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Original Article

Design and Implementation of a Virtual Reality Platform for the Festo Compact MPS Machine

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Abstract - *The current system for monitoring water quality is manual, monotonous, and time-consuming. This paper proposes a water quality monitoring system based on virtual reality and the digital twin. The goal of this research is to create a virtual reality platform with the Festo compact machine using digital twin technologies to monitor and control the growth of E. coli in the water. MPN is an approach used to determine the presence or absence of microorganisms in each repeat portion of the original sample. IIoT infrastructures are used for integration and establishing a two-way communication protocol. DT gathers information from sensors mounted on actual objects to assess operating conditions, changes over time, and object performance in real-time. This work provides a comprehensive solution for the real-time monitoring and management of E. coli growth in mineral water facilities. The study used previous material to examine and understand the controllable factors that contribute to the proliferation of Escherichia coli in mineral water. The Parameters such as time, temperature, and chlorine dosage are remotely monitored and controlled via the combined VR, IIoT, and DT platforms. VR is used for supervisory control, in which directives and commands are transmitted to the actual station for implementation. Data obtained allowed the creation of an empirical model for the modeling and control of the growth of E. coli in water production plants.*

Keywords - *Escherichia coli, Digital Twin, IIOT, Virtual Reality, Chlorine disinfection.*

1. Introduction

The mineral water industry provides safe drinking water to people worldwide. Water is susceptible to contamination from microorganisms, which can cause severe health risks [1]. A lack of proper sanitation and groundwater quality contributed to 533,768 child deaths globally in 2018 [2]. Chlorine is a disinfectant commonly used in water treatment to remove bacteria and other contaminants.

Chlorine is very effective at getting rid of many types of harmful microbes, such as viruses, bacteria, and protozoa, so it is usually added to water to kill bacteria. It is a sensible and adaptable option for water treatment plants because of its rapid action, wide range of effects, and stability in water. Chlorine is also reasonably priced and simple to use on a large scale. However, excessive use can lead to the production of potentially dangerous by-products, so concentrations need to be carefully controlled to reduce risks to the environment and public health.

The method used to control the dosage of chlorine in the mineral water industry is through manual titration. This involves adding a chemical titrant solution, such as sodium thiosulfate, to the water sample until the chlorine is completely consumed. The amount of titrant used is then measured to determine the amount of residual chlorine remaining in the sample. This method is widely used in the industry due to its simplicity, accuracy, and low cost.

Many techniques are used to detect microorganisms in drinking water, including Polymerase Chain Reactions (PCR) [3, 4]. Polymerase Chain Reaction (PCR) and Enzyme-Linked Immunosorbent Assay (ELISA) methods, although faster, still require transportation of samples to the laboratory, high-cost equipment, and complex procedures, while highly sensitive, require complex standardized protocols and skilled workers to operate; biosensor-based techniques offer portability, miniaturization, and on-site testing advantages, but may not compete with conventional methods in terms of accuracy [5].

The Most Probable Number (MPN) method is used to determine the microbiological quality of drinking water [6, 7]. The MPN method is relatively simple and cost-effective compared to some other detection methods, making it accessible for routine testing in laboratories with limited resources.

It can be used for large-scale testing, as multiple samples can be processed simultaneously, and it can detect low levels of E. coli bacteria in water samples, which is important for assessing the safety of drinking water [6]. It may not be suitable for high-throughput analysis due to the need for multiple tubes and the time required for incubation and interpretation of results [6].

The accuracy, reactivity, and optimization of traditional automatic systems used to regulate and monitor the temperature and chlorine dosage in water are frequently compromised. Their inability to perform advanced control real-time remote monitoring causes delays in problem detection.

It makes it harder to maintain optimal performance while lowering risks to health; despite its proven influence on water quality, the temperature of water in the Drinking Water Distribution System (DWDS) is not regularly monitored [9]. Because of this, there is a need to develop a system that can remotely control and operate the system.

That is why using a digital twin and virtual reality system for temperature management and monitoring offers a more sophisticated and flexible solution than a conventional automated system. Accurate process modeling, real-time data analysis, remote monitoring, and continuous improvement are made possible by digital twins, which improve responsiveness to change, reliability, and decision-making.

Virtual reality offers employees more realistic and immersive training, enhancing their capabilities and reducing operational challenges. By integrating these technologies, companies can reduce expenditure and unplanned downtime by anticipating risks, optimizing efficiency, and ensuring better water quality.

This paper seeks to identify a methodology for using virtual reality to monitor and control water parameters in mineral water production plants. Rono et al. [20] employed VR, DT and IIoT technologies to link the physical and digital realms for instantaneous manufacturing process monitoring and control.

The understanding of how to combine VR, DT and IIoT in tandem to bridge the gap between actual machines and their corresponding virtual models has improved as a result of this research. It also offers insights on how to transfer data and information between these two worlds utilizing a bidirectional communication protocol, allowing for real-time monitoring and control over manufacturing processes.

Flow Cytometry (FCM) is used to assess the efficacy of chlorine disinfection for both pure culture bacteria (Escherichia coli) and microorganisms in treated water from operational Water Treatment Works (WTWs) [8]. The limitation of this method is the inability to detect low levels of E. coli bacteria in water samples.

