Assessing the impact of working pressure on water meter registration

Isaac G. Musaazi, Jotham I. Sempewo IWA, Mohammed Babu and Nicholas Kiggundu

ABSTRACT

Fluctuations in the network pressure of water supply systems affect hydraulic performance and water meter accuracy. The development of metering error curves requires steady-state conditions which are extremely rare in water distribution systems characterized by intermittent supply. Simple deterministic models are suggested and developed from monthly data collected over a 4-year period (2010–2014) for three most dominant meter models (Models 1–3) in the Kampala Water Distribution System (KWDS), Uganda. This study combines pressure and billing information at the same time to understand metering accuracy. Results showed that metering accuracy increased by 4.2% for Model 1, 8.4% for Model 2 and 2.9% for Model 3, when the pressure was increased from 10 to 50 meters head. Age did not influence the impact of pressure on meter accuracy. The most sensitive parameter in the model was the meter age. Metering accuracy was relatively constant after a period of 5 years. The least sensitive parameter was the working pressure which caused a slight change to the annual billed volume. The ability of the model to accurately predict the meter registration degenerated with an increasing annual billed volume. Model 2 meters were the best performing and probably the most suitable meters in the KWDS.

Key words | billed volume, meter age, meter registration, water meters, working pressure

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HIGHLIGHTS

- Working pressure showed a positive effect on meter registration which degraded with aging.
- Low median working pressure caused an increase in meter under-registration.
- Meter age was the most sensitive parameter.
- The ability of the model to accurately predict the meter registration degenerated with an increasing annual billed volume.
- Model 2 meters were the most suitable meters in the KWDS.

INTRODUCTION

Pressure fluctuations in water distribution networks are caused by old booster pumps failing mechanically, the interruption of power supply to water pumping stations and frequent pipe bursts. This not only affects the hydraulic performance of users but also disturbs the velocity profile of water which alters water meter accuracy. The gap in service delivery is lengthened by water losses through leakages on service connections and unauthorized consumption involving water theft, meter bypasses, meter tampering, meter reversals and illegal reconnections, particularly in the

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developing world (Mutikanga et al. 2011a, 2011b). Water meters can be tested in the laboratory for a range of flow rates to develop metering error curves fundamental to the understanding of precise consumption levels (Fontanazza et al. 2013; Arregui et al. 2018). However, the guidelines followed in these evaluations recommend that measurements are taken under steady-state flow conditions. For example, Fontanazza et al. (2013) in a study showed that increasing the pressure through meters had a negative effect on the average starting flow in new class meters (0–5 years) which under-registered water volumes in comparison to older class meters (>5 years). Achieving steady flow is extremely rare in water distribution systems characterized by intermittent supply and hence reasonable to assume either an under- or overestimate of the calculated metering error. Furthermore, the field monitoring of user consumption and evaluating specific household water-use characteristics require sufficient time and are further complicated by user stratification and the need for adequate instrumentation such as data loggers for the task (Arregui et al. 2006).

As part of the meter management process, data are collected and stored on a regular basis (monthly) by water authorities each time meters are read to aid in the issuance of water bills. In a study, Mbabazi et al. (2015) used this billing information to develop meter degradation profiles from which the most suitable meters were identified to navigate hindrances associated with the accurate determination of water meter accuracy. Unmetered water volumes from degradation rates were also calculated. However, the adoption of this approach to a large extent has proved difficult for flawed historical databases and the lack of technical competence to validate data (Sempewo & Kyokaali 2019).

To address the aforesaid limitations, simple deterministic models are suggested from the analysis of data collected over a 4-year period (2010–2014) on a routine basis by a water authority to predict water meter accuracy. The data used in this study have been the basis of generating monthly water bills and ensuring a reliable water service connection to users. Multivariate regression models for both volumetric and velocity-type meters are developed to assess the impact of working pressure on water meter accuracy. Degradation rates across three-meter models are compared from which the most suitable meters in the Kampala Water Distribution System (KWDS) are determined. To account for the probabilistic nature of water meter registration, a sensitivity analysis involving both the working pressure and meter age against the annual totalized volume is provided. This simple technique addresses differences in methodological competence that affects knowledge transfer from academia to stakeholders in the water industry. To the best of our knowledge, no work has been done previously to relate pressure and billing information at the same time to metering accuracy without the need to conduct laboratory experiments. The results from this study provide an understanding of the effect of working pressure on water meter accuracy across various meter models and encourage players in the water industry to continuously collect and keep metering information for future use.

