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MODERN POWER SYSTEM MONITORING AND CONTROL FOR NON-TECHNICAL LOSSES: CASE STUDY OF THE DEMOCRATIC REPUBLIC OF CONGO

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A dissertation submitted in full fulfilment to the University of Rwanda in accordance with the requirements of the Degree of MASTERS OF SCIENCE IN ELECTRICAL POWER SYTEMS ENGINEERING

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Dissertation title

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A Dissertation Submitted in full fulfilment of the requirements of the Degree of Masters of Science in Electrical Power Systems Engineering.

At the African Center of Excellence in Energy for Sustainable Development (ACE-ESD), College of Science and Technology (CST), University of Rwanda.

Kigali, December 2021

Declaration

I declare that this Dissertation is the result of my own work except where specifically acknowledge and it has not been submitted for any other degree at the University of Rwanda or any other institution. This dissertation has been passed through the anti-plagiarism system and found to be compliant and this is the approved final version of the Dissertation.

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Date: 24/10/2021

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This Dissertation work has been submitted for examination with my approval as a university advisor.

Dr.-Eng. Peter MUSAU

Thesis Advisor Signature

Dedication

To the incredible man who made unbelievable efforts to push me forward, who taught me the meaning of integrity, honesty, sacrifice, determination and love:

My Father.

To the woman whose continuous support and encouragement was the motive during the hardships, whose daily prayers granted me the favor to touch each success:

My Mother.

To the kind hearts whose sacrificial care of me and our entire family made it possible to complete this work, from them I learned; where there is a will, there is a way:

My two Elder Brothers.

To all those whose incessant support made me achieve new heights in my life:

Family, Church and Friends.

For all those and more, I present my humble Dissertation.

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MUZALIA KIKUNI Benjamin

Abstract

(Muzalia Kikuni Benjamin/219014710)

Power losses are still a measure problem in the electricity distribution sector. In fact, distribution system envisions the transfer of electricity of transmission system to customers for utilization in several activities. Nevertheless, a portion of the electric power produced by a utility is lost during the distribution process.

Therefore, it is crucial to assure continuous monitoring in order to maintain power losses within admissible range. This can help power companies not only to minimize commercial loss but also to optimize their profitability. It can also guarantee the beneficial power quality of furnished energy as well as distribution system efficiency and reliability. In this perspective, this dissertation present a modified methodology for Technical Losses (TL) and Non-Technical Losses (NTL) analysis per feeder. The monitoring for these losses is carried out with the conception of an Automated Control Chart (ACC) established on a statistical approach. The ACC enables to detect any deviation of energy consumption out of the admissible deviation limits set by control parameters. The analyses performed herein make use of time series data measured on feeders of a real power supply located at Rutsuru in the DRC. Hence, the monitoring of the original data recorded at the date of 31st December 2020 on the Goma feeder generated the following results: detection of 9 data points allied with abnormal TL across the line and 3 data points associated with the NTL, mostly caused by hooking electricity from distribution line.

Key words: *Modern Power System; Electric Power Distribution System; Monitoring & Control; Technical Losses; Non-Technical Losses; Automated Control Chart; Democratic Republic of Congo*

List of acronyms

ACC	Automated Control Chart
ACE-ESD	African Center of Excellence in Energy for Sustainable Development
AMI	Advance Metering Infrastructure
CC	Control Center
CTQ	Control to Quality
DRC	Democratic Republic of Congo
DSL	Digital Subscriber Line
DTs	Decision Trees
GK	Kessel clustering
GPRS	General Packet Radio Service
GPS	Global Positioning Systems
GW	Giga Watts
IMM	Intermediate Monitor Meter
IND	Independent Network Division
LAN	Local Area Network
LCL	Lower Critical Limit
LFC	Load Frequency Control
LSE	Linear System of Equation
LWL	Lower Warning Limit
M&C	Monitoring and Control
NTL	Non-Technical Loss
PMU	Phasor Measurement Unit
RTUs	Remote Terminal Units
SCADA	Supervisory Control and Data Acquisition
SVM	Support Vector Machine
TL	Technical Loss
TOE	Theft of Electricity
TS	Transient Stability
TV	Target Value
UAV	Unmanned Aerial Vehicle.
UCDL	Upper Critical Deviation Limit
UCL	Upper Critical Limit
UNs	Unit Networks
UWDL	Upper Warning Deviation Limit
UWL	Upper Warning Limit
VBA	Visual Basic Application
VMV	Voltage Magnitude Violation
VS	Voltage Stability
WAMC	Wide Area Monitoring and Control System

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Chapter 1

INTRODUCTION

1.1 Background

The Democratic Republic of Congo is situated in the center of the African continent. Bordered by the Central African Republic, South Sudan, Uganda, Rwanda, Burundi, Zambia, Angola, Republic of Congo, as well as Tanzania. The country extends a total land area of 2,267,048 km² and inland water of about 77,810 km², which makes it the largest country in Sub-Saharan Africa [1]. The DRC has a population of 75.71 million with an annual population growth of 2.7%.

Considering the infrastructures, the DRC’s power industries are facing significant challenges in monitoring power losses especially to detecting and preventing Non-Technical Loss (NTL). In fact, there is an ascendant power demand yet the protection of the entire distribution system is not enhanced. This might have been due to the huge investments that it requires. Moreover, the infrastructures are not equipped to handle many sensors on the lines. Consequently, it is difficult to perform the monitoring for NTLs detection and that can result in commercial losses and longer downtimes. Therefore, this dissertation presents a modified monitoring method that takes advantage of an Automated Control Chart that allows defining the target value and two deviation limits. As soon as a data point in the monitored data series surpasses the set limits (the warning and the critical limit lines) they are automatically highlighted. This method is estimated to be favorable for a developing country as it is the case for the DRC. In fact, the method developed in this labor does not require sophisticated sensors within the distribution system in order to perform the automatic inspection of energy consumption in the feeder. It makes use of the remote data measurement of the distribution system itself.

The analyses performed herein make use of time series data measured on feeders of a real power supply located at Rutsuru in the DRC. Hence, the monitoring of the Goma feeder’s data recorded on the 31st December 2020 generated the following results: 9 highlighted data points represent warming alerts as they are greater than the upper warning limit line and 3 highlighted data points represent the NTL since they surpass the upper critical limits. This result was identified by simulating the original feeder’s data with the help of an Automated Chart Control (ACC) rely up on the set control parameters.

1.2 Problem Statement

Power losses are still a central issue in Modern Power Systems, mostly in developing countries.

This has been the case in the Democratic Republic of Congo (DRC). It is ascending populating and economically moving forward. Furthermore, the energy demand increases accordingly. In fact, access to electricity in the DRC is no longer sufficient; around 19% of the inhabitants has access to electricity. In a particular way, there is a counterbalance regarding the electrification as about 50% of the urban population is supplied as compared to 1% in rural areas [2]. Combining these factors with poor infrastructures, there is an increase of theft of electricity no detected throughout the country resulting in non-reliability and NTL within the electrical networks. This difficulty to detecting NTL is because there is absence of enough communication nodes and limited automation within the distribution networks, but also the infrastructures are not equipped to handle many sensors on the lines. So far, the interaction between utilities and customers is established on monthly bases. Hence, utilities have to wait for monthly technical inspection and commercial report to realize energy losses caused by different factors especially electricity theft. This type of monitoring is not sufficient to determine accurate information about occasional energy theft.

For about 2.7 gigawatts (GW) of electrical capacity installed in the DRC through 50 power plants dispersed widely across the country [2], less than its half is actually exploitable due to ageing equipment and pour maintenance. Inefficient infrastructure and inadequate power system monitoring and control for electricity theft are also the cause of the capacity wasted. Over the past years, the consumption data and billing has been recorded manually during technicians' monthly visit to consumers' home; meanwhile electricity theft by hooking from the distribution line is frequently uncovered while inspecting energy meters visually. A non-technical loss detection strategy using an ACC that sets up a reliable region for monitoring the measured data on feeders is chore of this dissertation. The ACC is a powerful and advanced chart technique that can be applied to any time series that has to stay in a defined span. The Macro VBA simulation results have to demonstrate the efficaciousness of the applied methodology to monitoring TL and NTL with no need of sophisticated sensors.

1.3 Objectives

1.3.1 Major objective

The main objective of this dissertation work is to detecting non-technical loss caused by the hooking of the electricity from Goma feeder in the East province of the DRC.

1.3.2 The specific objectives

Furthermore, this work will particularly make its focus on the following issues:

i. Analyze the TL and NTL in the distribution network of the Matebe hydropower plant located at North Kivu in the DRC.

ii. Establish the control parameters after considering power losses calculation in a Distribution line,

iii. Simulate an automatic inspection procedure for detecting NTLs in Macro VBA in oreder to assure reliability of supplied electrical power through the Goma feeder.

1.4 Research Questions

In line with the aforementioned objectives, the survey addressed the following inquiries.

i. What is the monitoring and control system currently used by power supply company's distribution networks in the Democratic Republic of Congo?

ii. What challenges are the Democratic Republic of Congo's power supply companies facing in energy consumption management, losses and demand?

iii. Is the entire distribution system controlled thereby ensuring the safety of the distribution network operations within the Democratic Republic of Congo's power suppliers?

1.5 Justification

The creation of an Automated Control Chart enables to define the target value and two deviation limits. Then, as soon as a data point in data series surpasses the warning or critical limit lines they are automatically highlighted by the monitoring system.

Instability problems of the modern power systems is mostly caused by deregulation and the difficulty of adding new transmission capacity. The stressful operation level for modern power system are affecting their secure operation limits so far. Vigorous eventualities can also affect the system in terms of several security issues depending to the disturbance type and severity. Yet, commercial simulation packages by properly modeling system components offers the most accurate and practical measure to assess different security issues, such a detailed analysis method in a near real-time manner is still a great challenge due to the high nonlinearity and high dimensionality of large-scale power systems [3].

Therefore, a deep comprehension of the NTL contingencies and fraudulent electricity mechanism should lead to prompt detection when electricity theft occurs.

This dissertation, analyses the power losses in three feeders of a distribution network in the DRC. Next, the control parameters are set based on analysis results. Then an Automated Control Chart (ACC) is constructed in Excel Macro with a data simulation built on top.

The ACC automatically highlights deviations in statistical data chart based on established control parameters. A detection operation of the existence of power loss on a feeder is carried out by control parameters based on power loss analysis results from the analyses performed accordingly. The analyses define the target value (TV) taken as the average amount of power sold to the customers. Next, the warning limits is obtained by adding the absolute value of the admissible TL to the TV and the critical alerts is obtained by adding the absolute value of the standard deviation to the TV. Some NTL exist in the actual value data set whenever the variance is greater than the upper control limit (UCL) and the inspected feeder may probably have more NTL.

1.6 Scope of the study

The present work aims to construct an automated control chart in Excel Macro with a data simulation built on top in order to perform an automatic inspection of NTLs through a distribution line. The ACC is built in such a way to automatically highlights deviations of the target value relying on control parameters defined by power loss analysis. This enables to assure that all consumption data are within a defined span as it deals with time series in Excel Macro. Therefore, the ACC helps to keep track of any small or critical deviation of a target value that is the amount of energy sold to the customers. Nevertheless, the remote terminal units are not described herein and the network components architecture is not detailed. The focus is put on TL and NTL examination and the construction of the ACC for their detection in order to perform the automatic inspection of the feeder.

1.7 Conceptual Framework

The Figure 1 provides a simplified information architecture diagram of the conceptual framework methodology, which this research study is dedicated to.

