Use of sensors to support the monitoring and maintenance of pump services:

Literature Review

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Ask for Water

SonSetLink™
A ministry of SonSet Solutions

RWSN
Rural Water Supply Network

tearfund

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Front cover photo: International Lifeline Fund

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Abbreviations

CapEx	Capital Expenditure
GSM	Global System for Mobile Communications
GPRS	General Packet Radio Service
IOT	Internet of Things (IoT)
IWP	Intelligent Water Project
PSU	Portland State University
LWI	Living Water International
RUL	Remaining Useful Life
UoC	University of California
RFL	Rural Focus Limited
RWSN	Rural Water Supply Network
WDT	Water Data Transmitter
WPDEx	Water Point Data Exchange

Definitions

Ambulance (maintenance) model	A dedicated operation and maintenance team address specific problems and are triggered into action from data which has been generated from sensors and displayed on a dashboard as an alert.
Artificial Intelligence (AI)	A branch of computer science concerned with building smart machines (see smart tech below) capable of performing tasks that typically require human intelligence[3].
Attenuation	The reduction of the amplitude of a signal, electric current or other oscillation.
Circuit rider (maintenance) model	Mobile technicians travel on a circuit and undertake routine service visits of all pumps, regardless of functionality or performance status.
Community management	The community owns the handpump (or other water supply source), and pays for repairs, including the cost of spare parts. The community contacts local government and/or a handpump mechanic when the handpump (or other point source) breaks down and support is needed to repair it. Anecdotal evidence suggests that preventative maintenance is rarely undertaken. Major maintenance and rehabilitation are often beyond the affordability of the community and rely on external actors (mainly government and NGOs).
Downtime	Time until a repair is successfully implemented.
Fuzzy logic	An approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based.
Global System for Mobile Communications (GSM)	A standard developed by the European Telecommunications Standards Institute to describe the protocols for second-generation (2G) digital cellular networks used by mobile devices such as mobile phones and tablets.
General Packet Radio Service (GPRS)	Packet oriented mobile data standard on the 2G and 3G cellular communication network's global system for mobile communications (GSM).
Humanitarian contexts	Contexts which are dominated by ongoing crisis or emergency events such as natural or conflict-driven disasters, which can be defined as rapid onset, slow onset or protracted.
Internet of Things (IoT)	System of interrelated computing devices, mechanical and digital machines, objects, animals or people provided with unique identifiers and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction[4].
Machine learning	A sub-field of artificial intelligence. It enables a computer system to make predictions or take some decisions using historical data without being explicitly programmed. Machine learning uses a massive amount of structured and semi-structured data so that a machine learning model (sometimes referred to

3 https://builtin.com/artificial-intelligence

4 https://internetofthingsagenda.techtarget.com/definition/Internet-of-Things-IoT

	as a learner) can generate accurate results or give predictions based on that data[5].
Maintenance	To keep a building, machine or road in good condition by checking or repairing it regularly[6].
Nominal (maintenance) model	Repair services are provided on request when communities or officials contact the service provider.
Remaining Useful Life (RUL)	A subjective estimate of the number of remaining years that an item, component or system is estimated to be able to function in accordance with its intended purpose before warranting replacement[7].
Remote Sensing	The process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft). Special cameras collect remotely sensed images, which help researchers "sense" things about the Earth[8].
Repair	To restore something that it damaged, worn or faulty to a good condition[6].
SIM card	A SIM card is a subscriber identity module or subscriber identification module, and is an integrated circuit running a card operating system which is intended to securely store the international mobile subscriber identity number and its related key. These are used to identify and authenticate subscribers on mobile telephony devices such as mobile phones and computers[9.]
Smart handpump	The term smart handpump, as first coined by Oxford University, refers to a transmitter securely fitted inside the handle of the pump. The transmitter automatically sends data on handpump use via SMS over the mobile phone network. Presumably, future generations could use satellite transmissions.
Smart tech	"Smart" originates from the acronym "Self-Monitoring, Analysis and Reporting Technology". It has become a catch-all phrase for technology that is made possible by the proliferation of cheap, powerful sensors, which, using artificial intelligence, can distinguish between different states to provide information and even guide behaviour[10].
Telemetry	In situ collection of measurements or other data at remote points and their automatic transmission to receiving equipment (telecommunication) for monitoring[11].
Uptime	A measure of system reliability, expressed as the percentage of time a machine has been working and available[12].

5 https://www.javatpoint.com/difference-between-artificial-intelligence-and-machine-learning

6 Compact Oxford English Dictionary, third edition

7 https://www.partneresi.com/resources/glossary/remaining-useful-life-rul

8 https://www.usgs.gov/faqs/what-remote-sensing-and-what-it-used?qt-news_science_products=0#qt-news_science_products

9 https://en.wikipedia.org/wiki/SIM_card

10 https://www.netlingo.com/word/smart-tech.php

11 https://en.wikipedia.org/wiki/Telemetry

12 https://en.wikipedia.org/wiki/Uptime

Summary

Sensor technology, installed on handpumps operating in rural areas of low and middle income countries with the data generated used for remote monitoring, has received considerable attention and spawned several research projects over the past decade.

This short report reviews the major handpump sensor technology literature that has been published over the past ten years, and provides readers who are not familiar with the technology or its use with an understanding of how it works, where it has been used and some of the key challenges that have been faced. The report also describes some of the modelling work that has been undertaken with sensor data, as well as the costs and potential revenue of using this technology. It includes a short summary of select projects that have used or are using handpump (and electric pump) sensor technology, and concludes by reflecting on the potential that sensors have to improve rural drinking water supplies. It should be noted that sensor technology and sensor data for handpumps (and electric pumps) is an evolving field of research and development, and detailed information on all initiatives is not all readily available in the public domain. There may therefore be gaps in the literature review.

The report is intended for professionals and researchers with an interest in rural water supplies and who have little or no experience in the use of handpump sensor technology. A list of definitions is provided to help readers who are not familiar with some of the technical terminology.

1. Introduction

Ensuring that rural water supplies in Sub-Saharan Africa continue to operate over time has remained a challenge for decades, with alternatives to community management emerging (RWSN, 2021). Traditionally, mechanisms to monitor pump services in rural areas comprise regular site visits to the water points and users. Given that this can necessitate large distances to be covered, particularly in remote areas, the agencies responsible face a considerable time and financial resource burden. Further, if communities are not able to obtain immediate support when their sources break down and they cannot repair them themselves, infrequent monitoring may even delay repair.

The confluence of expanding mobile network coverage, widespread ownership of mobile phones, mobile banking applications and smart metering technologies could provide new solutions to improve water security and reduce poverty (Hope *et al.*, 2011). Smart Water Systems which measure, transmit and use accurate and timely data have the potential to contribute towards reducing transaction costs of payment for water, identifying and reducing non-revenue water loss as well as improving infrastructure maintenance, supply regularity and customer satisfaction (Hope *et al.*, 2011). Oxford/RFL (2014) and others (Nagel *et al.*, 2015; Thomas *et al.,* 2021) working on the field of sensor technology have gone further, suggesting that sensor-triggered systems could increase transparency, accountability, responsiveness and ultimately improve water services.

Remote monitoring of pumps in rural areas, facilitated by using sensors to measure and transmit data and provide information for maintenance, has been shown to reduce the downtime of handpumps in select field trials. Interest in sensors for handpumps as well as for pumped systems that rely on electric submersible pumps is growing. To date, relatively few handpump sensor initiatives have been undertaken on a large scale, and there is no available documentation of those that operate specifically in humanitarian contexts. The 2021/22 Tearfund Netherlands-led project to use handpump sensors in Northern Bahr el Ghazal, South Sudan, is a pioneer in trialling handpump sensors in a humanitarian context.

