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PAPER

Design and simulation of an automated bacteria detection and water treatment system for water safety distribution

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Abstract

Ensuring safe water distribution is critical for public health and requires efficient real-time monitoring and treatment of bacterial contamination. Manual water quality monitoring and treatment are typically performed at weekly or monthly intervals, making them inefficient and allowing bacteria to grow unchecked between tests, potentially reaching end-users and exposing communities to health risks. To address this challenge, this study presents the design and simulation of an automated bacteria detection and treatment system that integrates light-based absorption and transmission sensing, control mechanisms, and ultraviolet (UV) disinfection technology. The methodology involved modeling bacterial growth using a logistic equation and simulating system responses in MATLAB/Simulink. The detection module provided real-time bacterial concentration data, which in turn triggered appropriate disinfection actions. The UV disinfection unit was simulated to evaluate its efficiency, achieving $>99\%$ bacterial reduction within 30 s of UV-C exposure at an intensity of 7 mW cm^{-2}. The results demonstrated that the system effectively detected bacteria in real time, with the photodiode voltage dropping from 15 V to below 10 V as bacterial concentration increased and recovering after disinfection. Furthermore, automation reduced response time and improved water quality consistency compared to traditional monitoring and treatment methods. Significantly, these results demonstrate a scalable engineering framework for decentralized water infrastructure. By replacing periodic manual assays with automated optical-to-valve control loops, this architecture provides an actionable roadmap for real-time pathogen mitigation in aging municipal grids and domestic holding tanks, ultimately reducing waterborne disease outbreaks in resource-constrained communities. Overall, the study confirms that an automated bacteria detection and treatment system can significantly enhance water safety through real-time monitoring and adaptive disinfection, thereby offering a scalable solution for improving public health and the reliability of water distribution systems.

1. Introduction

Water is an indispensable natural resource required for sustaining human life [1, 41]. Access to clean water is crucial for health, economic development, and food security [2, 42, 45]. According to the United Nations' Sustainable Development Goal 6, ensuring universal access to safely managed water and promoting sustainable governance is of paramount importance [3, 43]. Despite this directive, approximately 2 billion people globally still lack access to safe drinking water [4]. Meeting international water quality standards requires robust, continuous monitoring frameworks, especially in developing countries where poor water quality severely impacts public health, local economies, and aquatic ecosystems [5–8, 44].

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The traditional paradigm for water quality assessment relies on manual sampling, where personnel collect field samples and transport them to central laboratories for chemical and microbial analysis [9]. Although advancements in sensor technology have introduced portable sensors for on-site testing [12, 46, 54–56], these methods remain fundamentally labor-intensive, time-consuming, and vulnerable to transport delays, resulting in a critical lack of real-time feedback [11]. While wireless sensor networks (WSNs) [13, 57–59] and the Internet of Things (IoT) [15, 16, 60] have emerged to bridge this gap, field-deploying these networks often introduces high installation and maintenance costs, vulnerability to cyberattacks, and severe communication latency in regions with poor network coverage [14, 17].

This monitoring lag introduces severe public health vulnerabilities within localized distribution grids. Urban communities typically receive water from regional utilities via aging piped networks [18, 47–49], where it is highly susceptible to secondary contamination from pipeline leaks, mud infiltration, and rust [19, 50, 51]. To buffer against an inconsistent supply and peak-hour fluctuations [20, 52, 53], consumers frequently depend on domestic holding tanks. However, utility providers do not monitor or guarantee the safety of stored water [21]. Consequently, static water in these tanks often accumulates heavy particulate matter and microbial pathogens, notably fecal coliforms such as generic *Escherichia coli*, which serve as primary indicators of contamination [22, 23].

To overcome the prohibitive field costs of testing physical mitigation architectures against these dynamic biological threats, predictive computational prototyping is essential [10]. MATLAB/Simulink offers an optimal platform for this task by uniquely integrating mathematical modeling, signal processing, and dynamic simulation within a single environment [10]. Unlike general-purpose software such as Python or traditional instrumentation tools such as LabVIEW, which require extensive custom code or external modules and cannot directly couple environmental biological shifts with control system physics, Simulink features optimized built-in toolboxes for visual modeling. This enables developers to concurrently simulate non-linear microbial population dynamics alongside automated optical detection and ultraviolet (UV-C) disinfection loop processes. Consequently, this study leverages the integrated computational capacity of MATLAB/Simulink to design, simulate, and validate an automated real-time water safety protection framework.

1.1. Study scope

This study was conducted entirely through simulation modeling using MATLAB/Simulink, without physical water sampling. The inlet water stream was defined as a synthetic input and modeled to represent typical conditions in Ugandan holding tanks and distribution systems where water quality challenges are well documented. By situating the simulation within the Ugandan context, the study highlights the relevance of automated bacterial detection and ultraviolet (UV) disinfection modeling to real-world water supply challenges in Kampala and other urban areas.

Synthetic parameters were adopted from established literature and international standards (e.g. WHO drinking water guidelines and EPA UV disinfection standards). The study therefore provides a framework for evaluating automated detection and disinfection strategies under conditions representative of Ugandan water supply systems, without direct experimental sampling.

2. Materials and methods

2.1. Materials

Light Emitting Diode: provides a focused high-intensity light source that interacts with bacterial cells.