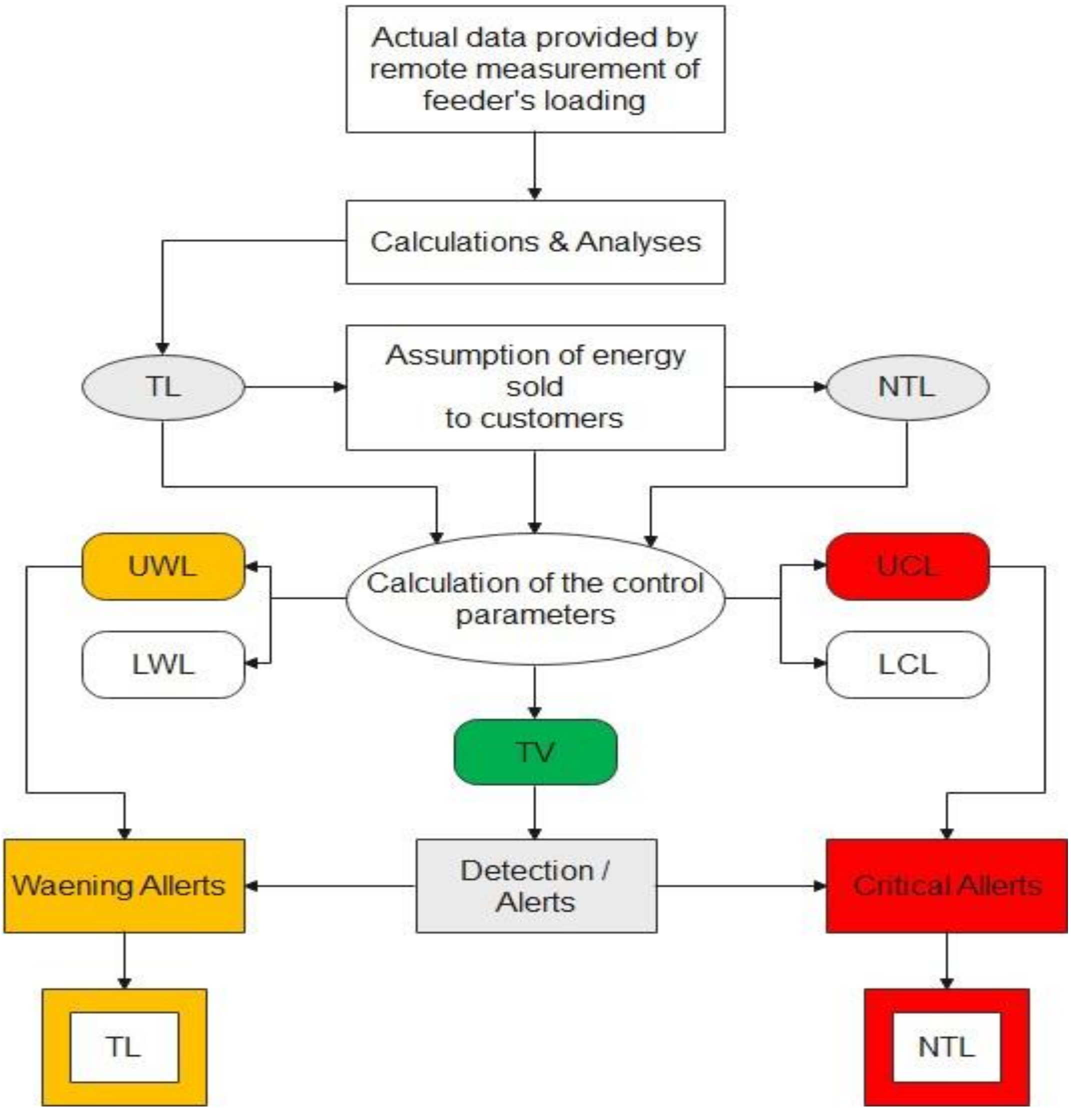

Figure 1-1 Conceptual Framework

1.8 Thesis Organization

This dissertation proposes a modified methodology for TLs and NTLs analysis per feeder as well as their monitoring. The focus is put on the creation of an Automated Control Chart based on a statistical approach. The ACC allows establishing a reliable region of monitoring dealing with the remote reading measures on feeders in order to detect any deviation of energy consumption beyond admissible region defined by the control parameters.

The introduction presents the background, the problem statement, the objectives, the research questions, the justification and scope of the study; all linked to the modern power system monitoring and control for NTL. The chapter two contains the comprehensive definitions of the key words within the topic such as Modern Power System, Monitoring, Control, TL and Non-Technical Loss. Next, it presents a review of numerous research studies conducted by different authors addressing the Modern Power

System Monitoring and Control challenges and providing different approaches adopted as relevant solutions. In addition to this, relevant studies introducing the theory of the NTL as well as the used algorithms and methods to the encountered results have been presented respectively. Moreover, the research gap is suggested. The chapter three provides a quick preview and analysis on various methods and technics used for energy theft detection and location as reviewed throughout the research studies in chapter two. Then it provides a theoretical background on the Control Chart for monitoring procedure. Next, in the chapter four the power losses analysis is performed and the control parameters for NTLs detection are established. Next in the chapter five, an Automated Chart Control for power losses monitoring is constructed. Finally, the chapter six provide an overall conclusion of the work.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

An electric power system is a group of electrical entities interconnected in order to serve for production, transmission and distribution of electricity. A power system generally supplies the electrical energy to the consumers throughout a large region via the electrical grid. For that, electrical networks are generally structured by the generators that supply the power, the transmission system that conveys the generated power to the consuming points and the distribution system that connect the users to the electrical grid.

Electric power distribution however, is the application of scientific and technological knowledge to planning, design, construction, operation and maintenance of various electric supply schemes for the benefit of the society [4]. Therefore, the distribution feeders assure the transfer of electricity of transmission system to users for utilization in numerous activities. Nevertheless, there is a loss of a portion of the electric power generated by a power supply that occurs within the distribution process. These losses happen within numerous elements of a distribution system including transformers and distribution lines. So far, the operating cost of electric utilities generally increases with the system losses. Even though the portion of power loss that is occurring in each of the electrical components may be minimum, the participation of several components in the distribution process makes it crucial to examine the power loss. Therefore, utility companies should enforce loss minimization measures. Monitoring the consumption profile of a distribution feeder is one option that can help to take action whenever it is necessary.

2.2 Technical and Non-Technical Losses

We generally classify the power losses based on their origin. Hence, we distinguish Technical Losses (TL) and Non-Technical Losses (NTL) accordingly. The TLs are related to power dissipation in different components of the electric distribution system during the process of transformation, transmission and energy measurements. Thus, TLs represent power losses that happen while carrying electricity from the transmission lines and substations to energy users. Minimizing these losses is a constant subject of the distribution system optimization. Nevertheless, eliminating TLs does not seem to be a practical option while making a causal connection with the physical phenomena [5]. On the other hand, the NTL result from unexpected actions not associated with the physical characteristics and function of power system, mainly by human's wrong actions (intentional or not). This could also result from conditions and loads that were not involved during the TL evaluation [6]. Computing these losses has been a big challenge since the system operators do not usually account for them because there is no information recorded relatively. Considering the importance of losses evaluation for technical and economic viability of the electric power distribution business, it is crucial to build up methodologies that carry out accurate results and give the image equivalent to the distribution feeder’s power flow for the remote inspection of TLs and NTLs. This allow establishing regulatory parameters for the electricity good as well as the power supply planning sectors.

2.3 Modern Power System Monitoring and Control

As far as power demand is increasingly remarkable in modern societies, an enhanced and reliable power grid becomes more and more crucial. The overgrowing in power demand however, is in conjunction with the need to connect appliances such as dishwasher, washing machine, ventilators, refrigerators, cookers and so on. As a matter of fact, the actual needs and requirements can no longer be satisfied by traditional electric grid, which is outstandingly relied on an ancient design that was conceived more than 100 years ago [7]. Furthermore, electric utilities are pushed to put into service higher cost energy sources such as thermoelectric plants in order to sustain the energy demand. Aligned with the set of factors aforementioned, there is also the increase in theft of electricity on distribution systems [8].

The goal of gradual improvement of modern power systems is to upgrade the reliability, power quality and system protection. Therefore, it is crucial to meet the monitoring and control requirements for modern power systems in order to improve the energy delivery process. Yet, power loss is one of the major problems that affects the distribution network’s efficiency and security [9]. The idea of a smart grid has also been spreading resulting in the increase of penetration of renewable energy sources in the conventional grid. In fact, the smart grid framework carries out the high emergences in information systems and communication technologies. One of its highest improvement cornerstones is the present large-scale deployment in several countries of advanced metering infrastructure (AMI) targeting to provide a high performance of energy metering system [10]. In smart grid networks, the traditional electrical networks automation is out-performed by the use of sensors and control algorithms to assure the flowing of control information in a communication network to the control center (CC) [11].

The function assured by the control center (CC) in modern power system is complex and vital. In fact, the CC is responsible for sensing the pulse of the power system, regulating new conditions, organizing its actions and taking measures against derived contingencies. In order to guarantee an efficient and reliable power supply, the power system operation is supported by a CC that utilizes real-time data [12].

Power controlling is all about exercising good judgment of power output transferred to the distribution system power so that the system can reach a better performance [13]. The context "good performance" is dependent to the context including the selection of best metrics such as link data rate, network capacity, outage probability, geographic coverage and range, durability of the system as well as its components. In same way, the use of power control algorithms intervene in several contexts such as cellular networks, sensor networks, wireless LANs, and DSL modems [14].

The conception of remote monitoring and control (M&C) systems are aimed at controlling enormously complex facilities such as factories, power plants, network operations centers, airports, and spacecraft, with some extent of automation. M&C systems enable data acquisition from sensors, remote easements and reading, exploiter inputs, and pre-programmed process. So far, it is possible to command the actuators and computer systems or similar equipment remotely by signal from software. In addition to this, M&C systems can process closed-loop control [15].

According to Marchall et al. [16], fault examination includes tracking the actions of the power system in order to determine the problems that affect the system's reliability and fix it. Hence, fault management can be responsive relatively to the type of the fault; for instance deploying technicians to fix conductor that a storm caused to fall. It may also consist of adopting advanced options like placing re-closers on segments of the system that are responsible causal contingencies that might result from vegetation, lightning or wildlife among others.

Furthermore, the best emerged measure that can be effective for numerous faults assessment considers commercial simulation packages matching accurately the system components model. Nevertheless, there is still great challenge with a typical elaborated examination method based on real-time procedure regarding the high nonlinearity but also the eminent dimensionality of larges-cale power systems [17].

The World Bank reported over 50% of theft estimating a vigorous extent of Non-Technical Losses in the developing countries. However, the developed countries are also still facing similar challenges. A yearly loss of about more than $96 billion is occurring within utility companies throughout the world caused by theft of electricity. As a matter of fact the utility companies (UCs) in the U.S. approximate a yearly loss of six billion dollars as result of this issue [18] regardless the penalty of $5,000 fine and up to 5 years prison established officially for energy theft [19].

So far, the NTL can affect the quality of electricity supply, resulting in equipment casualty, unstable voltage and consequently cause blackouts and threat to public safety [20]. The literatures have been reveling several other NTL’s negative impacts [21]. Therefore, a deep comprehension of the technical aspect of NTL contingencies and fraudulent electricity is aimed at a high level of quickness in detection whenever energy theft occurs. The immediate detection of NTL grants the capability to carrying out accurate estimation of the energy loss amount as well as to determining the geographical coordinates of the theft occurrence.

2.4 Modern Power System challenges and proposed solutions

Aligned with the above-mentioned factors, several studies have been addressing the modern power system challenges associated with relevant solutions:

The authors Gunvant C. Patil and A. G. Thosar [22] within their work entitled "**Application of synchro-phasor measurements using PMU for modern power systems monitoring and control**", provided a brief presentation of Phasor Measurement Unit (PMU) and synchro-phasor measurement technology. The study involved relevant applications aiming at the enhancement of monitoring, protection and control of power system. The research work also established the transcendence of PMU dealing with synchro-phasor technology over conventional SCADA technology. The outcome exalts the favorable position of synchro-phasor technology regarding the complexity of monitoring and control of modern power systems and the need to improving reliability**.**

Abhishek Chauhan [23] on "**Non-Technical Losses in Power System and Monitoring of Electricity Theft over Low-Tension Poles**", wherein theft of electricity (TOE) is detected making use of a model based on a hardware approach. The survey enlightened the strong effects of NTL up on economic aspects. Nevertheless, the monitoring system suggested is merely applicable to the pole divisions where no load is connected.

The authors Ruisheng Diao et al. [17] suggested the "**Design of a Real-Time Security Assessment Tool for Situational Awareness Enhancement in Modern Power Systems**". The research elaborated a real-time security assessment tool that involves decision trees (DTs) and PMUs. From the results, it is possible to determine four important post-contingency security issues that involve voltage magnitude violation (VMV), thermal limit violation (TV), voltage stability (VS) and transient stability (TS). Therefore, the properly trained decision trees are capable of determining several security problems in a near real time manner. In contrast to this, it is vital to consider the minimal PMU and optimal PMU location settings when the system requires many PMUs**.** This permit assuring the mitigation of investment as well as the accuracy and robustness of decision tree.

The authors Abdulmotaleb El Saddik et al. [24] addressed the topic on "**Load Frequency Control for Wide Area Monitoring and Control System (WAMC) in Power System with Open Communication Links**", which focuses on load frequency control (LFC) issues and communication delays within power system are assessed. The research established the modeling and design of a robust problems controller. Moreover, the authors evaluated a general case of the existence of time varying delays in two channels. One channel consider the feed-forward where control centers send control signals to remote terminal units (RTUs). On the other hand, the feedback channel where measurement signals are transferred from RTUs to the control centers. The results proved the that controller enables a robust stability to power system no matter the existence of time varying delays in both channels examined.

The authors Jin Young Kim et al. [25] in their work entitled "**Detection for NonTechnical Loss by Smart Energy Theft with Intermediate Monitor Meter in Smart Grid**", wherein separation of a network into most-minor and dependent networks named unit networks (UNS). The elaborated method aimed at analyzing power flow in order to make effective the detection of NTLs, particularly for both meter manipulating or malfunctioning and bypassing issues. The method made use of the intermediate monitor meter (IMM)-based power distribution network model. The detection of NTL, the method employed an algorithm that is capable of solving linear system of equations (LSE). Therefore, the conception made use of energy balance analysis with IMMs and the collector. Furthermore, the description of the hardware architecture of IMMs is provided. From results, the proposed detection framework has proven to be time-efficient and its detection accuracy can reach at least 95% when variability of meter reading value is 80%. However, this framework is design for a sophisticated power grid with smart devices, which imply an exorbitant implementation cost.