This short report provides an overview of the learnings from select initiatives undertaken between 2012 and 2021 that use sensors on handpump and electric pumps. It provides a narrative account of the types of sensors and sensor systems that have been used, an overview of past initiatives, a summary of technical challenges, sensor data and modelling, and a review of costs and potential revenue. It closes with a brief discussion. A visual summary of the key sensor technology aspects is provided in Annex 1.

This report is based on a search of the literature, supplemented with limited information from two workshops hosted by Tearfund in late 2021/early 2022. It is thus not a comprehensive and systematic review of current practice.

2. Sensor types and systems/node

The wide variety of handpump sensors used to date measure a range of physical parameters, using various measurement techniques. The main approaches are as follows:

- Accelerometers measure rate of change of velocity, and so can be used to detect movement or vibrations in pump components which are subject to variable velocity movement. Accelerometers have been installed on the pump handle to detect and count strokes, and on the pump head to detect vibration (implying use). Accelerometers do not affect user experience but, if installed on the outside of the pump, are visible and hence at risk of damage or vandalism.
- Pressure transducers measure water or air pressure. When submerged below the water level in the borehole, they can readily detect water level changes; accuracy can be improved by compensating for atmospheric pressure variations, utilising a second instrument which is located out of the water.
- Capacitance sensors, in the context of handpumps, detect the presence or absence of water by taking advantage of the different dielectric constants of air and water. When several are applied in an appropriate configuration, they can be used to estimate flow. This is the principle used in handpump sensors used by Charity: water. A capacitance probe can also measure variations in water level, as the capacitance of the probe varies in proportion to its submerged length.
- Electrical conductivity sensors detect presence or absence of water by taking advantage of the higher conductivity of water compared to air. Hence, when installed in the spout, they can be used to detect times of use and non-use of a handpump.
- A rotating impeller flow meter, with an integral Hall effect sensor, can be used to measure flow of water in a pipe directly.
- Flow meters are designed to measure flow in a full pipe, and become less accurate at lower flow rates (Thompson, 2021). Time varying flows may require separate calibration, as a quasi-steady flow assumption may not apply. Given that handpump flows, even in the rising main where the pipe is full, are intermittent, and that the spout is rarely full, a measurement system would need to create back-pressure, requiring more effort by the user or impairing the pump functionality.

Table 1 provides an overview of select different sensor systems that have been or are currently being trialled or used for remote handpump monitoring. It should be noted that while there is a considerable amount of published literature, including academic manuscripts for the early trials, information for later use of sensors is more diffuse, and so it was not always possible to draw out all of the details.

In the case of electric submersible pumps, electric current sensors have been used to measure whether the pump is in operation, mainly by measuring energy consumption. One sensor system used for other pump types (e.g., electric-driven diesel, solar or grid) is summarised in Table 2. It has been included because of its relevance to sensor learning and the fact that it is well documented.

Sensor systems, referred to by Greet *et al*. (2019) as *sensor nodes,* contain a sensor, battery and data transmitter. Sensor systems that use global system for mobile communications (GSM) technology comprise a control board, cellular radio chip, SIM card plus the specific sensors (Nagel *et al.*, 2015).

3. Overview of initiatives

Over the past decade, there have been several initiatives comprising proof of concept, as well as field testing and trials which have integrated handpump (and electric pump) sensors into rural water supply projects (summarised in Figure 1). There has been some learning between initiatives, with a few organisations collaborating, and new initiatives emerging which incorporate sensor technology, or ideas that were previously trialled by others. Sensor technology and sensor data for handpumps (and electric pumps) is an evolving field of research and development.

Table 1 Field trials involving handpump monitoring systems using sensors[13] (assembled based on published literature and Public Presentations)

Date	Sensor System Name Lead Organisation(s)	Trials/Use & Location	Sensor Type(s)	Data collected	Data relayed & transmission	Information generated & displayed
2011	Waterpoint Data Transmitter (WDT) **Oxford University**	Test pump and three 'live' pumps in Zambia	▪ IC-based accelerometer (Analog Devices ADXL335)	▪ Pump handle movement	▪ Handle tilt angle ▪ Estimated volume pumped ▪ Relayed through GSM modem as an SMS once per minute	▪ Count of number of times the pump handle has moved over a given time period and estimate of water abstracted
2012-2016	Intelligent Water Project (IWP) Monitor[14] **Messiah College**	Lab testing and field testing in Northern Ghana	▪ Accelerometer ▪ Sensor for water presence (measures difference in resistivity between air and groundwater)	*Lack of information*	▪ Number of upstrokes required to prime the pump, amount of water extracted and rate of leakage in the rising mains ▪ Daily transmission of data to IWP database	▪ Water extraction, handpump performance, borehole health, which is also used to predict degrading conditions before borehole failure ▪ Web and mobile application ▪ In the event of a handpump failure, or depleting condition, email and text message sent to community and handpump mechanics
2013	Smart handpumps **Oxford University**	Trials in Kenya 66 pumps	▪ Accelerometer	▪ Pump handle movement	▪ Hourly pump usage data, dispatched on a six-hourly basis ▪ SMS to database (MySQL with PHP interface) in Nairobi	▪ User interface including map layer indicating pumps that do not seem to be in regular use ▪ Half of the pumps were actively managed and sent signals for action, while half were 'silent', with use being recorded for later analysis.

[13] Sources: Thomson et al., 2012; Swan et al., 2017; Swan et al, 2018; GSMA, 2016a; Thomas, 2018; Nagel et al., 2015; Wilson et al., 2017; Gorder & Milanes, 2021; Koehler et al., 2015; Weaver et al., 2016; Charity: water, 2021; Greeves, 2021; Odial Solutions, 2020.
[14] IWP refers not only the hardware, but also the database, data transport, mobile app and web interface.

Date	Sensor System Name Lead Organisation(s)	Trials/Use & Location	Sensor Type(s)	Data collected	Data relayed & transmission	Information generated & displayed
2013-date	Dispatch Monitor **Charity: water**	Trials in Ethiopia, then Sierra Leone & Uganda	▪ Accelerometer ▪ Differential water pressure transducer	*Lack of information*	▪ Handle motion ▪ Flow of water (±10% error)	▪ Extent of cranking of handle vs water flow, thus energy usage in producing water
	AFD-1, AFD-2, IM2 **Charity: water**	Trials in Ethiopia, Mali, Ghana and from 2022 in Uganda, Sierra Leone, Central African Republic and Papua New Guinea	▪ Capacitance ▪ Temperature	▪ Level of water in the wellhead	▪ Measures twice every second, and converts it to litres per hour flowing through the pump	▪ Litres per hour flowing through the pump
2015-2019	MANTIS **Leeds Becket University, Environmental Monitoring Solutions and VisualWind Ltd**[15]	The Gambia, Sierra Leone, Mozambique, India	▪ Accelerometer ▪ Differential water pressure transducer	▪ Not described	▪ Pump usage (operations per day) ▪ Succinct data packages via SMS messages and SMS gateway	▪ *Lack of information* ▪ Displayed on online user interface

[15] In partnership with local representatives from the Rural Youth Development Organisation in the Bumpe Ngoa Chiefdom in Sierra Leone and the Glove Project NGO in the Gambia.