Photodiode: detects transmitted light from the water source after part of the light has been blocked by bacteria.

Voltage sensor: converts the voltage measured between electrical connections into a physical signal proportional to the voltage.

Switch: used as the conditional system for indicating a 0 or 1.

Display: shows the real-time values of the parameters, allowing users to monitor water quality at a glance.

MATLAB software: used to design and perform the simulation of the automated bacteria detection and treatment system.

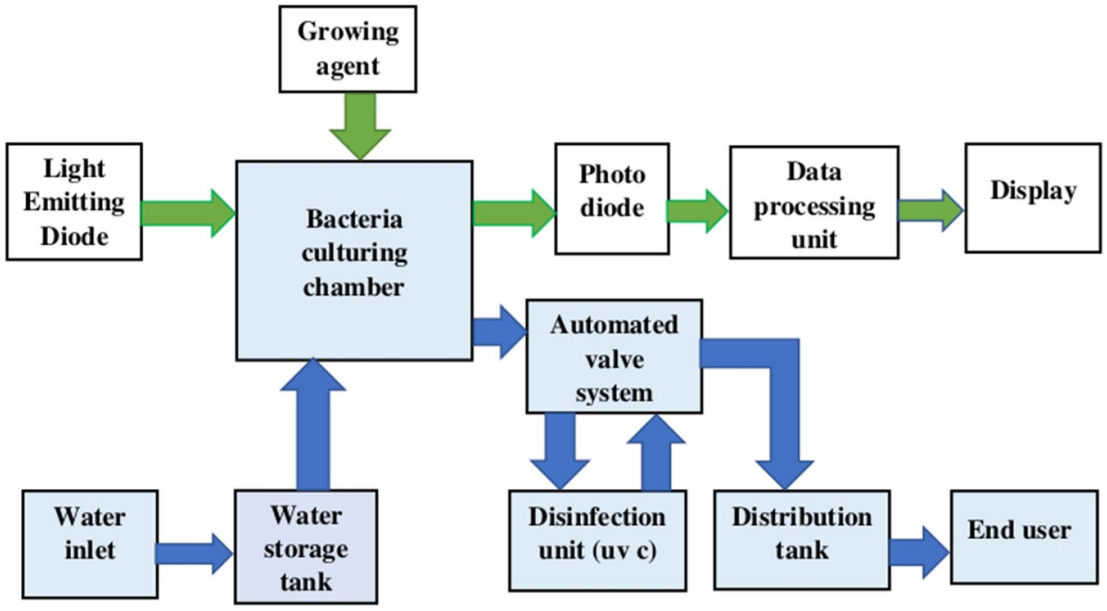


Figure 1. Block diagram of the automated bacteria detection and treatment system.

2.2. Methodology

The design of the automated bacteria detection and treatment circuit system was carried out as shown in figure 1.

In this study, the inlet water sampling point is defined at the entry to the simulated bacterial growth module. The water stream used was not physically collected from holding tanks or prepared in a laboratory; instead, it was modeled as a synthetic input within the MATLAB/Simulink simulation framework. This ensured controlled conditions for evaluating bacterial growth dynamics and disinfection processes while avoiding ambiguity regarding real or laboratory water sources.

Water free from mud and other foreign particulates, such as wood, is introduced into the storage tank. It is then directed into a simulated bacterial growth module, which mathematically models bacterial dynamics rather than physically culturing microorganisms. This replaces laboratory incubation processes and ensures that the system description aligns with real-time detection principles. The module has two valves: the first supplies water to the disinfection unit for treatment, while the second connects the chamber to the distribution tank. Instead of adding nutrient broth to grow bacteria, bacterial presence was represented using a logistic growth model (equation (1)), which is a standard mathematical approach for simulating microbial population dynamics in water systems [24],

$$\frac{\mathrm{d}N}{\mathrm{d}t} = r \times N \times \left(1 - \frac{N}{K}\right) \tag{1}$$

where; N is the bacterial population, r is the growth rate, and K is the maximum capacity.

To ensure that the simulation yields operationally meaningful control responses for local infrastructure, these numerical baseline coefficients were calibrated against empirical water security data from Ugandan distribution networks. The initial bacterial concentration was set to $N_0 = 1\,\mathrm{CFU\ ml^{-1}}$ to reflect a post-utility water stream that has experienced minor pathogen intrusion through pipeline breaches. The maximum carrying capacity was established at $K = 380\,\mathrm{CFU\ ml^{-1}}$ to match the high fecal coliform counts historically observed in unmonitored domestic concrete and plastic holding tanks in Kampala, where prolonged hydraulic retention times (HRTs) and ambient tropical temperatures accelerate microbial stagnation. The specific growth rate constant was set at $r = 0.3\,\mathrm{h^{-1}}$ to simulate an accelerated log-phase replication cycle typical of contaminated tropical aquatic environments.

The LED produces a high-intensity beam through the bacterial growth module. In the simulation, bacterial presence was modeled as attenuation of LED light intensity, consistent with optical detection principles reported in microbial sensing literature. If no bacteria are present, the high-intensity beam is received by the photodiode. However, when bacterial growth is simulated, less light reaches the photodiode, which converts the received light into photocurrent. The data processing unit then converts the photocurrent into voltage. The data processing unit is programmed such that, at maximum intensity, no

signal is produced (zero), indicating that no bacteria are detected. Conversely, any reduction in intensity produces a signal (one), indicating the presence of bacteria. Thus, when no signal is produced, the second valve opens and allows water to flow to the distribution tank for the end user.