Agudelo et al. [9] described the challenges of temperature to water quality. This lack of monitoring compromises the ability of water treatment infrastructure operators to maintain optimal conditions throughout the network. Temperature influences bacterial growth, the formation of disinfection by-products, and the chemical stability of water, underscoring the crucial importance of continuous monitoring to ensure safety and compliance with drinking water quality standards.

Using DNA extraction methods, molecular validation of presumed E. Coli test isolates was carried out; the study investigated the efficacy of various chlorine concentrations in removing Escherichia coli from wastewater effluents as well as the isolates' resistance to chlorine [10].

Stefan et al. [11] investigated the water treatment procedures used by 12 drinking water treatment facilities in Hungary, including the use of breakpoint chlorination. They found that the concentration of Disinfection By-Products (DBPs) increased during the water treatment process, particularly after the addition of chlorine reagent.

Controlling these physicochemical parameters, such as turbidity, pH, conductivity, total dissolved substances, chloride, Free Residual Chlorine (FRC), calcium, magnesium, sulfate, nitrite, and nitrate, is essential to ensuring mineral water quality, particularly regarding microbial contamination.

Mohammed et al. [12] analyzed physicochemical parameters, such as pH, turbidity, electrical conductivity, total dissolved solids, and microbial quality of groundwater. The study found that water pH significantly influenced the microbial quality of the mineral water, with pH levels below 7.0 being associated with higher microbial populations. In addition, higher levels of total dissolved solids and electrical conductivity were also associated with increased microbial populations in the mineral water.

An analytical cross-sectional study design was employed by Ondieki et al. [13] to examine the bacteriological and physicochemical quality of drinking water in Kisii town, Kenyan households. 422 samples of drinking water were collected at the point of consumption from the four zones of Kisii town using stratified random sampling. The samples were subjected to bacteriological analysis, which showed that 39.3% of the samples had total coliform contamination and

17.5% had E. coli contamination, both of which were higher than the WHO and Kenya Bureau of Standards' recommended limits.

Samdeep et al. [14, 10] examined the major Gram-Negative Bacteria's (GNB) resistance to chlorine, as seen in sewage that has been secondary treated in Jaipur, India. It was discovered that although the isolates' fatal doses varied from 0.5 to 1.25 mg/L, substantially greater chlorine doses were needed to completely suppress regrowth., ranging from 0.75 to 1.75 mg/L.

However, pH, temperature, and chlorine dosage are important factors in maintaining water quality in the mineral water industry; they can be complex to manage and require further study for several reasons. Firstly, the interrelationship between these factors can make it difficult to optimize their use in water treatment. For example, the optimal pH range for chlorine disinfection is typically between 6.5 and 7.5 [1].

However, pH can also affect the stability of chlorine, with lower pH levels causing faster depletion of free chlorine. Thus, it is necessary to balance the pH levels with the proper chlorine dosage to achieve effective disinfection. Secondly, the efficacy of chlorine disinfection is also influenced by temperature.

Higher temperatures can accelerate the decomposition of chlorine, reducing its effectiveness in controlling microorganisms. The rate of microbial growth can also increase at higher temperatures, specifically 15°C, which is more optimal for E. coli reduction during ClO_2 treatment, making it necessary to adjust chlorine dosages accordingly [15].

The chemical interactions between chlorine and other compounds in water, such as organic matter, can also affect chlorine dosage requirements. The presence of organic matter can react with free chlorine to form chloramines, which are less effective at disinfection.

This can increase the necessary chlorine dosage to achieve the desired level of disinfection [8]. Therefore, further studies are necessary to understand better the complex interplay between pH, temperature, and chlorine dosage in maintaining water quality in the mineral water industry. Efficient monitoring and control offer an opportunity for optimization of closely related parameters that impact water quality. In particular, Industry 4.0 offers new opportunities for real-time systems.

Chowdhury et al. [16] proposed a sensor-based mechanism for detecting water quality using the Internet of Things and Wireless Sensor Networks technology, which enables real-time data access and remote water monitoring with high frequency, high mobility, and low power consumption, which can help raise awareness of contaminated water and prevent water pollution. It also highlighted the potential of IoT in environmental monitoring and underscored the need for efficient and cost-effective real-time water quality monitoring systems [17]. The study acknowledges the limitations of the project, such as the exclusion of parameters like the variables total residual solids, chemical oxygen demand, and soluble oxygen that could be measured with more funding and system enhancement.

Lowe et al. [18] examined a range of AI and ML-enabled water-related applications, including automation and monitoring for aquaponics and hydroponics, adsorption, membrane filtration, water quality index monitoring, stream level monitoring, and chlorination. Some of the primary constraints observed were inadequate data management, limited explicability, and poor model replication.

Pesantez et al. [19] developed a digital twin framework integrating a hydraulic model with data from the Advanced Metering Infrastructure (AMI) to evaluate the effects of variations in water consumption related to COVID-19 on infrastructure.

The results show that this offers insightful analysis and guidance on optimizing operations and making sustainable plans for the management of water utilities. The use of digital twins and virtual reality technology can also enhance the efficiency of the plant and reduce the need for manual intervention. The contribution of this research lies in the development of a virtual platform dedicated to the control and regulation of temperature and contact time during chlorine dosing. This platform aims to evaluate the growth of Escherichia coli in water.

In addition, a mathematical model should be developed to understand and quantify the interaction between the various parameters influencing the proliferation of E. coli in water. These efforts are essential for making informed decisions and optimizing processes relating to water treatment and safety.