Date	Sensor System Name Lead Organisation(s)	Trials/Use & Location	Sensor Type(s)	Data collected	Data relayed & transmission	Information generated & displayed
2016-2017	SweetSense **The Water Project, University of California, Portland State University and Sweetsense Inc.**	Trials in Western Kenya – 42 Afridev pumps	▪ Accelerometer ▪ Differential water pressure transducer	▪ Standpipe[16] vibrations (induced by pumping activity) ▪ Pump basin[17] gauge pressure	▪ Data logged and sent at 10s intervals for times when there was activity at the pump.	▪ Data for 8,962 sensor-observed pump days
2013-2017	LifePump (SonSet Solutions Sensors) **Design Outreach, Messiah College & World Vision**	Sensor used to monitor select LifePumps in Ethiopia, Kenya, Mali, Malawi and Zambia	▪ Not specified (but mounted on spout)	▪ Not specified	▪ Data relayed not specified ▪ Transmission via satellite	▪ The sensors record daily usage information which is used to calculate use in gallons/day.
unclea r	MoMo **WellDone International**	*Lack of information*	▪ Different physical sensors (modular)	▪ Determined by requirements	▪ Built to work with standard GSM, requires a microSIM card, and supports GPRS and SMS data transfer	▪ Data are stored on servers for processing, analysis and communication of information through online portals or automated SMS messages.
2020-2035	E-PUMP **Vergnet Hydro/UDUMA**	In use in Mali	▪ integrated a water meter and data logger into their manual pumps, transforming them into 'E-PUMPS'	*Lack of information*	*Lack of information*	*Lack of information*

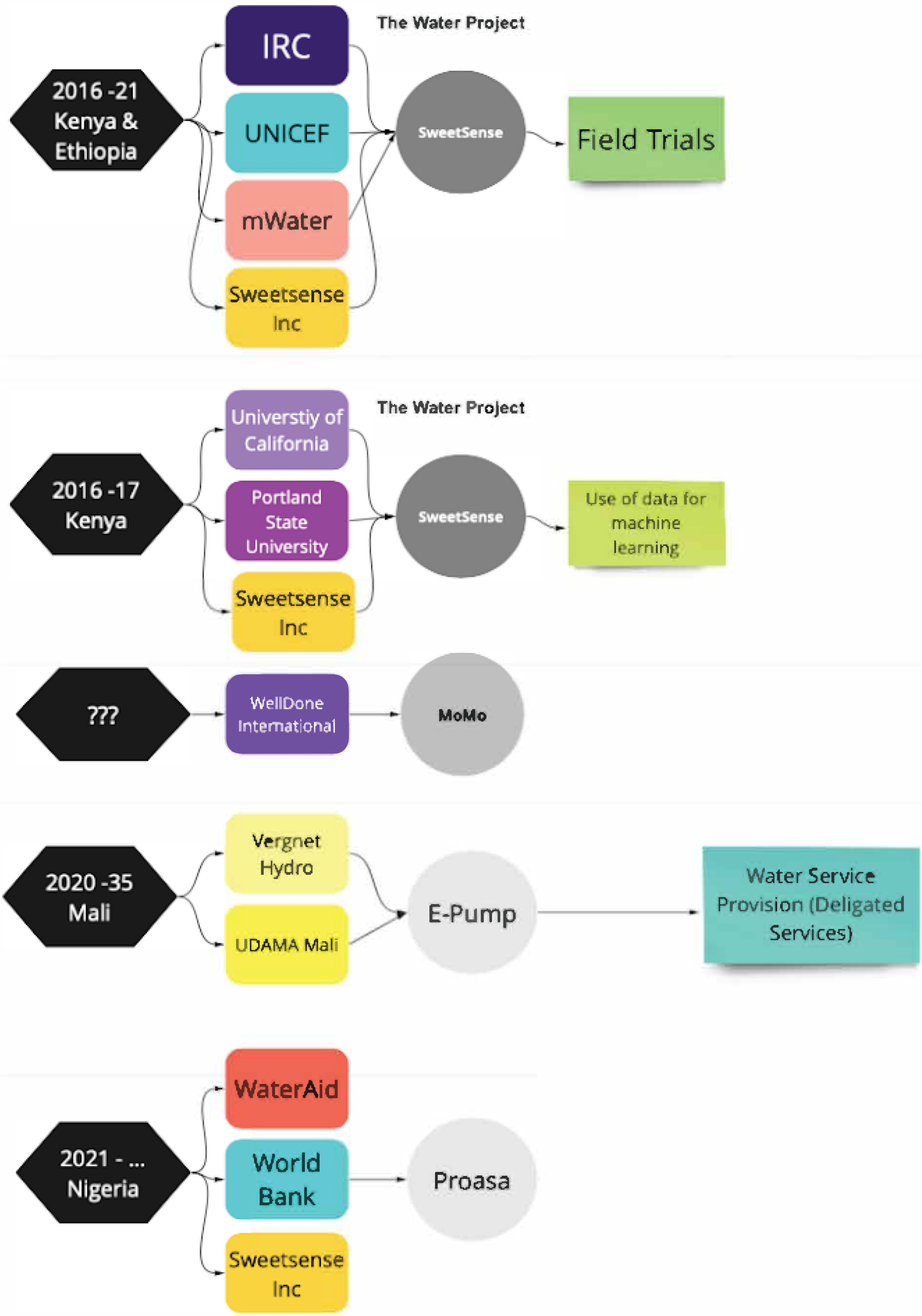
[16] Presumably the term "standpipe" refers to the pump stand.
[17] The term "pump basin" refers to the inside of the pump head where the water spills out of the rising main.

Date	Sensor System Name Lead Organisation(s)	Trials/Use & Location	Sensor Type(s)	Data collected	Data relayed & transmission	Information generated & displayed
	MANTIS: Monitoring & Analytics to Improve Service MoMo: Mobile Monitor				SweetSense sensors can be reconfigured remotely via GPRS	

Table 2 One Select Submersible/Electrically powered motorised pump Monitoring systems using sensors (Thomas et al, 2021)

Date	Sensor System Lead Organisation(s)	Trials/Use	Sensor Type(s) & gateway	Data collected	Data relayed & transmission	Information generated & processing
Jan 2016 to Feb 2021	Hybrid of multiple sensors, including SweetSense	Northern Kenya & Afar Region Ethiopia (480 electrical pumps in arid regions)	▪ Electrical current sensor (Pressac brand split-core current transformer) ▪ SweetSense-brand EnOcean gateway	▪ Current between motor controller and pump	▪ Samples compressed to one reading every 40 minutes ▪ Data sent once per day sent via GSM cellular networks or the Iridium satellite network ▪ Transmission of data via Iridium's 9602 Short Burst Data Modem	▪ Electrical runtime of pump ▪ Determine whether a lack of data is due to broken or disconnected sensor or if the pump is off ▪ Ground truthing of data for algorithm validation

Figure 1: Summary of select pump Sensor Initiatives



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Zambia (2011) – Waterpoint Data Transmitter Development and Test – Oxford University

Over a decade ago, Oxford University's development and trials of a Waterpoint Data Transmitter (WDT) in Zambia was one of the first initiatives to illustrate the possibility of real-time monitoring of rural handpump functionality. The University designed, built and tested a WTD, and demonstrated that a simple microprocessor, accelerometer and GSM components were able to record graduated time-step data of lever pumps, which could be modelled into a reasonable water volume use approximation (Thomson *et al.*, 2012). It should be noted that to produce accurate data on pumped water volumes with the WDT, each pump/borehole combination had to be characterised to generate correct weightings. Thomson *et al.* (2012) proposed that a significant deviation in the apparent volume use from previously observed patterns or levels may indicate leakage in the system or another pump performance issue, whereas a slowly increasing apparent volume may also indicate a problem with the pump.

Looking into the future at that time, Thomson *et al.* (2012) concluded that WDTs can provide "timely and unambiguous data on the non-functioning of a pump which can be swiftly acted upon", while historical usage data could be analysed to indicate the nature of failure. It was proposed that handpump performance data, if held by a suitable institution, could be used for oversight and performance incentives for maintenance service contracts.

Kenya (2013) – Smart hand pumps – Oxford University

By combining a new maintenance model with mobile-enabled data on 66 handpumps, trials in Kyuso, Kenya over one year in 2013, Oxford University were able to improve the operational and financial performance of handpump services (Oxford/RFL, 2014).

In order to provide economies of scale and pool service maintenance, communities were clustered. One single service provider was appointed via the District Water Office, and a spare parts inventory system was introduced, which ensured the availability of adequate stock (apart from rising main sections). All repair events and parts were logged. For 'actively-managed' pumps, information on handpump use was automatically transmitted to trigger maintenance visits, with information shared with the service provider, local government and regulator through a user interface. Other, 'crowd-sourced' pumps also had an installed sensor, but the users had to phone a number (which had been placed on the handpump with a sticker) to request a maintenance visit. Prior to the trial, communities for both the 'actively-managed' and 'crowd-sourced' pumps had been informed that the free maintenance service would last for one year, after which they would have the option to return to the former maintenance arrangements, or pay an external provider to continue the maintenance service (Oxford/RFL, 2014).