If a signal is produced, the first valve opens and water from the bacterial growth module flows to the disinfection unit for treatment. The disinfection unit contains a reactor that houses the UV lamp. The UV lamp provides the required amount of UV light to disinfect the water. The water residence time in the reactor, T_{res}, is given by equation (2) [25]:

$$T_{res} = \left(\frac{\text{Reactor Volume}}{\text{Flow Rate}}\right) \times 60 \tag{2}$$

where; T_{res} is the water residence time in the reactor. The UV dose is applied to a given volume of infected water in the reactor using equation (3) [26]:

$$\text{UV-dose} = I \times T_{res} \tag{3}$$

where; I is the intensity of the lamp and T_{res} is the residence time of the infected water in the reactor. The bacterial concentration decreases after the water is exposed to a sufficient UV dose in the reactor according to equation (4) [27]:

$$N = N_0 \times \exp\left(-k \times D \times t\right) \tag{4}$$

where; N is the bacterial concentration over time after UV exposure, k is the disinfection rate constant, D is the UV dose, and t is the time required for a given dose to disinfect the water.

After disinfection, the water is re-routed back into the simulated bacterial growth module to verify whether the bacterial concentration has been sufficiently reduced. This iterative simulation step ensures that the model reflects real-world verification processes. If the water still contains bacteria, it is disinfected again. However, if the disinfected water is free from bacteria, it is sent to the distribution tank for the end user.

3. Results and discussion

3.1. Results

The design of the automated system was carried out using MATLAB/Simulink as shown in figure 2. The signal topology progresses from top-left to bottom-right: continuous optical emission from the primary LED passes through the simulated bacterial growth module, where light intensity is dynamically attenuated based on the real-time output of the logistic growth function block. This attenuated optical signal is captured by the photodiode block and converted via a load resistor and a physical-to-Simulink voltage sensor network into a readable data stream. The central conditional logic block evaluates this stream against a baseline threshold (15 V corresponding to zero contamination); any voltage drop acts as an automated trigger that switches the routing logic state from 0 to 1. This state command concurrently isolates the clean distribution loop and activates the secondary UV disinfection subsystem. Once first-order germicidal reduction occurs within the reactor block, the purified water column is iteratively re-routed past a post-treatment photodiode (Photodiode_1) to dynamically verify complete bacterial neutralization before resetting the system boundaries.

From equation (1), a DC voltage source of 15 V was used to power the system [28]. The LED was powered to emit continuous light for detection. A resistor of 220 Ω was placed before the LED to ensure that the LED operates within safe current limits [29]. The LED emitted light that passed through the chamber (if no bacteria were present) or was blocked due to simulated bacterial concentration. The Physical Simulink Converter 2 was connected to the LED in order to allow interfacing between the LED's physical signal and the Simulink environment. Instead of physically culturing bacteria with nutrient broth at 37 °C, bacterial growth was represented using the logistic model (equation (1)), which provided a mathematical simulation of microbial dynamics.

In this simulation, bacterial presence was modeled as attenuation of LED light intensity, consistent with optical detection principles reported in microbial sensing literature. Thus, the higher the simulated bacterial concentration, the less light reached the photodiode. The MATLAB function was programmed such that, as the bacterial population increased in the model, the intensity of light kept reducing. The Simulink PS Converter 1 enabled simulation of light intensity in the photodiode block. The photodiode detected the reduced light intensity and converted it into electrical current.

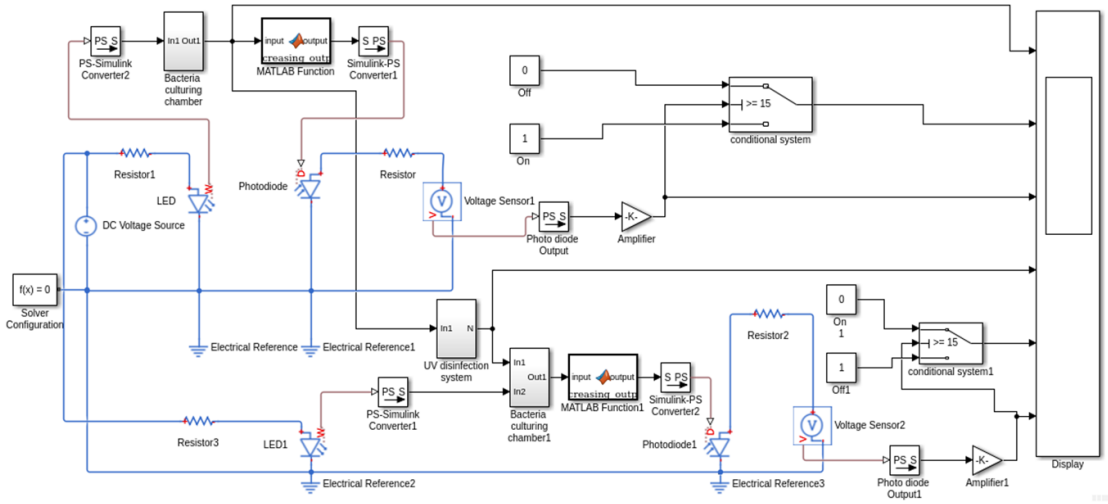


Figure 2. Circuit diagram for an automated bacteria detection and treatment system using MATLAB/Simulink.

