LoRa Water Quality Management System

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Abstract

To provide high-quality water to their customers, water utility companies must continuously monitor several factors which contribute to the overall health, safety, and taste of drinking water. In this paper, a proposal for a water quality management system which leverages wireless communication technology to produce a distributed network of low-power, battery-operated sensors is presented. The network of sensors communicates real-time turbidity, pH, and temperature data to a central gateway, which identifies anomalous readings and makes predictions about the future water quality of the system using an artificial neural network. The central gateway also relays incoming water quality data to a visual dashboard, providing technicians and engineers with valuable water quality data at a glance.

Communication between the network of sensor nodes and central gateway is facilitated by LoRa wireless technology, whose name is derived from "long range." LoRa has significantly reduced power consumption compared to traditional wireless technologies, such as cellular, therefore making it well-suited for long-distance, low bandwidth data communication applications such as water quality monitoring.

Acknowledgements

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1. Introduction

1.1. Introduction

To consistently deliver high-quality water to their customers, water utilities must monitor the quality of their water in every part of their system. This often requires labor-intensive manual testing, or sensors which provide this data in real-time. These systems often require a direct wired connection between each sensor and a Programmable Logic Controller (PLC), making retrofitting older plants with them more difficult. Though wireless options for these sensors are available, they communicate over cellular networks, requiring substantial power dissipation thus limiting battery life. Using LoRa, a wireless communication technology whose name is derived from "Long Range," water quality sensors can be implemented with a significantly reduced power consumption and communicate over long distances without needing access to cellular signal. Our LoRa-based Water Quality Management System will implement a network of sensors which communicate real-time water quality data back to a central gateway. The gateway will integrate this data with AI-driven analytics, and relay system-wide information to technicians and engineers through a visual dashboard and real-time alerts, enabling water authorities to gain valuable insights into the status of their water systems with reduced setup time and impact on legacy operations.

1.2. Technical History

Monitoring water quality has evolved from simple manual sampling methods to more polished, real-time, and automated technology. This is a result of the increased need for accurate, efficient, and comprehensive water quality analysis to ensure the safety of public health and the environment. As demand for clean water increases due to population growth, industrialization, and climate change, the need for innovation in water quality monitoring systems has become more critical.

1.2.1. Early Developments in Water Quality Monitoring

The quality of water has been monitored since ancient history with the Greeks and Romans using visual observation of clarity and building structures such as aqueducts to supply clear water. The ancient cultures appreciated the value of clean water but were only able to use primitive observation methods [1]. After Antonie van Leeuwenhoek discovered of the microscope in the 17th century, scientists could now examine waterborne organisms for the first time, paving the way for a better understanding of possible pollutants [2].

With the Industrial Revolution in the 19th century, there was a speeding up of industrialization that resulted in serious water pollution, and hence the development of chemical analysis techniques to measure pollutants like dissolved solids [3]. These advances paved the way for more systematic water quality monitoring. By the mid-20th century, techniques such as the Most Probable Number (MPN) method emerged, which allowed for the estimation of bacterial populations by serial dilution and observation of growth in culture tubes [4]. This was soon followed by the membrane filtration method, which counted bacteria directly on filter membranes, increasing the efficiency and precision of measurements of bacterial contamination [5].

1.2.2. Legislative Milestones: Clean Water Act and Safe Drinking Water Act

Two landmark legislations in the United States played a crucial role in strengthening water quality monitoring. The Clean Water Act (CWA) of 1972 enacted broad-spectrum regulations to avert water pollution, to safeguard the physical, chemical, and biological integrity of the waters of the United States [6]. It required monitoring of industrial waste and sewage treatment facilities while promoting the development of standard methods for measuring water quality. CWA also focused on the restoration of polluted waters, which led to the overall implementation of monitoring practices.

Similarly, the Safe Drinking Water Act of 1974 directly focused on drinking water quality, mandating that water suppliers meet health-based standards for contaminants [7]. The act initiated more testing demands on the public water systems regarding microbial, chemical, and radiological parameters. Both acts together established a legislative climate in which water quality monitoring became a regulated and organized endeavor in the United States.

1.2.3. Technological Advancements in the 1970s and 1980s

The 1970s and 1980s witnessed the use of advanced analytical instrumentation in water quality analysis. The most notable development during this time was the release of the computerized Gas Chromatography-Mass Spectrometry (GC/MS). This device enabled the precise identification and quantification of organic pollutants in water samples, a major leap in analysis [8]. The United States Environmental Protection Agency (EPA) implemented GC/MS as a standard analytical procedure in the determination of environmental pollutants, and this saw more accurate and detailed water quality determinations. The technology, apart from identifying pollutants more, also enabled the setting of regulatory standards of water quality for the entire country.

During this time, the Supervisory Control and Data Acquisition (SCADA) system deployment began to transform water quality monitoring. SCADA systems enable remote monitoring and management of water treatment processes with real-time data acquisition and process control [9]. SCADA systems enabled utilities to detect issues such as equipment failures or contamination events more quickly, improving operational efficiency and system reliability. Early SCADA systems often relied on wired connections for communication, which were effective for centralized facilities but presented challenges in monitoring widely distributed or remote locations. While these systems were capable of remote monitoring, reliance on wired infrastructure could limit scalability and increase costs. Over time, advancements in wireless communication technologies, such as radio, cellular, and satellite networks, have significantly enhanced SCADA's ability to monitor and control remote assets, reducing infrastructure costs and improving flexibility.

1.2.4. Emergence of Wireless Sensor Networks in the 1990s and 2000s

In the 1990s and early 2000s, the emergence of wireless sensor networks (WSNs) was a groundbreaking environmental monitoring approach. WSNs are made up of widely distributed sensors that wirelessly transmit data on various environmental factors, including water quality. This made it ideal for tracking water quality in vast, remote areas where traditional wired systems would be impractical and costly. [10]. These systems were very effective for surveillance of large bodies of water, for instance, rivers, lakes, and reservoirs, where older methods were not very practical.

1.2.5. Advancements in Low-Power, Long-Range Communication Technologies

Over the past few years, there has been an evolution of low-power, wide-area network (LPWAN) technologies that have overcome most of the shortcomings of previous WSNs. One such LPWAN technology is LoRa, which facilitates long-distance communication with minimal power usage. LoRa technology is particularly well-suited for deploying sensor networks in remote areas, allowing devices to operate efficiently on battery power. This makes LoRa a cost-effective solution for monitoring water quality in areas with limited access to traditional infrastructure.

The use of LoRa technology for water quality monitoring has simplified it to develop affordable and scalable solutions. The technology can send data in real-time across vast geographical areas without the need for heavy infrastructure, hence, why it is finding the interest of water management authorities [11]. These are technologies that will improve the measurement of water quality to augment post-treatment monitoring and confirm water for safe consumption before intake. Figure 1 illustrates the architecture of a LoRa-based water quality monitoring system.

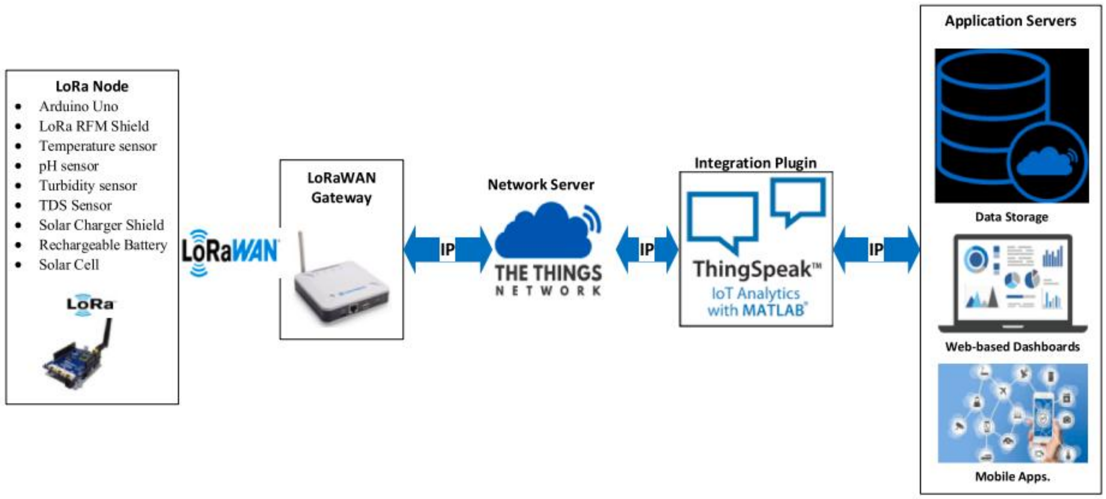


Figure 1: Example LoRa Water Quality Monitoring Architecture [11]

1.2.6. Current State and Gaps in Water Quality Monitoring

Today, water quality monitoring systems have become increasingly sophisticated, incorporating Internet of Things (IoT) devices, advanced sensors, and real-time data analytics. These systems can continuously monitor various parameters such as pH, turbidity, dissolved oxygen, and the presence of specific contaminants [12]. Data collected is transmitted to centralized platforms where it is analyzed to inform decision-making processes. Moreover, AI-driven analytics are beginning to play a critical role in anomaly detection and predictive maintenance, helping to identify issues before they escalate.

Despite these advancements, several gaps and challenges persist:

1. **Integration with Legacy Systems**: Many existing water treatment facilities operate with legacy SCADA systems that rely on hard-wired connections. Integrating modern wireless sensor networks with these systems can be complex and costly, often requiring significant retrofitting. Overcoming this challenge requires innovative solutions that ensure compatibility without extensive infrastructure overhauls.

2. **Power Efficiency**: Many wireless communication methods, such as cellular, Wi-Fi, and Bluetooth, consume a significant amount of power to maintain connectivity. This high-power demand drastically reduces battery life, requiring frequent battery replacements or consistent access to electrical infrastructure. In remote or off-grid environments, these limitations can make long-term sensor deployment impractical. For battery-powered or solar-powered systems, power efficiency is critical to ensure sustained operation without constant maintenance.

3. **Data Management and Analytics**: Traditional SCADA systems often overwhelm operators with large volumes of data, much of it lacking context or immediate relevance. Without clear interpretation, this data becomes difficult to act on and offers little practical value. Effective systems should prioritize delivering focused, actionable insights over raw data streams.

4. **Ensuring Consistent Data Transmission:** Existing technologies such as cellular and Wi-Fi rely on network coverage, which can be unreliable or nonexistent in remote or rural areas. This dependence limits their effectiveness for continuous monitoring in hard-to-reach locations. For applications like water quality monitoring, where consistent data transmission is critical, these coverage gaps pose a serious challenge and can compromise real-time visibility and response.

5. **Cost Constraints**: Budget limitations, especially in smaller towns or developing regions, can delay the adoption of advanced monitoring technologies. Addressing this requires developing scalable solutions that balance performance with affordability, enabling broader access to clean water monitoring.

