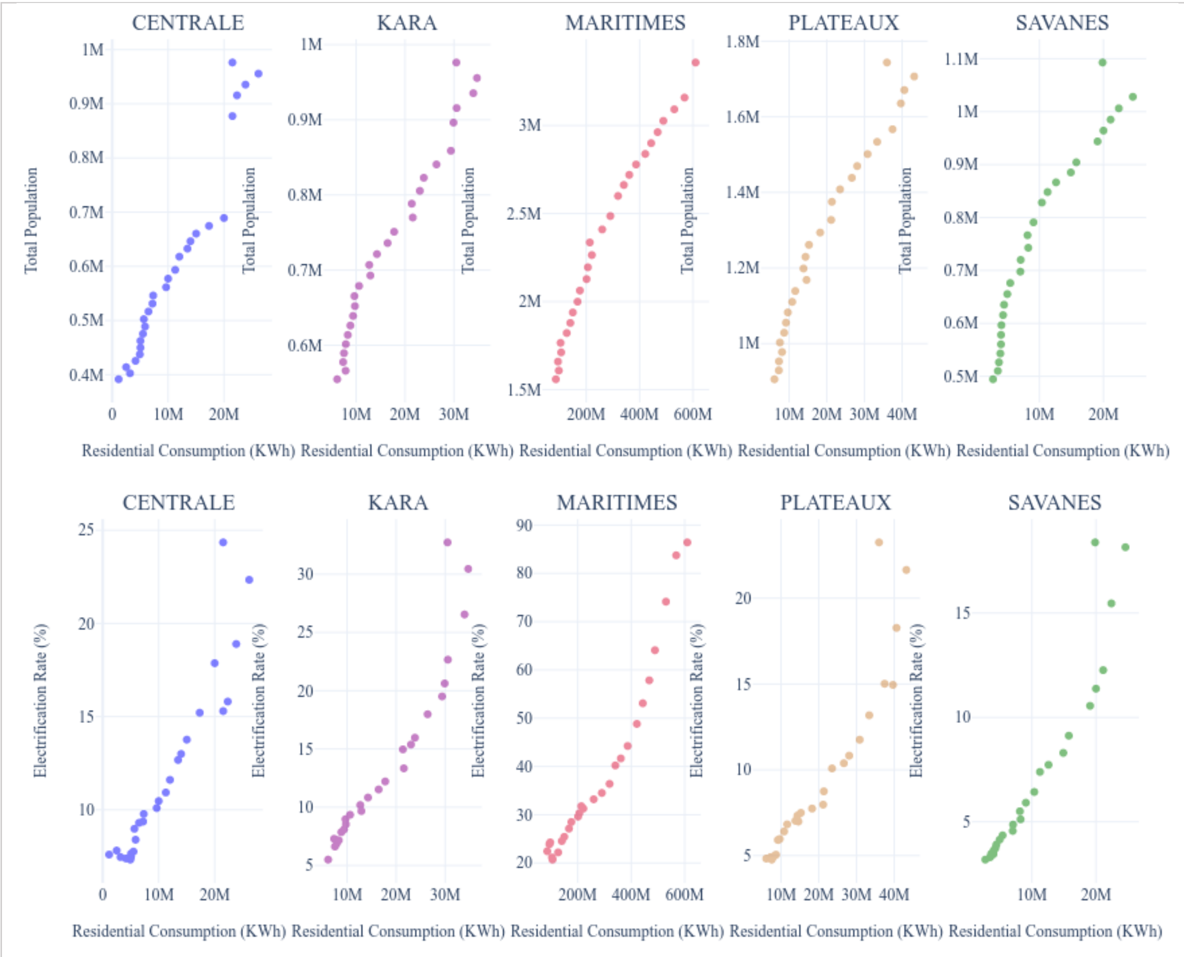


Figure 19: Scatter plot of independent variable versus dependent variable

4.2.3.4 Data normalization

Each time series in the data is on a different scale. Thus, each feature was normalized independently (to have a mean of 0 and a standard deviation of 1) so that they all take small values on a similar scale. Similar to input data, target data were also normalized because of their wide range of values. Data were normalized using formula (4).

$$X^k = \frac{x^k - \text{mean}}{std} \qquad (4)$$

In this formula, $\mathbf{X^k}$ is the normalized value of series k, $\mathbf{x^k}$ is the original input data value of series k, **mean** is the mean of the input data value of series k and **std** is the standard deviation of the input data of series k.