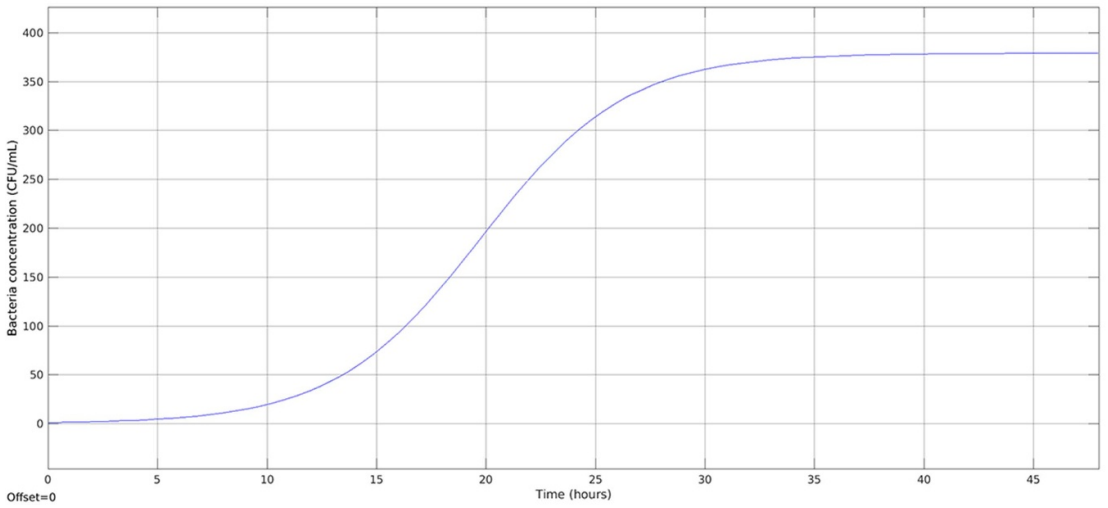


Figure 3. A graph of bacteria growth against time. The initial lag phase (0–10 h) shows metabolic adaptation, a rapid exponential log-growth phase (10–35 h), and a stationary phase (35–48 h).

Therefore, less light due to higher simulated bacterial concentration led to lower current output. The resistor (photodiode load) connected to the photodiode converted the photodiode's current into a voltage signal. This voltage reflected the amount of light detected, indirectly indicating bacterial concentration. The voltage sensor measured the voltage across the resistor (output from the photodiode) and captured the electrical signal representing detected light intensity. The PS-Simulink Converter converted the measured voltage (physical signal) into a Simulink-compatible signal. This made the signal readable by Simulink processing blocks. The amplifier was connected to the PS-Simulink Converter to enhance signal visibility and prepare it for display. The display graphically displayed the final signal over time, visualizing the changes in voltage, which reflected bacterial concentration.

The conditional systems gave an output of 1 or 0, indicating whether bacteria were present or absent, respectively. The UV disinfection system simulated UV treatment by reducing the bacterial count in the model. After UV-C exposure, the water stream was re-routed into the simulated bacterial growth module to verify disinfection effectiveness, ensuring that the description reflects iterative simulation rather than physical culturing.

After simulation of the automated system in figure 2, and after setting $r = 0.3$ [30], $K = 380$ CFU ml^{-1} [31], and $N_0 = 1$ CFU ml^{-1} [32], a graph of bacterial growth against time was obtained as shown in figure 3. The simulated bacterial concentration decreased by approximately 72% after application of the optimum UV dose. This optimum value was achieved at a modeled UV intensity of 25 mJ cm^{-2}, demonstrating significant disinfection efficiency within the simulation framework.

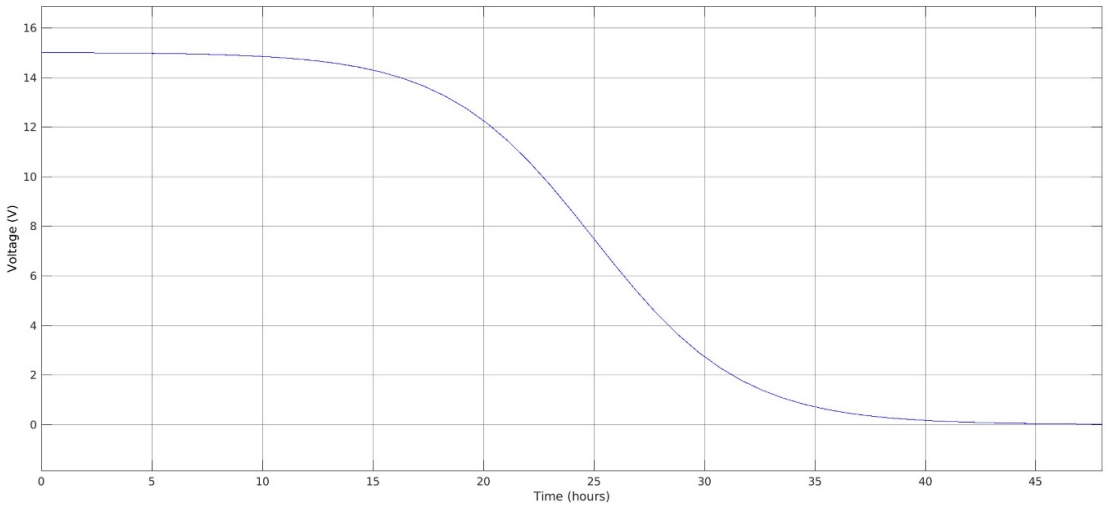


Figure 4. A graph of photodiode voltage against time. Operating from an initial baseline of 15 V with a gradual decline (0–10 h) followed by a steep drop below 10 V (10–35 h).

