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Upgradation of Metering Infrastructure of Low Voltage Distributed Network in Nottingham Road, Kwa-Zulu Natal, South Africa

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ABSTRACT The management of electricity distribution faces numerous challenges, including energy losses arising from technical and non-technical issues such as electricity theft. Energy losses due to theft have a significant global impact, including in South Africa (SA). SA rural areas are suffering from poor voltage, and technical and non-technical losses due to old power system systems. Hence, this research project is a proposal for the upgradation of an old and technically weak network of Nottingham Road, Kwa-Zulu Natal in South Africa. To reduce non-technical losses, this research examines the influence and potential solutions of using smart meters. The paper focuses on modeling real low voltage (LV) distribution systems and the energy meters that measure various parameters of the smart meters. This research also examines the effect of illegal links on the network. However, implementing the smart metering technology for lesser power consumers in developing countries such as South Africa can be challenging because of the greater initial costs. Therefore, this paper investigates the possibility of various technology choices and their return on investment in both urban and rural regions.

INDEX TERMS Distribution Networks, Load shedding, Non-technical Losses, Smart Metering, Power Losses, Energy Losses, Transformer Node

NOMENCLATURE

ADC	Analog to Digital Conversion	NTLs	Non-Technical Losses
DC	Data Concentrator	PF	Power Factor
HES	Head End System	PLC	Power Line Communication
IRR	Internal Rate of Return	SA	South Africa
LV	Low Voltage	TOU	Time of Use
MV	Medium Voltage	UB	Unbalance
NPV	Net Present Value		

I. INTRODUCTION

A. BACKGROUND

Reliable access to electricity is crucial for improving social and economic conditions in many developing nations [1]–[3]. Efforts to provide electricity to rural areas in countries such as China, Brazil, India, and South Africa have increased in the past decade [4]. The South African government has demonstrated a significant commitment to ensuring its citizens have access to electricity through the Integrated National Electrification Program. Though, despite increased investment in the energy division, South Africa experiences significant issues with power reliability and losses [4], [5]. An aging structure of the power stations of the country impedes their ability to generate sufficient electricity to meet the demand of the country. Shortages of electricity have been a continued issue for over a decade, negatively influencing economic activities and disturbing businesses of all sizes. These shortages have contributed to slower economic growth and reduced investor confidence [6], [7]. Technical losses, which result from energy dissipation in the process of distribution and transmission, as well as non-technical losses, which are caused by meter tampering, errors in billing, illegal connections, non-payment, and faulty meters, have a significant impact on utilities. They exacerbate electricity shortages and contribute to an unreliable power supply, which affects the agriculture, transportation, health systems, and overall economy [8]–[13].

Traditionally, South African distribution networks used electromechanical meters to measure customer consumption [14]. However, electronic meters have become the preferred replacement due to their improved accuracy and efficiency. Electronic meters may be pre-paid or post-paid, and also, the split metering technique is accessible, especially in high electricity theft areas [14]. The newest global technique being implemented in the metering situation is smart meters, which provides real-time power consumption data for households. Smart metering has proven effective in controlling electricity theft, reducing power losses, and increasing customer awareness of electricity usage. Utilities can access data from smart meters, manage power consumption levels, apply time-of-use tariffs, and customers can manage their usage patterns accordingly [15], [16]. According to a report, as of July 2014, approximately 50 million smart meters, which accounts for more than 43 percent of the country's total, have been successfully deployed and operational throughout the United States. This figure is projected to experience a consistent upward trend in the coming times [17], [18]. Smart metering uses the communication framework that allows for remote meter evaluation and data management [19]. Within the context of Advanced Metering Infrastructure (AMI), a crucial element known as the meter data management system (MDMS) assumes a vital role. The MDMS functions as a database responsible for the enduring storage and oversight of extensive volumes of consumption data and events. Within the conventional framework of AMI), a centralized MDMS is encircled by the principal operational and managerial services [20], [21]. Figure 1 shows the meter's functional block diagram [22], [23].

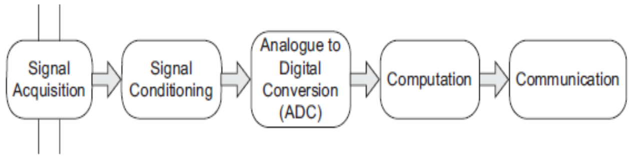

FIGURE 1. Smart meter's functional block diagram [22]

The global impact of non-technical losses (NTLs), which is estimated to be between $80-100 billion per year, was demonstrated by the author in [8]. This not only affects the safety and well-being of the population but also has a significant impact on the economy and environment. NTLs account for an estimated 1.4 trillion kW/h per year, which forces utilities to generate more electricity to meet the demand. In [24], the benefits of smart pre-paid meters for both utilities and end-users were presented, including an increase in electricity consumption, demand, revenue, and a reduction in losses. However, the study had some restrictions, as this was not capable to attain the customer information from the utility. In [25], it was shown that energy losses due to theft are still a major issue in many developing countries, whereas in developed countries, they are relatively small. The poor service quality in Latin America resulted in the government subsidizing electricity to help the population unable to afford the tariffs. Privatization of power division improves competitiveness and reduced NTLs by utilizing better technology to monitor consumption. For instance, the Power Limited Enterprise of North Delhi attained impressive outcomes in lessening energy losses from 85% to 15% from 2002 to 2009 by applying advanced metering infrastructure (AMI) [25], [26]. The major benefits of advanced metering infrastructure technology, including management of outages, power quality, and peak load, are illustrated in [17], [27]. In [28] the capacitated multicommodity flow (CMCF) for AMI strategy for neighboring Area Network is presented. For the increasing population of the smart meters this method gives the flexible solution for deployment and planning of wireless heterogeneous smart metering. Furthermore, due to this methodology it is possible to minimize the infrastructure cost in the heterogeneous network of the smart metering.

B. LITERATURE REVIEW

In [29], the method of communication between smart meters and the head-end system was examined, with Power Line Communication (PLC) being used to send data to the substation's data concentrator. [30] illustrates the crucial role of smart meters in the development of a smart power grid and their contribution to ensuring stable operations. The study utilized a simulated model of smart meters to measure the consumption of power under various loads. In [31] the influence of smart grids on the electrical distribution networks is analyzed, highlighting the differences in implementing smart meters in developed and developing states. [32] demonstrates the cost of executing smart housing technology, and regardless of the initial greater costs, the advantages could potentially compensate expenses in the lifespan of the project. Using NPV (Net Present Value) of the smart economic house model, this study found positive NPVs for all meters, demonstrating the feasibility of the solution. Finally, [33] explores the practical implementation of a smart grid and concludes that investing in minimizing losses and efficient power utilization is more advantageous than investing in equipment to support smart grid technologies. Table 1 presents the summary of the state of the art of the reviewed works.

TABLE 1
CONTRIBUTION OF THE REVIEWED WORK

Reference	Key Contribution
[34]	For the pinpointing electricity theft strategy, a correlation analysis is performed that may effectively recognize the behavior of electricity theft deprived of requiring any labeled information for training or the linearity supposition at the attack node.
[35]	For electricity theft detection in the smart grid frame, this research paper demonstrates the numerous data-driven methodologies.
[36]	Only regular energy usage data are needed to train the model for an anomaly pattern detection technique to detect electricity theft in data streams produced by smart meters.
[37]	Using improved random forest and synthetic minority oversampling techniques, a system is developed for detecting electricity theft.
[38]	A data analysis method for locating and identifying NTL brought on by unauthorized connection to distribution network when smart meters are presents.
[39]	An energy stealing detection algorithm that uses a variety of unique traits to identify the fraudulent users of a power distribution network utilizing data from monthly consumer consumption.
[40]	It advocates leveraging customers' consumption habits to create ensemble machine learning models for the detection of energy theft in smart grids.
[41]	K-nearest neighbor and support vector machine techniques were integrated with a decision tree.
[42]	It investigates the various latest detection methods of electricity theft which can provides the comprehensive and deep understanding of electricity theft related problems.
[43]	To enhance the accuracy of NTL detection, this paper proposed the new data set, the location data of the missing value. The association between the electricity stealing methods and the missing values is examined and the model of neural network is built by neural architecture search.
[44]	For the detection of fraud in LV system, it introduces the self-supervised detection strategy called the NTL detection contrastive predictive coding which can take out the long-term consumption patterns.
[45]	In extremely constrained distribution system, this research paper introduces a revolutionary NTL detection method based on the load estimation.
[46]	In order to deceitfully dodge the existing detectors, a new intermittent electricity theft attack behavior that alternates between stealing electricity and legitimately using it is given in this study. A new machine learning-based detection method is suggested to identify this attack on the basis of the presumption that the labels of intermittent adversaries are not available.
[47]	The Cross-Regional Adaptive Network for cross-regional electricity stealing detection is a suggested adversarial learning-based method for resolving the domain shift issue.
[48]	For the purpose of identifying energy fraud using metering data, a two-stage deep-learning-based approach is presented.