The trials saw a decrease in the average pump downtime to 2.6 days from the baseline of 27 days, for the 'actively managed' pumps with an automatic response having a mean of 2.0 days whereas the 'crowd-sourced' pumps had a mean of 3.0 days (Oxford/RFL, 2014). Overall, 89% of repairs were completed within five days, rising to 95% for the 'actively-managed' group; 'actively-managed' handpumps were 50% per cent more likely to have been fixed within two days than the ‘crowd-sourced’ handpumps (Oxford/RFL, 2014). It was found that at least eight of the stickers displaying the number to call the maintenance service had been removed by the end of the trial, but it is not known when this took place and how it affected the trials. In a significant number of cases for the ‘crowd-sourced’ pumps, the pump was working to some extent when the repair was undertaken, suggesting pre-emptive repair requests by the community. The results of the trials are summarised in Annex 3.

Laboratory and Ghana (2012–2016) – The Intelligent Water Project

Building on the original ideas by Oxford University (Hope, 2011) and innovations by the Sweetlab project (Thomas, 2013), Messiah College set out to develop a system that not only monitored handle movement, but also water flow and well water level (Weaver *et al.*, 2016). The Intelligent Water Project (IWP) set out to develop a system to automatically capture and organise data on handpump performance from both sensor and human sources. IWP refers to the hardware, the database, data transport, a mobile app and a web interface. IWP was developed in the lab in the USA, followed by field tests in Northern Ghana and, by 2016, had gone through four design iterations (Weaver *et al.*, 2016).

Ethiopia, Mali, Ghana, Uganda, Sierra Leone, Central African Republic and Papua New Guinea (2013 – date) – Charity: water

Charity:water have been involved in the development of sensor technology for handpumps for almost a decade now, commencing with first generation sensors that were tested in Ethiopia, followed by second and then third generation sensors (Charity: water, 2021). Initial sensors were designed for the Afridev Pump, with the new sensors designed for the India Mark II pumps (Gorder & Milanesi, 2021). Charity: water and REST in Tigray, Ethiopia, ran an ambulance model that was linked to sensors and SMS (Butterworth, 2021). Gorder (2022) stated that as of January 2022, between 800 and 4,000 sensors had been installed in each of Ethiopia, Mali and Ghana, with piloting of the new generation of sensors planned in Uganda, Sierra Leone, Central African Republic and Papua New Guinea. Charity:water’s current approach is to incorporate considerations of scale throughout the development and testing, e.g. by manufacturing in China and collaborating with the private sector regarding cloud platforms for hosting of large volumes of data (Gorder, 2022).

Ethiopia, Kenya, Mali, Malawi and Zambia (2013–2017) - LifePump

As part of a project to develop and test a new progressive cavity pump (LifePump), Design Outreach, in partnership with Messiah College and World Vision, installed sensors on a limited number of pumps in Malawi, Zambia, Kenya, Ethiopia and Mali (Bixter *et al.*, 2016). The sensors comprise satellite-based remote data loggers created by SonSet Solutions[18], which are mounted on the pump spout. The sensors record daily usage information which was transmitted via satellite to Design Outreach for analysis (Bixter *et al.*, 2016). Using efficiency information collected from the well site

[18] https://sonsetsolutions.org/

shortly after installation and the number of handle rotations for a given day, total gallons pumped per day are calculated (Figure 2). In this project, the sensor data was thus used to monitor pump use, rather than being part of a maintenance programme.

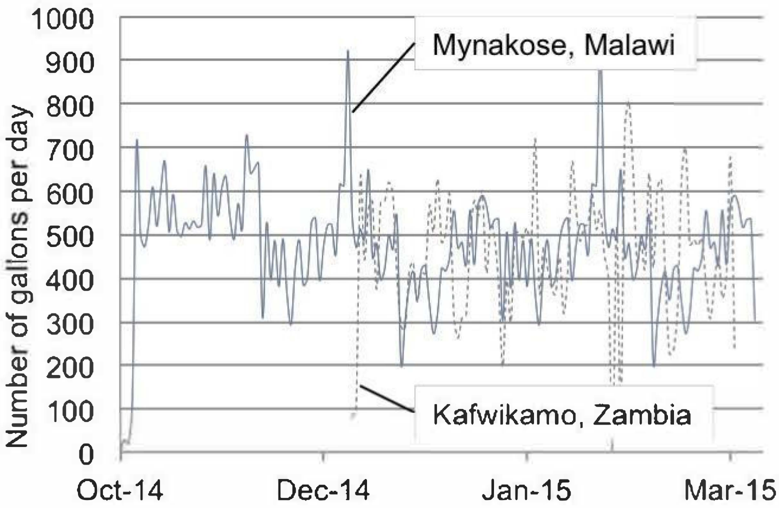

Figure 2 Satellite-based remote monitor data for Lifepump collected from two communities in Malawi and Zambia (Bixter et al, 2016).

Rwanda (2014–15) – Portland State University, Living Water International & SweetSense

In Rwanda, water service delivery and maintenance are typically delegated to local districts (GSMA, 2016b). Since 2007, Living Water International (LWI) has provided technical assistance to communities in 18 districts, where the organisation has installed and maintained over 300 handpumps. Prior to the sensor pilot project, LWI did not precisely monitor how many of 'their' handpumps were broken, but rather had been undertaking ad-hoc visits and responding to requests for maintenance by communities or officials. Such requests would be considered in light of other demands faced by staff, including obligations for new installations. LWI was planning to shift to a 'circuit rider' model.

In a collaboration between Portland State University, SweetSense Inc and LWI in 2014–15, a total of 181 sensors were installed on handpumps in the Districts of Ruhango (Southern Province) and Karongi (Western Province). Of these pumps, 53 were non-functional when the sensors were installed. The sensor data were used to identify pump failures by uncharacteristically long gaps in pump use. Repair times for three models were compared: the status quo, or 'nominal' model involving reporting by communities, a 'circuit rider' model involving visits to pumps by repair teams on a scheduled basis and an 'ambulance' model, which relied on sensor data to trigger repair visits (Nagel *et al.*, 2015).

In the preparation phase, 324 pumps in four of five of Rwanda's provinces were visited, of which 44% were not functioning. For 134 of the 141 pumps that were observed as non-functional, the mean reported downtime was 30.1 weeks and the median reported downtime was 20 weeks. In the subsequent trials of 168[19] pumps, comparisons were made between the different models for a number of parameters, including: (i) the rate of non-functionality (at time of baseline and endline), the amount of time that the pumps were functional (functional time) and time to repair. The average proportion of functional time was 67.1%, 77.1% and 89.9% for the nominal, circuit rider and ambulance models respectively, while the proportion of non-functional pumps at the end of the seven-month trial was 39.3%, 11.4% and 9.5% for the nominal, circuit rider and ambulance models respectively (Nagel *et al.*, 2015). Estimates of the median time to successful repair are 151.8 days, 56.8 days and 20.7 days for the nominal, circuit rider and ambulance models respectively[20]. The results of the trials are summarised in Annex 3.

It is important to acknowledge that other factors than the use of sensors influenced the results. In particular, whereas the ambulance team comprised two technicians with a pickup truck, equipped to repair, the circuit rider team consisted of staff on a motorcycle who had to call for a separate repair team if needed. By default, the ambulance model was thus able to be more responsive with a lower service interval.