2. Materials and Methods

The Most Probable Number (MPN) method was employed to quantify the Colony-Forming Units (CFU) of E. coli in the water sample. Water samples collected from the Dedan Kimathi University (DKUT) pond were subjected to preparation in tubes containing Peptone water and MacConkey broth, shown in Figure 1(b).

The tubes underwent a 24-hour incubation period at a temperature of 37°C to promote the development of E. coli [12]. After incubation, the examination was done for any observable changes in the color of the culture medium from a pink color to yellow, indicating the presence of microbial growth. Tubes with no discernible change remained clear, signifying the absence of E. coli, as depicted in Figure 1(a).

Fig. 1(a) Observation of result, and (b) Serial dilution.

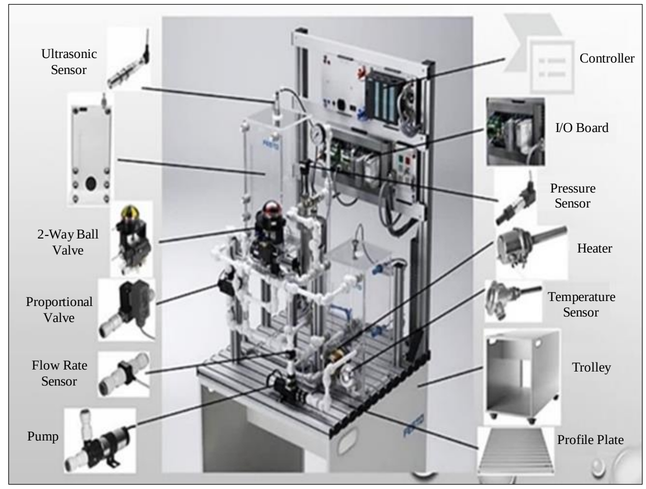


Fig. 2 Festo compact MPS

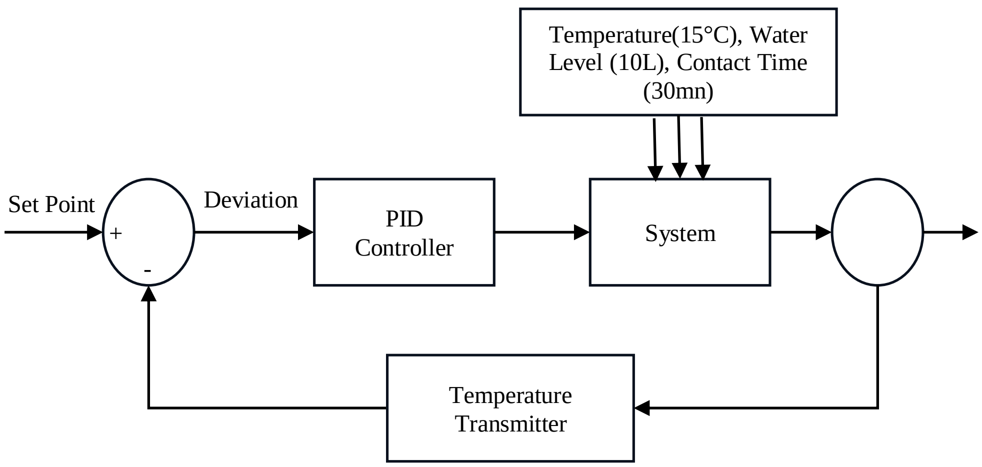


Fig. 3 Block diagram

A setup for monitoring and control was done using the Festo compact MPS PA process control and monitoring system with the PLC S7 1200, as shown in Figure 2. It is a closed-loop control system that allows for the control of parameters such as level, temperature, flow, pressure, etc. The system was used to monitor and control the temperature and contact time of chlorine dosages that impact microbial growth. This allowed for the automated modification of these parameters to keep them continuously within the desired range.

The control procedure is displayed in Figure 3. After taking a measurement, the sensor compares the actual water temperature to the set point. To maintain the water temperature at the specified level, the PID controller then computes the difference and modifies the incoming water temperature via the valve.

The Design of Experiment (DoE) was used to determine the number of simulations, and the independent variables for each simulation (temperature, time, and chlorine dosage) were classified as independent variables, as shown in Table 1. 54 experimental runs were conducted as shown in Table 2 shows the different experiments carried out. Multiple regression analysis was applied to generate relationships and the influence of temperature, time, chlorine dosage, and E. coli removal, using data Minitab software.

Table 1. Design of experiment

Independent Variables	Level		
	-1	0	1
Time (min)	10	20	30
Temperature (°C)	10	15	20
Chlorine Dosage (mg/l)	2	3.5	5

Siemens NX software was used to create the Festo machine 3D CAD model. As illustrated in Figure 4, Unity software was used to import the 3D CAD model and provide physics to the various components.

