Robustness of IoT-connected e-Taps for sustainable service delivery of rural water supply

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ABSTRACT

'e-Taps' monitor flow at rural water points in sub-Saharan Africa and enhance revenue collection using pre-paid tags. Real-time, high temporal resolution e-Tap usage data are available to service providers. In this paper, the robustness of the e-Tap is evaluated in the laboratory regarding (1) accuracy of the flow meter and (2) the flow rate reduction caused by addition of a *y-strainer* and debris build-up. An average relative error of $+3.63\%$ across varying flow rates is found. A general calibration will bring 95.45% of measurements within a $\pm 4.54\%$ error range. In the *y-strainer*, smaller gauze sizes, smaller debris sizes, and higher debris loads cause greater flow rate reductions. The maximum reduction observed was only approximately 68% of the baseline flow rate. These physical findings can be integrated into software solutions to management problems.

Key words | IoT, remote monitoring, robustness, rural water supply, sub-Saharan Africa, sustainability

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HIGHLIGHTS

- Technical evaluation of a novel technology that is scaling across rural water supply systems in sub-Saharan Africa.
- The findings contribute to solutions to inaccuracies and demonstrate that refinements can be made remotely, which has potential benefits to the sustainability of water supply.
- Based on direct flow measurement rather than proxy sensors.
- Results provide an empirical basis for predictive maintenance/cleaning, and for debris build-up or flow meter accuracy in other decentralised, small-scale, rural water technologies.

INTRODUCTION

Operating on the principle of Internet of Things (IoT) connectivity, eWATERpay taps (herein called e-Taps) are currently being deployed on communal standpipes in The Gambia, Tanzania, and Ghana. Pre-paid credit tag operation leads to the 100% revenue collection required for sustainable service delivery (Harvey & Reed 2006). Their usage data are reported in real-time. This innovation has a great potential for improving reliability and sustainability of water supply across rural sub-Saharan Africa (Eliamringi & Kazumba 2017; Ingram & Memon 2019). Greater understanding of e-Tap robustness will aid this deployment.

Such innovations for rural water supply in developing countries are of growing interest in the research and practitioner communities (Andres *et al.* 2018). Robustness of these technologies has not been well researched, and existing evaluations focus on impacts on water supply and

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management (e.g. Hope *et al.* 2014; Nagel *et al.* 2015). Remedial technical alterations have been concomitant with product development, and unreported.

Here, this study instead investigates potential limitations to robustness across longer time-scales of operation, which is a new contribution and especially important considering the expected increase in such IoT technologies. This research contributes new empirical understandings of flow measurement accuracy, and of flow rate reductions from debris build-up inside the e-Tap, which have not been well studied in such technologies. These novel contributions demonstrate that the added capacities from such IoT innovations not only allow for improved management, but also a new ability to remotely refine data collection measurements and create predictive maintenance alerts, both detailed here, and provide software solutions to hardware problems. Water delivery points tend to be imprecisely categorised as 'working' or 'broken' (Carter & Ross 2016). These findings now further show how timely usage data can provide more detailed narratives of functionality.

Robustness is of fundamental importance for long-term effectiveness (Klug *et al.* 2017; 2018; Kelly *et al.* 2018). Hardware that is more resilient to breakdowns shall: (1) reduce interruptions to water supply; (2) reduce operation and maintenance (O&M) costs; and (3) maintain community satisfaction. Breakdowns of other pre-paid urban water points have significantly hindered their sustainable implementation (Heymans *et al.* 2014), but have not been reported in depth. Specifically, moving components that are subject to physical pressures potentially reduce robustness.

First, the study evaluates the accuracy of flow measurement in the e-Tap

Accuracy of flow measurement underpins the accuracy of credit removal from users' tags. This is important for fairness, affordability, and accurate revenue collection. Accuracy is underpinned by the precision of the flow meter, but can be influenced by the Flow Count calibration factor. Inaccuracies in metering are the main cause of 'apparent losses' in the developed world (Criminisi *et al.* 2009), and poor metering or billing processes are estimated to cause 30 billion litres per year to be lost in developing countries (Andres *et al.* 2018). Here, findings reveal average inaccuracies for e-Taps. A new digital calibration tool designed to remotely improve e-Tap accuracy is detailed.

