CUSTOMER WATER METER ACCURACY UNDER VARIOUS FIELD CONDITIONS: CASE STUDY NWSC-KAMPALA WATER UGANDA

BY

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DECLARATION

I, Richard Nuwahereza (21/U/GMEW/14504/PE), hereby declare that this dissertation titled "**Customer water meter accuracy under various field conditions, case study NWSC-Kampala Water Uganda**" is entirely my developed work. It has never been submitted for the award of any academic degree to this university or any award from other higher institutions. The dissertation's material is original, with the exception of materials that are cited and referenced.

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APPROVAL

The undersigned certify that they have read and now recommend for acceptance by Kyambogo University a dissertation titled: ***Customer water meter accuracy under various field conditions, case study NWSC-Kampala Water Uganda*,** in fulfilment of the requirements for the award of a ***Master of Science degree in Water and Sanitation Engineering*** of Kyambogo University.

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DR. KENAN OKURUT

DEDICATION

This dissertation is dedicated to my family, whose steadfast support provided the bedrock of my education, serving as the cornerstone upon which I continue to expand my academic pursuits.

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ABBREVIATIONS AND ACRONYMS

%	Percentage
Km	Kilometer
Oc	Degree centigrade
ADB	African Development Bank
AFWA	African Water Association
AMI	Advanced Metering Infrastructure
AMR	Automatic Meter Reading
ANOVA	Analysis of variations
ARC-GIS	Aeronautical Reconnaissance Coverage Geographic Information System
AWWA	American Water Works Association
CI	Confidence Interval
CV	Coefficient of variation
DMAs	District Metered Areas
DN	Diameter Nominal (Pipe Size)
ERROR 1	Meter errors 1
ERROR 2	Meter errors 2
ERROR 3	Meter errors 3
ERROR 4	Meter errors 4
EU	European Union
FAO	Food and Agriculture Organization
FDC	Flow Duration Curve
F-statistic	Fisher Statistic (used in ANOVA)
GFI	Goodness of Fit Index
GIS	Geographic Information System
GPS	Global Positioning System
HDPE	High-Density Polyethylene
HGL	Hydraulic Grade Line
ISO	International Organization for Standardization
IWA	International Water Association
KCCA	Kampala Capital City Authority
KW	Kampala Water
KWDN	Kampala Water Distribution Network
LSR	Least Squares Regression

M^3	Cubic Metres
MAP	Maximum admissible pressure
MAT	Maximum admissible temperature
MDGs	Millennium Development Goals
MFI	Meter Failure Index
MPE	Maximum permissible error
MSE	Mean Square Error
MWE	Ministry of Water and Environment
NRW	Non-Revenue Water
NWSC	National Water and Sewerage Corporation
OIML	International Organization of Legal Metrology
PM	Preventive Maintenance
p-value	Probability Value
Pw	Working pressure
Q1	Minimum flow rate
Q2	Transitional flow rate
Q3	Permanent flow rate
Q4	Maximum flow rate
QGIS	Quantum Geographic Information System
R^2	Coefficient of Determination
RMSE	Root mean square error
SCADA	Supervisory Control and Data Acquisition
SDG	Sustainable Development Goal
SOP	Standard Operating Procedure
SPSS	Statistical Package for the Social Sciences
SS	Sum of Squares
UFW	Unaccounted for Water
UGX	Uganda Shilling
UNICEF	United Nations International Children's Emergency Fund
USD	United States Dollar
WB	World Bank
WDS	Water Distribution System
WHO	World Health Organization
WLM	Water Loss Management

ABSTRACT

One of the impending factors affecting water utility's ability to supply adequate and safe water worldwide is high water losses. Inaccurate metering contributes greatly to the apparent losses in many water supply utilities, including the National Water and Sewerage Corporation (NWSC). This research presents a platform for understanding the contributions of metering inaccuracies to non-revenue water while investigating the perceived effectiveness of establishing best technical practices and strategies for decisive selection, installation, and management of customer water meters to minimise losses. The study had three specific objectives, including; (i) Characterising the pressure rates in the distribution network of the study area. (ii) Assessing impacts of meter class on its performance accuracy (iii) Determining the influence of working age on water meter registration errors (iv) Producing geo-visualised pressure rate zoning maps for the water distribution network in the study area. Pressure data loggers were installed at selected customer premises and results were downloaded using Radwin software. Randomly selected sample water meters from the total population were collected from the field and subjected to different tests under different flow rates and pressure using a meter testing bench. The test results were analysed using descriptive analysis to obtain the favourite condition for better meter performance. To produce meter risk visualisation maps ArcGIS software was used. Using obtained pressure, meter age, and meter class test results, meter failure risks was georeferenced and visualised maps obtained. The pressure test results show pressure > 60m and < 10m in Kansanga and Kyengera respectively with an average of 70.2m and 42.1m maximum pressure. Water meter performance test results revealed better performance (3%) of meters at a flow rate of 1500 l/hr with a pressure rate of 5 bars and poor performance (- 7%) with a flow rate of 12 l/hr at 10m pressure rating. Meter age beyond 15years performed poorly at low flow rate. This implies that most water meters are dysfunctional at low flow and pressure rates, causing losses to water utilities. Meter age and meter class had significant ($p<0.05$) impacts on meter performance accuracy. Meter risk analysis and visualisation revealed blocks with water pressure and age risks on meter performance. The study recommends proper management of meter installations based on pressure zoning and flow regimes. The results of this study were pertinent in providing support policymakers in relation to forecasting and strategic development of robust metering systems that prevent meter dysfunction hence reducing non-revenue water.

Key words: apparent losses, water meter accuracy, water meter registration, water meter management meter age, water pressure

CHAPTER ONE: INTRODUCTION

1.1 Introduction

One of the water utilities main goals is to deliver high-quality water effectively and sustainably to residential, commercial, and industrial consumers at an acceptable pressure with minimal losses. Worldwide, rapid population growth, and urbanization coupled with climate change have led to growing pressure on the water resource hence the need for efficient management. Obtaining access to clean, safe water is challenging with over 2 billion people in the world today having difficulty accessing safe water. United Nations found it very important for all members of global society to access safe and clean water and sanitation by 2030 (United Nations, (2016) as clearly stated in its sustainable development Goals (No.6)

One of the impediments to achieving the above target is the effect of high non-revenue water. Globally non-revenue water volume is 346 million cubic meters per day or 126 billion cubic meters per year (Liemberger and Farley, (2004), Ronald Liemberger & Alan Wyatt, 2018). Reducing the current non-revenue water to 25 per cent in economically developing nations can save 29 billion US dollars, which can serve an additional 90 million people (Frauendorfer & Liemberger, 2010). The amount of water produced and supplied to consumers but does not generate revenue is termed as non-revenue water. It constitutes physical losses (real losses) through bursts, leaks, and reservoir overflow, and apparent losses (commercial losses) through unbilled consumption, water theft, illegal water connections, and metering inaccuracies (Mutikanga, Sharma, and Vairavamoorthy, 2011).

In well managed water supply systems, apparent losses mainly result from inaccuracies of water meters. Water metering status across the globe varies significantly, with developed nations increasingly adopting smart metering technologies. Smart water management solutions, including advanced metering infrastructure (AMI) are transforming how water is managed, monitored, and billed, offering benefits like reduced water losses, improved efficiency, and enhanced customer engagement. Many developing countries still grappling with challenges related to meter accuracy due use of mechanical water meters. Performance of water meters is affected from many key factors such as meter type, class, age, installation, and water consumption profile. This has majorly imparted high non-revenue water to developing countries. Non-revenue water across globally range from 5% in Netherlands and 60% in Bulgaria resenting Europe. In Sub-Saharan Africa non-revenue water range from 25% to 75% of the total water supply.

Metering inaccuracies are estimated to contribute between 1% and 10% of total non-revenue water globally, with higher values reaching 15-20% in developing water utilities (Arregui et al., 2018) largely due to aging meters, low-pressure conditions, and inadequate maintenance regimes

Non-revenue water for NWSC-Kampala water on average was at 40.3% (Dr Eng S Mugisha, 2021). Kampala water loses an average of 7 billion shillings or 2.5 million US dollars per month through non-revenue water (NWSC, 2022). The amount of losses has a significant impact on the utility's obligation to provide safe water at a fair cost to its consumers within entrusted areas due to increased demand and high operation costs. Many utilities close its water demand gap by improving the production capacity of existing plants or constructing new water production plants, and drilling boreholes while less has been achieved to improve the management and utilization of the available water through reducing the water losses. Reducing water losses saves more water to meet the demand and more revenue to expand the distribution network to new areas. It also significantly reduces the water tariff due to high turnover revenue collection through billing and minimises management and operation costs (World Bank, 2016; IWA, 2020).

The effect of non-revenue water, differs globally, developed countries such as Japan, Germany, and the UK typically maintain NRW below 10% due to advanced technology and strong governance (IWA Performance Indicators Report, 2020), while many developing utilities in Africa, Asia, and Latin America record losses exceeding 35-50% (World Bank, 2016). Therefore, high NRW, reduced sales, and declining revenue is universal, though its magnitude depends on regional infrastructure conditions, institutional efficiency, and metering practices.

Meter-related factors such as meter age, working pressure, and meter class have been widely identified in literature as major contributors to commercial losses. Meter age varies worldwide with some countries having replacement period ranging from 6-20year or even more. As meters age, mechanical wear causes under-registration of low and medium flows, leading to significant apparent losses and under billing (Mutikanga et al., 2011; Arregui et al., 2006). Studies show that meters older than 8-10 years can under-register by 5-15%, depending on water quality and usage patterns. Similarly, high or fluctuating operating pressures >60m accelerate wear on internal components and increase leakage through joints and service lines, amplifying both physical and apparent losses (Lambert, 2002). Furthermore, meter class which defines the meter's accuracy range and sensitivity directly influences registration efficiency at low flows. Class C and D meters (per ISO 4064) perform more accurately under variable flow conditions compared to older Class A or B meters, which often miss low domestic consumption, thus increasing NRW and reducing revenue.

To understand non-revenue water, water metering is essential for determining how much water is produced, and delivered to the distribution network. And how much water is billed to consumers (Inman & Jeffrey, 2006), Ethem Karadirek, 2020 (Mutikanga et al., 2013). Thus, effective operational management of water utilities largely dependent on its metering system that can account for the water produced and supplied to end users in return for revenue.

However, this has been successful in developed countries with advanced metering and good distribution network infrastructure. In Uganda, mechanical meters are mostly used by water utilities (National Water and Sewerage Corporation (NWSC)) whose metrology deteriorates due to wear and tear of its measuring components during their life span (Mutikanga et al., 2013). Standards (new meters, in-lab**)** permitted errors are typically ±2% (upper zone) and ±5% (lower/low-flow zone) for common accuracy Class B/C cold-water meters (ISO 4064). Field performance (installed meters) real world average errors vary widely but utilities commonly observe overall weighted under registration in the range -5% –15%**,** with individual customers (especially at low/intermittent flows or with aged meters) showing much larger under-registration Studies report apparent losses from meter under-registration of -15% to -40% for affected customers**.**

Thus, water metering has not been effective in achieving the anticipated benefits due to metering inefficiencies (Musaazi et al., 2021). Metering effects are mostly a result of; a) fluctuations in water pressures, b) consumer demand patterns, c) flow rates, d) metering positioning, e) poor quality of water, (Mutikanga et al., 2011),

To effectively mitigate these adverse impacts, policymakers and water utility managers require accurate, evidence-based insights to inform risk-based water meter management strategies aimed at reducing non-revenue water (NRW). This calls for the integration of both new and in-service meter error analyses, complemented by predictive models that holistically address all critical factors contributing to NRW reduction.

Evaluating water meter functionality is essential for identifying the sources of metering malfunction and performance degradation. This thesis focuses on the factors influencing metering accuracy under various field conditions, with a case study of the National Water and Sewerage Corporation (NWSC)–Kampala Water. The study aligns with Sustainable Development Goal (SDG) 6.4 Park and Ph, (2018) which emphasizes a substantial increase in water-use efficiency across all sectors and the sustainable withdrawal and supply of freshwater to address water scarcity

1.2 Problem statement

The drastic mechanical water meter effects identified in section 1.1 leave devastating effects on water utilities including; high non-revenue water, high water tariffs, increased water demand, intermittent water supply, and high operation management costs. Such effects affect various sectors such as water resources due to increased water withdraws, Environment due to energy used in production, Health due to unaffordable water tariff, education due to long distance looking for clean water, Water utilities due to increased management costs and water demand, Industries due to intermittent supply and denial of water extensions to the new population.

High Non-Revenue Water (NRW) continues to pose a serious challenge to water utilities worldwide, undermining financial sustainability and service reliability. Meter age is a key determinant of metering accuracy and apparent losses. Although the recommended service life of most domestic meters is 10 years, some developed countries have aged meters exceeding 20 years. Aged meters contribute a high percentage of non-revenue water. Similarly, apart from developed countries that use high-quality meter classes, developing countries are still using class A and B meters some countries are adopting class C meters. Combined with differences in meter replacement programs, this variation in meter class and age contributes to significant disparities in apparent losses worldwide

A significant portion of Non-Revenue Water (NRW) arises from meter-related inefficiencies, where inaccurate measurement leads to unbilled consumption and revenue loss. Over time, ageing meters experience mechanical wear that causes under-registration of actual consumption, particularly at low and medium flow rates. The typical service life of household meters exceeds 10 years, while that of commercial meters is about 5 years (Arregui et al., 2018; Mutikanga et al., 2011). Such degradation results in apparent losses, reduced sales volumes, and inaccurate customer billing. Additionally, the use of lower-class meters (e.g., Class A or B) with limited sensitivity to fluctuating flow conditions further amplifies measurement errors, especially in low-demand residential zones (Criminisi et al., 2009).

Inappropriate working pressures also accelerate meter deterioration and affect registration accuracy, while poor calibration and irregular meter replacement programs exacerbate these inaccuracies (Arsene et al., 2020). The combined effect of these factors widens the gap between water produced and billed volumes, increasing NRW, depressing revenue, and undermining cost recovery efficiency (Liemberger & Wyatt, 2019).

Although these challenges are globally recognized, their extent and manifestation vary widely. Utilities in developed countries equipped with advanced metering technologies often maintain NRW below 10%, whereas many developing nations particularly in Africa report NRW levels exceeding 35–50%, mainly due to aged meters, suboptimal meter class selection, inconsistent pressure management, and weak maintenance practices (Farley & Trow, 2003; Mutikanga et al., 2013).

It increased water demand, intermittent water supply, elevated management costs for water utilities, rising water tariffs, and greater health and social burdens on the population such as high medical bills and time wastage in search of water. The impacts extend across multiple sectors of which in return affect the local population:

a) Water resources due to increased water abstraction;

b) Environment from excess energy used in water production;

c) Public health resulting from unaffordable water tariffs and reduced access to clean water;

d) Water utilities due to increased management costs and elevated operational demand;

e) and denial of extensions to new connections to un served population.

For Kampala Water, Non-Revenue Water (FY2021/22) averages 39%, with metering inefficiencies contributing about 51% of commercial losses**,** equivalent to 869,237 m^3/month or UGX 4.01 billion in losses (NWSC, 2022). Reducing these inefficiencies could save 443,311 m^3 of water valued at UGX 2.05 billion, enough to supply 73,885 low-income households (369,425 people). However, households earning below Ugx 500,000 per month often struggle to afford water bills, leading to irregular payments and unaccounted-for consumption. This low affordability undermines utility revenue and limits investment in efficiency improvements. Consequently, high NRW and low ability to pay reinforce each other, perpetuating inequitable service delivery.

To effectively mitigate these adverse impacts, policymakers and water utility managers require accurate, evidence-based insights to inform risk-based water meter management strategies aimed at reducing non-revenue water (NRW). This calls for the integration of both new and in-service meter error analyses, complemented by predictive models that holistically address all critical factors contributing to NRW reduction.

Although several studies have been conducted on water meter performance accuracy in Uganda, none have addressed the above aspects of devastating challenges comprehensively. For example, earlier studies (Mutikanga et al., 2011, Mutikanga, 2014, Mbabazi et al, 2015) assessed general meter accuracy without focusing on onsite customer meter performance under varying field conditions. Most of these studies focused on new meter registration variability except for (Musaazi et al., 2021) which considered distribution network pressure. Furthermore, previous research relied heavily on secondary data from utility billing systems data often affected by estimation errors and limited field validation. Consequently, little is known about the influence of diverse field conditions on water meter accuracy in Uganda. This knowledge gap hinders the development of robust, efficient, and sustainable water supply systems.

Therefore, this study seeks to evaluate the accuracy of both aged and new water meters, quantify the magnitude of metering errors, and explore optimization strategies for improved water meter performance and reduced non-revenue water.

1.3. Research objectives

1.3.1 Main Objective

The main objective of the research was to analyse the performance accuracy of water meters

1.3.2 Specific Objectives

The study's particular goals were;

i) to characterise the pressure rates in the water distribution network of the study area,

ii) to assess the performance accuracy of water meter class subjected to different flow and pressure rates,

iii) to determine the influence of working age on water meter registration errors,

iv) to geovisualise meter failure risks zoning maps of the study area,

1.4 Research questions

The following questions were the focus of the study:

i) What is the current water pressure distribution in the water distribution network for Kansanga and Kyengera?

ii) Is there a significant correlation between meter registration errors and meter class subjected to different flow and pressure rates at the Kampala water distribution network?

iii) Is there a connection between inaccurate meter registration errors and water meter age at the Kampala water distribution network?

iv) How can water meter failure risks in water supply networks be visualised for effective management

1.5 Significance of the research

This research is crucial in making engineering recommendations while managing water utilities since they depend on water meters to measure their sales, which turns into revenue. The study provides insights into the effective metering of consumers depending on flow rates and network pressures while considering the effects of metering inaccuracies. It gives the basic practices that maintain the effectiveness of the cash registers through proper management of field conditions that affect their performance. This guides in developing and maintaining a metering data management system that provides effective decisions on metering. It promotes the value for money in procuring water meters. It also contributes to maximizing Revenues & other metering benefits during the life cycle of the meters. The study highlights meter management principles in water utilities through proper meter allocation and maintenance. The engineers and other stakeholders are informed on downscaling non-revenue through water management strategies that contribute to achieving Sustainable Development Goal number six (SDG 6). “To ensure the availability and sustainable management of water and sanitation for all through the efficient use of water”.

1.6 Scope and limitation of the study

The research was limited to the Kansanga and Kyengera water supply areas in the Kampala water distribution network (KWDN). It was limited to mechanical water meters of size

DN15mm, which constitute about 95% of water meters in the study area. The study evaluated pressure distribution, effects of meter class, age on meter accuracy and visualisation of pressure.

1.7 Outline of the research

Chapter One dealt with the introduction of this research in terms of the background, statement of the problem, main and specific objectives, research questions, study significance, and scope and limitation of the study.

Chapter Two This chapter examined earlier academic and research work that had been done on the study's primary problem. It includes definitions, concepts, and theories relevant to this research. Additionally, it provides excerpts from other authors' relevant works.

Chapter Three This chapter provided a detailed explanation of the procedures to be followed to complete the research. It gave more information about the following elements: the population and sample details, a description of the study region, data collecting, and analysis.

Chapter Four provided the discussion on results and conclusions on findings throughout the study exercise.

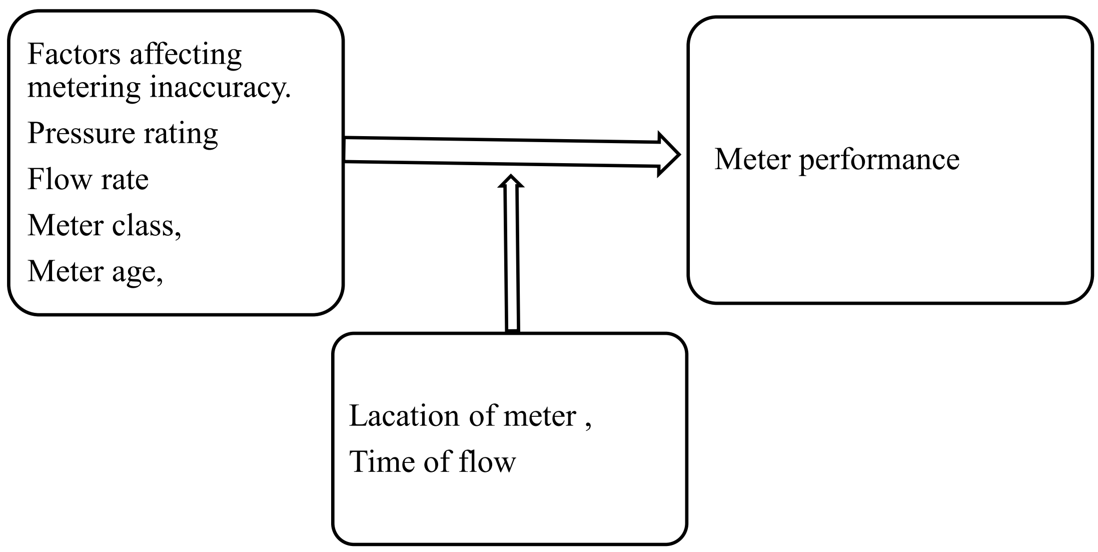
Chapter Five provided the detailed conclusion and recommendations about the findings from the study.

1.8 Conceptual framework

Factors influencing water meter accuracy (independent and dependent) were the study's two key variables. The independent variables were the water demand pattern, water meter class, and pressure rates. The elements thought to have an impact on the regular delivery of water services consequently influenced the level of meter performance and thus affected Kampala

Water's non-revenue. Figure 1.1 in the conceptual framework of the study illustrates the link between the factors.

Independent Variables **Dependent variable**



Moderating variable

Figure 1.1: Perceived conceptual framework

The dependent variables in this study therefore correspond to percentage water meter errors (under/over registration) high tariffs, Production costs, and the controlling factors refer to meter reading quality, and consumption rate.

1.9 Definitions of terms

Volume from own sources	The volume of water produced by the production system
Master meter error adjustment	This is a rough assessment of the level of error present in the master meters that measure the volume from their sources for example meter at production
Authorised consumption	Amount of water used by known consumers to utility whether metered or unmetered

Billed Authorised Consumption	This includes all billed consumption authorised by the utility whether, metered or unmetered.
Unbilled authorised Consumption	This includes water used by known consumers to utility but not billed whether metered or unmetered.
Billed metered consumption	This comprises water metered billed to consumers.
Billed unmetered consumption	This comprises all water billed based on assumptions or estimates.
Unbilled unmetered consumption	This includes any authorised consumption that isn't metered or billed.
Water Losses	The difference between system input and authorised consumption (= apparent losses + real losses)
Apparent Losses	Includes all types of inaccuracies associated with customer metering.
Unauthorised consumption	This is the water consumed illegally, including illegal connections, meter tampering
Customer metering inaccuracies	Apparent water losses caused by customer meter inaccuracies.
Real losses	This is the actual water loss up to the customer meter from the utility's storage tanks and pressurised system. Frequencies, flow rates, and the average duration of each leak, burst, and overflow all affect the volume lost as a result of these events. $V = QT$, where $Q = vA$, (v = water velocity (m/s), A = cross-sectional area of the pipe affected (m2), and T represents the time of the particular leak or burst, is used to compute the volume of water, V(m3), lost by leaks or bursts.
Non-revenue water	This water does not generate any revenue for the utility. (= Apparent losses + Real losses + Unbilled metered + unbilled Unmetered)

Revenue Water	This is water charged to customers to provide revenue to the utility.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter reviews previous research on the topic of the study, both globally and locally. Other academicians and researchers have researched these subjects. It focuses on pertinent data from sources concentrating on water supply and NRW components, the local study area factors, and global issues affecting other water utilities.

2.2 Water Supply Global View

According to the latest WHO/UNICEF Joint Monitoring Programme (JMP) report (2025), approximately one in four people worldwide still lack access to safely managed drinking water, representing about 2.1 billion individuals. Although global coverage has improved significantly over the past decade, substantial inequalities remain, particularly in rural areas and low- and middle-income countries. The report further indicates that 3.4 billion people lack access to safely managed sanitation, while 1.7 billion individuals are without basic hygiene services within their households. Overall, 74% of the global population now uses safely managed drinking water services, but the remaining 26% equivalent to 2.1 billion people continue to face barriers to safe and reliable water access (WHO & UNICEF, 2025)

The global volume of NRW has been estimated to be 346 million cubic meters per day or 126 billion cubic meters per year. Conservatively valued at only USD 0.31 per cubic meter, the cost/value of water lost amounts to USD 39 billion per year. Not only is this an enormous financial concern, elevated NRW detracts from water utilities from reaching their goals of full-service coverage, at a reliable level of service at an affordable price (Liemberger & Wyatt, 2019)

2.2.1 Water usage

Global freshwater use continues to increase due to population growth, industrialization, and the expansion of irrigated agriculture. However, access to safe and reliable domestic water supply remains highly unequal across regions. According to the World Bank (2024) and the WHO/UNICEF Joint Monitoring Programme (JMP, 2025), per capita domestic water availability and consumption vary significantly depending on national income levels, climatic conditions, and infrastructure efficiency.

In high-income countries, daily per capita domestic water use typically ranges from 150 to 600 (L/p/d). For instance, residents of the United States consume an average of 575-600 L/p/d, while those in the United Kingdom use approximately 150 L/p/d (Our World in Data, 2024). In middle-income regions such as Latin America and Southeast Asia, domestic consumption ranges from 100-250 L/p/d, depending on urbanization levels and service reliability (World Bank, 2024).

In contrast, low-income and water scarce countries frequently experience consumption levels below the minimum threshold of 50-100 L/p/d recommended for adequate hygiene and health (WHO/UNICEF, 2025). For example, average domestic supply in Sub-Saharan Africa remains within this range, while Jordan a chronically water stressed nation records an average household consumption of about 80 L/p/d (World Bank, 2024).

Globally, the average domestic water use is estimated at 180 L/p/d, whereas the total per capita water footprint, which includes water used for food production, energy, and industrial goods, exceeds 3,500 L/p/d (Our World in Data, 2024). These figures underscore substantial inequalities in water accessibility and utilization, with developing regions particularly rural communities continuing to face critical shortfalls in daily water supply.

2.2.2 Non-revenue water (NRW)

Non-revenue water ranging from 90% to 5% has been reported across the globe with Netherlands and Denmark leading with 5% and 7% NRW respectively in Europe. 83% of non-revenue water has been reported in Armenia and 70% in the Northern Mariana Islands. In Africa, the highest 66% of non-revenue water has been reported in Madagascar followed by 60% in Somalia and 52% in Zimbabwe, Zambia and Ghana and the lowest non-revenue water of 9% in Sudan. In Uganda, non-revenue water has been rated at 35% (Liemberger & Wyatt, 2019)

2.3 The non-revenue water concept

One of the technical barriers affecting water distribution is non-revenue water. IWA, (2003), defines non-revenue water as the difference between water produced and the amount of water sold to all customers. It is represented with the following formula;

$$\text{NRW} = \left(\frac{\text{Water produced m3} - \text{water billed in m3}}{\text{water production m3}}\right) \times 100 \qquad (2.1)$$

Both actual (physical) losses and ostensible (commercial/apparent) losses make up non-revenue water. Physical losses are caused by pipe main leaks, service connection failures, and storage tank overflows while apparent losses are typically brought on by inaccurate customer water meters, data handling errors, and unauthorised water usage (McKenzie and Seago, 2005, Arregui et al., 2018). According to AL-Washali et al, (2016), real losses are the amounts of lost water through leakages, whereas apparent losses are the total of the amounts of lost water that are consumed but not compensated.

A water audit that shows results in the water balance can be used to gauge the extent of water losses (Frauendorfer & Liemberger, 2010; Liemberger & Farley, 2004).

Table 2.1: Standard IWA water balance (Liemberger & Farley, 2004)

<table>
<tr><td rowspan="9">System input volume</td><td rowspan="4">Authorised consumption</td><td rowspan="2">Billed authorised consumption</td><td>Billed metered consumption</td><td rowspan="2">Revenue water</td></tr>
<tr><td>Billed unmetered consumption</td></tr>
<tr><td rowspan="2">Unbilled authorised consumption</td><td>Unbilled metered metered consumption</td><td rowspan="7">Non-revenue water</td></tr>
<tr><td>unbilled unmetered metered consumption</td></tr>
<tr><td rowspan="5">Water losses</td><td rowspan="2">Apparent losses</td><td>Unauthorised consumption</td></tr>
<tr><td>Metering inacuracies and Data handling errors</td></tr>
<tr><td rowspan="3">Real losses</td><td>Leakage on Transmission and or Distribution mains</td></tr>
<tr><td>Leakage and overflows at utility's storage tanks</td></tr>
<tr><td>Leakage on service connection up to point of customer metering</td></tr>
</table>

2.4 Computation of physical losses

Physical water losses are computed as the amount of net relative worth (non-revenue water) minus the total amount of commercial losses and approved unbilled (IWA, 2000). The value helps at the beginning of the evaluation to estimate the amount of physical losses that may be anticipated. All water balance measurements are subject to 95% confidence level. These set the parameters that utility managers can use to determine what the true value of a given component.

