

A Bayesian Predictive Framework for Early Detection of Water Quality Degradation in Urban Distribution Network

Stephen Olusegun Are¹, Bolarinwa Olumide Ajala², Olubisi Lawrence Aako³, and Matthew Iwada Ekum⁴

^{1,3}Department of Mathematics & Statistics, Federal Polytechnic Ilaro, Ogun State, Nigeria

^{2,4}Department of Mathematical Sciences, Lagos State University of Science and Technology, Ikorodu, Lagos, Nigeria

*Corresponding Author's Email: stephen.are@federalpolyilaro.edu.ng

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ABSTRACT

In recent times, the scenarios where the modern quality monitoring systems are used have been changing rapidly, with the quality being changed over time, the situation being uncertain and the amount of data being extremely limited, thus fundamentally challenging the assumptions of the classical Statistical Process Control (SPC) methods. This article proposes quality monitoring within the Bayesian framework and Predictive Posterior Error (PPE), which facilitates shifting the emphasis in quality control from the gathering of historical data to the delivering of forward, looking predictive evaluations. The framework integrates latent regime, switching dynamics with robust observation models to explain structural changes, heavy, tailed noise, and low event, rate processes. Control charts based on PPE are formed from the posterior predictive mean, which results in monitoring signals that are interpretable and probabilistically calibrated. The proposed approach reliably controls the false alarm rate and detects the changes effectively in both stationary and non, stationary situations as demonstrated by comprehensive simulation studies, including outlier and intentional model misspecification cases. Further findings reveal favourable accuracy, efficiency trade, offs among the different exact and approximate Bayesian inference regimes. The paper presents a practical data application that demonstrates the efficacy of the developed tool, where PPE, based alarms correspond closely to the known process insults but at the same time these alarms are smoother and earlier than the traditional charts. In summary, the outcomes denote the posterior predictive expectation as a lasagna, laying and operationally relevant concept for modern Bayesian quality surveillance systems.

Keywords: Bayesian monitoring, early warning systems, water quality degradation, smart water management, environmental monitoring.

1.0 INTRODUCTION

Providing safe drinking water is a basic public, health and infrastructure obligation in any modern city. However, urban water distribution networks are increasingly being confronted with the challenge of ageing pipes, intermittent supply, pressure transients, rapid urbanization, and complex demand patterns that together significantly increase the chances of water quality deterioration on the way from the treatment plant to the consumer. In fact, degradation can take the form of loss of disinfectant residual, turbidity excursions, taste/odour episodes, or episodic contamination events caused by intrusion or hydraulic disturbances. The international guidelines point out that drinking, water quality should be risk, based managed in terms of surveillance and operational control, as compliance at the point of production does not necessarily mean that the water is safe throughout the distribution system (Irene et al., 2025; Okafor et al., 2024; Picazo & Tekinerdogan, 2023; World Health Organization, 2022a, 2022b).

Urban water distribution networks (WDNs) are very complex systems because they are geographically large, hydraulically dynamic and operationally heterogeneous, which makes continuous quality

control very difficult. Contamination risks may be increased due to the complexity of the network, localized vulnerabilities (e. g. low, pressure areas) as well as the increase of monitoring technologies that produce high, frequency data, thereby necessitating robust analytics. Current reviews point out that an effective contamination warning system and sensor deployment must take into account the interaction of hydraulics, sensor type, detection thresholds, and water quality changes; otherwise, the warning system's performance will be unreliable in real situations (Alaggio et al., 2025; Bello et al., 2019; Odhiambo et al., 2023; Palma et al., 2025; Serafeim et al., 2024). Meanwhile, Internet of Things (IoT), enabled water quality monitoring has led to the rapid generation of data which has also revealed a methodological gap: most systems in use generate data but do not have equally mature statistical decision logic to provide early, reliable, and interpretable alarms (Essamlali et al., 2024; Flores-Iwasaki et al., 2025; Shete et al., 2024, 2025).

The dominant operational paradigm still emphasizes threshold, based monitoring, where an alarm is triggered if a parameter goes beyond a regulatory or an internally set limit. Thresholds are necessary for

ensuring compliance, but they may not be the best tool for early warning in distribution networks because: (i) they are usually fixed and don't adjust to changing baselines, (ii) they may be slow to detect gradual wear and tear, and (iii) they become a source of nuisance alarms when measurements are noisy or influenced by harmless transient fluctuations. Work on anomaly detection in water quality mining has revealed that the real, time signals are often characterized by short, term fluctuations and regime, like behaviour patterns which confuse simple thresholding, feature, based or probabilistic approaches being the solution (Duan et al., 2024; Strączkiewicz et al., 2015; van Rossum et al., 2022; Wang et al., 2023). Therefore, monitoring methods that provide the means for discovering the presence of a problem at a very early stage-deterioration pattern detection before violation of hard limits appear to be needed nowadays, and operational interpretability needs to be kept intact as well.