MATERIALS AND METHODS

Data sets used in the study

In this study, data from an existing water utility meter management program were provided to the authors. This information comprised two data sets used for monitoring and the assessment of domestic meters in the KWDS: (1) billing data set containing anonymous customer billing information with variables such as water meter types, meter serial numbers, field installation date, date of last meter reading and totalized volume (m^3), and (2) pressure data set containing readings from working pressure tests conducted over a short period (less than 24 h) at anonymous customer premises. While the apparent loss from domestic meters might be small compared to large meters for industrial users, the cumulative effect from the numerous domestic meters can be significant (Mantilla-Peña et al. 2018). Some of the billing data included an estimate of readings based on previous user consumption trends for two reasons: (1) customer premises are closed during the day making it difficult for personnel to access readings from an installed meter and (2) the irregular update to the GIS database renders the tracing of installed meters in the KWDS impossible (Mutikanga et al. 2011a, 2011b).

The sole purpose for conducting working pressure tests was not to provide data for this study but rather to analyze the actual hydraulic conditions in the network to ensure

(1) that newly connected water meters were not subjected to premature wear and tear because of unfavorable hydraulic overload conditions, (2) that users received an appropriate water flow at both low and peak demand times, and (3) smooth meter separation (NWSC personal communication). However, there is uncertainty on whether the provided values in the database guaranteed adequacy and reliability to all consumers in the network since the pressure monitoring tests were conducted for a limited time.

Customer property numbers in the pressure data set were matched with customer reference numbers in the billing data set. This resulted in a small data set comprising 724 meters from eight different manufacturers. The variability in meter models reduced the risk of using a single meter model to generalize meter failure. Investigations on the pressure data revealed property references (location on water meter network block maps) which showed meters were captured from different parts of the KWDS hence creating a homogenous population to justify a smaller sample size population for the analysis (Mutikanga *et al.* 2011a, 2011b). The pressure readings assessed were also conducted during meter separation procedures which are special circumstances less likely to generate enough data. Finally, the data availed by the water authority were not readily usable in its current form which imposed the need for further data preprocessing. Nonetheless, there was a fair representation of the meter types and the frequency of usage of the meters based on KWDS characteristics.

A selection of three-meter models (Models 1–3) constituting 80% of the data was carried out. Of these, 91 (15.7%) were Model 1, 137 (23.4%) were Model 2 and 351 (60.6%) were Model 3. The data had the following variables: the customer reference numbers, property reference numbers, average working pressure, meter type, installation date, date of last meter reading and totalized volume.

Preliminary data analysis

Recent studies have shown the significance of considering water consumption patterns when determining water meter accuracy (Arregui *et al.* 2016; Karadirek 2020). The percentage of consumption taking place at specified flow rates can be used to estimate the weighted error, thus directly impacting degradation rates. Consumption patterns also affect the average starting flow, an aid in the understanding of meter under-registration or non-registration over time. However, the problem with using the billing database in this study was that clear water consumption patterns for the different users, meter types and sizes could not easily be established. Therefore, determining individual water consumption patterns required visiting customer properties but given the cost and time implication of this task, this option was not viable. Also, it is common for water authorities to reserve the right to keep consumer information confidential even if it is available. An average daily consumption for this research was assumed to be 0.78 m^3/day based on findings from a demand profiling study in Kampala that found single-family users with a storage tank accounting for 80% of the total water consumption (Mutikanga 2012). This consumption pattern also aligns well with low flows experienced in the developing world (Fourie *et al.* 2020).

The age of the meters was based on the frequency of use. Obtaining the time elapsed between the date of field installation and date of last reading used previously by Mbabazi *et al.* (2015) and Fourie *et al.* (2020) was not appropriate for this study. This is because water meters, in particular volumetric-type meters constituting 76% of the total installed meters in the KWDS, have been found to fail less than 5 months after installation due to water quality problems (Mutikanga 2012). Also, the numerous date inconsistencies in the billing data set could have resulted into a significant loss of data.