The pilot project in Rwanda developed a partnership with the mobile network operator MTN in Rwanda to provide SIM cards at no cost to enable mobile to mobile communications for the remote monitoring of the handpumps (GSMA, 2016b). In the pilot, it was envisaged that the partners would become service providers to the Government of Rwanda, who would pay an annual service fee of USD 100 to access the data and dashboard, but at the time of writing, this had not been achieved (GSMA, 2016a). However, LWI has switched to the ambulance service model for all sensor-equipped handpumps and took on the costs of sensor operations for five months following the end of the pilot (GSMA, 2016b).

Sierra Leone & Gambia (2015-2018), Mozambique and India – MANTIS

Leeds Beckett University partnered with Environmental Monitoring Solutions and VisualWind Ltd to develop a system which can remotely monitor handpump sources, reduce the heavy time and resource demands for physical post-construction monitoring and thus improve monitoring, as well as maintenance (Swan *et al.*, 2017). The MANTIS trials, undertaken on India Mark II and Afridev pumps in the Gambia (12 locations) and Sierra Leone (11 locations), found that that in one particular handpump, a sudden change from a stable use pattern of over 5,000 to 11,000 operations[21] per day dropping to less than 2,000, and then to almost zero over 5 days was indicative of a pump rod breaking on the day that the use dropped to 2,000 (Swan *et al.*, 2018). The partners have continued working on the Mantis project in Mozambique and India (Greaves, 2021).

[19] Of the original 181 sites, 14 did not have sufficient data to determine pump function during the period and were dropped from the analysis.

[20] A review of the statistical methods used to assess the differences in pump characteristics between the service models to calculate the functional time and time to repair, as well as the model-based estimates of attempted and successful repair days, is beyond the scope of this review, but considerable expertise is required.

[21] It is not clear from the paper specifically what the term "operations" means.

Kenya (2016-2017) – The Water Project of the University of California, Portland State University & SweetSense

In a collaboration between The Water Project, University of California (UOC), PSU and SweetSense Inc., sensors were installed on 42 Afridev pumps in Western Kenya, with data on standpipe vibrations and basin gauge pressure (proxy for flow rate) collected from mid-January 2016 to March to 2017 for 8,962 sensor-observed pump days. In this project, the data was used to explore how sensors and supervised ensemble machine learning could be used to increase handpump uptime. The research indicates that it was possible to forecast pump failures and identify existing failures very quickly, as discussed further in the section on modelling below.

Ethiopia and Kenya (2016 – 2021) – UNICEF, IRC, mWater and SweetSense

The two USAID-funded programmes using in situ-borehole sensors are 'Lowland WASH' in Ethiopia and 'Kenya Resilient Arid Lands Partnership for Integrated Development' (Thomas *et al.*, 2018). Sensors have been installed on electrically powered motorised pumps in Afar and Somali Region, Ethiopia and Northern Kenya. Partners include SweetSense, IRC and UNICEF (Short *et al.*, 2018). While there were challenges with the sensors' technology in supporting maintenance, they did provide very useful data for research, which otherwise would have been extremely difficult to collect (Box 1).

Box 1 Sensor data for Research

Using the sensor data from submersible pumps at 221 water points in northern Kenya and Afar Region in Ethiopia, combined with satellite time series rainfall data, relationships between rainfall and pump use were analysed (Thomas *et al*, 2019).

It was found that in Kenya, a 1.0 mm increase in rainfall was associated with a 1.1% decrease in borehole use the following week, with the equivalent decrease of 1.3% in Ethiopia. In cases where there had been weeks without rainfall, a 19.9% and 27.1% increase in borehole use was found in Kenya and Ethiopia respectively. Relying on sensor data, this study provided "quantifiable information on water extraction that is otherwise difficult to collect" (Thomas *et al.*, 2019). Analysis of sensor data from electrically powered motorised pumps in arid areas of Ethiopia and Kenya has provided information on use of boreholes in relation to rainfall and the availability of surface water, and found an overall 23% increase in borehole runtime following weeks with no rainfall compared to weeks preceded by rainfall (Thomas *et al.*, 2019). This echoes findings by Thomson *et al*. (2019) in Kenya that in the wet season, handpump use was 1/3 lower than in the dry season.

4. Technical challenges

Cooper *et al*. (2014) identify a number of barriers to the uptake of handpump sensor technology, i.e. cost, reliability, functionality, security and user acceptability, to which Swan *et al.* (2017) add access to electricity (triggered by low battery life in the sensor) and mobile network coverage. The main technical challenges faced by sensor systems trialled in the field are summarised in Box 2.

Box 2 Technical challenges of sensors

Energy source and battery life

- In the 2013 trials of SweetSense in Rwanda, the system was powered by five AA batteries, with a design life of 6–12 months, but battery life was shorter than hoped.
- The MANTIS system claims to have an operational battery life of more than five years (Swan et al, 2019).
- MoMo sensors are optimised for low-power use to preserve battery power including only turning it on to initiate a communication transmission (MoMo, 2021).

Sensor robustness

- SweetSense units struggled with extended exposure to fluctuating temperature, humidity/moisture and wet/dry cycles in their first trials in Rwanda, and the waterproof seal in the unit occasionally leaked, resulting in sensor failure. SweetSense was rolling out an improved sensor design (long-life battery, watertight enclosure) to be placed outside the pump head (Swan et al, 2018).

GSM signal and transmission

- The original SweetSense sensors were designed to operate inside the pump-head, but suffered from attenuation[22] of the GSM signal (GSMA, 2016b)
- Not all areas have cellular network connectivity (Nagel et al., 2015).
- There is likely to be the need for a back-up system, or use of satellite sensors for water points where mobile coverage is poor.

GSM transmitters

- There was variation in the success rate of different transmitters in the initial Smart handpump trials (Swan, 2018) and early MoMo trials (Pearce et al., 2015). The new MoMo sensors have built in automatic feedback and retry mechanisms (MoMo, 2021).

GSM network

- Trials in Kenya found that local GSM services were unreliable, and that 40% of SMS messages were lost (Behar, 2013 in Swan, 2017).

[22] Attenuation is the reduction of the amplitude of a signal, electric current or other oscillation.

5. Data

Data analysis

Most of the sensor systems measure accelerometer and/or water pressure data, which are used to estimate pump use and flow rates. There are however, different ways that these data are collected, analysed and combined including:

- Gaps –> separate usage events –> thresholds -> classification –> trigger: accelerometer data is used to estimate the number of distinct pump usage events in a set time frame. The number of events per time frame unit is classified, and an alert is triggered if the fault classification threshold is reached. The PSU (2014-15) Rwanda trials assumed that gaps in accelerometer data exceeding 60 s indicate separate usage "events" (Table 1).
- Summary metrics for pumping events: summary metrics from raw pressure and acceleration time series data are calculated for distinct pumping events
  - The machine learning study using 2017-2018 data defined an event to end when the handle stops moving for three or more minutes (Wilson et al., 2017).

Data validity and ground-truthing of data

In the case of the 2014–15 PSU trials in Rwanda, the data reported on pump usage by the sensors "*were matched to sites and maintenance cohorts based on sensor installation records*" which was generally tracked through barcodes on the sensors and pumps which could be scanned on smartphones.

Ground-truth data was used to classify the training set for machine learning in the 2016–2017 SweetSense study of electrical pumps in Kenya and Ethiopia. Ensuring ground-truth data of pump conditions was required to build and validate their classification algorithms that predict whether a pump is functional or broken: *"An iterative process of pump report reviews, sensor data comparisons and verification through routine communication with field teams has led to a set of ground-truth training data for algorithm validation"* (Thomas *et al,* 2021)[23].

Experience of using sensors on deep motorised boreholes, of which some were solar and many were diesel, in Afar, Ethiopia was that a large number of false negatives (i.e. sensors which indicated that pumps were not working when they actually were). This was due to the fact that in some remote areas, with nomadic populations, the pumps were generally not in use all of the time, with considerable irregular pumping regimes in practice (Butterworth, 2021).