2.4.1 Estimating physical losses components

In-depth component analysis is employed to precisely dissect real losses into their constituent parts. However, a few fundamental estimates can be used to make an initial estimate.

a) Leakage on distribution mains or key transmission lines

The majority of physical losses along distributing pipes, particularly primary mains are large-scale occurrences that are easily noticed, disclosed, and typically fixed fast. The number of significant leaks fixed within the reporting period might be determined using the information contained in the maintenance records. So, can the average flow rate and the total annual volume of the main leakage. This can be computed as follows; number of reported bursts times average leak flow rate multiplied by average leak duration (to say 1 day 24 hours), to which a certain amount can be added for background losses and leaks on mains that have not yet been discovered (AL-Washali et al, (2016).

b) Leaks and overflows at the storage reservoirs

a) Overflowing water and leaks from reservoirs are typically identifiable and measurable. This may be achieved by subtracting outflow from inflow and considering the volume of water in the tank

c) Leaking service connection to customer meter point

The approximate amount of leakage in the service connection can be computed by subtracting the leakage from the storage tank and mains from the entire amount of actual losses. This amount of leakage comprises background losses from service connections, hidden (as of yet unknown) leaks, and reported and fixed leaks in service connections. Water balancing is a valuable tool for analysing inflows, (AL-Washali et al, (2016) outflows, and consumption; nevertheless, issues arise from an overall deficiency in data. Data gaps make it challenging to determine the type and location of physical losses as well as to quantify commercial losses. The actual losses are, however, confirmed using one of the following two approaches because it is always important to remember that the water balance may contain mistakes. (i) Component analysis and (ii) Assessing real losses from the bottom-up

a) Component Analysis

The total length of the pipe network and the number of service connections, the average length of the service connection between the curb-stop and the customer meter (AL-Washali et al, (2016). The total number of reported and unreported distribution main repairs per year, and the total number of reported and unreported service connection repairs per year are the essential data required for a real loss component analysis of a water distribution system, according to (Liemberger & Farley, 2004). The remaining ones include the mean pressure in distribution system for the whole network, estimates of awareness time, location, and required time for repairs, plus approximations of overflows and leakages in utility storage tanks.

2.4.2 Determining losses from bursts that are recorded and unrecorded

Incidences brought to the water utility's attention by members of the public or staff are referred to as recorded bursts. Any leak or rupture that appears at the surface under normal circumstances will typically be reported to the water utility. Leak detection teams find unreported bursts as part of their routinely scheduled, proactive leakage management tasks. Flow rates and time must be determined after gathering the total annual reported bursts on mains and service connections. It is advised to utilise the numbers from (Table 2.2) in situations when the water utility has not looked into typical rates of leak flow.

The total annual leak volume from distribution mains is computed from the number of recorded bursts multiplied by the average flow rate and average response time to leaks.

Table 2.2: The rates of flow for bursts and leaks, both disclosed and undisclosed

Location of Burst/leakage	Flow Rate for Reported Bursts (l/hour/m pressure)	Flow Rate for Unreported Bursts (l/hour/m pressure)
Main	240	120
Service Connection	32	32

Source: (Lambert, 2003)

Background loss and excess loss estimates (undiscovered leaks) are added once the number of reported and unreported bursts is determined. Weeping joints and tiny leaks are examples of isolated occurrences known as background losses that occur too slowly for an active leak detection scan to find (Al-Washali et al., 2019). After they have gotten so bad that an active leak search cannot find them, they are eventually found, either by accident or else. In an average infrastructure condition, Table 2.3 displays background losses from different network components. Leaks and Burst losses from the water balance known as physical loss components are considered excess losses. The amount of water lost as a result of leaks that are not located and rectified in compliance with the present leakage management policy is known as the volume of excess losses (Musaazi et al., 2021).

Table 2.3: Computing hidden background water losses (Lambert, 2003)

Leak/ Burst location	Litres	Measurement Unit
Distribution/ Transmission	9.6	Litres per kilometre of mains, day, per pressure unit.
Connection service mains	0.6	Litres per day per meter of pressure for each service connection.
Service Connection property boundary to the customer meter	16.0	Litres per day per meter of pressure and per kilometre of service connection.

b) Bottom-up evaluation of actual water losses

24-Hour zone measurements

Considering there are no created DMAs, regions of the supply network that are shortly cut off and sourced from a single or a pair of inflow points are chosen. The goal of selecting suitable locations is to gather a representative sample of the distribution system from different portions of the system (Mutikanga et al., 2013). Portable flow measurement types of equipment are used in selected areas, to measure the inflow continuously. Pressure readings are always taken in conjunction with flow measurements. Readings are taken at the point(s) of the inlet for the zone, the mean pressure threshold, as well as the critical pressure spots (AL-Washali et al., 2016). Every pertinent piece of information about the zone is gathered, including the quantity and kinds of non-household properties as well as the length of mains, service connections, and household properties (Özdemir, 2018).

2.5 Quantifying apparent water losses

It is always a challenging process to separate the non-revenue water volume into real and apparent losses once the volume of total water losses is known.

2.5.1 Estimating apparent losses

Arregui et al., (2020); Yazdandoost & Izadi, 2018)) lists metering and data handling mistakes, as well as unlawful consumption (theft and criminal usage), as apparent losses. These quantities are best calculated using strong local procedures or systematic sampling techniques. Furthermore, Lambert (2001) advised utilities not to assume that apparent losses are a nominal percentage of system input volume, based on figures for other utilities, instead, they should attempt to assess the elements of apparent losses for their systems.

2.5.2 Unauthorised consumption

It is challenging to offer broad recommendations for estimating unlawful water usage. It is never easy to estimate illegal consumption, but it is done in a clear, component-based manner that makes it easy to assess the assumptions later. (Cassidy et al., 2021) state that the volume of non-revenue water is subtracted from water losses to determine the amount of unlawful use. This is done by adding up the quantity of authorised unbilled use, actual loss, and inaccurate meter measurements.

2.5.3 Customer meter registration errors and data handling errors

Globally, meter age is a key determinant of metering accuracy and apparent losses. Although the recommended service life of most domestic meters is 10 years, studies show that developed-country utilities with active replacement programs maintain average fleet ages between 6 and 12 years, whereas developing-country utilities often operate meters averaging 8-12 years, with a substantial proportion exceeding 15-20 years (Mutikanga et al., 2011; Arregui et al., 2018). This disparity, largely influenced by financial and asset management constraints, contributes to higher apparent losses and revenue shortfalls in developing regions

Meter class defined by international standards such as ISO 4064:2014 and OIML R49 specifies the permissible error limits and flow range over which the meter maintains acceptable accuracy. Class C and D meters, designed for higher accuracy and wider dynamic ranges, outperform Class A and B meters, particularly at low flow conditions common in domestic consumption. However, many developing country utilities still operate older Class B meters that are more prone to under-registration, while utilities in developed countries have progressively adopted Class C and D models with advanced measuring technologies. Combined with differences in meter replacement programs, this variation in meter class and age contributes to significant disparities in apparent losses worldwide

It is necessary to determine the customer meter registration errors, namely under or over registration, through testing a representative sample of meters. The sample's makeup should represent the different age groups and types of domestic meters (Musaazi et al., 2021). Average meter inaccuracy values (as a percentage of metered consumption) are determined for various user groups based on the outcomes of the accuracy testing. Metering errors are the main cause of apparent losses in a well-run water supply system. (F. J. Arregui et al., 2018). Metering errors caused by water quality, improper meter installations, inadequate meter servicing, the wrong class of meter, and sizing, as well as customer water demand profiles, have a substantial impact on apparent losses (Criminisi et al., 2009). The customer meter inaccuracies that consist of under or over-registration can be determined based on comparing tested representative meter samples with known volume. The structure of the meter sample reflects the various meter classes, ages, and customer categories. The mean meter error values (as a percentage of metered consumption) are determined for various user groups based on the outcomes of the accuracy testing. Pressure per connection should be considered for comparing different supply areas of the same water utility, or different utilities with systems operating at different pressures. High distribution system pressures are largely a management issue and can be controlled to reduce losses (Musaazi et al., 2021). Data handling errors sometimes form a substantial component of apparent losses

2.6 Theoretical framework

The water balance theory of the International Water Associations served as the study's foundation. According to this idea, the input volume of produced water and sent into the system can be divided into two parts; water losses and consumed water. Consumed water is additionally subdivided into billed and unbilled consumption. The idea also recommends further dissecting water losses into real loss and apparent loss. The hypothesis ultimately suggests that billed consumption should be considered revenue water, but the sum of commercial loss, real losses and unbilled authorised consumption be considered non-revenue water. This was the main objective of this research, focusing on metering inaccuracies, which forms part of commercial or apparent losses (F. J. Arregui et al., 2018).

2.7 Categorisation /Types of water meters

Water meters come in many varieties, including mechanical (positive displacement, Multi-jet, and turbine flow meters), electromagnetic, and ultrasonic. They are categorised according to how they measure water flowing through them. The most widely used kind of water meter is the single jet meter (Criminisi et al., 2009).

2.7.1 Positive displacement

The most common type of water meter for homes and small businesses is the displacement type. They have moving elements, such as an oscillating piston, that are displaced when water

Meter image	meter type	**mode of functioning**
		
	singe Jet meters	
	Multi jet meters	
	Electromagnetic flow meter	
	Ultrasonic flow meter	

Figure 2.1: Meter types and mode of functioning

passes through the main chamber of the meter. The moving components detect the water's volume and raise the meter's reading by the appropriate amount. These meters have moving parts, which makes them prone to failure and significant pressure loss (Mutikanga, 2014).

2.7.2 Single-Jet water meters

A single-jet water meter is a velocity-type meter that measures water flow by directing the entire flow of water through a single tangential jet onto an impeller (rotor).

When water enters the meter body, it is channeled through a single nozzle so that the jet strikes the impeller vanes, causing it to rotate. The speed of rotation of the impeller is directly proportional to the velocity of the incoming water, and therefore to the flow rate[3] (F. J. Arregui et al., 2018).

The impeller's rotational motion is transmitted, through a magnetic coupling, to a gear train and register mechanism located in the dry upper chamber. This ensures that the measuring elements are isolated from the water, preventing corrosion or clogging.

The total volume of water passing through the meter is obtained by integrating (summing) the number of rotations of the impeller over time, displayed on the mechanical or electronic register as cubic meters (m^3) (F. J. Arregui et al., 2018) .

2.7.2 Multi-jet Flow Meter

Multi-jet meters are widely used by home and small business users up to 50mm diameters because they are particularly precise in small sizes. Multi-jet meters generate several water jets against an impeller, whose rotational speed is dependent upon the water's velocity, by encircling the impeller with various ports (F. J. Arregui et al., 2018). Since they lack the straight-through flow channel required for the high flow rates utilized in big pipe diameters, they are not available in large quantities. prone to malfunction due to moving components. They capture both the water's forward and backward flow (Mbabazi et al., 2015).

2.7.3 Turbine Flow Meter

Turbine meters are specifically offered for pipe sizes ranging from 40mm to 14mm diameter. As water passes through the chamber, turbine blades inside spin. Large commercial distribution systems frequently use them. The turbine's velocity, which correlate with the water's flow rate through it, produces a voltage pulse that indicates the flow rate. An indicator of the overall flow is the total number of pulses. In comparison to displacement and multi-jet meters, turbine meters are less precise. Installation of long, straight pipe sections is necessary, calls for regular calibration, prone to making errors and keeps track of airflow (Mbabazi et al., 2015).

2.7.4 Electromagnetic Flow Meter

The prevalence of electromagnetic flow meters is higher in commercial and industrial structures (Kroner et al., 2022a). An electromagnetic coil that creates a magnetic field and electrodes that measure voltage are found inside an electromagnetic flow meter. The transmitter processes the voltage detected by the electrodes to produce a standardised output signal, which is then displayed in the proper metering unit (Electromagnetic Flow Meter Maintenance Practices, 2023). These are pricey gadgets. In order for magnetic coils to function as conductors, the fluid passing through the pipe needs to have a higher conductivity. Errors may arise from gas bubbles that collect inside the meter. Therefore, Regular mechanical and electrical cleaning is necessary for electromagnetic flowmeters (F. J. Arregui et al., 2018).

2.7.5 Ultrasonic Flow Meter

Two transducers that produce sound waves are included with ultrasonic flow meters. The sound waves in a pipe carry information about the water's velocity (Kroner et al., 2022b). The frequencies of an ultrasonic wave that enters a pipe and the waves that the fluid reflects back are the same when there is no flow. The reflected wave has a different frequency when it is flowing. To calculate the flow rate, the transmitter processes signals from the wave that is sent and its reflections. The actual volume of water flowing through the sensor is calculated using the flow velocity provided by the signal and the known tube cross-section (Electromagnetic Flow Meter Maintenance Practices, 2023). Ultrasonic meters have a long lifespan and don't need to be calibrated because they don't have any moving parts. These meters can monitor incredibly low flows of 0.1 l/m of pressure drop and have very little pressure loss (Mutikanga, 2012).

2.7.6 Water meter sizing

Water meters work properly within a predetermined flow rate by the manufacturer detailing the highest and low flow rates. Large meters do not detect very low flows below the minimal threshold (Cassidy et al., 2021). Understanding the kind of water demand and expected consumption of each consumer, water supply utilities carry out consumer audits. With the use of this information, the proper meter size for each consumer category may be determined. The flow pattern of the most recent installed meters is examined to determine if the right meter size is being used for clients. When meter size is poorly selected, mostly with bulk consumption water utilities experience high water losses due to under-registering of wrong meter size. Meter sizing should depend on consumption trends, therefore, monitoring consumer consumption patterns is very paramount in minimising metering errors (Arregui et al., 2020).

When a storage tank with a ball or float valve controlling water flow, is installed on the customer's property, low flow issues may arise. These valves work by gradually shutting as the water level in the tank rises (Musaazi et al., 2021). This results in a reduction in the measurement of the meter since the flow into the tank is below the flow standard. Where overhead tank capacity is greater than the water demand profile for the consumer, the float valve does not ever fully open and the flow through the meter is always low (Mutikanga et al., 2011).

2.7.7 Water meter classification

Standards such as (ISO 4064 and OIML R 49) classify water meter accuracy into classes such as Class 1 and Class 2, or the older A, B, C, and D classes, which denote the meter's precision across various flow rates. Class C and D are more accurate than Class A and B, respectively, with higher accuracy grades allowing for smaller maximum permissible errors (MPE) at various flow rates, essential for accurate billing.

2.7.7.1 Accuracy classes based on ISO and OIML Standards

Modern international standards classify water meters into different accuracy classes based on their maximum permissible error (MPE):

Class 1 (ISO 4064):

These are more precise meters. Upper Flow Zone (Q2 to Q4): The MPE is ±2%. Lower Flow Zone (Q1 to Q2): The MPE is ±3%.

Class 2 (ISO 4064):

Less precise than Class 1, they have a larger MPE. Upper Flow Zone (Q2 to Q4): The MPE is ±2%. Lower Flow Zone (Q1 to Q2): The MPE is ±5%.

2.7.7.2 Historical A, B, C, D Classes

Some manufacturers and older systems still use a classification system based on letters:

a) Class A, can measure higher flow rates.

b) Class B, Offers higher accuracy than Class A, with good performance even at low flow rates.

c) Class C, The most accurate class, but often more expensive and less common for residential use.

d) Class D, Generally the least accurate, used for very specific, less demanding applications.

2.7.7.3 Accuracy Grades (R-value)

Another common accuracy classification uses the "R-value," which indicates the ratio of the maximum flow rate to the minimum flow rate at which the meter maintains its accuracy.

R80, R100, R160, R250, R400, these numbers represent the accuracy ratio. A meter with an R100 rating is more accurate than one with an R80 rating **(ISO 4064 1 2014)**.

2.7.7.4 Identifying the Meter's Accuracy class

You can find the accuracy class of a water meter: On the meter dial: The manufacturer is obligated to label the accuracy class on the meter's face.

On calibration certificates**:** The proofs of measurement accuracy are documented in calibration certificates. While all meter classes are on market, their prices defer according to the accuracy level, with class 1 meters varied the most expensive meters **(ISO 4064 1 2014)**

2.7.8 Water meter selection

When choosing the proper meter class, customer consumption data must be more precise. Class B meters are a great choice in areas with poor water quality since the sediments have no a substantial influence on the meter (Cordeiro et al., 2022). Class D meters are used in situations where properly installed overhead tanks are used and the water quality is satisfactory since they have a lower minimum flow rates that accurately measure the input into the overhead tank. Class B meters have lower measuring accuracy than class C, Class D is more accurate than class C. Most water utilities prefer using class C since they are less expensive than class D (Cordeiro et al., 2022). The largest size of the meter used by water utilities for domestic simple commercial connections is DN15mm followed by DN20mm. Larger industries and commercial connections, DN 25mm to D150mm are most appropriate. Connections larger than 150mm electromagnetic meters are the most suitable option (Kroner et al., 2022b). Common types of meters include positive displacement (PD), multi-jet, single-jet, turbine, and electromagnetic ones (Mutikanga, 2014).

2.7.9 Water meter age

The age of a water meter is one of the most critical factors influencing its measurement efficiency and overall accuracy. Globally, studies across different utilities have consistently shown that as water meters' age, their ability to register actual consumption declines, leading to systematic under-registration and consequently increased Non-Revenue Water (NRW).

With prolonged use, internal moving parts particularly in mechanical meters such as single-jet and multi-jet types experience frictional wear caused by continuous exposure to suspended impurities, sediments, and scale deposits. This mechanical degradation reduces meter sensitivity, especially at low flow rates, resulting in progressive under-registration (Arregui et al., 2018; Mutikanga et al., 2019). Empirical research by the American Water Works Association (AWWA, 2020) indicates that the average accuracy of domestic mechanical meters typically declines by 1–2% per year after 8-10 years of operation, depending on water quality, meter class, and installation conditions. Similar findings by Karadirek **(2020)** and Arregui et al. (2018) revealed that meter age significantly correlates with increased metering error, particularly in low-flow ranges where frictional losses dominate. Beyond 12–15 years of service, most mechanical meters fall below the permissible accuracy limits defined in ISO 4064:2014, necessitating recalibration or replacement to maintain billing integrity and reduce apparent losses

Although the recommended service life of most domestic meters is 10-15 years, studies show that developed country utilities with active replacement programs maintain average fleet ages between 6 and 12 years, whereas developing-country utilities often operate meters averaging 8-12 years, with a substantial proportion exceeding 15-20 years. This disparity, largely influenced by financial and asset management constraints, contributes to higher apparent losses and revenue shortfalls in developing regions

2.7.9.1 Decline in Sensitivity at Low Flows

Older meters typically lose the ability to accurately record small, intermittent flows such as household leaks or low tap flows. These low-flow volumes accumulate significantly over time, causing a large discrepancy between actual and recorded consumption. Utilities in Germany and Japan report that meter sensitivity to low flows drops by more than 10% after 8 years of service (Arregui et al., 2007).

2.7.9.2 Environmental and Hydraulic Effects

Prolonged exposure to environmental conditions such as temperature fluctuations, pressure surges, or corrosive water chemistry accelerates internal wear. This effect is more pronounced in regions with poor water quality or high sediment load, leading to faster meter deterioration. In South Africa and India, utilities have observed that meters in high-turbidity zones lose accuracy after only 5-7 years, compared to the global average lifespan of 10-12 years (Criminisi et al., 2009).

2.7.9.3 Resolving Meter Age Effects to Improve Accuracy

The degradation of water meter accuracy with age is a well-documented phenomenon resulting from mechanical wear, material fatigue, scaling, and hydraulic erosion of internal components. Aged meters tend to under-register flow, particularly at low flow rates, contributing significantly to non-revenue water (NRW) (Arregui et al., 2006; Mutikanga et al., 2011). To mitigate these effects, researchers and utilities have developed several effective methodologies ranging from proactive replacement and recalibration to the adoption of smart metering technologies and analytical correction models.

2.7.9.4 Meter Replacement Optimization Based on Age Error Modelling

Studies have established empirical relationships between meter age and accuracy decline, enabling predictive replacement scheduling.

Arregui et al. (2006) demonstrated that mechanical meters lose between 1.2-2.5% accuracy per year of operation, depending on water quality and pressure conditions. Utilities such as Aguas de Alicante (Spain) and Melbourne Water (Australia) apply age error regression models to optimize meter replacement before cumulative under-registration exceeds economic thresholds (Criminisi et al., 2009). Mutikanga et al. (2011) proposed a cost–benefit-based replacement model integrating meter age, flow rate profile, and revenue recovery potential achieving up to 8% improvement in billing accuracy in Kampala, Uganda. Reduction in meter under-registration and extension of replacement intervals based on actual degradation rates rather than arbitrary lifespans was evident *(*Arregui et al., 2006; Criminisi et al., 2009; Mutikanga et al., 2011).

2.7.9.5 Recalibration and Reconditioning Programs

Another proven methodology is systematic meter recalibration or reconditioning instead of total replacement. Studies by Pappa et al. (2017) and AWWA (2020) show that recalibration of meters aged 5-8 years restores up to 95% of original accuracy at a cost 40–60% lower than new installations. Reconditioning includes cleaning, impeller bearing replacement, and recalibration using ISO 4064 test benches. Gravimetric and comparison-based calibration programs are used to correct accumulated mechanical drift and low-flow sensitivity loss (ISO, 2014; OIML, 2013). Significantly improves was evident with meter performance in utilities with limited budgets for large-scale replacement, while maintaining regulatory compliance. (ISO 4064-2, 2014; AWWA, 2020)

2.7.9. 6 Transition to Non-Mechanical and Smart Meter Technologies

Several studies recommend transitioning from mechanical to electronic (ultrasonic or electromagnetic) meters to mitigate age-related wear. Ultrasonic meters, having no moving parts, maintain accuracy within ±0.5% over time, unlike mechanical meters whose wear increases error (Zhao et al., 2021). Research in the Netherlands and Denmark showed that replacing mechanical meters older than 10 years with ultrasonic models reduced NRW by 6-9% within three years (van der Bruggen & Vreeburg, 2018). Smart meters with self-diagnostic and auto-calibration functions detect drift in real time, flagging meters that require servicing (Mounce et al., 2019). Meter maintains long-term stability of accuracy and supports predictive maintenance through real-time monitoring. (Zhao et al., 2021; van der Bruggen & Vreeburg, 2018; Mounce et al., 2019)

2.7.9.7 Analytical Correction and Computational Calibration Models

Modern research integrates data analytics and computational modeling to compensate for age-induced accuracy loss without physical replacement. Sharma et al. (2019) developed polynomial error-correction algorithms based on historical test data to digitally adjust meter readings according to predicted age-related bias. Similarly, Hosseinifard et al. (2020) used machine learning regression models trained on flow and pressure data to estimate true consumption, improving overall accuracy by 3-4%. Utilities using digital twins of their metering systems (e.g., Thames Water, UK) now apply continuous error curve recalibration through simulation models. This method enables cost-efficient compensation for aging effects and supports smart NRW management frameworks. (Sources: Sharma et al., 2019; Hosseinifard et al., 2020)

2.7.10 Water quality and meter registration errors

Water quality exerts a critical influence on meter accuracy, with its impact varying according to meter type, nominal size, and hydraulic loading conditions. In mechanical meters such as single-jet, multi-jet, and volumetric designs suspended solids, scaling, and biological deposits increase internal friction and impede the movement of measuring elements, resulting in progressive under-registration of flow. This deterioration is more pronounced in small-sized meters (DN 15–25 mm), where the proportion of obstructed flow area is greater and the moving parts are lighter and more sensitive to impurities (Arregui et al., 2006, 2016, 2018; Mutikanga, 2012).

Conversely, electromagnetic meters, though free from moving components, are affected by non-conductive or aerated water, which disrupts the induced voltage signal, while electrode fouling can cause zero drift and output instability (AWWA, 2017). Ultrasonic meters maintain superior performance in clean water but show accuracy degradation in turbid or multiphase conditions due to scattering and signal attenuation (Boquinstrument, 2020). Overall, the influence of water quality is moderate to highly significant, depending on meter technology and size. Persistent exposure to poor water quality accelerates metrological degradation, alters calibration characteristics, and contributes directly to apparent losses and Non-Revenue Water (NRW) in distribution systems

Since meter ageing is accelerated by abrasive particles, scaling, and pressure fluctuations, effective water quality control and pressure zoning are essential. Studies in South Africa and Portugal found that high turbidity (>5 NTU) and hardness (>250 mg/L $CaCO_3$) accelerate impeller wear by up to 40%, while stable pressure conditions reduce degradation (Arregui et al., 2006; Fonseca et al., 2018). Implementing pressure management valves and inline filtration extends meter lifespan and reduces calibration drift. This method mitigates mechanical degradation, sustaining metrological stability in aged meters. (Fonseca et al., 2018; Arregui et al., 2006)

Impact on Non-Revenue Water (NRW)

As meters age and under-register, utilities experience increasing volumes of unaccounted-for water, resulting in higher NRW percentages and reduced revenue recovery. Older meters therefore, contribute directly to financial losses and operational inefficiencies. A study by Sydney Water (Australia) showed that replacing 10-year-old meters improved revenue recovery by 3–5%, equating to several million dollars annually (Farley & Liemberger, 2022).

2.7.11 Water demand and metering errors

In water pipe network with intermittent water supply and users that use private storage tanks fed by float valves, errors in water meter registration are magnified (Al-Washali et al., 2019). Overestimate meters when they are not registered, resulting in additional apparent losses for the customers examined in the study of between 15% and 40% (Walter et al., 2018). According to the American Water Works Association, measuring meter performance and pinpointing the primary reasons for malfunction can help minimise non-revenue water (NRW), which is brought about by inaccurate meters and inadequate water meter management (AL-Washali et al., 2020; Arregui et al., 2020). The research conclusions were reached after looking into the effectiveness of installed water meters in Kampala water. Meter separations (sub-metering) in Kampala resulted in 18% decrease in utility revenue from water. The distinct ageing of each sub-meter and the low network pressures were the causes of this under-registration of sub-meters (Mutikanga et al., 2011).

2.7.12 Influence of Meter Positioning on Accuracy

Meter positioning greatly affects measurement accuracy depending on meter class and flow conditions. According to ISO 4064 and OIML R49, improper orientation or inadequate straight pipe lengths distort the velocity profile, leading to significant metering errors.

Studies by Arregui et al. (2006) and Mutikanga (2012) revealed that installing single-jet or multi-jet meters vertically instead of horizontally causes under-registration at low flows due to partial impeller wetting, and over-registration at high flows from turbulence. Higher accuracy meters (Class C and D) are less sensitive to such positioning errors compared to Class A and B meters.

Inadequate upstream straight lengths (<10D) and downstream runs (<5D) also introduce swirl and asymmetrical flow, producing ±3-5% deviations in readings (AWWA, 2017). Electromagnetic meters show better tolerance but still require stable flow.

Overall, incorrect meter positioning shifts the calibration curve, especially at low flow rates (Q_1 & Q_2), leading to systematic under-registration and contributing up to 8 – 10% apparent losses in Non-Revenue Water (Mutikanga et al., 2011).

2.7.13 Impact of network water pressure on meter performance

Hydraulic performance and the accuracy of water meters are both impacted by Network pressure variations in water supply systems. Water distribution systems with intermittent supply, and steady-state conditions, which are relatively rare, are needed to construct metering error curves. Working pressure has a beneficial impact on water meter registration, which deteriorates over time (Musaazi et al., 2021). The rate of meter under-registration increases as a result of low working pressure.

2.7.14 Meter reading interpretation

Interpreting meter readings also plays a big role in increasing water meter errors. Some large meters are set with a multiplier effect that must be incorporated into the meter reading. The water meter reading multiplier is identified by critical observation of the meter specification or through meter calibration.

2.8 Metering Inaccuracies and Non-Revenue Water (NRW)

Globally, reported meter registration errors range between ±2% and ±10%, depending on meter type, size, and operating environment. A study in Spain by Arregui et al. (2018) found that older mechanical meters under-registered by an average of 6.3%, with errors increasing significantly after 10 years of service. Similarly, research in Uganda by Mutikanga et al. (2014) reported average under-registration errors between 5-12%, primarily attributed to ageing meters and low domestic flow rates. In Brazil, Silva et al. (2021) identified a mean error of -7.8% for domestic meters over eight years old.

Studies in developed regions show comparatively lower inaccuracy levels due to proactive meter replacement and calibration programs. For example, a study in the United Kingdom reported an average under-registration of 2-3%, with volumetric meters showing better performance at low flow rates compared to mechanical types (Of wat, 2020). Conversely, developing countries often exhibit larger deviations sometimes exceeding 10% due to intermittent supply, sediment presence, and inadequate maintenance (Farley & Liemberger, 2022). Overall, meter inaccuracies contribute 5-15% of total NRW in many utilities, with a higher burden in developing countries (World Bank, 2023).

Metering inaccuracies are a major source of apparent losses, directly impacting Non-Revenue Water (NRW). The effect varies with meter type, size, age, installation, and water quality.

Mechanical meters (single-jet, multi-jet) exhibit progressive under-registration, especially with aging, poor water quality, or low flows. Domestic meters (DN 15-25 mm) can under-register by 3-10%, contributing significantly to NRW (Arregui et al., 2006; Mutikanga et al., 2011). Electromagnetic meters are less sensitive but can experience 1-3% error due to electrode fouling or entrained air (AWWA, 2017).

