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Water Net: An IoT-Based Framework for Drinking and Irrigation Water Quality Monitoring

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ABSTRACT

Humans, animals, and plants all need water to thrive. Despite its significance, not all available water is safe for human consumption, household use, or commercial production. Industrialization, mining, pollution, and natural disasters are just a few of the many factors that reduce the quality of our drinking water and make it unfit for other uses as well. The World Health Organization has issued recommendations detailing the maximum allowable concentrations of different factors in drinking and irrigation water. In order to quantify the significance of these factors in establishing water quality, we devised the Water Quality Index (WQI) and the Irrigation Water Quality Index (IWQI). It can be extremely challenging to gather water samples from different locations, move them, measure them, and compare the results to standards while also sticking to a number of guidelines.

Keywords

Water quality indicator, water surveillance network, machine learning, LoRa, cyber physical system, potable water, irrigation water.

INTRODUCTION

The availability of potable water is now widely recognized as a fundamental human right. One of the United Nations' 17 goals for an improved future for all people is universal access to pure water by 2030 [1]. To guarantee and maintain access to water and hygiene for all [2] is the sixth target of the Sustainable Development Goals.

The third Sustainable Development Goal (SDG) is good health and well-being, and clean water is directly related to this because it prevents the spread of diseases like cholera, typhoid, and diarrhoea, which together account for the majority of deaths (especially among children) in developing countries in Africa and Asia [3]. Agriculture and food manufacturing rely heavily on water resources as well. It has been estimated that about 45% of new born mortality can be attributed to hunger in poor nations, where malnutrition affects about 10% of the global population [5]. Therefore, ensuring worldwide food security is.

crucially significant. Goal 2 of the SDGs is dedicated to achieving food security by encouraging healthy cultivation and enhancing food delivery, in an effort to put an end to world starvation. Water is essential in food production and cultivation in general, both for use in irrigation and for human and livestock sustenance. The supply and effective handling of water suitable for farming use is thus of paramount importance. Rivers, creeks, weather, and groundwater are just some of the places you can get water to use for consumption and gardening. (Accessed through wells and boreholes). Oftentimes, the most important variables in

determining the composition of water samples are the source's makeup and traits. Human activities like mining, crude oil extraction, and Indus trial pollutants produce chemical wastes that ultimately find their way into streams, rivers, and other sources of water, altering the character and qualities of these waterways in ways that cannot be reversed by natural means alone. These fluids are eventually consumed by humans, used to hydrate animals, or put to use in agricultural endeavours. This water poses serious health risks and may even be fatal if ingested. Therefore, it is crucial to establish an appropriate procedure to guarantee complete water tracking from the point of origin to the point of final consumption. Water purity or "ability for use" for human (and animal) intake, irrigation, and household (or commercial) purposes must be evaluated using samples gathered at each surveillance site.

Literature Review

Here, we take a look at some previously published works that cover similar ground. This part is broken up into three sections, the first of which discusses cellular network uses in water parameter tracking. Water quality standards for human consumption come in at number two, followed by studies that evaluate water for its potential in agricultural farming.

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USE OF WIRELESS NETWORKS IN WATER CONTROL MONITORING

A network for detecting and tracking water characteristics in a Brazilian metropolis with a metal-producing economy was created in [12].

pH, dissolved particles, Zinc, Lead, and other physicochemical water factors are being measured at we've water surveillance sites. The data was then analysed using main components. In a similar vein, [13] established a network of 23 monitoring sites to evaluate the physicochemical and microbiological characteristics of the water in the Limpopo River Basin in Mozambique. The authors of [14] created a fiscally feasible model that merged evolutionary algorithm with 1-D water quality simulation to handle the difficulties of optimum location of sensors and sampling rates, which are commonly encountered when creating water monitoring systems. The writers were able to answer the NP-hard issue of ideally situating tracking sites, even though the work was only approximated using a genetic algorithm. It is common practice to take samples from a body of water at regular intervals in order to monitor its characteristics. Physical, molecular, and microbial indicators may be included here, such as hydrogen potential (pH), temperature, salt concentration, etc. The data from a water surveillance network's sensor must be sent back to a central location in order for the appropriate actions to be taken. Lightweight communication protocols that can send relatively tiny data over long distances are necessary for water surveillance networks due to the scattered character of the transferred data. According to the available material, LPWAN technologies are the best option for use in this context. In [19], LPWAN systems are extensively discussed. Several sub-GHz options were evaluated and contrasted for their range, data velocity, and number of available channels. The claimed maximum range for Ingenu in urban areas is 15 kilometers, followed by SigFox at 10 kilometers in urban areas and 50 kilometers in rural areas, and finally LoRa at 5 kilometers in urban areas and 15 kilometers in rural areas.