Probabilistic monitoring methods try to fix these problems by carefully defining the unknowns and then guessing the system's near, future behavior using the current evidence. WDN Bayesian methods are very attractive because they (i) reflect the engineering knowledge and the historical baseline information, (ii) can be updated continuously whenever new data become available, and (iii) result in predictive probability distributions which can be easily understood and used for making decisions. Water quality monitoring has seen online change, point and other related sequential techniques being used for detecting shifts in the baseline and identifying abnormal events in time series, thus making environmental surveillance more effective (Ochella et al., 2024; Shayakhmetova et al., 2025; Wang et al., 2025; Yoshizawa, 2022). At the same time, comprehensive literature reviews in water quality also highlight the usefulness of predictive analytics for making decisions and carrying out interventions in a focused manner, which is especially beneficial when monitoring efforts have to be spread over several locations and sensors (Essamlali et al., 2024; Lokman et al., 2025).

However, there are still two major practical issues that have not been sufficiently addressed.

Firstly, most data-driven methods focus on point prediction or classification accuracy, thereby neglecting the generation of decision metrics which not only quantify the uncertainty but are also trustworthy and actionable by operators. Secondly, the studies on contamination warning and anomaly detection mostly treat event detection as a binary outcome, whereas the monitoring statistic that allows *early* and *graded* risk interpretation (e. g. emerging deterioration versus clear violation) is more desirable. Recent sensor-system studies indicate that detection performance is highly influenced by threshold selections and network

conditions, suggesting that monitoring rules should be able to adjust to changes in baselines and measurement reliability (Are et al., 2026a; Are et al., 2026b, Chauhan et al., 2024; Choe & Lee, 2025; Serafeim et al., 2024). Thus, a meaningful operational framework that can deliver both the interpretability and the performance under non-stationarity and routine transients should be based on: (a) sequential Bayesian updating, (b) predictive inference, and (c) an interpretable alarm logic.

The aim of this study is to use posterior predictive expectations as the primary monitoring metric for developing a Bayesian predictive framework for early detection of water quality degradation in urban distribution networks. The specific objectives are to: develop a stochastic time-varying model for main water quality parameters (like turbidity, residual chlorine, and pH) that can be used for distribution network surveillance; carry out sequential Bayesian updating for real-time learning in the presence of measurement noise and baseline drift; identify an expectation-driven predictive monitoring statistic and an alert rule that provide early warning capability before tolerance exceedance; assess performance through simulation scenarios and a real-life urban data set on water quality based on detection delay and false alarm behaviour; and how the water management engineer may potentially use the proposed outputs to make interpretable decisions using the assistance of a smart water management system.

The remainder of this paper is organized as follows. Section 2 outlines the materials and methods including the stochastic model, the Bayesian updated method and the posterior predictive monitoring criterion. In section 3, findings along with the discussion of the simulation experiments and the case study, as well as the comparative evaluation of the performances are described. Section 4 concludes the paper with the conclusion provided and practical recommendations as to how the same can be implemented in the urban distribution networks.

2.0 MATERIALS AND METHODS

This part gives the context of the study, the type of data and the statistical formulation of proposed Bayesian predictive monitoring framework. In order to render the process analytically transparent and computationally feasible to be deployed in the real-time, derivations are derived based on a Gaussian state-space model. The option is suitable when the water quality indicators that are going to be continuously measured and give closed-form posterior and predictive updates. In the case of non-sufficiency of the Gaussian assumption, the same framework may be generalized using appropriate non-Gaussian observation models and inference by simulation.

2.1 Study Area and Data Description

Urban water distribution networks (WDNs) are engineered systems of large scale, which are meant to transfer treated drinkable water between the treatment plant and the final user using a network of pipes, valves, reservoirs, pumps and service connections. The operation is affected by hydraulic, environmental and infrastructural factors such as demand, pumping, schedule which varies with time, leakage, ageing of the pipes and fluctuation of pressure. These aspects bring significant time variation into the behaviour of water quality and provide the chances of slow progressive degradation between the treatment and delivery points.