The water meter size was assumed to be DN 15 mm because the data were obtained from a distribution network studied in prior investigations (Mutikanga *et al.* 2011a, 2011b; Mbabazi *et al.* 2015). The water volume registered by a meter each year (hereafter, annual billed volume) was calculated from two variables, i.e., last reading of the totalized volume (m^3) and age as shown in Equation (1):

$$\text{Annual billed volume } (m^3/\text{year}) = \frac{\text{Last reading of the totalized volume } (m^3)}{\text{Meter age (years)}} \quad (1)$$

Incomplete records of 193 meters related to: no registered volume (zero current reading) assumed to be newly installed meters and nonfunctional (stuck) or abandoned meters were excluded from the analysis. Additionally, water meters with meter misreadings (negative totalized volume) and abnormal spikes or dips in consumption (abnormally high or low volumes) caused by poor data handling from capturing data to the customer billing database were also excluded.

Figure 1 shows the distribution of the meter models that met the inclusion criteria and considered for further statistical analysis.

Development of multivariate linear regression models

The annual billed volumes for Models 1–3, along with the information about select operating conditions for each meter model, were used to develop regression models to predict the annual billed volume in RStudio (R Core Team 2019). The meter age and working pressure were considered predictor variables, while the annual billed volume was the response variable. A linear relationship was assumed between the response and predictor variables which took the general form in Equation (2):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \quad (2)$$

where y is the annual billed volume (m^3/year), β_1 and β_2 are regression coefficients for the meter age and working pressure, respectively, x_1 and x_2 are meter age (years) and average working pressure variables, respectively, and ε is the error term accounting for other factors not included in the model.

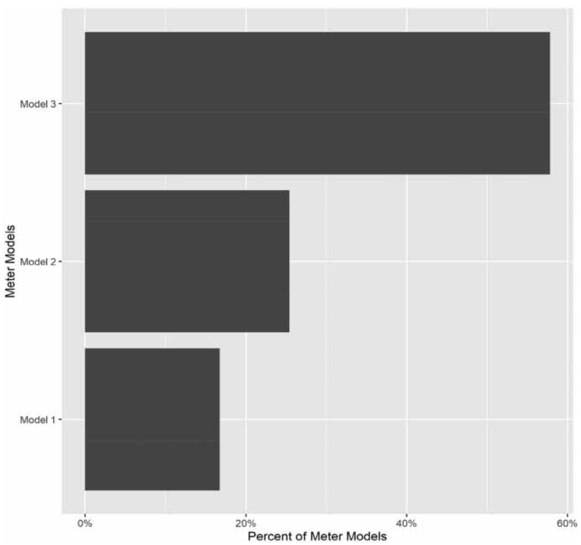

Figure 1 | Bar plot showing the distribution of the various meter models used for data analysis.

Sensitivity analysis and model validation

The mode of data collection such as the consistency in the precision of the measuring instruments used and the technical competence of the operators could influence the quality of data used in this study. Unfortunately, this could not be controlled at the time of model development. Therefore, a total run of 10,000 Monte Carlo simulations was completed to test the sensitivity of the model and evaluate the performance of the regression models developed in this study. This approach was also chosen for the reason that information captured in water utility historical databases, particularly in the developing world, is embodied with imprecision and high levels of uncertainty (Sempewo & Kyokaali 2019).

Water consumption patterns at the household level vary depending on the temporal user demand pattern determined by family size, time of consumption and supply reliability. For this analysis, however, the water consumption pattern was assumed to remain uniform during an individual meter's service life because of the complexity in quantifying changes in consumption patterns.

The values of the model inputs (meter age, working pressure and totalized volume) were varied randomly, and the distribution of output (annual billed volume) was evaluated against each of the model inputs. The sensitivity of the model was indicated by Spearman's rank correlation coefficient. Beta and log-normal distributions were tested to fit the data but produced negative values which were considered undesirable for analysis. A uniform random distribution was, therefore, deemed an appropriate fit for the data. The ranges of values for meter age, working pressure and totalized volume were selected based on the lowest and highest values in the data set and taken as the minimum and maximum values, respectively, for the uniform distribution (Table 1). The annual billed volume was determined from Equation (1).