[23] In the project using 480 sensors on electrical pumps in Kenya and Ethiopia, reports submitted on the pumps through mWater by field visits were used to ground-truth the status of pumps and sensors, including providing information on false negatives (i.e. sensors reporting non-use of a pump when it was in use).

6. Modelling initiatives and results

A number of initiatives have used statistical modelling and/or machine learning to understand and demonstrate how handpump sensor data could be used to increase the uptime of handpumps. It should be noted there is an underlying assumption that there are institutions, finance and systems in place which dispatch maintenance personnel to repair the pumps.

Statistical modelling using SweetSense data in Kenya and Ethiopia (2016–2021)

In-situ data generated from the sensors that measure electrical current, installed on 480 electrical groundwater pumps in arid regions of Kenya and Ethiopia between January 2016 and February 2021[24], have been combined with ground truth data and remote sensing data (on rainfall and surface water) to develop algorithms to predict whether the pumps are functional or not. Two systems of statistical modelling were evaluated: (i) expert classification relying on explainable and consistent logic statements and (ii) machine learning – a complex statistical model which is not immediately comprehensible to a typical user and is hence sometimes referred to as a “black box” (Thomas *et al.,* 2021).

Data from the electrical current sensor do not distinguish between “not running on purpose” and “broken”, while a disconnected sensor would also indicate that the pump is not running. Thus, a more sophisticated classification was introduced with the pump status classified as either (a) functional (true positive), which could either be “running” or “not-running on purpose” or (b) broken (true negative). A false negative refers to a case where the sensor reports that a pump is not used, when it actually is. The classification algorithms used ground-truth data developed from a digital survey of pump reports on the platform mWater and field reports. These enabled the identification of running pumps as well as false negatives. The expert classification system reflected the best judgement on the balance between utility and interpretability and included typical run-time data for the pump as well as recent rainfall near the pump from remote sensing data. Machine learning included additional data on the average run-time of nearby pumps in the same week and nearby surface availability (from remote sensing data), and was trained to differentiate between the “no use” conditions of “seasonal disuse” and “broken” (Thomas *et al.,* 2021).

Validation indicated that the expert classification system accurately classified functional pumps (including those not in use) over 82.1% of the time, whereas the rate for the machine learner was 84.5%. When a pump is being used, both systems’ models predict this 100% of the time. However, when a pump is not being used, the expert system accurately predicts that such a pump is broken 49.4% of the time (which is no better than chance), whereas the machine learning rate is 65.2%, showing that the machine learner had a higher performance (Thomas *et al.,* 2021).

[24] System described in Table 2.

Assuming an average drought-period uptime of 60% in the region (using data from McAllister *et al*, 2020), and assuming that it takes two weeks to repair a pump, and applying the potential rates for correct detection of broken pumps and false alarm rates, Thomas *et al.* (2021) estimate that the drought-period uptime could be increased to 84.5%. The paper further provides an illustration of the cost savings that this could make. Given the sensitivity to the assumptions, these figures are not reproduced in this review.

Machine learning using SweetSense data from Kenya (2016–2017)

The sensor data collected from 42 Afridev pumps in Western Kenya between mid-January 2016 and March 2017 provided 8,962 sensor-observed pump days, which were used to train and test a 'supervised ensemble machine learning tool', Super Learner (Wilson *et al.*, 2017). Accelerometer and pressure transducer data were used as proxies for handle motion and water flow.

Whereas the field trials in Rwanda by PSU (described above) used uncharacteristically few pump events in one day as the rule of thumb for pump failure and service dispatch, this study trained a model on human-verified and sensor-observed pump failures and analysed the ability of the learner (software) to forecast failures and identify them quickly after they happen. Ground-truth data about when and why pumps failed was used to classify a training set, with manual inspection of sensor data used to estimate the start time for field-verified pump failures. Twenty-four pump failures were identified, including short-term pump failures or non-use that did not initiate a service call. The duration of the failures ranged from 1 to 42 days[25] and amounted to 288 observed failure days out of the observed 8,962 pump-days.

The 24 failure events were used to train the learner, with data from 'broken days and data from 1–7 calendar days before failure used. Summary data metrics from pumping events were calculated, and rolled up into day-wise features, based on domain knowledge which the study team believed were predictive of imminent pump failure. Nine features that were identified to predict failure were grouped into the following four categories – features based on:

- Number of pumping events per day
- Pump flow rate
- Duration of pumping events
- Ratio of pump flow rate to amount of handle motion (i.e. volume of water per human effort).

Wilson *et al.* (2017) notes that as some of the features capture properties of the pumps, the model is not a purely statistical model, but partially a physical model. At forecast horizons of over seven days, the model was unable to forecast failure any more than a random guess. The learners do not directly predict a binary outcome, but provide a probability of failure (0-1) for each day. In order to turn this output into a binary "not failed vs. failed" or "won't fail vs. fail", a threshold has to be set. The closer that the threshold is to 1, the fewer false positives (pump considered broken when it is not), but this needs to be balanced with an increased number of false negatives (pump considered to be working

[25] With a mean and standard deviation of 12.0 and 9.8 days respectively.

when it is not). The learners in the study detected 22 out of 24 failure events within one day of failure.

A number of assumptions were made about how an implementation agency would incorporate information from the machine learner, and how preventative maintenance would affect pump performance, including dispatch delays, dispatches resulting from forecasted failure, preventative maintenance actions and re-dispatch following an earlier false positive. By analysing the hypothetical performance of the fleet of pumps, the study argues that sensors and supervised machine learning could be used to increase fleet uptime from a best-practice baseline of 70% to >99% (Wilson *et al.,* 2017).

7. Costs and potential revenue

Actual and estimated costs

Although remote monitoring of handpumps may have the potential to reduce the labour and travel costs of regular monitoring, the sensor technology and required human resources also have associated financial costs. This includes costs of hardware, energy, software, data transmission, repairs, maintenance and replacement. There is also need to invest in training the operators of the dashboard. Studies have published actual costs of sensors, or of the maintenance programme, while some have estimated the savings that could be made through the introduction of handpump sensor technology as summarised below:

- The SweetSense system used in the ambulance model in Rwanda in 2013/14 was estimated to have a sensor hardware cost of USD 500 over two years plus the cost of sensor servicing/maintenance of USD 115 per pump per year. The documented costs of servicing per site per month were USD 39.4, USD 30.0 and USD 15.4 for the ambulance, circuit rider and nominal model respectively[26], with an additional USD 9.5 per site for sensor servicing. Using an assumed capital cost of USD 15,000 for the handpump and borehole, and straight line depreciation over ten years, Nagel et al. (2015) estimate an annual capital expenditure of USD 1,500. This was divided by the model-based estimates for mean pump functionality for the three models (see footnote[27]) to estimate the annual capital expenditure (CapEx) per functional year. Likewise, the operating expenditure (OpEx) was calculated per functional year. Comparing the three service models (ambulance, circuit rider and nominal), the cost per pump per functional year is almost the same (UDS 2,561, 2,611 and 2,508 respectively) (Nagel et al., 2015).

[26] Costs include lodging and meals, salaries, tools, parts and supplies and transportation.

[27] The data for the actual proportion of functional time for the three models is presented in Annex 3. Univariable and multivariable fractional response models were used to adjust for age, pump type and cylinder depth and determine model-based estimates for mean pump functionality (90.82%, 72.94% and 67.63%). These values are 0.2 to 1.2 percentage points higher than the actual values.