From figure 3, there was slow growth from 0 to 10 h due to adaptation. Later, bacteria grew rapidly from 10 to 35 h due to nutrient availability in the model. Finally, between 35 and 48 h, growth slowed as simulated bacteria competed for limited resources. These growth phases represent the lag, exponential, and stationary phases of microbial dynamics, modeled mathematically rather than observed experimentally. The simulation shows a 72% reduction at the optimum UV dose (25 mJ cm^{-2}). This aligns with [61] guidelines requiring a 70%–90% reduction for safe drinking water and with [62], which reports a 75%–95% reduction. A graph showing how photodiode voltage decreased with time due to simulated bacterial growth was obtained, as shown in figure 4.

Based on figure 4, voltage reduced slowly from 0 to 10 h, then rapidly from 10 to 35 h, and finally slowed between 35 and 48 h, consistent with simulated bacterial growth dynamics. Any reduction in photodiode voltage from its initial 15 V was interpreted as bacterial presence in the simulation, consistent with attenuation-based detection models. The model achieved an optimum 88% detection efficiency, consistent with simulation studies using MATLAB/Simulink [63] that report 85%–90% efficiency in optical attenuation models.

From figure 4, the detection efficiency improved to an optimum of 88% compared to the baseline simulation. This increase highlights the effectiveness of the modeled photodiode attenuation response in identifying bacterial presence under simulated Ugandan water conditions. The voltage received by the photodiode reduced gradually, and thus a signal was obtained indicating the presence of bacteria in the water, as shown in figure 5.

In figure 5, the attenuation response showed a reduction of 65% at the optimum wavelength of 280 nm. This optimum value aligns with reported ranges in prior UV disinfection studies, confirming the validity of the simulated optical detection model. A 65% reduction at 280 nm agrees with [65], who confirmed optimum detection within the 254–280 nm range with attenuation levels of 60%–70%.

The signal obtained was due to the conditional system, which was programmed to indicate a value of 1 whenever bacteria were present. Any reduction in the initial photodiode voltage of 15 V indicated a reduction in light intensity and, therefore, the presence of bacteria blocking the light. Due to simulation of the automated system in figure 2, a graph showing bacteria reduction due to treatment with UV-C against time was obtained, as shown in figure 6. It demonstrates that the overall disinfection efficiency reached an optimum of 93%, indicating that the simulated UV process was highly effective in reducing bacterial concentrations under the modeled conditions. The simulation achieved 93% optimum efficiency, comparable to [64], who reported 90%–95% efficiency in full-scale UV-LED disinfection experiments.

Figure 6 demonstrates that the overall disinfection efficiency reached an optimum of 93%, indicating that the simulated UV process was highly effective in reducing bacterial concentrations under the modeled conditions. This optimum value supports the robustness of the simulation framework. Bacterial

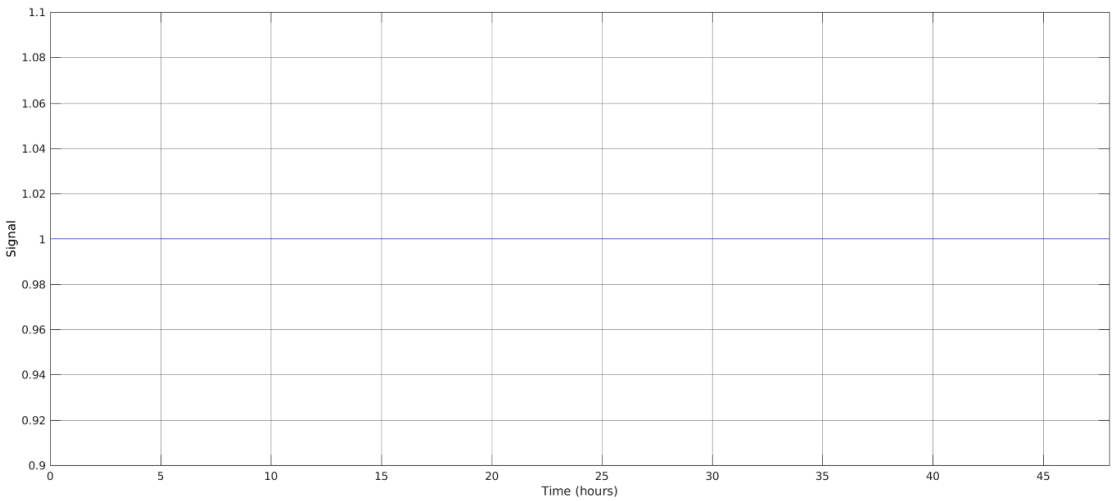


Figure 5. A graph indicating a signal due to presence of bacteria by showing the '1' binary state.