Based on study findings by Mbabazi *et al.* (2015), Model 3 meters had the lowest meter accuracy degradation rates and considered the most suitable meters for KWDS characteristics. Therefore, the water authority provided an independent set of data on Model 3 meters to aid in the

Table 1 | Distributional assumptions for each of the model inputs used in the sensitivity analysis

Variable	Distributional assumption
Meter age (years)	unif(0.08, 12)
Working pressure (m)	unif(2, 80)
Totalized volume (m^3)	unif(5, 3,500)

validation of the model. These data were characterized by consumption levels ranging from 0 to 2,000 m^3/year.

RESULTS AND DISCUSSION

Summary statistics from the screened data set

For all the meter models, the mean age, pressure and totalized volume were greater than the median age, pressure and totalized volume, respectively, as shown in Figures 2–4. This indicated that the distributions were skewed to the right (positive skew). Model 3 meters had the lowest mean age (Figure 2) which corresponded to the lowest mean totalized volume (Figure 4) when compared with Models 1 and 2. Therefore, Model 3 meters were considered newer meters than Model 1 and Model 2 meters. Model 1 was subjected to the lowest mean pressure than Models 2 and 3 as shown in Figure 3. The relationship between totalized volume with meter age and totalized volume with working pressure is non-linear (see Supplementary Material, Figures S1 and S2).

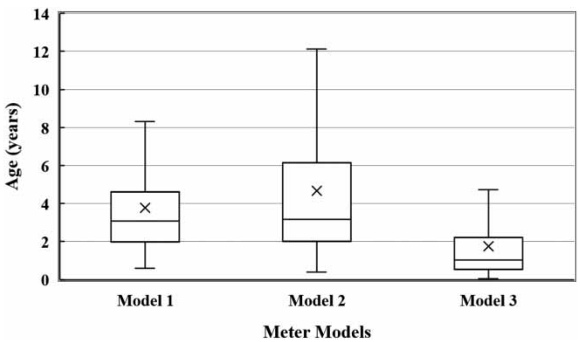

Figure 2 | Box plot showing the age for Models 1–3 meters.

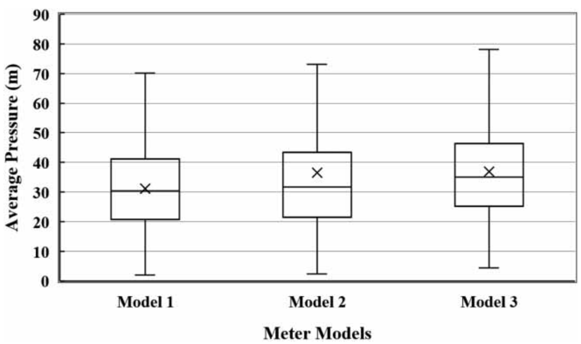

Figure 3 | Box plot showing the pressure for Models 1–3 meters.

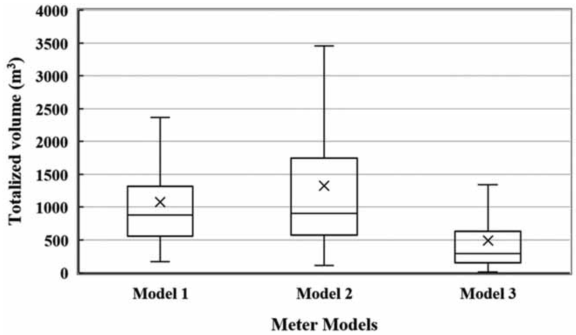

Figure 4 | Box plot showing the totalized volume for Models 1–3 meters.