- Oxford/RFL (2014) detail the operational recurrent costs of the overall maintenance system for the 66 handpumps in Kyuso, Kenya: annualised, recurring cost per repair in the trial was USD 62; with 136 repair visits, the cost was a total of USD 8,368 in 2013, i.e. a crude average of USD 127 per handpump[28]. The study used estimates of the water pumped per handpump and repair costs to calculate the annual unit cost of water production for each pump, and found them to range from less than 0.5 to over 18 USD/m^3. Notably, the high costs are associated with low volume pumps (providing ≤10m^3 compared to the sample average of 289m^3 per year). Handpumps with high costs of production were linked to low volumes of water pumped, while lower unit costs of water production were associated with more heavily used handpumps[29].
- The SweetSense system in the machine learning study based on data from 42 Afridev pumps in Kenya in 2016/17 assumes a capital cost of USD 360 and annual costs of USD 410 for the sensors plus annual operating costs of USD 300 for Kenya and USD 820 for USA-based administration for each pump (Wilson et al., 2017). With the incorporation of a large number of assumptions (see modelling section above), it was estimated that the machine learner model would cost USD 2,240 per pump per working year compared to USD 2,387 for a circuit rider model with no use of sensors indicating a cost savings of 7% (Wilson et al., 2017). However, while the study makes numerous assumptions with respect to how the implementation agency would incorporate this data, it does not include a sensitivity analysis.
- The Charity: water 3rd generation sensor device (i.e. there was the AFD-1, AFD-2, and the third generation is the IM2), including 10 years of data costs about USD 250 (Gorder & Milanesi, 2021).

The use of different metrics to estimate costs (e.g. cost per pump/functional year and cost per m^3) render it very difficult to make meaningful comparisons. However, they do provide starting points for the development of future costing methodologies. Thomas *et al.* (2021) note that the common question when considering the benefits versus cost of an instrumentation system to support pump repairs is whether the sensor could be replaced with a pump operator, caretaker or other authority calling a service provider.

[28] This is broken down into spare parts (26%), information, (including message and battery replacement (27%), transport (26%) and labour (19%).

[29] It is worth noting that ≤10m3/year is extraordinarily low use, equating to slightly more than one 20-litre jerrycan per year assuming that source is pumped every day.

Revenue

Will the use of sensor technology also help to generate much-needed investments to support maintenance services? This remains a largely unanswered question. GSMA (2016) speculates that given the fact that consumer fees are unlikely to cover all capital and maintenance costs, proof of uptime based on sensor data could provide a basis for government or donor subsidies. This remains to be proven and fully documented, although incentivisation of uptime has been incorporated into water supply services that rely on solar-driven pumps by the Uptime Consortium (Chitwood, 2022).

Another question in relation to revenue is whether handpump users would actually pay towards, or pay on a regular basis for maintenance, and maintenance services if downtime could be kept very low (and supported by sensor technology). Based on a willingness to pay study undertaken in communities that had been involved in the sensor technology testing and maintenance services trialled by Oxford University in Kenya in 2013, Koehler *et al.* (2015) suggest that working pumps may elicit a virtuous cycle whereby reliable water delivery can unlock user payments, which can in turn be used to maintain pumps. (Box 3). It is important to note, however, that in this example, in order to recover all maintenance costs, the revenue would need to be pooled. While this study is promising, in practice, the generation of sufficient revenue from communities from pooled maintenance services remains far from certain.

Box 3 Findings of a willingness to pay study in Kenya (Koehler et al., 2015).

Focus group discussions with 66 communities that each used a community handpump and had experienced a free maintenance service over a period of one year (described in Chapter 2 – *Kenya (2013 – Smart hand pumps*, expressed:

- a fivefold increase in the willingness to pay (from USD 0.2 to USD 1 per household per month) among users that had experienced a reliable water supply service in the previous year
- the number of handpump groups intending to contribute monthly – rather than making post-breakdown payments – increased threefold

The aspects of service delivery that were most valued by the water users were the speed of service (77%), the quality of the service (54%), and the knowledge that the service is guaranteed (31%)

However, it should also be noted that of the sample of 66 handpumps, 70% required at least one repair in 2013, with 63% of broken handpumps requiring more than one repair, and the average cost of each repair was USD 62 (Oxford/RFL, 2014). If the stated willingness-to-pay of all pump user groups reflected the actual future payment collected, this would raise sufficient revenue to have covered all repair costs in 2013; however, if communities chose not to pool revenue, 43% of communities would not have met their individual costs (Oxford/RFL, 2014).

8. Use of sensors in water supply service provision projects

Several projects have incorporated the use of sensors to support water supply service provision, including those listed below.

- Following the field trials in Rwanda in 2014–15, PSU revised their business model to focus on 'sensors as a service', and were reported to subsequently have contracts with NGOs and donors valued at over USD 2 million (GSMA, 2016b).
- Sensors communicating with the satellite network to remote electrically powered boreholes were introduced in USAID programmes from 2015/16 Ethiopia (One WASH/Sustainable WASH) and Kenya (Kenya Resilient Arid Lands Partnership for Integrated Development – Kenya Rapid) under a community management model (Thomas, 2018). However, the adoption of sensor-based technology was limited by the nearly non-existent budgets for borehole pump repairs (Thomas et al. (2021).
- In Mali, UDUMA has a delegated service contract to supply 560,000 villagers in the Bougouni region with reliable access to water over a 15-year period (2020–2035). Users are charged a fixed tariff of 500 CFA per m^3, or 10 CFA per 20 L jerrycan (€0.015), and UDUMA Mali is striving to manage the E-PUMP fleet continuously (maximum breakdown interruption of 72 hours) over the long term (Odial Solutions, 2020).
- The Uptime Consortium, which includes financial incentives to service providers of solar driven pumps to reduce downtime to less than a day (Chitwood, 2022).
- Fundifix (Kenya), whereby communities sign up for an O&M service guarantee (repair within three days). If the conditions are not met, communities are given a free month's service. Notably most repairs are in the same day, as there is regular interaction with communities, who are able to call immediately if there is a failure. There is also preventative maintenance, which fixes a problem before a bigger breakdown. However, when pumps function for the whole year, communities become conditioned not to pay for the service and users might not understand paying for preventative maintenance. Sensors and sensor data are being incorporated into the Fundifix operation, with current efforts being made to predict failure (RWSN, 2021).

9. Discussion

Over a decade ago, Hope *et al.* (2011) essentially set a challenge for the sector: to explore how sensor technology could contribute towards reducing transaction costs of payment for water, identifying and reducing non-revenue water loss, and improving infrastructure maintenance, supply regularity and customer satisfaction. Thomas *et al.* (2013) argue that instrumented monitoring via distributed data collection platforms may overcome challenges of subjective, self-reported data that is collected sporadically and communicated at a later date. Oxford/RFL (2014) suggest that improved information on water services which flows from users and water service providers to local government to regulators to national governments and international donors could be used to improve accountability and ultimately enable regulators to align performance with measurable outcomes. Others have suggested that sensor-triggered systems could increase transparency, accountability, responsiveness and ultimately improve water services (Nagel *et al.*, 2015; Thomas *et al,* 2021).

However, based on experiences to date, when considering sensor technologies and sensor-supported monitoring and maintenance systems, there are a number of topics that need to be fully considered:

- Improving downtime and the importance of the underlying maintenance system – field trials have demonstrated that sensor systems can contribute to improving handpump monitoring and maintenance services, and reduce pump downtimes. However, due to the many factors, including different maintenance regimes and levels of external support, as well as different definitions, there is need for caution when comparing downtime between different sensor projects. Simplistic comparisons are misleading. For example, as well as the use of sensors, other factors influenced the results in the promising initial PSU trials in Rwanda (2014–2015) and by Oxford University in Kenya (2013). In both cases, the maintenance systems contributed significantly, although differently, to the good sensor results[30]. While Sensor technology is able to provide data, these data alone are not able to make up for gaps in maintenance services or their required finance. Data needs to plug into a financed maintenance service system which is able to respond rapidly to breakdowns. Thomson (2021) emphasises that it is more important to focus on the 'management model', with sensor data part of that, while Thomas et al. (2021) call for a better understanding of the factors that affect the utilisation of real-time data and effective adoption of sensor-based technologies to improve service delivery.
- Sensor maintenance – by introducing a new technology, sensor projects also introduce additional maintenance requirements, namely maintenance of the sensor itself.
- Sensor data and accountability – in order to unleash the full potential of the information generated by remote handpump monitoring for accountability, one needs to ask "who receives the information" and "what will they do with it" (Swan et al., 2017). Reflecting on the latent, transformative potential of sensor technology, Swan et al. (2017) suggests that in addition to the information being seen by those who are directly responsible for pump

[30] In Rwanda, whereas the ambulance team comprised two technicians with a pickup truck, equipped to repair, the circuit rider team consists of staff on a motorcycle, who had to call for a separate repair team in case maintenance was required – by default, the ambulance model was thus, able to be more responsive with a lower service interval. In 2013 the maintenance service in Kenya was provided free of charge.

maintenance (referred to as a closed loop of information), there is scope to widen access to water users themselves, local community organisations, civil society, NGOs, the media and political leaders. However, the use of sensor data to improve accountability remains to be proven in practice.