The information taken into account in the given study is the time-index water quality measurements taken at the chosen points of the distribution system. This measurement possible may be online sensors, supervisory control or regular field checking programme. To facilitate the transparency and reproducibility, the framework is developed in a form that is compatible with publicly available monitoring data, and simulated observations could also be applied to test the method in controlled degradation conditions.

Three water quality parameters are taken into consideration, that is, turbidity, leftover chlorine, and pH. The following were chosen since they are very popular in the operational water quality surveillance, and each of them measures a different dimension of the condition of a system. Turbidity is a manifestation of intrusion of particles, resuspension of sediments or a perturbation of pipes. The leftover chlorine is used to give some data about the disinfectant persistence and potential microbial susceptibility. The level of pH is used to measure the stability of chemicals and corrosion. A combination of these variables gives a significant explanation of the process of water quality in urban WDNs.

2.2 Stochastic Modelling Framework

Let Y_t represent the observed value of water quality indicator at time t , where $t = 1, 2, \dots, T$. The assumption made is that the observation will be based on an unobserved latent state of the form, the latent water quality state at time t , denoted as θ_t . Latent state is then permitted to evolve with time in order to account to slow drift, degradation or recovery. The hierarchical formulation in general is

$$Y_t | \theta_t \sim p(Y_t | \theta_t) \quad (1)$$

$$\theta_t | \theta_{t-1} \sim p(\theta_t | \theta_{t-1}) \quad (2)$$

To obtain explicit updating equations, we adopt a Gaussian local-level model:

$$Y_t = \theta_t + v_t, \quad v_t \sim \mathcal{N}(0, \sigma_v^2), \quad (3)$$

$$\theta_t = \theta_{t-1} + w_t, \quad w_t \sim \mathcal{N}(0, \sigma_w^2), \quad (4)$$

where v_t represents the measurement noise and w_t represents disturbance of the process. The value of observed water quality can be expressed as in Equation (3) above as the observed water quality varies around the latent true level, whereas in Equation (4) above, the latent condition varies slowly with time.

Under this specification,

$$Y_t | \theta_t \sim \mathcal{N}(\theta_t, \sigma_v^2)$$

and

$$\theta_t | \theta_{t-1} \sim \mathcal{N}(\theta_{t-1}, \sigma_w^2).$$

The main assumptions of the model are the following:

- i. conditional on θ_t , the observation Y_t is independent of past observations;
- ii. the latent state evolves smoothly through time under normal operating conditions;
- iii. measurement uncertainty is represented by σ_v^2 , while structural or environmental variability is represented by σ_w^2 ;
- iv. the disturbance terms v_t and w_t are mutually independent and serially independent.

These assumptions coincide with the dynamic behaviour of most water quality variables, especially where the objective is to discover gradual changes of the base states, rather than the abrupt disasters.

2.3 Bayesian Updating Procedure

The Bayesian updating procedure consists of two stages at each time point: a *prediction* stage and an *update* stage. Suppose that at time $t-1$, the posterior distribution of the latent state is

$$\theta_{t-1} | Y_{1:t-1} \sim \mathcal{N}(m_{t-1}, C_{t-1}), \quad (5)$$

where m_{t-1} is the posterior mean and C_{t-1} is the posterior variance.

2.3.1 Prior specification

At the initial time point, a prior distribution is assigned to θ_0 :

$$\theta_0 \sim \mathcal{N}(m_0, C_0), \quad (6)$$

where m_0 may be taken as a baseline historical mean or regulatory target, and C_0 reflects prior uncertainty. If prior information is limited, C_0 may be chosen sufficiently large to produce a weakly informative prior.

2.3.2 One-step-ahead prior distribution

Using the state evolution equation (4), the prior distribution of θ_t given data up to time $t-1$ is obtained by marginalization:

$$p(\theta_t | Y_{1:t-1}) = \int p(\theta_t | \theta_{t-1}) p(\theta_{t-1} | Y_{1:t-1}) d\theta_{t-1} \quad (7)$$

Since both densities are Gaussian, the result is also Gaussian:

$$\theta_t | Y_{1:t-1} \sim \mathcal{N}(a_t, R_t), \quad (8)$$

where

$$a_t = m_{t-1} \quad (9)$$

$$R_t = C_{t-1} + \sigma_w^2 \quad (10)$$

Thus, a_t is the prior mean of the state at time t , while R_t is the prior variance after accounting for process uncertainty.