Multivariate regression analysis

Multivariate regression analysis was performed on square root transformations of the annual billed volume to normalize the residuals. Model 1 (Figure S3), Model 2 (Figure S4) and Model 3 (Figure S5) indicate the residual plots (see Supplementary Material). Equations (3)–(5) indicate the mathematical models with the corresponding coefficients of determination (R^2) obtained for Models 1–3, respectively.

$$\text{Model 1: sqrt}(y) = 21.19 - 1.38\,(x_1) + 0.02\,(x_2) \qquad R^2 = 0.17 \tag{3}$$

$$\text{Model 2: sqrt}(y) = 17.88 - 0.94 \cdot \text{sqrt}\,(x_1) + 0.04 \cdot (x_2) \qquad R^2 = 0.20 \tag{4}$$

$$\text{Model 3: sqrt}(y) = 27.74 - 1.89 \cdot \text{sqrt}\,(x_1) + 0.02 \cdot (x_2) \qquad R^2 = 0.10 \tag{5}$$

where y is the annual billed volume (m^3/year), x_1 is the age of the meter (year) and x_2 is the working pressure (meters head).

In Equations (3)–(5), the regression coefficients for all the meter models associated with meter age were generally negative, implying that the ability to register the volume through the meters depreciates over time. Palau *et al.* (2018) in a study reported similar results on the effect of age on the metrological performance of single jet meters at a flow rate of 0.03 m^3/h, which is within the range of the study's assumed daily water consumption. In fact, Mbabazi *et al.* (2015) in another study showed that the annual billed volume decreased with age influencing the degradation profiles for the meter models under-investigation. The change in the metering error over time can be attributed to severe wear and tear which increases friction in the metering mechanism, creates more resistance to start the movement of meter components (Van Zyl 2011) and decreases the meter starting flow. However, starting flow is often neglected because of the complex quantification processes (Fontanazza *et al.* 2013).

Model 2 had the lowest coefficient with respect to meter age (Equation (4)) and was subjected to the greatest mean working pressure (Figure 3). This implies that higher working pressure has no effect on meter age, i.e., Model 2 meters did not degrade faster when subjected to high working pressure as expected. The time over which pressure readings were taken was rather small and may not have been representative of the pressure fluctuations experienced during the service time of the meters probably explains this disparity. Therefore, the need to monitor pressure for longer times may address this uncertainty.

The regression coefficients for Models 1–3 associated with working pressure were generally positive (Equations (3)–(5)). This shows that working pressure has a positive influence on the volume registered by both old (Models 1 and 2) and new (Model 3) meters. However, this was not significant for all the meter models ($p > 0.05$). Therefore, age did not influence the effect of pressure on water meter registration. This observation differs from a study finding by Fontanazza *et al.* (2013) that showed the influence of pressure on meter accuracy on the basis of starting flow degraded with age. The starting flow for each of the meters could not easily be determined in this study since this would involve extracting meters from the field and running experimental tests. Model 1 was subjected to the lowest median working pressure (Figure 3) and had a low coefficient with respect to working pressure (Equation (3)). Model 2 with a closely related registration mechanism to Model 1 (both positive displacement meters) was subjected to a slightly higher median pressure but had the greatest coefficient with respect to working pressure (Equation (4)). The need for a deeper investigation to understand the subtle difference toward metering error levels not easily determined in this study is necessary between Models 1 and 2.

The coefficients of determination (R^2) were low, showing a weak linear influence of both working pressure and meter age on the annual billed volume. This contravenes the observation of an equal spread of the residuals with no distinct patterns around a horizontal line (a good indication of a linear relationship) in the residuals vs. fitted plot (Supplementary Material, Figures S3–S5). Outlying points in the residuals vs. leverage plots (Supplementary Material, Figures S3–S5) could have potentially been influential against the regression lines. This statistic is in agreement with results from a study by Fontanazza *et al.* (2013) which showed that while the influence of working pressure on meter starting flow (flow rate required to drive the metering mechanism from rest) which directly translates to metering accuracy was linear, the influence of meter age was exponential. Additionally, the age and totalized volume have been determined to have a logarithmic relationship to metering accuracy (Moahloli *et al.* 2019). Therefore, the relationship of both working pressure and age on meter registration (annual billed volume) may not be fully described linearly, hence the need to investigate for non-linearity. However, the latter approach may require a large skill, not readily available in the developing world. A linear assumption was preferred because of the less technical skill required to complete the analysis and simplicity in interpreting the results.