Second, the study evaluates the impact on flow rate of the addition of the *y-strainer*, and of debris build-up inside of the *y-strainer*

This evaluation considers flow rate reduction from (1) addition of *y-strainer* and interior gauzes and (2) built-up debris inside the *y-strainer* that could restrict water flow. Accumulation of debris in drinking water distribution systems is observed globally (Neilands *et al.* 2012) and is especially relevant in rural sub-Saharan Africa where infiltration of grit, sand, organic matter and plastic waste can be high. Reduced flow rates could lead to longer water collection times, queuing, and community dissatisfaction. Results reveal flow rate reductions from different debris and gauze variables, and novel flow rate threshold alerts for predictive *y-strainer* maintenance are proposed.

e-Tap operation

e-Taps (Figure 1), on community standpipes, are operated using near-field communication (NFC) tags that are preloaded with purchased water credits and held onto the e-Tap's NFC tag reader until the desired amount of water has been dispensed. Tag removal closes the tap. Flow and time of each operation are measured, and the volume dispensed and associated credit taken is reported in real-time to a data management system, along with flow rate and other supplementary data.

Other similar IoT technologies reported in the literature are based on proxy flow rate measurements, such as handpump handle accelerometers (Hope *et al.* 2014). Such sensors do not interfere with flow or water point functionality, and report accuracy of approximately ±15% (Thomson *et al.* 2018). e-Taps, however, benefit from higher-accuracy direct measurement of flow, credit-based pay-as-you-go collection, and holistic data collection across a whole water distribution network.

The single-jet flow meter impeller, pictured in Module 2 in Figure 1, is rotated by water flow (Walter *et al.* 2017) when the motorised ball-valve is opened, creating an electrical signal via the Hall effect for each rotation. Volume in

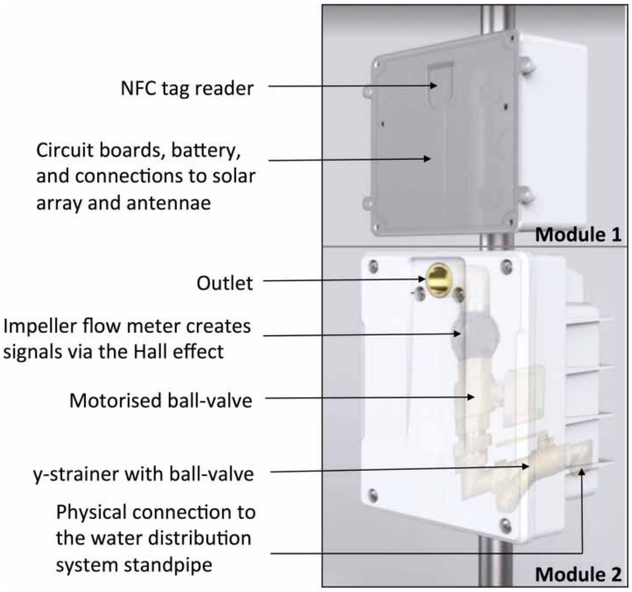

Figure 1 | General components of e-Tap.

litres is calculated by dividing Flow Count by the flow meter's standard calibration value of 330, with flow rate derived from time. Single-jet flow meters are cheap, however they are also subject to blockages and varying inaccuracies.

A *y-strainer* with interior metal gauze was added to Module 2 to limit debris that occasionally blocks the flow meter impeller, causing non-functionality (automated closure of ball-valve). The *y-strainer* can be opened for cleaning and gauze replacement.

EXPERIMENTAL AND DATA COLLECTION METHODS

Accuracy of flow measurement

The experimental set-up emulated real-life operation, using a hydrobench. A three-way ball-valve manually directed flow either 'into' or 'away' from Module 2. A separate flow meter (with custom-built and calibrated digital reader) was positioned on the 'away' flow to allow for approximate adjustment of baseline flow rate ($Q_{baseline}$). A pressure dial was added between the three-way ball-valve and Module 2.

Once water flow was directed 'into' Module 2, an NFC tag was placed on Module 1 as soon as possible to open the e-Tap motorised ball-valve and begin measurement. A digital timer was started as soon as water was observed to flow from the end of the outlet tubing into a calibrated custom 20 l measuring cylinder. Once the water level reached exactly 15 l, measured manually, the timer was stopped, giving an accurate real flow rate measurement (Q_{real}, l min^{-1}), and the tag was removed. The potential of imprecise reading was negated by the choice of a large enough volume and by inducing a swirl in the measuring cylinder. Total volume dispensed once flow had fully stopped was measured, giving V_{real}. This allowed for additional flow caused by the slow shutting of the motorised ball valve.