Meter under-registration directly inflates NRW. For example, a 5% average under-registration in a utility producing 10,000 m^3/day translates to 500 m^3/day of apparent loss. In urban utilities with aging meter, such metering errors often account for 30-50% of apparent losses (Mutikanga et al., 2011; Arregui et al., 2006).

Table 2.4: Meter registration errors considering meter type

Meter Type	**Nominal Size (DN)**	**Flow Range**	**Under - registration (%)**	**NRW Contribution**	**Reference**
Single-Jet (mechanical)	15-25 mm	Low (Q_1-Q_2)	5-10%	Moderate to High	Arregui et al., 2006; Mutikanga et al., 2011
Multi-Jet (mechanical)	15-50 mm	Low to nominal (Q_1 -Q_3)	3-7%	Moderate	Arregui et al., 2006
Volumetric (piston)	15-25 mm	All flows (Q_1 -Q_4)	1-5%	Low to Moderate	Mutikanga et al., 2011
Electromagnetic	15-100 mm	Nominal to high (Q_2-Q_4)	1-3%	Low	AWWA, 2017
Ultrasonic	15-100 mm	All flows, clean water	1-3%	Low	Boquinstrument, 2020

Accurate meter selection, installation, and maintenance are critical for minimizing metering-induced NRW and improving revenue capture.

2.8.1 Determination of meter errors

Determination of meter errors is the process of quantifying the deviation between the indicated volume (V_i) registered by a water meter and the actual reference volume (V_a) measured by a calibrated proving system. It is the most direct method of assessing a meter's accuracy and reliability. The error is computed as:

$$\text{Meter Error (\%)} = \frac{Vi - Va}{Va} \times 100 \quad \text{(ISO 4064-2:2014)} \qquad (2.1)$$

A positive error indicates that the meter over-registers, while a negative error indicates under-registration. Tests are performed under controlled laboratory or field conditions following ISO 4064-2:2014 and OIML R49-2:2013 standards.

The water meter metrology is impacted by changes in flow rates and temporal demand patterns (F. J. Arregui et al., 2016); (Albaina et al., 2020).

2.8.2 Meter testing for accuracy

Meter testing for accuracy is a critical process in ensuring that water consumption is measured correctly for both billing and system management purposes. According to the International Organization of Legal Metrology (OIML R 49-1:2013), water meter accuracy testing verifies whether a meter operates within the Maximum Permissible Error (MPE) limits under defined flow conditions (OIML, 2013). Accurate metering underpins fair billing, revenue protection, and effective non-revenue water (NRW) management.

Testing involves comparing the volume of water indicated by the meter against a known reference volume under controlled conditions. The process typically assesses meter performance at three flow rates minimum (Q_1), transitional (Q_2), nominal or permanent (Q_3) and extending up to Q_4 (overload flow) as prescribed by ISO 4064-2:2014, which defines methods for accuracy testing and calibration (ISO, 2014). These flow conditions reflect the meter's operational range and help identify performance deviations at both low and high flows.

The American Water Works Association (AWWA M6, 2020) emphasizes that even small deviations in meter accuracy can lead to substantial financial losses or customer dissatisfaction. For instance, a 2% under-registration on a large customer's meter can translate into significant revenue loss over time. Therefore, utilities are encouraged to implement periodic meter testing programs using certified test benches or portable proving systems that meet AWWA C715 and OIML R49 standards.
Moreover, meter accuracy testing is not only a technical verification but also a regulatory requirement in most jurisdictions to ensure compliance with trade measurement laws and maintain public trust (AWWA, 2020; ISO, 2014).

Meter testing for accuracy ensures that water meters provide reliable, reproducible measurements within acceptable error limits. This is vital for revenue assurance, customer equity, and accurate water balance assessments within utilities.

Any one of the following three methods can be adopted for checking the accuracy of a water meter; Volumetric, Gravimetric and Comparison (Chandapillai, 2020).

2.8.2.1 Meter errors influenced by field conditions

There are some common categories of meter registration error, how they present, and what causes them:

Starting flow meter error / low flow error

Many meters have a minimum flow rate below which the meter's measurement mechanism does not reliably register flow (the "starting flow"). Flows below this threshold may pass through the meter but not be recorded, or recorded at a much lower efficiency. This leads to under-registration especially when a consumer has many very low flows (e.g., leakage, trickle flows) or when the supply is intermittent and/or has small intermittent flows. For example, the

Italian study on meter under-registration showed that private storage tanks (resulting in low flows) increased apparent losses between 15%-40% (Sharma et al., 2019).

The effect is that meter accuracy is worse at low flows (since friction and mechanical inertia dominate, or sensor sensitivity is inadequate) .

2.8.2.2 Flow range nonlinearity/high-flow error

A meter is typically designed for a certain flow range (Qmin to Qmax) and has an accuracy band within those flows. If flows regularly exceed the designed maximum flow (or fall outside the optimum range) then the meter may deviate (either under- or over-register) because of mechanical or hydraulic constraints. Example: If the meter is undersized for the installation (i.e., actual flows higher than rated), this causes increased velocity, turbulence, wear, and thus registration error.

2.8.2.3 Aging / wear & tear error

Over time, moving parts in mechanical meters' wear, friction increases, seals degrade, bearings wear out, and sensitivity decreases. These lead to increasing error (typically under-registration) with age. The Italian study found that meter under-registration increased rapidly with meter age. However, age alone is not always a reliable predictor of error in all contexts the guidance manual notes that while older meters are more likely to be inaccurate (Sharma et al., 2019).

2.8.2.4 Meter positioning error

Meter installation quality significantly influences measurement accuracy and long-term performance. Poor installation practices such as incorrect orientation, inadequate straight pipe lengths upstream or downstream, proximity to bends or valves, and the presence of air bubbles disturb the hydraulic flow entering the meter and alter its internal velocity profile (Mutikanga et al., 2014) These disturbances cause turbulence, eddies, or flow separation, which impair the measuring mechanism and result in systematic under or over-registration of flow. For instance, installing a meter immediately after a bend or valve without sufficient straight pipe run induces asymmetric flow conditions that reduce accuracy (Arregui et al., 2018). Likewise, intermittent water supply conditions characterized by air entrainment and pressure surges can lead to erroneous readings, as the meter may register air passage as water flow or mis-register water during unstable flow periods. Such conditions are common in intermittent and low-pressure systems typical of many developing countries, and they substantially contribute to apparent losses and unreliable billing. (Sources: ISO 4064:2014; OIML R49:2013; Liemberger & Wyatt, 2019; Farley & Trow, 2020.)

2.8.2.5 Water quality error

Water quality has a significant and measurable impact on meter accuracy, with its effect varying by meter size, class, and type. Poor-quality water containing suspended solids, rust, biofilms, or chemical contaminants increases internal friction, obstructs moving parts, and alters flow conditions within the meter. Small mechanical meters (DN15–DN25), particularly older Class A and B types, are most affected due to their narrow clearances and dependence on free-moving components. Sediment deposition and corrosion cause drag and sticking, leading to progressive under-registration, especially at low flow rates typical of domestic use. Higher-accuracy Class C and D meters exhibit greater tolerance but still deteriorate under prolonged exposure to scaling and debris (Arregui et al., 2018).

Non-mechanical meters such as electromagnetic and ultrasonic types are less sensitive to suspended solids but are affected by air bubbles, electrode fouling, and biofilm formation, which distort signal transmission (Liemberger & Wyatt, 2019). Larger-diameter meters generally experience lower proportional accuracy loss, as higher velocities limit sediment accumulation. Empirical studies report that in turbid or high-sediment environments, mechanical meters can under-register by 5–15% within a few years of operation, depending on meter class and flow conditions (Arregui et al., 2018; Mutikanga et al., 2014). Therefore, maintaining good water quality through filtration and corrosion control is essential to preserve metering accuracy and reduce apparent losses.

2.8.2.6 Pressure/head differential / intermittent supply effects

Meter accuracy can be sensitive to working pressure/ head. A paper in Uganda found that increasing pressure improved accuracy modestly but ageing remained the dominant parameter.

In intermittent supply systems, air entrainment, frequent starts and stops, and use of storage tanks disrupt steady flows and can lead to under-registration (Liemberger & Wyatt, 2019).

Electronic / smart meter-specific errors

For newer smart meters or meters with electronic registers, errors may occur due to sensor drift, electronic interference, firmware or memory errors, power supply instability. For example, memory write failures in smart meters can lead to accumulation of errors over time. Also, mis-match between meter register and billing system (serial numbers wrong, MIU number mismatch) can create "registration errors" from a billing perspective (i.e., the meter reading may not be properly associated with the customer) (Arregui et al., 2018).

2.8.2.7 Methods for checking the accuracy of water meter

Accurate water metering ensures reliable billing, equitable distribution, and proper management of Non-Revenue Water (NRW). To verify meter performance, accuracy testing is conducted to determine how closely the indicated volume on the meter corresponds to the actual volume of water that has passed through it (Sharma et al., 2019). Three internationally recognized methods are used for this verification: volumetric, gravimetric, and comparison methods (Sharma et al., 2019). These are standardized under ISO 4064-2:2014 and OIML

R49-2:2013, and are widely applied by water utilities and calibration laboratories (ISO, 2014; OIML, 2013; AWWA, 2020).

2.8.2.8 Gravimetric method

The gravimetric method measures the mass of water (M_a) collected using a precision weighing system, and converts it to volume using the water density (ρ) at the test temperature:

$$Va = \frac{Ma}{\rho} \tag{2.2}$$

This method provides high accuracy and traceability to SI units (mass) and is preferred for laboratory calibration of large meters or high-precision reference meters (OIML, 2013). It eliminates uncertainties linked to tank geometry and temperature corrections. *(*Sources: OIML R49-2:2013;

2.8.2.9 Volumetric method of testing water meters

In this method, the water passed through the meter under test is collected in a volumetric tank. Meter performance is determined by evaluating the difference between the known volume measured by the tank and measured water through the meter. In the volumetric method calibrated volume tanks of different capacities are required for covering the entire flow range of the meters that can be tested in the test facility (Ethem Karadirek, 2020). Calibration of these tanks is not easy at its installed location.

2.8.2.10 Gravimetric method of testing water meters

In this method, a weighing system is used instead of a volume tank. The gravimetric method is the primary and most accurate method used to measure flow or volume. In this method, any quantity of water can be measured within the capacity of the weighing system (Ethem Karadirek, 2020). This is not possible in standard volume tanks used in the volumetric method. The calibration of weighing system is much easier compared to the calibration of references used in volumetric and comparison methods. The accuracy of the gravimetric method can be improved by using high-resolution weighing systems (Koech, 2015).

2.8.2.11 Measurement and Analysis Approaches

Meter accuracy is evaluated using a reference test bench that measures flow rate and totalized volume under controlled pressure and temperature conditions. The core measurements include:

a) Instantaneous Flow Rate (Q, m^3/h)

b) Cumulative Volume (V_i, V_a, m^3)

c) Pressure (P, bar) and Temperature (°C), as they affect meter response and water density.

Beyond traditional flow-bench testing, modern verification methods employ advanced analytical and computational tools:

Real Time Computation: Smart and electromagnetic meters integrate self-diagnostics and flow-signal processing algorithms to compute instantaneous error and drift in real-time (Zhao et al., 2021).

Error Curve Analysis: Error–flow rate curves (±% error vs. Q) are plotted to visualize performance trends across flow ranges and identify zones of instability or bias Sharma et al., (2019.

Analytical Modelling: Polynomial regression or machine-learning-based models are used to fit computational patterns, predict future error drift, and optimize recalibration schedules (Sharma et al., 2019).

Uncertainty Analysis: Quantifies the combined influence of measurement devices, calibration method, and repeatability, enhancing traceability and confidence in test results (OIML R49-2, 2013, Sharma et al., 2019).

2.8.2.12 Comparison method of testing water meters

In comparison method, another meter with high accuracy is used. It may be noted that in all cases the reference system should have a better accuracy than the accuracy of the meter. The comparison method is generally used in test facilities for testing large-size water meters where the test flow rates are very high (Ethem Karadirek, 2020).

The standard says, that when the test is conducted, the accuracy in determination of the actual volume passing through a water meter should not exceed one-fifth of the applicable maximum permissible error for model approval and one-third of the applicable maximum permissible error for initial verification (Sharma et al., 2019). The resolution of the water meter contributes to errors in meter readings as well as testing. Even if the accuracy of the reference is very high the uncertainty in the determination of the meter can go high due to poor resolution of the meter (Arregui et al., 2018). As per the standard, the subdivisions of the meter resolution should be small enough to ensure that the resolution error of the indicating device does not exceed 0.25% for accuracy class C meters, and 0.5 % for accuracy class B meters, of the volume passed during 90 min at the minimum flow rate Q1. The resolution error is the ratio of maximum error in each reading due to meter resolution to the actual volume of water collected during testing expressed in percentage (Gonza et al., 2021). For minimizing the resolution error more quantity of water should be passed through the meter. However, the duration of testing is limited to 90 minutes. Hence, the resolution of the meter should be high enough to achieve this criterion related to volume collected at minimum flow rate.

2.8.3 Integration of Analytical and Computational Approaches

Recent studies combine real-time computation, error curve analytics, and pattern recognition algorithms to enhance meter testing precision. Using digital data acquisition, error curves can be dynamically plotted and analyzed to detect non-linearities or transient biases.

Zhao et al. (2021) demonstrated that real-time error computation and pattern analysis reduce test uncertainty by up to 0.3%, while Sharma et al. (2019) showed that polynomial regression models effectively predict meter deviation patterns across flow ranges.

Thus, a combination of traditional methods (volumetric, gravimetric, comparison) and computational error analytics provides a comprehensive framework for evaluating both mechanical and smart meter performance in modern water utility applications.

2.9 Pressure zoning

The network pressure fluctuates with time, that is, customers use the available water for household tasks during the day, which lowers working pressure (L-Washali et al., 2020). At night, fewer people use the water, which raises working pressure. The pressure measurements should be monitored for more than 24 hours to capture the day and night pressures in different network pressures. It is crucial to take into account when water is used, but doing so will probably require more thorough and complex water meter testing to replicate real-world field settings. (Frauendorfer & Liemberger, 2010; Musaazi et al., 2021).

2.10 Impact of metering inaccuracies on water losses

Meter under-registration occurs when a portion of the water that flows through the meter goes uncounted. As a result, the consumer only pays for that portion registered by the meter. Factors that contribute to the meter under registration include; wear and tear of internal moving components, wrong meter installation procedures, lack of meter servicing or calibration, plus inappropriate sizing of meters. Water meter malfunctions may exist to be the most serious and challenging to quantify (Mutikanga et al., 2011).

Socially, the pricing of water requires accurate water use measurement (Kanakoudis et al., 2016), understanding water meter accuracy is essential for water loss control. Suggested management techniques based on the use of billing data for the best water meter selection and replacement time. The strategy is based on comparing annual readings from operational water meters. This method requires a comprehensive billing database, and issues with data management and reading may have an impact on the water meter selection (Arregui et al., 2016) The results show that higher flow and pressure rates impact measurement accuracy; nonetheless, its effects on water meter inaccuracies are minor. Despite research on how water pressure rates affect the measuring accuracy of meters, additional study is required to evaluate water meter accuracy at extremely high and low pressure and flow levels that could exist in some water supply networks (Musaazi et al., 2021).

2.10.1 Strategies for managing water meter inefficiencies

Globally, water utilities have adopted various strategies to reduce meter inaccuracies and enhance billing efficiency. These strategies focus on ensuring measurement reliability, extending meter life, and improving customer confidence. The table below presents some of the most common approaches, their purposes, and examples of utilities implementing them worldwide.

Table 2.5: Strategies used to manage metering inefficiencies in water utilities.

No.	Strategy	Purpose	Example Utility / Country
1	Regular Meter Testing and Calibration	To ensure continued meter accuracy and detect drift beyond permissible error limits.	Thames Water (UK), Sydney Water (Australia)
2	Meter Replacement and Lifecycle Management	To replace ageing or under-registering meters based on age, volume, or accuracy data.	Johannesburg Water (South Africa), New York City Water (USA)
3	Deployment of Smart Meters / AMI Systems	To enable real-time data collection, leak detection, and error diagnostics.	Singapore PUB, Tokyo Waterworks (Japan), Thames Water (UK)
4	Meter Sizing and Selection Optimization	To ensure meters operate within optimal flow ranges, minimizing low-flow under-registration.	Melbourne Water (Australia), Nairobi City Water (Kenya)
5	Adoption of International Accuracy Standards (ISO 4064 / OIML R49)	To guarantee consistency, reliability, and traceability in meter performance.	Germany, Netherlands, South Africa
6	Field Audits and Parallel Testing	To verify installed meters against reference standards and detect systemic inaccuracies.	Manila Water (Philippines), Rand Water (South Africa)
7	Data Analytics and Consumption Pattern Monitoring	To identify anomalous readings and predict meter failure for proactive maintenance.	Veolia (France), Singapore PUB
8	Technician Training and Capacity Building	To reduce human errors in installation, reading, and maintenance.	National Water Commission (Jamaica), NWSC (Uganda)
9	Environmental and Installation Protection Measures	To protect meters from magnetic fields, debris, heat, and flooding that affect accuracy.	Dubai Electricity & Water Authority (UAE), K-Water (South Korea)

The majority of effective metering inefficiency are used in developed countries with well-designed water supply system. (Arregui et al., 2018); (Richards et al., 2010); (Ethem Karadirek, 2020). Little remain un know on impact of meter class, age coupled with different field conditions on meter errors. The geo-visualisation of metering inefficiency has never been focused to as a strategy of reducing meter inaccuracies. Hence the need for this study to bridge this knowledge gap.

2.11 Visualisation of meter inaccuracies

Visualising meter failure risks in water supply networks is critical for efficient utility management. Spatial representation of meter inaccuracies helps identify areas with high non-revenue water (NRW), prioritize meter replacement, and optimize resource allocation (Farley & Trow, 2003; Khosravi et al., 2019). Visualization also enables targeted operational interventions, such as leak detection and network balancing, while enhancing transparency and customer trust. By integrating meter performance data with geospatial information, utilities can plan infrastructure upgrades, reduce financial losses, and improve water service reliability (Gustavsson, 2018).

How visualisation can be achieved

Data Collection, record geospatial coordinates of meters, measured and billed flows, meter type, age, and pressure zones. Error Calculation, compute meter inaccuracy as: GIS Integration, import data into QGIS or similar GIS software and apply, graduated color mapping to indicate error magnitude, Point sizing to represent meter age or flow volume Categorical mapping for risk levels (e.g., low, medium, high). Spatial Analysis, identify clusters of high-risk meters, correlate with pipe age/type, and inform replacement or maintenance programs.

This approach provides a visual and analytical tool for water utilities to manage meter failure risks proactively and reduce NRW efficiently (Arregui et al., 2018).

2.11.1 Prediction of Meter Failure

Meter failure can be effectively predicted by analyzing meter age, accuracy class, and prevailing field operating conditions. Studies have shown that meter age is the strongest predictor of accuracy degradation, with most mechanical meters exhibiting measurable under-registration after 5-10 years of service, depending on water quality and usage intensity

(Arregui et al., 2018; Khosravi et al., 2019). Meter class, which defines the meter's permissible error range and sensitivity to flow variations, determines its resilience to wear and hydraulic fluctuations (ISO 4064:2014). Lower-class meters (e.g., Class B) are more susceptible to performance decline under variable pressures and intermittent flows compared to higher-class meters (e.g., Class C or D) (Mutikanga et al., 2011).

Field operating conditions such as high suspended solids, fluctuating pressures, and intermittent supply accelerate meter wear and internal friction losses, leading to premature failure or bias toward under-registration (Couvelis & Van Zyl, 2015). Predictive models using regression or reliability analysis have demonstrated that combining these parameters meter age, class, pressure, and water quality can accurately estimate failure probability and residual meter life (Arregui et al., 2018). Such predictive approaches enable utilities to schedule proactive replacements, improve accuracy, and reduce non-revenue water

2.11.2 Model Formulation for Predicting Meter Failure

Predictive modelling of water meter failure is essential for utilities to forecast accuracy degradation and plan cost-effective replacements. Several researchers have applied statistical and reliability-based models to quantify how meter age, class, and operating conditions influence failure probability and measurement error.

According to Arregui et al. (2018) and Khosravi et al. (2019), meter failure can be expressed as a function of age-dependent deterioration influenced by environmental and operational stresses. The generalized predictive relationship is formulated as:

$$Pf = f(A, C, P, Q, W) \tag{2.3}$$

where:

Pf = Probability of meter failure or inaccuracy beyond allowable limits;

A = Meter age (years);

C = Meter class (accuracy class, e.g., B, C, D);

P = Operating pressure (bar);

Q = Flow pattern variability (intermittency, frequency of low flows);

W = Water quality index (turbidity, suspended solids, hardness).

Empirical studies have shown that failure probability increases exponentially with meter age, particularly for mechanical meters operating under high-pressure and poor water quality conditions (Couvelis & Van Zyl, 2015). Regression-based models typically adopt a Weibull or exponential distribution to represent meter aging and survival characteristics:

2.12 Meter performance errors

Globally, water utilities employ several strategies to manage and reduce meter inefficiencies. Regular meter calibration and replacement programs are common, with utilities such as Sydney Water (Australia) and Thames Water (UK) replacing small customer meters every 8-10 years to maintain accuracy. Smart metering and Advanced Metering Infrastructure (AMI) systems have been widely adopted in countries like Singapore and Denmark, enabling real-time monitoring, early leak detection, and automated billing (García-Serra, J. (2018). Pressure management is also integrated to reduce stress on meters and extend their operational lifespan. Additionally, utilities apply meter testing and performance benchmarking frameworks following ISO 4064:2014 and OIML R49 standards to ensure compliance with metrological accuracy. Collectively, these approaches have proven effective in improving metering accuracy, enhancing revenue collection, and reducing non-revenue water in both developed and developing water utilities. Arregui, F. J., Cabrera, E., Cobacho, R., & García-Serra, J. (2018)

Studies in developed countries show comparatively lower inaccuracy levels due to proactive meter replacement and calibration programs. For example, a study in the United Kingdom reported an average under-registration of 2-3%, with volumetric meters showing better performance at low flow rates compared to mechanical types (Silva et al., 2021). Conversely, developing countries often exhibit larger deviations sometimes exceeding 10% due to intermittent supply, sediment presence, and inadequate maintenance (Farley & Liemberger, 2022).

Errors mainly result from meter wear, low-flow conditions, poor water quality, and aging meters (Arregui et al., 2018; Silva et al., 2021). Under-registration at low flows is most common, particularly in domestic areas with intermittent supply (Mutikanga et al., 2014). However, research gaps remain in long term field performance data**,** evaluation of smart meter technologies, and localized studies in developing regions. Moreover, integration of metering error models into NRW management frameworks remains limited.

Studies reveal that water meter inaccuracies significantly contribute to apparent losses, accounting for 5-15% of total Non-Revenue Water (NRW) globally (World Bank, 2023; Farley & Liemberger, 2022). Errors mainly result from meter wear, low-flow conditions, poor water quality, and aging meters (Arregui et al., 2018; Silva et al., 2021). Under-registration at low flows is most common, particularly in domestic areas with intermittent supply (Mutikanga et al., 2019). However, research gaps remain in long term field performance data**,** evaluation of smart meter technologies, and localised studies in developing countries. Moreover, integration of metering error models into NRW management frameworks remains limited

CHAPTER THREE: METHODOLOGY

3.1 Introduction

It refers to the group of techniques or procedures adopted for data collection and sampling for a specific study (Taherdoost, 2018). The measures that were followed to accomplish the research are described in depth in this chapter. It includes information tackling the following components: design of research and approach, population and sample details, study area description, and data collection and analysis. Authorisation (Appendix E) to use the corporation data and facilities was secured from the research and development directorate.

3.2 Research design

The study assumed that all data obtained from water meter testing at the National Water and Sewerage Corporation (NWSC) were accurate and reliable after clean up. A multi-method quantitative research approach was employed to describe and analyze the data obtained from both field investigations and controlled laboratory tests Ethem Karadirek (2020). In assessing the relationship between meter age, meter class, and registration error, a deductive quantitative research design was adopted. The primary objective of the study was to evaluate the accuracy of customer water meters operating under varying field conditions specifically examining the influence of distribution pressure, meter age, and meter class on measurement performance (Arregui et al., 2018). Accordingly, the independent variables comprised water meters of different ages and classes, while the dependent variable was the percentage registration error.

Flow rate and pressure variations were considered as control factors influencing meter performance under test conditions (Mutikanga et al., 2011).

3.2.1 Objective (i): To characterise the pressure rates in the water distribution network of the study area

A cross-sectional field monitoring design was adopted. Continuous pressure measurements were undertaken at strategically selected points in the distribution network using calibrated digital pressure loggers. Sampling points was stratified by elevation, hydraulic zones, and proximity to key network assets such as reservoirs and pumps. Each logger recorded static pressure at 10-minute intervals for at least 4 consecutive days to capture diurnal variations.

Pressure Measurement data was statistically summarised (minimum, maximum, mean, at unmonitored nodes.

3.2.2 Objective (ii): to assess the performance accuracy of water meter class subjected to different flow and pressure rates,

A Water meters of classes (B and C) and of size (DN15) was tested under controlled flow and pressure conditions using a calibrated volumetric or gravimetric test bench. Each meter was subjected to multiple operating points low flow (Qmin), Transitional flow (Qt), nominal flow (Q_n), and maximum flow (Qmax) and at varying pressures to simulate field conditions.

Meter error (%) was computed as the deviation from reference volume was calculated using equation 2.1. Results was analysed using Analysis of Variance (ANOVA) and mixed-effects linear regression to test the influence of meter class, flow, and pressure on accuracy. The approach follows methodologies established in metrological studies by Arregui et al. (2018), Creaco et al. (2021), and Mutikanga et al. (2011).

3.2.3 Objective (iii): To Determine the Influence of Working Age on Water Meter Registration Errors

A cross-sectional analytical design will be employed. In-service meters will be sampled across age categories (<1yr, 1-3yrs, 3–6yrs, 6-9yrs, 9-12yrs, 12-15yrs, 15-18yrs, >18yrs) and tested for accuracy errors using the same procedure as in Objective (ii). Data on installation date, and operating pressure was recorded.

Using excel analysis tool, two-way ANOVA was used to validate the performance of water meters. This design is appropriate for quantifying deterioration effects over time and aligns with approaches by DeOreo & Mayer (2014) and Stoker (2017), who demonstrated age-dependent bias in domestic meter registration.

3.2.4 Objective (iv): To Geovisualise Risk of Meter Failure Rate Zoning Maps in the Study Area

A spatial GIS-based analytical design was applied. Pressure variability (from Objective i), meter error data (Objectives ii & iii), and meter age information was integrated to compute a composite meter-failure risk index. Each parameter was normalised and weighted to derive a combined score representing likelihood of meter failure or inaccuracy.

The risk index was spatially interpolated using Inverse Distance Weighting (IDW) or Ordinary Kriging within ArcGIS or QGIS to generate a continuous surface. Pressure and meter failure risk layers was then classified into low, moderate, high, and critical zones using Jenks Natural Breaks classification. The result formed geovisualised meter failure-risk zoning map, providing a decision-support tool for targeted meter replacement and pressure management (Mair et al., 2023; Mutikanga et al., 2011).

Table 3. 1:Research design summary

Objective	Design Type	Key Instruments / Data	Main Analysis Techniques
(i) Characterise pressure rates	Cross-sectional field monitoring, hydraulic model calibration	Pressure loggers,	Descriptive statistics, RMSE/NSE validation
(ii) Assess class accuracy under flow & pressure	Experimental (bench),	Flow/pressure rig, reference meter,	ANOVA, mixed-effects regression, performance curves
(iii) Determine age effect on errors	Cross-sectional analytical study	In-service meters with known age, installation data	Linear/mixed-effects regression, correlation analysis
(iv) Geovisualise meter-failure risk	Spatial GIS analytical design	GIS software, node coordinates, pressure and meter data	Risk index modelling, spatial interpolation

3.3 Study Approach

The assumption was that all the data obtained from water meter testing at the National Water and Sewerage Corporation and a multi-method research approach was used to describe quantitative data and relate variables in the research question for interpretation. When employing statistical analysis to investigate the relationship between water meter ageing, class, and error, a deductive quantitative technique was chosen as the method of investigation. As previously stated, the goal of this research was to evaluate the accuracy of customer meters subjected to a variety of field conditions, specifically the distribution pressure in study area, effects of meter age, and meter class. The independent variables in this study therefore correspond to water meters at various ages, and classes, the dependent variable was the percentage of meter error, and the controlling factors refer to various flow and pressure rates.

3.4 Description of the study area

Kampala Water is one of the 255 towns entrusted by the Ugandan government under the National Water and Sewerage Corporation to provide equitable and safe water and sewerage services. The study area presented in Figures 3.1 (a, b) was one of the branches of Kampala water. It covers two branches Kansanga and Kyengera located to the south and west of Kampala city respectively. The boundary coordinates of the Kansanga branch are 00°17'42.5494", 032°38'04.9776" to the East 00°18'17.5838", 32°35'16.4090" to the west, 00°16'39.9828", 32°35'30.5984" to the South and 00°17'13.7458", 32°34'42.7678" to the North. Kyengera branch boundaries lies on 00°18'33.6150", 32°30'56.0988" East, 00°18'33.2233", 32°25'19.9319"to the North, 0°14'46.3988", 32°30'50.7254" to the South and 00°15'13.7250", 32°25'44.0958" to the West.