The proposed research presents the up gradation of existing power system network of Nottingham Road, Kwa-Zulu Natal in South Africa. The primary goal of this research is to enhance our understanding of the existing smart metering technology and investigate the best practices implemented globally, particularly in developing countries with comparable distribution networks to South Africa. Additionally, the research aims to gather evidence on crucial factors and insights into the energy losses caused by theft, and how the implementation of smart metering could mitigate its impact and yield benefits. The following are the key objectives of this study:

- This research undertakes a thorough examination of energy losses resulting from theft and their effects on the electrical network system. Furthermore, it investigates the current industry practices and research on smart metering technology that would be the most suitable for the environment of South Africa and establishes a framework for managing smart metering in rural network areas.
- Developing a model of an energy meter capable of measuring multiple parameters similar to a smart meter. The model will then be applied to the case study scenarios to gain a better understanding of how the theft of electricity impacts the low voltage distribution system and how it affects measured parameters.
- The research aims to examine the feasibility of investing in various forms of smart metering communication technology and assess the viability of implementing smart meters in both rural and urban areas.
- The outcomes of this research are of significant value to the power industry and utilities in the field of electrical engineering, not only in the South Africa but also in other developing countries with comparable system layouts and facing similiar NTL challenges. The analysis of feasibility will provide utilities with an improved comprehension of the investment in smart meters' technology and might aid in the development of tools for making informed decisions regarding future smart grid implementation. The findings from the case studies and the lessons learned from the pilot projects will assist in the establishment of best practices for smart metering implementation and enhance the effectiveness of strategies to mitigate energy losses in the future.

The paper is organized as follows: Section 2 delivers an overview of the methodology employed in this study, including a description of each component, data collection, model simulation, as well as case study scenarios and formulas utilized in the feasibility analysis. In Section 3, simulation results and analysis are illustrated, which apply the methodology to Case Studies 1, 2, and 3. Finally, Section 4 presents the research's conclusions and findings.

II. METHODOLOGY

The research paper adopts a methodology that comprises three primary sections:

- Modeling the power system,
- Conducting a comparative analysis of smart metering technologies, and
- Carrying out a feasibility study.

The flow diagram presented in the Figure 2 and the Algorithm 1 illustrates the step-by-step procedure of the methodology from beginning to the end. The selected methodology aims to provide a pragmatic perspective on the implementation of smart metering technology in rural areas.

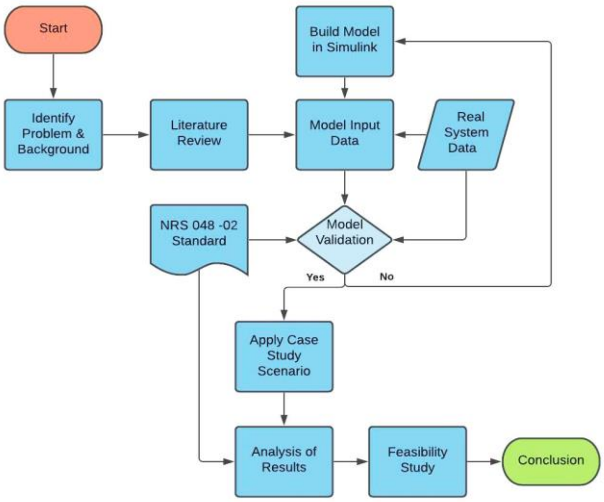

FIGURE 2. Methodology Flow Chart

Algorithm-1. Upgradation of Metering Infrastructure LV Distributed System in Rural Area of SA (Nottingham Road, Kwa-Zulu Natal).

1. Site Selection: Transformer nodes, labeled NTT610 in the rural region in Nottingham Road, located in Kwa-Zulu Natal region of the SA is selected for this project. NTT610 is supplied by an MV/LV step-down transformer, which in turn provides electricity to 9 small power consumer customers (NMD<50kVA);
2. Data Collection: Technical details and characteristics of the MV/LV node of transformer and the substation and were gathered from the software of Small World system utilized through the utility;
4. Model Validation: Validation of the model is performed in the MATLAB/SIMULINK;
5. Quality Standards: Compared the results with NRS 048 Quality Standard [49].
6. If the results of model are in their range specifies by NRS 048 Quality Standards then model accurately represents LV network and the node of transformer of NT610. Otherwise losses are present in the model.

C. SITE SELECTION

This research project is focused on the rural region of Nottingham Road, located in Kwa-Zulu Natal region of the South Africa. The open street map of Nottingham Road, Kwa-Zulu Natal, South Africa is shown in the Appendix A. Specifically, the study examines a zone/node of transformer within the LV distribution system serving the region. The Nottingham Road was chosen due to its characteristics, which include being a rural farming area with households located far apart and few households per transformer node. The Gowrie substation supplies power to the Nottingham Road area, as shown in the Single Line Diagram (SLD) depicted in Figure 3. The Gowrie Substation is comprised of the incoming line of 132kV and the step-down transformer of the 132kV/11kV.

The Gowrie NB21 11kV overhead line is divided into multiple nodes through four 11kV MV feeders. One of these transformer nodes, labeled NTT610 in Figure 4, is the main focus of the model. NTT610 is supplied by an MV/LV step-down transformer, which in turn provides electricity to 9 small power consumer customers (NMD<50kVA).

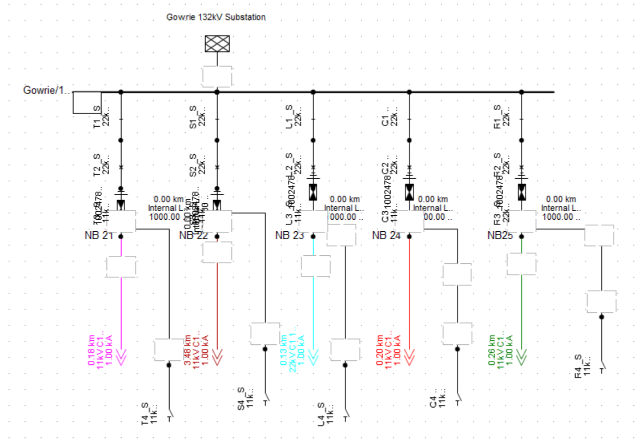

FIGURE 3. **The single line diagram of substation of Gowrie (Power Factory)**

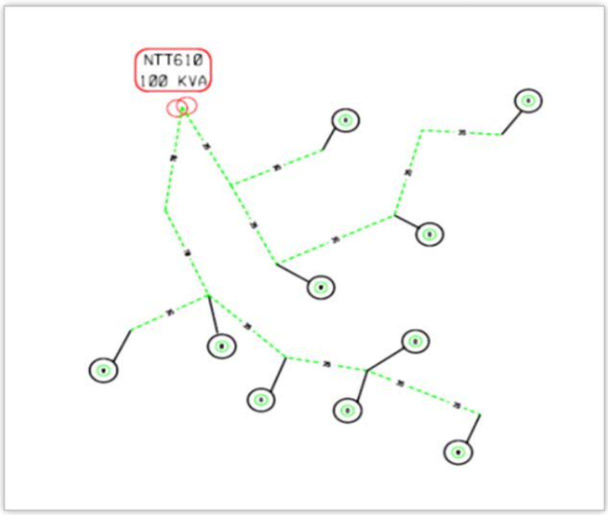

FIGURE 4. **NTT-610 Node of Transformer (The Small World software)**

D. COLLECTION OF DATA

Technical details and characteristics of the MV/LV node of the transformer and the substation and were gathered from the software of the Small World system utilized through the utility. In addition, the monthly consumption records for the 9 households within the node were retrieved from the customers of the utility database and presented in Appendix B. A summary of this records is provided in Table 2.

TABLE 2
THE MONTHLY CONSUMPTION DATA OF CUSTOMERS

	Yearly Consumption kWh	Real system load (W)	Real System Voltage (V)	Real System Current
Household 1	7,946	907	230	3.9
Household 2	17,522	2,200	230	8.7
Household 3	12,703	1,450	230	6.3
Household 4	14,894	1,700	230	7.4
Household 5	12,996	1,480	230	6.4
Household 6	11,564	1,320	230	5.7
Household 7	21,114	2,410	230	10.5
Household 8	13,054	1,490	230	6.5
Household 9	15,595	1,780	230	7.7

E. MODEL CONFIGURATION

Figures 5 and 6 illustrate the proposed model's schematic block diagram and detailed simulation circuit diagram. The distribution sub-station is the power source for the network, with the utilization of ideal voltage source. The chosen parameters conform to the collected real system data specifications. The network of MV is composed of a 3-φ 11kV system with an RL-load representing the remaining network of MV, as in the real network. The load represents several nodes of transformer with a mix of commercial, industrialized, and residential consumers. The MV/LV transformer is attached to a branch of MV network. The node of transformer has a 3-φ 11kV primary winding side and a secondary side with a voltage stepped down to 230V. The transformer used in the simulation is rated at 100kVA with a D/Y configuration, and it supplies nine households, with three households connected to each phase. The model of an energy meter, which is positioned in each connected home, displays parameters that can be observed from the information received at the HES (Head end System) of the smart metering framework. The model of energy meter includes two sub-systems: the measurement system and the load. The load subsystem is simulated using a simply the RL-load, with the parameter of active power set according to the average used data of the real system. The energy measurement subsystem includes voltage and current measurements, which are processed by the block of Fourier to perform a Fourier analysis of input signals. The output of the Fourier block includes two signals for each input signal: magnitude and phase

F. QUALITY STANDARDS

The scope of the study is the evaluation of the South African distribution network, and the benchmark used to assess the outcomes is the NRS 048 Quality standard [49].