This procedure was repeated 180 times over a varying Q_{real} of 4.3–38.6 l min^{-1}. Below 4.3 l min^{-1} a 'low flow' error is activated; 38.6 l min^{-1} is the hydrobench pump limit. This range suitably replicates the observed range in The Gambia (4–32 l min^{-1}) and Tanzania (20–60 l min^{-1}). Three different flow meters of the same model were used to discount the effects of testing one faulty unit.

The volume and the flow rate measured by the e-Tap ($V_{e\text{-}Tap}$ and $Q_{e\text{-}Tap}$) were manually calculated to two decimal places using Flow Count and reported seconds ($t_{e\text{-}Tap}$), avoiding rounding errors (normalised mean of 1.54%).

The percentage differences (%Δ) between 'real' experimentally measured volumes and volumes measured by the e-Tap are calculated using Equation (1) (Criminisi *et al.* 2009):

$$\%\Delta V = \frac{(V_{e\text{-}Tap} - V_{real})}{V_{real}} \times 100 \quad (1)$$

The international standard ISO 4064 permissible error range for water meters is ±5% at flow rates lower than the transitional flow rate (Q_2, specific for each meter), and ±2% at flow rates above Q_2 (ISO 2014; Walter *et al.* 2017). Once operating in the field these are suggested to increase to ±8% and ±3.5% respectively (van Zyl 2011). Here, an error range of ±5% across flow rates is taken as a permissible range.

Flow rate reduction from *y-strainer* and debris

Decrease in $Q_{baseline}$ was measured across varying gauze sizes, debris sizes and debris loading of the *y-strainer*.

Individual components of Module 2 were set up as above, with flow meters before the three-way ball-valve, and after the Module 2 components (with digital reader, calibrated).

Percentage flow rate reductions from a maintained Q_{baseline} between set-ups without the *y-strainer* (and associated elbow) and with the *y-strainer* were measured across a Q_{baseline} range of 3.0–17.6 l min^{-1}. This was then repeated, keeping the *y-strainer* in place, with seven gauzes of varying pore size (0.05–3.24 (and 63) mm^2; see Supplementary Material), across a comparable $Q_{\mathrm{baselines}}$ range.

Next, debris size (μm) and debris loading (g) were varied across the variable gauze sizes. A constant Q_{baseline} of 6.7 l min^{-1} was used as varying this was shown to be insignificant. A T-inlet between the *y-strainer* and three-way ball-valve allowed for 'spiking' of debris while maintaining the required flow rate. Silica sand was chosen (Puig-Bargiés & Lamm 2013) to simulate the effect of observed heterogeneously sized debris and provide generalisable flow rate reduction results. Sand causes blockages in around 5% of e-Taps across two villages in The Gambia (Ingram *et al.* 2018). Six sand size ranges were selected (300–425 to 2,000–2,360 μm; see Supplementary Material), collected using vibrating sieve stacks, washed and oven-dried.

The cylindrical interior space of the *y-strainer* gauze (7.1 cm^3) fills with 10–11 g of sand. Variable loads were: 0, 4, 7, 10, 13, 16, 19, and 22 g. Variable combinations were (in order): 6 × gauze sizes, 6 × debris (sand) sizes, and 8 × debris loads (cumulative), giving 288 measurements. Percentage decrease from Q_{baseline} (measured as the flow rate at 0 g of debris loading, for each new gauze size) was measured for each. Gauze 1's pores (63 mm^2) were too large to allow any build-up, and it was excluded.

RESULTS

Accuracy of flow meter

$V_{\mathrm{e\text{-}Tap}}$ is larger than V_{real} by a mean of 3.63% (%ΔV) across all measurements. The standard deviation across these %ΔV is 2.26%. There is significant variation between the accuracies of each flow meter tested (shown in Figure 2(a)). This variation was verified by an additional ten repeats across the Q_{baseline} range on flow meters 1 and 2.

Flow meter 1 is most inaccurate, with a higher mean %ΔV and standard deviation values, and also an evident negative correlation of %ΔV with increasing Q_{real}. Flow meter 3 is the least inaccurate. In general, volume inaccuracies seem not to be sensitive to variation in flow rate within this range. The inaccuracy revealed here can be addressed by a general recalibration of all e-Tap data by −3.63%, as shown in Figure 2(b) (see Discussion).