Water quality monitoring has evolved from basic visual inspections to advanced real-time systems, driven by the need for accuracy and efficiency. Innovations like SCADA, wireless sensor networks, and LoRa technology have improved monitoring capabilities, enabling cost-effective and scalable solutions. However, challenges remain in integrating modern systems with legacy infrastructure, managing data, ensuring power efficiency, and addressing cost constraints. Continued advancements and collaboration are essential to overcoming these barriers and ensuring reliable, real-time water quality monitoring for the future.

1.3. Review of Technical Literature

1.3.1. IoT in Modern Water Utilities

IoT-based water management systems have become ubiquitous in modern water utilities, primarily with the advent of smart metering. These devices communicate real-time individual usage data back to utility-owned software, where that data can be used for applications such as billing or usage monitoring system-wide. One such IoT device, the Honeywell Merlin NB-IoT, is shown below in Fig. 1.

Figure 2: Honeywell Merlin NB-IoT Clip-On Water Meter [13]

This Honeywell IoT Device clips onto existing water meters and transmits real-time water usage data over Narrowband IoT (NB-IoT), a subset of low power wide-area networks (LPWAN) that utilizes existing 3G and 4G cellular infrastructure and frequency bands [13], [14]. Using a low-power communication technology such as NB-IoT allows this device to have a battery life of up to 15 years, making it advantageous over traditional cellular communications, which is quite power-hungry [13], [15].

1.3.2. Applications of LoRa in IoT Water Systems

The low power consumption advantages of NB-IoT systems can also be found in LoRa-based communications systems. Compared to the NB-IoT communication technology used in the Honeywell Clip-On NB-IoT smart meter, LoRa technology enables IoT communications at an even lower power consumption. A typical NB-IoT node has a peak current draw of 100-320 mA and a sleep current of 5μA, while a comparable LoRa node has a peak current and sleep current of 32mA and 1μA, respectively. LoRa obtains these increased power savings at the cost of a significantly reduced data rate, with a maximum speed of just 20% of an NB-IoT-based system, although with a much higher immunity to interference [14].

Thus, the power-saving capabilities of LoRa are quite attractive for use in IoT applications where battery life is of greater concern than the data rate, such as in water quality monitoring applications. One such LoRa-based water quality monitoring system was proposed during the 3rd International Conference on Advancement in Electronics and Communication Engineering in 2023 [16]. The system utilizes a series of sensor nodes that communicate with a central gateway which processes the raw data and communicates with an external microcontroller unit to upload the information to an IoT cloud server over Wi-Fi. A block diagram of the system is shown below in Fig. 2.

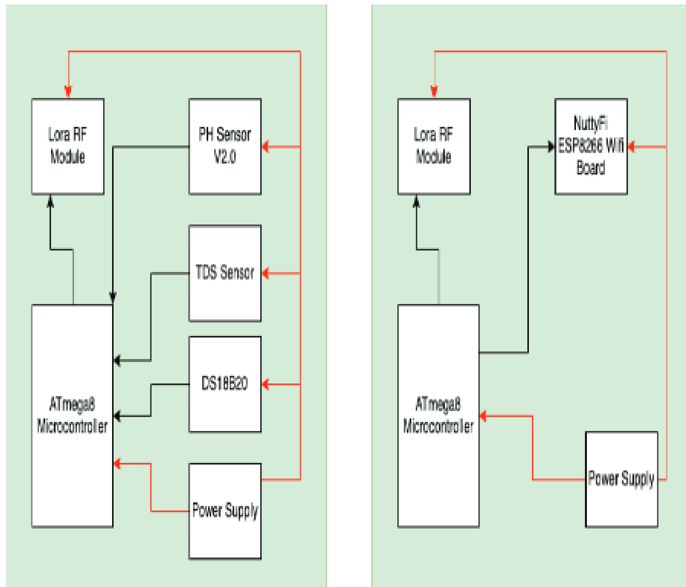


Figure 3: Block Diagram of Proposed LoRa-Based Water Quality Monitoring System [16].

Though this system provides a promising proof-of-concept solution for a LoRa-based water quality management system, the proposed sensor nodes do not support several key metrics of concern for water utility companies, such as turbidity, total suspended solids, or contaminant levels. Furthermore, the system described in the conference paper has not been implemented beyond the prototyping phase, and the raw data is not appreciably processed or analyzed by any software tools, requiring constant human monitoring of the data to identify anomalies or issues in the system. Finally, the system's use of an ATmega8 microcontroller unit in addition to an ESP8266 development board in the gateway adds unnecessary redundancy and failure points to the system, and reduces the overall power savings of the system [16].

1.3.3. Wireless Water Quality Monitoring

Traditional water quality monitoring systems, such as those produced by In-Situ, report real-time data over traditional cellular networks, requiring increased power consumption and therefore larger battery capacity to reach an industry-acceptable battery life. The In-Situ VuLink wireless probe adapter requires three D-cell Lithium Ion Manganese Oxide batteries for a total capacity of 39,000 mAh, to achieve a battery life of up to 12 years with data reporting only once every 24 hours. Using a traditional Alkaline formulation reduces this battery life to three years at the same reporting interval [17]. The VuLink wireless probe adapter is designed to work with a multiparameter sonde, which supports measurements such as temperature, conductivity, pH, turbidity, chloride concentration, nitrate levels, and contaminant concentration [18]. Fig. 3 shows a picture of this system, where the Aqua TROLL Multiparameter Sonde is on the left, and the VuLink Wireless Probe Adapter is on the right.

Figure 4: In-Situ Real-Time Water Quality Monitoring System [18].

In the absence of the wireless probe adapter, the multiparameter sonde can write data to an RS485, Modbus, SDI-12, or Bluetooth output, enabling integration with existing PLC infrastructure. Additionally, the multiparameter probe can be powered by an external DC input, meaning battery life is not a concern for permanent applications where power accessibility is not a concern [6].

1.3.4. Usage of Artificial Neural Networks in Water Quality Management

Though there are several commercially available water quality sensors capable of providing real-time data on a variety of metrics, the raw telemetry provided by these sensors still needs to be manually reviewed and monitored by a human to determine where issues or anomalies may arise within the water system. Thus, one significant area for improvement with these sensors is the integration of artificial intelligence and artificial neural networks (ANNs) with this raw data, meaning anomalies and issues with the system can be detected outside of a simple check of the incoming data against some pre-set threshold. A potential implementation of neural networks in the prediction of water quality index was proposed in a 2023 paper by Murivhami, Tartibu, and Olayode [19], in which previously-obtained water quality data on seven key metrics was used to train an ANN. The ANN was then used to predict the future water quality index of the system, which was computed using a weighted average calculation shown below in Equation 1.

Equation 1: Water Quality Index (WQI)

$$WQI = \frac{\sum_{i}^{N} q_i \times w_i}{\sum_{i=1}^{N} w_i}$$

Once trained, the ANN was able to predict the water quality of the system with a typical deviation of less than 1%. Using an ANN to predict future water quality metrics based on real-time data allows water utility companies to adjust equipment and take corrective action on their systems before problems arise, ensuring continuous high-quality water delivery to their customers. Additionally, the forecasted data can be used to create advanced warning systems and execute remedial actions.

1.4. Lifecycle of Similar Products

The lifecycle for an electronic product can be portrayed with the following four stages: Development, Growth, Maturity, and Decline. The development stage includes the design and manufacturing of the product. In the growth stage, the product is introduced to the market and there is an increasing demand for the product. It includes the distribution, operation and maintenance of the product [20]. The product reaches maturity when sales reach their peak, manufacturing begins to be phased out and replaced by improved products, and maintenance stops being offered. Finally, the decline or end stage occurs when the product is no longer manufactured and the remaining products in the field are replaced, until there are no products in operation, making the end-of-life of the product.

The design and manufacturing stage time depend on the complexity of the electronic product. A similar product to our LoRa Water Quality Monitoring System is the TX3100 Wireless Transmitter from Sensorex, which replaces the TX3000. It measures pH and Oxidation-Reduction Potential (ORP) and transmits data wirelessly [21]. The TX3100 to have been introduced around 2018 [22], while the TX3000 appears to have been introduced before 2012 [23]. This gives the product a lifecycle, from design to end-of-life, of about 10 years, with an additional estimated 10 years of decline, before the products in operation are replaced. This gives a total life cycle of about 20 years for water quality monitoring products similar to our LoRa Water Quality Monitoring System. The figure below shows an estimated time for each of the four stages. In reality, the decline and maturity of an older product and the development of a newer product happen simultaneously, thus the time from introduction of an older product to a newer product is less than the whole lifecycle of a product.

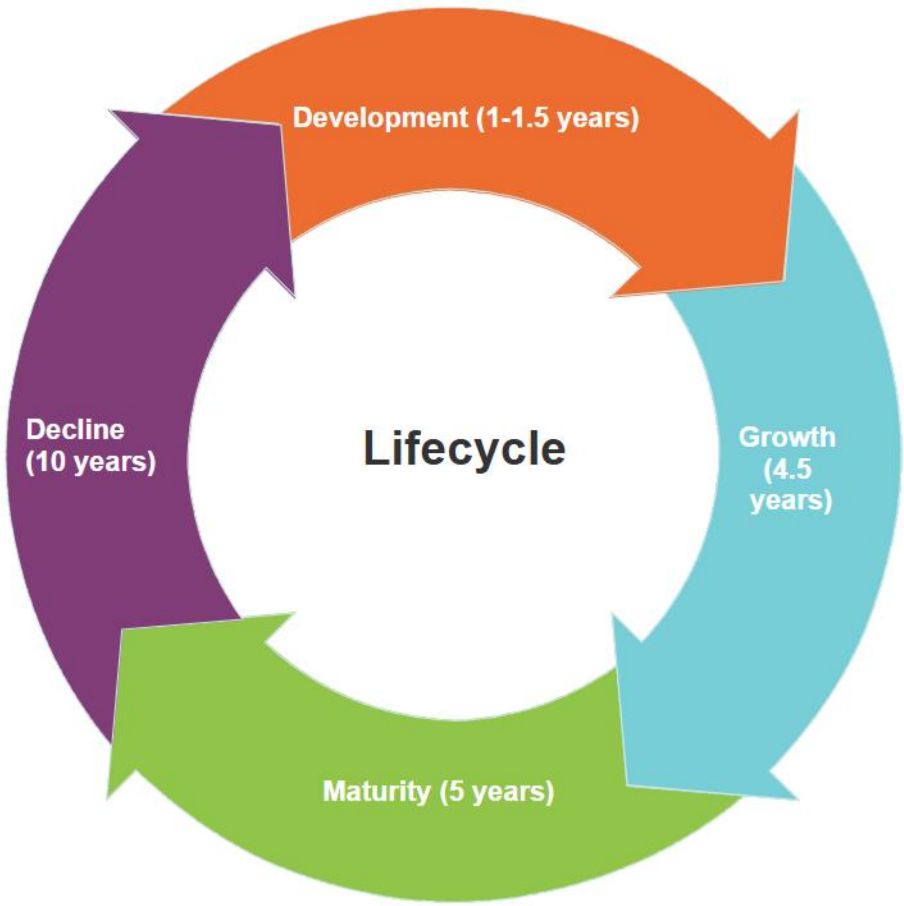


Figure 5: Estimated lifecycle of LoRa Water Quality Monitoring System

2. Experimental Method

2.1. Engineering Requirements Development

2.1.1. Customer Requirements

The marketing requirements for this project were established based on data collected from a survey distributed to three water authorities, resulting in a total of seven responses from water quality technicians. The survey itself can be found in Appendix A. Additionally, Dr. Yen-Chih Chen, an associate professor of environmental engineering at Penn State Harrisburg, provided expert insights on water quality treatment and industry standards.