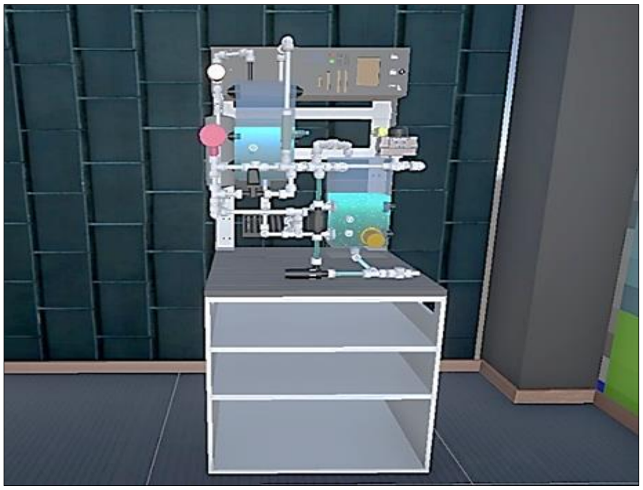


Fig. 4 CAD model in unity Software

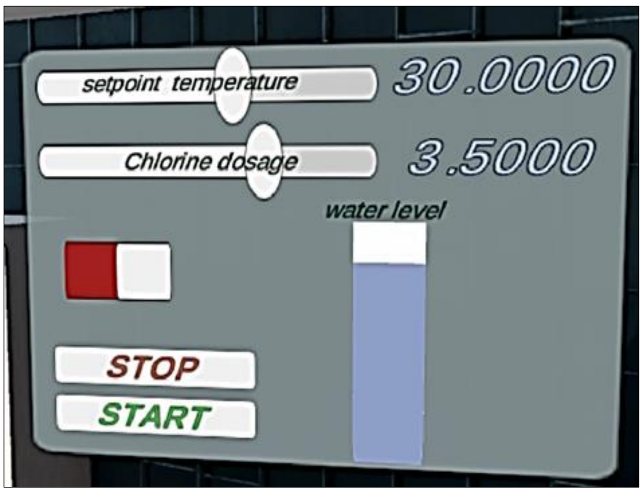


Fig. 5 User interface

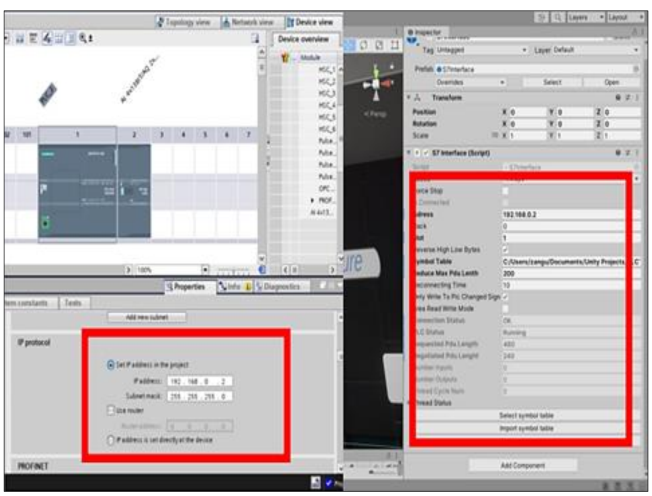


Fig. 6 S7 1214 PLC and virtual unity

A realistic virtual environment and the integration of virtual reality platform devices were created using Unity3D. The temperature and contact time of chlorine dosage were programmed to conform to automatic machine operations. C-sharp script was used to complete the physics, which aids in the creation of the machine's digital counterpart. In the immersive environment, a user interface panel was created to monitor functions and facilitate user involvement. To create a Digital Twin, the control logic for the machine was written to simulate the PLC controller. The machine control logic was developed using Totally Integrated Automation (TIA). Software-in-the-Loop (SiL) setup was used to verify communication through the ProfiNET gateway. To test and evaluate the control logic of the machine, Unity software was used to simulate the behavior of the actuators, sensors, and controllers.

The virtual machine's temperature and chlorine dosage patterns were shown via the user interface shown in Figure 5 within the immersive setting. To observe the machine in real-time in a virtual world to navigate and interact with the scene's components, a virtual reality site and handheld controllers were integrated. A continuous flow of information transferring between virtual and real models was ensured by the real virtual communication system shown in Figure 7. To interface with the S7 PLC, classes from the real virtual script were added to the unity project. A suitable, accessible IP address was chosen for use in establishing the connection with the S7 1214 PLC, as shown in Figure 6.

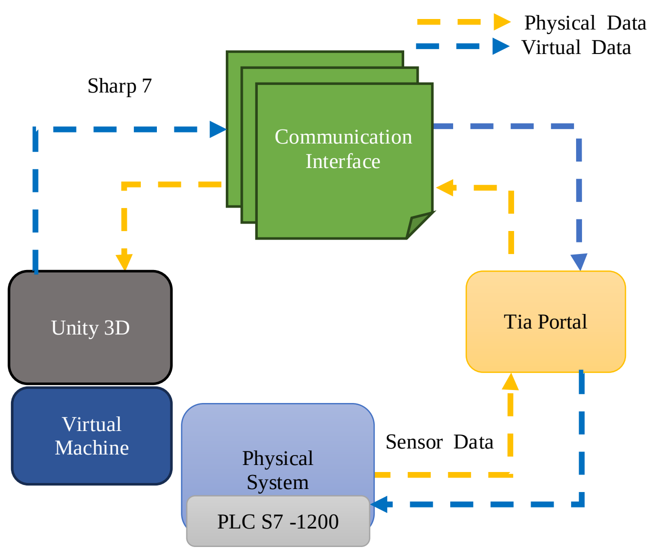
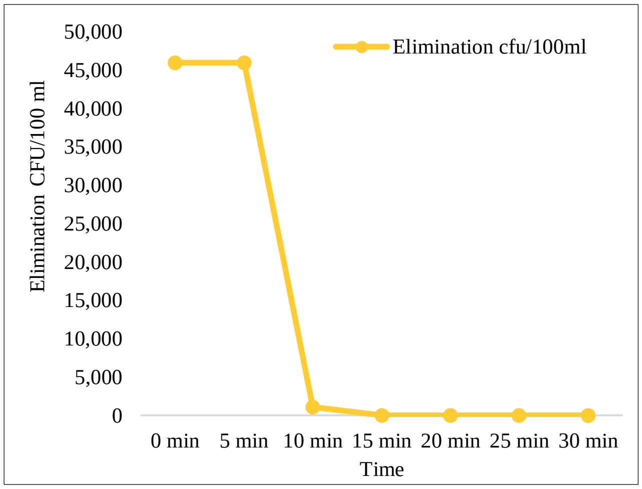