The argument over whether software models or real-world testing is more effective when evaluating communication technologies has raged on for quite some time. Although this discussion is still ongoing, many studies have shown that simulation findings are comparable to or even better than those from actual experiments. In [20], for instance, the writers contrasted simulation findings with real-world tests of inter-vehicle communication using LoRa. For the simulations, they used NS3, and for the real-world experiments, they used an Arduino UNO with a Dragino LoRa module. They measured things like propagation loss, covering packet inter-reception (PIR), packet delivery ratio (PDR), and received signal strength indicator (RSSI). They determined that the simulator's findings were aligned with those of the actual exams. Hassan [21] also examined the performance of LoRa as a Wi-Fi gateway, comparing modelling findings (from Radio Mobile emulator) with real-world experiments (using microprocessors + LoRa modules). Unlike [20], [21] did not provide a comprehensive analysis of virtual versus real-world outcomes across all metrics studied, but still reached the same positive conclusion regarding the simulator's efficacy. [22] installed seven Bee module pairs and contrasted their ability to communicate on 800/900MHz and 2.4GHz bands. They came to the conclusion that the Radio Mobile simulator's findings were consistent with those of actual evaluations.

THE SYSTEM FOR CHECKING WATER QUALITY

Creating a practical network for real-time tracking of water factors is a primary goal of this effort. Our goal in creating this network, which we call "Water Net," is to facilitate a Cyber-Physical System for Water. (CPS-W). Like other CPS [32], CPS-W utilizes a Fog/Cloud computing [17] infrastructure alongside an Internet of Things (IoT) sensor and actuation component. This combination has found use in many fields, including medicine [33], transit [34], and environmental observation [36]. A two-tiered LoRa network would electronically link the devices in Water Net. The LoRa (Long Range) LPWAN prioritizes battery consumption over data transfer speed [19]. In optimal conditions (clean line of sight, excellent antenna height, antenna gain, transmission strength, and transmission frequency), it has been demonstrated that LoRa can send data up to a length of 300 km at the expense of data capacity [37]. The monitoring data being shared between Water Net devices is relatively tiny, so we only need a small amount of capacity.

WATER SYSTEM IN CAPE TOWN

The city of Cape Town in South Africa's Western Cape region is proposing a network called Water Net to keep tabs on water quality. Water for Cape Town (abbreviated CCT) and its surrounding area is stored in fifteen large ponds. The CCT owns eleven of these ponds [38], while the Department of Water and Sanitation is responsible for the remaining four. In Figure 2, we see a bird's-eye view of the city's dam infrastructure. This study creates a network model for tracking water quality

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metrics for consumption and agricultural reasons, with a particular emphasis on the 11 ponds held by CCT. Water amounts, consumption, and replenishment rates can all be monitored with this device in addition to its "fitness for use" for imbibing and watering. Some of these structures have tracking systems, but the vast majority rely on human operators or are completely independent. The goal of our network development effort is to create a system for live, real-time tracking of water quality metrics across all of the structures in a community.