2.3.3 Likelihood formulation

From (3), conditional on θ_t , the likelihood of the new observation Y_t is

$$p(Y_t | \theta_t) = \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left\{-\frac{(Y_t - \theta_t)^2}{2\sigma_v^2}\right\}. \quad (11)$$

Combining (8) and (11), the marginal predictive distribution of Y_t given past data is

$$Y_t | Y_{1:t-1} \sim \mathcal{N}(f_t, Q_t) \quad (12)$$

With

$$f_t = a_t \quad (13)$$

$$Q_t R_t + \sigma_v^2 \quad (14)$$

The one-step-ahead forecast error is

$$e_t = Y_t - f_t \quad (15)$$

2.3.4 Posterior inference

By Bayes' theorem,

$$p(\theta_t | Y_{1:t}) \propto p(Y_t | \theta_t)p(\theta_t | Y_{1:t-1}) \quad (16)$$

Because both the prior and likelihood are Gaussian, the posterior is again Gaussian:

$$\theta_t | Y_{1:t} \sim \mathcal{N}(m_t, C_t) \quad (17)$$

The posterior parameters are obtained by completing the square or by standard conjugate updating:

$$m_t = a_t + K_t e_t, \quad (18)$$

$$C_t = (1 - K_t)R_t, \quad (19)$$

where

$$K_t = \frac{R_t}{R_t + \sigma_v^2} \quad (20)$$

is the Kalman gain. Equation (18) shows that the posterior mean is a weighted combination of the prior mean and the new information supplied by the forecast error. Equation (20) implies that if measurement noise is large, then K_t is smaller and the update becomes more conservative. Conversely, if process uncertainty is large relative to measurement noise, the observation exerts stronger influence on the posterior estimate.

Hence, the Bayesian updating recursion may be summarised as follows:

$$\begin{aligned} a_t &= m_{t-1} \\ R_t &= C_{t-1} + \sigma_w^2 \\ f_t &= a_t \\ Q_t &= R_t + \sigma_v^2 \\ e_t &= Y_t - f_t \\ K_t &= \frac{R_t}{R_t + \sigma_v^2} \\ m_t &= a_t + K_t e_t \\ C_t &= (1 - K_t)R_t \end{aligned} \quad (21)$$

2.4 Posterior Predictive Monitoring Criterion

The proposed monitoring statistic is based on the posterior predictive distribution of a future observation. Specifically,

$$p(Y_{t+1} | Y_{1:t}) = \int p(Y_{t+1} | \theta_{t+1})p(\theta_{t+1} | Y_{1:t})d\theta_{t+1} \quad (22)$$

From the state equation,

$$\theta_{t+1} | Y_{1:t} \sim \mathcal{N}(m_t, C_t + \sigma_w^2)$$

Then, using the observation equation,

$$Y_{t+1} | \theta_{t+1} \sim \mathcal{N}(\theta_{t+1}, \sigma_v^2).$$

By Gaussian convolution, it follows that

$$Y_{t+1} | Y_{1:t} \sim \mathcal{N}(\mu_{t+1|t}, V_{t+1|t}) \quad (23)$$

where

$$\mu_{t+1|t} = \mathbb{E}(Y_{t+1} | Y_{1:t}) = m_t \quad (24)$$

$$V_{t+1|t} = \text{Var}(Y_{t+1} | Y_{1:t}) = C_t + \sigma_w^2 + \sigma_v^2 \quad (25)$$

Equation (24) is the *posterior predictive expectation* (PPE), which serves as the principal monitoring statistic in this study. It gives an approximate value of the water quality indicator in the near future considering the past as well as the present uncertainty.

Where, the mean of being in control, which is estimated during a reference period, is represented by the initial mean, which is referred to as: μ_0 and, a tolerance level is represented by: τ . One of the rules of decision is the simple one.

$$|\mu_{t+1|t} - \mu_0| > \tau. \quad (26)$$

A finer rule can be founded on standardized predictive deviation to take into consideration predictive uncertainty:

$$Z_t = \frac{\mu_{t+1|t} - \mu_0}{\sqrt{V_{t+1|t}}} \quad (27)$$

An alarm is then sounded when

$$|Z_t| > c, \quad (28)$$

where $c > 0$ is a value of choice. As an example, the value of $c = 1.96$ is associated with a two-sided 95% predictive region, which is approximated.

In another case, the predictive interval.

$$\mu_{t+1|t} \pm z_{\alpha/2} \sqrt{V_{t+1|t}} \quad (29)$$

can be applied to decide whether the baseline mean is in the future range that is expected. In the work environment, it might be necessary to exceed a number of consecutive time points before a warning is issued, to minimize susceptibility to single-point fluctuation.