The authors Nikolai Voropai et al. [26] introduced the "**Improving Power System Monitoring and Control in Russian Modern Megalopolises**"; in the purpose to monitor and to control the operation of a complex multi-loop power system a new intelligent system. The system offers the capability to overcome severe contingencies in emergencies as well as preventing their increase into large-scale blackout. Nevertheless, the elaborated system is suitable to the complexity of a multi-loop power system operation.

Several researches in line with modern power system monitoring and control can be seen in Anca Purcaru and Dorina Purcaru [27]; Julio Romero Agüero [28]; Sergey Kovalenko et al. [29] and Jônatas B. Leite & José R. S. Mantovani [30] among others.

However, none of the research referred to deal directly with the aspect of simplified monitoring and control that targets the reduction of commercial losses. Yet the full protection of an information system is very expensive for a power supply company that is in developing stage it is necessary to develop a simplified method, which does not require many sensors within the distribution system. Therefore, the present research's contribution to the gap is a specific focus on a modified monitoring and control system capable of detecting theft of electricity caused by the hooking from the distribution line. The proposed method can be easily implemented modern power system.

The Table 2-1 summarizes the review of modern power system challenges by presenting the types of challenges addressed and the approach undertaken by researchers in order to provide solution.

Then it present the particularity of the approach performed in this thesis.

Table 2-0-1 Summary on the review of modern power system challenges

Reference	**Challenge addressed**	**Approach utilized**
[8]	"Non-Technical Losses Detection: An Innovative No-Neutral Detector Device for Tampered Meters"	The approach applied the residual magnetism principle in toroid fabricated in amorphous material. The toroid is associated with an electronic circuit that perform signal treatments and transfer it to a microprocessor.
[12]	"Power System Control Centers: Past, Present and Future"	Provides essential information on the subsequent development of control centers involving large-scale perspectives
[11]	"Communication Networks and Non-Technical Energy Loss Control System for Smart Grid Networks"	The control center performs the identification of the electricity theft within specific sections of the monitored feeder and determines the exact location of it occurrence. The framework made use of unmanned aerial vehicle (UAV). Therefore, the control center finds the nearest staff personnel using Global Positioning Systems (GPS) and conveys power loss and theft details using General Packet Radio Service (GPRS) network to control the electrical theft.
[17]	"Design of a Real-Time Security Assessment Tool for Situational Awareness Enhancement in Modern Power Systems"	The study elaborated preventive controls making use of a decision tree (DT) assisted approach, which allows enhancing system security.
[23]	"Non-Technical Losses in Power System and Monitoring of Electricity Theft Over Low-Tension Poles"	The research carries out the detection of theft of electricity (TOE) making use of hardware approach.

[24]	"Load Frequency Control for Wide Area Monitoring and Control System (WAMC) in Power System with Open Communication Links"	The research put its focus on assessing the load frequency control (LFC) issues and communication delays within power system. In addition, it modeled and designed a robust problems controller. Then, it evaluated a general case of the existence of time varying delays in two channels. Therefore, one channel considered the feedforward where control centers send control signals to remote
		terminal units (RTUs). On the other hand, the feed backward channel, which transfers the measurement signals from RTUs to the control centers.
[25]	"Detection for Non-Technical Loss by Smart Energy Theft with Intermediate Monitor Meter in Smart Grid"	The approach established the intermediate monitor meter (IMM)-based power distribution network model. In addition, it employed an algorithm that is capable of solving li near system of equations (LSE) to detect NTL. The framework combined the energy balance analysis with IMMs and the collector.
[26]	"Improving Power System Monitoring and Control in Russian Modern Megalopolises"	The study established the Powertrain System Analysis Toolkit (PSAT), which is the equivalent of a software environment with an open code. It can operate on the platform such as MaLab or GNU/Otave. The use of JADE intervenes as an agent platform of the research into the multi-agent emergency control system. These environment and agent platform were chosen because PSAT and JADE can be integrated using the JAVA language.
[27]	"System for Remote Control and Monitoring Using Optical Fiber and GSM Communication for Load break Cutouts"	The system performed remote control and monitoring using both GSM network and optical fiber network.

Proposed approach	**The approach adopted for the present research is slightly different in terms of its use of an Automated Chart Control to establish a reliable region of monitoring and control. The approach suggested herein permits the use of time series in Excel Macro in order to make sure that all values are within a defined span. The automated control chart enables to keep track of any small or critical deviation of a target value, which is the amount of energy sold to the customers.**

2.2.4 Non-Technical Loss (NTL) Detection and Location

The trend to electricity theft can mainly be due to the wish to lessen electricity bill and many other aspects for instance, social regional politics, customer illegal use of electricity and corruption among others. The studies that involve solutions for detecting and locating non-technical losses have aroused the interest of researchers over recent decades.

Tanveer Ahmad [31] addressed research study on "**Non-technical loss analysis and prevention using smart meters**" wherein an investigation over the non-technical losses in terms of the power distribution systems were conducted. Moreover, the study made use of information relative to the consumer energy consumption for analyzing the NTLs from Rawalpindi region from the different feeder source in Pakistan. However, the discussion herein only determines analysis and prevention techniques of NTLs to safeguard from the illegal use of the electricity in the distribution of electrical power system.

Abhishek Chauhan and Saurabh Rajvanshi, [32] developed a review on "**Non-Technical Losses in Power System**" wherein a recapitulation technologies as well as their methodologies is conducted carefully. The active approach aimed for the enhancement of the network security making a particular accent on the means to estimating and to reducing NTLs. The review enlightened the sources of NTLs as well as the way they affect the economy.

H. Nizar and Z. Y. Dong, on "**Identification and Detection of Electricity Customer Behavior Irregularities**" [33] have put in fact the deviation of customer behavior related to NTL activities on the distribution line. Therefore, an investigation based on the comparison between the efficacy of the Support Vector Machine (SVM) technique and the newly emerging techniques of Extreme Learning Machine (ELM) allowed to classify and to predict NTLs. In fact, the research used customer load-profile data in conjunction with the ELM-based approach to reveal irregular behavior susceptible to be highly correlated with NTL activities. This approach however, implies data mining involving extracting patterns of customer behavior from historical kWh consumption information. The results yield classification of classes referenced to when determining whether any significant behavior that emerges are due to irregularities in consumption.

Xiang Liu and Daoxiong Gong, [34] developed "**A Comparative Study of A-star Algorithms for Search and rescue in Perfect Maze**" wherein algorithms used to perform search in several application are compared including the A-star and D-star algorithm. Relevant applications involve the deployment of robots over a great extent of domains including searching and rescuing people trammeled during various tragedies. Typical disasters might be the damages of earthquake, a ruined building, the fallen mine and the conflagration of houses. Consequently, searching efficiency or search time is crucial in such applications account of the emergency to detecting the position of the subjects in the ruins and relieving them promptly. These complex situations tragedies can be abstracted as a maze. Hence, the maze-searching algorithm has similarly been thoroughly studied and can be equipped on an electric power system so as to enhance its capacity and efficiency of detecting and locating point of occurring of NTL [30]. Joaquim L. Viegasa et al. [35] elaborated **"Clustering-based novelty detection for identification of non-technical losses".** The detection method can discover sources of NTLs in smart grids with the help of a method that conceives several categories of losses subjected to the changes in the consumption data. For that reason, a SM collect data and transmit information to the utility. In addition, the fuzzy Gustafson Kessel clustering (GK) served for determining consumption models subjected to the existence of NTLs. Nevertheless, this method fits well to a smart grid that can detect significant aggregated NTLs through computation of the difference between supplied and billed electricity. As result, the method can pinpoint the thieving individual or faulty equipment.

George M. Messinis et al. [36]; on **"A Hybrid Method for Non-Technical Loss Detection in Smart Distribution Grids"**; in this research work the NTL is detected in distribution network making use of Super Vector Machine (SVM) in conjunction with voltage sensitivity method and power system optimization in different conditions. The study performed features extraction from consumption time-series using breakout detection and training an SMV. The framework can also estimate the network's self-sensitivity with the help of generalized least squares. Moreover, the NTL detection problem is formulated as a non-linear non-convex optimization problem that is solved with semi-definite programming relaxation. According to the authors, the proposed NTL detection system was demonstrated under different scenarios to test its strength.

The Table 2-2 resumes the review of NTL detection and location problems and points out different methods used accordingly, and then it mentions the method proposed herein.

Table 2-0-2 Summarized review of Non-Technical Loss (NTL) Detection and Location

Reference	Challenge addressed	Method used

[33]	"Identification and Detection of Electricity Customer Behavior Irregularities"	The comparison between the efficacy of the Support Vector Machine (SVM) technique and the newly emerging techniques of Extreme Learning Machine (ELM) allowed to classify and to predict NTLs. The use of the customer load-profile data in conjunction with the ELM-based approach allowed revealing irregular behavior susceptible to be highly correlated with NTL activities. However, the approach implies data mining including extracting patterns of customer behavior from historical kWh consumption information. The results yield classification of classes that are used to reveal whether any significant behavior that emerges are due to irregularities in consumption
[35]	"Clustering-based novelty detection for identification of nontechnical losses"	The use of fuzzy Gustafson Kessel clustering (GK) in determining consumption models subjected to the NTLs existence. The method developed fits sell to a smart grid that can detect significant aggregated NTLs through computation of the difference between supplied and billed electricity. As result, the method can pinpoint the thieving individual or faulty equipment.
[36]	"A Hybrid Method for Non-Technical Loss Detection in Smart Distribution Grids"	The use of a NTL detection system relied on voltage sensitivity analysis, power system optimization and Support Vector Machines (SVM), breakout detection that extracts features from consumption time series and training an SVM classifier. The system uses a Generalized least squares for estimating the network voltage self-sensitivities. However, the NTL detection problem is formed as a non-linear nonconvex optimization problem solved with semidefinite programming relaxation.

The methodology proposed in the present research takes advantage of an Automated Control Chart which is a powerful and advanced chart technique that can be applied to any time series that has to stay in a defined span. The creation of an Automated Control Chart allows us define the target value and two deviation limits, and as soon as a data point in data series surpasses these limits they are automatically highlighted in orange or red color as they surpass warning or critical limit lines. Therefore, an automatic inspection procedure for detecting NTLs in an electrical Distribution Line is performed.

2.3 Research Gaps

Aligned with the aforementioned research studies linked with the topic dedicated herein, in many cases, individuals and private's organization of researchers are already leading the way toward Power Systems Monitoring and Control for Non-Technical loss. The literature presents various innovative resolutions accordingly providing the mitigation actions across different levels. Indeed, this scope is wide and yet a comprehensive overview and linking with basic palliation to the issues of the theft of electricity by hooking from the distribution line is essential. The monitoring method for NTL detection relied on construction of an ACC can be viable for the electric facilities across the DRC to establishing an automatic inspection through the distribution lines. In addition, the monitoring method used allows minimizing losses due to illegal consumption of electricity by hooking from distribution lines.

In fact, the present work aims to construct an ACC in Excel Macro with a data simulation built on top enabling the automatic inspection of NTLs in the Goma feeder. Therefore, the ACC helps to keep track of any small or critical deviation of a target value, which is the amount of energy sold to the customers. Nevertheless, the dissertation does not provide the description of the remote terminal units neither deepen details on the network components architecture. The focus is put on TL and NTL examination exploiting production data collected from Matebe hydroelectric plant in the DRC, and the construction of the ACC for relevant detection in order to allow the automatic inspection of the feeder.

So far, there is still a great interest to pend research on the ACC visualization technics for time-series and functional data, including the curves corresponding to the estimated control limits as well as it communication with other software such as SCADA, Power World Simulator or DG silent.

Chapter 3

METHODOLOGY

3.1 Introduction

There is significant motives for electric utilities to monitor as well as to control energy consumption behavior on distribution line in order to discover irregularities that can affect the system reliability and efficiency as well as the utility profitability. So far, power losses minimization within the system is incontestably one of the major objectives of the worldwide electric utilities. The overall losses within electrical power system involve TL and NTL.

Customary ways to control TL involve installation of transformers, which size match with the distribution features and low voltage capacitors, but also an appropriate design of the system components. Nevertheless, controlling NTL by making use of typical devices is impractical because it happens because of exogenous actions to the electric grid, as it is the case for theft of electricity by hooking from the grid or by bypassing the energy meter. Statistical Process Control (SPC) tools are being used broadly in areas outside the manufacturing industries in recent years since they showed their effectiveness in continuous monitoring and improvement. This study takes advantage of Automated Control Chart (ACC) for monitoring TL and NTL through transmission and distribution system. The case study discusses and illustrates the concept. In this case, the Non-Technical Loss has been defined as the malicious use of electricity by hooking from a distribution line or by bypassing the energy meter. The method logy developed herein involves TL and NTL analysis using data that are being provided by RTUs to conform to the

ACC's control capability.