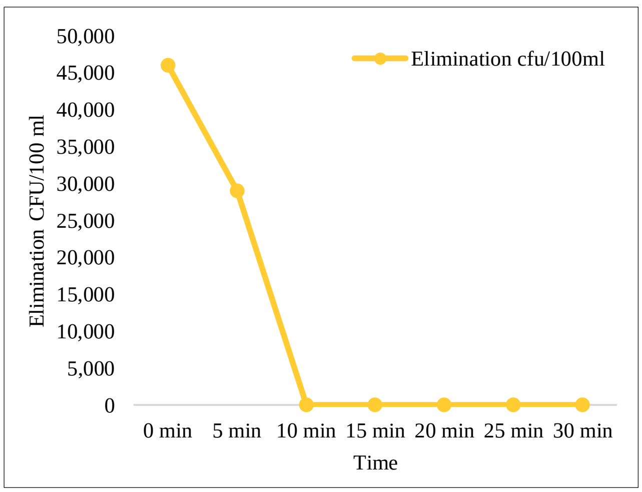
Fig. 7 Physical–virtual system integration

3. Results and Discussion

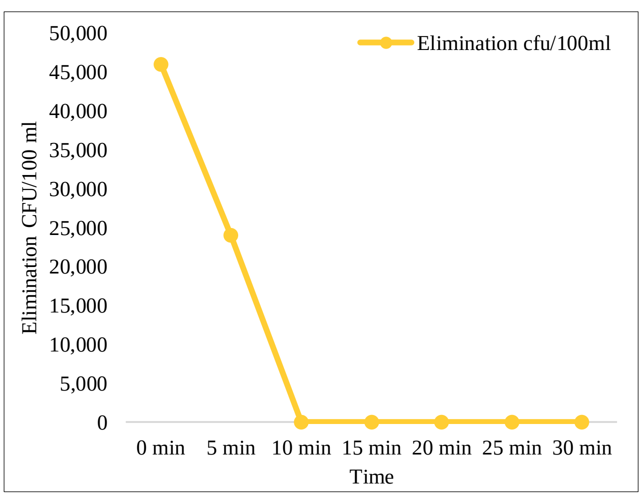
The removal of E. Coli at times between 0 and 30 minutes was investigated in Figures 8, 9, and 10, with chlorine dosages ranging from 2 to 5 mg/L at 10°C to 20°C, respectively. At 5 min, chlorine dosages 3.5 mg/L and 5 mg/L in Figures 8(b) and 8(c) show more appreciable efficacy than the lower dosage (2 mg/L) in Figure 8(a) at 5 min, the contact time of chlorine was not enough to eliminate the number of CFU in the water.



(a)

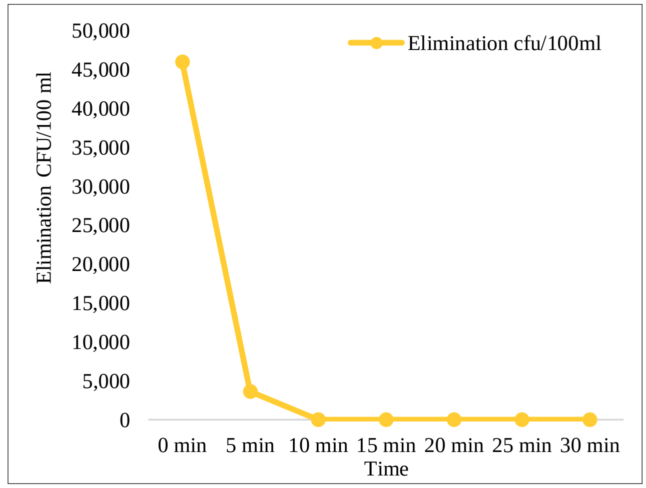


(b)

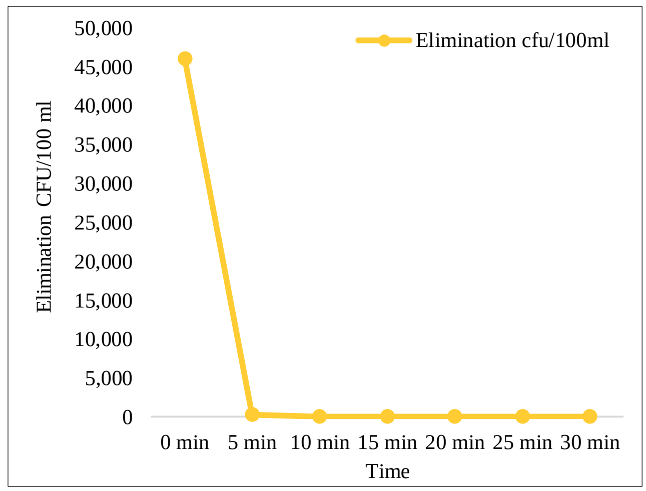


(c)