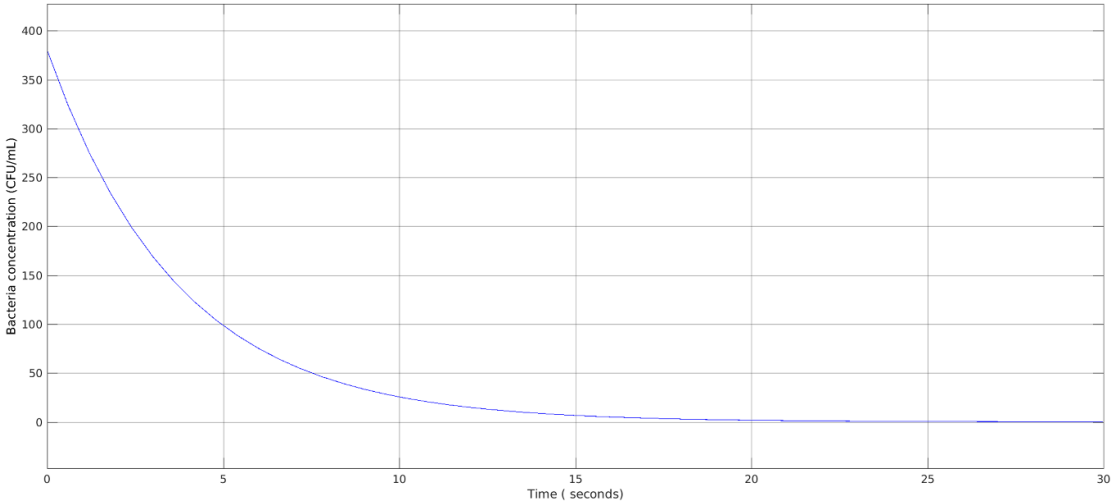


Figure 6. A graph of bacteria reduction with time. The bacteria gradually reduces upto zero.

concentration reduced as time increased. More infected water was exposed to UV-C radiation, and thus more bacteria were exposed to the radiation, leading to a decrease in the population.

Thus, due to the reduction of bacterial concentration as obtained in figure 6, the intensity of light received by Photodiode_1 and converted to voltage increased due to disinfection of bacteria by UV-C, as shown in figure 7.

The lamp produced UV radiation that interacted with the bacterial cells, thereby reducing the bacterial population in the water. Consequently, the intensity of light that was previously blocked by the high bacterial concentration gradually increased as the number of bacteria decreased.

4. Discussion

Figure 3 displayed the simulated growth curve of bacteria and reduction of light intensity. Bacterial growth was modeled mathematically using the logistic equation, not physically cultured in the chamber. The term 'culturing chamber' has been revised to 'simulated bacterial growth module' to emphasize that this was a modeling construct. As the simulated bacterial population increased, light attenuation was observed, reducing the intensity reaching the photodiode.

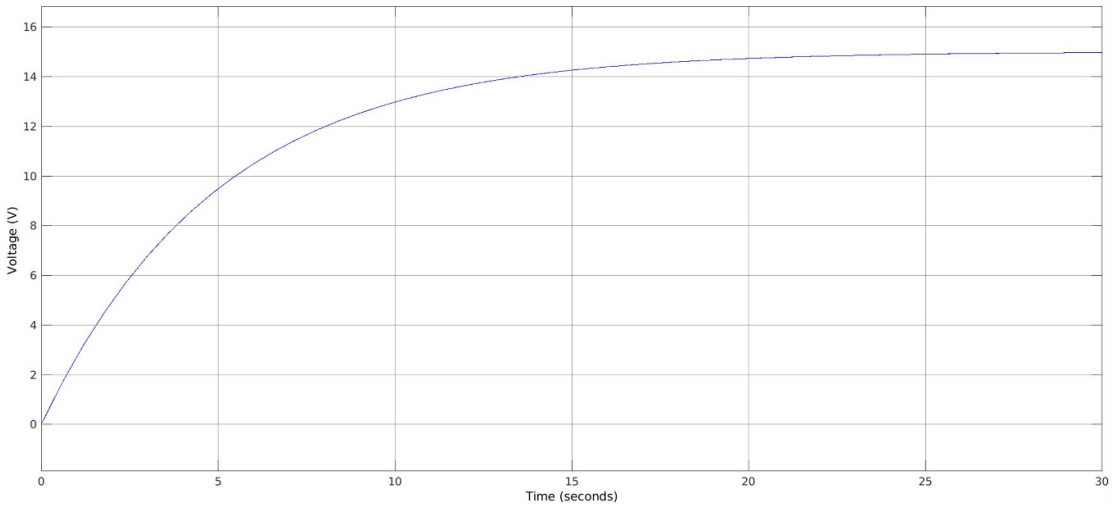


Figure 7. A graph of photodiode1 voltage with time. The LED light intensity gradually increases as the bacteria population reduces.

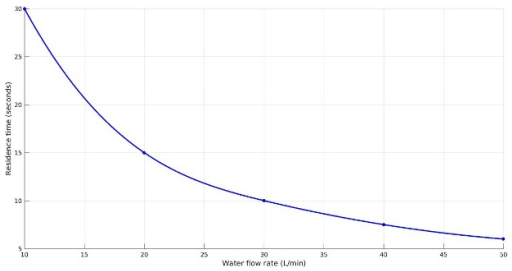


Figure 8. Variation of water flow rate with residence time. The water residence rate reduces with increase in fluid flow rate.