1) REFERENCE VOLTAGE

According to the NRS 048 standard, the reference voltage for LV networks (which operate below 1000V) must be the standard phase-to-phase 400V voltages and the phase-to-neutral 230V voltages, as specified in the Rules of Electricity Act, Act:41,1987 [49].

2) COMPATIBILITY LIMITS

The compatibility limits refer to the degree of distribution in which equipment operating in that particular environment must possess immunity within a given margin. The supply agreement contract with the customer may specify otherwise, but the degree of the compatibility levels for supply voltage should fall within the range outlined in Table 3.

The study is centered on LV networks with a standard supply voltage of 230V/400V, which falls under the category of networks with a voltage below 500V. Therefore, the compatibility level for deviation of the supply voltage, as defined in Table 3, is $\pm 10\%$. This value is utilized to verify the results obtained from the Scenario B (case study 1) model, and to match the deviation of voltages from the standard in Scenario B (case study 2).

TABLE 3
DEVIATION FROM STANDARD OR DECLARED VOLTAGES

Voltage Levels (V)	Compatibility Levels (%)
<500V	±10%
>500V	±5%

3) LIMITS OF VOLTAG

Table 4 specifies that for supply if electricity delivered directly to consumers at the voltage lower than the 500V, the allowable range for deviation of voltage should not exceed the $\pm 15\%$.

The voltage utilized in this research is 230V/400V, and in accordance with the standard, the allowable voltage deviation limit of $\pm 15\%$ will be applied to the results of the case study as a reference.

TABLE 4
MAXIMUN DEVIATION FROM STANDARD OR DECLARED VOLTAGES

Voltage Levels (V)	Limit (%)
<500V	±15%
>500V	±10%

4) VOLTAGE UNBALANCE

As per the standard, LV, MV, and HV three-phase networks must adhere to a compatibility level of 2% for voltage unbalance, with an unbalance voltage limit of 3% constantly. To determine unbalance, equation below can be used along with the instantaneous measurement of the three line-to-line RMS voltages.

$$UB = \sqrt{\frac{1-\sqrt{3-6\beta}}{1+\sqrt{3-6\beta}}}\ x\ 100 \tag{1}$$

Where,

$$\beta = \frac{{V_{ry}}^4 + {V_{yb}}^4 + {V_{br}}^4}{({V_{ry}}^2 + {V_{yb}}^2 + {V_{br}}^2)^2}$$

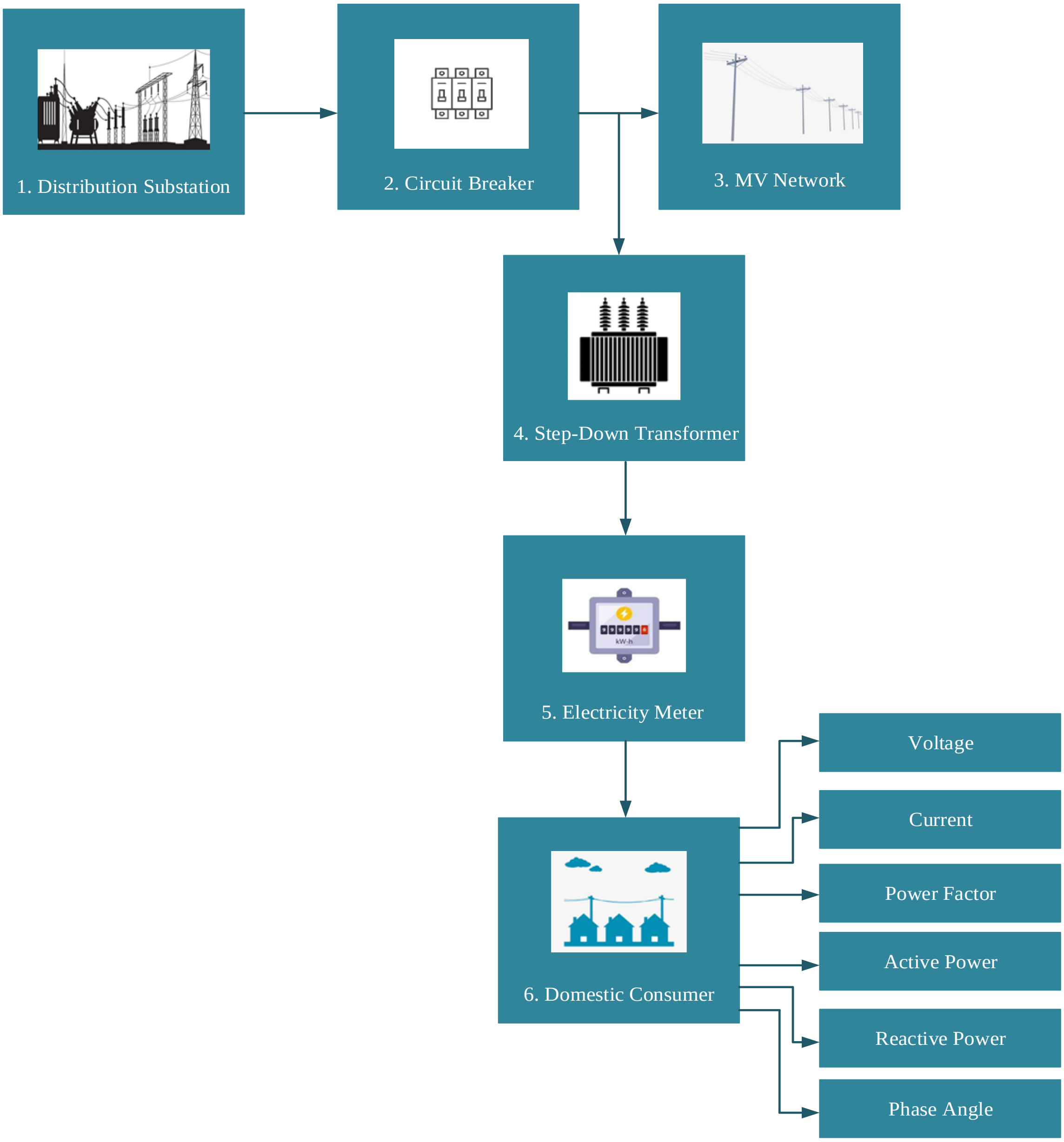

FIGURE 5. **Schematic Block Diagram of the Model**

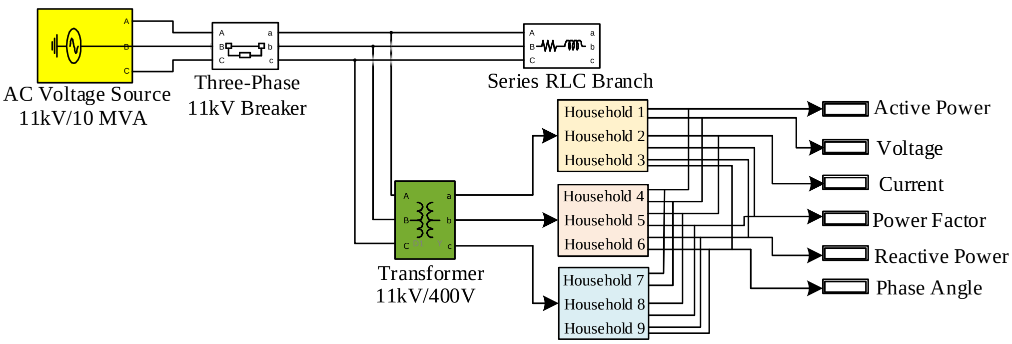

FIGURE 6. **Circuit diagram of the proposed model**

Where, V_{ry}, V_{yb} and, V_{br} are the line voltages of the respective phases.