4.2.3.5 Time series to supervised learning

Time series forecasting is a supervised learning problem. Supervised learning is a learning process where there are known targets (also called labels or annotations) associated with input data (also called features), and where loss is computed as a function of these targets and the model's predictions. Thus, consumption data and consumption growth ingredients were re-framed to inputs-targets as illustrated in Figure 20. This was done using Tensorflow's TimeserieGenerator function. The dataset has a regional spatial resolution and yearly temporal resolution.

n Time steps	**m** inputs				Targets			
$_1t_1$	$_1X_{11}$	$_1X_{21}$	…	$_1X_{m1}$	$_1Y_1$	$_2Y_1$	…	$_kY_n$
$_2t_1$	$_2X_{11}$	$_2X_{21}$	…	$_2X_{m1}$	$_2Y_1$	$_3Y_1$	…	$_1Y_1$
…	…	…	…	…	…	…	…	…
$_kt_1$	$_kX_{11}$	$_kX_{21}$	…	$_kX_{m1}$	$_kY_1$	$_1Y_2$	…	$_{k-1}Y_1$
…	…	…	…	…	…	…	…	…
$_1t_n$	$_1X_{1n}$	$_1X_{2n}$	…	$_1X_{mn}$	$_1Y_n$	$_2Y_n$	…	$_kY_{n-1}$
$_2t_n$	$_2X_{1n}$	$_2X_{21}$	…	$_2X_{mn}$	$_2Y_n$	$_3Y_n$	…	$_1Y_n$
…	…	…	…	…	…	…	…	…
$_kt_n$	$_kX_{1n}$	$_kX_{21}$	…	$_kX_{mn}$	$_kY_n$	$_1Y_1$	…	$_{k-1}Y_n$

Figure 20: Time series to supervised learning

The datasets comprise **k** parallel inputs of **n** time steps with **m** features.

- **k** parallel inputs: These parallel inputs represent inputs from each region (k=5).
- **n** time steps: Inputs are yearly records from 1994 to 2020 (n=27).
- **m** features: the features are the variables (dependent and independent variables)
- **Targets**: residential consumption data (independent variable)

The dataset counts a total number of 27x5=135 data points and each data point contains all features.

Evaluating a model always boils down to splitting the available data into three (3) sets training, validation, and test. The model is trained on the training data while being evaluated on the validation data. Once the model is ready, it's tested one final time on the test data. The reason for validating a model is that developing a model always involves tuning its configuration (called hyper-parameters). There is no universal rule regarding the computation of the number of samples for each data sample. However, data representativeness, the arrow of time, and data redundancy are used as indicators for data splitting.

For this forecasting problem, the dataset was split as follows:

- Training sample (80%): Dataset from 1994 to 2014 for the five regions: 21*5=105 data points.
- Validation sample (15%): Dataset from 2015 to 2018 for the five regions: 4*5=20 data points.
- Test sample (5%): Dataset from 2019 to 2020 for the five regions: 2*5=10 data points.

4.2.3.6 Modelling

The experiment was run on four (4) different models: MLP, CNN, LSTM, and CNN-LSTM ensemble model. Table 6 lists the hyper-parameters for each model. This setting was found to be the best after many trials and fine-tuning.

Table 6: Hyper-parameters

Models	**Parameters**	**Epochs**	**Learning rate**
MLP	8 466 437	120	1e-5
CNN	43 305	256	1e-3
LSTM	43 305	70	1e-3
CNN-LSTM	147 737	50	1e-3

Figure 21 illustrates the architectural design of each model. All models use an RMSprop optimizer with Mean Square Error (MSE) as an objective function (loss).