3.2 Review of previous methods

Numerous investigation studies on theft identification and detection in electrical power systems are presented. The studies include Support Vector Machine (SVM); External Learning Machine (ELM) and its Online Sequential-ELM (OS-ELM) [36], [33]; the Decision Trees (DT) assisted approaches [3] aiming the creation of preventive controls but also to upgrade distribution system security, detection of theft of electricity (TOE) using a hardware approach [23]; Independent Network Division (IND) algorithm [25] for NTL detection by solving the LSE (Linear System of Equations) constructed by energy balance analysis with IMMs and collector and [24] the modeling of robust controller of load frequency control (LFC) for power system with communication delays. These research studies nearly employed data mining approach that imply direct application towards customer database as inputs.

In [35], fuzzy Gustafson-Kessel clustering (GK) enables to determine consumption behaviors allied with the presence of NTLs through a distribution network. This detection method for NTL identification achieved 63.6% of accuracy and 24.3% of false positive rate, thus it outperform other state-of-the-art unsupervised learning methods. As alternatives, in [26], a complex multi-loop power system operation is monitored by an intelligent system to overcome severe circumstances and emergency states as well as preventing relative largescale instabilities. Moreover, in [24] LFC for WAMC systems is applied to power system with open communication links. This controller enhance the power system stability no matter the existence of time varying delays in channels. Most of these studies, however consider methods presenting a general framework that requires customer databases as its input data source within complex system equipped with many sensors.

3.3 Proposed Method

3.3.1 Background

Univariate and multivariate control charts are commonly used in factories to detect deviations in industrial process but also to handle the operation quality as well as products [38]. However, the emergence in industry's frameworks allied with the penetration of advanced sensors and communicating system yield distinctive data. For this reason, the participation of sophisticated tools dealing with the presence of autocorrelation in critical to quality (CTQ) variables for the monitoring process has become inevitable [39]. Furthermore, the modified methods such as the control charts based on the fitting of autoregressive integrated moving average (ARIMA) models [41]; exponentially weighted moving average chart (EWMA) control charts [40]; and the control charts for profiles, which is understood as the control of the parameters that define the relationship between two different CTQ variables [42] are being applied recently. Another trend is the use of techniques based on the control chart concept for anomaly detection such as machine learning techniques (neural networks and support vector machines among others) and time series [43]. This trend yield the adaptation capability of these tools to the new paradigm of data (in the framework of Industry 4.0) defined by the continuous monitoring of numerous variables. In contrast to this, the traditional control charts cannot be applied to many of the new cases due to their noncompliance with their starting hypotheses.

Up to this moment, few studies allied with the pertinence of the topic and the frequent monitoring of this type of power loss and the control of malicious use of electricity (mostly when the data to be monitored are time series) have been released. Among the most outstanding research in this context, Reference [30] that applied a multivariate control chart to establish a reliable region for monitoring the measured variance as alternative NTL detection strategy.

2.4 Problem Formulation

2.4.1 Data collection for the analyses of power losses in distribution feeders

Analyses of TL and NTL on Matebe electric grid are performed by making use of data collected from Electrical and Mechanical Operation Data Sheet and Production Data of Rutsuru Hydropower Station for three years (January, 2018 to December, 2020) [37]. The feeder route lengths were obtained from the single-line diagram of the Matebe distribution network. The analysis results are presented in tables.

Data collection was performed on:

a) Monthly return on loading of the 33kV feeders.
b) Feeder route length

i) Goma 33kV feeder (F I) route length 70km ii) Rusturu 33kV feeder (F II) route length 8km iii) Kiwanja 33kV feeder (F III) route length 12km

Aluminum conductor (AAC) of size 148mm^2 with resistivity of $2.82\times 10^{-8}\Omega$m was used for the three feeders.

The sample data collected are shown in Tables 4-1, Table 4-2 and Table 4-3 from which power losses were obtained from January 2018 to December 2020.

The power losses are calculated with the help of the monthly maximum loading on the feeders, resistance, size of each feeder conductor, route length of each feeder and maximum current drawn from each feeder conductor are shown as follows:

Current drawn from feeder (I_L) is given by:

$$I_L = \frac{P_F}{\sqrt{3}\, V\, pf} \qquad (3.1)$$

Line Resistance (R_l) is given by:

$$R_l = \rho \frac{L}{A} \qquad (3.2)$$

In the expression (3.1) P_F is active power in Mega Watts, V is voltage in Volts, and p.f is the power factor.

In the expression (3.2) R is resistance in Ω, ρ is resistivity in Ω-m, L is route length of the feeder, and A is cross sectional area in mm^2.

Therefore, Technical Power Loss in each feeder is calculated with the help of the equation:

$P_{TL} = {I_l}^2 R_l$ *(3.3)*

Where I_L is the current drown from the feeder and R_L is the line resistance and P_{TL} represent the Technical Power Loss.

Power consumed P_C or power supplied to the load is given by the difference between the amount of power sent to the distribution line P_F and the technical power losses P_{TL}. This is given by:

$P_C = P_F - P_{TL}$ (3.4)

Total losses in the Goma feeder are calculated, from the total injected active power and from the billed power, assumed at 3MW, according to the equation:

$T_l = P_{ij} - P_B$ *(3.5)*

Here we merely are going to perform calculations related to Goma feeder since it is the one in which power demand are growing quickly as compared to another feeder. Hence the monitoring model will be conceived accordingly.

2.4.2 Determining and analyzing the Distribution Network Efficiency without taking the Non-Technical Losses into account

The efficiency of the distribution network at a technical aspect is determined by the ratio of average power received and average maximum loading.

On the other hand, the line efficiency is inversion proportional to the (TL):

$E_L = 1 - \frac{\overline{P_C}}{\overline{P_F}}$ (3.6)

2.4.3 Calculation and analysis of the Global Distribution System Efficiency considering the Non-Technical Losses

The efficiency of the distribution network at an economic aspect is determined by the ratio of power sold and power injected to the distribution line or average maximum loading.

On the other hand, the global line efficiency is inversion proportional to the (NTL):

$E_{DS} = 1 - \frac{P_S}{P_F}$ (3.7)

As the power sold is decreasing with the increase of NTL, this causes the profitability to decrease accordingly.

2.4.4 Building an Automated Control Chart in Macro

While dealing with time series in Excel Macro and aiming to make sure that all values are within a defined span, the automated control chart will allows keeping track of any small or critical deviation of a target value, which is the amount of energy sold to the customers.

This advanced data visualization technique allows the viewer to monitor time series data and automatically detect deviations. With a dynamic chart range, it is possible to add as many data points to the existing data set and the chart range will automatically expand and display the new data being measured from the feeder. It is also possible to create data simulation module with Excel Visual Basic Application.

The control process is divided into three major parts:

2.4.5 Creating a static data set

The ACC can be built starting with a simple static dataset of around 24 data points collected hourly in a day on a feeder. The monitoring performed herein considers the Goma feeder. Therefore, the first step is to create a simple line chart and format in an appealing way. Then dynamic limit lines can be added to represent the allowed span of values before any deviation to be highlighted.

2.4.6 Setting up the control parameter section

The following three control parameters need to be defined to create a dynamic span of allowed values:

i. **Target Value:** The optimum value of the data series
ii. **Warning Deviation Limit:** Maximum upper and lower deviation before a warning alert
iii. **Critical Deviation Limit:** Maximum upper and lower deviation before a critical alert

Basing on these three values, four additional data series that will represent the upper and lower limits in the ACC can be set. The relation for these limits is given by:

$$L_l = TV \pm D_L \qquad (3.8)$$

Where L_l represents the limit line in the control chart is, TV is the target value and D_L is the deviation limit.

The control parameter cells will be referenced with absolute cell references, to allow the use of autocomplete in adding the limit values for each respective actual value in the data set.

2.4.7 Adding and formatting the limit lines in the chart

The aim at this step intends the expansion of the chart source data area thereby including the four data series that define lines limits into the chart. Once they are included, then they can be formatted in a style enabling a perfect view.

2.4.8 Adding alert data series and format them

Integrating alert data series is the crucial part of the ACC to allow the detection of any deviation. Therefore, the two data series that are responsible for the highlighting alerts in the chart have to be integrated in order to allow the viewer to monitor the TL and NTL from the data series being monitored on the distribution line. For that purpose two data series can be created, one for the Warning Alerts and one for the Critical Alerts.

The syntax for creating Critical Alerts data series is given by:

$$I(ABS(Actual\_Value - Target\_Value\ ) > Limit, Actual\_Value, 0)$$
(3.9)

For the Warning Alert series, the exact same syntax is used. However, it is crucial to check if the Critical Alert value is 0.0, because only then a Warning Alert can be thrown. Otherwise, all Critical Alerts would also be warning alerts automatically. To check multiple conditions, the **AND function** is used.

2.5 Chapter conclusion

First, this chapter provides comprehensive definitions of the key words within the topic such as Modern Power System, Monitoring, Control and Non-Technical Loss. Next, it presents a review of numerous research studies conducted by different authors addressing the Modern Power System Monitoring and Control challenges, and by the way, providing different approaches adopted in such a way to establish relevant solutions. Then, relevant studies introducing the theory of Non-Technical Loss, which this research study is dedicated, are presented. Used approaches and methods to the encountered results are pointed out respectively. Finally, the research gap and problem formulation are presented.

3.5 Mapping of Method to Problem

3.5.1 Procedure for Building a Control Chart for Phase I (Stabilization)

As it is mentioned in the previous section, in Phase I the time-series data that coincide with a calibration sample of size *n* is analyzed for evaluating the accuracy of the power consumption profile which values is discovered throughout a period of time also for approximating the parameters of the control chart [44].

The Phase I makes use of a control chart which enables to test the hypothesis that there is no deviation in the distribution of observations of the variable measured with respect to time {P_1 (t), P

$2(t)...P_n(t)\}$.

The hypothesis tested in Phase I is: $H0 : (t) = (t), \forall i \in \{1, . . . , n\}$ (3.10)

$Ha : (t) \neq (t)$, for some $i \in \{1, . . . , m\}$. (3.12)

Where m is the module of the space F of deviations data.

The accuracy phase of a process consists of setting syntaxes that allows the detection of those observations with no deviation corresponding to the values range of the recorded power sold through the feeder.

Throughout this analysis, the outlier detection procedure performed in [30] has been adapted to approximate a specific quantiles of the level distribution that play the role of the critical limit (CL) and the warning limit (WL) for the Phase I.

The control chart proposed for Phase I is stated and plotted from a sample of a set measurements and only the upper control limit (UCL) is responsible for detecting whether the process is out-of-control (in the case that the level of the curve is greater than the UCL). In addition to this representation, the upper warning limit line yield the detection of the Technical Losses that occurs out-of-control. The auxiliary lower limit lines are proposed for the completeness of the ACC to provide an intuitive idea about the cause behind the identified anomaly and thus to identify assignable causes.

The Phase I takes into account the hourly active power values $P_i(t)$, from which a basic sample is drawn $\{P_1(t), P_2(t)...P_n(t)\}$. These values are also used to direct the elaboration of the following steps while building the ACC:

i. Representing a time-series data sample to be monitored in the ACC,
ii. Plotting the curve representing the consumption profile on the monitored feeder,
iii. Setting the stage that coincide with different values of the measurement dataset and building the ACC based on the degree of each datum with respect to time.
iv. Defining the control parameters according to the significance level of the ACC, that is the range of accurate data (measurements under control) and the range of NTL (erroneously detected as out-of-control).

The sequences to fix the UCL are the following:

- The target value (TV) attested as the amount of power sold to customers is assumed first. This is because the objective is to ensure that there is no unbilled power that is being consumed by a customer. The power sold is estimated after the analyses of the TL and NTL within the distribution network.

- The UCL is defined by the target value in conjunction with the absolute value of Critical Deviation. Where the Critical Deviation is given by:

$$CD = |3 \times SD| \qquad (3.13)$$

In the equation (3.13), *CD* is the Critical deviation and *SD* is the standard deviation.

From a statistics standpoint, standard deviation (SD) of a dataset is a measure of the magnitude of deviation between the values of the observations contained in the dataset. The SD is calculated by:

$$SD = \sqrt{\frac{\sum|x-u|^2}{n}} \qquad (3.14)$$

Where ∑ means "sum of", x is a value in the data set, μ is the mean of the data set and *n* is the number of data points in the data sample. The SD squared is the variance calculated by:

$$\sigma^2 = \frac{\sum_{i=x}^{n}(x_i-u)^2}{n} \qquad (3.15)$$

Where: x_i= the ith data point, μ= the mean of all data points and *n*= number of data points. The warning limit is defined by the target value in conjunction with the absolute value of admissible technical power loss in the distribution system.

$$UWL, LWL = TV + |TL| \qquad (3.16)$$

The admissible TL is of the order of 22.5% of the power injected in the distribution system. From the calculations, this value is 0.84MW annually that is the 22.5% of the 3.741MW injected in the Goma feeder for the year 2020.

The detection procedure is based on the level of the dada with respect to the control limits set:

The level of the original data set $X_1 \ldots X_n$ curves are obtained.