To assess compliance with the standard's compatibility level and limit, Equation 1 will be employed in calculating the unbalance for both case study 1 and case study 2. After calculation, the outcomes will be matched to the prescribed limits

G. FEASIBILITY ANALYSIS

1) SCENARIO A

In first study, Scenario A, three types of metering solutions are compared: a traditional electronic meter, the smart meters using PLC/RF to link to a DC, and the standalone smart meter using a module of GSM. To determine most cost-effective option, both the cost of the meter itself and the installation cost are taken into account, with data provided by Landis & Gyr, the manufacturer and utility. The prices for the smart meters will continue to be valid for a period of 3-years, as per the supply contract with the manufacturer. Feasibility analysis in this scenario may guide utility in selecting the most viable technology based on the consumer's number in a node of transformer.

The feasibility study compares two kinds of communication way out for smart metering, namely:

1. A RF/PLC based smart meter and connects to a DC (data concentrator) for connection to the Head End System.
2. A stand-alone smart meter using a module of embedded GSM that connects directly to the Head End System.

The price of each type of meter is analyzed in conjunction with the number of households, as numerous smart meters may connect to the single DC. While DC may be costly, their services are applicable in larger areas with a higher concentration of households, making them a more practical solution.

To compute the feasibility of first study, the subsequent formula is utilized:

Option 1:

$$C_n = \sum_0^n C_{dc} + (nC_1) \tag{2}$$

Where, C_n represents the cost for the total number of selected households, while C_{dc} denotes the cost of a single data concentrator, and C_1 represents the cost of a smart meter that connects to the data concentrator. The value of "n" refers to the number of households selected for analysis.

Option 2:

$$C_n = \sum_0^n nC_2 \tag{3}$$

Where, C_n represents the cost of the total number of households selected, while C_2 denotes the cost of a standalone meter in option 2. The number of households to be analyzed is denoted by "n," and all values are expressed in South African Rands (ZAR). As of March 2021, the average exchange rate between ZAR and USD was 14.965 (ZAR/USD). The study involves incrementally increasing the quantity of houses in a node of transformer by one and applying the formulas for both the option 1&2. The outcomes are then investigated to compare the costs of the both options and determine the most cost-effective solution

2) SCENARIO B AND SCENARIO C

In the feasibility analysis of the Scenario B & C, the period of payback and return on the investment for the utility are being analyzed. To compare the feasibility and return on investment between upgrading smart meters in urban and rural areas, various factors must be taken into account. These factors include:

- The price of the primary investment for upgrading,
- The houses consumption where the meters are being upgraded,
- The kW/h price,
- The average annually rises in tariff of electricity,
- The worth of money over time, the total houses at a node of transformer in both urban and rural areas, and
- The energy losses.

Despite the considerable upfront and ongoing expenses associated with the implementation of smart metering technology, advantages might potentially compensate the costs over the lifespan of the project. To determine this, the feasibility study will utilize economic concepts as below:

- Net Present value (NPV),
- The payback period, and
- Internal rate of return (IRR).

These concepts are deemed reliable indicators that can lead to secure conclusions regarding the project's economic feasibility.

a) Net Present Value

To ensure the feasibility study's reliability, it is crucial to analyze the time value of money. To assess the project's individual profitability, the NPV calculation is employed, which involves estimating future cash flows over a specified time frame[32]. One of the benefits of this technique is that it reflects the real cash flow via considering discount rate. In this study, discount rate used will be the rate of inflation in the SA, which is determined via historical and the predicted values outlined in Appendix F. To determine the net present value of the investment, the following formula may be utilized.

$$NPV = \sum_{i=1}^{n} \frac{FV}{(1+i)^n} \tag{4}$$

Here, the FV and NPV represents the future value of cash flow and the present value in Rands (R). The discount price, denoted as "i" and represented in a percentage, and the period of time in years, denoted as "n," are also taken into account. It is important to consider the value of money over time when comparing any parameter over a period of time, including the yearly revenue, IRR, and period of payback.

b) Payback Period

The period of payback is a valuable tool for evaluating a project's feasibility by calculating the length of time, usually in years, necessary to recover the initial investment. This method is commonly employed due to its simplicity and effectiveness in assessing investment risk [33]. However, the period of payback has certain restrictions as it does not consider the money's time value. For Scenario B, the payback time may be calculated using the formula below:

$$Payback\ Period = \frac{C_{PT}}{I_{AR} - C_{OP}} \quad (5)$$

Where, C_{PT} represents the price of total project price, I_{AR} represents income in terms of annual revenue, and C_{op} represents the annual operating costs.

c) Internal Rate of Return

The IRR is a metric utilized to evaluate the investment and net benefits of a project, expressed as a yearly rate. It may be determined by utilizing the subsequent formula. [32]:

$$0 = NPV = \sum_{n=0}^{N} \frac{CF_n}{(1+IRR)^n} \quad (6)$$

Which then gives the following,

$$0 = NPV = CF_0 + \frac{CF_1}{(1+IRR)^1} + \frac{CF_2}{(1+IRR)^2} + \frac{CF_3}{(1+IRR)^3} + \frac{CF_4}{(1+IRR)^4} + \ldots \frac{CF_n}{(1+IRR)^n}$$

Where, CF_0represents the preliminary investment, $CF_1, CF_2, CF_3 .. CF_n$, represent the cash flows, *n* represents the yearly duration, *N* represents the period of holding, *NPV* represents the net present value, and *IRR* represents the internal rate of return.

In the 1st Option, the rural region selected for the example will be Nottingham Road zone transformer node, that was before utilized in 1 & 2 case study. The study will consider average annual usage of 9 households, which will increase depend on the average rise in tariff over the past 10 years.

In the 2nd Option, the example will focus on an urban area consisting of a node of transformer connected to 45 houses. This is usual for urban areas with up to hundred houses, particularly those in densely populated regions.

d) Upgradation of the cost of project

When determining the cost of upgrading to smart metering, various factors are taken into account, such as the cost of the meters, DC, further metering framework (including kiosks, din rails, and installation materials), fees of designing, and cost of commissioning and installation. These costs are obtained from a utility costing tool that relies on contract prices from manufacturers and agreed-upon labor rates with contractors for installation. It must be observed that the cost analysis does not include the prices of the Head End System, as the study is focused on the local region, and the HES is the national frame.

e) Yearly Revenue

Formula below is used to calculate the annual cost of electricity consumption based on the accumulative consumption for one year in rural and urban areas:

$$Total\ yearly\ Revnue = yearly\ Consumption\ x\ (\ a + \ t_i\ )^n\ x\ (1 + i)^n \quad (7)$$

Where, the Yearly consumption indicates the accumulative consumption for 1 year (KW/hrs), current cost per *kW/hr.* is represented by a, t_i indicates the increase in tariff per year, the year is represented by *n*, and *i* represents the interest per year because of inflation.

The relevant tariff increase and rates are available in Appendices C and D, respectively.

III. SIMULATION RESULTS AND ANALYSIS

The distribution network being modeled is relatively simple and can be constructed using logical function blocks to build the meter and power system. MATLAB/Simulink was chosen as the software for modeling because it has specialized power system blocks that are suitable for 3-phase distribution systems, as well as electronic components that can be used to model electronic energy meters [50]. The research utilizes the MATLAB/Simulink model presented in Figure 6 for analysis, which is further explained in Section 2.

The proposed research includes three case studies. Case Study 1 compares the results obtained from the model after metering upgrade with the actual system data. Two scenarios were analyzed in this study:

- **Scenario A**: This scenario presents the actual system data before metering upgrade.
- **Scenario B:** This scenario reviews the results obtained from the model after metering upgrade and compares them with the actual system data outcomes.

The 2nd Case Study of proposed research focuses on comparing the results of model with and without the losses in energy caused by theft of electricity. That is accomplished by adding a load to 2 phases of the system. After that the results are examined against actual data of the system and NRS 048-02 quality standards. Two scenarios are studied in this case:

- **Scenario A:** This scenario presents the model results without any theft of electricity.
- **Scenario B:** This scenario represents the results of model with the extra load indicating the theft of electricity. The results are then compared to the actual data of system and NRS-048-02 quality standards.

In the 3rd Case Study of proposed research involves comparing the possibility of various communication technologies and investigate the optimal numeral of standalone meters using modules of embedded GSM versus smart meters using DC. Additionally, it calculates the required time for the primary upgrade investment to surpass accumulated costs in Scenario B. The IRR is also examined in Scenario C. The study includes the following three scenarios:

- **Scenario A:**
    - **Option 1:** Compares the price of standalone meters using GSM modules to the number of consumers.
    - **Option 2:** Compares the price of smart meters linked to data concentrators to the number of consumers.
- **Scenario B:** Deliberates only two features, the payback duration of the cost of upgrade project versus revenue over a specific duration of time for both rural and urban regions. The both Option 1 & 2 are applied in the Scenario B.
    - **Option 1:** Determines the payback duration of investment versus yearly revenue over time in the rural region.
    - **Option 2:** Determines the payback duration of investment versus yearly revenue over time in the urban region.
- **Scenario C:** Deliberates multiple cost and benefit aspects and quantifies them in the calculations of IRR.
    - **Option 1:** Calculates the return on the primary investment in the rural region.
    - **Option 2:** Calculates the return on the primary investment in the urban region.