- Improved real-time monitoring – an outstanding question is whether sensor data could be linked to large global, publicly accessible databases such as WPDEx or mWater to enable real-time updating. The number of initiatives which provide proactive and reactive maintenance services for groups of handpumps through a subscription or insurance system seem to be growing, e.g. Pump for Life by MSABI in Tanzania (Kanyeto et al., 2016) or the circuit-rider model by Water for Good in the Central African Republic (DeArmey, 2016), among others (see RWSN, 2021). Both Pump for Life and Water for Good use on-site electronic reporting, which is completed during each maintenance visit with the data used to monitor program activities. While these initiatives do not appear to be currently using sensor technology, if such sensor systems prove to be reliable and cost-effective, they may well be encouraged to so in the future.
- Predicting failure – looking into the future, there is potential for the 'simplistic information' on pump use patterns to be analysed using rule-based algorithms such as artificial intelligence or fuzzy logic to differentiate between data signatures that indicate pump wear, increasing use, falling water tables and inaction (Swan, 2019). However, such predictions require information on when usage patterns deviate significantly from a pump's normal operational range (Swan, 2019). Using failure predictions could result in dispatching resources in response to measured or predicted faults. Failure predictions have the advantage of allocating limited resources for maintenance when and where required, rather than spreading resources evenly, including where they are not needed. Although modelling work by Wilson et al. (2017) indicates that the preventative maintenance of handpumps could be enhanced by machine learning, this has not yet been proven in practice.

10. Conclusion

While there have been considerable trials of handpump sensors in the field, they have been incorporated into some water supply projects, and there are some promising results, the extent to which sensor systems will actually improve infrastructure maintenance, including payment by water users or increase accountability remains unproven. In order for sensor data to be effectively used to respond rapidly to actual (or impending) breakdowns, they need to feed into well-resourced management and maintenance systems which are adequately staffed and motivated and able to respond. User payment is likely to depend not only on the water supply service itself, but also its affordability to the users and other contextual factors.

The actual costs of sensor-enabled maintenance models at scale are not fully understood, and not all cost data are readily available in the public domain. Handpump sensor systems, including dashboards, are increasingly being developed by the private sector, and with rising interest, as well as growing competition, it is unlikely that cost data will be made available in the future. Operating as businesses, companies will most likely charge a price for the provision of sensor technology and sensor-enabled services. Will these businesses be dominated by those from the North, or is there a chance for Southern-based businesses, operating in the country where the services are provided to gain a foothold?

While pump performance data has potential to improve the accountability of service providers, this will depend on who has access to which data, and how the data are used. Going forward, there may be a need for the development of clear, easy-to-understand data-sharing standards and protocols, and even regulation with respect to data protection and use.

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Annex 1: Hand pump sensor visual summary

Sensors, data and transmission	Considerations & Results

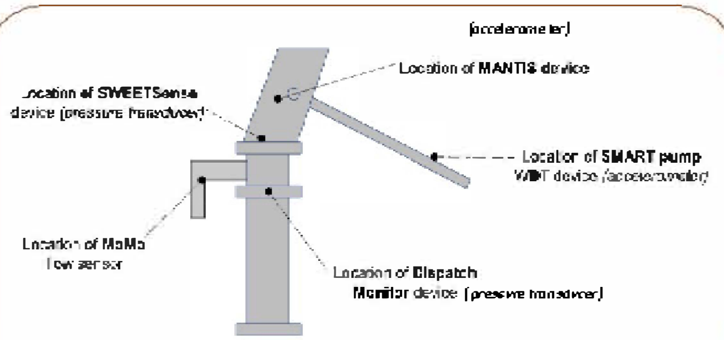
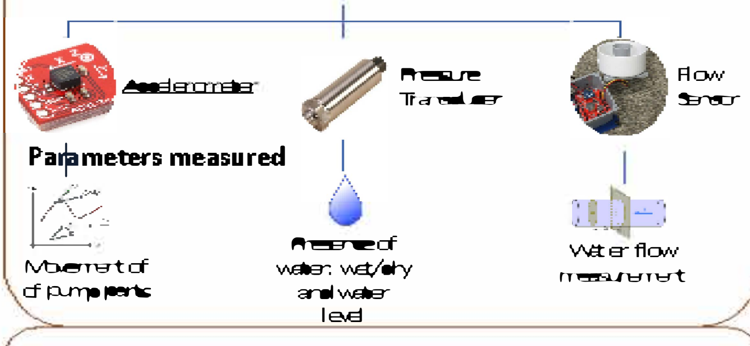


Figure: Five hand pump monitoring systems (adapted from Swan et al, 2018)

Sensor devices



On board processing

- Data sampling
- Packaging of data

Data Transmission

GSM
Satellite

Data Storage, Post-processing & Analysis

- Data ownership & access
- Database location
- Duration of storage
- Data cleaning and verification
- Data processing
- Results

Information & Dashboard

- Levels of access

Sensor Issues

Hardware

- Battery life & charging
- Electronics close to water

Software

- Drift in accuracy as pump components wear => calibration

Transmission

- Cellular network connectivity

Preparatory work to turn data into information that can be used

- Ground truthing
- Interpretation of the data
- Assumptions
- Statistical analysis
- Validation of algorithms

Results

Information obtained

- Pump activity/inactivity
- Pump functionality/non-functionality/seasonal use

Action

- Information used to trigger response

Achievements

- Reduced downtime/increased uptime

Embedding

- For sensor data to be used for action, there is need for budgetary support and systems that act on pump breakdown.

Annex 2 Demonstrated monitoring systems, downtime & functionality

Trials	Model & Data			
Rwanda Portland State University (2014–15) (Nagel et al, 2015)	Baseline (324 pump sites in four of five provinces)	-	Proportion of non-functional pumps: 44%	-
	Baseline (134 non-functional pumps in four of five provinces)	Mean downtime: 30.1 weeks Median downtime 20 weeks		
	Sensor trial 168 pumps[31]			Average proportion of functional time: 0.739
	Sensor trial – Nominal Model 82 pumps	Median time to successful repair: 151.8 days	Proportion of non-functional pumps: 39.3%	Average proportion of functional time: 0.671
	Sensor trial - Circuit Rider Model 44 pumps	Median time to successful repair: 56.8 days	Proportion of non-functional pumps: 9.5%	Average proportion of functional time: 0.717
	Sensor trial – Ambulance Model 42 pumps	Median time to successful repair: 20.7 days	Proportion of non-functional pumps: 11.4%	Average proportion of functional time: 0.899
Kyuso, Kenya Oxford University and Rural & Rural Focus Ltd in Kenya (2013) (Oxford/RFL, 2014).	Baseline	Average days to repair: 27[32] Median downtime: 6 days		
	'Crowd-sourced' handpumps (water users trigger maintenance alerts via a phone call to a specific number)	Mean time to repair: 3.7 days Median time to repair: 3 days		
	'Actively managed' handpumps with automatically triggered maintenance visits from sensor data	Mean time to repair: 2.0 days Median time to repair: 1 day		

[31] A total of 24,495 functional days across all models

[32] Likely to be a conservative estimate based on previous research in Kwale county (Oxford/RFL, 2014).