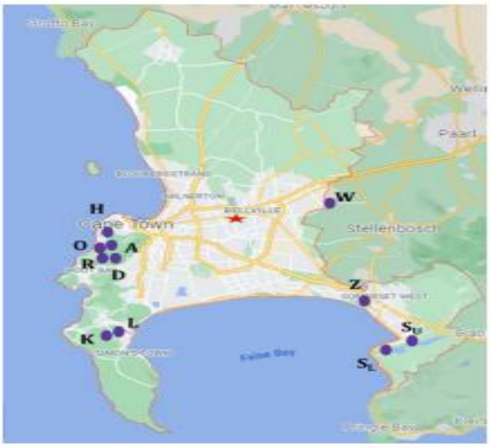

FIGURE 1. Locations of CCT-owned dams across the City of Cape Town, South Africa. Where A = Alexandra Rest. Dam; D = DeVilliers Dam; H = Hely-Hutchinson Resv. Dam; K = Kleinplaas Dam; L = Lewis Gay Dam; O = Woodhead Dam; SL = Steenbras Dam – Lower; SU = Steenbras Dam – Upper; R = Victoria Dam; W = Wemmershoek Dam; Z = Land-en-Zeezicht Dam.

WATER QUALITY EVALUATION

The goal of WaterNet is to collect information about the quality of the city's water supply at various facilities. Water's "fitness for use" (for things like imbibing and drainage) is evaluated using these standards. Machine learning (ML) models are proposed in this work as an alternative to traditional instrumental and physic-chemical analysis for evaluating water parameters in the lab. These models can automatically ascertain whether or not a given water sample is suitable for human consumption or agricultural irrigation by considering a wide range of water quality indicators. The goal is to simplify and reduce the time and money needed to test and analyse water samples to ascertain their quality. Results could be achieved in a matter of minutes by transferring a pre-trained ML model from one place to another using ML and transfer learning. Detailed explanations of each step in the process depicted in Figure 4 are provided below.

CURATION OF DATA

To study ML, a sample is usually necessary. Our own was necessary because there were no publicly available, comprehensive databases covering Africa's potable and agricultural water. We mainly used Elsevier's Data in Brief to compile several "small" databases on potable water and irrigation/agriculture. (Dib). Dib is an online, peer-reviewed publication that publishes study data and methods [40]. To find relevant papers, we used the terms "irrigation water," "potable water," "groundwater," and "drinking water," before removing any that weren't directly about these topics. Overall, we found 11 papers (7 of which included irrigation water statistics) with the majority coming from Asia. Using Microsoft Excel, we collected the data, merged it, and stored it as two csv files: one for potable water and one for irrigation. The most important thing we needed to get started on this project was access to data for training and testing machine learning models to categorize water samples. These water attribute data should ideally have come from a water surveillance network, but as far as we can tell, no such network exists, so we had to invent. Since this is just a proof of concept, we aren't too picky about where the data came from, but we did make sure that all the datasets had very comparable feature sets. (Water parameters). The work here resembles that of [24]. The characteristics (water factors) from the various papers examined are compared in Tables 1 and 2.

IMPLEMENTATION

There were two stages to our rollout plan: A and B. Phase A concentrated on Water Net, the water surveillance network, and Phase B evaluated water purity using data collected by Water Net.

PART ONE: Mocking Up a Water Network

Radio Mobile software [57] was used in conjunction with Google Maps and Topographic map.com to model a citywide water surveillance network (Water Net). Topographic-map.com is a free online tool that gives information about the topographical topography of a region, including hills, mountains, and Val leys, in contrast to Google Maps, which is a web-based mapping and real-time position sharing service by Google [58]. Radio Mobile is a radio-frequency dispersion

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simulation network planner [57]. Coverage and Pt. broadcasts are simulated using a dispersion model that takes into account the effects of rough topography. Because Cape Town is built on a series of rolling areas, with several valleys wedged between mountains and hills, Radio Mobile's topography transmission feature makes it perfect for our application. Since most transmission bands do not travel through hills and/or mountains, the city's irregular topography makes direct line of sight radio dispersion challenging and presents an intriguing networking task. Therefore, Radio Mobile is ideally suited for evaluating Water Net's radio reachability, signal levels, and line of sight. We started by making a Google Maps overlay with all the important landmarks and attractions.