A. CASE STUDY 1

1) SCENARIO A

In this Scenario of the proposed research, data is collected from the actual network, including the field records from the equipment presently installed on site. Collected data comprises the ratings of equipment and consumption information from each of the 9 houses situated on transformer node in Nottingham. Table 5 below presents the collected data.

Based on the field data, it is evident that there are nine households connected to the NTT610 transformer node. These households are spread across the LV network, with three households connected to each phase (Phase a, b, and c). The rated voltage of the LV output of the transformer is supplied to each household.

2) SCENARIO B

In this scenario of the proposed research, a simulation model is used to obtain results from the nine energy meters installed in each of the households. The parameters taken by model include real and reactive power, PF, current, phase angle, and voltage, with recorded results presented in Table 6 for each phase.

It is observed from the outcomes that the model of energy meter for every house effectively measures the electrical parameters. The comparison between the outcomes obtained in Scenario A & B reveals less than the 1% deviation between the data of real network and the results noted from model.

Table 7 compares the outcomes obtained from Scenario A (real network data) and Scenario B (model outcomes) in terms of load, voltage, and current. It can be observed that the deviation values range from 11-31 percentile, indicating a minimal difference between the real and modeled data. Based on this finding, it may conclude that according to the 1st criteria the model is valid. Moreover, the voltage is balanced across all three phases, which satisfies the 2nd criteria. Voltages are within the compatibility levels of less than 5% and in the voltage limits of +_15%. Therefore, it may be inferred that model accurately represents LV network and the node of transformer of NT610 in the Nottingham Road zone.

B. CASE STUDY 2

The presented case study showcases the results of a modeled system with and without the occurrence of electricity theft.

1) SCENARIO A

Table 6 presents the results of the energy meters installed at the 9 households in Scenario A, which reflects a typical operating state where the system is designed based on load profiles.

2) SCENARIO B

The 2nd Case study introduces scenario B, which simulates theft of electricity theft 2 phases, Phase A & B, by adding 7 additional loads of 2kW each to the model. The outcomes of this scenario are presented in Table 8, revealing voltage and current variations across all phases. The deviation between the model and real system data ranges from 11% to 31%. Additionally, the modeled system results are compared to the NRS standard, and the deviation is also displayed in Tables 9 and 10.

The second case study aims to analyze the influence of NTLs resulting from theft of electricity. The outcomes indicate that the extra load on phases a & c causes changes to whole network. One noticeable change is the unbalanced load on every phase of system, resulting in different measurements of load. The 2nd observation is the rise in current. The 3rd observation is the reduction in voltage on phases “a” & “b”, where illegal linkages are present, and the rise in voltage on phase “c” deprived of any illegal connections. These changes cause an unbalanced voltage on each phase, potentially leading to network faults or tripping and poor quality of supply.

As per the NRS-048-02 standard, the analysis indicated that the deviation of voltages on all phases surpassed both 15% limits of voltage and the 5% compatibility level of voltage. Moreover, the unbalanced voltages of the system, calculated using Equation (1), was found to be 35.6%, which is significantly higher than the required voltage balance limits of 3% and 2% compatibility levels stated by the NRS 048 standard.

The accessibility of information from smart meters which can be remotely accessed at any time presents an opportunity to analyze trends in current, voltage, and unbalanced systems. This data can be valuable for detecting illegal activity and managing loads on networks.

C. CASE STUDY 3

1) SCENARIO A

The third case study examines viability of upgrading smart metering. Specifically, Scenario A compares costs of the two smart metering choices to determine the more practical technology based on the number of consumers in the node of transformer. In both Option 1 & 2, the expenses are limited to equipment costs, which are presented in Table 11, while a comprehensive cost breakdown can be found in Appendix C.

Figure 7 displays a graph that compares the cost of technology Options 1 & 2 based on the number of consumers per transformer region. The graph reveals that utilizing a stand-alone meter using a module of GSM is more cost-effective than utilizing a DC when the consumers are <7. It is because of the higher initial price of the DC in comparison to the stand-alone meter using the module of GSM. However, when the consumer's increases, the cost per household consumer for a stand-alone meter becomes more expensive, as its cost is almost twice that of a smart meter without the module of GSM. In contrast, since a DC may be utilized for a larger number of household consumers per transformer node, only one data concentrator is required, and the increase in cost would be because of the accumulative price of the smart meters without the module of GSM as the numeral of consumers increases. So, the findings suggest that Option 1, which involves using a data concentrator with smart meters using RF/PLC, is a better practical choice if there are greater than 7 houses linked to a node of transformer. On the other hand, if the number of households connected to a transformer zone is less than 7, then Option 2, GSM module based stand-alone meter, is more feasible. These results may assist utilities in selecting the appropriate technology when evaluating various transformer zones, especially in rural areas with fewer customers per transformer node.

2) SCENARIO B

This Scenario involves computation of the period of the payback against annual revenue. The yearly revenue and primary investment are estimated based on the collected costing data. To consider the time value of money, the NPV equation is applied to all values. The comparison is made between two options for upgrading meters: Option 1 pertains to a rural area network consisting of 9 households, while Option 2 relates to an urban area network comprising 45 customers.

a) **Option 1: Rural Area**
Table 12 presents the initial investment cost, while the annual revenue cash flow per year is computed and can be found in Table 13. The annual revenue incorporates yearly consumption and tariff increases, as illustrated in Table 13. Table 14 displays the net present value of the yearly revenue and preliminary investment. Based on Figure 8, the period of the payback for the primary investment of upgrading a rural system consisting of 9 households can be observed to be 1.5 years when compared against the annual revenue.

b) **Option 2: The Urban Region**

c) The payback time is also determined for the urban region with 45 customers in this research. The consumption trend for urban customers is assumed to be the identical as for rural consumers. Table 15 indicates the primary investment cost for the urban zone, while Table 16 displays the annual cash flow revenue from electricity consumption sales with compounded tariff increases. The net present value of the primary investment and the yearly revenue for the urban region is presented in Table 17. Figure 9 shows the period of payback of the preliminary investment against the yearly revenue. This may be observed that the period of the payback for capitalizing in smart meters in the urban region with the node of transformer containing 45 consumers and identical consumption configuration just like the rural sector consumers is one year. Afterward the first year of investment, annual revenue reflects a return, demonstrating that the capitalizing in the smart metering technology is the viable choice.

The comparison of preliminary investment and yearly revenue for both rural and urban areas reveals a payback period of less than 2 years after investment. In the case of rural regions, the payback duration is the 1.5 years afterward the preliminary investment, while for the urban regions, it is the 1 year. it demonstrates that the advancement to the smart meter is a viable choice. Additionally, there are additional benefits such as lessened repairs and substitutions of cheap electronic meters, decreased revenue loss from defective meters, saves energy resulting from less electricity theft, and decreased meter reading price. Although these advantages might contribute to the yearly cash flow as savings, they are not involved in this research. Also, it is assumed that the HES and meter data management system price are not considered since they are invested nationally and might not affect a local task.

3) SCENARIO C

Scenario C in Case Study 3 examines the rate of the return on the investment, which are measured by the IRR (internal rate of return). This metric takes into account the primary investment and the whole benefits of the smart metering upgrade project, expressed as an annual rate. The calculation of the IRR is done using Equation (6), and the cash flows from Table 18 can be used to compute it.

a) **Option 1: Rural Area**
According to the outcomes of the calculation, the IRR on investment for a rural sector with 9

households was 50% over a period of 10 years. This rate of return is considered favorable for utilities since a higher internal rate of return over a longer period of time would be more advantageous for them to invest in.

b) Option 2: Urban Area

Based on the outcomes, it may be concluded that for an urban area with 45 households, the IRR on the investment in smart metering is 107%, which is a very favorable return. A high rate of return like this indicates that the investment in smart metering would yield positive results in the long run for the utility company.

Comparing the IRR between rural and urban areas, the results show that the IRR for urban areas is twice as high as that for rural areas. This finding is significant as it can help utilities prioritize which area networks to invest in first based on the expected return on investment.