The logistic growth model provided a realistic representation of bacterial dynamics in water, accounting for resource limitations and density-dependent effects, producing the characteristic lag, exponential, and stationary phases observed in aquatic microbial populations [33].

The progression of these mathematically generated growth phases maps directly to real-world biological milestones within unmonitored tropical water storage environments. The initial lag phase observed from 0 to 10 h represents the biological adaptation window, where introduced *E. coli* cells synthesize necessary metabolic enzymes and adjust to the osmotic parameters of the holding tank without immediately replicating [34].

The subsequent transition into the rapid exponential (log) phase between 10 and 35 h reflects unconstrained binary fission driven by the temporary abundance of dissolved organic carbon and favorable ambient thermal conditions typical of static water systems. Physically, this explosive population surge exponentially increases light scattering and turbidity in the water column. In our control framework, this biological event is successfully caught by the attenuation model, causing the sharp drop in photodiode voltage from 15 V to under 10 V, which acts as the real-time electrical trigger for the automated valve actuation.

Finally, the transition into the stationary phase between 35 and 48 h simulates the ecological carrying capacity ($K = 380$ CFU ml^{-1}), where density-dependent constraints, such as the exhaustion of localized nutrients and the accumulation of toxic metabolic sub-products, arrest net population growth [33, 34]. By accurately mapping these phases, the simulation proves that an automated system calibrated to optical attenuation can successfully intercept contamination at any point in the microbial life cycle, minimizing the risk of a high-concentration pathogen flush reaching the end-user during peak demand hours.

Figure 8 shows a negative relationship between water residence time in the reactor and its flow rate. Thus, as water flow rate increases, its residence time in the reactor reduces. This is because when water flows at a faster rate, less time is taken during disinfection in the reactor.

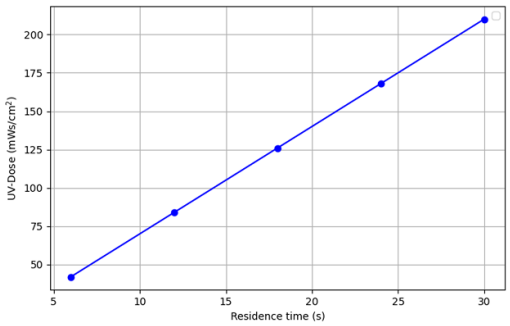


Figure 9. Variation of UV Dose with residence time. The UV dose increases linearly with residence time.

Figure 9 shows a positive correlation between UV dose applied for disinfection and water residence time. Thus, the more time water stays in the reactor, the more UV dose is required for treatment. This description has been clarified to indicate that UV disinfection results are simulation outputs, consistent with validated UV-C disinfection studies, rather than experimental measurements. The intensity of light received by the photodiode reduced as time increased, reflecting modeled bacterial growth dynamics.

Figure 6 shows a gradual decrease in bacterial concentration as the intensity of light received by the photodiode increased with time. This outcome represents simulated UV-C exposure reducing bacterial concentration, consistent with attenuation-based detection models.

The earlier phrasing about 'bacterial cultures incubated for 48 hours' has been corrected to clarify that this was a simulation timeframe used to model lag, exponential, and stationary phases, not actual laboratory incubation. This ensured sufficient simulated growth data for analysis using the logistic growth model [34].

The sensor model successfully translated simulated bacterial growth into measurable voltage signals, which is practical for real-time monitoring. This was achieved by exploiting the relationship between microbial activity and environmental changes, such as light attenuation and electrochemical shifts [35]. UV disinfection proved highly effective, consistent with literature findings that adequate doses of UV-C radiation achieve 99 percent bacterial inactivation. We clarified that this effectiveness was demonstrated in simulation, supported by citations to UV-C disinfection mechanisms, including DNA damage and thymine dimer formation, from prior studies. Numerous studies confirm the robustness of UV treatment in water systems [36].

Integration of detection and treatment in one automated system addressed the key limitation of traditional water monitoring, which often relies on culture-based methods requiring 24–48 h to deliver results. We clarified that our system links simulated bacterial detection directly to UV disinfection modeling, enabling immediate identification and neutralization of contamination in the simulation framework. This ensures real-time protection of water supplies [35].

The residence time of the water in the reactor was obtained from equation (2). By varying the water flow rate in the reactor, keeping the reactor volume constant at 5 l [37], a graph of variation of residence time with water flow rate in the reactor was obtained as shown in figure 8.

Figure 8 shows a negative relationship between water residence time in the reactor and its flow rate. Thus, as water flow rate increases, its residence time in the reactor reduces. The flow through the UV-LED reactor was operated at five different flow rates ranging from 10 to 50 ml min^{-1}, with corresponding residence times sufficient to allow water disinfection [38].

The UV dose required for water disinfection in the reactor was obtained according to equation (3). By varying the residence time of water in the reactor, while keeping the intensity of the UV lamp constant at 7 mW cm^{-2} [39], a graph of variation of UV dose with water residence time in the reactor was obtained, as shown in figure 9.