Kansanga is at 1165m asl while Kyengera is 1176m asl The choice of the study area largely depended on water supply zoning, Kansanga lies at the heart of Kampala Water which houses the largest reservoirs. The area also was characterised by an old high-pressurised distribution network with the oldest water meters. Kyengera lies at the end of Kampala water in the west. Intermittent water supply, water pumping, water distribution rationing, and low pressures describe the Kyengera branch.

The study area consisted of 23,384 active domestic consumers of DN15mm water meters as of June 10, 2023. They were consuming 420,395 cubic meters of water on average each month, which equates to a total monthly average billing of about 1,774,311,390 Uganda shillings (I USD = 3740 UGX). This amounts to an average monthly revenue collection of USD 474,415.

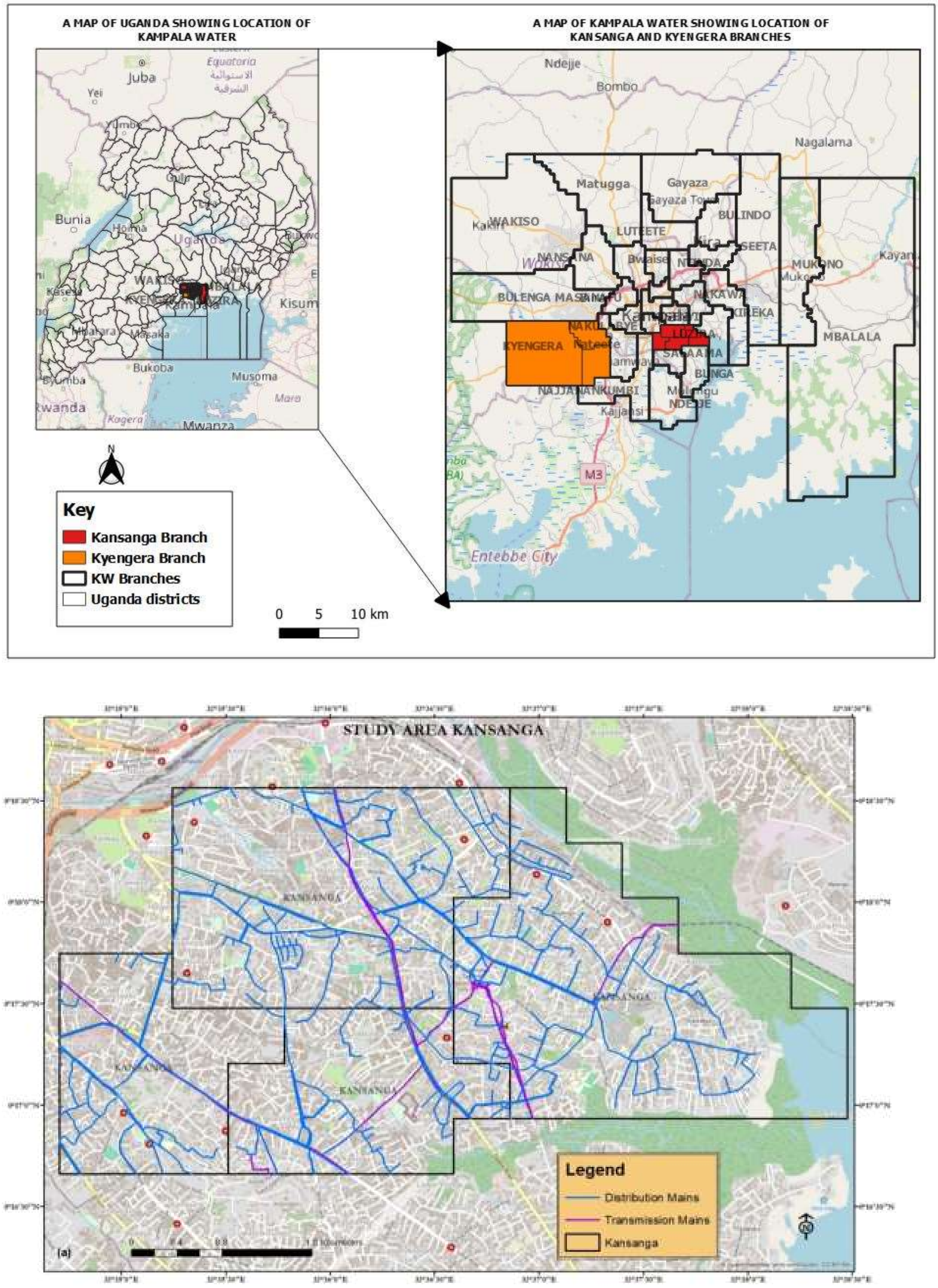


Figure 3.1: (a, b) Geographical location of Kyengera and Kansanga study area

The Kansanga branch was typically hilly, and Muyenga Hill at the elevation of 1320m above sea level. This was home to the largest major water reservoirs owned by the NWSC with five reservoirs, of 4,000 cubic meters of water for each tank. Water received at Muyenga is further transferred to secondary reservoirs in Mutungo and Rubaga.

Lastly delivered to the customers from these auxiliary reservoirs. Except for Konge Makindye, where water is pumped to the reservoir and network, the majority of the branch enjoys nearly constant supply, with few complaints reported on no water and low pressures by consumers. The Namasuba primary reservoir, which was 30km from the branch boundary, supplies Kyengera. The water supply status of the Kyengera branch was the opposite of Kansanga branch.

The meter sizes make, and classes installed for consumers differ across all branches. These meters were put in place over time. Some of which have since been changed because of wear and tear or malfunction, while others have just been installed. As a result, the various meters provide varying degrees of precision in their ability to accurately measure the amount of water used by the respective consumers.

Choice of the water meters to be used in the study

Most domestic water meters operate at low flow rates due to the nature of household water use. In Kampala Water, DN15 meters account for approximately 95% of the total meter population. Despite their dominance, these small-sized meters are rarely prioritized for performance monitoring. Although individual domestic customers consume relatively small volumes of water, their collective contribution represents nearly 70% of the utility’s total water sales. Consequently, inaccuracies within this meter category have a substantial impact on the utility’s overall revenue and non-revenue water levels.

3.5 Data collection

The primary data for the research was obtained by carrying out field pressure testing and meter accuracy testing on a calibrated meter test bench, following procedures specified in ISO 4064:2014 standards. Meter error was determined at different flow rates (Q_1, Q_2, Q_3, and Q_4), pressure levels, and meter ages according to the research design. The secondary data was also obtained from National Water and Sewerage Corporation billing database. Authorisation to use the data was obtained for research and capacity building directorate for NWSC (Appendix E)

Data use authorisation

The main research and development office, at the National Water and Sewerage Corporation granted the researcher permission (Appendix E) to use its facilities and data required for the research. To avoid any miscommunication between the researcher and the responders, extreme caution was taken while conducting the meter testing process and other research questions.

3.5.1 Population

This research targeted the registered population of active water domestic connections (Table 3.2) in the study area. The meters' data for Kampala Water domestic active accounts was obtained from the database with details of meter type, class, meter serial number, meter reading, branch, property references, and installation date. Data cleanup was done to rectify errors such as registration of the wrong meter makes, serial numbers, and errors in meter numbers to obtain a realistic dataset. The data to use for the project area was selected from the bigger volume of Kampala water. It was then sorted to ascertain the various consumer categories, meter make, class, and the associated age (Table 3.1).

Table 3. 2: Distribution of water meter size population in the study area

S/N	Size	Active	Inactive	Total	% Active	% Inactive	% Total
1	DN15	27,880	5,943	33,823	82%	18%	98%
2	DN20+	596	132	728	82%	18%	2%
	Total	28,476	6,075	34,551	82%	18%	100%

Table 3. 3: Population distribution of DN15 water meters in the study area

S/N	Category	Active	Inactive	Total	% Active	% Inactive	% Total
1	Domestic Meters	23,214	4,657	27,871	83%	17%	82.4%
2	Commercial	3782	1081	4863	78%	22%	14.4%
3	Institution	353	124	477	74%	26%	1.4%
4	PSP	531	81	612	87%	13%	1.8%
	Total	**27,880**	**5,943**	**33,823**	**82%**	**18%**	**100%**

3.5.2 Sampling methodology

The target population was based on the active number of domestic accounts of size DN15, which comprises 82% (Table 3.2) of the total meters within the study area. The sampling process in Figure 3.2 (Taherdoost, 2018) was used.

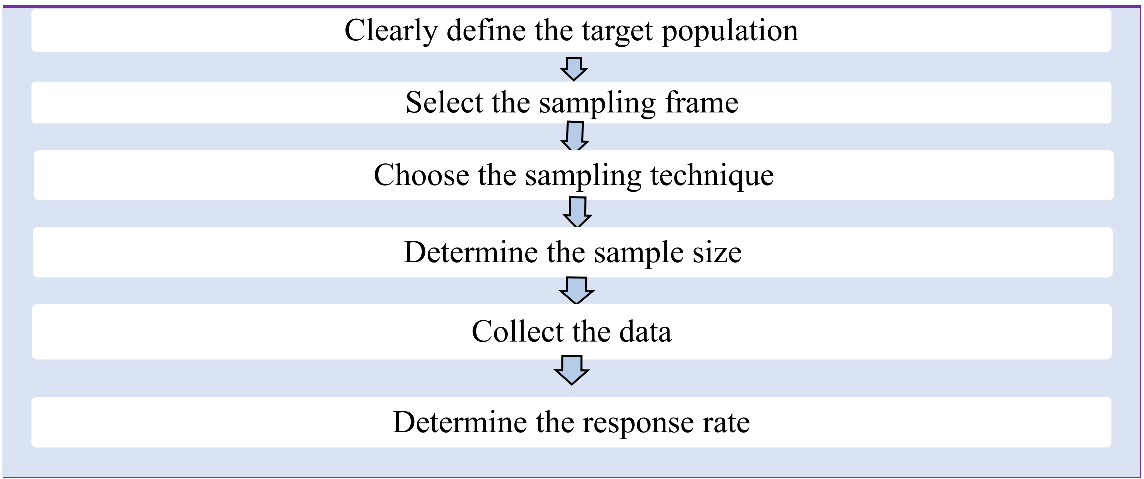


Figure 3.2: Sampling Process (Taherdoost, 2018)

3.5.3 Defining a sampling frame

The sampling frame contained the Domestic meters identified in the data population with their types, classes, ages, locations and sizes.

3.5.4 Sample size determination formula and margin of error

This study had a finite known population (N) size of water meters (23,214), therefore, the Taro Yamane Statistical formula with a 95 per cent confidence interval (e = 5%) was used to obtain the sample size. A significance level of 0.05 means there's a 5 per cent chance of rejecting the null hypothesis when it is true (type 1 error). A larger sample size would be appropriate for robust results despite that, due to time and resource limitations, 5 per cent confidence level was chosen. This formula used by (Oribhabor & Anyanwu, 2019; Taherdoost, 2016) was as follows,

$$n = \frac{N}{[1+N(e)^2]} \tag{3.0}$$

Where; n = sample size

N = the finite population = 23,214

e = the level of significance or limit of tolerable error (5%)

1 = unit or a constant

Therefore, 393 registered active water user connections (Table 3.3) were the intended sample size. The Taro Yamane formula has several advantages over other models or methods, including being simple to use, convenient, flexible, and accurate in figures. It is also widely accepted and used, offers a simplified formula, is easy to remember and apply, and can be applied to qualitative and quantitative research. The sample size used was not higher than 10% because the investigation would require additional resources and time to carry out the necessary tests. Taking the above factors into consideration the researcher adopted the above approach.

Table 3.4: Sample size determination using the Taro Yamane formula

S/N	Category	N	$(e)^2$	$1+ N (e)^2$	$N/1+ N (e)^2$	Sample Size (n)
1	Domestic Meters	23,214	$(5)^2$	**$1+ 23{,}214(5)^2$**	**$23214/1+ 23214(5)^2$**	393
2	Domestic Meters	23,214	0.0025	59.04	393.22	393
	Total	**23,214**				**393**

The random section formula was used in excel format to identify the individual sample members from the bigger population. Using the same formula and 393 samples population, 198 sample of the sample points for pressure testing were determined.

3.5.5 Sample profiles

The elevations of the pipe network majorly determine the hydraulic and pressure zoning of the distribution water system. The coordinates of each consumer sampling point were extracted from the NWSC billing database. This gave a geographical location of the sampling points in the study area.

3.5.6 GIS input data

The Corporation's GIS section was the source of all GIS datasets. These included the following among others;

3.5.7 Administrative branch block boundaries.

The GIS unit provided a polygon-shaped file representing the branches, which serve as administrative divisions for Kampala's water supply and sewage services. Blocks were allotted to a certain administrative branch to create the branch's administrative boundaries. As a result, several blocks describe each branch with some consumers. Periodically, the blocks that make up a branch were examined to determine whether new branches should be created or current ones should be expanded. This dataset was used to specify the exact position of the

Kansanga and Kyengera branches inside the Kampala water supply area and to choose each of the branch's unique block grids.

3.5.8 Spatial locations of water meters.

The coordinates of all connected water meters were stored in a point shape file continuously updated in the geodatabase of the GIS unit. It was affected when a successful application was connected to the water grid. GIS unit only saves the property reference associated with the customer property when saving the data. This property reference was used to connect the point files to the database in the billing system that contains the details of the meter to obtain those details. To choose specific meters inside the study area, ArcGIS software used the branch's grid shapefile as the source layer and the meter shapefile as the target layer. applicants who joined

3.6.0 Accuracy test measurement

The flow rater and pressure conditions were measured directly and partially simulated to represent the actual hydraulic and environmental parameters influencing water meter performance in distribution system. Measurements focused on pressure, flow rate, and temperature variations, complemented by visual assessment of installation conditions (pipe material, orientation, and environment). Pressure and flow rate were measured using portable digital pressure loggers and ultrasonic flow meters installed at selected consumer connections and test points across different pressure zones. Data were logged continuously over a 72-hour period to capture fluctuations due to intermittent supply. Temperature was not considered since Uganda temperature is much lower than the designed maximum (T50) meter temperature The observed field conditions were then replicated on the test bench during meter verification to simulate actual operating scenarios under controlled conditions. This approach ensured that the evaluation of meter accuracy reflected the true hydraulic behavior of the network rather than ideal laboratory standards

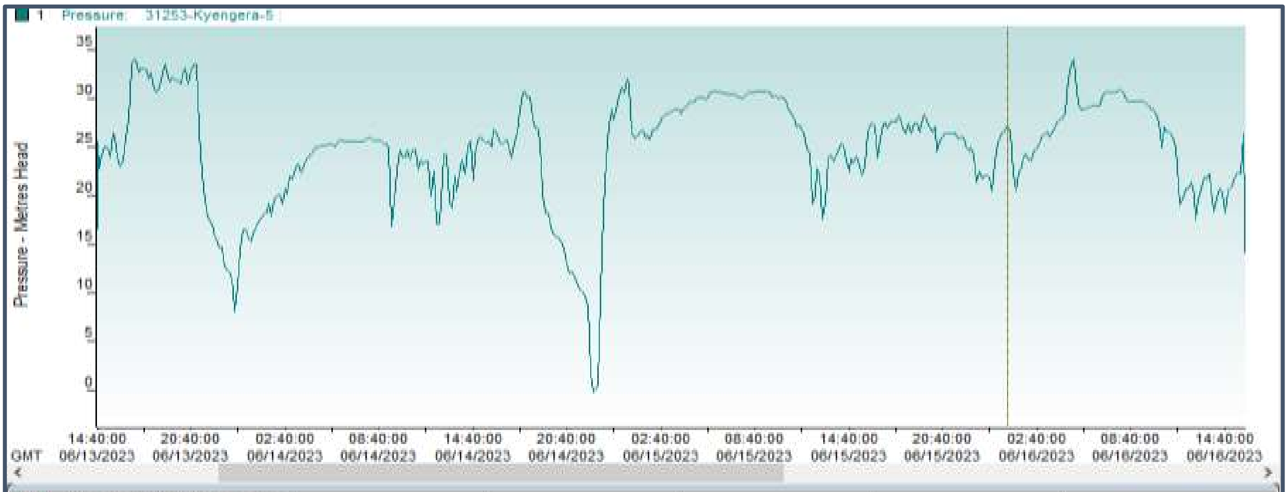
3.6 Determination of Pressure in the pipe distribution network

Data pressure loggers for pressure measurement were coded, and installed in the distribution network at selected consumer sampling points (Figure 3.3). It was allowed to record pressure measurements for more than 72 hours to obtain a realistic representative sample that contained day and night pressures. Loglog 450 highly flexible data logger was used in this study. The HWM RadWin soft View V4.84 software downloaded pressure data (Figure 3.4) from the data loggers.

Determination of pressure measurements points

Due to limited resource the sample for pressures measurements was calculated from meter testing sample (sample of the sample). Using equation 3.0 and considering a population of 393. The sampling population was determined as 198 points

Figure 3.3: Installation of the pressure data logger at customers' meter and downloading pressure data.



1 - Pressure: 31253-Kyengera-5 :					
Data Start Time:	14:50:00	06/13/2023	Tuesday		
Data End Time:	16:00:00	06/16/2023	Friday		
Sample Rate:	00:10:00				
Minimum:	-0.200	Metres Head	22:20:00	06/14/2023	Wednesday
Maximum:	34.000	Metres Head	05:00:00	06/16/2023	Friday
Average:	24.820	Metres Head			

Figure 3.4: Downloaded Pressure measurement results from the sample point

3.6.1 Distribution of pressure in the study area

The pressure data obtained from pressure data loggers was grouped from minimum, maximum, and mean permissible pipe network pressure. The pressure data provided pipe network pressure profile at each consumer sampling point. The average pressure was used to describe the pressure in the study area using consumer profile coordinates obtained from the utility billing system.

3.7 Water meter performance accuracy testing

Meter representative samples (393) were collected and subjected to different tests to come up with the realistic results for the whole population.

3.7.1 Collection of water meter samples for testing

Following the specific goals of the study, a diverse representative sample of water meters (Table 3.3) was obtained from the field for the examination.

National Water and Sewerage Corporation designed and approved a letter advising the meter owner of the meter testing exercise. The method shown in Figure 3.5 was used to create a comprehensive testing approach. Determining the number of meter samples to be examined was the first stage in the water meter testing process. The independent variables were classified into the following two metrological accuracy classes and eight age class groups as outlined in Table 3.5

Table 3.5: Grouped water meters age for testing

Meter Metrology Class	Model Class	
B=228	1	meter aged between 0 and 1 year
	2	meter aged between 1 and 3 years
	3	meter aged between 3 and 6 years
	4	meter aged between 6 and 9 years
C = 165	5	meter aged between 9 and 12 years
	6	meter aged between 12 and 15 years
	7	meter aged between 15 and 18 years
	8	meter aged between 18 years and above

3.7.2 Water meter distribution based on age

The age of the water meters sampled was another goal of the investigation (table 3.6). The purpose was to ascertain whether meter age and registration error (meter accuracy) were related. The highest populated age bracket of water meters in the study area was between 1 to 3 years which constituted 23% of the total sample. The working age of the water meter was determined from its installation, which was in line with the Kampala water billing database (table 3.5).

Table 3. 6:Age-based meter distribution

Meter Age	Frequency	Percentage
0-1 year	17	4%
1-3 years	91	23%
3-6 years	77	20%
6-9 years	85	22%
9-12 years	46	12%
12-15 years	35	9%
15-18 years	26	7%
18 and above years	16	4%
Total	**393**	**100%**

3.7.3 Transportation process of sample meters

. Water meters were gently removed using adjustable spanners. The creation of the water scale drying up, which could cause the water-meter mechanism to malfunction and ultimately contribute to the meter errors was not considered due unavailability of plastic stoppers. Rather the meters were taken for testing immediately after removal to avoid drying of its chambers. Transportation of water meter samples was done using motorcycles and cars.

3.7.4 Testing of water meters

Sample meters removed from the consumer sampling points were subjected to different tests using predetermined flow and pressure rates. The 'collecting method' approach was used to identify the measurement errors (ISO 4064-1-2014). With this technique, water was pumped through the meters, and collected in a water tank that had been calibrated. The actual water quantity was calculated by weighing. Meter measuring errors were then determined using equation (2.1). In this instance, the recorded volume was determined by the water meter readings, and the real water volume was obtained by weighing the water. According to ISO 4064 2-2014, the average of the flow rates provides the metering specifications for water meters, as shown in table 3.6 standard meter error curve. The starting flow (Q1), transitional (Q2), nominal /permanent flow (Q3), and maximum flow rate (Q4), or overload flow rate, were all clearly displayed.

For DN15 domestic meters, Q3=2.5 m^3/h (= 41.67 L/min). Depending on the meter's class, the theoretical Q_1 values range between 0.26 L/min and 1.04 L/min. However, field measurements from pressure and consumption monitoring revealed that many domestic customers experience lower flows, especially during night hours or intermittent supply periods. Therefore, a practical Q_1 value of 0.13 L/min at 10 m pressure head was adopted in the simulation to realistically represent the lowest flow conditions observed in the Kampala

Water system. This ensured that the bench testing closely reflected actual domestic water usage and leakage conditions rather than idealized laboratory situations.

Table 3.7: Mimicked flow rates

	Water meter metrological test flows				
Meter Class	Minimum (m^3/h)	Trans Flow	Nominal (m^3/h)	Maximum (m^3/h)	R range
B	0.01875	0.0300	3.0	3,125	160
C	0.00938	0.0150	1.5	3,125	160

The limitation of the ISO standards to brand-new meters is a problem. Consequently, it is essential to distinguish between testing for legal metrology and tests to determine the real performance of the meters in the field, i.e., the weighted error, when choosing the flow rates at which the meters should be evaluated. (F. J. Arregui et al., 2018). Metrological testing for the sample water meters took flow rates between 8 l/h and 3500 l/h (Table 3.5) into consideration. This was to depict correctly and closely characterize the customer profiles, including the meter starting flow rates. The number of samples subjected to these four flow tests was limited due to the long flow times required to measure the extremely small flow rates (Mutikanga et al., 2011).

3.7.4 Meter testing procedure

Figure 3.5 gives the precise summarised procedure followed in carrying meter testing. The testing was done in collaboration with the National Water and Sewerage Corporation. NWSC took a front lead in retrieving meter samples for testing from consumer premises.

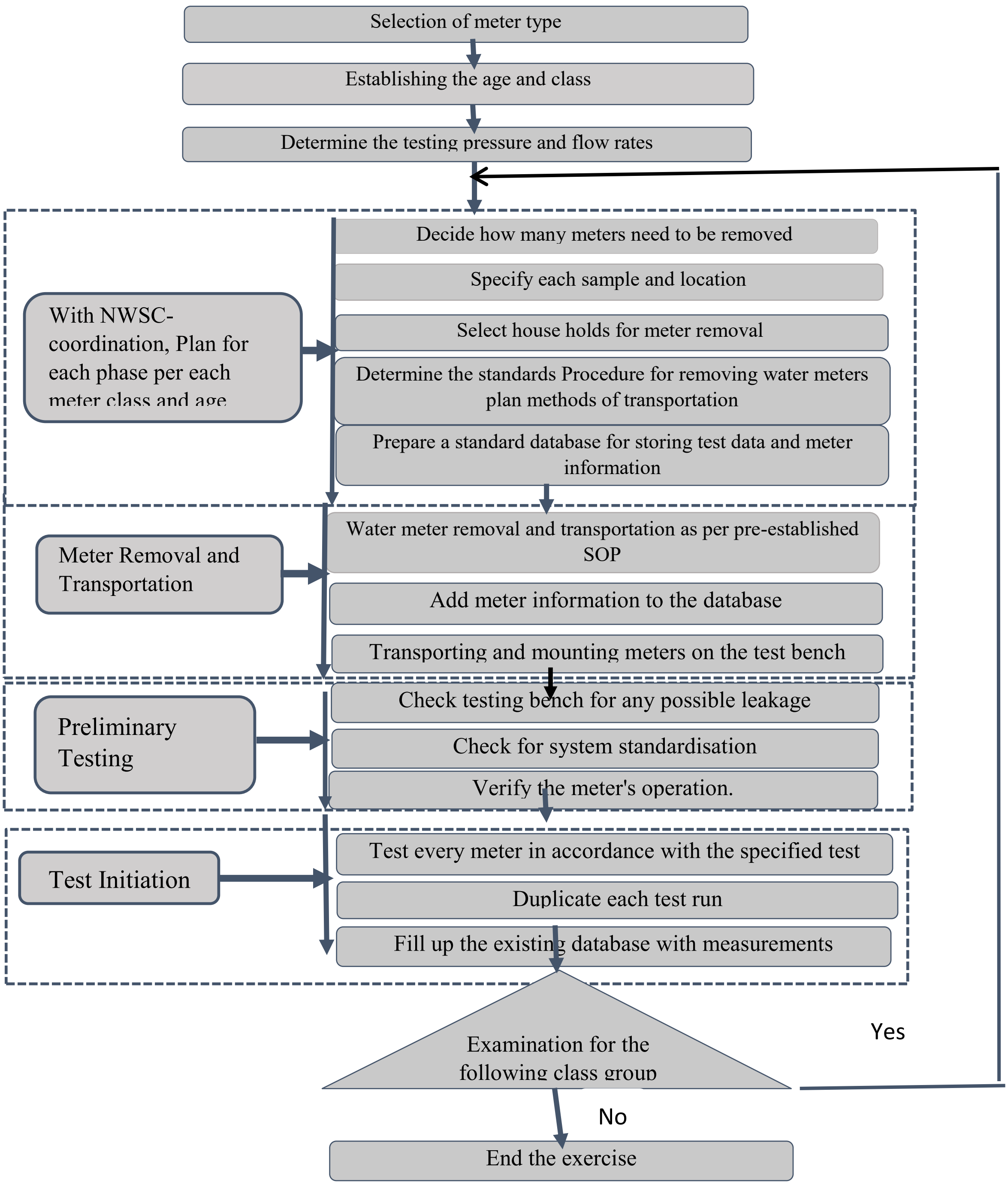


Figure 3.5: Meter testing procedure (Mutikanga et al., 2013)

3.7.5 Water meter testing bench

Figure 3. 6: Water meter Testing bench

To experiment tests at steady, high, and intermittent flow circumstances as required by specific objectives, one volumetric test bench built specifically for the purpose was employed. The testing bench was adhering to the rules for testing meters for hot and cold potable water. (Albaina et al., 2020), (ISO4064-1,2014). It included the ground collection tank illustrated in Figures 3.6 & 3.7, and Appendix, a pressure pump, pressure gauges, a compressor, a drain pipe, water flow controls, and meter installation positions. Speed pumps were used to pump water out of the underground tank. The inclusion of a pressure-lowering valve ensures the sustainability of steady flow and pressure at the bench's inlet. The test bench featured two parallel lines so that twice as many meters could be tested and processed at once. The bench allowed testing on each pipeline of ten (10) DN15 water meter samples in sequence. The tank 5000L capacity, received water from the two parallel testing pipelines, downstream of the test bench, there was a control panel equipped to test lines and valves that allowed the test's flow rate to be adjusted to the required value. Upstream of the two parallel testing lines, there was a series of regulating valves that allowed control of the flow rate through the meters. To measure the amount of pressure in the pipeline, the line additionally included a pressure data lodger and a pressure gauge.