Survey results were analyzed by calculating averages and creating graphs to better understand the key requirements for this project. These findings are summarized in Appendix B. Respondents expressed strong interest in a wireless, battery-powered design. Notably, chlorine monitoring was rated as the highest priority. However, due to budget limitations and sensor availability, a chlorine sensor could not be obtained. As a result, turbidity and pH were selected as the two most important parameters to monitor.

Based on the data collected, four primary marketing requirements were identified: system capabilities, system feedback & notifications, ease of use, and deployment flexibility. The weights assigned to these categories, based on their importance, are shown in Table 1. The highest priority requirement is system capabilities, as it defines the core functions of the product, forming the foundation upon which all other features depend. The second most critical requirement is system feedback & notifications, as survey results indicated that technicians require 24/7 visibility into water quality levels. Following this, deployment flexibility was ranked as the third priority, with technicians expressing interest in a versatile, battery-powered solution that offers long operational life. Finally, while ease of use remains important, it was determined to have the lowest relative priority, as it was considered less critical than the other primary requirements.

Table 1: Customer Primary Requirements

Category	System Capabilities	System Feedback & Notifications	Ease of Use	Deployment Flexibility	Total	Weight
System Capabilities	1	4/3	4/1	2/1	8.33	0.41
System Feedback & Notifications	3/4	1	3/1	3/2	6.25	0.31
Ease of Use	1/4	1/3	1	1	2.58	0.13
Deployment Flexibility	1/2	2/3	1	1	3.17	0.16
				Total	20.33	1.00

The system capabilities category consists of the following subcategories: turbidity monitoring, pH monitoring, wireless communication, AI analytics & predictions, and PLC integration, as displayed in Table 2. Given that the primary function of the product is water quality monitoring, turbidity and pH sensing were identified as the highest-priority features. Turbidity monitoring was ranked the most critical, as it serves as a federally recognized standard for determining water quality. Following this, wireless communication ranked as the next priority, with survey results demonstrating strong technician interest in long-range wireless communication, such as LoRa, that does not rely on Wi-Fi or cellular networks. The lowest-priority subcategories were PLC integration and AI analytics, with technicians showing minimal interest in AI-driven predictions, making it the least essential function of the system.

Table 2: System Capabilities Subcategory Breakdown

System Capabilities	Turbidity Monitoring	pH Monitoring	Wireless Communication	AI Analytics & Predictions	PLC Integration	Total	Weight
Turbidity Monitoring	1	5/4	5/3	5	5/2	11.42	0.34
pH Monitoring	4/5	1	4/3	4	2	9.13	0.27
Wireless Communication	3/5	3/4	1	3	3/2	6.85	0.20
AI Analytics & Predictions	1/5	1/4	1/3	1	1	2.78	0.08
PLC Integration	2/5	1/2	2/3	1	1	3.57	0.11
					Total	33.75	1.00

The system feedback & notifications category is composed of dashboard display, alerts, and battery life indicator, as shown in Table 3. Among these, dashboard display was ranked as the highest priority, followed by alerts. These features are essential to technicians' workflow, as they must be able to visually assess water quality levels in real time and receive instant alerts if readings fall below critical thresholds. The battery life indicator was deemed the lowest priority, as it is not a strong need for the feature.

Table 3: System Feedback & Notifications Subcategory Breakdown

System Feedback & Notifications	Dashboard Display	Alerts	Battery Life Indicator	Total	Weight
Dashboard Display	1	5/4	3	5.25	0.48
Alerts	4/5	1/1	2	3.80	0.35
Battery Life Indicator	1/3	1/2	1	1.83	0.17
			Total	10.88	1.00

The ease of use category includes low maintenance, user interface clarity, and field replaceable components, as presented in Table 4. Technicians expressed a strong preference for a low-maintenance product, making low maintenance the highest priority. Closely related to this, field replaceable components, including easily swappable batteries and sensors, were also deemed essential for reducing downtime and simplifying maintenance. User interface clarity, while still relevant, was ranked as the lowest priority in this category.

Table 4: Ease of Use Subcategory Breakdown

Ease of Use	Field Replaceable Components	User Interface Clarity	Low Maintenance	Total	Weight
Low Maintenance	1	8/5	4/3	3.93	0.42
User Interface Clarity	5/8	1	2/3	2.29	0.24
Field Replaceable Components	3/4	3/2	1	3.25	0.34
			Total	9.48	1.00

The deployment flexibility category includes long battery life, scalability for expansion, and environmental durability, as shown in Table 5. Survey results indicated that technicians prefer a battery-powered product, with a desired operational lifespan of at least one to three years before requiring battery replacement. Resulting in long battery life being ranked as the highest priority. Scalability for expansion, allowing for the addition of future sensors, was identified as the second priority. Environmental durability was ranked as the lowest priority, as the product will most likely be placed indoors, reducing the need for extreme weather resistance.

Table 5: Deployment Flexibility Subcategory Breakdown

Deployment Flexibility	Long Battery Life	Scalability for Expansion	Environmental Durability	Total	Weight
Long Battery Life	1	3/2	3	5.50	0.50
Scalability for Expansion	2/3	1	2	3.67	0.33
Environmental Durability	1/3	1/2	1	1.83	0.17
			Total	11.00	1.00

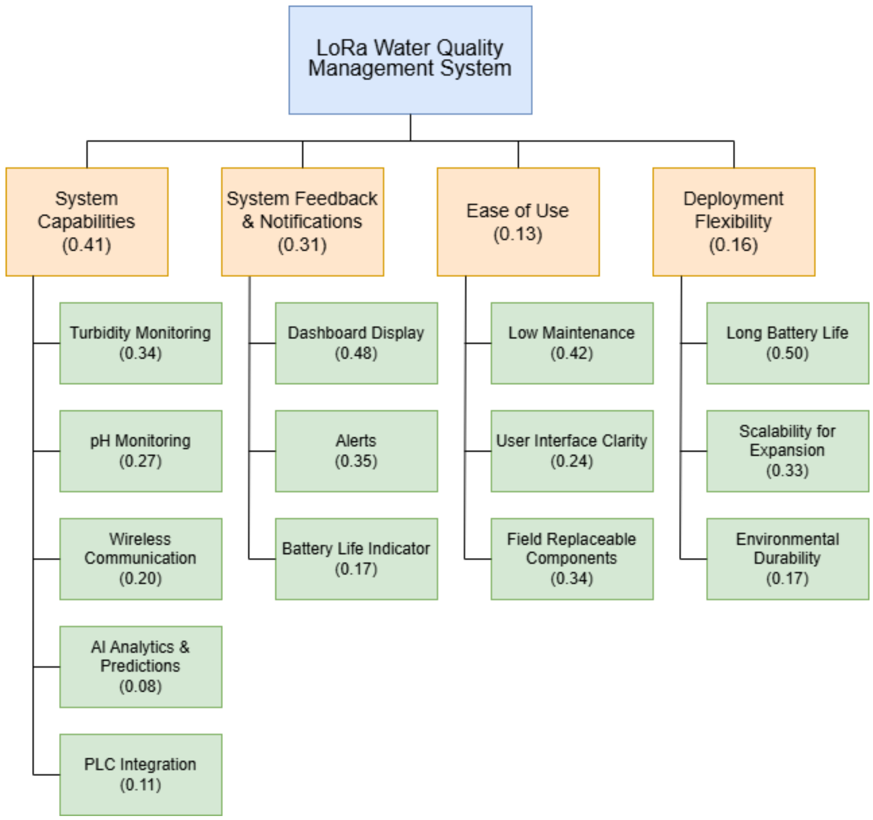


Figure 6: Hierarchical Representation of Marketing Requirements

2.1.2. Constraints

The design of the LoRa Water Quality Management System must meet several key constraints to ensure regulatory compliance, efficient operation, and seamless integration with existing infrastructure. These constraints define the boundaries for the design decision of the system. When defining design constraints, we consider ideal user experience, reliability, and regulatory compliance. Below is a list of constraints that are vital to the operation and functionality of the technology:

- 15 weeks to define the project (this semester), followed by another 15 weeks to finish the design and build the project (next semester), as required by the EE 405 course.
- Completely designing one of the subsystems, as required by the EE 405 course.

- Budget of 500 USD with option of additional funding from sponsors, as provided by the EE 405 course.
- US915 902–928 MHz radio frequency bands used by LoRa, as required by Title 47 CFR Part 15.
- Water ingress protection for encasing electrical equipment exposed to water.
- Battery operated sensor nodes.

2.1.3. Standards

Public water systems must adhere to strict regulatory standards to ensure the safety and quality of drinking water. The Environmental Protection Agency (EPA) has established the National Primary Drinking Water Regulations, commonly referred to as the primary standard, which set these regulatory guidelines. The primary standard specifies the approved methodologies for conducting pH and turbidity analysis. The permitted methodologies for these analyses and their relevant standards are outlined in Table 1 [24] Additionally, the state of Pennsylvania has a MCL for turbidity that supersedes the EPA MCL standard. It requires that, the turbidity not exceed 0.3 NTUs in 95% of the monthly samples for public water systems with conventional or direct filtration, 1.0 NTUs for slow sand filtration or diatomaceous earth, and 0.15 NTUs for membrane filtration [25].

Table 6: Approved Methodologies and Relevant Standards for pH and Turbidity Analysis.

Contaminant	Methodology	EPA Standard	ASTM Standard	SM (18th, 19th ed.)	SM (20th ed.)	SM Online
pH	Electrometric	150.1, 150.2[1]	D1293-95, 99	4500-H^+ B	4500-H^+ B	4500-H^+ B-00
Turbidity	Nephelometric Method	180.1	-	2130 B	-	-

In addition to the primary standard, the EPA has established the National Secondary Drinking Water Standards, which define Secondary Maximum Contaminant Levels (SMCLs). These secondary standards are non-mandatory but help ensure better color, odor, and taste of drinking water. Specifically, the secondary standards recommend maintaining a pH range between 6.5 and 8.5 [26].

Furthermore, the standard establishes record maintenance requirements. Turbidity analysis records must be retained for at least five years. Additionally, specific data must be collected and documented, including the date, location, and time of sampling, along with the analysis results [24].

Other standards that apply due to the use of LoRa are: the Code of Federal Regulations (CFR) Title 47 Part 15, which governs operation within the 902-928 MHz, 2400-2483.5 MHz, and 5725-5850 MHz frequency bands [27]; IEEE Std 802.15.4, which specifies requirements for low-data-rate wireless connectivity with devices with no or very limited battery consumption [28; IEEE Std 1528.7, which provides a methodology for classifying IoT devices based on radio frequency (RF) exposure [29]; and TS001-1.0.4, which specifies the LoRaWAN network protocol for connecting devices to the internet using LoRa [30].