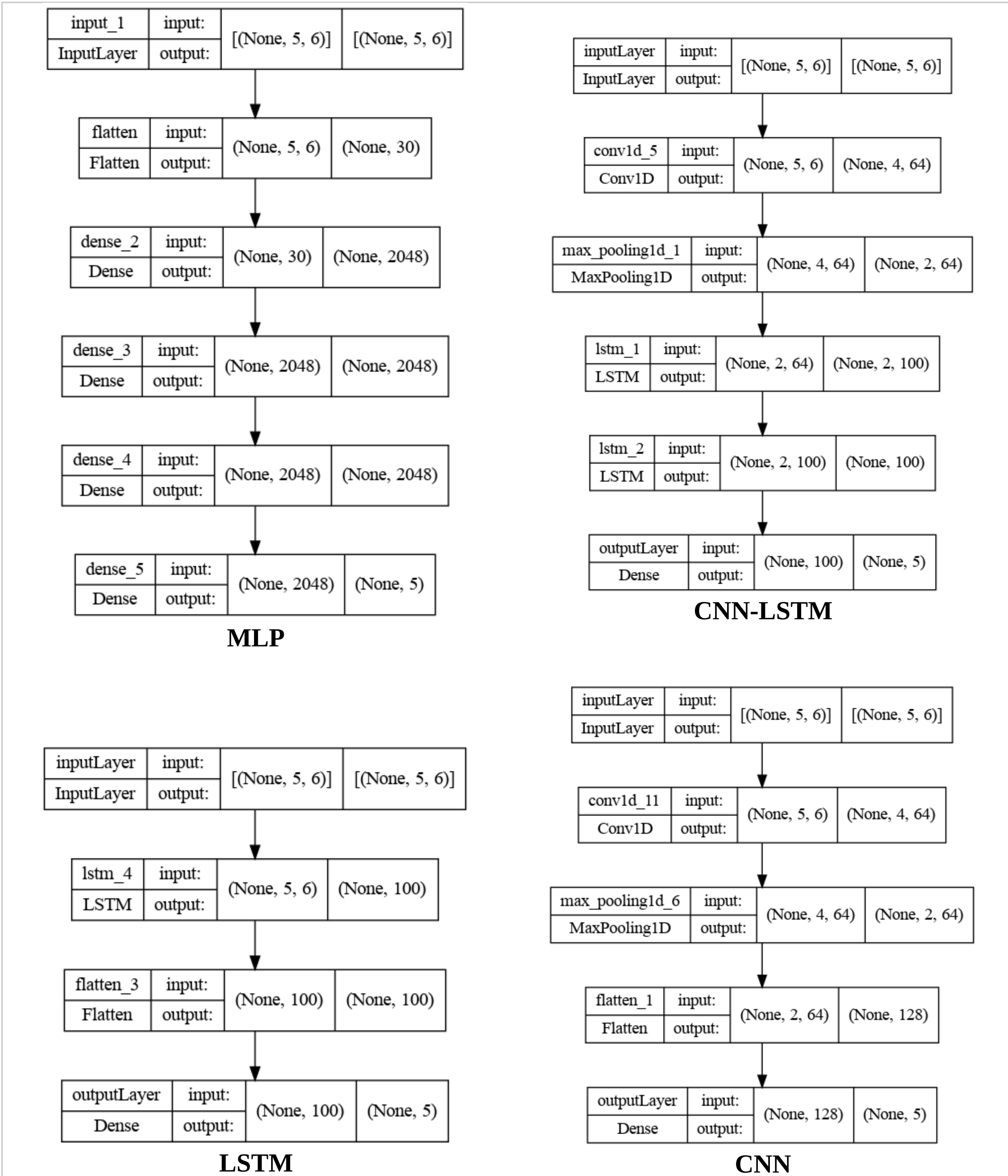


Figure 21: Model architecture

4.2.3.7 Models evaluation

The mean absolute error (MAE) is used as a metric to evaluate the performance of models. MAE evaluates the absolute distance of the observation to the prediction. MAE takes the average of absolute errors for a group of predictions and observations as a measurement of the magnitude of error for the entire group (formula (5)). A small value of MAE indicates good performance.