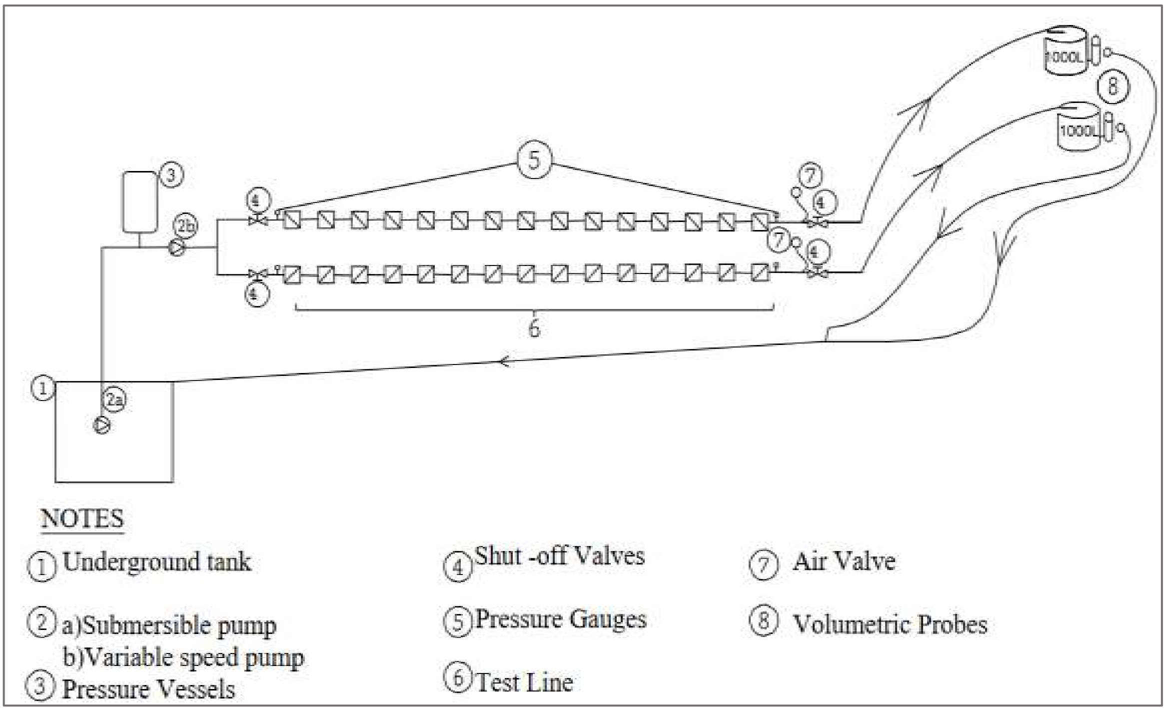


Figure 3.7: Test bench flow diagram

3.7.6 Determination of meter errors

For calculating meter errors, the so called "collection" method (ISO 4064-2 2014) was used. The measured volume of water by meters was determined by subtracting the final from the initial meter reading. The amount of water passing through the meter (actual volume) was determined by gathering water in the calibrated water tank. The equation gave the percentage meter error.

$$\varepsilon = \frac{V_m - Va}{Va} \times 100 \tag{3.1}$$

Where;

Va = the amount of water going through the meter, ignoring time taken,

ε = the proportion of the metering inaccuracy in %age

Vm = (measured volume) actual volume measured by meter

The dynamic range (R) ratio of the permanent flow rate to the minimum flow rate, R= Q3/Q1,

Q2; transition flow rate 1.6Q1, and Q4 overload flow rate 1.25Q3 was used to identify the flow rates used to determine meter standard errors (ISO4064-1 2014) in comparison with meter error curve. Maximum permissible errors (MPE) for water meters at each flow rate were considered to determine water meter errors. The Maximum permissible error accuracy for class Two water meters was ±5% between minimum and transitional flow rates, according to (ISO4064-1 (2014). However, the maximum permissible error is ±2% between transitional and overload flow rates. Between minimum and transitional flow rates, the Maximum Permissible Error for accuracy class 2 water meters is ±5%, and between transitional and overload flow rates, is (±2% for temperatures ranging from 0.1°C to 30°C; ±3% for temps over 30°C). In this study, the class B and C water meters. A standard water meter error curve (Figure 3.8) was used to determine the flow regime and fluctuation of meter error at different flow rates.

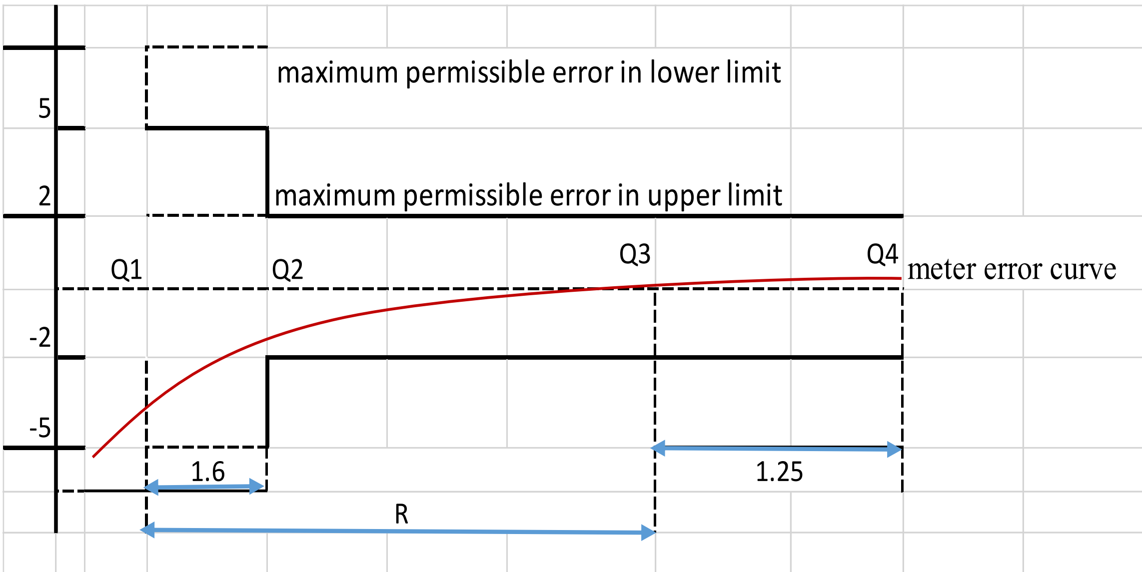


Figure 3.8: Standard water meter curve (ISO 4064-1:2014)

The accuracy of water meters was specified using the nominal flow rate and the ratio R of the permanent flow (Q3) to the lowest flow (Q1) (ISO4064-1, 2014). The accuracy range of water meters was defined extremely well using (ISO 4064_1-2014) R-value. The recommended working pressure was between 1 and 5.5 bars (10-55m) head, and the ratio R for DN15 meters ranged from, R100, R125, and R160.

3.7.7 Meter Errors

The accuracy of a water meter is determined by its ability to register flow correctly over the entire measurement range, defined by four key flow rates n minimum (Q_1), transitional (Q_2), nominal (Q_3), and overload (Q_4) as per ISO 4064:2014. Each range characterise a distinct operational regime with different expected error behavior (ISO, 2014; Arregui et al., 2018).

Minimum Flow Rate (Q_1, Error 1)

At the minimum flow rate (Q_1), meter operates near its starting threshold, where the velocity and torque generated by the flow are just sufficient to initiate movement of the measuring mechanism. Errors at Q_1 are highest and predominantly negative (under-registration).

To achieve the lowest flow rate for this study the observed field flow rate and designed flow rate for the meter were compared to mimic the real field condition. The same procedure was applied to the remaining three tests.

Transitional Flow Rate (Q_2, Error 2)

The transitional flow rate (Q_2) defines the boundary between the low-accuracy and high-accuracy zones. At this range, the flow is sufficient to stabilize the motion of the measuring element, reducing random fluctuations. Errors at Q_2 are lower and approach the standard tolerance band, as viscous and mechanical losses become less significant (Arregui et al., 2018). Permissible error: ±2% for cold water meters (ISO, 2014).

Nominal Flow Rate (Q_3, Error 3)

At the nominal flow rate (Q_3), the meter operates within its optimal accuracy range, where hydraulic and mechanical forces are balanced. The meter exhibits maximum precision and stability, and the error typically remains well within the permissible ±2% tolerance (Cabrera et al., 2020). Permissible error: ±2% for $Q_2 \leq Q \leq Q_4$ (ISO, 2014).

Overload Flow Rate (Q_4, Error 4)

The overload flow rate (Q_4) represents the upper operational limit, beyond which mechanical stress or hydraulic turbulence may affect performance. While meters are designed to withstand Q_4 without damage, slight negative errors may occur due to bearing load, cavitation, or increased head loss (Criminisi et al., 2019). Continuous exposure to flows near Q_4 accelerates wear and long-term drift. Permissible error: ±2% (ISO, 2014).

3.7.8 Distribution of meters by class

The water meter samples in the study area were grouped according to their R-Values and their classes were determined. Using the meter location coordinates, and created GIS their geographical locations were marked using different colors (Appendix K)

3.7.9 Data analysis

Data analysis was conducted to evaluate water pressure**,** meter class, and meter age performance using descriptive statistical techniques implemented in Microsoft Excel section 3.7.9.1, and 3.7.9.2**.** Further analysis focused on determining the probability of meter failure through the Meter Failure Index (MFI) and assessing meter criticality using the Criticality Index (CI). In estimating both criticality and failure probability, the analytical framework proposed by Schultz (2012) was adopted, with modifications in the parameter specifications as outlined in Sections 3.8.1, 3.8.2, 3.8.**3,** and 3.8.4. Data preparation and advanced analysis were performed using SPSS**,** Microsoft Access, Microsoft Excel, and ArcGIS 10.2, enabling both statistical and spatial evaluations.

Several meters (5) were excluded due to incomplete or inconsistent data, yielding a final analytical dataset of 388 meters. To validate the developed model, actual meter failure data were collected and correlated with the average age of meters within each block to assess the reliability and predictive accuracy of the model outcomes. This approach aligns with recent studies emphasizing data-driven reliability assessment and predictive maintenance of water metering assets

3.7.9.1 Analysis of Meter Performance errors

The collected data from the meter test bench was classified, coded, summarised, and presented for analysis. Uncertainties in data analysis, were calculated to conclude the outcomes. The meter error curve was analysed to determine the accuracy of each meter at different flow rates by comparing meter errors with standard errors. Meter testing data was analysed using statistical data analysis tools in MS Excel. Additionally, the performance assessment of each meter class model at every flow rate involved descriptive statistics analysis (C.R. KOTHARI, 2004).

Mean meter error $\overline{x} = \frac{\sum x_i}{n}$ (3.2)

Where; x_i = total error

n = number of test errors

Variance between meter class errors

Variance $S^2 = \frac{1}{n-1}\sum_{i-1}^{n} f_i(x_i - \overline{x})^2$ (3.3)

Where S^2 =Error Variance

x_i = the value of one observation error

$\overline{x}$ = the mean value of all observed errors

n = the number of observed test errors

3.7.9.2 Coefficient of variation in meter errors

Coefficient of variation $CV = \frac{Standard\ Deviaton}{Mean\ value}$ (3.4)

Standard deviation $S = \sqrt{\frac{1}{n-1}\sum_{i-1}^{n} f_i(x_i - \overline{x})^2}$ (3.5)

The coefficient of variation (CV) is the ratio of the standard deviation to the mean. The higher the coefficient of variation, the greater the level of dispersion around the mean. It is generally expressed as a percentage. The coefficient of variation differs based on the composition of data points observed. Typically, a coefficient of variation between 20 and 30 is acceptable, while a coefficient of variance greater than 30 is unacceptable Equation (3.4).

To evaluate the best water meter class and age models, Root mean square error (RMSE) Adjusted coefficient of determination (R^2), Analysis of variances (ANOVA), and Multivariate methods of analysis were used.

$$RMSE = \sqrt{\sum_{i=1}^{n} f_i \frac{{x_i}^2}{n}} \tag{3.6}$$

Where; f_i = frequency of one observed error

${x_i}^2$ = square of one observed error

n = number of observed errors

The root mean square error is the measure of the differences between values that are predicted by a model and values that are observed

$$R^2 = \left(\sum \frac{(x-\overline{x})(y-\overline{y})}{\sqrt{\sum (x-\overline{x})^2 (y-\overline{y})^2}}\right)^2 \tag{3.7}$$

Graphical regression analysis was performed on error results to normalize the residuals. Error 1 (minimum flow rate) error 2 (Transitional flow) error 3 (Nominal flow rate) error 4 (Overload flow rate). Equations (3.8) to (3.11) show the mathematical models that relate to the correlation coefficients (r) obtained for errors at three flow rate tests, respectively.

At minimum flow rate, (y) = -0.1991x + 20.295, (3.8)

r = 0.0055

At Transitional flow rate, (y) = -0.5487x + 19.103, (3.9)

r = 0.0144

At nominal flow rate, (y) = -0.3582x + 15.482, (3.10)

r = 0.0372

Overload flow rate, (y) = 0.1731x + 19.175, (3.11)

r = 0.0019

$$\text{Lower quartile range} = L_i + \left(\frac{\frac{1}{4}(\sum f+1)-cf_b}{f_i}\right) \times c \tag{3.12}$$

Median or 50th Percentile $= L_m + \left(\frac{\frac{1}{2}(\sum f+1)-cf_b}{f_m}\right) \times c$ (3.13)

Upper quartile range $= L_u + \left(\frac{\frac{3}{4}(\sum f+1)-cf_b}{f_u}\right) \times c$ (3.14)

Where

$l_i =$ lower for the class with the lower quartile

l_m= lower limit for the median class

l_u= lower limit for the class with upper quartile

f_i= frequency in the class with the lower quartile

f_m= frequency of the median class

f_u= frequency of the with the upper quartile

cf_b=Cumulative frequency before the class under consideration

c = class interval

3.7.9.3 Distribution of meter errors

Skewness of meter errors distribution.

The statistical measurement of how asymmetric a distribution is around its mean was used to describe meter errors. It indicated whether the values in a data set are more frequent on the high or low ends of the x-axis. A perfectly symmetrical data curve has a skewness of zero. The sign of skewness describes the direction of the long tail points not the location of the mode.

Skewness – Measures and Interpretation

Positive Skewness (Right Skew)

Negative Skewness (Left Skew)

Zero Skewness (Symmetrical Distribution)

Skewness of the meter errors $= \frac{n}{(n-1)\,(n-2)} \sum \left(\frac{x_{i-}\overline{x}}{S}\right)^3$ (3.15)

Where

$\overline{x}$= mean meter error

n= sample size

n= standard deviation

Kurtosis

Kurtosis characterised the relative peakedness or flatness of the distribution compared to the normal distribution. Positive Kurtosis describes a relatively picked distribution and negative indicates flat distribution

Kurtosis of meter errors $= \left\{ \frac{n\,(n+1)}{(n-1)\,(n-2)\,(n-3)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^4 \right\} - \frac{3\,(n+1)^2}{(n-2)\,(n-3)}$ (3.16)

3.8 Meter failure Risk analysis

Risk levels were determined by combining factors such as meter age, error magnitude, flow condition, pressure variability, 84and meter class. A risk score was computed using a weighted index model, and results were spatially visualized using GIS-based mapping to identify high-risk zones across the study area. Meters were categorized into Very low, low, medium, high, and very high-risk classes based on their probability of under-registration and contribution to apparent losses. The risk analysis process involves meter failure prediction, probability of meter failure, and meter failure criticality.

Meter failure in this study was effectively predicted by analyzing three key parameters: meter age, accuracy class, and prevailing field operating conditions. Empirical studies have demonstrated that meter age is the most significant predictor of accuracy degradation, as mechanical water meters tend to exhibit progressive under-registration after approximately 5 to 10 years of operation. The extent of this degradation is influenced by factors such as water quality, pressure variability, and usage intensity (Arregui et al., 2018; Khosravi et al., 2019).

The accuracy class of a meter, defined by the ISO 4064:2014 standard, determines its permissible error limits and sensitivity to flow rate variations. This classification also reflects the meter's resilience to wear, hydraulic stress, and fluctuating flow regimes. Research by Mutikanga et al. (2011) indicates that lower-class meters (e.g., *Class B*) are more prone to performance deterioration when subjected to variable pressures and intermittent flows, whereas higher-class meters (e.g., Class C or D) maintain superior accuracy and operational stability under similar conditions.

These relationships provide the analytical foundation for predicting meter failure risk, as they directly link measurable physical and operational parameters to the likelihood of meter performance decline within a water distribution network.

Meter failure was effectively predicted by analyzing meter age, accuracy class, and prevailing field operating conditions. Studies have shown that meter age is the strongest predictor of accuracy degradation, with most mechanical meters exhibiting measurable under-registration after 5-10 years of service, depending on water quality and usage intensity (Arregui et al., 2018; Khosravi et al., 2019). Meter class, which defines the meter's permissible error range and sensitivity to flow variations, determines its resilience to wear and hydraulic fluctuations (ISO 4064:2014). Lower class meters (Class B) are more susceptible to performance decline under variable pressures and intermittent flows compared to higher class meters (Class C) (Mutikanga et al., 2011).

3.8.1 Probability of meter failure

The probability of water meter failure is a critical parameter in assessing the operational reliability and economic efficiency of metering infrastructure. Meter failure, often manifested as under-registration or complete inaccuracy, occurs when a meter's mechanical or magnetic components degrade over time due to wear, sediment accumulation, or hydraulic stress (Arregui et al., 2011; Mutikanga et al., 2010). Several empirical studies have established that the accuracy of mechanical water meters diminishes progressively with age, leading to systematic under-registration of actual consumption and increased apparent losses (Davis, 2005; Couvelis & Van Zyl, 2015).

In this study, the probability of meter failure was quantified through a Meter Failure Index (MFI), adapted from Schultz (2012), who proposed a similar index for estimating the probability of pump failure. The MFI provides a probabilistic measure of the likelihood that a meter has entered a defective state, based on its operational age and observed performance deviations at various flow conditions. Following Schultz's (2012) principle, the Meter Failure Index (MFI) was calculated using the formula:

$$MFI = A/D \qquad 3.17$$

where:
A = age of the meter (years),
D = design life of the meter (assumed as 10 years).

The design life of 10 years aligns with recommendations by Van Zyl (2011), who proposed that domestic meters should be verified or replaced before 10 years, and bulk meters before 5 years of service. In this study, meters exceeding 10 years were considered to have a high probability of failure (MFI ≥ 1.0), indicating likely performance deterioration.

Descriptive statistics from the field data show meter ages ranging from 0-18 years and above, with a mean of 7.1 years, median of 6 years, and standard deviation of 5.3years. Each age group's performance was assessed using four flow rate-based error categories:

Table 3.8: Descriptive statistic of meter age

	Descriptive statistic	
Meter age	Mean	7.1
	Standard Error	0.3
	Median	6
	Mode	2
	Standard Deviation	5.3
	Sample Variance	27.8
	Kurtosis	-0.02
	Skewness	0.8
	Range	25.0
	Minimum	0
	Maximum	25

The range of meter failure indices was divided into ten equal class intervals, with scores from 1 to 10 assigned to each range. The lowest index class interval received a score of 1, while the highest was assigned a score of 10, as illustrated in the table below

Table 3. 9: Meter failure index scoring

No	Failure Index Scoring Range	Score assigned
1	0-0.25	1
2	0.26-0.5	2
3	0.51-0.75	3
4	0.76-1.0	4
5	1.01-1.25	5
6	1.26-1,50	6
7	1.51-1.75	7
8	1.76-2.00	8
9	2.01-2,25	9
10	2.25-2.5	10

The meter failure index scores were aggregated by block using a crosstab query in MS Access. In this process, the probability score field was calculated as the average value, while the block field was designated as the row header. A Make Table query was then used to generate a new table containing the average scores for each block. This table was subsequently linked to the ArcGIS block shape file and visualized using a color ramp to illustrate variations in average scores across the blocks.

Five classification categories Very Low, Low, Moderate, High, and Very High were applied to represent the relative ranking of each block. This ranking served as a proxy for the probability of meter failure within the respective areas. The classification was derived using the Natural Breaks (Jenks) method**,** selected for its robustness in identifying inherent data patterns and natural groupings within the dataset (ESRI, 2006). The resulting map from the above analysis is presented in Figure 4.12 (a, b), Section 4.5.1 below

Table 3.10: Ranking probability of meter failure scores with in each block

No	Failure Index Scoring	Failure probability ranking
1	0-1.4	Very low
2	1.5-2.8	Low
3	2.9-4.2	median
4	4.3-5.6	High
5	5.7-7.0	Very high

3.8.2 Meter failure criticality

The concept of criticality is based on the understanding that water meters hold significant value to a utility; therefore, their failure has a direct and tangible impact on utility operations. Water meter criticality reflects the consequence of failure that is, the extent to which a meter's malfunction affects the utility's ability to achieve its service delivery objectives. Assessing criticality is essential for guiding decisions related to routine monitoring, maintenance scheduling, and asset replacement planning. Meters identified as more critical warrant more frequent inspection and monitoring.

In this study, the average test error recorded for each meter was used to determine its criticality index. Although other factors such as customer consumption category (which relates to varying tariff rates) and meter size or class (which influence procurement cost) could also inform criticality, these variables were excluded due to inconsistencies in the utility's data management practices. Furthermore, average meter error was considered the most meaningful indicator of criticality, as it directly affects monthly revenue collection and, by extension, the financial sustainability of the utility.

Table 3.11: Descriptive statistics of Average meter error

Descriptive		Statistic	
Average meter error for the tests Q1-Q3	Mean	-6%	
	Standard Error	0%	
	Median	-4%	
	Mode	-2%	
	Standard Deviation	6%	
	Sample Variance	0%	
	Kurtosis	1%	
	Skewness	-83%	
	Range	29%	
	Minimum	-23%	
	Maximum	5%	

Descriptive analysis of the meter error data from 388 water meters revealed consumption values ranging from a minimum of 5% to a maximum of -23%. The minimum value of -23 was attributed to old meter under registration at low flow rates and pressure. The average meter error was found to be -6%, as summarized in the table above.

Average meter errors were categorized into ten equal class intervals, with each interval assigned a criticality score ranging from 1 to 10 in ascending order. Meters with the lowest average error received a score of 1, while those with the highest received a score of 10. The equal class interval classification method was selected for its ability to clearly highlight the relative magnitude of attribute values within a dataset (ESRI, 2006). In this context, the approach was intended to emphasize variations in the average meter error among individual meters, given that this parameter served as the basis for determining meter criticality.

Table 3.12: Meter criticality score

No	Meter error interval	Score
1	0-2.9	1
2	3.0-5.8	2
3	5.9-8.7	3
4	8.8-11.6	4
5	11.7-14.5	5
6	14.6-17.4	6
7	17.5-20.3	7
8	20.4-23.2	8
9	23.3-26.1	9
10	26.2-29	10

Using the table of individual meter error averages, each water meter was assigned a criticality score corresponding to its average error value, as defined in the classification table. To visualise the spatial distribution of meter criticality across the Kansanga and Kyengera branches, the individual meter scores (ranging from 1 to 10) were aggregated by block. This aggregation was performed using a crosstab query in Microsoft Access, where the average consumption field was used as the value field, the branch name served as the column header, and the block name as the row header. Block-level averages were prioritized since a block represents the smallest operational spatial unit within the utility.

The resulting table of average block criticality scores was then joined to the block shape file of the study area using the Block field. To support further analysis of criticality, probability of failure, and overall risk, a Likert scale framework was applied. According to Harry (2012), Likert scale items are constructed by calculating a composite score (sum or mean) from several Likert-type items, and such composite scores are appropriately analyzed at the interval measurement scale. However, as Blaikie (2003) notes, although Likert categories exhibit rank order, the intervals between values cannot be presumed to be equal.

Table 3.12: Ranking probability of meter criticality scores with in each block

No	Average meter criticality scoring per block	Criticality ranking
1	0-1.2	Very low
2	1.3-2.4	Low
3	2.5-3.6	median
4	3.7-4.8	High
5	4.8-6.0	Very high

Within QGIS, the average criticality scores for each block were classified into five Likert-like rating categories Very Low, Low, Moderate, High**,** and Very High using the Jenks Natural Breaks classification method, selected for its capability to identify inherent groupings and natural data patterns (ESRI, 2006). The resulting map from the above analysis is presented in Figure 4.13, Section 4.5.2 below

3.8.3 Meter Risk determination

Risk is assessed from an engineering standpoint, which defines it as the product of the probability of an undesirable event occurring and the extent of the expected harm resulting from that event (Damodaran, 2008; Harlow, 2005). In this study, risk is expressed as the product of the probability of occurrence represented by meter age and the consequence of failure, measured through criticality.

Accordingly, the risk associated with a water meter can be described as the product of its probability of failure and the potential impact or damage resulting from such failure. To determine the meter risk, the meter failure index for each meter (as computed in Section 3.3.1) was multiplied by the corresponding criticality score (as defined in Section 4.5.3). This computation produced a risk index for all meters across the Kansanga and Kyengera branches.

The individual meter risk indices were subsequently aggregated and averaged by block using a Crosstab query in Microsoft Access to obtain the average block-level risk. A descriptive statistical analysis of meter risk across the blocks was then conducted using SPSS, and the results are presented below.

Table 3.13: Descriptive of average risk per block

	Descriptive	Statistic
Average meter risk	Mean	13.5
	Standard Error	0.7
	Median	8.0
	Mode	6.0
	Standard Deviation	12.9
	Sample Variance	167.4
	Kurtosis	1.0
	Skewness	1.3
	Range	59.0
	Minimum	1
	Maximum	60
	Count	388

The Kansanga and Kyengera Branches comprises a total of 54 and 267 blocks respectively. Analysis of the risk data revealed that the highest average risk score was 60, while the lowest was 1.0 The mean average risk score across all blocks was 13.5, with a median value of 8.0. These results were saved using a Make Table query in Microsoft Access and subsequently linked to the GIS shape-4file of blocks within both Kansanga and Kyengera branches using the Block Number field as the common key.

In ArcGIS, the data were symbolized to visualize the spatial variation in risk. Five risk classes were generated using the Jenks (Natural Breaks) classification method, which groups similar values while maximizing differences between classes. Each class was then assigned a Likert-based ranking of Very Low, Low, Moderate, High, and Very High to represent different levels of risk across the blocks.

The five-tier ranking system was adopted to clearly convey the relative degree of risk associated with each block where a lower average risk class interval corresponds to a lower rank (lower risk), and a higher interval corresponds to a higher rank (higher risk).

The resulting classification and corresponding statistics are presented in the table below. The resulting map from the above analysis is presented in Figure 4.14, Section 4.5.3 below

Table 3. 14: Risk ranking of blocks within Kansanga and Kyengera

No	Meter Risk Index Scoring	Risk probability ranking
1	3.0-9.6	Very low
2	9.7-16.2	Low
3	16.2-22.3	median
4	22.4-29.4	High
5	29.4-36.0	Very high

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Introduction

This chapter covers data analysis, presentation, interpretation, and discussions of results based on the four specific objectives that were investigated in the research, specifically: i) to characterise the pressure rates in the water distribution network of the study area; ii) to access customer water meter class performance accuracy subjected to different flow and pressure rates. iii) to determine the influence of meter age on its registration errors; iv) to geo-visualise meter criticality zoning maps in the study area.

4.2 Distribution of pressure in the study area

The pipe network Pressure was characterised by high pressures in Kansanga and low pressures in Kyengera. The average minimum distribution water network pressure in Kansanga was 15.6m (1.56bars) >10m recommended by IWA and WHO (IWA, 2006) The average maximum pressure for Kansanga was 70.2m (7bars) > 60m allowable maximum pressure. Kyengera's supply had an average of 4.1m < 10m allowable minimum pressure, with 43.1m as the average maximum pressure (Figure 4.1). The Kansanga area was characterized by high distribution pressures exceeding 6 bars, primarily due to the presence of large elevated storage reservoirs situated within the supply zone. The relatively low population density and demand compared to the reservoir storage capacity contributed to the sustained high-pressure levels observed across the network. Whereas Kyengera's situation was found to be the opposite of that of the Kansanga area. It was characterised by pressures less allowable due to its location from the supply reservoirs (Namasuba). The reservoirs were located about 20km from the supply zone. Kyengera is located at the dead end of the Kampala water supply area to the west. Some hilly profiled areas in Kyengera had water pumping system directly to the consumers (Kings College Budo) and other pumping system to the reservoir of Bandwe. The area had one borehole supplementing the low supply from Rubaga and Namasuba reservoirs.

Except for areas that receive water on direct pumping, most parts in Kyengera receive water at a pressure below the recommended 1.0 bar (ISO 4064-1-2014) to effectively measure volumes passing through the installed water meters.

The 72-hour pressure monitoring indicated a distinct diurnal variation in water pressure across the study areas. Kansanga exhibited higher nighttime pressures, ranging from 70 to 120 meters of head, while daytime pressures were comparatively lower due to increased consumption. In contrast, Kyengera recorded nighttime pressures between 30 and 55 meters of head, suggesting that some consumers in this branch primarily receive water during nighttime hours. This pattern reflects intermittent supply conditions and pressure management practices aimed at optimizing limited system capacity

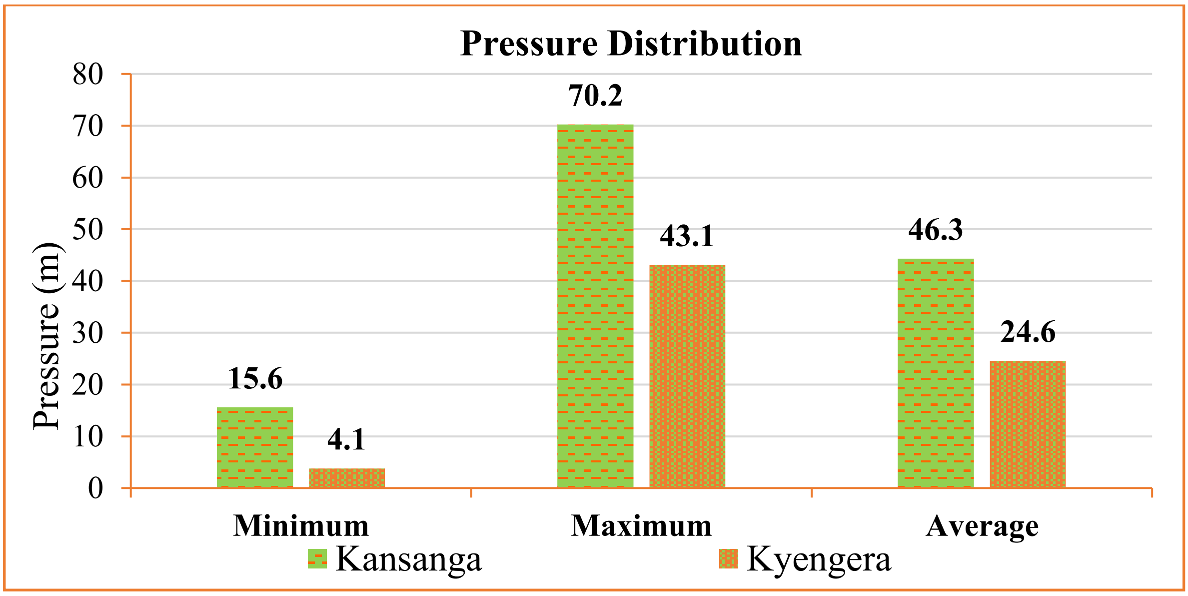


Figure 4.1: Distribution of pressure measurement results for the study area

Most water consumers in Kyengera receive water at minimum pressure due to high demand compared with supply. The low supply results into low flows that affect the water meter's performance, with some meters dispensing unregistered volumes. Figure 4.2 (a) and (b) show the distribution of pipe network pressures in the study area.