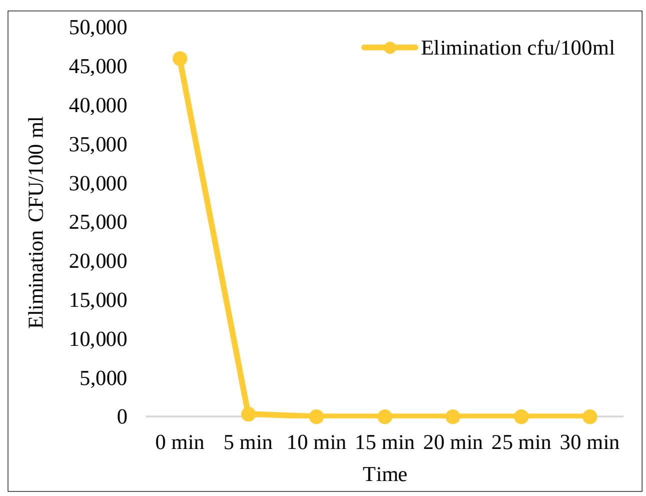
Fig. 8 Elimination of E. coli at temperature of 10°C for (a) 2 mg/l chlorine dosage in 0 to 30-minute intervals, (b) 3.5 mg/l chlorine dosage in 0 to 30-minute intervals, and (c) 5 mg/l chlorine dosage in 0 to 30-minute intervals.



(a)

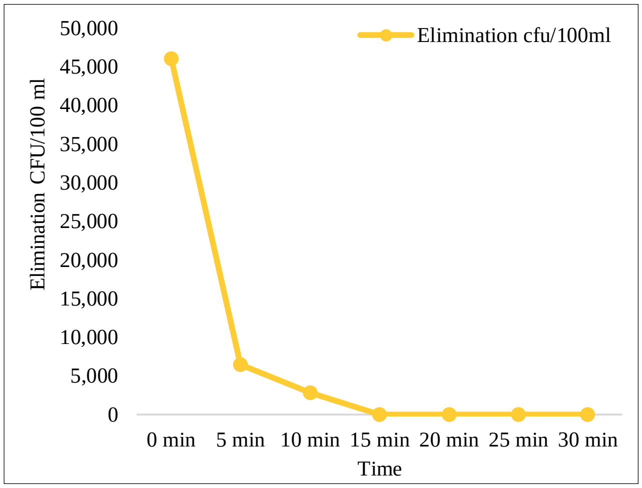


(b)

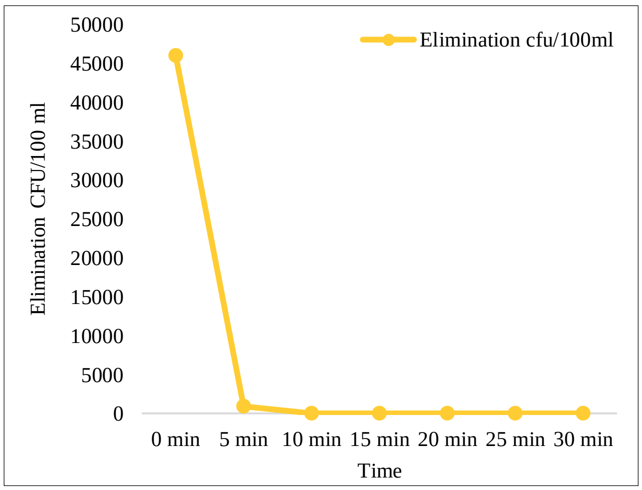


(c)

Fig. 9 Elimination of E. coli at temperature of 20°C for (a) 2 mg/l chlorine dosage in 0 to 30-minute intervals, (b) 3.5 mg/l chlorine dosage in 0 to 30-minute intervals, and (c) 5 mg/l chlorine dosage in 0 to 30-minute intervals.



(a)



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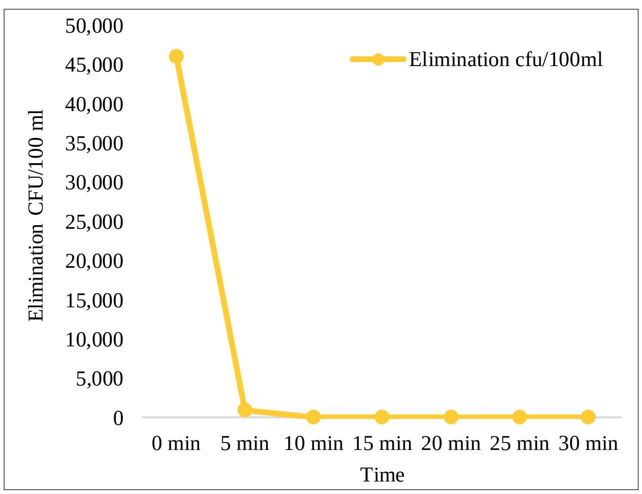


(c)

Fig. 10 Elimination of E. coli at temperature of 15°C for (a) 2 mg/l chlorine dosage in 0 to 30-minute intervals, (b) 3.5 mg/l chlorine dosage in 0 to 30-minute intervals, and (c) 5 mg/l chlorine dosage in 0 to 30-minute intervals.