The percentage error between 'real' and measured flow rates (%ΔQ) was also calculated as above for each measurement, and is shown in Figure 3(a); %ΔQ against Q_{real} shares the characteristics of %ΔV against Q_{real} for the flow meters,

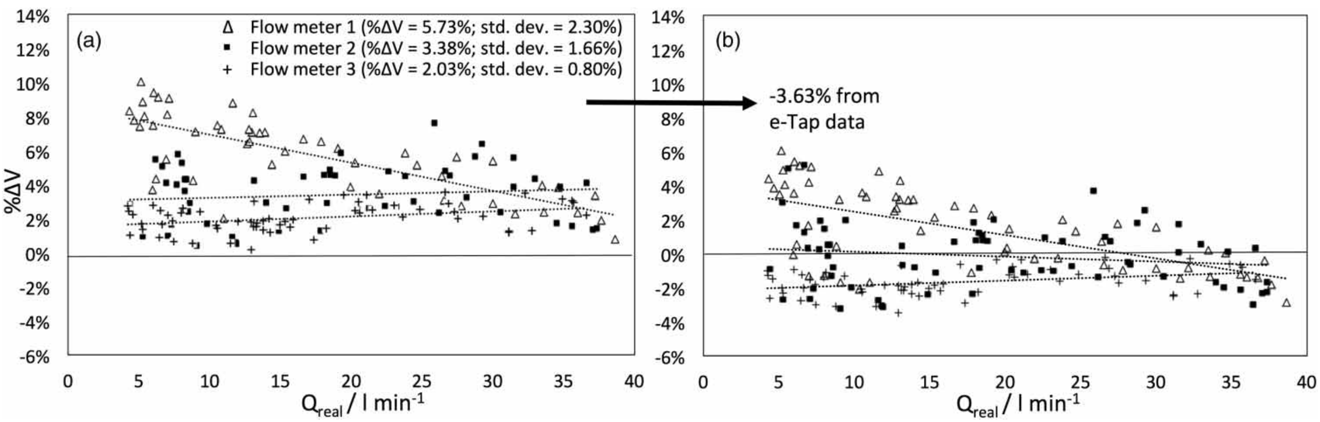

Figure 2 | (a) %ΔV against Q_{real}, disaggregated for flow meters tested; (b) reduction of inaccuracies by general calibration of data from Figure 2(a) downwards by −3.63%.

however with a significant positive correlation and higher errors. This apparent misalignment is due to an erroneous time constant that incorrectly increases each $Q_{\text{e-Tap}}$. An addition of 3.95 s to each e-Tap recorded time ($t_{\text{e-Tap}}$) brings both the mean $\%\Delta Q$ and the correlations of each flow meter into alignment with $\%\Delta V$, as seen in Figure 3(b). The motorised ball-valve was measured to take a mean of 4.00 s to fully open. This erroneous time constant therefore results from the time difference between the addition of the tag to the e-Tap and water flowing from the e-Tap outlet, which is ~50 cm from the motorised ball-valve in this experimental set-up.

Flow rate reduction from *y-strainer* and debris

The addition of the *y-strainer* in Module 2 causes negligible flow rate reduction across the Q_{baseline} range tested. Decreasing gauze pore sizes without debris causes insignificant reductions, with a maximum 4.8% decrease with the smallest pore size (0.05 mm^2).

Figure 4(a) shows that loading of debris in the *y-strainer* generally leads to decreased Q_{baseline}. Flow rate decreases become significant at approximately 13 g of loading (with a mean flow rate reduction of 1.57%). This corresponds to when the cylindrical gauze has filled with sand (10–11 g) and the horizontal *y-strainer* interior also begins to fill. After this point, Q_{baseline} decrease is more significant for gauzes with smaller pore sizes. Smaller pore sizes in the range of ~0.05–0.36 mm^2 (Gauzes 6 and 7) cause an average ~15% decrease with 22 g of debris.

Smaller sand sizes cause greater reductions in flow rate (until the sand is small enough to pass through pores). Figure 4(b)–4(h) demonstrates the significance of this, and the ~13 g threshold. Sand A (300–425 μm) shows Q_{baseline} decreases of ~32% with both Gauzes 7 and 6 with 22 g loading, shown in Figure 4(c) and 4(d). Figure 4(e) shows that at a large enough gauze size, the smaller sand sizes (Sand A) begin to pass through. Here, sand <425 μm was too small to ever block the impeller. The second flow meter was blocked in 33% of all measurements, emulating blockages in the field.