The ANSI/IEC 60529 standard also applies, as electrical equipment may be exposed to water. It defines a classification system for the degree of protection provided by electrical enclosures against water and solid particles [31].

2.2. Engineering Requirements

The engineering requirements for the LoRa Water Quality Management System were developed from the customer requirements, constraints, and standards found in previous sections of this proposal. The engineering requirements for the project are listed in Table 1 below. Each row of the center column of the table lists one of the engineering requirements, with the corresponding marketing requirements denoted in the left column, and a justification in the right column.

Table 7: Engineering Requirements for the LoRa Water Quality Management System

Marketing Requirements	Engineering Requirements	Justification
9, 11, 23	Uses internal, readily commercially available batter(ies) to produce 3.3V ±0.3V DC input power.	An internal battery should be used for water resistance, and to make the battery easily replaceable in the field, it should be one easily obtained commercially, (i.e. AA or D cell instead of a custom Li-ion battery). A 3.3V level is

		chosen because of its compatibility with a wide range of microcontrollers and sensor equipment, with some tolerance to allow some small battery voltage deviations.
3, 12, 13, 16, 17, 18, 22	Should utilize a wireless communication technology with a transmit current consumption of under 150mA, and under 5mA idle current consumption, on the US915 (902-928 MHz) frequency band	Wireless communication that did not need access to cellular or Wi-Fi was a significant concern to technicians. To have a longer battery life, the chosen standard should have minimized power consumption. Additionally, the wireless technology chosen must operate within legally permissible frequencies (902-928 MHz in the United States and Canada)
1, 2, 15	Each senor node must be capable of producing real-time pH data within $\pm$0.3 of actual, and turbidity within 0.1NTU of actual under 1.0 NTU, at maximum 15 minute intervals.	These two metrics were the top concern for technicians, and are essential metrics for maintaining utility legal compliance. The specified tolerances , limits, and time interval for these measurements will keep the system consistent with Pennsylvania drinking water regulations.
4, 6, 7, 8, 10, 15	System must be able to process data with backend software at minimum every 15 minutes, and alert technicians when either the turbidity or pH is within 15% of thresholds	Processing the real-time data and providing an overview of the system with some analytics assists technicians and engineers with making determinations regarding the water quality of the system. Processing this data every 15 minutes keeps the system consistent with Pennsylvania Regulations. To help utilities maintain compliance, the system should alert

	set by Pennsylvania, which are 1.0 NTU and between 6.0-9.0, respectively, or those set by the Water Utility.	technicians when their water is within 15% of the Pennsylvania Turbidity and pH limits, which are 1.0 NTU maximum, and 6.0-9.0, respectively.
3, 5, 8, 9, 13, 14, 23	System should be easily integrated with existing utility infrastructure, and minimize the impact on existing operations	Makes the system more desirable for utilities and more useful to technicians already familiar with existing PLC and SCADA systems. Wireless communication reduces the need for retrofitting, and reduces additional maintenance burdens.
Customer Requirements **1.** Turbidity Monitoring [R] **2.** pH Monitoring [R] **3.** Wireless Communication [R] **4.** AI Analytics & Predictions [D] **5.** PLC Integration [D] **6.** Dashboard Display [R] **7.** Alerts [R] **8.** Battery Life Indicator [D] **9.** Low Maintenance [R] **10.** User Interface Clarity [D] **11.** Field Replaceable Components [D] **12.** Long Battery Life [R] **13.** Scalability for Expansion [R] **14.** Environmental Durability [D]		
Standards		

15. Pennsylvania Code, Title 25, Chapter 109: Maximum Contaminant Level (MCL) **16.** Code of Federal Regulations (CFR) Title 47, Part 15: Radio Frequency Devices **17.** TS001-1.0.4: LoRaWAN Specification **18.** IEEE 802.15.4: Low-Rate Wireless Personal Area Network (LR-WPAN)
Constraints **19.** Must be Completed by December 2025 **20.** Must satisfy project requirements of the EE 406W capstone course. **21.** Cost of project must not exceed $500 budget **22.** Must use permissible wireless frequencies as defined by Federal Regulations **23.** Water ingress protection for encasing electrical equipment exposed to water

2.3. Level 1 and 2 Functional Decomposition

2.3.1. Level 1 Decomposition

The level 1 decomposition of the LoRa Water Quality Management System is shown in Figure 1 below. The system is comprised of four main functional blocks: Data Collection, Data Processing, Controlling, and Alerting & Reporting. Power to the system is supplied by an internal battery in each sensor node and is provided externally at the central gateway of the system. Each sensor node has a direct connection to the water and outside environment to take measurements. From there, the raw data is processed and analyzed to make decisions about the overall health of the system. The processed data and analysis are then reported to technicians and engineers through a water quality dashboard and alerts when issues arise.

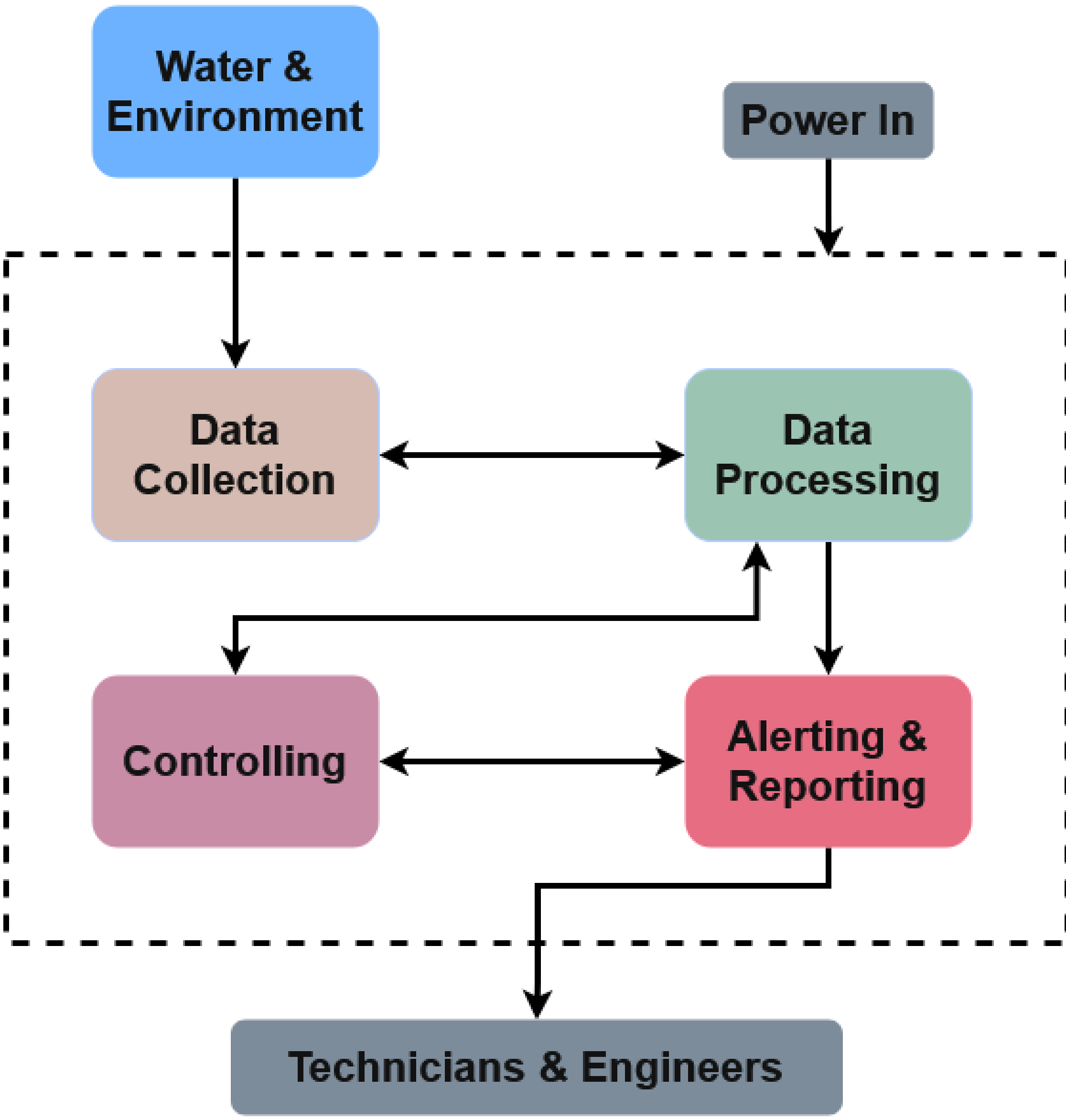


Figure 7: Level 1 Decomposition of the LoRa Water Quality Management System

2.3.2. Level 2 Decomposition

The level 2 decomposition of the LoRa Water Quality Management System is shown in Figure 2 below. The overall design of the system is broken up into two distinct subsystems, which are the sensor node and central gateway. These are connected via a wireless communication link, shown with a dashed arrow between both wireless transceiver blocks. Each sensor node, which is depicted in the left subsystem of the diagram, is responsible for collecting the raw data from the pH, turbidity, and temperature sensors, interpreting the sensor output (e.g. analog voltage value) as a measurement, and formatting the data to be sent to the central gateway over the wireless communication link. Once the interpreted and formatted data is received by the central gateway, it is further formatted so that it can be analyzed through an Artificial Neural Network, compared against thresholds, and be reported to an external dashboard to be used by Technicians and Engineers. Based on the analyzed data output, decision making logic is used to raise alerts to notify technicians and engineers of issues in the system, or post warnings and other valuable information to the system dashboard.