$$\text{MAE} = \frac{1}{n}\sum_{k=1}^{n} | y^{real} - y^{pred} | \qquad (5)$$

4.3 Results

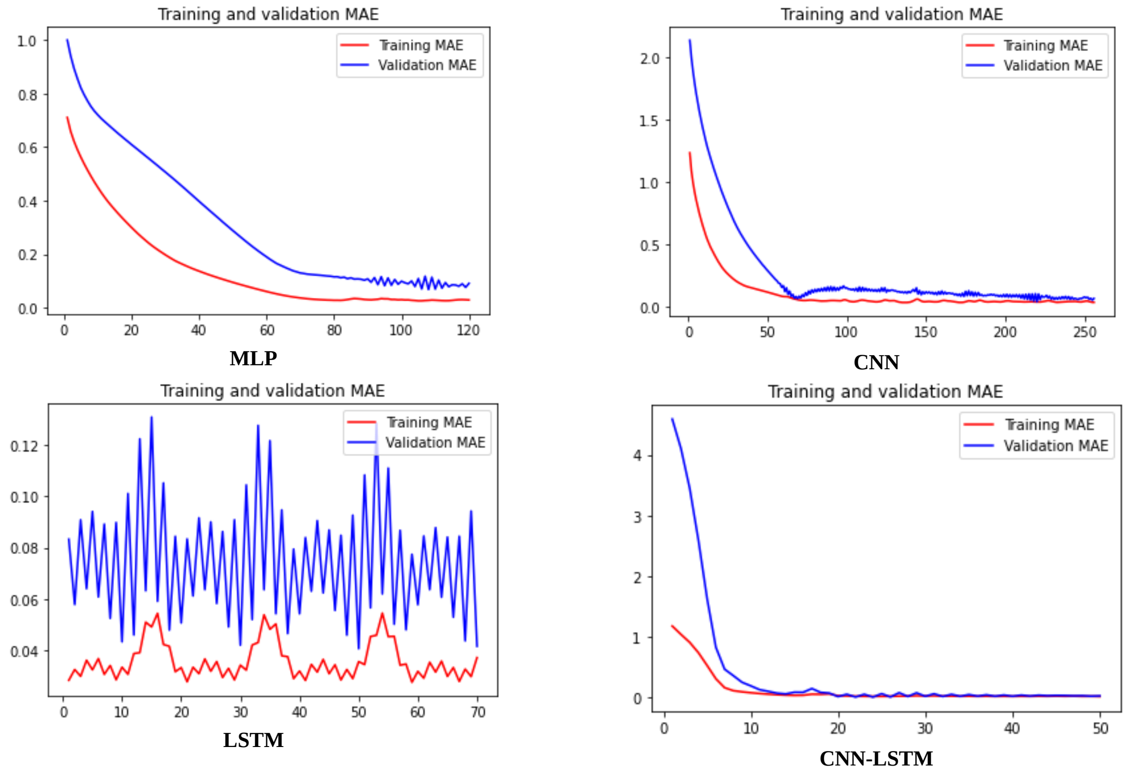
4.3.1 Model training and testing

The residential electricity consumption forecasting experiment was performed using four (4) separate models. Models were trained and evaluated using the same training, evaluation, and testing data. Figure 22 shows the models' training and validation results. All models performed well on the validation sets. These results were obtained with the best hyper parametrizations as mentioned earlier. Table 7 lists models' validation performances obtained at the end of the training, with the MAE metric.

Table 7: Validation performance

Models	Validation performances
MLP	0.067
CNN	0.042
LSTM	0.041
CNN-LSTM	0.027

CNN and LSTM have similar performance on the validation set. These two models have the same number of parameters and the same learning rate. However, CNN requires more epochs (250 epochs) to get this performance than LSTM which requires 70 epochs. CNN-LSTM model (ensemble model) combines both CNN and LSTM properties.



the x-axis represents the number of epochs while the y-axis represents MAE values

Figure 22: Model training and validation.

On the one hand, the feature extraction process is performed at the CNN level (spatial information) and on the other hand, the extracted features are fed to the LSTM model that has a memory (temporal information). Thus, the Spatio-temporal CNN-LSTM model will require more parameters to perform the forecasting. It has achieved the best performance on the validation set with a few epochs (50 epochs). The experiment was also carried out with the MLP model that is used as a baseline. MLP unlike the precedent models is a feed-forward model. MLP processed the temporal series as a single data point. Thus, the temporal dependence is ignored. The best hyper-parameters (ending having the lowest validation performance) for this model were found with huge computational resources with more than 8 Million parameters (see Table 6 and Figure 22). After the training process, final models were evaluated using test sets. Unlike validation sets, test sets are data that models have never seen before. Such data sets are used to evaluate the performance of a trained model. Figure 23 shows models' performances on validation and test sets. The graph shows that the average error of the forecast outcomes is within a reasonable range.