Disaggregated reductions of Q_{baseline} for different gauzes in Figure 4(c)–4(h) show that smaller gauze sizes allow for build-up of smaller sand sizes, and a combination of both small gauze size and small debris size results in the greatest Q_{baseline} decreases.

DISCUSSION AND IMPACT ON E-TAP DESIGN

Accuracy of flow meter

Calculation of more precise values directly from Flow Count avoids rounding errors equivalent of up to ±0.6 l out of a 20 l collection bucket, and $\%\Delta V$ is a better indicator of flow meter inaccuracy than $\%\Delta Q$ as it excludes the additional uncertainty from experimental measurement of

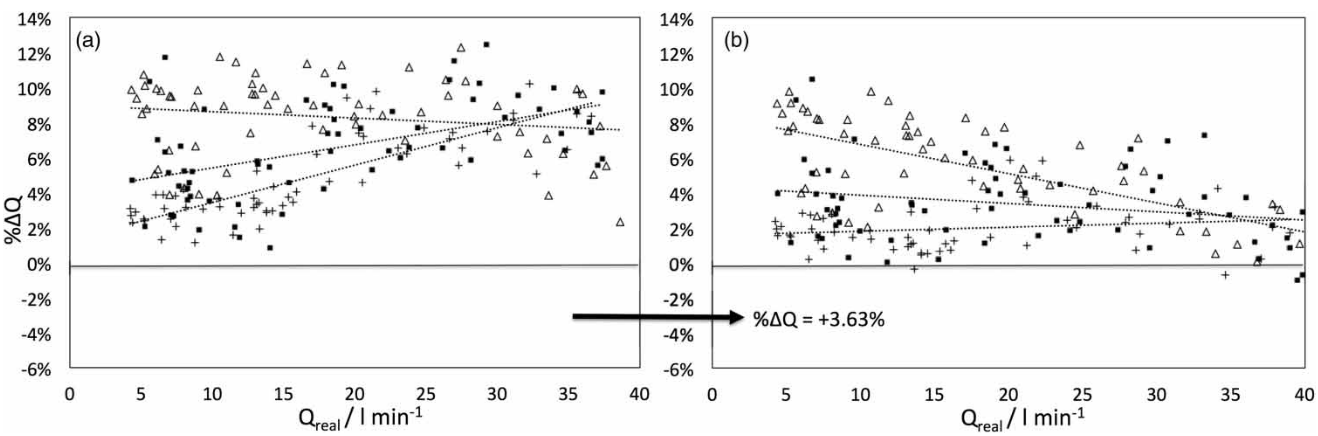

Figure 3 | (a) $\%\Delta Q$ against Q_{real}, disaggregated for flow meters tested; (b) addition of 3.95 s to each measurement in Figure 3(a).