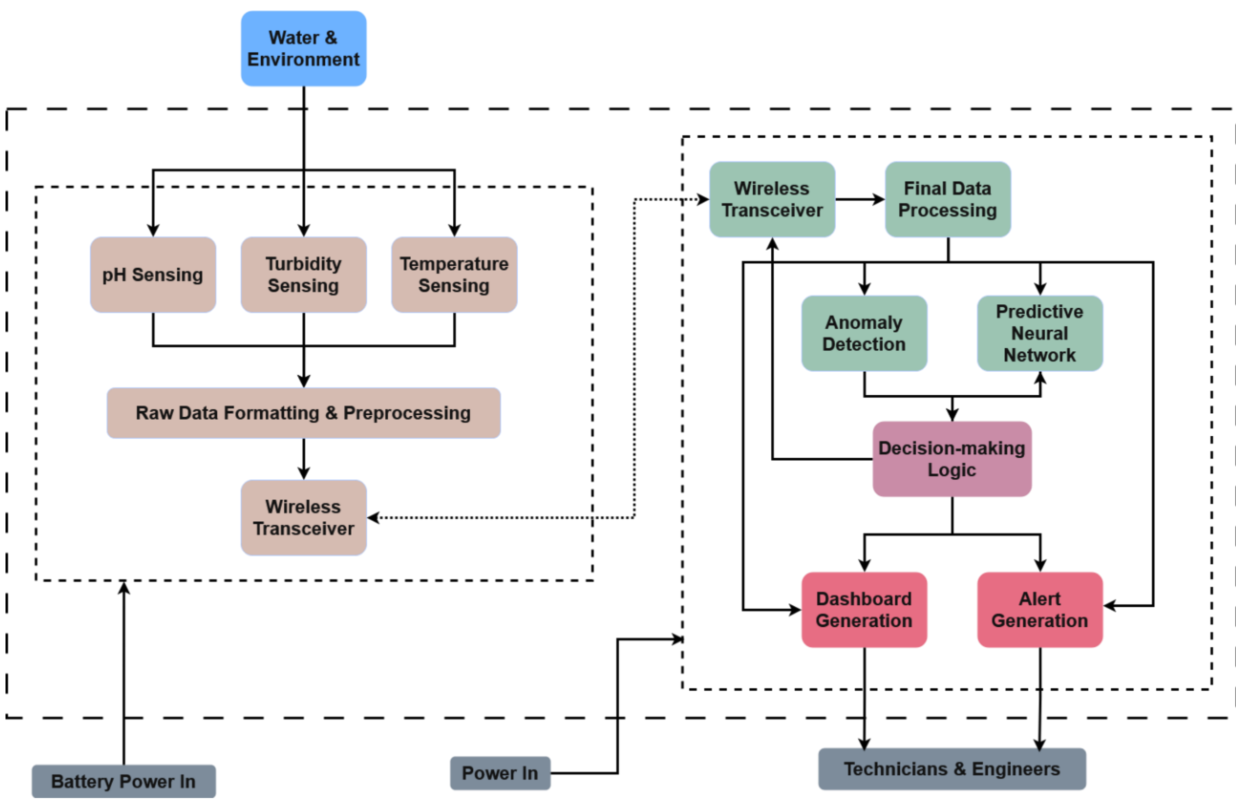


Figure 8: Level 2 Decomposition of the LoRa Water Quality Management System

Table 8: pH Sensor Function Table

Module	pH Sensor
Inputs	• Raw water sample pH
Outputs	• Analog voltage corresponding to the pH of the water
Functionality	• Converts the pH of the water to an analog voltage value interpretable by a microcontroller

Table 9: Turbidity Sensor Function Table

Module	Turbidity Sensor
Inputs	• Raw water sample Turbidity
Outputs	• Analog voltage corresponding to the Turbidity of the water
Functionality	• Converts the Turbidity of the water to an analog voltage value interpretable by a microcontroller

Table 10: Temperature Sensor Function Table

Module	Temperature Sensor
Inputs	• Raw water sample temperature
Outputs	• Analog voltage corresponding to the temperature of the water
Functionality	• Converts the temperature of the water to an analog voltage value interpretable by a microcontroller

Table 11: Raw Data Formatting and Preprocessing Function Table

Module	**Raw Data Formatting and Preprocessing**
Inputs	• Analog pH data • Analog turbidity data • Analog temperature data
Outputs	• Formatted digital data for the pH, turbidity, and temperature
Functionality	• Interprets the analog voltages produced by the sensors as digital data • Converts the digitized analog voltage readings to relevant measurement units for pH, turbidity, and temperature • Formats the data to be sent to the central gateway module

Table 12: Data Collection Wireless Transceiver Function Table

Module	**Wireless Transceiver (Data Collection)**
Inputs	• Formatted digital pH, turbidity, and temperature readings
Outputs	• Wireless signal to be sent to central gateway wireless transceiver
Functionality	• Broadcasts the formatted sensor data wirelessly to be read in by the central gateway

Table 13: Data Processing Wireless Transceiver Function Table

Module	Wireless Transceiver (Data Processing)
Inputs	• Wireless signal from sensor node containing formatted digitized sensor data • Inputs from decision making logic to mediate data transfer
Outputs	• Formatted, digitized sensor data ready for final processing • Acknowledge signal to sensor node transceiver indicating successful data transmission
Functionality	• Interprets the broadcasted wireless data into useable data for further data processing

Table 14: Final Data Processing Function Table

Module	Final Data Processing
Inputs	• Formatted, digitized sensor data originating from sensor nodes
Outputs	• A .CSV file containing updated sensor data from all nodes
Functionality	• Combines and formats data from all sensor nodes into a commonly used file type, which can be interpreted by the dashboard generation software, neural network, and anomaly detector

Table 15: Anomaly Detection Function Table

Module	Anomaly Detection
Inputs	• CSV data with updated sensor readings from all sensor nodes
Outputs	• A simplified report of anomalous sensor readings and readings outside the thresholds set by the utility and legal regulations
Functionality	• Looks through incoming sensor data to identify readings that are outside of legal compliance and compliance with utility specifications

Table 16: Predictive Neural Network Function Table

Module	**Predictive Neural Network**
Inputs	• CSV data with updated sensor readings from all sensor nodes • Signal to cause the neural net to begin running from decision-making logic
Outputs	• Predictions for future system water quality based on training data
Functionality	• Makes predictions for the overall health of the system based on incoming and past sensor data • Proactively identifies future water quality issues.

Table 17: Decision-making Logic Function Table

Module	**Decision-making Logic**
Inputs	• Anomalous sensor readings • Sensor readings outside legal or utility-set thresholds • System water quality predictions from Artificial Neural Network
Outputs	• Selected anomalous readings to report on the dashboard • Readings and predictions requiring attention from technicians and engineers • Wireless data reception mediation signals
Functionality	• Takes in all available system data and makes determinations on what requires attention from engineers and technicians, and the severity of system-wide issues

Table 18: Dashboard Generation Function Table

Module	Dashboard Generation
Inputs	• CSV data with updated sensor readings from all sensor nodes • Sensor readings and system water quality predictions of note as determined by decision-making logic
Outputs	• A visual display of current system-wide data, anomalous readings of note, and future system water quality predictions
Functionality	• Summarizes system-wide data in a visual format easily readable by technicians and engineers

Table 19: Alert Generation Function Table

Module	Alert Generation
Inputs	• Sensor readings falling outside legal or utility-set thresholds • Significant anomalous sensor readings • Water quality predictions of concern as determined by decision-making logic
Outputs	• Automated email sent to technicians and engineers of concern
Functionality	• Informs technicians and engineers immediately when issues arise in the system, or when issues are predicted to arise, so that proactive corrective action may be taken

2.4. Preliminary Simulation

As a part of the preliminary design process of the LoRa Water Quality Management System, the functionality of the turbidity sensor pre-processing circuit was simulated using LTSpice.

The purpose of this circuit is to condition the output of the turbidity sensor, which has a nonlinear response to the measured turbidity value and has minimal voltage variation for small changes in turbidity, making it difficult to reliably use with a traditional analog-to-digital converter (ADC) and microcontroller. Using selected points on the response graph of the datasheet of the chosen turbidity sensor, the Amphenol Sensors TSW-10 Turbidity Sensor, the response curve was approximated using Microsoft Excel [32]. The response of the sensor is given by Equation 2 below, where the independent variable, T, is the turbidity of the water in NTU. A plot of this nonlinear response is shown in Figure 9.

Equation 2: Turbidity Sensor Output Voltage

$$v(T) = 0.0000005T^2 - 0.0018T + 3.6679$$

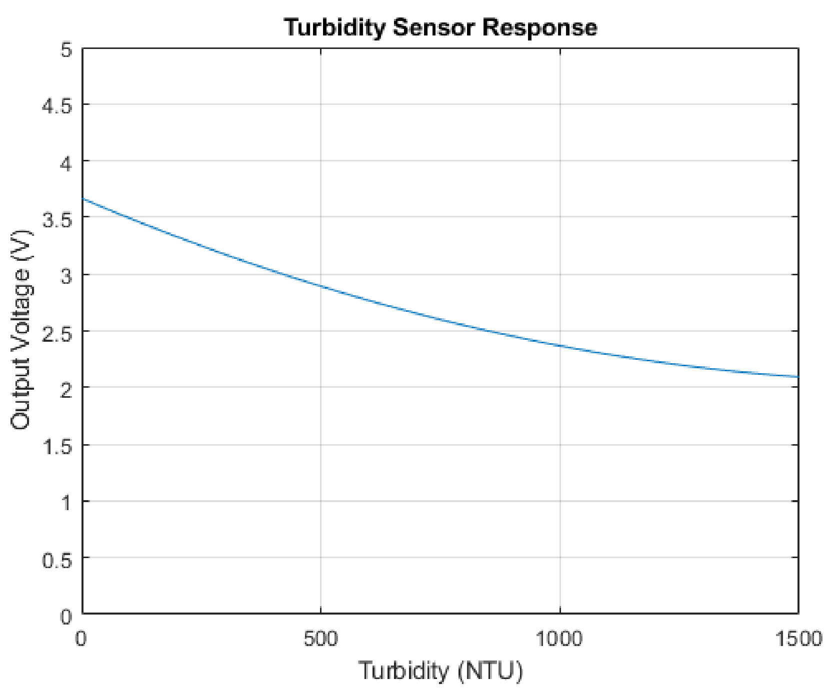


Figure 9: Turbidity Sensor Output Voltage Plot

To linearize and condition the output signal, the instrumentation amplifier circuit depicted in Figure 10 below was designed and simulated in LTSpice. The output voltage of this circuit is given by Equation 3.

Equation 3: Instrumentation Amplifier Output Voltage

$$V_{out}(t) = \left(V_{ref}(t) - V_{sensor}(t)\right)\left(1 + \frac{2 \times R_3}{R_2}\right)\left(\frac{R_8}{R_5}\right), given\ R_3 = R_4, R_5 = R_6, and\ R_7 = R_8$$

This configuration of the instrumentation amplifier was chosen for its high input impedance, easily adjustable gain, and differential operation. Since the gain of the entire circuit can be adjusted by changing the value of R_2, the gain of the circuit could be calibrated by a microcontroller using a digitally controlled potentiometer in place of this resistor. Since the output voltage of the amplifier is a multiple of the reference voltage minus the sensor voltage, the output of the circuit is directly proportional to the turbidity of the water instead of being inversely proportional, making the output voltage easily interpretable by the microcontroller. Since the range of expected turbidity measurements for the LoRa water quality management system is from 0 to approximately 5 NTU, a total gain of 80 was chosen for the amplifier. As a result, the output of the amplifier saturates for turbidity levels above approximately 20NTU, however the response of the amplifier produces an appreciable voltage difference for changes in NTU within the desired range. A Zener diode with a breakdown voltage of 3V was placed at the output to clip output voltages which could be damaging to a 3.3V microcontroller.