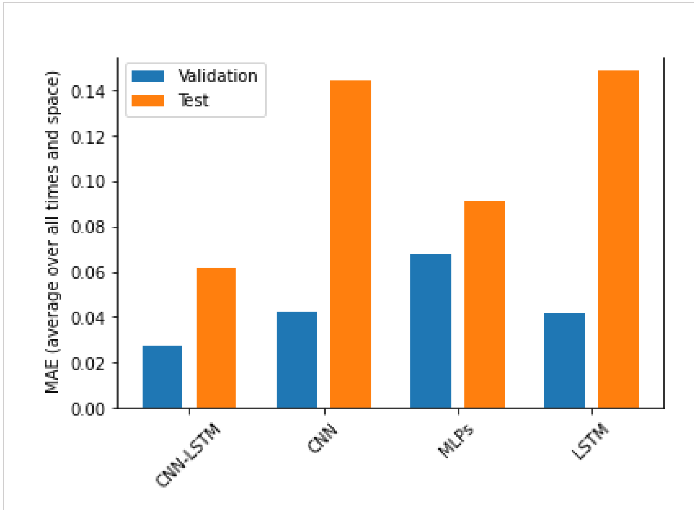


Figure 23: model evaluation

Table 8 lists models' performances on testing sets. MAE calculations are carried out both at the training level and testing level as well. The MLP performed better on unseen data than CNN and LSTM models that performed similarly.

Table 8: Testing performance

Models	**Test performances**
MLP	0.091
CNN	0.144
LSTM	0.148
CNN-LSTM	0.062

4.3.2 Model Ranking

All four models are configured using different hyper-parameters. In addition, they have different scores in terms of training and testing. Taking into account the three criteria (Table 6, Table 7, and Table 8), the four models can be ranked as shown in Table 9. The ensemble CNN-LSTM model performs the best at all levels. Then comes the LSTM model.

Table 9: Model Ranking based on hyper-parameters, training, and testing scores

Models	**Rank**			
	Hyper-parameters	Training	Testing	Overall
MLP	4	4	2	**4**
CNN	2	3	3	**3**
LSTM	1	2	2	**2**
CNN-LSTM	3	1	1	**1**

Figure 24 presents the actual electricity consumption versus CNN-LSTM predictions.