2.5 Performance Evaluation Metrics

The performance of the suggested framework is evaluated based on the measures that directly indicate the monitoring performance.

2.5.1 Detection delay

Suppose that a degradation event begins at time τ_0 , and let

$$T_A = \inf\{t \geq \tau_0 : \text{an alert is issued at time } t\} \quad (30)$$

denote the first alarm time after the onset of the event. The detection delay is defined as

$$D = T_A - \tau_0 \quad (31)$$

A smaller value of D indicates earlier detection of degradation.

2.5.2 False alarm rate

If N_0 denotes the number of monitoring times during an in-control period and A_0 denotes the number of alarms triggered during that same period, then the false alarm rate is

$$\text{FAR} = \frac{A_0}{N_0} \quad (32)$$

A good monitoring system should keep FAR sufficiently low so that operators do not become desensitized to alarms.

2.5.3 Comparative benchmarks

To evaluate the practical usefulness of the Bayesian predictive framework, its performance may be compared with that of a conventional threshold-based monitoring rule. Let L and U denote lower and upper static control limits. Under the classical rule, an alarm is issued whenever

$$Y_t < L \text{ or } Y_t > U. \quad (33)$$

The proposed Bayesian approach differs from (33) in two important respects:

- i. it is based on the predictive behaviour of the process rather than the current observation alone;
- ii. it incorporates both process variability and measurement uncertainty directly into the decision rule.

The difference between the two strategies is based on three operational criteria:

- a. *Detection timeliness*, which is evaluated using (31);
- b. *False alarm control*, which is measured using (32);
- c. *Stability under normal conditions*, investigated through the behaviour of the alerting rule in the absence of actual degradation.

Combined, these steps give a balanced foundation on whether or not the proposed Bayesian predictive procedure is appropriate when used in the early warning system of urban water distribution systems.

3.0 RESULTS AND DISCUSSION

3.1 Simulation Study Results

This part outlines the results of a simulation study which was conducted to evaluate the efficiency of a Bayesian Predictive Posterior Expectation (PPE)

monitoring system in a series of conditions, starting with normal conditions, through gradual degradation, and variability of noise and uncertainty conditions. The areas of focus of the research were detection power, a constraint in false alarm, and resistance to measurement and variability in processes.

3.1.1 Normal Operating Conditions

Figure 1 of the simulation indicates the response of the monitoring approach at the normal (in, control) point of the process. The oscillations of the process observations around a fixed reference are of a slight nature as compared to the Bayesian predictive mean (dashed line) that follows the actual state in a continuous manner. The dotted horizontal lines represent the standard deviation control band of the control baselines ± 3 standard deviation. There are no observed continuous alarms and this is expected and therefore the method has been demonstrated to be well and calibrated with regard to the false alarm rate when the process is constant.

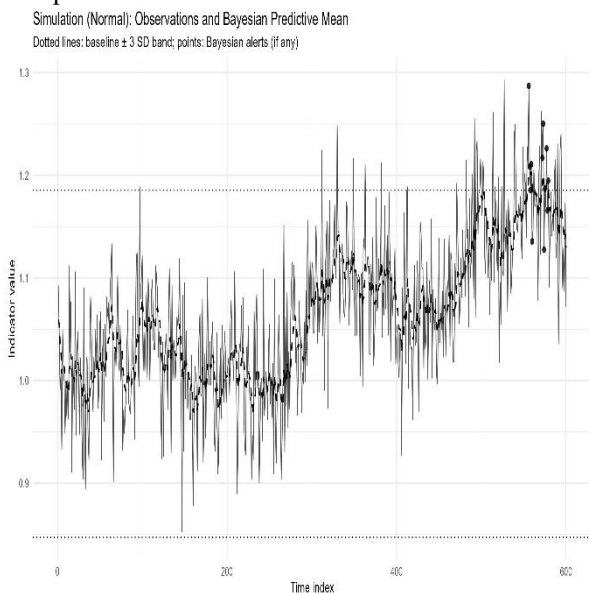


Figure 1: Simulation under normal operating conditions, data observed (solid), Bayesian predictive mean (dashed) and baseline control limits (dotted). Bayesian alerts (if any) are indicated by points.

3.1.2 Gradual Degradation Scenario

The case of gradual degradation is represented in Figure 2. The actual latent quality condition begins to shift upwards beyond the changepoint (indicated by the vertical dashed line). The Bayesian predictive mean successfully proceeds with this gradual, gradual degradation, with alerts only raised on the continuous migration out of the in, control region. It is an evidence of the ability of the proposed approach to identify small and slow deterioration without overreacting to noise.