If there is any portion of the curve such that $D(X_i) \geq$ UCL for a set UCL, then it would be considered NTL and the energy consumption would be out-of-control.

If there is any portion of the curve such that $D(X_i) \geq$ UWL for a set UWL, then it would be considered as additional TL in the distribution line, and the distribution system would be inefficient.

3.5.2 Procedure for building an ACC for process monitoring (Phase II)

Phase II deals with process monitoring; it involves quick detection of changes from the calibrated region of accuracy established in Phase I [39]. For the scalar and multivariate cases, the energy consumption in distribution line is monitored by taking the calculated control limits in Phase I [45] as a reference. In this phase, the visual basic application (VBA) is used to evaluate the performance of the control chart [38].

In this context, we test if there are deviations between the data obtained by remote reading of feeders loading and the calibrated region of accuracy in Phase I. In other words, the difference between the detected NTL sample, $\{X_{n+1}(t), X_{n+2}(t). . . X_m (t)\}$ and the reference data $\{X_1(t), X_2(t)$.

. . $X_n (t)\}$ or calibration sample is tested, considering its distribution.

In Phase II, in the univariate case, an *F* distribution for the under-control process is estimated from a calibration sample or reference data. It is assumed that *F* is the distribution of the control to quality (CTQ) variable of an under-control process (Phase I). This distribution is used to generate random values that will be used to test the monitoring accuracy of the process in Phase II. The sample of the distribution Y comprises an interval that will cover new observations of the process with a high probability, assuming that the process is under control. In Phase II, a sample of the Y distribution can be monitored. Therefore, in this stage, the method for programming the *ACC* simulation is based on contrasting the hypothesis:

$$Pn: F = Y \qquad (3.17)$$

$$Pn + m: F1 = Y \qquad (3.18)$$

The *ACC* plots the rank statistic as a function of time. The central control line TV = 3MW serves as a reference point for observing possible patterns or trends. The lower limits are LCL = δ, LWL =λ where δ and λ are the false alert rate for NTL and TL respectively.

The values of the rank statistic, the lower control limits (LCL, LWL) and central line TV (the expected value of the rank statistic) are plotted, thereby generating the control chart. This is a graphical tool that allows the operator to identify the possible assignable causes of the out-of-control states.

The Table 3-1 gives the summary of the previous methods used for detecting NTL and present the particularities of the method analyzed in this thesis.

Table 3-0-1 Summarized previous methods and methods used in this work

References	Methods used	Force and weaknesses
[33]	Support Vector Machine (SVM), External Learning Machine (ELM) and its Online Sequential-ELM (OS-ELM)	Data mining methods for fraud identification and detection in electrical power systems. They don't offer the possibility to locate the point with abnormal consumption.
[17]	Decision Trees (DT) assisted methods	Design preventive controls in order to improve system security
[23]	A hardware approach	Helps for the detection of theft of electricity (TOE)
[25]	Independent Network Division Algorithm	A solution for detection of the NTLs by solving the LSE (Linear System of Equations) constructed by energy balance analysis with IMMs and collector
[35]	fuzzy Gustafson-Kessel clustering (GK)	Detect consumption patterns resulting from the presence of NTLs in an electricity distribution network has been proposed. The clustering-based novelty detection method for identification of nontechnical losses, using the Gustafson-Kessel fuzzy clustering algorithm, achieves a true positive rate of 63.6% and false positive rate of 24.3%.
Method used in this thesis	**In this thesis, a methodology of automated control chart (ACC) for timeseries variables X, which extracts values in a data space E = P_i (T) is elaborated. The functional space E is the set of time-series data measurements of active power values P_i (T) on the considered feeder.** **Therefore, the obtained time-series X variables constitute a sample subjected to the calibration and monitoring procedure. As a matter of fact, these are functional datasets of sizes *n* which allow to build the ACC in the case of references establishment for Phase I but also in the process for sample monitoring in Phase II.** **While constructing the ACC, any out-of-control outputs is associated with the assignable causes of variation emerging from irregularities and avoidable events resulting in commercial loss.** **Phase I involves the development of the detection technic as well as the approximation of the significance stages. By the way, in Phase II the process is assumed to be under monitoring figuring out the stages of significance**	

	fixed.

3.6 Case study

The focus of this dissertation is principally the refinement of a statistical methodology for monitoring an electric distribution line (named Goma feeder) of a power company's distribution system in the North Kivu Province in the DRC. Therefore, TL is first calculated with the help of data collected on feeder's remote measurement, next the amounts of power sold is estimated in order to carry out the NTL. Then, the control limits are calculated in order to define the region of accuracy and an ACC is built. Finally, the graphic is plotted by monitoring procedure in Macro with Visual Basic Application enabling the detection and of nontechnical losses caused by the hooking of electricity from the Goma feeder.

The *ACC* chart plots the rank statistic as a function of time in Macro with Visual Basic Application VBA. The central control line TV serves as a reference point for observing possible patterns or trends. The lower limits are LCL = δ, LWL =λ where δ and λ are the false alert rate for NTL and TL respectively. This graphical tool allows the operator to identify the possible assignable causes of the out-of-control states. Thus, it enables the monitoring for TLs and NTLs after considering power losses calculation in a distribution system, which allow to set control parameters. Hence an automated inspection is performed.

3.7 Chapter conclusion

This chapter provides a quick preview and analysis on various methods and technics used for energy theft detection and location as reviewed throughout the research studies within chapter two. Next it discus charts control methodology for monitoring procedure, then a theoretical background on the following concerns: presentation of the automated control chart which is the modified method for monitoring TL and NTL on a distribution line, the explanation of procedure of building control charts corresponding to Phases I and II. Finally, it presents the case study that gives the focus of this research and its validation.

Chapter 4

RESULTS AND ANALYSIS

4.1 Introduction

Distribution system envision the transfer of electricity of transmission system to customers or utilization in different activities. Nevertheless, it occurs in the distribution process, a substantial loss of the electric power produced by a utility. Transformer and distribution lines and different other components in the distribution system are source of these losses because of a portion of power dissipated in them. Although it may be generated some minor losses in each of these components, a significant number of associated components makes it crucial to analyze the losses impact on distribution system. However, the principal sources of technical losses in the distribution system are transformers and power lines. Transformer losses that are core (iron) losses and copper (I2R) losses occur due to the current flow in the coils and alternating core magnetic field. Therefore, technical losses are losses that occur due to physical nature of the power systems component or equipment, that is, I^2R loss or copper loss in the conductor cables, transformers, switches and generators.

Power losses in Matebe distribution network were computed from data collected from Electrical and Mechanical Operation Data Sheet and Production Data of Rutsuru Hydropower Station for three years (January, 2018 to December, 2020) [37]. The feeder route lengths were obtained from the single-line diagram of the Matebe Distribution Network. The analysis results will be shown graphically.

Data were collected on:

a) Monthly return on loading of 33kV feeders.
b) Feeder route length and distance between transformers.

Following are the feeder's route length:

i. Goma 33kV feeder (F I) route length 70km
ii. Rusturu 33kV feeder (F II) route length 8km iii. Kiwanja 33kV feeder (F III) route length 12km Aluminum conductor (AAC) of size $148mm^2$ with resistivity of $2.82\times 10^{-8}\Omega m$ was used for the three feeders.

The sample data collected are show in Tables 4-1, Table 4-2 and Table 4-3 from which technical losses were obtained from January, 2018 to December, 2020.

Table 4-0-1 Monthly Return Loading on GOMA 33KV Feeder from January, 2018 to December, 2020.

Month / Year	**Goma**	**Feeder I Loading (M V)**	
	2018	**2019**	**2020**
January	0.60	1.00	2.50
February	0.60	1.50	2.60
March	0.60	1.40	2.80
April	0.50	1.00	2.90
May	0.50	1.00	3.40
June	0.50	1.80	3.60
July	0.60	1.00	3.90
August	0.70	2.20	4.20
September	0.70	1.70	5.10
October	0.60	1.80	4.00
November	0.60	1.80	4.40
December	0.70	2.10	5.50

Table 4-0-2 Monthly Return Loading on RUTSURU 33kV Feeder (F II) from January, 2018 to December, 2020.

Month / Year	**Rutsuru Feeder II Loading (**		**[W)**
	2018	**2019**	**2020**
January	0.30	0.20	0.20
February	0.20	0.20	0.20
March	0.20	1.30	0.20
April	0.20	1.20	0.12
May	0.20	1.10	0.11
June	0.20	1.10	0.93
July	0.10	0.80	0.18
August	0.10	0.10	1.36
September	0.20	0.70	1.45
October	0.10	0.70	1.00
November	0.10	0.60	1.00
December	0.10	1.20	0.19

Table 4-0-3 Monthly Return Loading on KIWANJA 33kV Feeder (F II) from January, 2018 to December, 2020

Month / Year	**Kiwanja Feeder III Loading (IW)**		
	2018	**2019**	**2020**
January	1.36	1.02	1.26
February	1.17	1.11	1.35
March	1.21	1.15	1.41
April	1.05	0.70	1.30
May	0.95	0.80	1.27
June	0.92	0.97	1.31
July	0.97	1.03	1.34
August	0.91	1.04	1.44
September	0.91	1.08	1.28
October	1.00	1.05	1.50
November	0.97	1.00	1.31
December	1.05	1.05	1.51

4.2 Results and Analysis

The TL on each of the three 33kV feeders are obtained on the basis of the monthly maximum loading on the feeders, resistance, size of each feeder conductor, route length of each feeder and maximum current drawn from each feeder conductor are shown as follows:

Current drawn from feeder (I_L) is given by:

$$I_L = \frac{P_F}{\sqrt{3}\,V\,pf} \qquad (3.1)$$

Line Resistance (R_l) is given by:

$$R_l = \rho \frac{L}{A} \qquad (3.2)$$

In the expression (3.1) P_F is active power in Mega Watts, V is voltage in Volts, and p.f is the power factor.

In the expression (3.2) R is resistance in Ω, ρ is resistivity in Ω-m, L is route length of the feeder, and A is cross sectional area in mm^2.

Therefore, Technical Power Loss in each feeder is calculated with the help of the equation:

$$P_{TL} = {I_l}^2 R_l \qquad (3.3)$$

Where I_L is the current drown from the feeder and R_L is the line resistance and P_{TL} represent the Technical Power Loss.

Power consumed P_C or power supplied to the load is given by the difference between the amount of power sent to the distribution line P_F and the technical power losses P_{TL}. This is given by:

$P_C = P_F - P_{TL}$ (3.4)

4.2.1 Determining TL on Goma Feeder

The Table 4-1 represent the Goma feeder's monthly loading data collected from the Rutsuru Hydropower Station Production Data for three years (January, 2018 to December, 2020).

Therefore, monthly power losses in Goma feeder for three years (January, 2018 to December, 2020) presented in the Table 4-4 is calculated with the help of the expression (2.3).

$P_{TL} = I_l{}^2 R_l$ *(3.3)*

Table 4-0-4 Calculated TL from January, 2018 to December, 2020

Month / Year	**TL (MW) on Feeder I**		
	2018	**2019**	**2020**
January	0.001499	0.004165	0.026032
February	0.001499	0.009371	0.028156
March	0.001499	0.008163	0.032655
April	0.001041	0.004165	0.035029
May	0.001041	0.004165	0.048149
June	0.001041	0.013494	0.053979
July	0.001499	0.004165	0.063352
August	0.002040	0.020158	0.073474
September	0.002040	0.012036	0.108337
October	0.001499	0.013494	0.066642
November	0.001499	0.013494	0.080637
December	0.002040	0.018368	0.125998

4.2.2 Determining TL on Rutsuru Feeder

With the help of the relations (1) and (2) the current drawn from the feeder and the line resistance are determined respectively. Therefore, the monthly coper losses on the Rutsuru Feeder are determined with the help of the expression (2.3).

The coper losses calculated in the Table 4-5 represent the monthly technical losses in the Rutsuru feeder for the period of 3 years from January 2018 to December 2020. The results show that technical losses are as less as the feeder loading are. Thus, the copper losses are directly proportional to the feeder loading as well as the current drawn in the feeder is directly proportional to the feeder loading according to the expression (2.2).

Table 4-0-5 Calculated TL from January, 2018 to December, 2020

Month / Year	**Power loss (MW) Feeder II**		
	2018	**2019**	**2020**
January	0.000042	0.000019	0.000019
February	0.000019	0.000019	0.000019
March	0.000019	0.000804	0.000019
April	0.000019	0.000685	0.000006
May	0.000019	0.000575	0.000005
June	0.000019	0.000575	0.000411
July	0.000004	0.000304	0.000015
August	0.000004	0.000004	0.000880
September	0.000019	0.000233	0.001
October	0.000004	0.000233	0.000475
November	0.000004	0.000171	0.000475
December	0.000004	0.000685	0.000017

4.2.3 Determining TL on Kiwanja Feeder

The monthly TL in Kiwanja feeder for three years (January, 2018 to December, 2020) presented in the Table 4-6 is calculated with the help of the expression (2.3).

Table 4-0-6 Calculated TL from January, 2018 to December, 2020.