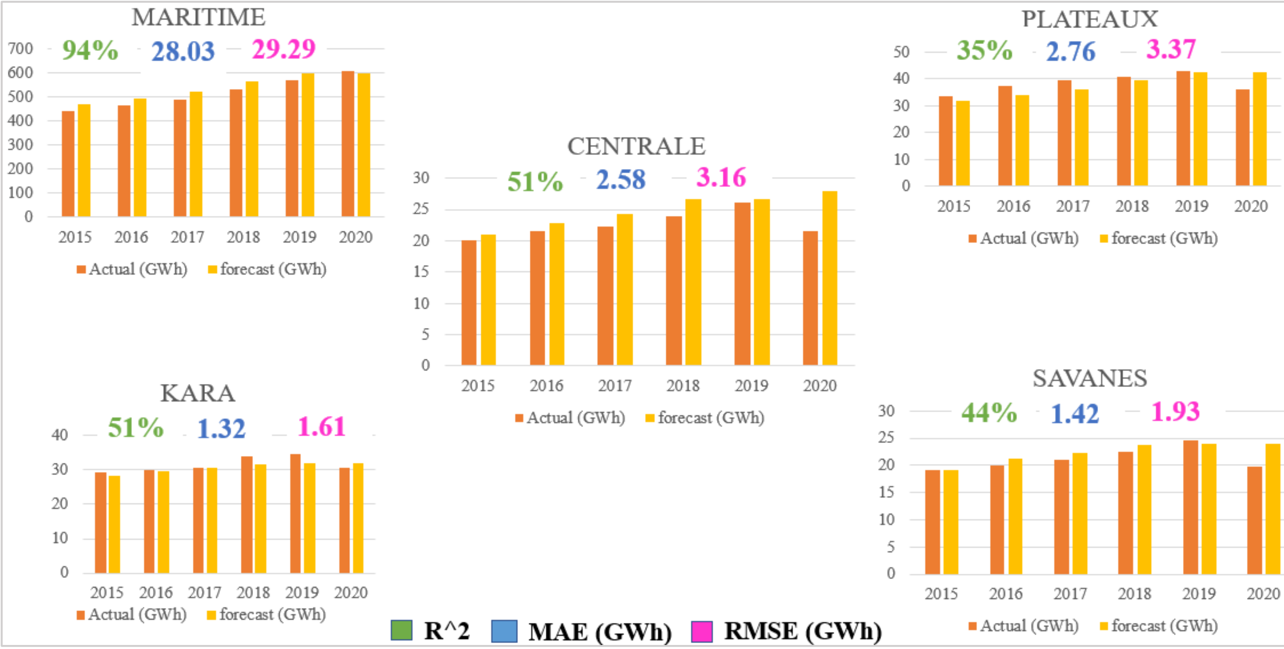


Figure 24: CNN-LSTM 's forecasts versus actual values

As a recall, models were trained with datasets covering the 1994 to 2014 period. It can be noticed that globally CNN-LSTM model is good.

4.4 Conclusion and discussion

This chapter presents predictive modeling of CEET residential electricity supply in the five regions of the country. The modeling was performed using ANNs (deep learning). The experiment was carried out on four deep learning models: MLP, CNN, LSTM, and an ensemble of CNN-LSTM models. These models are designed to predict the yearly residential electricity consumption of the five regions simultaneously. The LSTM model appears to perform the best at predicting yearly residential electricity consumption, however, combined with CNN, it becomes more accurate. Such a model can be used at CEET to predict the yearly residential electricity demand in the different regions. The model can assist the CEET in its resource allocation to extend access to electricity. Even more, with the decrease in consumption rate, forecasting demand before deciding how to connect customers can result in an underutilized grid connection allowing more customers to be reached, thereby reducing connection cost to the CEET.

CONCLUSION AND PERSPECTIVES

1. Conclusion

This project aimed to investigate the dynamics of electricity consumption growth in Togo, and to build the most suitable deep learning model for predicting yearly electricity consumption. As a result of this research, the average consumption decreases as the electrification rate increases (1). It was also found that the multivariate and multi-steps LSTM model is suitable for predicting the yearly electricity consumption of Togo’s five regions (2).

In contrast to the electrification rate that increases over the study period, the average consumption increased until 2013 when most of the consumers reached their steady state. Then it starts decreasing. Regarding forecasting tasks, MLP, CNN, and LSTM are the commonly used DL models. The yearly electricity forecasting experiment carried out on these models and evaluated using the MAE metric indicates that the LSTM model is the most suitable model for predicting CEET's yearly residential electricity supply. These findings confirm the stated assumptions of this work:

- H1: Average electricity consumption decreases as the electrification rate increases.
- H2: LSTM is the most effective DL model for predicting yearly residential electricity consumption.

2. Research contributions

Electrical energy plays a vital role in daily life. Understanding energy consumption remains a fundamental aspect of energy planning. This thesis contributes to understanding consumption dynamic, and give insights to decision-makers. (1) helps Togo Electricity Company as well as the government to formulate residential electricity supply policies. Since the average consumption is decreasing, low consumers can be aggregated on the same transformer. In addition, off-grid solutions are suitable for areas located far from the grid connection. This could considerably reduce the cost of grid extension. (2) Can be considered as a first step in the application of ANN in electrical energy modeling in Togo. The multivariate and multi-step LSTM model can forecast electricity consumption in the five regions simultaneously without the need of building a specific model for each region. Deep learning methods present undeniable advantages compared to traditional forecasting methods. The CEET could use these forecasts techniques to right-size resource allocation regarding grid extension.

3. Limitations and future work

This study was built upon a postpaid electricity consumption dataset. However, Togo Electricity Company counts postpaid as well as prepaid customers. Future work will be needed to extend our understanding of consumption growth among prepaid customers. (1) suggests the extension of electricity access using off-grid solutions in the area far from the grid. Solar home systems and mini-grid solutions are the most common solutions used in the electricity sector. A comparative study of these off-grid solutions could give insights to decision-makers with the choice of least cost off-grid solutions. (2) indicate that the LSTM model is good at forecasting yearly residential electricity consumption. However, from the experiment, it can be seen that the model accuracy can be increased when combining it with the CNN model. Further work on ensemble ANNs models regarding residential electricity consumption forecasting could be interesting.

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