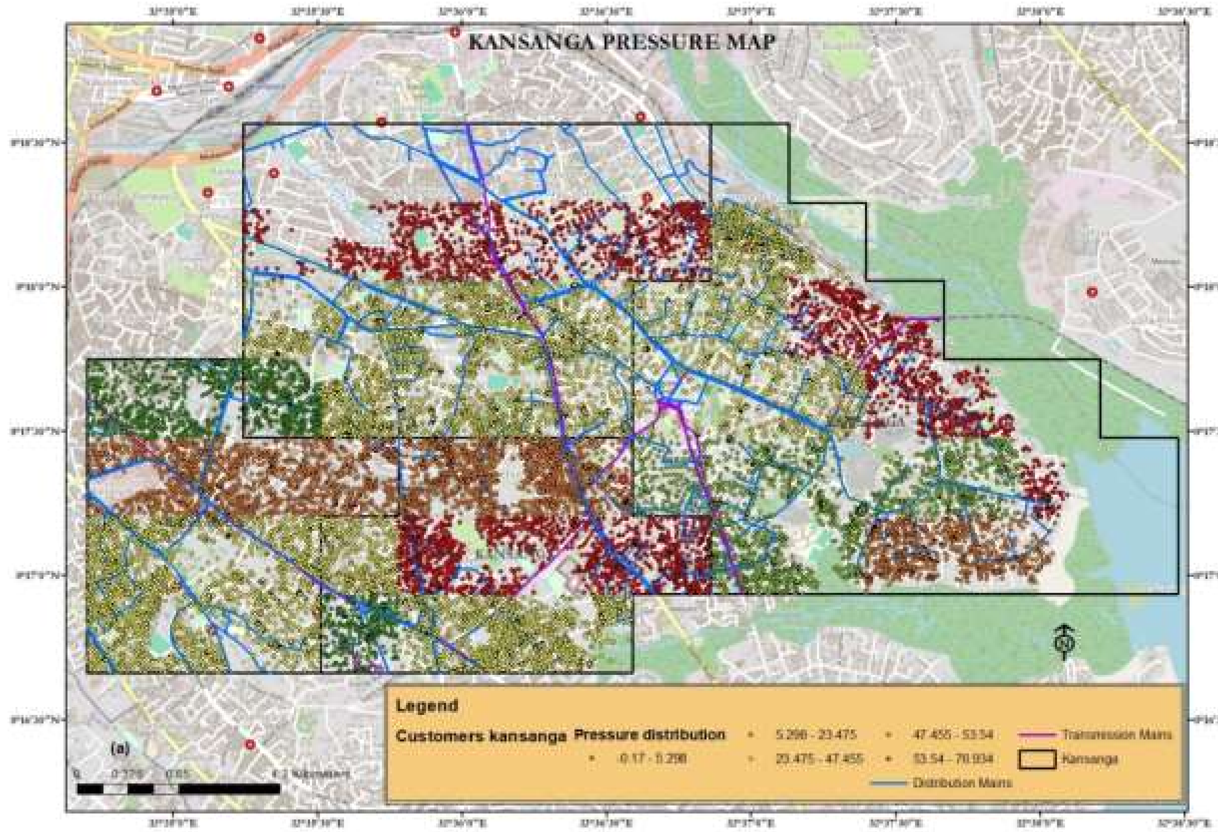


Figure 4.2: (a) Distribution of pipe network pressure in the study area

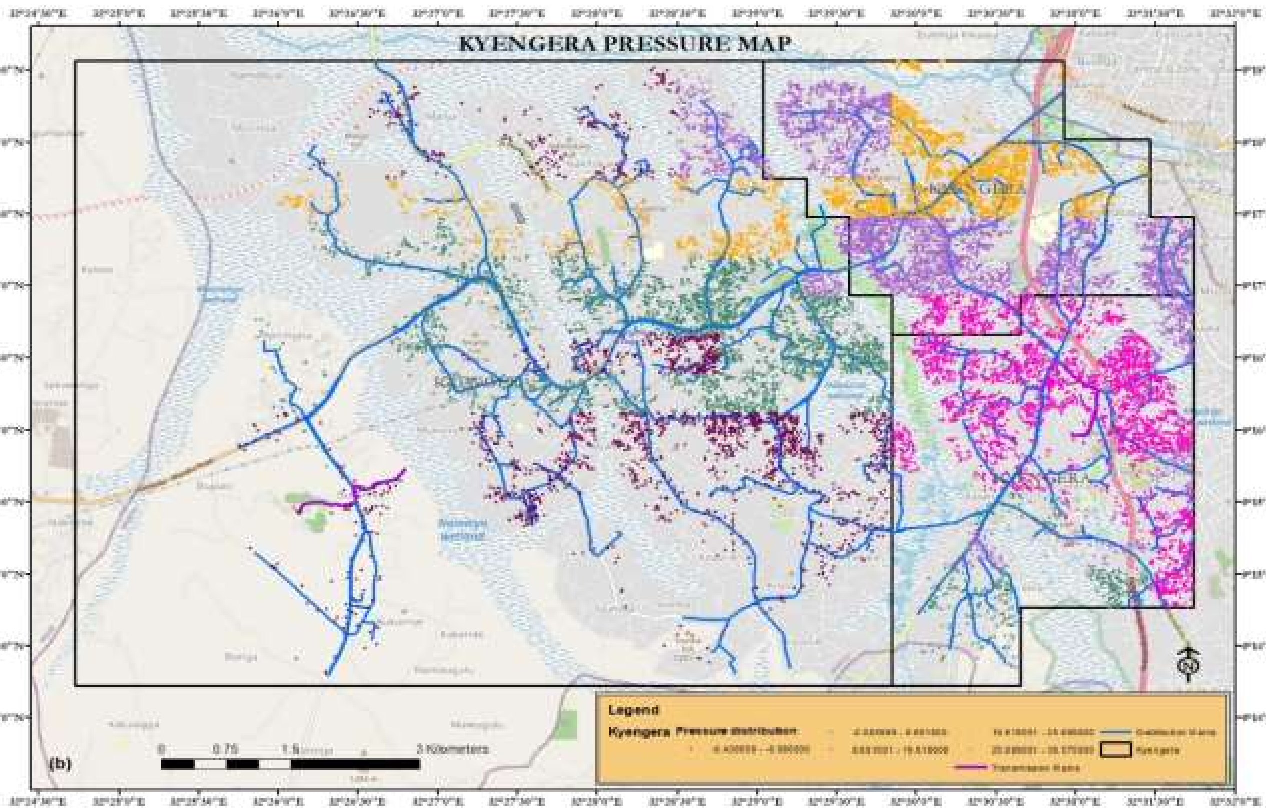


Figure 4.2 (b); Distribution of pipe network pressure in the study area

The Kansanga high-pressure areas were located in low-lying areas of Bukasa, Namuwongo, Kiwafu and Kabalagala compared to the supplying reservoir elevations. The water pressure between 4.8 - 6.2m was located in hilly areas of Makindye Kizungu that was supported by an online pumping system stationed at Lukuli.

The pressure areas of Kyengera > 60m were supported by direct supply areas from Bandwe and Budo pumping system. The pressure below 10m (< 1bar) was manifested in areas of Nsangi, Kitemu, Maya, Manja, Nakitokoli and Kisozi. These areas were characterised by negative pressures due to intermittent water supply or no water at all. The pressures negatively affect water supply system including performance of water meters since most of it operates below the minimum flow and pressure rates. (Musaazi et al., 2021). Such areas need supply improvement to avoid such commercial losses. Meters of low starting flow rates are recommended for such areas. While pressures greater 60m also affect meter functionality by causing water hammer, which mostly affect internal moving parts of the meter. Thus, balanced water pressure desirable for better functionality of the meter can achieved by installation of pressure regulating valves.

The creation of the water scale drying up, which could cause the water-meter mechanism to malfunction and ultimately contribute to the meter errors was not considered due unavailability of plastic stoppers

4.3 Water meter performance accuracy

4.3.1 Water meter performance per meter class category

The classified sample water meters were tested against their standard metrological performance (ISO 4064-1-2014) at minimum, transition, nominal and overload flow rates.

A two-way ANOVA was conducted to evaluate the effects of meter class, pressure, and their interaction on meter performance. The results, summarized in Table 4.1, indicate that all factors significantly influence meter accuracy at the 95% confidence level

Table 4.1: ANOVA Relationship between water meter inaccuracies and meter Class

Source of Variatio	SS	df	MS	F	P-value	F-critical
Meter class	4.66E-05	1	4.66E-05	**0.040359**	**0.840839**	3.85501
Metering inaccuracies	0.875543	3	0.291848	253.0254	1.3E-110	2.617849
Meter class*metering inaccuracies	0.006986	3	0.002329	**2.018797**	**0.109955**	**2.617849**
Errors	0.793561	688	0.001153			
Total	1.676136	695				

From ANOVA results, meter class effect (F = 0.043<3.855, p=0.841> 0.05) indicates an insignificant difference in performance among meter class. This demonstrates that differences in meter design and measurement technology exert a substantial impact on registration accuracy., with some classes performing better under the same flow and pressure conditions.

The pressure factor exhibits the largest influence (F = 336.94 > 2.61, p < 0.001), confirming that pressure variations strongly affect meter accuracy. High or low pressures alter flow dynamics and internal resistance, leading to significant measurement deviations consistent with findings by Farley & Trow (2021) and Arregui et al. (2018). The interaction between meter class and pressure (F = 24.32 > 2.61, p < 0.001) is also significant, implying that the effect of pressure depends on meter type. Different meter classes respond uniquely to pressure changes, reflecting non-linear performance behavior under varying hydraulic conditions. The small within-group mean square (0.00483) and large F-values show that most variability is explained by the tested factors rather than random error, indicating a robust model. Overall, both meter class and pressure significantly influence meter accuracy, with pressure being the dominant factor.

4.3.2 Performance of Class B water meter samples

The error results from meter measurement for class B sample meters at four measured flow rates are presented in Figure 4.3 and 4.4. The test results errors were negatively skewed at minimum, transition, and overload flow rates with minimum errors of -57%, -57%, -9%, and maximum errors of +1%, +7%, and +12 % respectively. At the nominal flow rate test, results were positively skewed with minimum and maximum errors of -2% and +22% respectively.

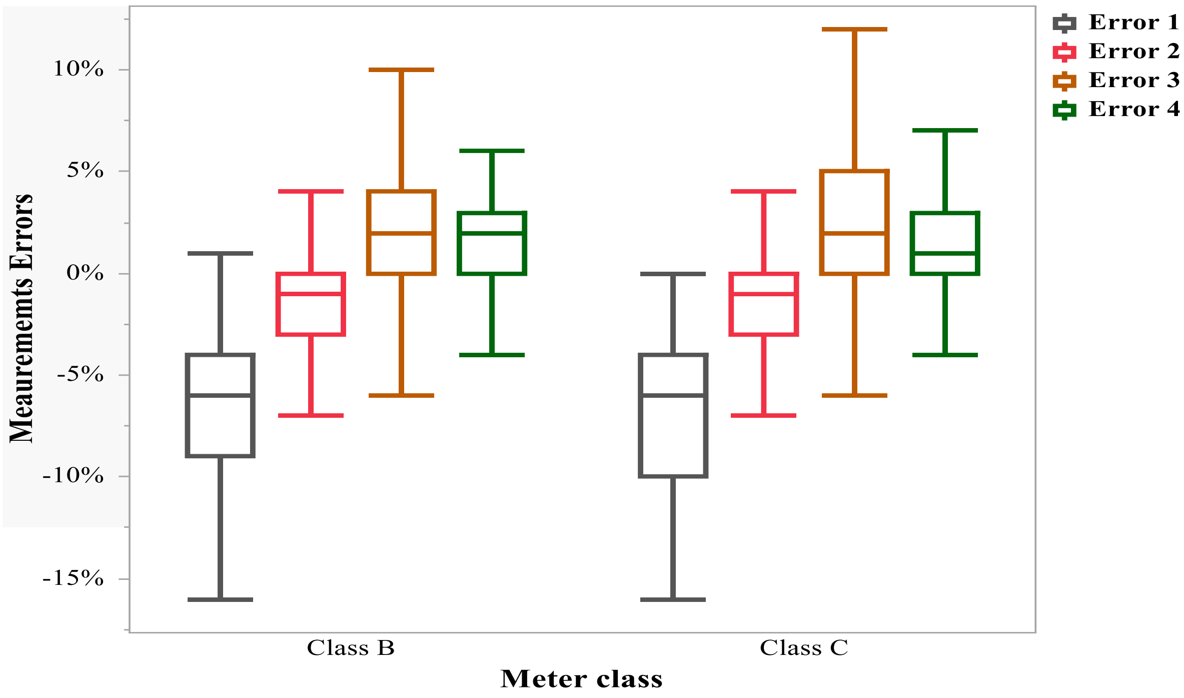


Figure 4.3: Water meters class performance

The median error range was -6%, -1%, for starting, and transitional flow rates, and +2% for nominal and overload flow rates respectively.

Test results revealed 61%, 5%, and 4% of water meter samples under-registering at minimum, nominal, and overload flow rates compared with ±5%, and ±2% maximum permissible errors respectively, for class B &C water meters. Multivariate correlation matrix (Appendices C, D, and F) carried out indicate that Class be meters perform better at high flow rates than low flow rates.

4.3.3 Performance of Class C water meters

The test error results for class C meters at four standard flow rates was presented in Figure 4.3. The test results had minimum and minimum errors of -16%, -10%, at minimum flow rate and maximum errors of -6%, and +10% respectively. The median error range was -6%, -1%, +2%, and +1% for minimum, and transitional.

Test results revealed 57%, 50%, and 63% of water meter samples passed at minimum, nominal, and overload flow rates compared with ±5%, and ±2% maximum permissible errors respectively for class B &C water meters. A multivariate correlation matrix (Appendices E and F) carried out indicates that Class C meters perform better at low flow rates.

The summary results show class C water meters perform better than class B at Minimum and transitional flow rates (Figure 4.3) this is because class C meters have a lower start flow rate than class B. (Mutikanga, 2014), reported the same results (Musaazi et al., 2021), and also discovered the same trends of performance behavior for both meter classes B and C. At the permanent flow rate, class B performed better than class C, the same results were reported by (Ethem Karadirek, 2020)

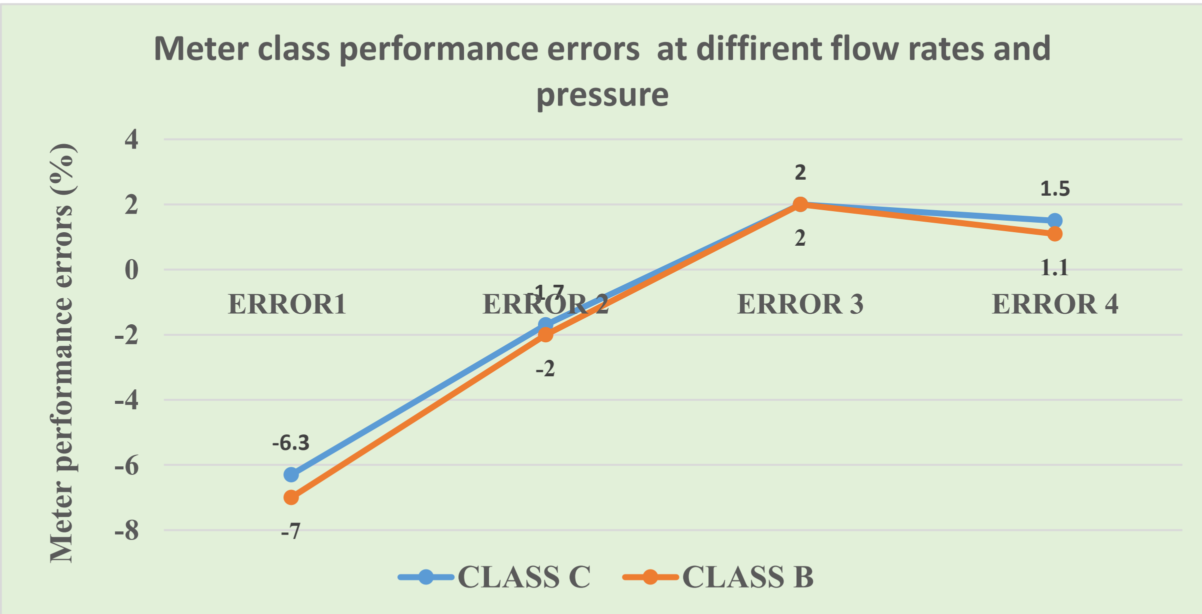


Figure 4. 4: Meter class performance

Overall, the trend (Table 4.2) confirms that meter accuracy improves with increasing flow rate, with maximum under-registration occurring at the lowest flow and minimal error at the upper flow range. The performance difference between Class B and Class C meters is small but consistent, supporting previous studies (Arregui et al., 2007; AWWA, 2016) that report higher accuracy and sensitivity in Class C meters under low-flow conditions. These findings highlight the importance of selecting appropriate meter classes based on the prevailing flow profiles in the distribution network

4.4 Performance of meters by age

4.4.1 Minimum (Starting flow rate)

At minimum flow rate, meter performance exhibited a clear age-related decline in registration accuracy (Figure 4.5). The median error increased in magnitude from approximately –3% for new meters (0-1 years) to around -40% for meters older than 18 years. The observed minimum and maximum errors ranged between 0% and -7% for new meters, extending to -50% for the oldest group.

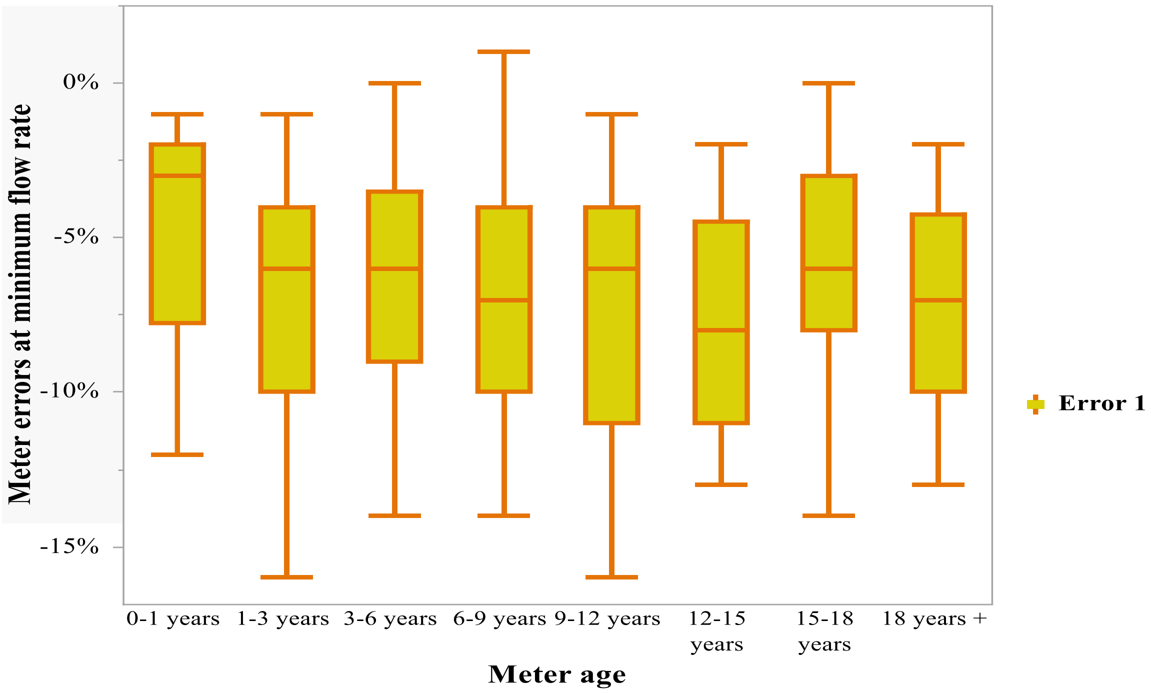


Figure 4. 5: Boxplots illustrating tested water meters' measurement inaccuracies at minimum flow rates.

Based on the ±5% permissible tolerance defined in ISO 4064:2014 and OIML R49 standards, approximately 90% of new meters passed the minimum flow accuracy test, while the pass rate progressively declined to 75%, 55%, and 25% for the 1-3, 3-6, and 6-9-year categories, respectively. Beyond 9 years of service, fewer than 10% of the meters met the required accuracy limit, and by 15-18 years of operation, nearly all meters failed the test.

The results indicate that the ability of mechanical meters to measure accurately at low flows deteriorates substantially with age. The widening interquartile range in older meters suggests increased performance variability, likely resulting from wear of internal components, increased bearing friction, and partial blockage due to debris or scaling. Similar findings were reported by Arregui et al. (2007), Criminisi et al. (2009), and AWWA (2016), who observed that meter under-registration at low flow increases by 20–40% after 10–15 years of operation. This trend confirms that hydraulic sensitivity loss rather than calibration drift is the dominant cause of metrological degradation. The results highlight the importance for utilities to implement routine testing and replacement programs targeting domestic meters older than 8–10 years to minimise apparent losses and sustain billing accuracy.

4.4.2 Transitional flow rate

The test error results for sample meters at a transitional flow rate of 24 l/h at 3bars pressure measurement revealed the following as shown in figure 4.6

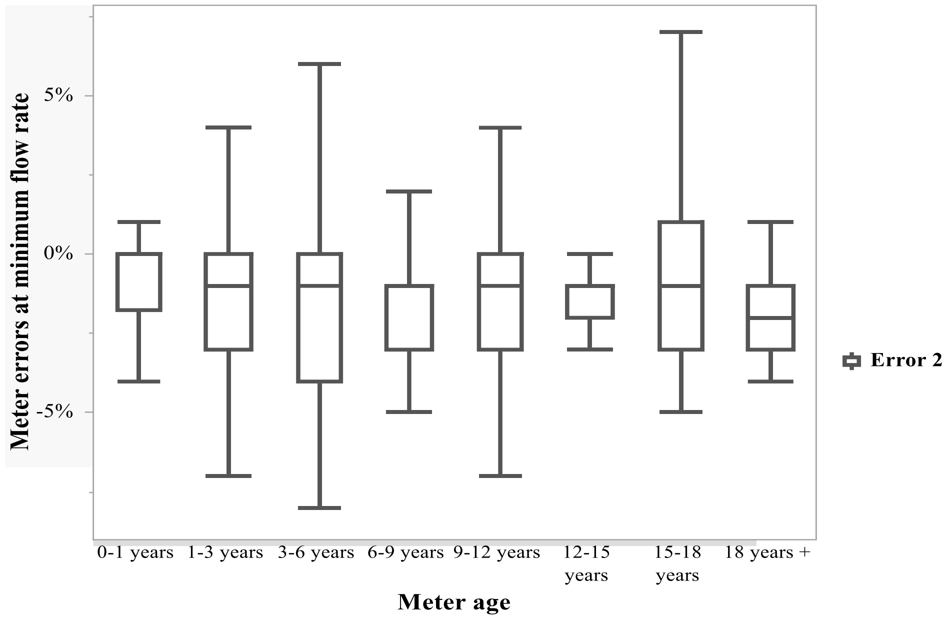


Figure 4. 6: Box plots illustrating tested water meters' measurement inaccuracies at transitional flow rates

The test results showed varying degrees of errors in water meters at transitional flow rates, with minimum and maximum errors were -12% and +2%, respectively with median error of +2%. 77% of all meter ages passed the standard minimum permissible error for class B&C at a transitional flow rate.

4.4.3 Permanent/ Nominal flow rate

The test results for water meters at a permanent flow rate (1500l/h) revealed a varying degree of errors (figure 4.6).

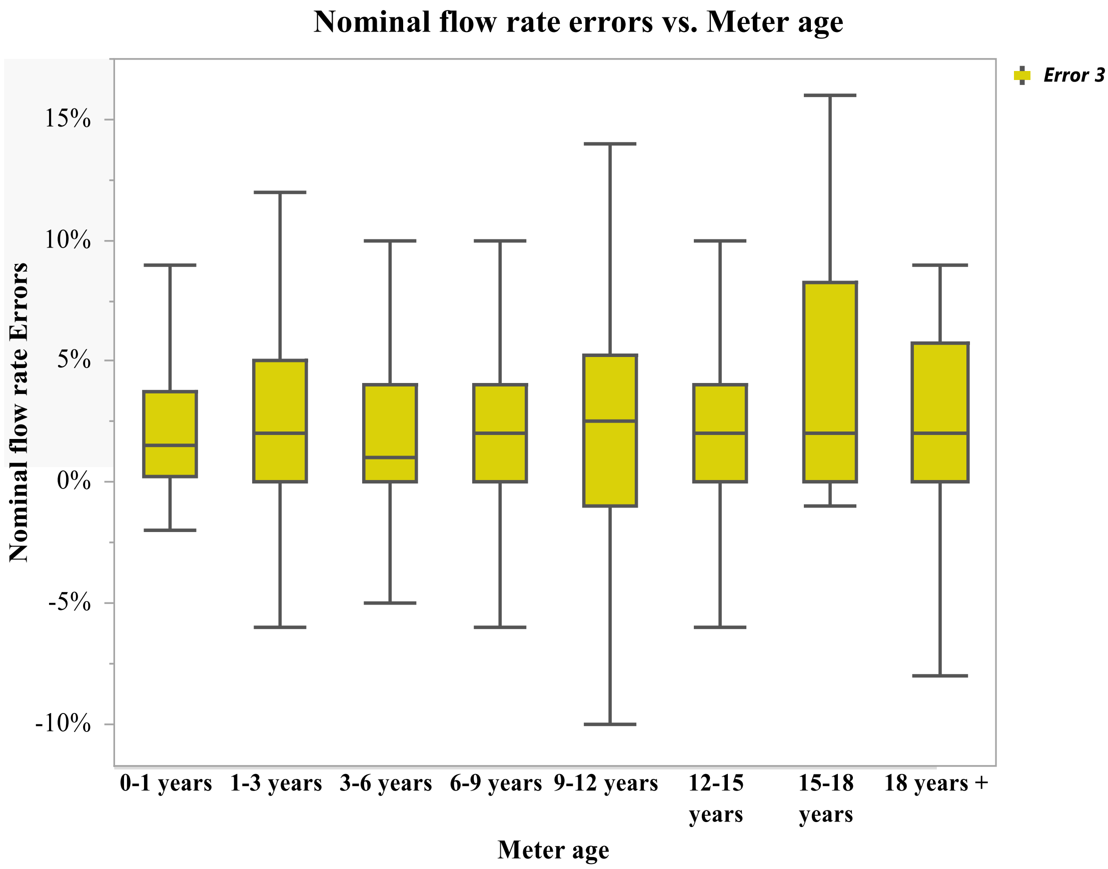


Figure 4.7: Box plots illustrating tested water measurement inaccuracies at a nominal flow rate

The test results showed varying degree of errors in water meters at transitional flow rates, with positively skewed errors for meter age brackets 0-12 years and 15-18+ years. The minimum and maximum errors were -12% and +22%, respectively.

4.4.4 Maximum flow rates

The test results for water meters at overload flow rate (3200l/h) revealed a varying degree of errors (figure 4.7).