The E. coli is constantly completely inactivated after 15 minutes, and at 10 minutes with greater dosage significantly reduces the number of bacterial colonies in comparison to lesser dosages shown in Figures 8(a) and 8(b).

At 20°C and 2 mg/L in Figure 9(a), chlorine dose shows consistent efficacy, with a significant decrease at 10 minutes and total inactivation at 15 minutes. On increasing the chlorine dose to 3.5 mg/L, as shown in Figure 9(b), no decline is seen right away; however, after 5 minutes, there is a notable decrease that lasts until 10 minutes, at which point the chlorine is completely inactivated. Consistent efficacy is seen at 5 mg/L in Figure 9(c); after 10 minutes there is total inactivation.

This analysis indicates that higher chlorine dosages and higher temperatures contribute to faster inactivation of E. coli. E. Coli SAMRC-3 was exposed for 30 minutes, during which time chlorine decay and inactivation at a concentration of 1.5 mg/L took place. Bacterial survival and chlorine decay were measured at intervals of 10 minutes.

This agrees with the study of Balachandran et al. [21], who observed that chlorine showed higher inactivation of both multidrug-resistant E. coli efficient processes. The effect of chlorine doses (2 to 5 mg/L) on the removal of E. coli at a temperature of 15°C is illustrated in Figure 10.

A significant decrease in E. Coli Colony-Forming Units (CFU) after 10 minutes and total inactivation by 15 minutes indicate consistent efficacy at 2 mg/L in Figure 10(a). at the 3.5 mg/L shown in Figure 10(b) after 5 minutes, there is a notable decline achieved in total inactivation after 10 minutes. Comparably, with a dosage of 5 mg/L in Figure 10(c), at 5 minutes full inactivation of CFU. Experience shows that different chlorine dosages are effective in eliminating E. coli at 15°C after 10 minutes, with variations in the time required for complete inactivation [10].

Niu et al. [22] showed that phages were effective at 37°C and 22°C. Temperature variations affected phage interactions, with some combinations showing increased efficacy at particular temperatures. Bacteriophage efficacy against Escherichia coli O157 varied according to incubation temperature. Temperature was a determining factor in the activity of Tequatrovirus T1 and Vequintavirus rV5, with the former being active at 22°C and the second more active at 37°C.

The regression model developed is shown in Equation 1. The regression results reveal the different coefficients of the linear equation, which represent the influence of the temperature and time of chlorine dosage on the elimination of E. coli from the water.

$$y = 4832 + 191.4x_2 + 1167x_3 - 46.7x_2x_3 \quad (1)$$

In this model, Escherichia coli (E. coli) concentration is the dependent variable, while time (x_1), temperature (x_2) and chlorine dosage (x_3) are the independent variables. This empirical equation seeks to establish a quantitative relationship between these variables, enabling us to predict E. coli elimination as a function of contact time, water temperature, and the amount of chlorine used in the disinfection process.

The relationship between the concentration of Escherichia coli (E. coli) and the independent variables x_1 time, x_2 temperature, and x_3 Chlorine dosage is expressed mathematically in Equation 1. While the parameters related to 191.4, 1167, and 46.7 quantify the individual effects of time, water temperature, and chlorine dosage on the concentration of E. coli, 4832 represents the value of y when the independent variables are zero.

Furthermore, the way in which x_2 and x_3 interact to affect E. coli eradication is demonstrated by the interaction term between these two variables. The efficacy of water disinfection may be predicted and optimized thanks to mathematical modeling, which offers useful quantitative insight into the process dynamics.

This procedure is essential to the safety of drinking water. The R-squared in Figure 11 indicates the extent to which the data fit the regression model. The calculated R-squared value of 68.75% indicates the extent to which the variation in response elimination of E. coli can be explained by the time, temperature, and chlorine dosage in the regression model.

S	R-sq	R-sq(adj)	R-sq(pred)
676.506	68.75%	12.50%	0.00%

Fig. 11 Model summary

This agrees with the study of Gracia et al. [23], who used mathematical models and procedures to quantify the chlorine bulk decay coefficient and determine the reaction constant of chlorine with the mass of water. The model was validated by a comparative analysis of residual chlorine concentrations over time for different reaction orders (zero-order, first-order, and second-order).

The coefficient of determination (R-squared) values obtained during the validation process are as follows: 0.8386 for zero-order reaction kinetics, 0.9409 for first-order reaction kinetics, and 0.7715 for second-order reaction kinetics. These R-squared values served as indicators of the model's performance and provided insight into its ability to represent experimental data in different reaction kinetic scenarios accurately.

Khan et al. [24] proposed a Superposition-based Learning Algorithm (SLA) for observing ANN-based sensitivity analysis models to predict the presence of E. coli in groundwater. They used MATLAB software to evaluate model performance, calculating the Root Mean Square Error (RMSE) and coefficient of determination (R^2) to validate its model with an R-squared of 0.90.

A communication script was implemented to integrate the virtual and physical models in Unity for data interchange between the environments. Figure 12 illustrates how TIA and Unity are used to monitor and operate both the remote physical station and the virtual world.

Once the virtual and physical models had been integrated, data and movement analysis in both systems was ensured by synchronization. Real-time monitoring of the system revealed that the sensor data's output corresponded to the system's actual values and that the virtual model updated instantly.