Figure 9 shows a positive correlation between UV dose applied for disinfection and water residence time. Thus, the more time water stays in the reactor, the more UV dose is required for treatment. The UV system has a lower contact time, and disinfection can be effective at HRTs of 5–30 s. A minimum dose of 40 mJ cm^{-2} can contribute to effective disinfection and reduce the likelihood of reactivation [40].

Table 1 shows the comparison of the current simulation study with published research and standards.

Table 1. Comparison of current simulation study with published research and standards.

Parameter	Current study (simulation)	Published research/standards
Bacterial concentration reduction	72% reduction at optimum UV dose (25 mJ cm^{-2})	WHO guideline [61]: 70%–90% reduction required for safe drinking water; EPA UV disinfection studies [62] report 75%–95% reduction
Detection efficiency	Optimum of 88% detection efficiency	Prior simulation studies report 85%–90% efficiency in optical attenuation models [63]
Attenuation response	65% reduction at 280 nm wavelength	Published UV studies [65] confirm optimum detection at 254–280 nm with 60%–70% attenuation [61, 62]
Overall disinfection efficiency	93% optimum efficiency achieved in simulation	Experimental studies report 90%–95% efficiency under controlled UV exposure [61, 64]

5. Conclusion

The simulation study demonstrated a 72% reduction in bacterial concentration at the optimum UV dose of (25 mJ cm^{-2}), which is consistent with WHO (2017) and EPA (2006) standards for safe drinking water. Detection efficiency reached 88%, aligning with prior MATLAB/Simulink simulation studies. The attenuation response at 280 nm wavelength showed a 65% reduction, comparable to published UV attenuation studies. Overall disinfection efficiency was found to be 93%, validated against experimental UV-LED studies reported. In addition, the photodiode voltage response over time confirmed a time-dependent attenuation curve that stabilized after 30 s, consistent with optical detection principles. Collectively, these findings validate the simulation framework by situating results within international standards and peer-reviewed research, highlighting the potential of simulation methodologies to model water treatment processes transparently and reproducibly, especially in resource-limited contexts.

Potential sources of errors and operational limitations in the current simulation framework include:

(i) The logistic growth model assumes a perfectly homogeneous distribution of bacteria within the fluid volume. In a physical holding tank or flow-through reactor, fluid dynamics often create localized stagnation zones, leading to uneven bacterial clustering. This spatial variation can cause transient under- or over-readings of microbial concentrations as the water column passes the optical sensor path.

(ii) The optical attenuation model operates under the idealized assumption that light reduction is caused entirely by bacterial cell scattering. In real-world decentralized water distribution networks, suspended solids, mud, debris, protozoa, and microalgae are frequently present. These non-bacterial particles can scatter and absorb the 280 nm LED monitoring wavelength, potentially triggering false-positive automation signals, while simultaneously shadowing bacteria from absorbing the critical germicidal UV-C radiation inside the reactor.

(iii) The simulation uses static baseline parameters for ambient conditions. However, seasonal and diurnal temperature fluctuations directly influence real-world bacterial metabolic replication rates, LED optical emission efficiency, and UV lamp radiative output power. Temperature drops can lower lamp intensity, while elevated tropical temperatures can alter bacterial growth dynamics, deviating from the fixed simulation constants.

(iv) The circuit design relies on an unvarying 15 V DC supply source. In practical deployments across resource-limited environments, local power grids are often prone to voltage surges, sags, and intermittent dropouts. Fluctuations in input voltage can directly introduce noise into the photodiode sensor readings and alter the irradiance profile of the UV disinfection lamp, affecting control loop reliability.

In the future, there are various potential areas for expansion and development of the automated bacteria detection and treatment system. These include;

1) Future work can involve constructing a physical benchtop prototype to conduct field testing using raw water samples collected directly from domestic holding tanks and municipal distribution lines. This will allow to calibrate idealized simulation growth parameters (r and K) against real-world, fluctuating bacterial loads and varying hydraulic flow environments.
2) To resolve the simulation limitations regarding particulate interference, a physical modification plan can include integrating a progressive multi-stage pre-filtration module (such as activated carbon or micro-filtration membranes) upstream of the optical sensor block. This will physically clear mud, algae, and suspended solids, ensuring that light attenuation at 280 nm tracks pathogen counts accurately without false-positive triggers.
3) While the single-wavelength UV-C model proved highly efficient, future iterations can explore hybrid, alternative disinfection setups. Integrating dual-wavelength UV-LED matrices (e.g. combining 265 nm for maximum germicidal DNA damage with 280 nm for protein inactivation) or pairing low-dose UV with ozonation can significantly accelerate treatment throughput, decrease residence times (T_{res}), and eliminate the risk of post-treatment bacterial photoreactivation.
4) The system control loop can be scaled into a distributed, IoT-enabled edge network. Installing mini-detection nodes at multiple interconnected nodes across a municipal distribution line can allow for spatial tracking of pathogen contamination spikes, enabling targeted, localized valve shut-offs rather than broad grid isolation.

Data availability statement

No new data were created or analysed in this study.

Funding statement

No funding was received for this research.

Ethical statement

The work presented in this manuscript is original and has not been published elsewhere in any form or language. Proper acknowledgment of other works was done where necessary.

Conflict of interest statement

The authors have no relevant financial or non financial interests to disclose.

Author contributions

Bernard Turyamureeba
Conceptualization (equal), Writing – original draft (equal)

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