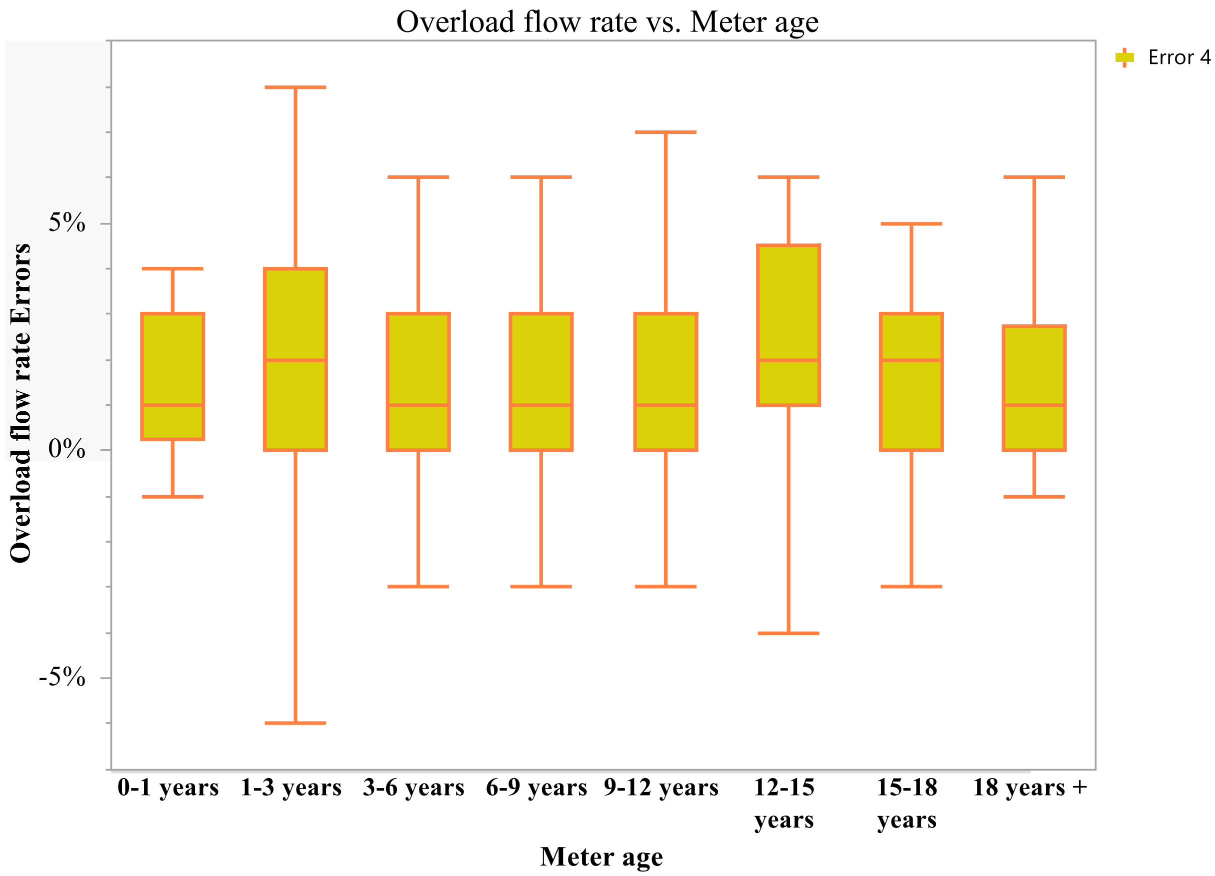


Figure 4.8: Box plots for water meters' measurement inaccuracies at maximum/overload flow rates

The minimum and maximum error were -10%, and +12%. The median error was +2%. 69% of water meters passed the standard measurement test of class B and C at overload flow rates respectively. It further revealed that 32% of water meters were over-registered while 6% of the sample under-registered beyond the maximum permissible error of ± 2%.

The maximum permissible error performance tests for sample meters of different ages revealed that most water meters under-registered at minimum flow rates with an average of -7%. Water meters of less than one year had better performance compared to the rest. The results explain the degradation of in-service meter accuracy due to its measurement components' deterioration. Water meters have a low degradation rate when subjected to moderate flow rates and pressure Mutikanga et al., (2011) discovered the same trends, Mbabazi et al., (2015) in the study assessing the impact of working pressure on meter registration, revealed that meter age did not influence the accuracy of the water meter. This was because their study data was based on totalised water meter consumption from the billing database to determine the meter age. The data used wasn't precise since consumer consumption varies from time to time. Similarly, consumption from billing consists of unrealistic consumption due to estimated consumption and high Consumption due to leakages after meters.

The weighted error test results gave a clear representation of the onsite performance of water meters rather than using totalized volume. Nearly three-quarters of Kampala's water domestic meters operate below 15l/h due to intermittent water supply. The influence of ball valves installed in overhead tanks at customer residences, negatively affects the performance of water meters according to the test results at minimum flow rates. The effect of sub-metering also affects the performances of water meters in Kampala water since most of the sub-meters are affected by individual consumption which is always below the minimum flow rate of the mother meter (Mbabazi et al., 2015)

4.4.5 Summary of meter performance by age

The ANOVA analysis (Table 4.2) revealed that metering inaccuracies associated with flow rate had a statistically significant influence on registration accuracy ($F = 160.211$, $P < 0.001$), whereas meter age ($F = 1.558$, $P = 0.146$) and the interaction between meter age and metering inaccuracies ($F = 1.143$, $P = 0.301$) were insignificant at the 95% confidence level. This suggests that registration errors are mainly driven by variations in hydraulic flow conditions rather than by meter age. The findings corroborate previous studies (Arregui et al., 2007; Criminisi et al., 2009; AWWA, 2016) that identified flow dynamics and low-pressure operation as major contributors to apparent losses in urban water supply systems. also statistically insignificant, indicating that the combined influence of both factors is minimal.

Table 4.2: Relationship between meter age and meter accuracy.

Source of Variation	SS	df	MS	F	P-value	F critical
Meter age Flow rates	0.012088	7	0.001727	**1.558377**	**0.146377**	**2.033439**
Metering inaccuracies	0.532605	3	0.177535	160.2108	2.45E-67	2.628149
Meter age *Metering inaccuracies	0.02659	21	0.001266	**1.14262**	**0.300616**	**1.583457**
Errors	0.425523	384	0.001108			
Total	0.996806	415				

These findings imply that hydraulic operating conditions, particularly the flow regime, play a dominant role in influencing metering accuracy, while the effect of meter aging becomes secondary. This aligns with earlier studies by Arregui et al. (2007) and Criminisi et al. (2009), who reported that low flow conditions and pressure fluctuations are the principal sources of apparent losses, whereas meter age primarily affects performance after long service periods or under poor maintenance conditions.

The results further support AWWA (2016) guidance that emphasizes the need for utilities to test meters under realistic field flow ranges rather than relying solely on laboratory calibration, since field flow variability can have a more pronounced effect on measurement accuracy than meter wear over time.

In summary ANOVA analysis revealed that metering inaccuracies associated with flow rate had a statistically significant influence on registration accuracy ($F = 160.211$, $P < 0.001$), whereas meter age ($F = 1.558$, $P = 0.146$) and the interaction between meter age and metering inaccuracies ($F = 1.143$, $P = 0.301$) were not significant at the 95% confidence level. This suggests that registration errors are mainly driven by variations in hydraulic flow conditions rather than by meter age. The findings corroborate previous studies (Arregui et al., 2007;

Criminisi et al., 2009; AWWA, 2016) that identified flow dynamics and low-pressure operation as major contributors to apparent losses in urban water supply systems.

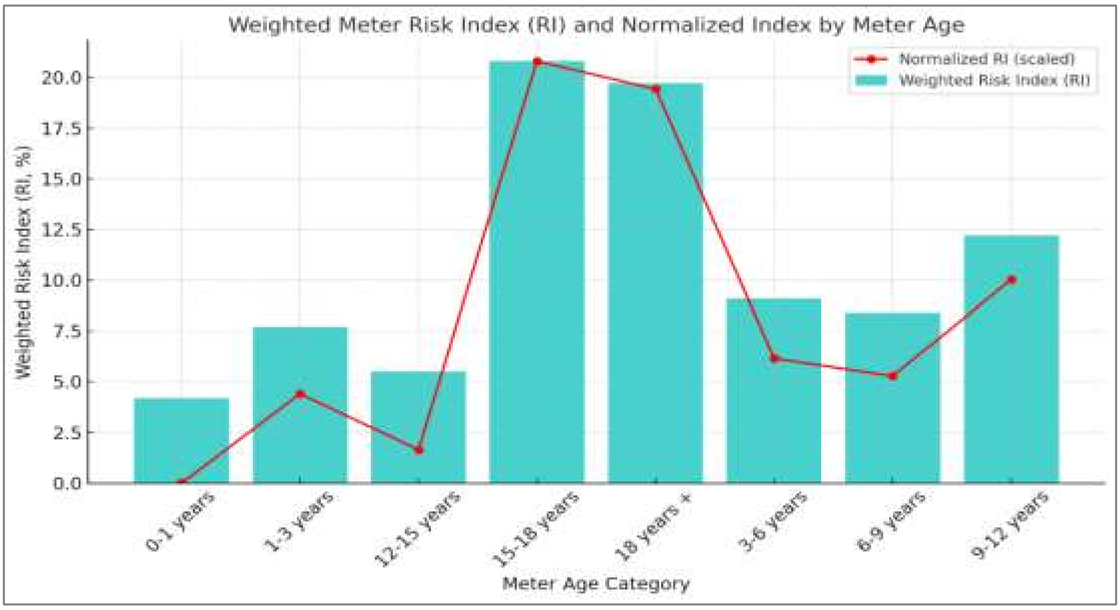


Figure 4.9: Degradation of weighted risk index with age

From Figure 4.9, it was observed that meters (age bracket 1 to 15 years) tend to behave the same at nominal flow rates. Water meters aged 15 years and above show slightly higher performance risks. This behavior can be explained by the working principle of mechanical meters, which degrades with age due to wear and tear of the internal moving parts (F. J. Arregui et al., 2018, 2020). Other factors like working conditions, water quality, and so on might have an impact on how quickly they change.

4.4.6 Meter registration errors

Table 4.6 shows that, 59% of the total sample under-registered at minimum flow rate with 1 bar pressure rates, 30% under-registered transitional flow rate with 3 bar residual pressure rate compared to standard errors of ±5% and ±2% for minimum, nominal and overload flow rates for class B and C water meters. 7%, and 6% under-registered with 5 bars and 10 bar pressure rates respectively (ISO 4064-1, 2014).

Table 4.3: Distribution of sampled water meter errors.

Meter Accuracy errors (%)	Frequency at Q1	% age Frequency	Frequency at Q2	% age Frequency	Frequency at Q3	% age Frequency	Frequency at Q4	% age Frequency
- 7 and blow	157	40%	8	2%	7	2%	2	1%
- 7 to -5	73	19%	16	4%	8	4%	9	2%
- 5 to -3	65	17%	54	14%	8	14%	4	1%
- 3 to -1	74	19%	87	23%	20	23%	8	2%
-1 to 0	14	4%	106	27%	25	27%	23	6%
0 to +1	2	1%	64	16%	58	16%	73	19%
+1 to +3	2	1%	26	7%	97	7%	144	37%
+3 to +5	-	0%	17	4%	69	4%	70	18%
+5 to +7	1	0%	3	1%	38	1%	47	12%
+7 and above	-	0%	7	2%	58	2%	8	2%
Total	388	100%	388	100%	388	100%	388	100%

The water meter samples were subjected to different flow rates in correlation with the field pressures to come up with the best water meter class that suits the field conditions. From the results, the highest consumption was achieved at 100l/h with a 5-bar residual pressure rating. The lowest consumption was achieved at a low flow rate of 10l/h. This trend of consumption was revealed by Mutikanga et al., (2011) while investigating the impact of private meters installed on apartments. Their findings revealed monitoring meters registering higher volumes than individual meters since the flow is divided into many segments than flow through one meter. this scenario represents areas with low flows and intermittent supply where water meters receive very low flows. The same scenario applies to consumers with ball valves installed in their storage tanks, the ball valves regulate the flow to the tank according to the usage downstream. When the downstream usage is low then the meter registers low consumption.

4.5 Geo-visualisation of meter error performance per block

A total of 388 meters from the Kansanga and Kyengera branches were analyzed to assess meter risk based on their likelihood of failure and potential impact. The probability of failure was estimated using meter age, assuming that older meters are more prone to inaccuracy due to wear and tear. The criticality of each meter was derived from performance errors by meter class, obtained from tests conducted under different flow and pressure conditions.

Meter risk was computed as the product of the probability of failure and the criticality of failure, representing both the likelihood and consequence of meter malfunction. High-risk meters are those combining advanced age with high performance error. The subsequent sections present the spatial and statistical distribution of meter risk across the two branches, providing insights for prioritizing meter replacement, calibration, and maintenance to reduce non-revenue water (NRW) and enhance measurement accuracy (Arregui et al., 2018).

4.5.1 Geo-visualisation of failure Risks

The meter failure index, representing the probability of meter failure, was analysed using descriptive statistics in SPSS. Results show a median age of 6 years and a mean age of 7.1 years. Since the mean is slightly higher than the median, the data is slightly positively skewed, indicating that most meters are younger than 6 years, with fewer older meters extending the upper tail of the distribution. This suggests that the system is dominated by relatively new meters still within their effective operational lifespan. However, the presence of a smaller number of older meters implies a gradual increase in failure risk as meter age advances, underscoring the need for targeted meter replacement and calibration programs to sustain measurement accuracy and minimize non-revenue water (NRW).

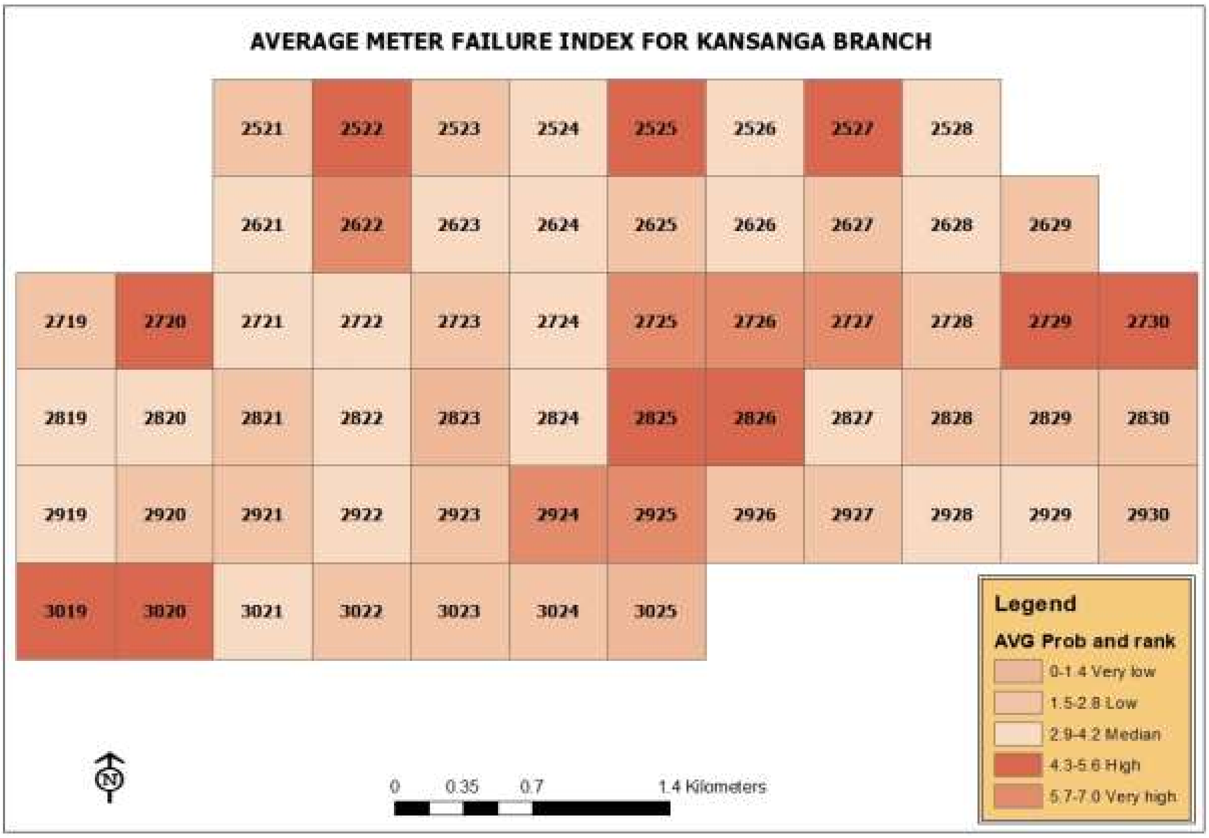


Figure 4. 10 (a): average meter failure indices Kansanga branch

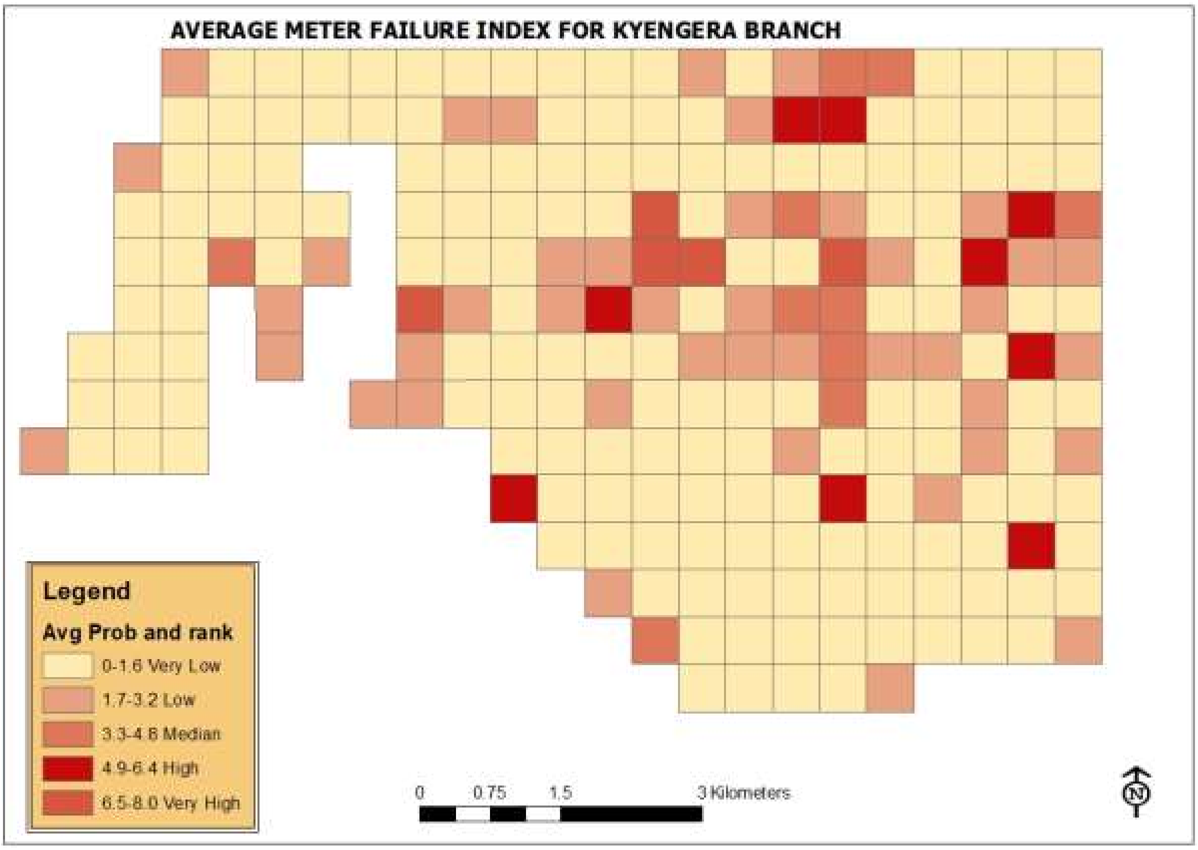


Figure 4:10 (b): average meter failure indices distribution for Kyengera branch

Figures 4.10 (a, b) illustrates the spatial distribution of meter failure probability across the Kansanga and Kyengera branches. The maps show that darker colored blocks represent areas with older meters and higher average probability of failure indices, whereas lighter-colored blocks indicate areas with new meters and lower failure probabilities. This spatial variation reveals that meter aging and hence the likelihood of failure is unevenly distributed within the two branches. Blocks with older meters present a higher operational risk and may require prioritised replacement or recalibration, while areas with newer meters reflect a lower probability of failure and more reliable performance

4.5.2 Criticality of the water meter

The descriptive statistics of average meter performance errors show a median of -4% and a mean of -6%, indicating that the distribution is negatively skewed (skewness = -0.83; Table 3.10). This suggests that most meters' exhibit errors greater than the mean, consistent with domestic consumers operating at flows below the meter's minimum starting flow (Pallant, 2013; Rogerson, 2001).

Figure 4.11 (a, b) highlights that certain blocks have higher average meter performance errors than others, indicating areas of greater criticality to the utility. These blocks represent locations where meters consistently under-register consumption, contributing to **n**on-revenue water (NRW) and requiring prioritized monitoring, calibration, or replacement to improve metering accuracy.

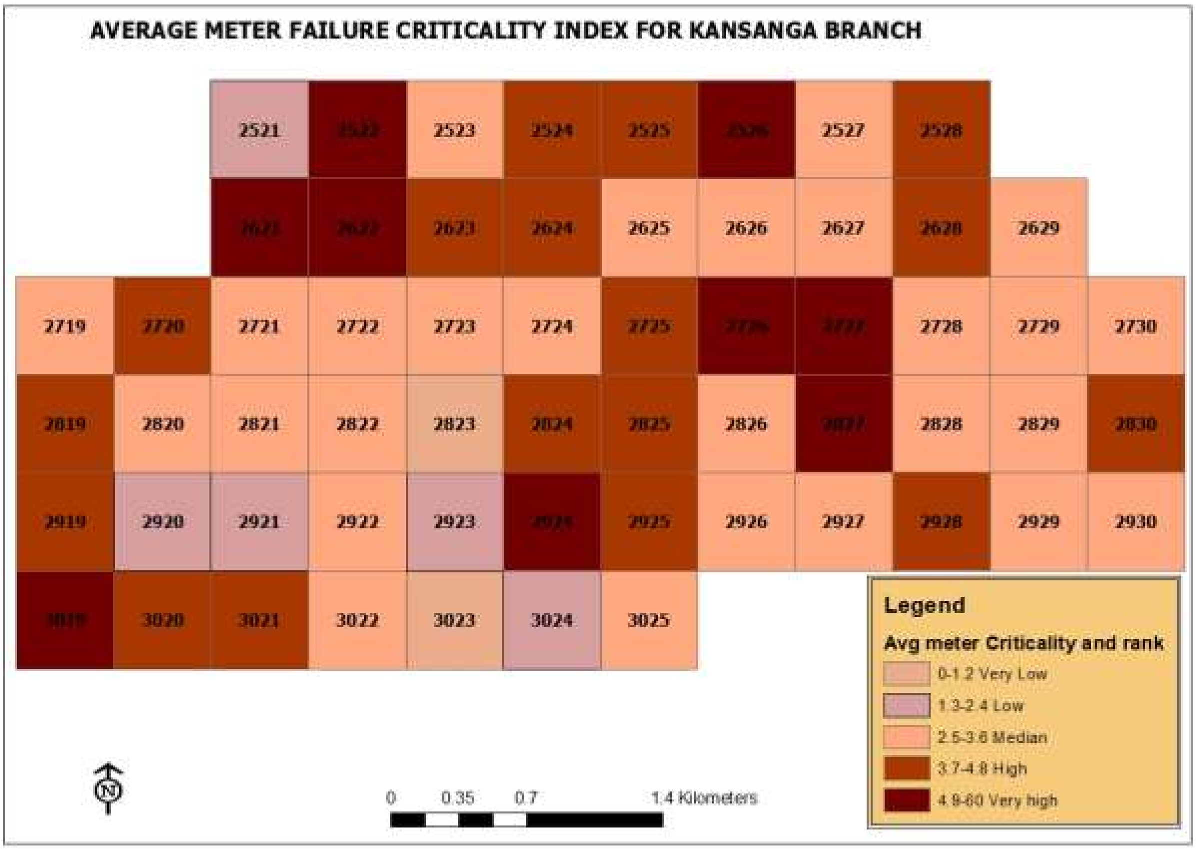


Figure 4.11 (a): Average meter criticality indices distribution for Kansanga branch

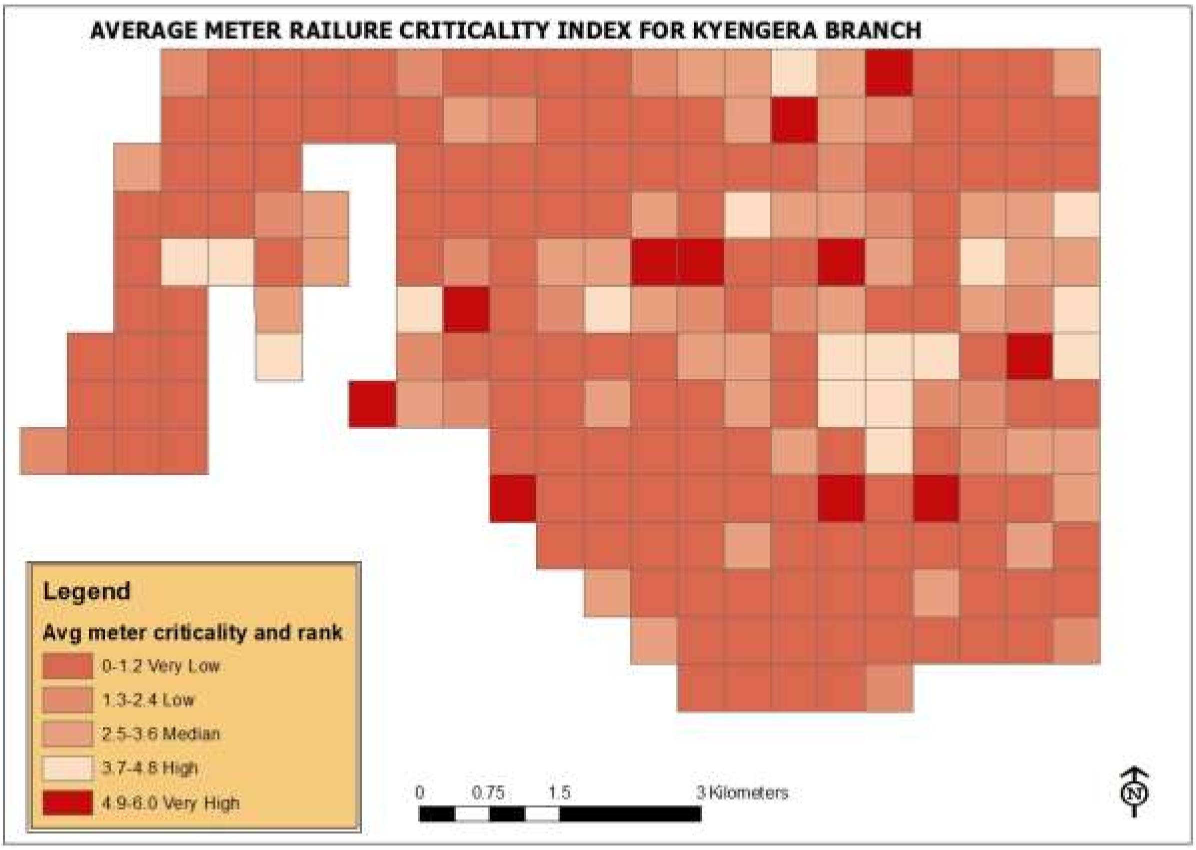


Figure 4:11 (b): Average meter criticality indices distribution for Kyengera branch

4.5.3 Risk of the water meter

Figure 4.12 (a, b) presents the spatial distribution of meter risk across the Kansanga branch. Darker colored blocks indicate areas with higher meter risk, while lighter colored blocks correspond to lower risk levels. The distribution shows that the median risk value is lower than the mean, suggesting a slightly positively skewed distribution most blocks have risk levels below the mean, with fewer blocks exhibiting higher than average risk. In this analysis, criticality was measured using average monthly water consumption, while the probability of failure was derived from meter age. The risk assessment revealed that certain meters pose a higher operational and financial risk to the utility than others.