TABLE 5
REAL SYSTEM DATA OF 9 HOUSES LOCATED IN THE NOTTINGHAM REGION ON THE NODE OF TRANSFORMER

Household	Phases	Voltage (V)	Current (A)	Load (W)
1	a	230	3.9	907
2	a	230	8.7	2,000
3	a	230	6.3	1,450
4	b	230	7.4	1,700
5	b	230	6.4	1,480
6	b	230	5.7	1,320
7	c	230	10.5	2,410
8	c	230	6.5	1,490
9	c	230	7.7	1,780

TABLE 6
MODEL RESULTS OF ENERGY METER PARAMETERS

Household	Phases	Voltages (V)	current (A)	Phase Angle	PF	Real Power (W)	Reactive Power (VAR)
1	a	228.9	4.64	0.56	0.85	896.8	568.20
2	a	228.9	8.66	0.15	0.99	1,960	291.70
3	a	228.9	6.28	0.20	0.98	1,408	290.00
4	b	229	7.36	0.18	0.98	1,658	299.10
5	b	229	6.40	0.20	0.98	1,436	297.70
6	b	229	5.71	0.23	0.97	1,274	297.10
7	c	227.8	10.38	0.10	0.99	2,352	233.50
8	c	227.8	6.42	0.15	0.99	1,444	224.00
9	c	227.8	7.67	0.13	0.99	1,732	223.90

TABLE 7
MODEL RESULTS COMPARED TO REAL SYSTEM DATA

Household	Real Power (W)	Real system Load (W)	Deviation (%)	Model Voltages (V)	Real network Voltages (V)	Deviation (%)	Model Current (A)	Real network Current (A)	Deviation (%)
1	896.8	907	1.1%	228.9	230	0.5%	4.0	3.9	2.4%
2	1,960	2,000	2.0%	228.9	230	0.5%	8.7	8.7	0.4%
3	1,408	1,450	2.9%	228.9	230	0.5%	6.3	6.3	0.4%
4	1,658	1,700	2.5%	229	230	0.4%	7.4	7.4	0.4%
5	1,436	1,480	3.0%	229	230	0.4%	6.4	6.4	0.5%
6	1,274	1,320	3.5%	229	230	0.4%	5.7	5.7	0.5%
7	2,352	2,410	2.4%	227.8	230	1.0%	10.4	10.5	0.9%
8	1,444	1,490	3.1%	227.8	230	1.0%	6.4	6.5	0.9%
9	1,732	1,780	2.7%	227.8	230	1.0%	7.7	7.7	0.9%

TABLE 8
MODEL RESULT WITH AND ILLEGAL CONNECTION

Household	Phases	Voltages (V)	Current (A)	Phase Angle	PF	Real Power (W)	Reactive Power (VAR)
1	a	181.8	3.68	0.60	0.82	548.9	362.70
2	a	181.8	6.87	0.16	0.98	1,233	206.60
3	a	181.8	4.99	0.22	0.97	883.3	201.70

4	b	204.2	6.56	0.19	0.98	1,314	259.20
5	b	204.2	5.71	0.22	0.98	1,137	258.60
6	b	204.2	5.09	0.25	0.97	1,007	258.00
7	c	298	13.58	0.09	0.99	4,027	400.40
8	c	298	8.40	0.16	0.99	2,470	399.10
9	c	298	10.03	0.13	0.99	2,962	399.60

TABLE 9
RESULTS COMPARED TO STANDARD LIMITS

	No illegal	**With Illegal**		**No Illegal**	**With Illegal**		**No Illegal**	**With Illegal**	
Household	Active Power (W)	Active Power (W)	Load Deviation	Model Voltage (V)	Model Voltage (V)	Load Deviation	Model Current (A)	Model Current (A)	Load Deviation
1	896.8	548.9	39%	228.9	181.8	21%	4.64	3.68	21%
2	1960	1233	37%	228.9	181.8	21%	8.66	6.87	21%
3	1408	883.3	37%	228.9	181.8	21%	6.28	4.99	21%
4	1658	1314	21%	229	204.2	11%	7.36	6.56	11%
5	1436	1137	21%	229	204.2	11%	6.40	5.71	11%
6	1274	1007	21%	229	204.2	11%	5.71	5.09	11%
7	2352	4027	-71%	227.8	298	-31%	10.38	13.58	-31%
8	1444	2470	-71%	227.8	298	-31%	6.42	8.40	-31%
9	1732	2962	-71%	227.8	298	-31%	7.67	10.03	-31%

TABLE 10
RESULTS DEVIATION TO VOLTAGE AND COMPABILITY LIMITS

Household	**Phases**	**Voltages of Model (V) having illegal connections**	**Voltage Limits**	**Compatibility Level**	**Deviation**
1	a	181.8	195.5-264.5	207-253	21%
2	a	181.8	195.5-264.5	207-253	21%
3	a	181.8	195.5-264.5	207-253	21%
4	b	204.2	195.5-264.5	207-253	11%
5	b	204.2	195.5-264.5	207-253	11%
6	b	204.2	195.5-264.5	207-253	11%
7	c	298	195.5-264.5	207-253	-30%
8	c	298	195.5-264.5	207-253	-30%
9	C	298	195.5-264.5	207-253	-30%

TABLE 11
COST OF OPTION 1 AND OPTION 2

Meters cost for the Option 1 & 2			
	Item	**Explanation**	**Unit Charge (R)**
Option 1	**Smart Meter**	E460 Landis & Gyr DIN Rail Single Phase PLC Smart Split Meter with CIU up to 80A	1,207
	DC	DC450 Gateway/Data Concentrators (DCU) + Internal/Plug - in GSM Modem	9,338
Option 2	**Smart Meter**	E460 Landis & Gyr BS Standard with plug in GSM modem Split Meter with CIU up to 80A	2,624

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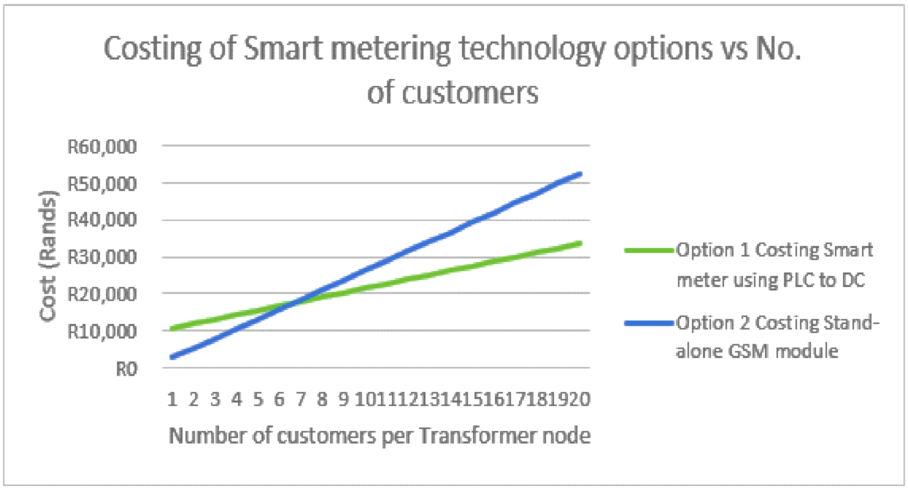


FIGURE 7. **The Costing of the Smart meter technology versus the number of consumers**

TABLE 12
PROJECT COSTING FOR RURAL AREA [1]

Category	Item	Quantity	Unit Price (R)	Total Price (R)
	Smart Meters	9	1,207	10,863
	DC	1	9,338	9,338
Material	Metering Structure	2	22,500	5,000
	Cable and Accessories	9	1,200	10,800
	Grand Total			36,001
	Fees of Design	1	200,000	200,000
Project Price	Project Management	1	150,000	150,000
	Grand Total			350,000
	Installation	9	5,000	45,000
	Transportation	9	1,000	9,000
Labour	Commissioning	9	1,500	13,500
	Grand Total			67,500
	Project Total Cost			453,501

TABLE 13
ANNUAL REVENUE INCLUDING TARIFF INCREASES

	Yearly 8% increase in Tariff (R)	Yearly Revenue (R)
Year 0	15,680	195,995
Year 1	16,934	211,674
Year 2	18,289	228,608
Year 3	19,752	246,897
Year 4	21,332	266,648
Year 5	23,038	287,980
Year 6	24,882	311,019
Year 7	26,872	335,900
Year 8	29,022	362,772
Year 9	31,344	391,794
Year 10	33,851	423,138

TABLE 14
SHOWS ACCUMULATED REVENUE AND INVESTMENT OVER TIME

	NPV of Collected Revenue (R)	NPV of Investment (R)
Year 0	181,932	453,501
Year 1	378,074	434,055
Year 2	589,801	415,284
Year 3	818,466	397,401
Year 4	1,065,423	380,288
Year 5	1,332,138	363,912
Year 6	1,620,189	348,241
Year 7	1,931,285	333,245
Year 8	2,267,269	318,895
Year 9	2,630,131	305,163
Year 10	3,022,022	292,022