Month / Year	**TL (MW) on Feeder III**		
	2018	**2019**	**2020**
January	0.00132	0.000742	0.001133
February	0.000977	0.000879	0.001301
March	0.001045	0.000944	0.001419
April	0.000787	0.000349	0.001206
May	0.000644	0.000456	0.001151
June	0.000604	0.000671	0.001225
July	0.000671	0.000757	0.001281
August	0.000591	0.000772	0.001480
September	0.000591	0.000971	0.001169
October	0.000713	0.000787	0.001606
November	0.000671	0.000713	0.001225
December	0.000787	0.000787	0.001627

The values presented in the first three rows of the Table 4-7 represent the means of annual Technical Losses estimated on each of the three feeders and the last row represents the total annual of these Technical Losses for 3 years from 2018 to 2020. It is seen that the average power losses increase with the growing of power demand in the distribution network since the current drawn in the distribution line is function of current demanded by loads connected to the power line. Thus:

$$P_{TL} = {I_l}^2 R_l \qquad (3.3)$$

Therefore, the power company should pay much attention to these technical losses since they influence the non-technical losses.

Table 4-0-7 Average TL from January, 2018 to December, 2020

Feeders	**Average TL (M.W)**		
	2018	**2019**	**2020**
Goma Feeder	0.001519	0.010436	0.06187
Rutshuru Feeder	0.000014	0.000358	0.000278
Kiwanja Feeder	0.000783	0.000735	0.001318
Total	0.002316	0.011529	0.063466

The average maximum loading on each of the three feeders are presented in the table 4-8. These results show how there is over growing of energy demand in the distribution network.

Table 4-0-8 Average Maximum Loading of 33kV feeders from January, 2018 to December, 2020.

Feeders	**Average Maximum Loading (M.W)**		
	2018	**2019**	**2020**
Goma Feeder	0.600	1.525	3.741
Rutshuru Feeder	0.166	0.766	0.578
Kiwanja Feeder	1.039	1.000	1.356
Total	**1.805**	**3.291**	**5.675**

Power received P_C or power supplied to the load is given by the difference between the amount of power sent to the distribution line P_F and the technical power losses P_{TL}. This is given by:

$$P_C = P_F - P_{TL} \qquad (3.4)$$

The Table 4-9 present the results of the calculation of power received per feeder and per year.

Table 4-0-9 Average Power received (M.W) on feeders

Feeders	**Average Power received (M.W)**		
	2018	**2019**	**2020**
Goma Feeder	0.598481	1.514564	3.67913
Rutshuru Feeder	0.165986	0.765642	0.577722
Kiwanja Feeder	1.038217	0.999265	1.354682
Total	**1.802684**	**3.279471**	**5.611534**

Total losses in the Goma feeder are calculated, from the total injected active power and from the billed power assumed at 3MW, according to the equation:

$$T_l = P_{ij} - P_B \qquad (3.5)$$

This study considers the calculations related to Goma feeder since it is the one in which power demand are growing fast as compared to other two feeders. Hence the monitoring model will be conceived accordingly.

$Tot.\ Loss = 3.741 - 3$

$Tot.\ Loss = 0.741MW$

As NTLs cannot be computed and measured easily, but it can be estimated from preliminary results, thus the result of TL are first computed and subtracted from the total losses for the estimation of NTLs [5],[23],[28],[31].

$$NTLs = T_l - P_{TL}$$

Where: T_l is the total power loss and P_{TL} is the technical loss

$NTLs = 0.741 - 0.0618$

$NTLs = 0.6792MW$

It should be noted that an unbalanced loading is another factor that results to losses in an electric distribution network. The more one of the phases is loaded compare to others, the more loss will result than it would have been for the case where the load is balanced. The resistance has not to be neglected since the current level has impact on electric line losses.

The Table 4-10 shows that the average TL is influenced by the route length complying with expression (2.2) and the average maximum loading of the distribution line according to the equation (2.1).

Table 4-0-10 Relationship between route length, average maximum loading and average TL

Feeder	**F I**	**F II**	**F III**
Route Length (km)	**70**	**8**	**12**
Average Maximum Loading (MW)	**1.955**	**0.503**	**1.135**
Average Power Losses (MW)	**0.024**	**0.0002**	**0.0009**

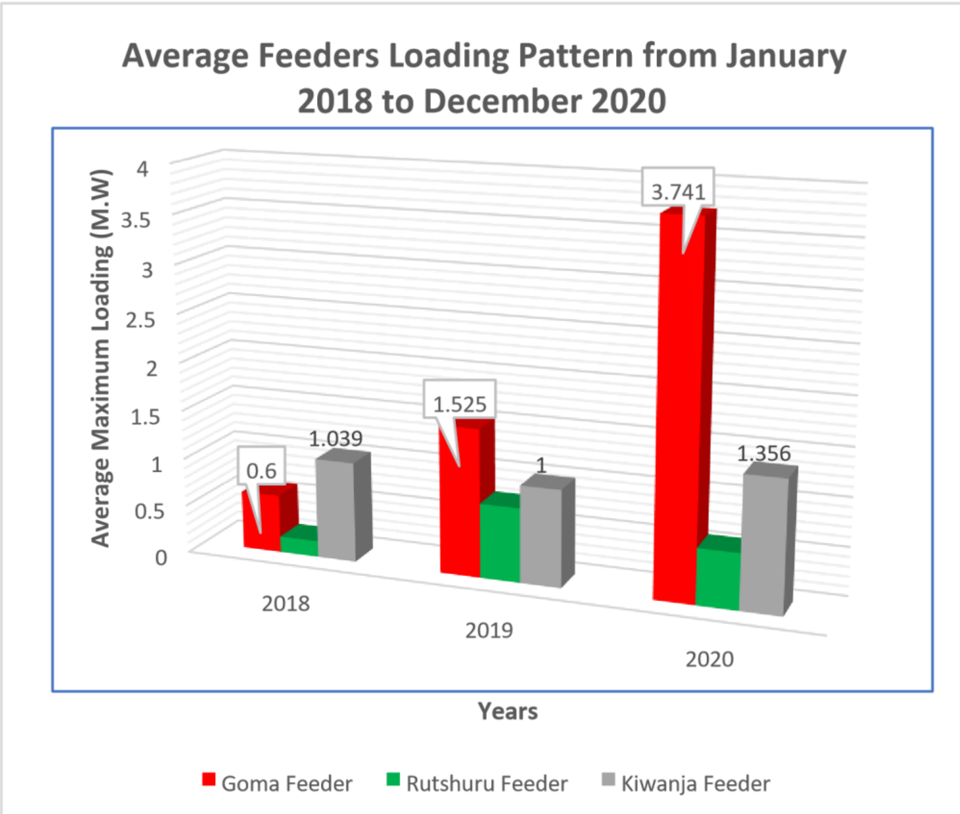

Figure 4-0-1 Graphical representation of the Average Feeders Loading Pattern from January 2018 to December 2020

4.2.4 Determining and analyzing the Distribution Network Efficiency without taking the Non-Technical Losses into account:

-The efficiency of the distribution network at a technical aspect is determined by the ratio of the average power received and the average maximum loading. The Table 4-11 present the calculation results accordingly.

On the other hand, the line efficiency is inversion proportional to the TL:

$$E_L = \frac{\overline{P_C}}{\overline{P_F}} \qquad (3.6)$$

Table 4-0-11 Distribution System Efficiency at technical aspect

Feeders	Distribution System Efficiency at technical aspect		
	2018	2019	2020
All Feeders	0.998	0.996	0.988

4.3 The monitoring procedure of the Goma feeder for Non-Technical loss detection

This section is dedicated to the construction of an automated control chart (ACC) in Excel Macro with a data simulation built on top. The ACC automatically highlights deviations in statistical data chart relied upon the control parameters established by calculations performed in the section 4.2.

Monitoring time series in Excel Macro allow to ensure that all values are within a defined span, thus the ACC helps to keep track of any small or critical deviation of a target value which is considered to be the amount of energy sold to the customers. This advanced data visualization technique allows the viewer to monitor time series data and automatically detect deviations.

Following are the three major steps to establish the control process:

4.3.1 Creating a static data set

To build the ACC, a sample of static dataset of around 24 data points collected hourly in a day on the Goma feeder is created for the monitoring. Therefore, the first step is to create a simple line chart and format in an appealing way. Then dynamic limit lines are added so as to represent the allowed span of values before a deviation is highlighted.

With a dynamic chart range, it is possible to add as many data points to the existing data set and the chart range will automatically expand and display the new data.

The table 5-1 presents the data measured on the Goma feeder by its RTU. The maximum loading values given in MW constitute the sample from which the ACC is constructed.

Table 5-1 Data collected on the Goma feeder on 31st December 2020

Date & Hour	**Goma Feeder** **Statistic Data set**			
	P **[MW]**	**Q** **[Mvar]**	**S** **[Mva]**	**Cosϕ**
Thursday 31 December 2020 00:00	3.1	0.3	3.1	1.00
Thursday 31 December 2020 01:00	3.1	0.3	3.1	1.00
Thursday 31 December 2020 02:00	2.9	0.3	2.9	0.99
Thursday 31 December 2020 03:00	3.0	0.3	3.0	0.99
Thursday 31 December 2020 04:00	3.0	0.3	3.0	0.99
Thursday 31 December 2020 05:00	3.0	0.3	3.0	1.00
Thursday 31 December 2020 06:00	2.7	0.1	2.7	1.00
Thursday 31 December 2020 07:00	2.9	0.1	2.9	1.00
Thursday 31 December 2020 08:00	3.4	0.4	3.4	0.99
Thursday 31 December 2020 09:00	4.0	0.7	4.0	0.98
Thursday 31 December 2020 10:00	4.1	0.8	4.1	0.98
Thursday 31 December 2020 11:00	4.2	0.9	4.2	0.98
Thursday 31 December 2020 12:00	4.5	0.8	4.6	0.98
Thursday 31 December 2020 13:00	4.8	0.8	4.9	0.98
Thursday 31 December 2020 14:00	4.2	0.7	4.2	0.98
Thursday 31 December 2020 15:00	4.4	0.8	4.4	0.98
Thursday 31 December 2020 16:00	3.8	0.6	3.8	0.99
Thursday 31 December 2020 17:00	4.0	0.6	4.0	0.99
Thursday 31 December 2020 18:00	4.4	0.7	4.4	0.99
Thursday 31 December 2020 19:00	5.2	0.8	5.2	0.99
Thursday 31 December 2020 20:00	4.7	0.6	4.8	0.99
Thursday 31 December 2020 21:00	4.4	0.5	4.4	0.99

Thursday 31 December 2020 22:00	3.8	0.3	3.8	1.00
Thursday 31 December 2020 23:00	3.5	0.2	3.5	1.00

The Figure 5-1 is the graphic representation of the active power values measured by the Goma feeder's remote terminal unit. Actually, the graphic in the Figure 5-1 shows the consumption behavior of the feeder in concern.

Hours	Actual Value (MW)
1	3.1
2	3.1
3	2.9
4	3
5	3
6	3
7	2.7
8	2.9
9	3.4
10	4
11	4.1
12	4.2
13	4.5
14	4.8
15	4.2
16	4.4
17	3.8
18	4
19	4.4
20	5.2
21	4.7
22	4.4
23	3.8
24	3.5

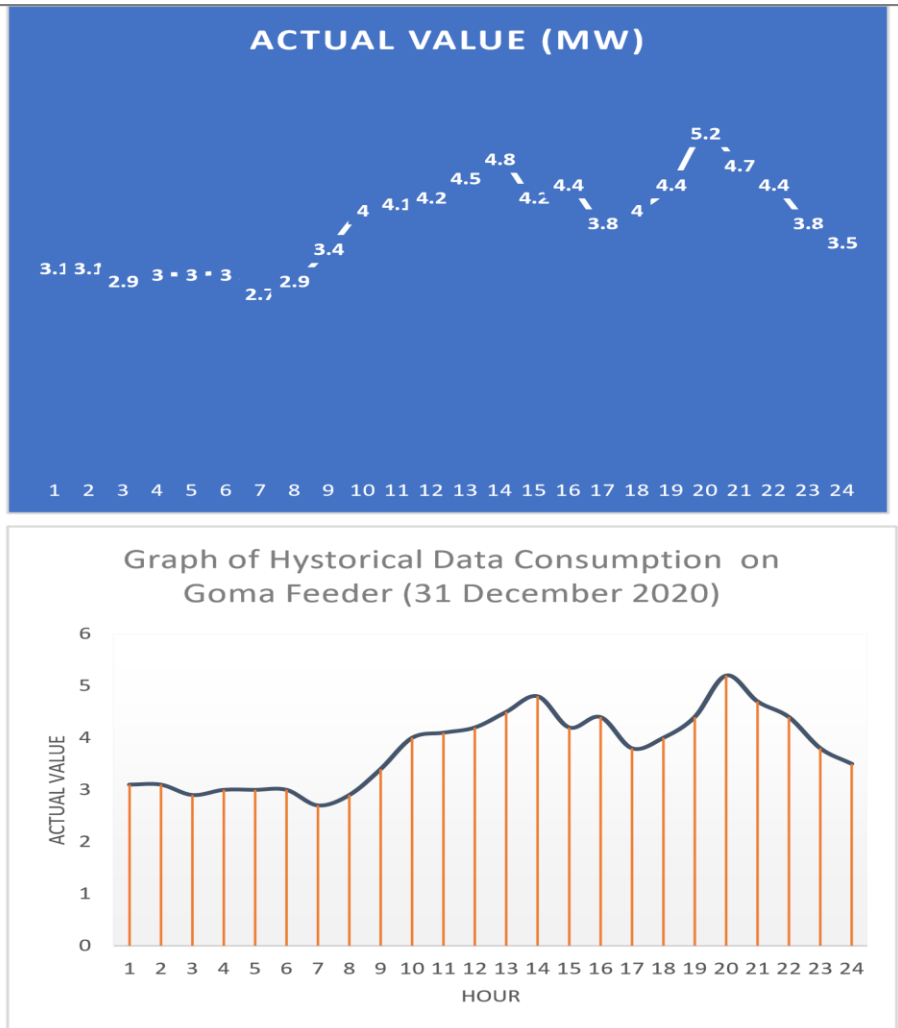

Figure 5-1 Graphic representation of active power profile within the Goma feeder

4.3.2 Setting up the control parameter section

To create a dynamic span of remote reading values, it is indispensable defining three control parameters:

• **Target Value (TV):** The optimum value of our data series

- **Warning Deviation Limit (WDL):** Maximum upper and lower deviation before a warning alert
- **Critical Deviation Limit (CDL):** Maximum upper and lower deviation before a critical alert

i. The target value is the assumed amount of power sold to customers as the aim at this point is to make sure that there is no power consumed illegally or maliciously. Thus, target value is equal to 3MW as assumed in the analyses.

ii. The warming limits are going to be defining by the target value in conjunction with the absolute value of admissible technical power loss in the distribution system. These admissible TLs is of the order of 22.5% of the power injected in the distribution system. From the calculations this value is 0.84MW annually which is the 22.5% of the 3.741MW injected in the Goma feeder for the year 2020.

iii. The Critical Limits are defined by the target value in conjunction with the absolute value of Critical Deviation Limit. This Critical Deviation Value is of the order of 3times the Standard Deviation calculated in the control chart; whereas the standard deviation is defined by the actual value (our data set) in conjunction with the mean value of this data set.

Based on the above three values, four additional data series representing the upper and lower limits in the chart are set up. The formula for these limits is given by:

$$UDCL, LCDL = TV \pm CD \qquad (4.1)$$

$$UWDL, LWDL = TV \pm WD \qquad (4.2)$$

Where *UCDL* is the Upper Critical Deviation Limit, *LCDL* is the Lower Critical Deviation Limit; *UWDL* is the Upper Warning Deviation Limit and *LWDL* is the Lower Warning Deviation Limit

The control parameter cells have to be referenced with absolute cell references in order to autocomplete the added limit values for each respective actual value in the data set.

4.3.3 Adding and formatting limit lines in the ACC

The aim at this step is to expand the chart data area's source thereby including the four data series that define lines limits into the chart as presented in the Figure 5-2.

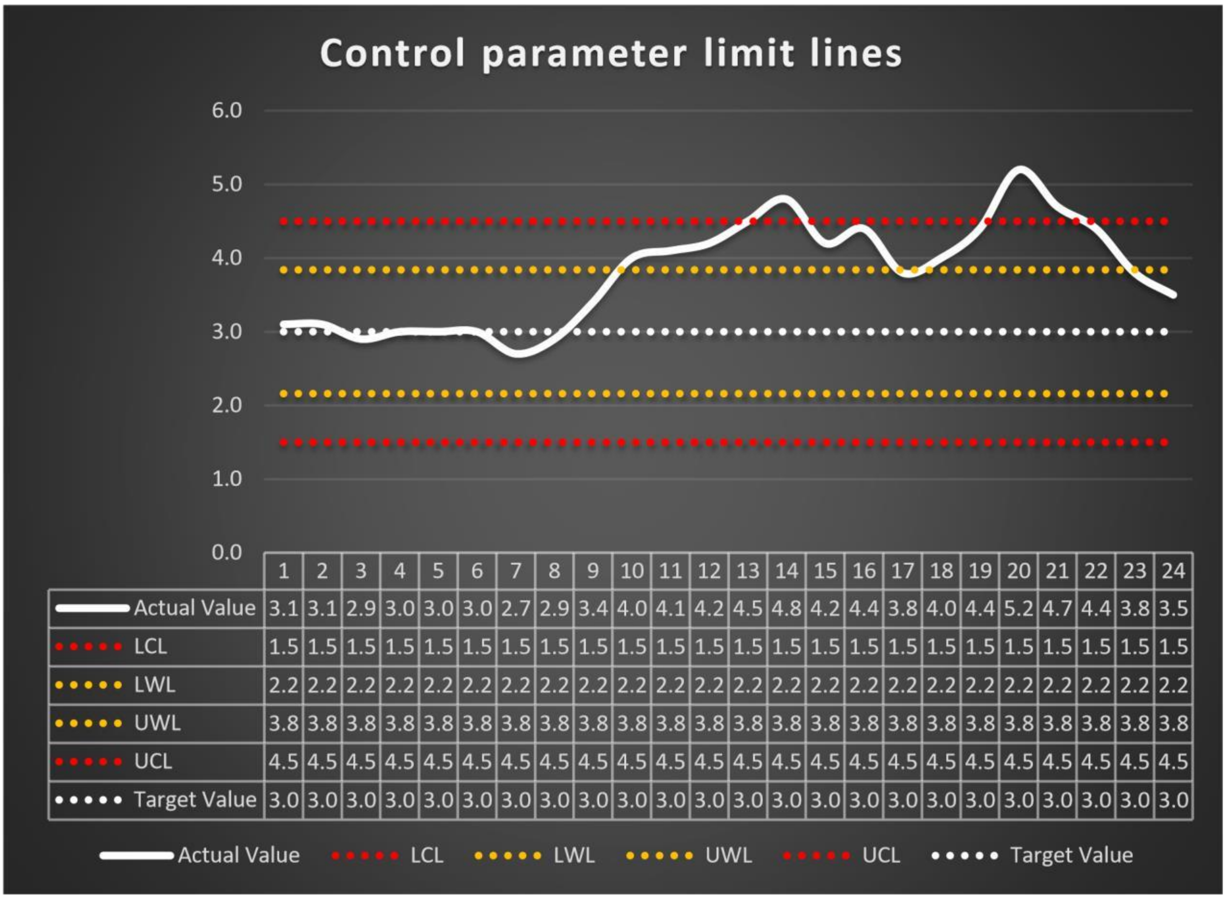

Figure 5-2 Control parameter lines of the ACC

4.3.4 Adding alert data series in the ACC

Integrating alert data series is the crucial part of the ACC. The integration of two data series that are responsible for the highlighting alerts in the chart allow the viewer to monitor the power losses of consumption data in the distribution line. In fact, one of the two data series controls the Warning Alerts (WA) generation while the other one controls the Critical Alerts (CA) generation. For that, the CA data series is added first and then the WA data series with the help of the following syntax:

$$((Actual\_Value - Target\_Value) > Limit, Actual\_Value, 0)$$

For the Warning Alert series, the exact same syntax is employed (of course with the warning alert limit), but it is necessary to check if the Critical Alert value is 0.0, because only then a Warning

Alert can be thrown. Otherwise, all Critical Alerts would also be Warning Alerts automatically.

To check multiple conditions, the AND function is used. For the first setup, we use 0.0 as the value for all cells, that do not meet the criteria of an alert.

The monitoring process detects 9 warning alerts data points that are identified as TL deviations (values out of control) since they are greater than the UWL and 3 critical alerts data points that are identified as NTL since they surpass the UCL. The figure 5-3 presents the detection results cared out with the help of the ACC.

Automated Control Chart

With Process Simulation

Control Parameters

Target Value:	3.00	Optimal Value
Varning Deviation Limit:	±.84	Max. Deviation allowed Upwards & Downwards
Critical Deviation Limit:	±1.50	Max. Deviation allowed Upwards & Downwards

	Original Data		Limit lines			Limit Alerts		
	Actual Value	**LCL**	**LVL**	**UVL**	**UCL**	**Varnig**	**Critical**	**Mean**
1	3.1	1.5	2.2	3.8	4.5			3.00
2	3.1	1.5	2.2	3.8	4.5			3.00
3	2.9	1.5	2.2	3.8	4.5			3.00
4	3.0	1.5	2.2	3.8	4.5			3.00
5	3.0	1.5	2.2	3.8	4.5			3.00
6	3.0	1.5	2.2	3.8	4.5			3.00
7	2.7	1.5	2.2	3.8	4.5			3.00
8	2.9	1.5	2.2	3.8	4.5			3.00
9	3.4	1.5	2.2	3.8	4.5			3.00
10	4.0	1.5	2.2	3.8	4.5	4.0		3.00
11	4.1	1.5	2.2	3.8	4.5	4.1		3.00
12	4.2	1.5	2.2	3.8	4.5	4.2		3.00
13	4.5	1.5	2.2	3.8	4.5	4.5		3.00
14	4.8	1.5	2.2	3.8	4.5		4.8	3.00
15	4.2	1.5	2.2	3.8	4.5	4.2		3.00
16	4.4	1.5	2.2	3.8	4.5	4.4		3.00
17	3.8	1.5	2.2	3.8	4.5			3.00
18	4.0	1.5	2.2	3.8	4.5	4.0		3.00
19	4.4	1.5	2.2	3.8	4.5	4.4		3.00
20	5.2	1.5	2.2	3.8	4.5		5.2	3.00
21	4.7	1.5	2.2	3.8	4.5		4.7	3.00
22	4.4	1.5	2.2	3.8	4.5	4.4		3.00
23	3.8	1.5	2.2	3.8	4.5			3.00
24	3.5	1.5	2.2	3.8	4.5			3.00

Figure 5-3 9 warnings and 3 critical alerts data points detected by the ACC

4.3.5 Data Simulation Module in Macro

A data simulation module is programmed using Visual Basic Application. Thus, it is also possible to set up a normal distribution with the chosen parameters and then take this distribution in order to randomly create new data points from it and add to the existing data series. For instance, the standard deviation can be added and that means the next simulated data point will have bigger variation and more likely to surpass limits. If standard deviation is reduced, the process will be a lot more stable. It is also possible to simulate the level shift by changing the target value, now all the new data points ring around the upper warning deviation line resulting in a lot of warnings on the chart. To start over again, it requires just hitting the restart button and resetting the simulated data set.

For the data simulation, two input fields that enable to enter the values for the mean and standard deviation of a normal distribution are set up. For that, it is necessary to create a normal distribution chart that instantly visualizes the distribution based on these parameters. Next, is the creation of two buttons that will be connected to the macros for the simulation test. One button for the Data Generation and one button to Restart the simulation process.

The figure 5-4 is the display of the continuous monitoring process with the detected data out of control being automatically highlighted by the ACC.

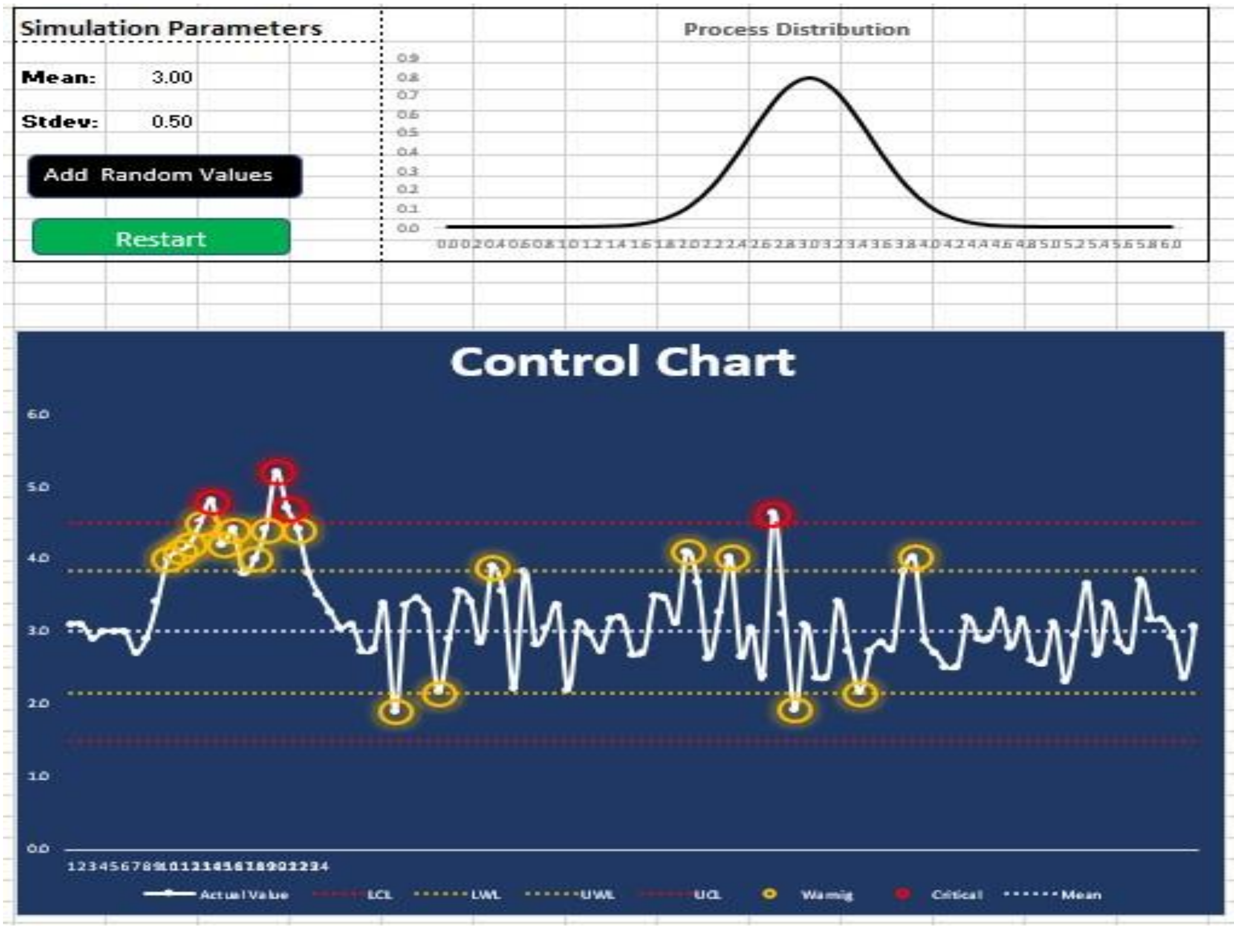

Figure 5-4 The detected NTL data points automatically highlighted in Red color and TL alerts in Orange color