In Figure 5, Model 2 had the lowest change in accuracy (1.85% per year) with respect to meter age and the greatest change in accuracy (8.4%) when the pressure was increased from 10 to 50 meters head than Models 1 and 3. Therefore, Model 2 meters were considered the best meters in the study. This differs from findings in a study by Mbabazi *et al.* (2015) which showed that Model 3 meters had the lowest meter accuracy degradation rates. The difference could be attributed to variability in the calculation of meter age. Mbabazi *et al.* (2015) determined the age from the time elapsed between the last two readings, implying

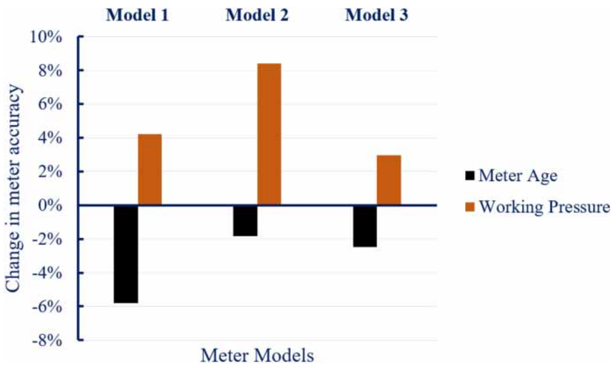

Figure 5 | Change in meter accuracy for different meter models.

that, irrespective of the totalized volume, meters had the same age if the installation date and date of last meter reading were the same. This may not be applicable under circumstances with varied consumption patterns and intermittent supply.

Model 1 had the highest degradation rate (5.8% per year) when compared with all the other meter models. This finding is similar to results from a study by Mbabazi *et al.* (2015) which indicated that Model 1 meters were the worst meters with the highest meter accuracy degradation rates. However, the degradation rate is greater than the 2% per year degradation rate reported by Couvelis & van Zyl (2015) on the same size of meters (DN 15 mm) extracted from a water meter database in South Africa. No stratification into age groups was done in this study, and the assumption of a flat consumption rate of 0.78 m^3/day considered rather than the observed decreasing trend in consumption patterns over the study period in Couvelis & van Zyl (2015) probably explains the variation. The inclusion of working pressure in the model shows that metering accuracy increases by 4.2% when pressure levels are increased from 10 to 50 meters head. Therefore, the performance of Model 1 improves under high-pressure conditions.

The KWDS has been characterized by high burst frequencies (Mutikanga *et al.* 2009) which introduce particulates in the distribution network, and the response to this phenomenon is a function of the meter model and the design adopted by a specific manufacturer. When particulates grow so large, they clog the space between the piston and the wall chamber and cause meters to stop running leading to meter under-registration at low flows but over-registration at medium and high flows (Arregui *et al.* 2005). However, the impact on meter accuracy caused by particulates was not modeled in this study and may require further investigation.

Water storage tanks at the customers' facilities affect the sizing of meters, and the meter starting flow was found to have significant impacts on metering errors (Fontanazza *et al.* 2013). Unreliable water supply has caused 80% of the customers to install private storage tanks which induce low flows and hinder the capacity of meters to accurately measure consumption (Mutikanga *et al.* 2011a, 2011b). When the water supply is off, the tank empties (water levels drop) leaving the float valve fully open and the tank fills at high flow rates when water supply returns at high working pressure, and thus the float valve has a reduced influence on metering accuracy (Criminisi *et al.* 2009). Models 1 and 3 meters may represent conditions of low consumption, continuous water supply and low working pressure levels where the water level in the tank does not fall causing low flow rates which force meters to work in the lower measuring ranges (Criminisi *et al.* 2009). User consumption behavior was not readily available for this study and may need to be gathered to verify this assertion before inclusion to the model in future studies.

The consumption of water varies according to time, i.e., during the day, the working pressure is low as consumers utilize the available water for domestic chores and, in the night, fewer individuals utilize the water available resulting in higher working pressure. It remains unclear whether the pressure recordings were taken during the day or night, but this might likely explain the difference in the effect of working pressure on the annual billed volume across the three-meter models. Model 2 seems more influenced by nighttime consumption phenomenon than Models 1 and 3. The need to consider the time of water use is essential, though this is likely to involve more elaborate and comprehensive water meter testing to duplicate actual field conditions.