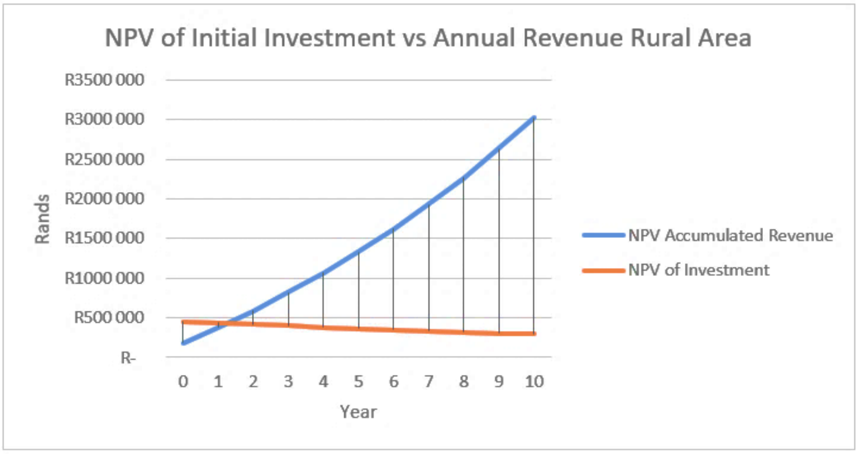


FIGURE 8. The Payback duration of the NPV of revenue and investment over time

TABLE 15
PROJECT COSTING FOR URBAN AREA

Classification	Components	Quantity	Unit Price (R)	Entire Cost (R)
Particulars	DC	1.00	9,338	9,338
	Smart Meters	45.00	1,207	54,315
	Metering Infrastructure	5.00	2,500	12,500
	Grand Total			76,153
Project Price	Fees of Design		350,000	350,000
	Project Management		250,000	250,000
	Grand Total			600,000
Labour	Transport	45.00	1,000	45,000
	Installation	45.00	5,000	225,000
	Commissioning	45.00	1,000	45,000
	Grand Total			315,000
	Project Total Cost			991,153

TABLE 16
ANNUAL PROFITS FOR THE URBAN REGIONS WITH THE TARIFF INCREASES

	Yearly 8% increase in Tariff (R)	Total Yearly Revenue (R)
Year 0	7,892	986,550
Year 1	85,238	1,065,474

Year 2	92,057	1,150,712
Year 3	99,422	1,242,769
Year 4	107,375	1,342,190
Year 5	115,965	1,449,566
Year 6	125,242	1,565,531
Year 7	135,262	1,690,773
Year 8	146,083	1,826,035
Year 9	157,769	1,972,118
Year 10	170,391	2,129,887

TABLE 17
CALCULATED NPV OF INVESTMENT AND REVENUE

	NPV of the Investment (R)	NPV of Collected Revenue (R)
Year 0	991,153	915,767
Year 1	948,653	1,903,059
Year 2	907,628	2,968,797
Year 3	868,544	4,119,793
Year 4	831,143	5,362,870
Year 5	795,352	6,705,392
Year 6	761,102	8,155,316
Year 7	728,327	9,721,234
Year 8	696,964	11,412,426
Year 9	666,951	13,238,913
Year 10	638,231	15,211,519

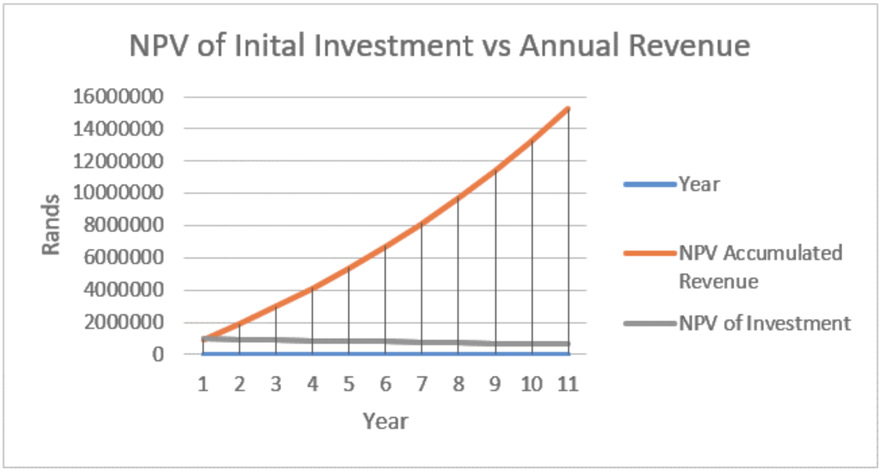


FIGURE 9. The Payback duration of annual revenue and NPV investment over time in an urban region

TABLE 18
THE NPV OF THE CASH FLOWS AND THE INITIAL INVESTMENT OVER TIME ALONG WITH THE IRR VALUE

	Urban Area	Rural Area
Initial investment (R)	- 991,153	- 453,501
Cash Flow_1 (R)	986,550	195,995
Cash Flow_2 (R)	1,065,474	211,674
Cash Flow_3 (R)	1,150,712	228,608
Cash Flow_4 (R)	1,242,769	246,897
Cash Flow_5 (R)	1,342,190	266,648
Cash Flow_6 (R)	1,449,566	287,980
Cash Flow_7 (R)	1,565,531	311,019

Cash Flow_8 (R)	1,690,773	335,900
Cash Flow_9 (R)	1,826,035	362,772
Cash Flow_10 (R)	1,972,118	391,794
IRR	**107%**	**50%**

IV. CONCLUSION

SA rural areas are suffering from poor voltage, and technical and non-technical losses due to old power system systems. Hence, this research project is a proposal for the upgradation of an old and technically weak network of Nottingham Road, Kwa-Zulu Natal in South Africa. This study examines the issue of power loss in South Africa and explores how the implementation of smart metering could help mitigate this problem. It provides background information on the causes and impacts of power losses on the electricity grid, power utilities, and legitimate customers. The study uses a methodology that involves gathering actual field data to create a model of a low-voltage distribution system transformer located in South Africa (Nottingham Road, Kwa Zulu Natal). The accuracy of the system is confirmed by comparing it to real-world data and the NRS-048 PQ standard. Several case study situations were conducted, and the subsequent outcomes are observed:

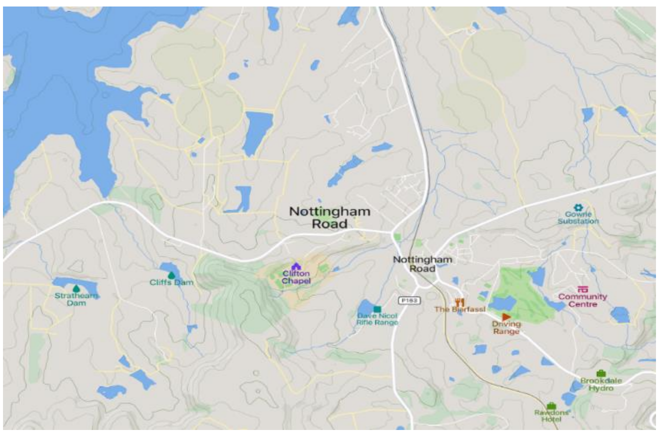
- The suitable system of an energy meter is established and verified by testing.
- The model generated accurate results that closely resembled the actual system.
- By adding more load to the model, unauthorized connections were simulated.
- The simulation results indicated a drop in voltage on phases with illegal connections as well as those without.
- A comparison was made between the results and the NRS 048 power quality standards, which revealed a deviation that exceeded the acceptable limit range.
- The study also assessed the viability of upgrading the system to smart metering by comparing various technological options and analyzing the financial returns in both urban and rural areas. The main findings are as follows:
- Data concentrator smart metering is more feasible than the stand-alone GSM module smart meter option for transformer nodes with fewer than 7 customers.
- Urban zones are shown to be more financially feasible than rural zones when considering the payback period of investment.
- The IRR is greater in the urban areas and lesser in the rural regions. Nevertheless, both rural and urban areas demonstrated a better rate of return on the investments.

In conclusion, the study suggests that investing in smart meters might be a wise decision for power practicalities, provided that the necessary financial resources are available. The study provides useful insights into which technology would be utmost realistic to implement depend on the total number of the consumers on the node of the transformer, which can help prioritize area networks for implementation.

In the future, it would be worthwhile to implement a complete smart metering system in the field, beginning with pilot sites that are prioritized based on various criteria. This would enable the collection of project costs, metering data, and valuable lessons that can be compared with the findings of this research. The statistics collected from the smart meters in a field may be analyzed more to identify trends of the consumption and detect reductions in the power losses. Whole, the advancement in the metering network might be advantageous for power utilities and customers alike in South Africa's prospect.