This was exported to a KML file with the locations embedded, and then loaded into Radio Mobile. A two-layer hierarchical network architecture was developed in Radio Mobile. LoRa networks were set up at the lower level to link the dams to the WTPs (FNs), with a transmitting strength of 14 dBm, a reception cut-off of 80 dBm, and antennas standing 10m tall. Using a 2.4 GHz LoRa network [60] set up with a frequency range of 2.41-2.46 GHz, transmit strength of 22 dBm, reception cut-off of 75 dBm, antenna gain of 21 dB, and height of 30 m, the FNs were linked to the ILLIFU Cloud data center. Figure 5 depicts Water Net's two-tiered Cyber Physical hierarchical network, with X-GW representing the gates (edge devices) at each dam and FN1 representing the core network. .The FN7 WTPs are where all the fog nodes are located. We used a dispersal multiplier of 12 to increase our reach. Since we are only transmitting tiny sensor data at regular periods, we can live with the reduced data rates that come from a larger dispersion factor [19].

CONCLUSIONS & RESULTS

In keeping with the execution portion that came before, we share our findings in two parts: the first covers how the water surveillance network (Water Net) performed, and the second examines how ML can be used to evaluate water purity for human consumption and agricultural irrigation. Table 4 provides a summary of the findings and insights gained from simulating the network in Radio Mobile for the purposes of A. WATER MONITORING NETWORK. Only two FNs (FN3 and FN4) are able to access ILLIFU with a single step of connectivity. For this reason, we will be using a star-based, point-to-point network.

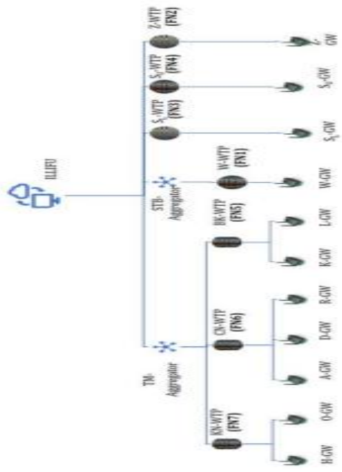

FIGURE 2. Hierarchical Cyber Physical Network for Water Net.

topology cannot be used, instead a partial mesh with node rebroadcast is considered. FN1 is located close to the ground level and almost fully surrounded by high grounds, hence the need for a repeater (STA) mounted on a 1136 m high hilltop at Stellenbosch farms (-33.90989, 18.74262). Despite this repeater, FN1 (via the repeater) is still unable to directly reach ILLIFU but has FN4 in its line of sight. FN1 can therefore reach ILLIFU by hopping through STA and FN4. Like FN1, FN2's LOS to ILLIFU is obstructed by a hill and has to be rebroadcasted via FN3. FN5 requires an antenna of about 40-50 m height to reach FN4, from where its signal is rebroadcasted to ILLIFU. FN6 and FN7 are somewhat isolated and unreachable by all FNs, because they are located behind Table Mountain. To allow reachability to both sites, a repeater (TMA) is placed on a hill around Hoot Bay in Cape Town. Figure 6 is a snapshot of the partial mesh network extracted from Radio Mobile. The figure reveals that most traffic traverse through FN3 and FN4, hence were the most critical nodes in the network. A reasonable explanation for this is that both FN3 and FN4 have clear line of sight to ILLIFU, as there is no high-rise geographical structure on their paths.

ECONOMIC VIABILITY

In this section, we discuss some basic financial considerations to highlight the advantage of our proposed LoRa-based Water Net over pre-existing solutions such as cellular networks. A. INFRASTRUCTURE COST Table 10 is a high-level hypothetical bill of materials (BOM), showing the main components required for Water Net and their approximate costs in US Dollars

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(USD). The cost reported are based on prices obtained from various online retailers and were correct as at the time of writing. Though certain components such as cables, power adapters, connectton jacks, software were not included, the BOM reveals that the solution is achievable with an estimated budget of