Sensitivity analysis and model validation

The sensitivity of the model output (annual billed volume) to the working pressure and meter age was assessed using Spearman's rank correlation coefficients after 10,000 Monte Carlo simulations. Table 2 provides a summary of

Table 2 | Summary of correlation coefficients from the sensitivity analysis of the model

Working pressure		
0.01	Meter age	
0.001	−0.66	Annual billed volume

the correlation coefficients. The most sensitive parameter in the model is the meter age, while the least sensitive parameter is the working pressure.

The meter age had a high negative correlation to the annual billed volume (rho = −0.66), implying that a capability of water meter registration decreases over time, i.e., new meters are more likely to have lower metering errors than older meters.

In Figure 6, the change in the annual billed volume is minimal and can be assumed to remain relatively constant after 5 years. This finding shows that meters may need to be replaced when the totalized volume is equivalent to a 5-year usage period. This will reduce the average life cost replacement of a water meter too early due to fixed initial costs or late during its service life because of meter under-registration (Moahloli *et al.* 2019). Mutikanga *et al.* (2011a, 2011b) in a study estimated the replacement of meters greater than 7 years is one of the key strategies to reduce apparent losses in Kampala. The metering error of new meters (<1 year) indicated by regions of low accuracy is attributed to inherent systemic errors in meter design (Fontanazza *et al.* 2013). Arregui *et al.* (2005) also found that low flow rates caused by water leakages at consumers' properties correspond to low meter accuracy levels. However, this assertion was not given consideration in the analysis and may need to be substantiated in future studies.

The working pressure has a very low positive correlation with the annual billed volume (rho = 0.001) which shows that the working pressure has a positive effect on the annual billed volume. However, since this effect was not noticeable (figure not shown), the prediction prediction of meter registration based on only working pressure may not be sufficient.

The calculated annual billed volume was not always equal to the predicted annual billed volume. However, the prediction was better at smaller volumes (<500 m^3/year) than at higher volumes (>500 m^3/year) (Figure 7). Therefore,

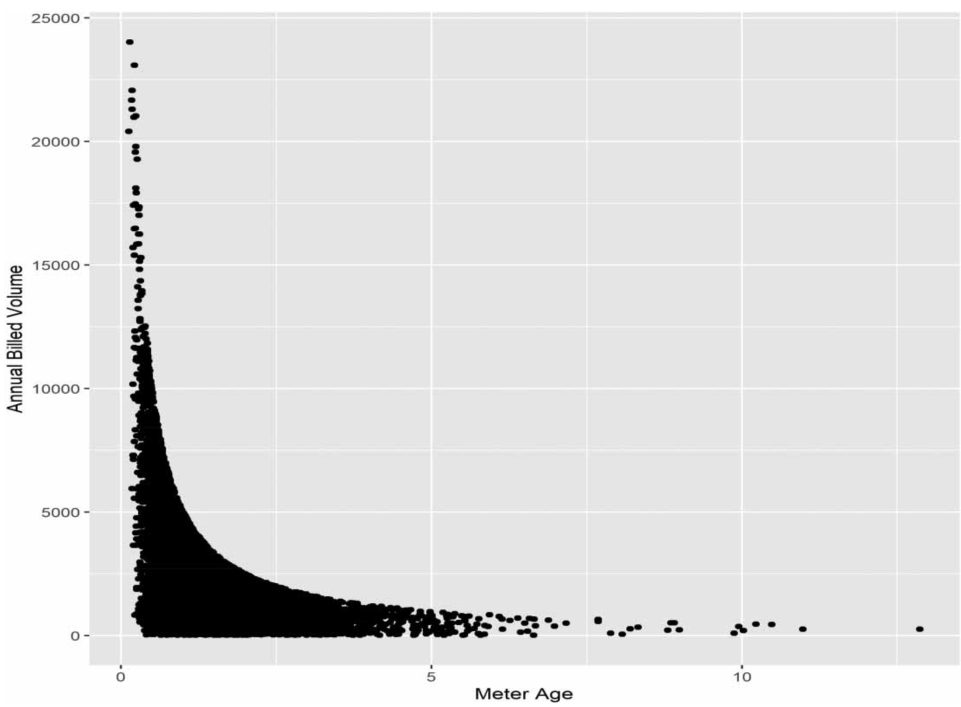

Figure 6 | Annual billed volume with meter age.