4.4 Discussion

Herein the automated control chart (ACC) methodology is developed for time-series variables, X, extracting values in a space E = P_i (T), with $T \subset$ R. The functional space E is the set of hourly measurements of active power values P_i (T) that are being displayed by a RTU of the monitored feeder.

Customary the application of control charts in controlling process involve the following two main phases [39]:

1) Phase I that fixes the stable state or determine the reference points of the process

2) Phase II which direct specific emphasizes attached to the process monitoring.

For Phase I, the focus is put on building a control chart, which establishes relation that links the target value (TV) to the UCL and LCL; all aligned with the logic of TL and NTL detection.

On the other hand, the Phase II establishes a nonparametric range ACC, relied on the data acquisition of the feeder's remote reading parameters via RTU in such a way to perform the monitoring of the feeder for TL and NTL detection purpose.

Therefore, the obtained time-series X variables constitute a sample subjected to the calibration and monitoring procedure. In fact, these are functional datasets of sizes *n* that allow to build the ACC in the case of references establishment for Phase I but also in the process for sample monitoring in Phase II.

When constructing the ACC, any out-of-control outputs is associated with the assignable causes of variation emerging from irregularities and avoidable events resulting in commercial loss.

Phase I involves the development of the detection technic as well as the approximation of the significance stages. However, in Phase II the process is assumed to be under monitoring determining the stages of significance fixed.

However, details pertaining to a sequential set of steps involved in the construction of the ACC relating to Phases I and II are provided in the next section. The results of its performance are shown through a simulation analyze including diverse scenarios.

The proposed ACC methodology for TL and NTL detection is developed and programmed in Macro Visual Basic Application (VBA) adapting various functions pertaining to the "Quality

Control Review" package, which can be easily accessed by the practitioners. This visual tool allows users and maintenance managers to relate each anomaly to an intuitively assignable cause. From results of the simulation analyzes making use of the real data, there is huge motives for enhancing the potential of this control chart methodology in detecting NTL when the process is defined by time-series of functional data, specifically the daily curves of energy consumption in feeders.

4.5 Validation

Technical losses mean losses that occur due to physical nature of the equipment and infrastructure of the power systems, that is, I^2R loss or copper loss in the conductor cables, transformers, switches and generators. Non-technical losses are losses due to human errors and social issues. Nontechnical losses are more difficult to measure because these losses are often unaccounted for by the operators and thus have no recorded information. Thus, the accuracy of the estimated of nontechnical losses depends hugely on the accuracy of the estimation of technical losses.

The loading on the three feeders from January, 2018 to December, 2020 is presented in Tables 41, 4-2 and 4-3 while the calculated monthly TL on the feeders (coper loss) are presented in Tables 4-4, 4-5 and 4-6. The average maximum loading on the feeders, the average power losses on the feeders are presented in Tables 4-7 and average power consumed is calculated. The relationship between route length, average maximum loading and average power losses are shown in Table 4-9.

4.6 Chapter conclusion

Power losses monitoring and control is a fundamental issue in the electricity distribution sector in developing countries. The protection of the entire distribution system being very expensive to implement, it is crucial to assure a continuous monitoring of power distribution losses in order to maintain these losses within acceptable levels. Consequently, power companies can minimize commercial loss and optimize their profitability thereby assuring the good power quality of supplied energy as well as distribution system efficiency and reliability. This chapter considers a modified method using an Automated Control Chart (ACC) for monitoring TLs and NTLs after considering power losses calculation in a distribution system, which allows the setting of control parameters.

The ACC is a powerful and advanced chart technique that can be applied to any time series that has to stay in a defined span. The application of this method can be helpful to power companies with poor infrastructures for monitoring power losses in a distribution feeder.

The creation of an ACC allowed establishing the target value and two deviation limits. Therefore, the ACC automatically highlights a data point in data series as soon as they surpasses the warning or the critical limit lines. The case study simulation carried out 9 NTL and 3 TL alerts data points within the monitored feeder data points. Hence, the automatic inspection procedure enables detecting NTLs in the Goma feeder. The ACC is at first built with the static data set and then the data range is made dynamic so that whenever new data points are added, these new data points are included in the chart as the chart range is dynamically expended. Next, a data simulation module is programmed using VBA

Chapter 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusions

Electrical power system consists of generation, transmission and distribution, regulated either by single entity or by a number of entities. Electric power distribution is the application of scientific and technological knowledge to planning, design, construction, operation and maintenance of various electric supply schemes for the benefit of the society. Electric power when generated is sent through transmission lines to many distribution circuits that the utility operates. The purpose of distribution system is to take electric power from transmission system and deliver it to consumers to serve their needs. However, a significant portion of the electric power that a utility generates is lost in the distribution process. These losses occur in numerous small components in the distribution system, such as transformers and distribution lines. While each of these components may have relatively small losses, the large number of components involved makes it important to examine the losses in distribution system. Transformers and power lines are major sources of losses in power distribution systems. Core (iron) losses and copper (I^2R) losses occurs in transformers. As load increases, the copper losses become significant, until they are approximately equal to the core losses at peak load. It is very important for electric utilities to consider these losses and reduce them wherever practical. Losses are a function of the square of the current flow through the line. Transformer losses occur due to the current flow in the coils and alternating core magnetic field. Load losses can be reduced by increasing the conductor cross sectional area and complying with the manufacturer's guideline as regards temperature. Unbalanced loading is another factor which results to losses in electric distribution line. If one of the phases is loaded more than others, the loss will be more than it would have been when the load is balanced. As the current level has effect on electric line losses, the resistance of the line cannot be neglected.

This dissertation proposes a modified methodology for TLs and NTLs analysis per feeder as well as their monitoring. The creation of Automated Control Chart based on a statistical approach that allows to establish a reliable region of monitoring of remote reading measures on feeders in order to detect any deviation of energy consumption beyond admissible region defined by control parameters.

The literature review provides comprehensive definitions of the key words within the topic such as Modern Power System, Monitoring, Control and Non-Technical Loss. Next, it presents a review of numerous research studies conducted by different authors addressing the Modern Power System Monitoring and Control challenges, and by the way, providing different approaches adopted in such a way to come up with relevant solutions. Then, relevant studies introducing the theory of Non-Technical Loss which this research study is dedicated are presented. Used approaches and methods to the encountered results are pointed out respectively.

The focus is put on monitoring an electric distribution line (named Goma feeder) of a power company's distribution system in the North Kivu Province in the DRC. Therefore, TL is first calculated with the help of data collected on feeder's remote measurement, next he amounts of power sold is estimated to 3MW in order to carry out the NTL. Then, the control limits are calculated in order to define the region of accuracy and an ACC is built. Finally, the graphic is plotted by monitoring procedure in Macro with Visual Basic Application enabling the detection and of nontechnical losses caused by the hooking of electricity from the Goma feeder.

The *ACC* chart plots the rank statistic as a function of time in Macro with Visual Basic Application VBA. The central control line TV serves as a reference point for observing possible patterns or trends. The lower limits are LCL = δ, LWL =λ where δ and λ are the false alert rate for NTL and TL respectively. This is a graphical tool that allows the operator to identify the possible assignable causes of the out-of-control states. Thus, it enables the monitoring for TLs and NTLs after considering power losses calculation in a distribution system, which allow to set control parameters. Hence an automated inspection is performed.

The case study shows that the simulation of the monitoring of the Goma feeder's data at the date of 31st December 2020 generated the following results: 9 highlighted data points represent warming alerts as they are greater than the upper warning limit line and 3 highlighted data points represent the NTL since they surpass the upper critical limits. This result was identified by monitoring original data on Goma feeder with the help of an ACC that makes use of the set control parameters with simulation in Macro.

5.2 Contribution to knowledge

A specific monitoring procedure that takes the advantage of control charts used in statistics is developed but also an automatic control chart is built. Therefore, an automatic inspection of energy consumption in a distribution line with no advanced sensors to detect TL and NTL is performed. This method allows to monitor a given sector of feeder in distribution system after performing statistical analysis of original data of the concerned feeder that are provided by an Intelligent Electronic Device such as an Auto-reclose Relay 7SJ8041-5EB90-1FC1/DD or a SENTRON PAC3100. With the help of SCADA software the data sensed form a feeder can be mining and proceed on computer to perform TL and NTL by making use of the Automated Control Chart which this thesis is dedicated to.

5.3 Recommendations

Following are some recommendations that might be effective to increase the security, reliability and electric grid's efficiency thereby minimizing the TLs and NTLs in the Distribution line.

I. Monitoring the energy consumption per sector and per class in a statistical procedure is effective for inspection of energy utilization in a distribution line. In addition, geographical setup should be employed.

II. For consistent results, an online prepaid energy meters and billing system have to be integrated.

III. Cognizance among customers about rigorous laws that can be used against them if they detect during theft of electricity.

IV. To customers whom were willing to pay the electricity timely, should be granted some rebated prices in addition to regular discounts.

V. Incentives should be offered for utility agents in order to strengthening the regular onsite check-up mechanism of theft detection.

VI. Fastidious legal reforms are required in such a way to grant the utilities several punitive options against the offender's in-spite of disconnection or penalty merely.

VII. Special prominence should be given to the theft detection equipment manufacturing companies. This will attract more manufacturing firms to invest in this field which in-turn increase the completion and reduce equipment cost.

VIII. Along with the full cyber-security, the dynamic optimization of the grid operations should take place. Therefore, Smart Grid and Smart Metering are used in conjunction to minimize the theft.

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Appendices

Set up simulation parameter section

For the data simulation, we set up two input fields where we can enter the values for the mean and standard deviation of a normal distribution. For that we create a normal distribution chart that instantly visualizes the distribution based on these parameters.

As the next step, we create two buttons that we will connect to the macros for the simulation later.

One button for the *Data Generation* and one button to *Restart* the simulation process.

Define named cells and code VBA macros

As the last preparation step, we create named cell references for

- The header cell of the *Actual Value* data series: **Actual_Value_Header**
- The *Mean* input field: **Simulation_Mean**
- The *Standard Deviation* input field: **Simulation_Std**

Based on these named ranges, you can then use the following VBA code to create the two required macros:

Sub Simulate()

```
  With ActiveSheet

     mean                              =
 .Range(“Simulation_Mean”).Value        std
 =            .Range(“Simulation_Std”).Value
 With .Range(“Actual_Value_Header”)

        If .Offset(1, 0).Value = “” Then
```

```
            .Offset(1, 0).Value = WorksheetFunction.Norm_Inv(Rnd(), mean, std)

          Else

            .End(xlDown).Offset(1,    0).Value    =    WorksheetFunction.Norm_Inv(Rnd(),
mean, std)

          End If


        End With


    End With


End Sub
```

Sub Restart()

```
    With ActiveSheet


        mean                                        =

.Range("Simulation_Mean").Value          std

= .Range("Simulation_Std").Value



        first_cell_ref = .Range("Actual_Value_Header").Offset(1, 0).Address

        .Range(first_cell_ref & ":C100000").ClearContents

        .Range(first_cell_ref).Value = WorksheetFunction.Norm_Inv(Rnd(), mean, std)
```

```
    End With

End Sub
```

Once created, connect both macros to the respective buttons by right-clicking and clicking on assign, and everything is set up perfectly for a clean simulation of new data points.

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