TABLE 1. High-level bill of material for waterjet

Item	Description	Qty	Approx. Unit Price (USD)	Total Price (USD)	Comment
Sensors	Composite sensor module (such as Libelium Smart Water Ions [63])	11	7000	77000	A cheaper option could be to purchase the individual sensors and connected them to the Edge nodes
Edge Nodes	Single board computer (such as Raspberry Pi)	12	40	480	
	Micro-controller with Analog to Digital Converter (such as Arduino Mega)	12	30	360	Interface between analog sensors and the Edge module
LoRa Modules	800/900 MHz LoRa module (such as Semtech SX1272)	14	50	700	Interconnects the FNs and ILLIFU
	2.4 GHz LoRa module (such as Semtech SX1280)	18	75	1350	Interconnects the GWs and FNs
LoRa Antennas	Outdoor antennas for the LoRa modules	32	100	3200	Boosts LoRa's range
Fog Nodes	High end computer e.g., Core i7 Gen 11, 16GB RAM, 1TB HDD, RTX3070	7	1500	10500	
TOTAL				93,590	

about US$ 100,000. In essence, with this budget, a water monitoring network covering 11 widely dispersed (and sometimes remote) locations can be deployed in a matter of days. In comparison, setting up a single standard base transceiver station (cellular tower) in a remote location without cellular coverage, costs between US$ 100,000 – US$ 150,000. This cost is exclusive of foundation and concrete works, fencing and brick works, the air-conditioned control room, electrification and wiring, antennas, and backup power generator(s), all of which could raise the cost of the tower to about US$ 250,000. Beyond the cost, erecting cellular towers require extensive site surveys and environmental impact assessment prior to approvals from regulatory authorities, both of which can take several months to complete. To put this in context, setting up WaterNet to monitor water parameters using cellular networks would cost at least double the cost of using LoRa and would take significantly longer time. This is based on the assumption that only one cellular tower needs to be erected. In situations where all the locations to be monitored are in remote locations with no cellular coverage, the time and cost would grow astronomically. An argument can be made for situations where cellular coverage already exists. In such scenarios, WaterNet could piggyback on the existing infrastructure, thus, the cost

TABLE 2. SWOT analysis of waternet.

Strengths	Weaknesses
• LoRa is significantly cheaper compared to other technologies. • Operates on open / license-free radio frequencies. • Coverage in remote areas. • Easy to deploy. • No recurrent subscription bills. • Secure and dedicated network • Can run autonomously with little human intervention	• Susceptible to obstructions from mountains, buildings, trees etc. • 2.4GHz might be susceptible to interference from Wi-Fi, Microwave ovens and other 2.4GHz RF waves emitters. • Requires erecting long antennas.
Opportunities	**Threats**
• Modular and highly scalable. • Other functionalities such as usage prediction and microbial monitoring can be incorporated. • Can be expanded to other locations and provinces. • Output of data analysis at the Fog and Cloud nodes can give useful insights to help stakeholders make development plans.	• Competition from cellular carriers e.g., 3G and 4G LTE. • Permits might be required to mount antennas. • Can be hindered by Government policies.

would be left out of the bill of materials (BOM), costing US$5,250 for the LoRa devices and antennas. By excluding the LoRa modules and peripherals (which together only account for about 5% of the overall cost, as shown in Table 10), we can save about US$ 88,340, or 95.7% of the initial budget. Using cellular networks also introduces additional costs, such as the price of cellular ports, SIM cards, recurring data membership fees, etc., which would drive the final price well above the projected US$ 100,000. These results demonstrate the superior fiscal viability of our suggested LoRa-based WaterNet system.

CONCLUSION

The first significant idea explored in this work was the suggestion of a real-time water surveillance network to collect data on water factors from water bodies. Second, evaluating water purity through the use of machine learning (ML) algorithms. The City of Cape Town served as a case study for the development of the LoRa-based water surveillance network. LoRa is a low-power, long-range system for data transfer. Based on the Radio Mobile modeling results, a partial mesh network design was found to be the most suitable network to encompass the metropolis. With the help of machine learning algorithms, the Cloud computer where this surveillance network stores its data can determine whether or not the water is safe for human consumption or agricultural use. In this study, two appropriate datasets were constructed to train and evaluate the three Machine Learning (ML) models, Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM). (SVM). Test results revealed that LR was

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the most effective method for classifying potable water, with the lowest erroneous positive and negative values, while SVM did better when classifying irrigation water. Finally, a model was investigated using iterative feature reduction to determine the water parameter(s) most important to classification accuracy in ML models. (RFE). The obtained findings demonstrated that SSP was the least influencing measure for irrigation water, while pH and total hardness were the least influential for potable water.

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