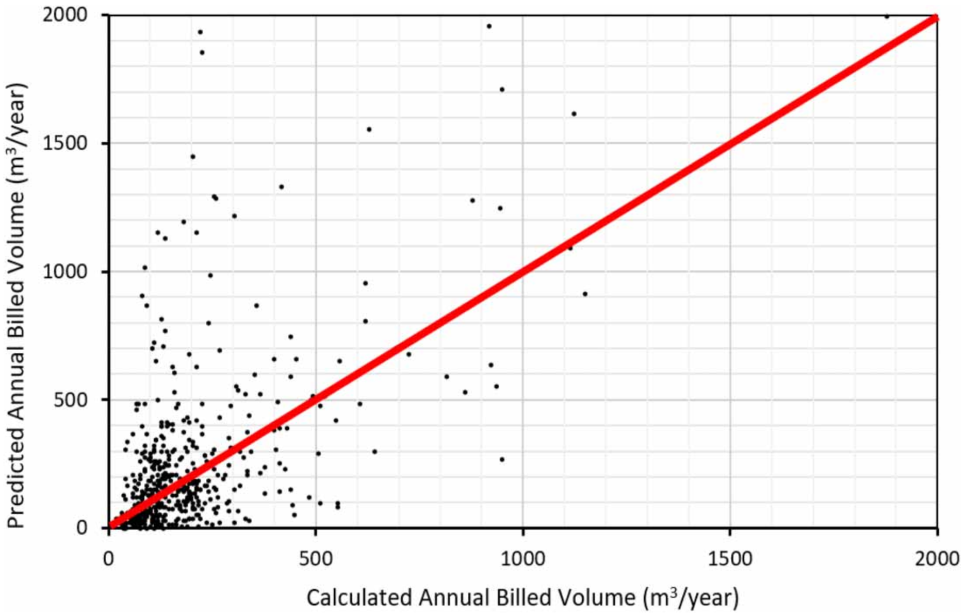

Figure 7 | Validation of the annual billed volume.

the ability of the model to accurately predict the meter registration degenerates with an increasing annual billed volume.

CONCLUSIONS AND RECOMMENDATIONS

An assessment of the impact of working pressure on water meter accuracy was performed with multivariate regression models for both volumetric- (Models 1 and 2) and velocity-type (Model 3) meters. Working pressure showed a positive effect on meter accuracy for both old (Models 1 and 2) and new (Model 3) meters, implying that age has no influence on the effect of pressure on water meter accuracy. Model 2 had the lowest change in accuracy (1.85% per year) with respect to meter age and the greatest change in accuracy (8.4%) when the pressure was increased from 10 to 50 meters head than Models 1 and 3. Therefore, Model 2 meters were the best meters in this study. From the sensitivity analysis, the most sensitive parameter was the meter age. Metering accuracy was relatively constant after a period of 5 years. The least sensitive parameter was the working pressure and did not result in a noticeable change in the annual billed volume. The ability of the model to accurately predict the meter registration degenerated with an increasing annual billed volume.

A study in which both consumption and pressure readings are taken at the same time can check the legitimacy of the regression models developed in this study. Otherwise, results from this study show that meter accuracy can be determined from data collected on a regular basis by water authorities. The data used in the study were specific to Kampala; however, the methodology can be adopted for use by water utilities which prioritize data collection and storage but lack the financial resources to carry out laboratory tests on individual meters suspected to misrepresent water consumption patterns. This study provides vital information to water utility managers that only replace meters after vandalism, theft and meter failure. In addition, this study will improve meter replacement programs and prepare more accurate cost-based calculations of the water value as it relates to meter models and meter registration, which are both important components in water utility charge structures.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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