APPENDIX

Appendix A - Open street map of Nottingham Road, Kwa-Zulu Natal, South Africa



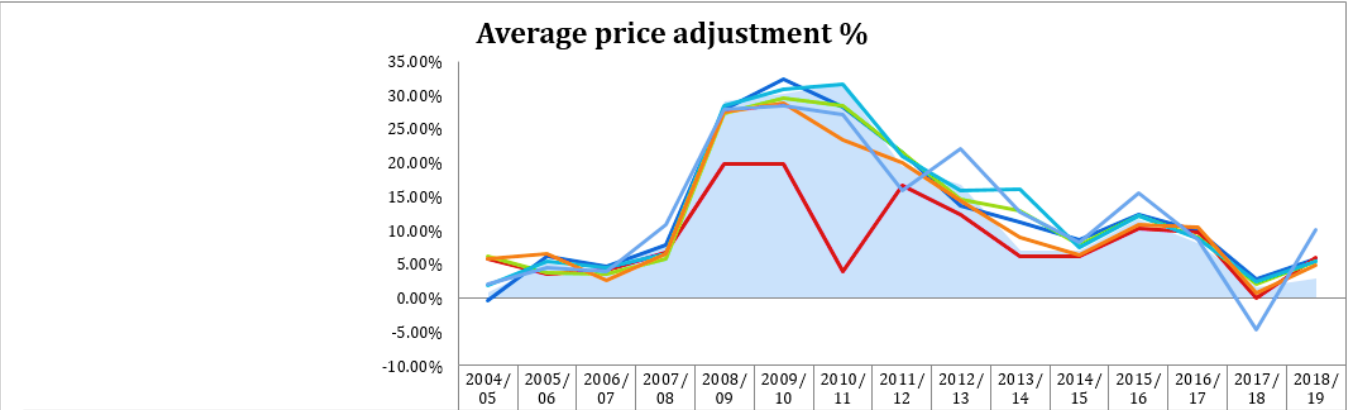
Appendix B - Full Consumption Data

Consumer ID	SERVICE_AREA	TRANSFORMER	Y2019_07_KWH	Y2019_08_KWH	Y2019_09_KWH	Y2019_10_KWH	Y2019_11_KWH	Y2019_12_KWH	Y2020_01_KWH	Y2020_02_KWH	Y2020_03_KWH	Y2020_04_KWH	Y2020_05_KWH	Y2020_06_KWH
Household 1	NOTTINGHAM ROAD	NTT610	600	856	742	765	531	979	904	745	620	750	923	960
Household 2	NOTTINGHAM ROAD	NTT610	4170	4027	1025	1016	1100	1100	726	760	870	904	1449	2200
Household 3	NOTTINGHAM ROAD	NTT610	2805	1769	1662	-728	959	843	1810	791	651	744	721	651
Household 4	NOTTINGHAM ROAD	NTT610	2084	2000	2163	1535	1118	980	671	803	689	877	877	1100
Household 5	NOTTINGHAM ROAD	NTT610	2768	1645	1545	518	1316	845	297	902	743	849	822	743
Household 6	NOTTINGHAM ROAD	NTT610	1200	1231	1156	1150	1021	1051	800	754	775	903	807	729
Household 7	NOTTINGHAM ROAD	NTT610	4170	4027	3016	1016	1118	980	671	803	689	877	1449	2265
Household 8	NOTTINGHAM ROAD	NTT610	1775	1345	1263	761	1195	1050	1161	1009	831	950	920	831
Household 9	NOTTINGHAM ROAD	NTT610	965	1452	1364	1572	1557	1368	769	1380	1136	1525	1333	1204

Appendix C – Estimation of the smart metering choices

	Option 1 Costing	**Option 2 Costing**
No. of customers	Smart meter using PLC to DC	Stand-alone GSM module
1	R10 545	R2 624
2	R11 752	R5 248
3	R12 959	R7 872
4	R14 166	R10 496
5	R15 373	R13 120
6	R16 580	R15 744
7	R17 787	R18 368
8	R18 994	R20 992
9	R20 201	R23 616
10	R21 408	R26 240
11	R22 615	R28 864
12	R23 822	R31 488
13	R25 029	R34 112
14	R26 236	R36 736
15	R27 443	R39 360
16	R28 650	R41 984
17	R29 857	R44 608
18	R31 064	R47 232
19	R32 271	R49 856
20	R33 478	R52 480

Appendix D – Increase of Tariff



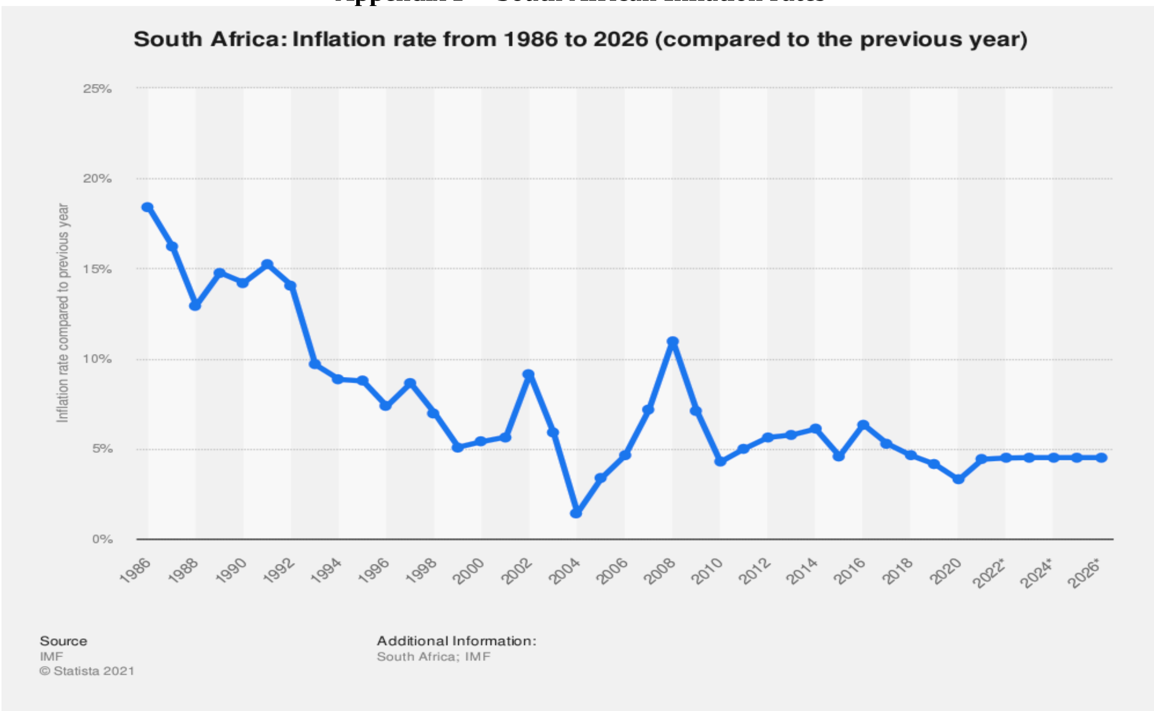
	2004/05	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19
Average standard tariff increase(Excld NPA and Int'l)	0.85%	5.15%	3.92%	8.18%	28.98%	30.15%	31.60%	19.50%	16.66%	6.92%	7.05%	11.70%	8.18%	1.62%	2.82%
Local-authorities	-0.36%	6.22%	4.62%	7.90%	27.89%	32.38%	28.17%	21.51%	13.68%	11.13%	8.66%	12.42%	9.80%	2.86%	5.77%
Residential	5.80%	3.56%	4.14%	6.76%	19.88%	19.76%	3.86%	16.64%	12.31%	6.17%	6.11%	10.26%	9.70%	-0.04%	6.05%
Commercial	6.14%	3.68%	3.58%	5.75%	27.20%	29.60%	28.45%	21.45%	14.59%	12.86%	7.86%	12.23%	9.02%	1.98%	5.44%
Mining	1.95%	5.35%	4.41%	6.47%	28.49%	30.84%	31.50%	20.93%	15.88%	16.00%	7.52%	12.22%	8.70%	2.48%	5.44%
Agriculture	5.79%	6.58%	2.52%	6.61%	27.47%	28.80%	23.33%	19.94%	14.37%	9.02%	6.36%	10.83%	10.54%	0.76%	4.91%
Traction	2.06%	4.55%	3.93%	10.75%	27.75%	28.36%	27.01%	15.83%	22.08%	12.65%	8.13%	15.50%	8.64%	-4.62%	10.07%

Appendix E – Small Power User Tariff

Landrate - Local Authority

	Energy charge [c/kWh]		Ancillary service charge [c/kWh]		Network demand charge [c/kWh]		Network capacity charge [R/POD/day]		Service charge [R/POD/day]	
		VAT incl		*VAT incl*		*VAT incl*		*VAT incl*		*VAT incl*
Landrate 1	**148,91**	*171,25*	**0,57**	*0,66*	**36,71**	*42,22*	**R 39,20**	*R 45,08*	**R 32,09**	*R 36,90*
Landrate 2	**148,91**	*171,25*	**0,57**	*0,66*	**36,71**	*42,22*	**R 60,25**	*R 69,29*	**R 32,09**	*R 36,90*
Landrate 3	**148,91**	*171,25*	**0,57**	*0,66*	**36,71**	*42,22*	**R 96,35**	*######*	**R 32,09**	*R 36,90*
Landrate 4	**321,63**	*369,87*	**0,57**	*0,66*	**36,71**	*42,22*	**R 31,22**	*R 35,90*		
Landrate Dx*									**R 69,43**	*R 79,85*

Appendix F – South African Inflation rates



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