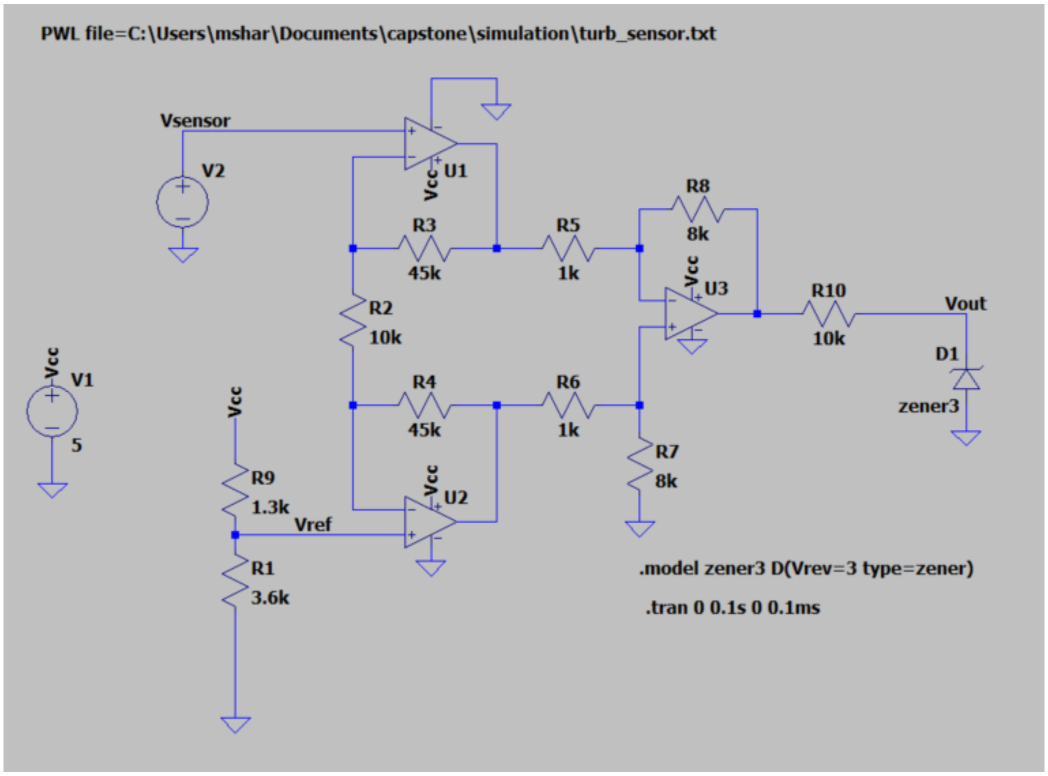


Figure 10: Instrumentation Amplifier Circuit as Simulated in LTSpice

To simulate the response of the circuit over the full range of sensor output values, the output voltage function given in Equation 2 was modeled in a piecewise linear (PWL) file, generated using the C code depicted in Figure 11. Using this code, a PWL file was produced that made the simulated turbidity reading equal to the simulation time in milliseconds. The LTSpice simulation output is shown in Figure 12. With this data, this instrumentation amplifier circuit was shown in Microsoft Excel to linearize the sensor output within the desired range with an R^2 value of 100%. Since the output of the sensor varies over a larger range for the expected turbidity readings, the precise turbidity value can then be measured more easily using a standard analog to digital converter.

```c
#include <stdio.h>
#include <stdlib.h>
#include <math.h>

double turbiditySensor(int time_ms) {
    return (0.0000005 * powf(time_ms, 2)) - (0.0018 * time_ms) + 3.6679;
}

int main(void) {

    char * filename = "C:\\Users\\mshar\\Documents\\capstone\\simulation\\turb_sensor.txt";

    FILE * fptr = fopen(filename, "w+");

    if (fptr == NULL) {
        printf("Failed to open %s!\n", filename);
        return 0;
    }

    for (int k = 0; k <= 1500; k++) {
        fprintf(fptr, "%dm %f", k, turbiditySensor(k));
        if (k != 1500) {
            fprintf(fptr, "\n");
        }
    }

    fclose(fptr);

    printf("Successfully wrote %s.\n", filename);

}
```

Figure 11: C Code Used to Model the Response of the Turbidity Sensor

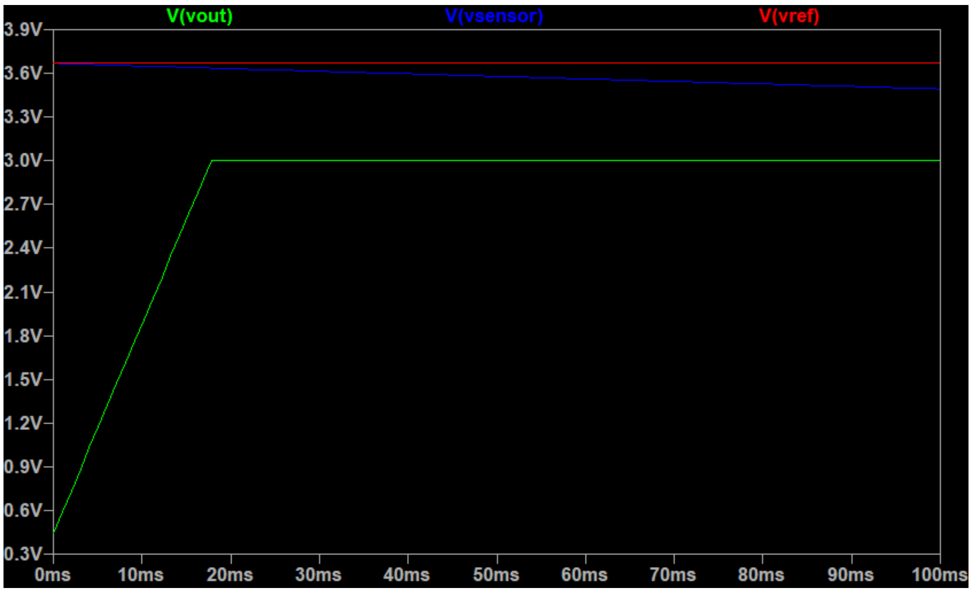


Figure 12: Instrumentation Amplifier Simulation Output, as produced in LTSpice

3. Project Management

3.1. Project Work Breakdown Structure (WBS)

Figure 13, shown on the following page, presents the work breakdown structure (WBS) for the development of the LoRa Water Quality Management System. Based on the scope of the project, five main tasks were outlined: research, design, fabrication, testing & validation, and documentation. Based on the prior skills, experience, and areas of interest of each of the team members, the tasks and subtasks were then assigned to distribute the overall workload as fairly as possible. To make the scope of the overall project more feasible, PLC integration was removed from the WBS as technicians viewed this feature less desirable than other portions of the project.

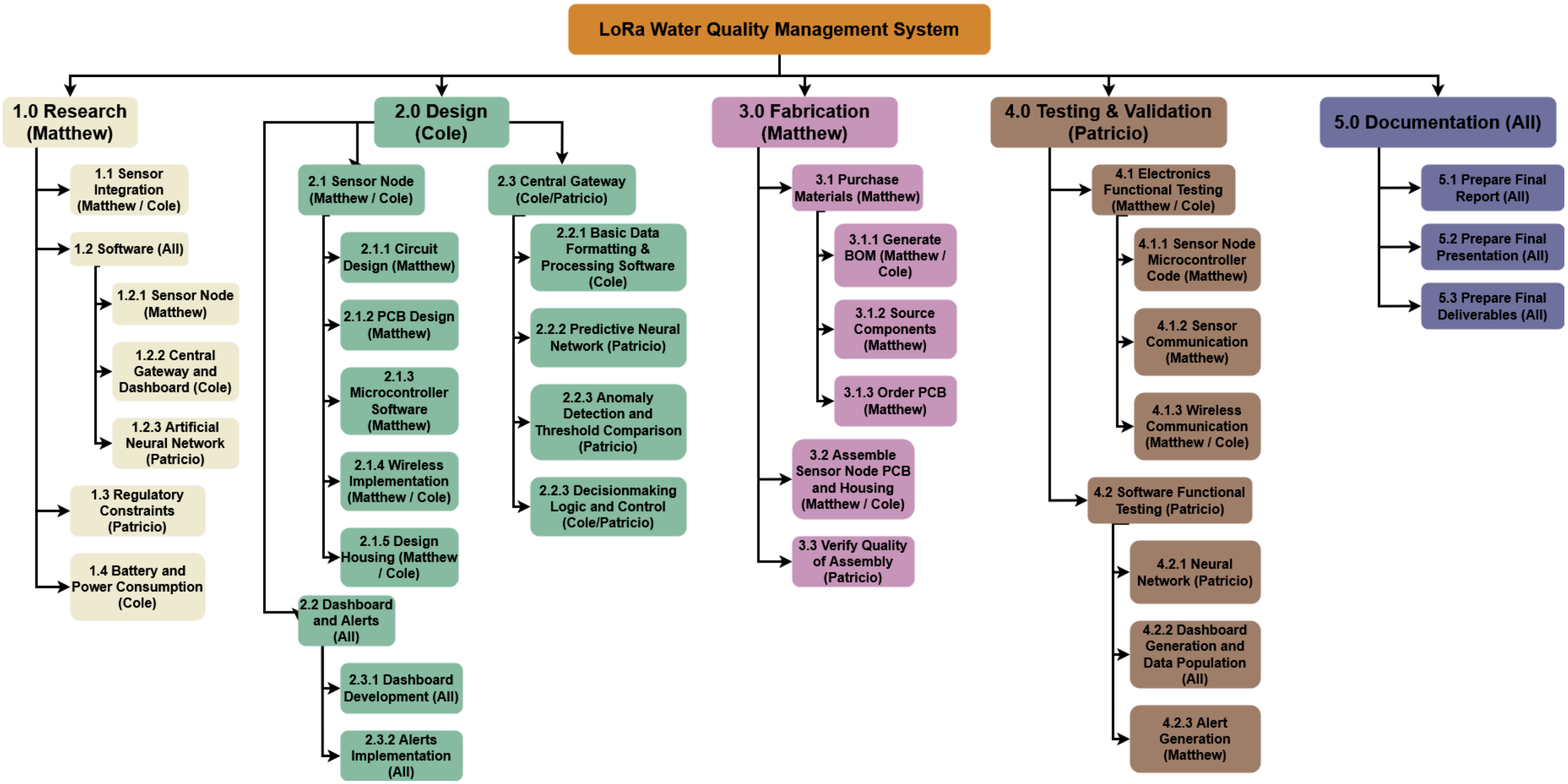


Figure 13: Work Breakdown Structure for the LoRa Water Quality Management System

3.2. Project Schedule (Gantt Chart)

Table 20, shown on the following page, presents a proposed schedule for completing the development LoRa Water Quality Management System. This schedule includes the work already completed for this project, including the project proposal and portions of the research needed for the project design. We intend to complete work over the Summer break, with expected work completion for the Capstone Design Conference at the end of the Fall 2025 semester. The schedule includes some buffer times and extended project work completion deadlines to ensure the project is completed in time for the Capstone Design conference.