A Likert scale (Very High, High, Moderate, Low, Very Low) was applied to categorize risk levels, enabling effective geo-visualization of high risk blocks. This approach provides a clear framework for identifying priority areas for meter replacement, maintenance, or calibration to mitigate risk and enhance metering accuracy

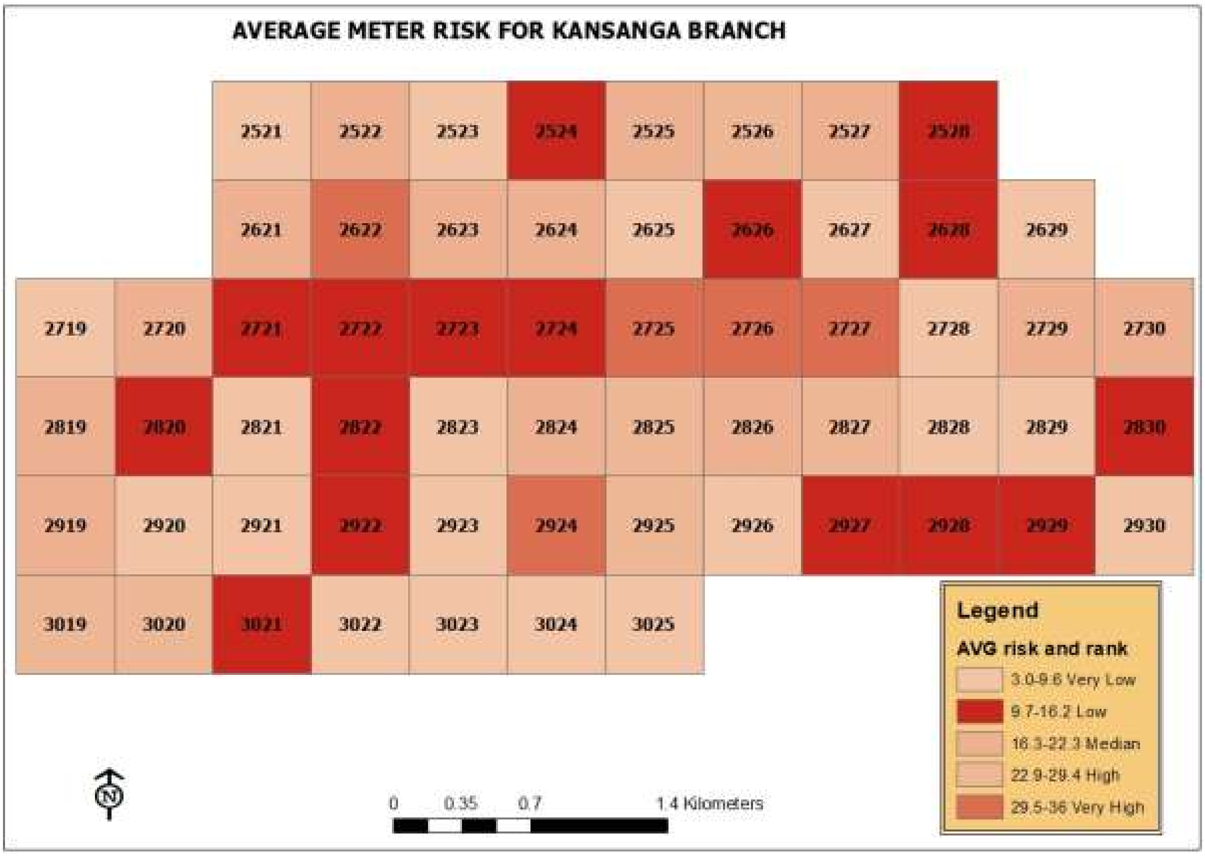


Figure 4. 12 (a): Meter risk indices distribution for Kansanga branch blocks

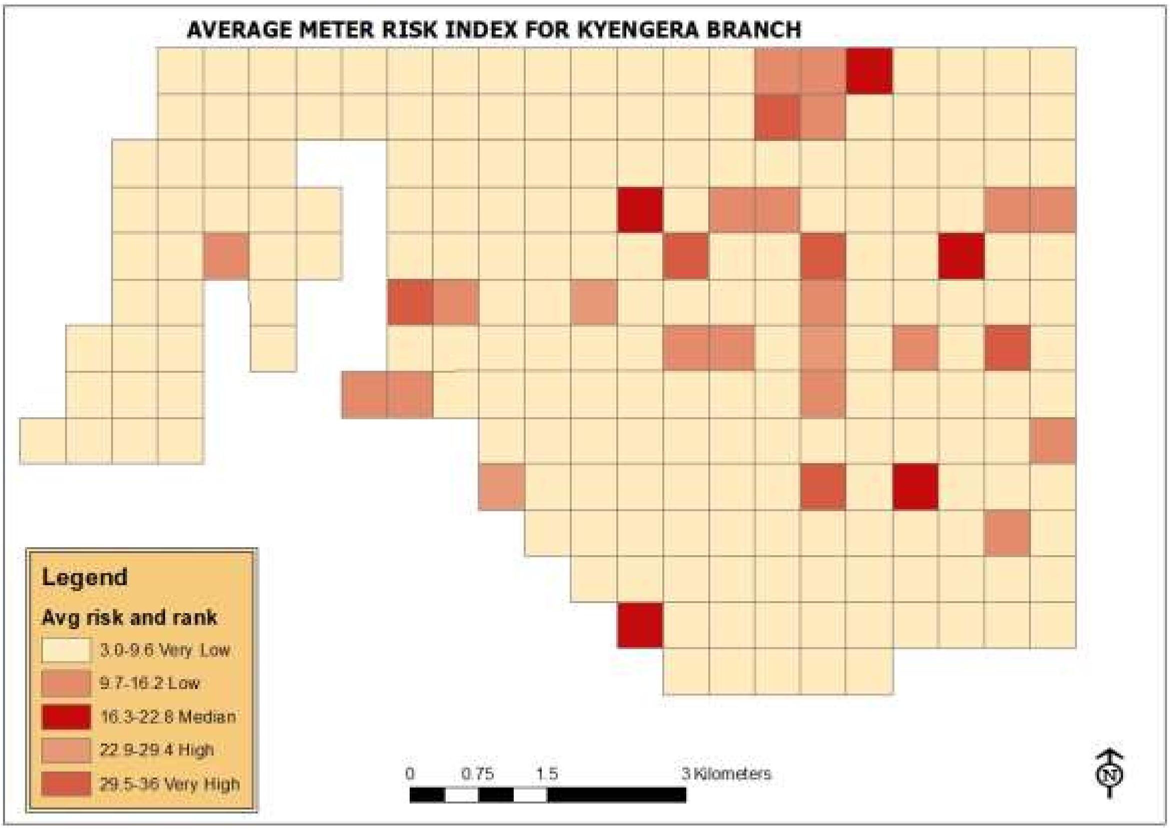


Figure 4:12 (b): Meter risk indices distribution for blocks in Kyengera branch

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusions and implications of findings

(i) This study evaluated water meter performance in Kampala water and developed a solution to the impact of low pressures, meter working age and meter class on meter registration errors. The average water pressure of 4.1m and negative pressures observed in Kyengera negatively affect proper meter functionality. This makes the wet meter chamber to dry out during hot weather. Consequently, prolonged periods without water supply lead to loss of lubricants, causing moving parts to stick and allowing unregistered water passage when pressure builds up. Regular meter servicing and testing should be carried out when such areas takes long without water to scale down meter malfunctioning. Similarly, pressure > (70.1m) observed in Kansanga also affects the meter functionality by causing water hammer and consequently damage to water meters. With the above findings, water pressure in the distribution network should be kept to standard to influence the flow rate that mainly affects the water meter performance. Therefore, there shouldn't be very high and very low pressure as both affect the water meter functionality.

(ii) Meter class; ANOVA analysis confirmed that metering inaccuracies are predominantly influenced by flow rate variability ($F = 253.03$, $p < 0.001$), while meter class ($F = 0.040$, $p = 0.841$) and its interaction with flow rate ($F = 2.019$, $p = 0.110$) were statistically insignificant. This implies that the hydraulic operating environment, including flow instability, pressure fluctuations, and water quality, exerts a stronger effect on meter accuracy than the meter's design class or nominal specifications. The results underscore that maintaining stable hydraulic conditions and minimizing low-flow occurrences are essential to achieving sustained metering accuracy and reducing apparent losses.

From a policy and operational perspective, utilities should adopt performance-based metering programs that incorporate flow profiling, periodic field testing, and predictive maintenance to identify underperforming meters early. Policymakers should update metering standards and procurement guidelines to account for environmental and hydraulic conditions typical of local networks rather than relying solely on international meter class certifications. Investments should also prioritize training, calibration facilities, and data-driven asset management systems that enable continuous accuracy monitoring.

(iii) The influence of meter age on metering inaccuracies was insignificant ($p = 0.841 > 0.05$). The analysis revealed that water meters with an age of 15 years or older exhibited notably higher registration errors, indicating that meter age beyond this threshold significantly impacts metering accuracy. The age of the meters and registration errors were not to the study results. Therefore, water utilities should put in place meter servicing and replacement programs to non-revenue water thorough such meters. With the above findings, the efficiency of the ageing water meter should be kept in check to determine the appropriate time of replacement before causing losses to the water utility. Testing the efficiency of such meters is very critical to maintaining robust data for meters that need replacement.

(iv) Geovisualisation of meter risks. The meter failure analysis shows that meter age, accuracy class, and operating conditions are key determinants of meter performance. The field data indicate that meters ranged from 0 to 25 years, with a mean age of 7.1 years and a median of 6 years, highlighting that a significant portion of the fleet is approaching or exceeding its design life of 10 years. Meters exceeding this age threshold ($MFI \geq 1.0$) were classified as having a high probability of failure, consistent with established empirical findings (Arregui et al., 2018; Khosravi et al., 2019).

The average meter error across 388 meters was –6%, with individual meter errors ranging from –23% to 5%, indicating that under-registration is a significant contributor to NRW. Error analysis and criticality scoring revealed that blocks with higher average meter errors are associated with higher financial and operational consequences. Criticality scores per block ranged from 0–6.0 (Very Low to Very High), with five-tier Likert classification applied to highlight relative risk levels.

Combining probability of failure (MFI) and criticality scores, meter risk indices across 54 Kansanga and 267 Kyengera blocks ranged from 1 to 60, with a mean of 13.5 and a median of 8.0. Spatial visualization using ArcGIS and the Jenks Natural Breaks method revealed clusters of High and Very High risk meters concentrated in low-pressure areas and zones with older meter installations. Approximately 10–15% of blocks fell into the High to Very High risk categories, indicating priority zones for intervention.

A concrete summary of the findings has demonstrated a high level of meter risk identification using spatial planning in advance for their replacement. "For sample sections 4,5.2and 4,5,3, the criticality and risk clearly demonstrate where to put resources rather than random meter replacement."

This study contributes new knowledge by demonstrating how actual field conditions, specifically low flow, pressure fluctuation, and pipe material, affect the accuracy and longevity of domestic water meters in developing urban systems. It introduces a field-calibrated assessment framework that quantifies these effects and integrates them into a spatial risk model for meter management. Unlike prior studies that relied on laboratory tests, this work establishes empirical evidence under real operating environments, offering practical and scientific insight for utilities aiming to reduce apparent losses and improve revenue assurance.

This study has provided practical evidence and analytical tools that can guide both policymakers and water utilities in addressing apparent losses and improving metering efficiency. For policymakers, the study offers new knowledge on the need to align national water measurement standards with realistic field conditions, rather than relying solely on laboratory-based performance certifications. The findings demonstrate that low and fluctuating network pressures, intermittent supply, and ageing meters significantly distort revenue measurements, calling for regulatory frameworks that enforce periodic meter verification, calibration, and replacement policies adapted to local conditions.

5.2 Recommendations

The study's key findings led to the following recommendations Utility Policy Focused and Future Research

5.2.1 Utility policy-based recommendations;

Proactive Meter Replacement and Maintenance: Older meters (>10 years) and lower-class meters, which are most susceptible to performance degradation under variable pressure and flow conditions, should be prioritized for replacement or calibration. By integrating risk mapping into maintenance planning, the utility can adopt a proactive, data-driven approach to allocate resources efficiently, reduce meter failures, and improve overall service reliability.

Targeted Maintenance for High-Risk Blocks: Blocks with high Meter Failure Index (MFI) and criticality scores represent the greatest risk to revenue collection and service reliability. Regular calibration and maintenance schedules should be established, particularly for DN15 meters, which comprise the majority of the customer base and have a significant impact on revenue comprise the majority of the customer base and have a significant impact on revenue. Enhanced Meter Monitoring and Targeted Interventions: Implementing targeted interventions in high-risk blocks, combined with the integration of smart or remote-reading meters, can significantly reduce NRW by improving detection of under-registration and leakages in real time, thereby enhancing billing accuracy and overall financial sustainability.

Targeted Risk Management and Proactive Monitoring: The methodology provides a replicable framework for ongoing monitoring, enabling proactive maintenance and data-driven resource allocation. By leveraging spatial risk mapping, the utility can focus monitoring and interventions on blocks with high meter risk, particularly where pressure fluctuations, aged meters, or poor installation practices compromise meter accuracy, billing accuracy and overall financial sustainability.

This study demonstrates how water meter accuracy is influenced by pressure variability, meter class, and age, with negative and very high pressures, older meters, and lower-class meters causing significant under-registration. It introduces a GIS-based Meter Failure Index and risk mapping framework to identify high-risk blocks, enabling targeted maintenance, proactive meter replacement, and smart monitoring. These findings provide a data-driven approach for reducing NRW, improving billing accuracy, and enhancing utility financial and operational sustainability.

5.2.2 Recommendations for Future Research

Meter Installation Position and Hydraulic Conditions: Future studies should investigate the effect of meter placement (e.g., distance from tanks, elbows, and pumps) and pipe orientation on metering accuracy under varying flow conditions. Understanding these influences can guide optimal meter positioning to reduce registration errors.

Impact of Water Levels in Storage Tanks: Research should examine how fluctuations in water levels in elevated and ground storage tanks affect downstream pressure and flow, and consequently, meter performance.

Influence of Pipe Material and Condition: Conduct studies to assess the interaction between different pipe materials (PVC, steel, Hdpe, etc.), pipe ageing, and meter accuracy. This can inform targeted interventions in ageing infrastructure.

Advanced Risk Quantification Methods: Further research should refine risk scoring and mapping methodologies, integrating dynamic hydraulic modeling, historical meter failure data, and environmental factors to improve predictive accuracy.

Longitudinal and Field-Based Studies: There is a need for long-term field monitoring across multiple branches to capture seasonal and operational variations in meter performance, which can help validate bench testing and simulation studies.

Integration with Smart Water Networks: Investigate how combining spatial risk mapping with real-time sensor data (pressure and flow rates) can improve predictive maintenance, optimize NRW reduction strategies, and enhance revenue assurance.

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APPENDICES

Appendix A: Water meter testing bench

Appendix B Data and test bench use authorisation

NATIONAL WATER AND SEWERAGE CORPORATION

TELEGRAMS WATERS KAMPALA
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HEAD OFFICE

P. O. BOX 7053
PLOT 3, Nakasero,
KAMPALA

Ref.: BSS/R&D/23-03

Date: March 23, 2023

The Sen. Manager, NRW Management
NWSC Kampala Water

Re: Permission to carry out research in NWSC – Kampala Water

This is to introduce to you Mr. NUWAHEREZA Richard, a student of Kyambogo University, pursuing an MSc. In Water and Sanitation Engineering, who has been granted permission to carry out research in Kampala Water. His research study is titled ***"Analysis of customer water meter accuracy under various field conditions"***.

The student would like to have access to data on meter performance and management in Kampala. It is expected that the findings from this research will be made available to NWSC and key recommendations beneficial to the corporation will be adopted to improve our operations. In this regard, you are kindly requested to provide him with the necessary access and assistance to enable him successfully accomplish his study. This permission will be valid until the end of June 2023.

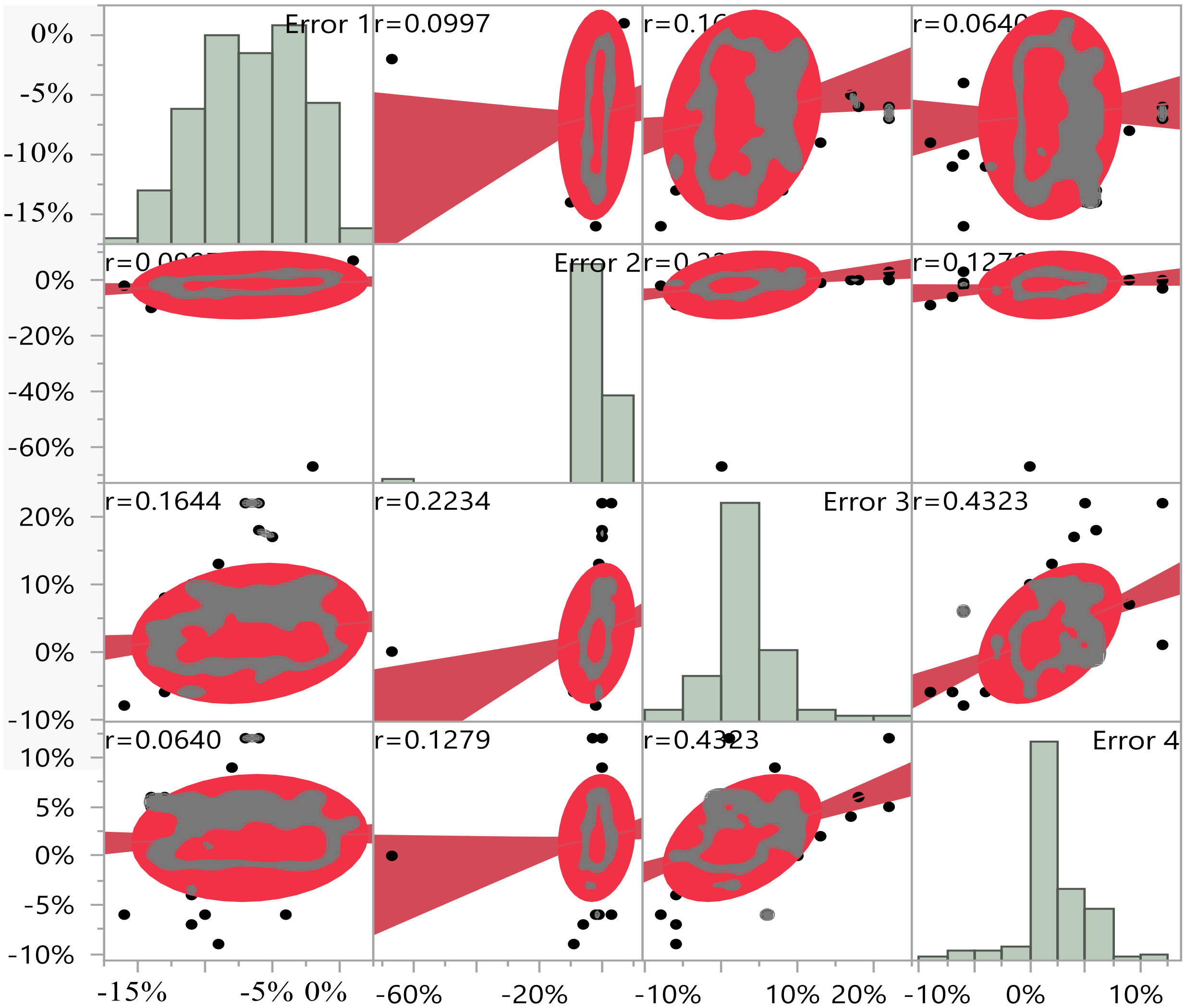
Anticipating your usual cooperation.

Christopher Kanyesigye
Manager, Research and Development

Appendix C: Multivariate correlations of meter errors for class B

	Error 1	Error 2	Error 3	Error 4
Error 1	1.0000	0.0997	0.1644	0.0640
Error 2	0.0997	1.0000	0.2234	0.1279
Error 3	0.1644	0.2234	1.0000	0.4323
Error 4	0.0640	0.1279	0.4323	1.0000

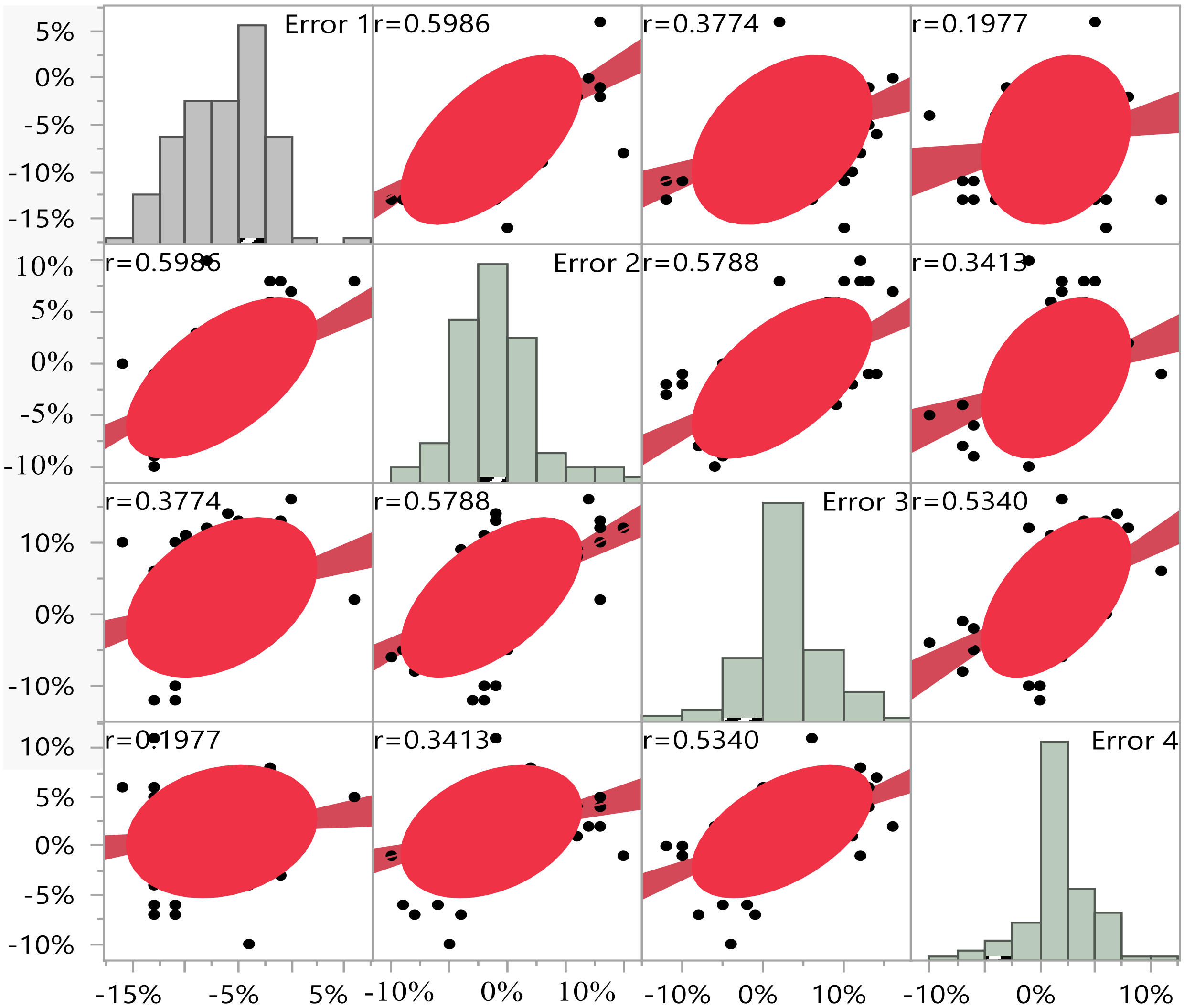
Appendix D: Scatter plot matrix correlation for class B meters



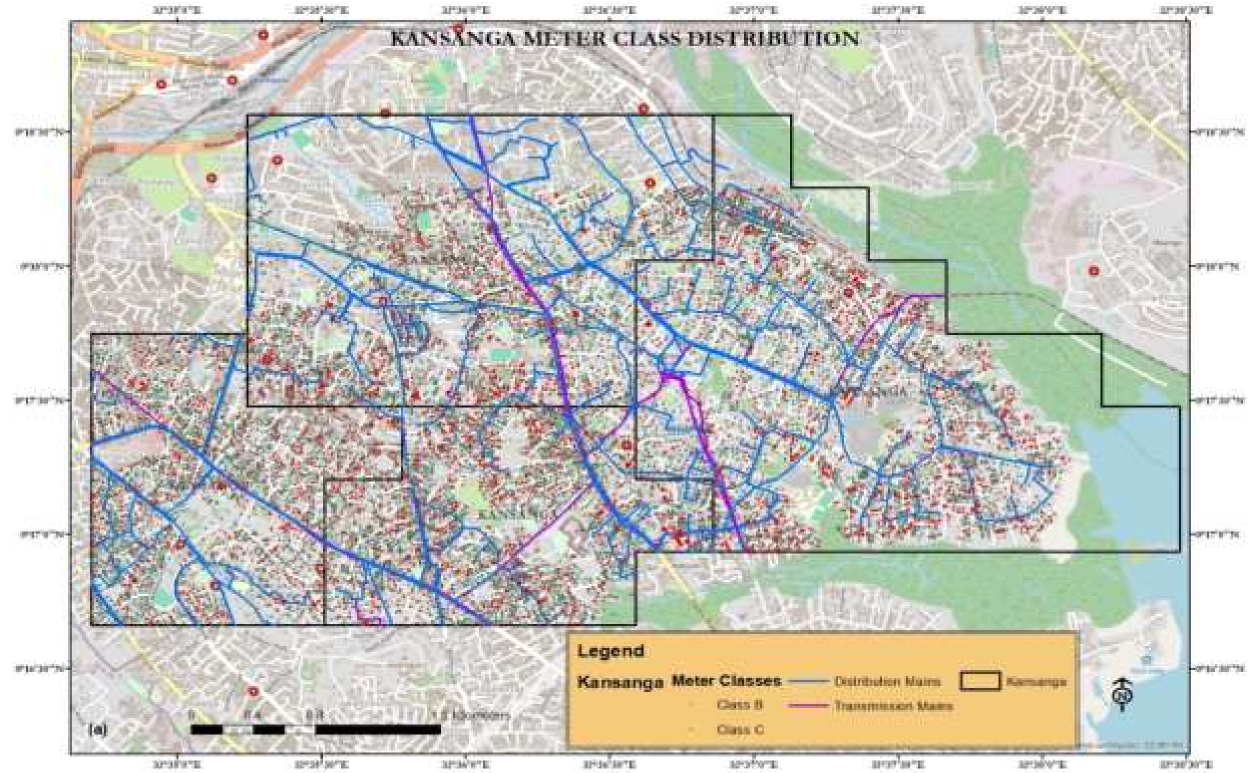
Appendix E: Multivariate Correlations of Meter Errors for Class C

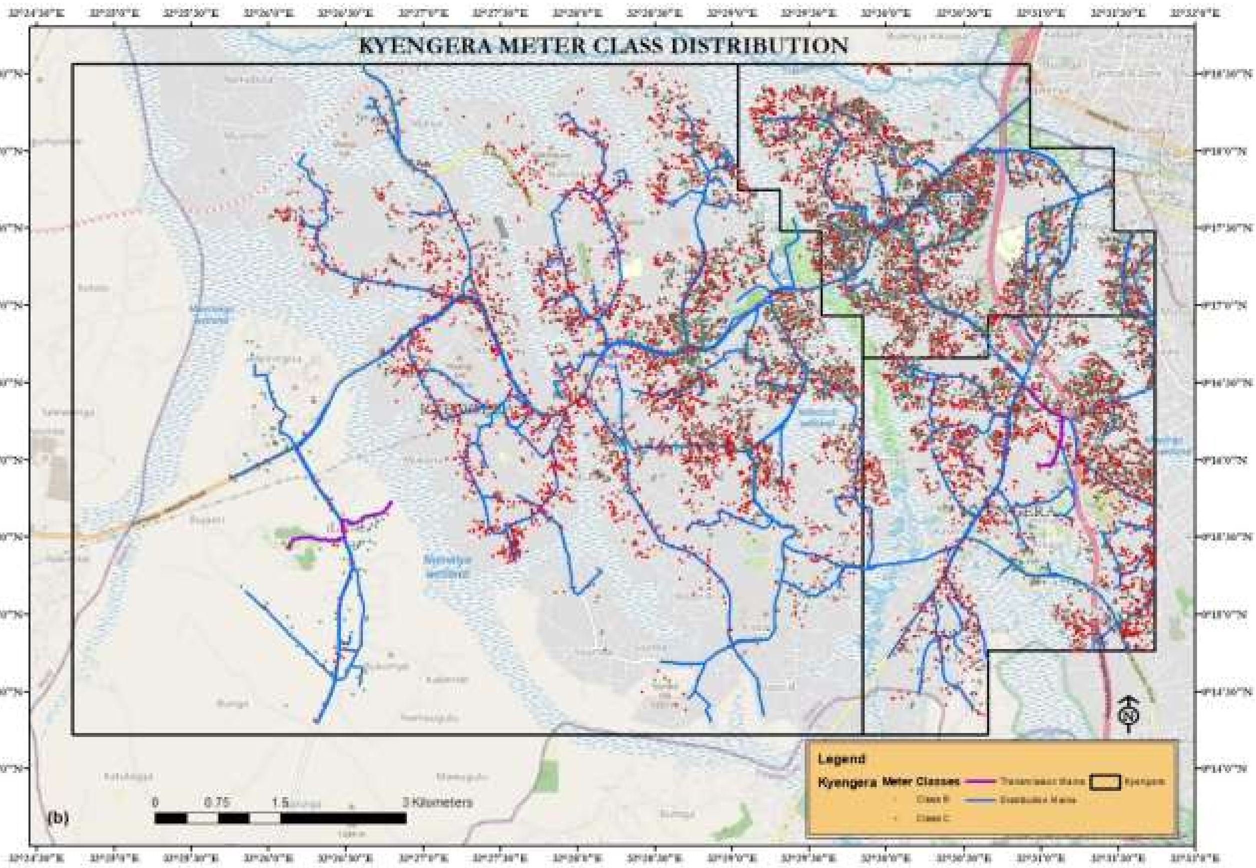
	Error 1	Error 2	Error 3	Error 4
Error 1	1.0000	0.5986	0.3774	0.1977
Error 2	0.5986	1.0000	0.5788	0.3413
Error 3	0.3774	0.5788	1.0000	0.5340
Error 4	0.1977	0.3413	0.5340	1.0000

Appendix F: Scatter plot matrix Correlation for class C Meters



Appendix G; Meter class distribution in the study area





Appendix H: Plagiarism Test Results