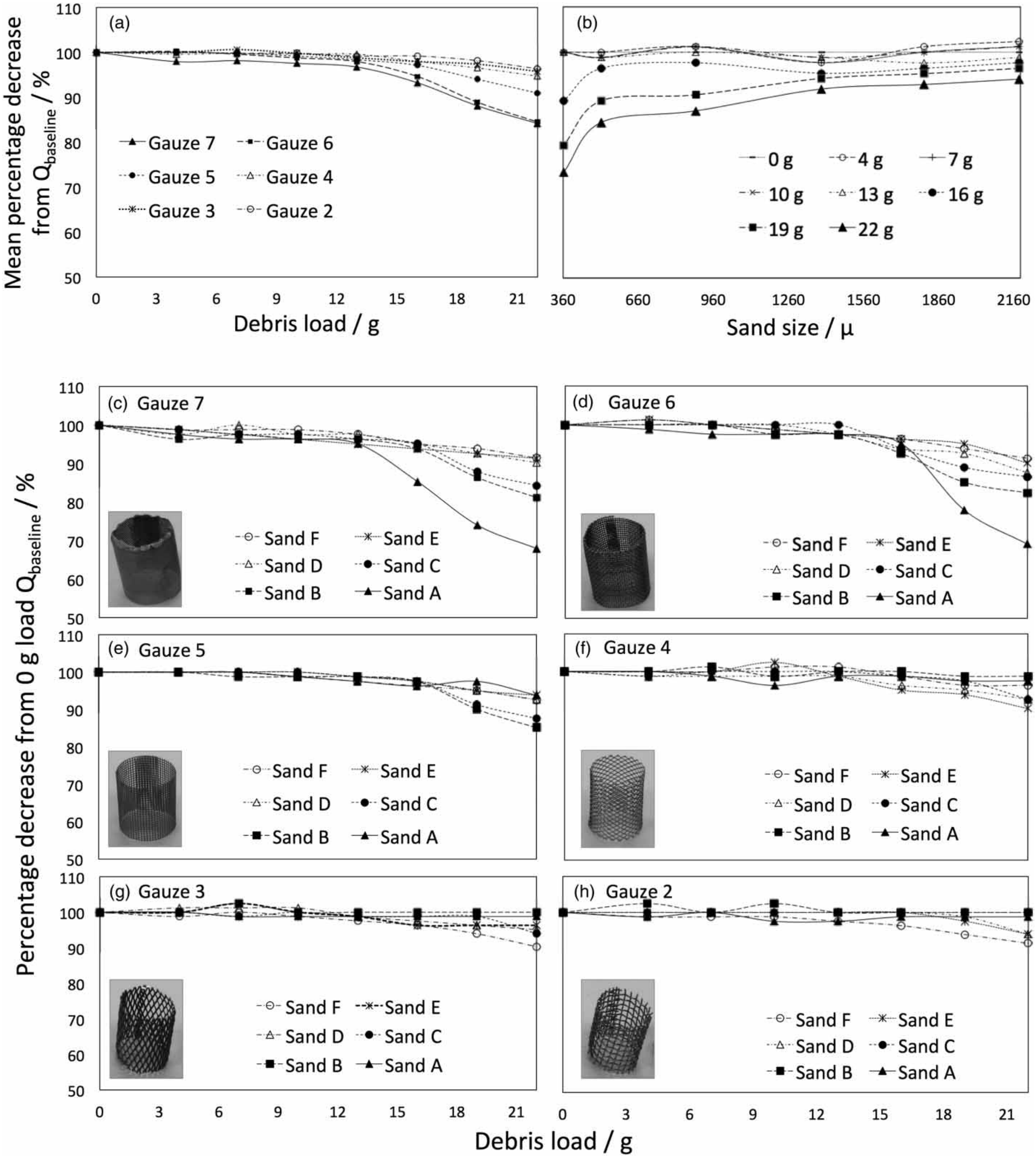

Figure 4 | (a) Mean percentage $Q_{baseline}$ decreases over increasing debris loads for each different gauze size, averages for all six sand sizes; (b) $Q_{baseline}$ decreases for Gauze 7 with increasing debris loads, across varying sand size; (c)–(h) disaggregated $Q_{baseline}$ decreases per gauze size with varying sand sizes, across increasing debris loads.

time. Volume is also a more relevant metric of water collection than flow rate. An average of 3.63% too much water is being recorded by the e-Taps, shown in both $\%\Delta V$ and $\%\Delta Q$. This marginal inaccuracy may be because of incorrect calibration in the measurement of volume from Flow Count. This average is within the ±5% acceptable inaccuracy, however 25.9% of measurements are greater than +5% inaccuracy. Mean standard deviation equals 2.26%, which extends to +5.89% inaccuracy.

Inaccuracy against Q_{real} or V_{real}, in accordance with flow rate variability in the field, extends the potential inaccuracy range to its maximum of 0.78%–10.05%. The overload flow rate (Q_4), where flow rates are high enough to cause the error curve of a meter to exceed the required error range, is likely to be far beyond the expected flow range here (van Zyl 2011). Axial wear reduces accuracy more when closer to 0 l min^{-1}, avoided here by the automated closure at low flows.

Therefore, it appears that very slightly excessive credit is currently being charged from users per use, and slightly excessive water collection is being reported, probably resulting from an incorrect flow calibration value.

High-precision flow meters are expensive and impractical. Instead, a general calibration of all reported data using the mean %ΔV reported of 3.63% will bring the mean %ΔV to 0%, as shown in Figure 2(b). Then 95.45% (two standard deviations) of the above measurements would fall within ±4.54% inaccuracy, within the acceptable ±5%. This can be practically achieved with an adjustment of the flow calibration value from 330 to 318.

To this end, eWATERpay developed a calibration application (for smartphone or web browser) for use at individual e-Taps in the field (or remotely). The application remotely commands the e-Tap to dispense a given volume of water, which is measured and re-entered to recalibrate the e-Tap. While the precision methodology employed in this paper is not possible in remote locations, repeats of the same principle will provide an acceptable accuracy range (ensuring flow rate is not unusually low or high for each water point). This protocol allows for community engagement and transparency.