Table 20: Gantt Chart

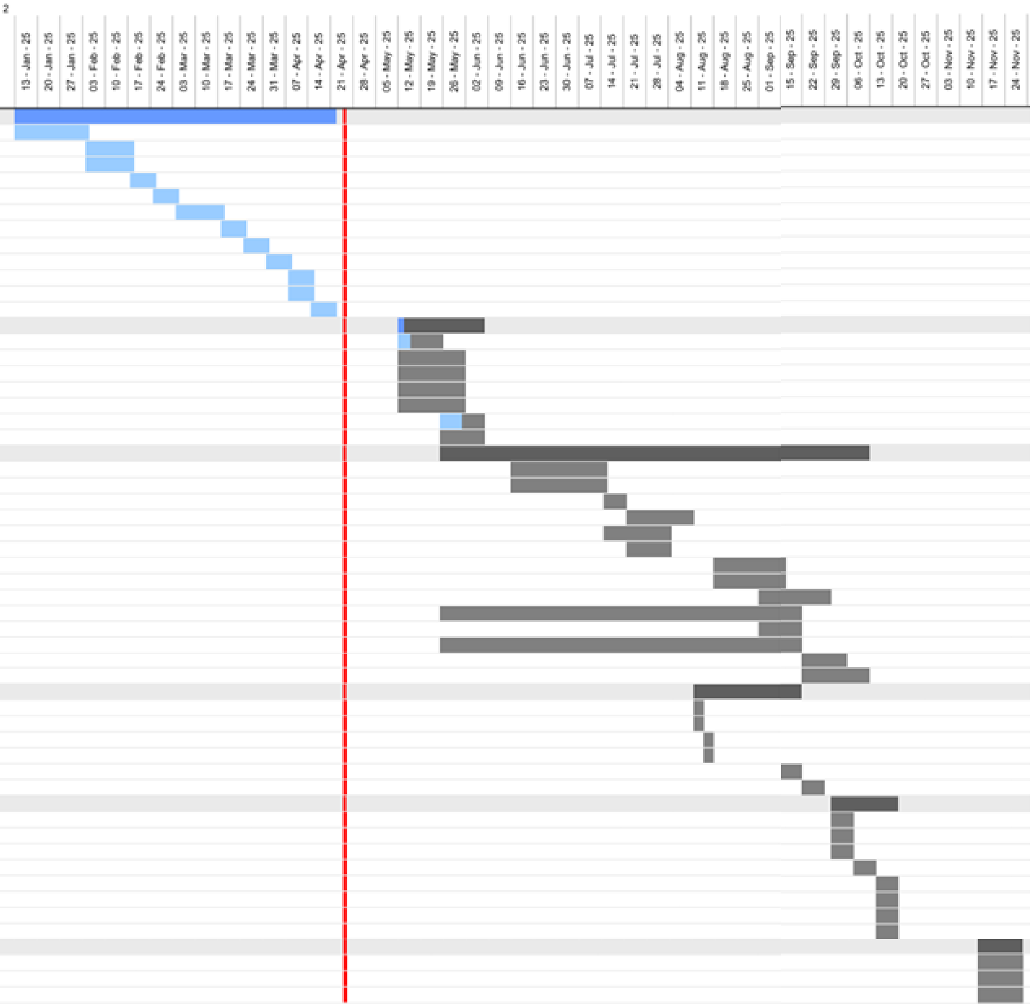
LoRa Water Quality Management System
The Pennsylvania State University

Today's Date: 2025-04-25 Friday
(vertical red line)

Project Names: Cole Hadley, Patricio Palermo, Matthew Sharp
Start Date: 2025-01-13 Monday

First Day of Week (Mon=2): 2

WBS	Tasks	Task Lead	Start	End	Duration (Days)	% Complete	Working Days	Days Complete	Days Remaining
0	**Develop Proposal**	All	1-13-25	4-22-25	100	100%	72	100	0
0.1	Introductory Paragraph	Matthew	1-13-25	2-4-25	23	100%	17	23	0
0.2	History of Problem	Cole	2-4-25	2-18-25	15	100%	11	15	0
0.3	Technical Literature	Matthew	2-4-25	2-18-25	15	100%	11	15	0
0.4	Customer Survey	Cole	2-18-25	2-25-25	8	100%	6	8	0
0.5	Standards & Constraints	Patricio	2-25-25	3-4-25	8	100%	6	8	0
0.6	Problem Statement	Cole	3-4-25	3-18-25	15	100%	11	15	0
0.7	Engineering Requirements	Matthew	3-18-25	3-25-25	8	100%	6	8	0
0.8	Product Lifecycle	Patricio	3-25-25	4-1-25	8	100%	6	8	0
0.9	Functional Decomposition	Matthew	4-1-25	4-8-25	8	100%	6	8	0
0.10	Gantt Chart	Matthew	4-8-25	4-15-25	8	100%	6	8	0
0.11	Work Breakdown Structure	Matthew	4-8-25	4-15-25	8	100%	6	8	0
0.12	Project Budget	Cole	4-15-25	4-22-25	8	100%	6	8	0
1	**Research**	Matthew	5-12-25	6-7-25	27	9%	20	2	25
1.1	Sensor Integration	Matthew / Cole	5-12-25	5-25-25	14	33%	10	4	10
1.2	Software	All	5-12-25	6-1-25	21	0%	15	0	21
1.2.1	Sensor Node	Matthew	5-12-25	6-1-25	21	0%	15	0	21
1.2.2	Gateway and Dashboard	Cole	5-12-25	6-1-25	21	0%	15	0	21
1.2.3	Artificial Neural Network	Patricio	5-12-25	6-1-25	21	0%	15	0	21
1.3	Regulatory Constraints	Patricio	5-25-25	6-7-25	14	50%	10	7	7
1.4	Battery & Power Consumption	Cole	5-25-25	6-7-25	14	0%	10	0	14
2	**Design**	Cole	5-25-25	10-12-25	141	0%	100	0	141
2.1	Sensor Node	Matthew / Cole	6-16-25	7-15-25	30	0%	22	0	30
2.1.1	Circuit Design	Matthew	6-16-25	7-15-25	30	0%	22	0	30
2.1.2	PCB Design	Matthew	7-15-25	7-21-25	7	0%	5	0	7
2.1.3	Microcontroller Software	Matthew	7-22-25	8-11-25	21	0%	15	0	21
2.1.4	Wireless Implemetation	Matthew / Cole	7-15-25	8-4-25	21	0%	15	0	21
2.1.5	Housing	Matthew / Cole	7-22-25	8-4-25	14	0%	10	0	14
2.2	Dashboard & Alerts	All	8-18-25	9-16-25	30	0%	22	0	30
2.2.1	Dashboard Development	All	8-18-25	9-16-25	30	0%	22	0	30
2.2.2	Alerts Implementation	All	9-1-25	9-30-25	30	0%	22	0	30
2.3	Central Gateway	Cole / Patricio	5-25-25	9-21-25	120	0%	85	0	120
2.3.1	Basic Data Processing	Cole	9-1-25	9-21-25	21	0%	15	0	21
2.3.2	Predictive Neural Network	Patricio	5-25-25	9-21-25	120	0%	85	0	120
2.3.3	Anomaly Detection & Threshold Comparison	Matthew	9-22-25	10-5-25	14	0%	10	0	14
2.3.4	Decisionmaking Logic & Control	Cole / Patricio	9-22-25	10-12-25	21	0%	15	0	21
3	**Fabrication**	Matthew	8-12-25	9-21-25	41	0%	29	0	41
3.1	Purchase Materials	Matthew	8-12-25	8-14-25	3	0%	3	0	3
3.1.1	Generate BOM	Matthew / Cole	8-12-25	8-14-25	3	0%	3	0	3
3.1.2	Source Components	Matthew	8-15-25	8-17-25	3	0%	1	0	3
3.1.3	Order PCB	Matthew	8-15-25	8-17-25	3	0%	1	0	3
3.2	Assemble Sensor Node PCB & Housing	Matthew / Cole	9-15-25	9-21-25	7	0%	5	0	7
3.3	Validate Quality of Assembly	Patricio	9-22-25	9-28-25	7	0%	5	0	7
4	**Testing & Validation**	Patricio	10-1-25	10-21-25	21	0%	15	0	21
4.1	Electronics Functional Testing	Matthew / Cole	10-1-25	10-7-25	7	0%	5	0	7
4.1.1	Sensor Node Microcontroller Code	Matthew	10-1-25	10-7-25	7	0%	5	0	7
4.1.2	Sensor Communication	Matthew	10-1-25	10-7-25	7	0%	5	0	7
4.1.3	Wireless Communication	Matthew / Cole	10-8-25	10-14-25	7	0%	5	0	7
4.2	Software Functional Testing	Patricio	10-15-25	10-21-25	7	0%	5	0	7
4.2.1	Neural Network	Patricio	10-15-25	10-21-25	7	0%	5	0	7
4.2.2	Dashboard Generation & Data Population	All	10-15-25	10-21-25	7	0%	5	0	7
4.2.3	Alert Generation	Matthew	10-15-25	10-21-25	7	0%	5	0	7
5	**Documentation**	All	11-15-25	11-28-25	14	0%	10	0	14
5.1	Prepare Final Report	All	11-15-25	11-28-25	14	0%	10	0	14
5.2	Prepare Final Presentation	All	11-15-25	11-28-25	14	0%	10	0	14
5.3	Prepare Final Deliverables	All	11-15-25	11-28-25	14	0%	10	0	14



3.3. Project Budget

The cost of labor was determined by using the Gantt chart and assuming two hours of labor per allotted workweek of each task, based on the credit hours of the class. The sections of the work breakdown structure were assigned to the labor hours as follows: The proposal development and documentation sections were included as consulting hours; the fabrication section was included as assembly hours; the design and research sections were included as design hours; the testing and validation section were evenly split unto testing and validation hours; finally, for the coding hours, each individual task that required coding, such as the predictive neural network task, was included. The estimated unit cost for labor was obtained from the website Indeed and used to calculate the total labor cost [33]. The total labor cost is $31,365.22, shown in Table 21.

Table 21: Engineering Labor Cost of Project.

Item	Unit	Unit Cost	# Units	Cost
Design	hr	49.00	235	$ 13,818.00
Coding	hr	52.96	360	$ 6,143.36
Assembly	hr	20.06	17	$ 409.22
Testing	hr	25.54	15	$ 459.72
Validation	hr	25.54	15	$ 459.72
Consulting	hr	41.98	200	$ 10,075.20
			Labor Subtotal	$ 31,365.22

The parts section was determined by analyzing the level 2 decomposition and determining which parts will be needed to implement each function and sub-processes. The miscellaneous parts at the end of Table 22 are estimated costs. The estimated cost for all the parts is $414. Corresponding citations for each component are provided in the second column of the table.

Table 22: Parts Cost of Project.

Item	Source	Unit	Unit Cost	# Units	Cost
Microcontroller	[34]	ea	5.00	1	$ 5.00
Single-Board Computer (SBC)	[35]	ea	80.00	1	$ 80.00
AI Accelerator for SBC	[36]	ea	110.00	1	$ 110.00
Wireless Transceiver	[37]	ea	15.90	2	$ 31.80
PCB	[38]	ea	0.40	5	$ 2.00
Water Temperature Sensor	[39]	ea	7.50	1	$ 7.50
pH Sensor	[40]	ea	29.50	1	$ 29.50
Turbidity Sensor	[41]	ea	9.90	1	$ 9.90
ADC Module	[42]	ea	15.50	1	$ 15.50
Batteries	[43]	ea	1.51	8	$ 12.08
Misc SBC Parts (microSD, Case, Power Cord)		ea	40.00	1	$ 40.00
Misc Microcontroller Parts (Case, Program Cord)		ea	20.00	1	$ 20.00
Misc PCB Parts (Resistors, Capacitors, OpAmp, Connectors, etc)		ea	50.00	1	$ 50.00
				Parts Subtotal	**$ 413.28**

In total, the project has an estimated cost of $31,778.50, shown in Table 23. Most of the cost of the project is due to labor costs, in particular, design and coding, with parts cost being minimal.