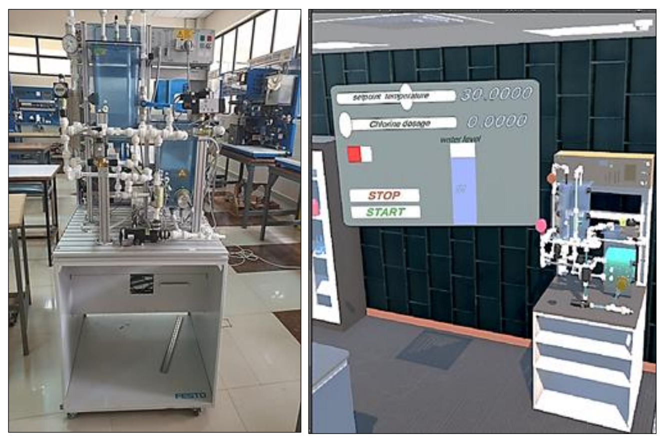
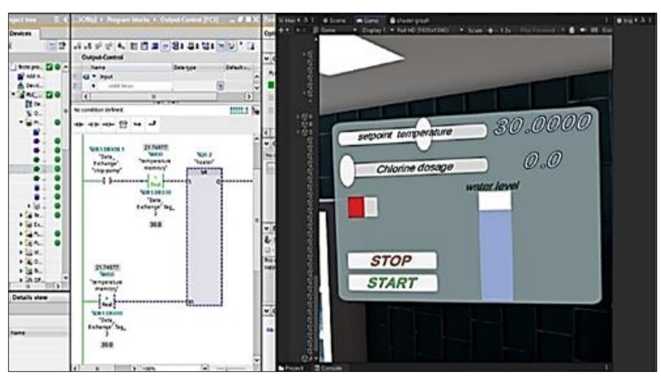


Fig. 12 Physical and virtual system developed



(a) **(b)**

Fig. 13 (a) Temperature reading on a physical machine, and (b) Temperature reading on a virtual machine.

The temperature readings in the physical and virtual models are shown in Figure 13. The temperature values displayed in the virtual model's user interface correspond to the temperature readings read by the sensors in the actual system, allowing process parameters to be modified.

The actuator status is also directly updated. Digital commands (start, stop) are implemented in the user to provide remote monitoring and control for the VR user of the device. Digital twins and virtual reality are used by [20] to remotely monitor and regulate the PH dosage of the silica scale manufacturing process. In [25], The study combined wearable sensor networks and virtual reality serious games to monitor the advancement of physical therapy and assess patient progression.

By effectively integrating an accurate digital twin of the water treatment system and the use of virtual reality for real-time monitoring, the study exceeded current state-of-the-art procedures. This novel method has made it possible to mimic and model various operating circumstances digitally and offers an immersive platform for proactive temperature and chlorine dosage monitoring.

Combining these advanced technologies has enhanced our knowledge of water treatment procedures and optimized management tactics for more efficient E. Coli removal, creating new opportunities for the global security of drinking water sources.

4. Conclusion

This study offers important information, especially regarding the effects of temperature and contact time on the use of chlorine to remove E. coli from drinking water. E. Coli eradication was successful in about 15 minutes at a temperature of 15°C and a chlorine dosage of 3.5 mg/L. A significant transmission advancement in the monitoring and control of water quality has been made possible by the automatic incorporation of a Virtual Reality (VR) platform, which has made it possible to monitor and regulate the growth of E. coli in water.

This study provides a strategic solution to the worldwide problems associated with the control of water by fusing innovative technologies such as digital twins and virtual reality. Its outcomes have far-reaching implications, acting as a model for creative fixes spanning the domains of science and the environment.

They not only contribute to the capacity to monitor and control parameters such as temperature and chlorine dosage contact time to eradicate E. coli from water, but they also give vital information to the scientific community that is engaged in water-related research. Through solving the particulars of water management, this research establishes a standard for a more modern and environmentally conscious method of protecting water resources.

Acknowledgments

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Appendix

Table 2. Range of experimental

Run Order	Temperature (°c)	Chlorine Dosage (mg/l)	Time (min)
1	10	2	5
2	10	2	10
3	10	2	15
4	10	2	20
5	10	2	25
6	10	2	30
7	10	3.5	5
8	10	3.5	10
9	10	3.5	15
10	10	3.5	20
11	10	3.5	25
12	10	3.5	30
13	10	5	5
14	10	5	10
15	10	5	15

16	10	5	20
17	10	5	25
18	10	5	30
19	15	2	5
20	15	2	10
21	15	2	15
22	15	2	20
23	15	2	25
24	15	2	30
25	15	3.5	5
26	15	3.5	10
27	15	3.5	15
28	15	3.5	20
29	15	3.5	25
30	15	3.5	30
31	15	5	5
32	15	5	10
33	15	5	15
34	15	5	20
35	15	5	25
36	15	5	30
37	20	2	5
38	20	2	10
39	20	2	15
40	20	2	20
41	20	2	25
42	20	2	30
43	20	3.5	5
44	20	3.5	10
45	20	3.5	15
46	20	3.5	20
47	20	3.5	25
48	20	3.5	30
49	20	5	5
50	20	5	10
51	20	5	15
52	20	5	20
53	20	5	25
54	20	5	30