In general terms, this demonstrates that software solutions can be used to overcome physical limitations to the precision of the e-Tap components. When compared with expensive manual calibration in laboratories, this finding demonstrates significant novel potential of such IoT-enabled technologies.

Flow rate reduction from *y-strainer* and debris

Any decreased flow rate from *y-strainer* addition is negligible (maximum 4.8% with the smallest gauze size). Build-up of the 13 g of debris in the *y-strainer* required before flow rate starts to reduce is likely to take some time in operating e-Taps, depending on debris levels in the water distribution system. Risk of 'non-functionality' because of the *y-strainer* is low; even with 22 g of debris and the smallest gauze size, flow rate only reduces by one-third. The benefit to robustness of the e-Tap by limiting flow meter blockages is therefore highly preferable.

If characteristics of the debris are previously known for specific water distribution systems, these results can inform the choice of gauze size using the findings reported in Figure 4(c)–4(h).

The *y-strainers* require periodic cleaning. For strainers in domestic or standpipe meters, the WHO and IRC advise cleaning at least once a year (Brikké & Bredero 2003). Water distribution systems in sub-Saharan Africa vary in flow rates and debris loads. Therefore, annual cleaning does not facilitate efficient maintenance, and some e-Taps may be left with high debris loads for long periods, which may trigger associated microbial health risks.

Now, the empirical understanding of flow rate reductions from different debris and gauze variables can be combined with remote visualisation of flow rate reductions in real-time via the online data management system. For example, gradual reductions in flow rate at an e-Tap, compared with either a longitudinal baseline or other e-Taps in the system, could alert service providers to significant debris build-up. This in turn can generate information about debris infiltration locations in the piped system, or average debris size from flow rate reductions across e-Taps or one specific e-Tap.

Predictive maintenance using flow rate

Recent work on IoT innovations on handpumps has succeeded in automating alerts of non-functionality and reducing maintenance response times (e.g. Hope *et al.* 2014; Nagel *et al.* 2015). Even with these successes, water points remain non-functional for at least some time.

Automatically predicting non-functionality before it happens using real-time data collection would allow pre-emptive maintenance per water point or system, with obvious resource efficiency benefits. Accurate predictions would theoretically reduce non-functionality time to zero (this is plotted in Figure 5), with disproportionate socio-economic and health benefits. Even short remissions to alternative unimproved water sources result in significant health impacts (Brown & Clasen 2012).

Wilson *et al.* (2017) have advanced 'preventative maintenance' for rural handpumps in Kenya using handpump sensors and supervised ensemble machine learning. Threshold-based outputs informed a decision whether to dispatch a mechanic. They were able to predict handpump breakdowns mostly on the breakdown day, or day before. The analysis was based on accelerometer and pressure gauge measurements as proxies for flow rate, bounded by three minutes after pump handle vibrations had stopped. Similarly, Greeff *et al.* (2019) have further combined lightweight, *in situ* machine learning methods with more powerful cloud-based ones for successful predictive failure of up to 61.6%.

In-line impeller flow meters, investigated here, offer greater potential for predictive maintenance than proxy measurements from handpumps, particularly regarding debris build-up. Real-time and remote use of high temporal resolution data has already been successful with remotely controlled pressure-reducing valves in municipal water distribution networks (Creaco & Walski 2018).

An effective method for e-Taps is to create alerts to unacceptable flow reduction thresholds, from a baseline derived from a longitudinal average of recent flow rates. This can be tailored to specific e-Taps and gauze sizes. Once a flow rate threshold is consistently passed over a long enough period of time to discount underlying flow rate fluctuations, an alert can be sent to the service provider. Q_{baseline} reduction alert thresholds are proposed in Table 1, based on the debris build-up measurements reported in Figure 4(c)–4(h) after the 13 g *y-strainer* filling threshold has been crossed. As seen, smaller gauze pore sizes would necessitate higher Q_{baseline} reduction alert thresholds. Thresholds should also decrease as gauze pore sizes get larger, however the error range of the flow meter revealed above would mean that thresholds lower than 5% would give higher likelihoods of 'false alerts'.

This technique would utilise the newly available high-quality data for accurate predictions, and would use empirical measurements that reflect real flow rates, rather than relying on probabilistic machine learning. Higher resolution and accuracy flow rate data from e-Taps now allow predictive maintenance to move beyond assessment of either 'working' or 'broken' water points (Carter & Ross 2016). Application of real-time flow rate data for predictive maintenance would be a tangible 'use' of data, so far overshadowed by 'collection', 'transfer' and 'analysis' with this kind of monitoring data (Ingram & Memon 2019).