Table 23: Total Cost of Project

Categories	Cost
Labor Subtotal	$ 31,365.22
Parts Subtotal	$ 413.28
Grand Total	**$ 31,778.50**

4. Summary and Conclusion

As outlined in this proposal, the LoRa Water Quality Management system presents an innovative solution to water utility companies for the monitoring and management of drinking water quality. Unlike traditional water quality monitoring systems, which often require labor-intensive manual water testing or sensors that must be hard-wired into legacy SCADA-based systems, the LoRa Water Quality Management System makes use of power-efficient LoRa wireless technology, whose name is derived from "Long Range," to transmit real-time water quality data back to a central gateway without the need for cellular service, a WiFi connection, or a hard-wired data link. The data transmitted from a network of LoRa-based sensor nodes is processed at a central gateway, which aggregates and summarizes system-wide water quality data in a visual dashboard, alerts technicians and engineers when measured data exceeds legal or utility-defined thresholds, and utilizes AI-driven analytics to predict future system water quality. Implementation of the LoRa Water Quality Management System enables technicians and engineers to monitor water quality system-wide and take corrective action before issues arise.

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Appendix A: Customer Survey

Introduction

Thank you for taking the time to complete this survey. We are a group of Electrical Engineering Students at Penn State Harrisburg. Our idea for our senior capstone project is to use a network of wireless battery-operated sensors to autonomously collect real-time data on a variety of water quality metrics. The telemetry data will be communicated wirelessly back to a central base station, where we will utilize AI-driven analytics to provide insights and make predictions about the health of the system and more efficiently allocate water resources.

Thank you for your time and expertise!

Section 1 - About You:

1. Job Title:

2. Company:

Section 2: Current Process

1. **How You Monitor Water Quality**
    - Which tools or tests do you use now to check water quality (for example, pH meters, turbidity, chlorine tests)?

    - How often do you collect or check water quality data?

    - What are some challenges you face with your current water quality monitoring system?

Section 3: Design Specifications

We plan to implement a network of wireless sensors that monitor a variety of parameters contributing to overall water quality. This data will then be transferred to a central hub which can then process that data and generate alerts as needed.

Sensor Features

1. On a scale from 1-10, with 10 being extremely important, how important would it be for the sensor equipment be battery operated?

   1 2 3 4 5 6 7 8 9 10

2. On a scale from 1-10, with 10 being extremely important, how important is it for each sensor node to have a long battery life (>10 years of operation). If being battery operated is not important or undesirable, leave this question blank.

   1 2 3 4 5 6 7 8 9 10

3. How often would you be willing to replenish batteries the sensor nodes? If battery operation is not important or undesirable, leave this question blank.

   Every: __ Year __ 1-3 years __ 3-5 years __ 5-7 years __ 7-10 years __10-15 years __15+ years

4. On a scale from 1-10, with 10 being extremely helpful, how helpful would it be if the sensors could send data from far away (even across large facilities) without needing access to Wi-Fi, Cell Service, or a Wired Connection?

   1 2 3 4 5 6 7 8 9 10

5. Please rank the following water quality metrics, with rank 1 being the highest importance to be monitored:

   __ Turbidity

   __ Dissolved Oxygen

   __ pH

   __ Temperature

   __ Conductivity

   __ Total Dissolved Solids

   __ Chlorine Concentration

   __ Contaminant Concentration (PFOA/PFOS)

   __ Other (Please Specify):

Base Station

On a scale from 1-10, with 10 being extremely desirable, how desirable is it for the system to:

1. Provide a dashboard containing real-time data?

   1 2 3 4 5 6 7 8 9 10

2. Produce alerts when measured data falls outside of pre-set thresholds?

   1 2 3 4 5 6 7 8 9 10

3. Send alerts directly to technicians (text message, phone notification, pager-like device, etc.) to address issues faster?

   1 2 3 4 5 6 7 8 9 10

4. Use predictive software tools on water quality measurements to identify and address possible concerns before they arise?

   1 2 3 4 5 6 7 8 9 10

5. Integrate with existing PLC systems or other existing controls equipment?

   1 2 3 4 5 6 7 8 9 10

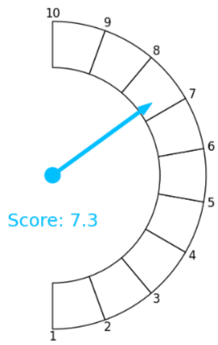
   If this is important to you, and you know, what platform/PLC manufacturer is used?

6. If you know, does your team have any budget range or cost limit for new equipment?

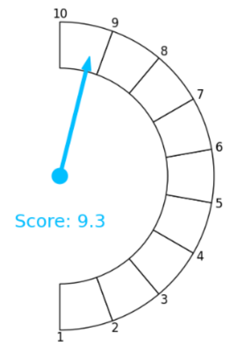
   - Under $1,000 | $1,000–$2,500 | $2,500–$5,000 | Over $5,000 | Not sure

Appendix B: Customer Survey Results

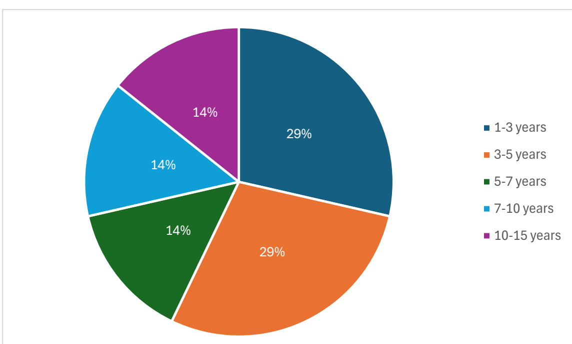
Sensor Features



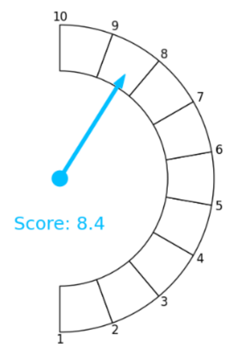
On a scale from 1-10, with 10 being extremely important, how important would it be for the sensor equipment be battery operated?



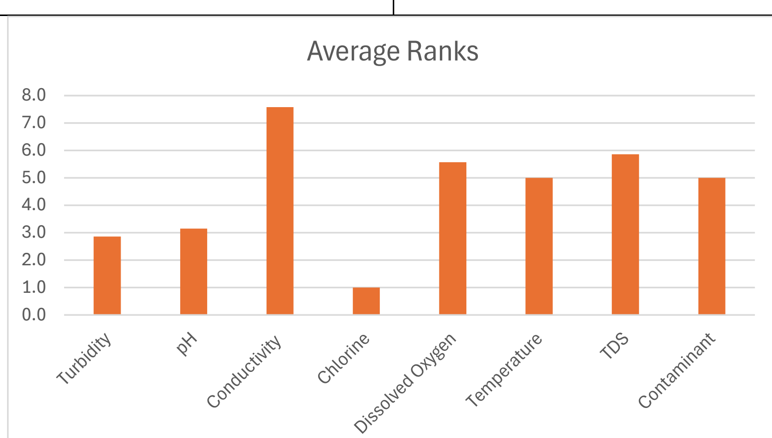
On a scale from 1-10, with 10 being extremely important, how important is it for each sensor node to have a long battery life (>10 years of operation). If being battery operated is not important or undesirable, leave this question blank.



How often would you be willing to replenish batteries the sensor nodes? If battery operation is not important or undesirable, leave this question blank.

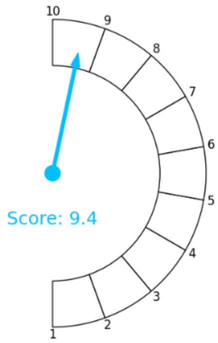


On a scale from 1-10, with 10 being extremely helpful, how helpful would it be if the sensors could send data from far away (even across large facilities) without needing access to Wi-Fi, Cell Service, or a Wired Connection?

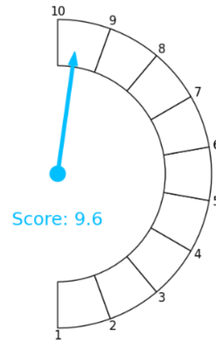


Please rank the following water quality metrics, with rank 1 being the highest importance to be monitored.

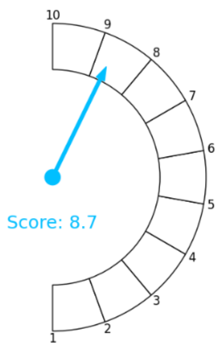
Base Station



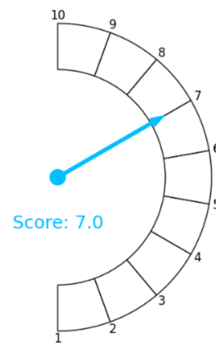
On a scale from 1-10, with 10 being extremely desirable, how desirable is it for the system to: Provide a dashboard containing real-time data?



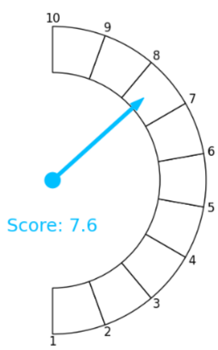
On a scale from 1-10, with 10 being extremely desirable, how desirable is it for the system to: Produce alerts when measured data falls outside of pre-set thresholds?



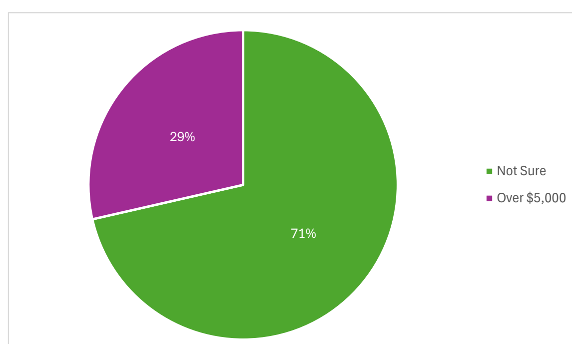
On a scale from 1-10, with 10 being extremely desirable, how desirable is it for the system to: Send alerts directly to technicians (text message, phone notification, pager-like device, etc.) to address issues faster?



On a scale from 1-10, with 10 being extremely desirable, how desirable is it for the system to: Use predictive software tools on water quality measurements to identify and address possible concerns before they arise?



On a scale from 1-10, with 10 being extremely desirable, how desirable is it for the system to: Integrate with existing PLC systems or other existing controls equipment?



If you know, does your team have any budget range or cost limit for new equipment?