It is important to note that benefits from predictive maintenance would be lost without a responsive maintenance team, financial sustainability, a robust water distribution system, and other requirements of resilient and

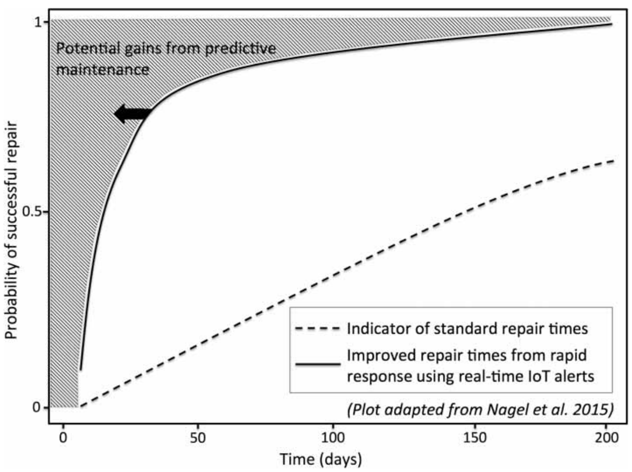

Figure 5 | Potential gains on time to successful repair of water points from predictive maintenance.

Table 1 | Recommended flow rate reduction thresholds for debris build-up alerts

	Mean measured percentage reduction from Q_{baseline} for all sand sizes (%) at:			**Recommended percentage reduction threshold for predictive cleaning alert, based on a longitudinal average**
Gauze pore size (mm^2)	13 g[a]	16 g	22 g	*(Recommendations in italics disregard 'false alerts')*
0.05	96.31	93.04	84.37	> 9% *(>9%)*
0.36	97.94	94.65	84.50	> 7% *(>7%)*
0.42	98.35	97.11	90.92	> 5% *(>4%)*
1.38	99.59	97.96	94.70	> 5% *(>3%)*
1.95	98.79	97.97	95.76	> 5% *(>3%)*
3.24	99.18	99.18	96.35	> 5% *(>2%)*

[a]*y-strainer* filling threshold.

sustainable water systems. However, when both accurate and prognostic, remote water point monitoring can enhance each of these requirements.

Application of flow rate threshold alerts in the field would allow refinement of the thresholds proposed here. A longitudinal study with control would be required (beyond the scope of this study) to assess the accuracy and gains from predictive cleaning, how this compares with other O&M required, and the feasibility of acting on such alerts. These alerts could apply to any similar technology in the future.

Limitations of the study

Evaluating accuracy across more flow meters would be more representative of the hundreds of e-Taps currently operating. Inaccuracies were similar enough to extrapolate general findings. It was also not possible to represent heterogeneous debris, however disaggregating sand sizes provides extrapolatable data.

CONCLUSIONS

In this paper, an evaluation of e-Tap operation has been outlined focusing on the accuracy of the flow meter reading and on flow rate reduction caused by *y-strainer* addition. Findings suggest that the e-Tap measurement of flow is marginally inaccurate with an average relative error of +3.63%. Varying baseline flow rate does not significantly impact this. This means that users have been collecting a slightly lower volume of water for the credit that they are paying for, however this is insignificant compared with broader benefits to rural water supply sustainability and access. A general calibration across e-Taps by −3.63% will fine-tune accuracy.

The benefits of blocking debris reaching the e-Tap flow meter with the addition of the *y-strainer* outweigh any minor flow rate reductions observed. These reductions are negligible for all gauze pore sizes measured until roughly 13 g of debris builds up inside the *y-strainer* gauze. The results here can inform decisions of approximate gauze size to install, refined when the nature of the debris is known.

These findings have direct application in planning and management. A calibration software application for staff use in the field has been developed. The flow rate reductions relative to debris build-up for specific gauze sizes can lead to accurate predictive maintenance using alerts based on thresholds proposed here. This benefits from high-accuracy flow meters on e-Taps (compared with proxy measurements used elsewhere). Both of these use software solutions for hardware problems. This ability for service providers to improve service delivery remotely has significant and original benefits. The study has demonstrated the enhanced capacity available from a combination of high-resolution sensing data and remote analytics, and shows that potential benefits of such IoT innovations go beyond those currently established, and can accelerate progress towards the Sustainable Development Goals.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this paper is available online at https://dx.doi.org/10.2166/ws.2020.128.

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