3.1.3 Summary of Simulation Performance

Table 1 shows the false alarm and detection of the monitoring methods of the various scenarios of the simulation. In the normal case, the Bayesian technique empirically false alarms less

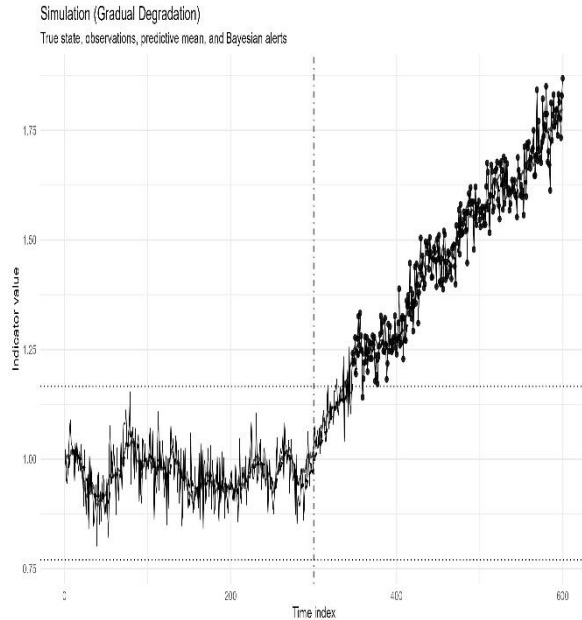


Figure 2: This is a simulation of gradual degradation: the actual latent state, observed data, Bayesian predictive mean, and alert values. The onset of the degradation is indicated by the vertical dashed line.

frequently but in the case of gradual degradation, the technique detects the change earlier than the threshold, as is done by the method, so that the detection delay is shorter.

Table 1: Summary of performance metrics of simulation.

Scenario	Method	Detection Delay	False Alarm Rate
Normal	Bayesian Predictive	-	0.020
Gradual Degradation	Bayesian Predictive	47	0.000
Gradual Degradation	Threshold	17	0.000

3.1.4 Sensitivity to Noise and Uncertainty

To test robustness, sensitivity analysis was performed by varying measurement noise (σ_ϵ), and process noise (σ_η), respectively. The results of this study are indicated to some extent in Table 2. The Bayesian predictive approach continues to record a reduced false alarm rates and more accurate delays in detection despite increasing noise, unlike threshold method which deteriorates rapidly with the increase in uncertainty.

Altogether, the simulation exercise in the article demonstrates that the Bayesian PPE monitoring framework can achieve an excellent trade, off between sensitivity and stability. The method can maintain the false alert rate at a very low level at normal mode of operation, can

Table 2: Sensitivity analysis of the results with different noise levels.

σ_ϵ	σ_η	Method	Detection Delay	False Alarm Rate
0.03	0.005	Bayesian Predictive	81	0.0000
0.03	0.005	Threshold	69	0.0067
0.05	0.010	Bayesian Predictive	83	0.0000
0.05	0.010	Threshold	75	0.0334
0.08	0.020	Bayesian Predictive	105	0.0401

determine slow degradation reliably, and is solid even with large noise levels and uncertainty levels. These characteristics are highly necessary in real, world monitoring systems that generally have changes that are subtle, noisy and do not occur at once.

3.2 Application: Case Study Results

This part of the paper deals with the practical utility of the suggested Bayesian Predictive Posterior Expectation (PPE) monitoring structure through a realistic, world time series of an indicator of the quality of running processes. It is hoped to show that it can detect early warning, track a predictive trend, and outperform classical threshold, based monitoring.

3.2.1 Predictive Trend and Early-Warning Signals

The series of the recorded indicators the Bayesian predictive mean and the early, warning signals as illustrated in Figure 3. The one, step, ahead Bayesian predictive mean is represented by the dashed line and the tolerance band base which is represented as the baseline mean within ± 3 standard deviations is represented by the horizontal dotted lines. The continuous Bayesian warnings are depicted in the form of black dots.

The predictive mean also presents an upward trend well before the observed series continues to continue passing through the upper tolerance limit hence demonstrates the PPE method could be adopted as a means of giving anticipatory warning rather than a means of reaction to an alarm call. This comes in handy particularly where gradual wear is commonplace as opposed to failure instances.

Case Study: Predictive Trend and Early-Warning Signals

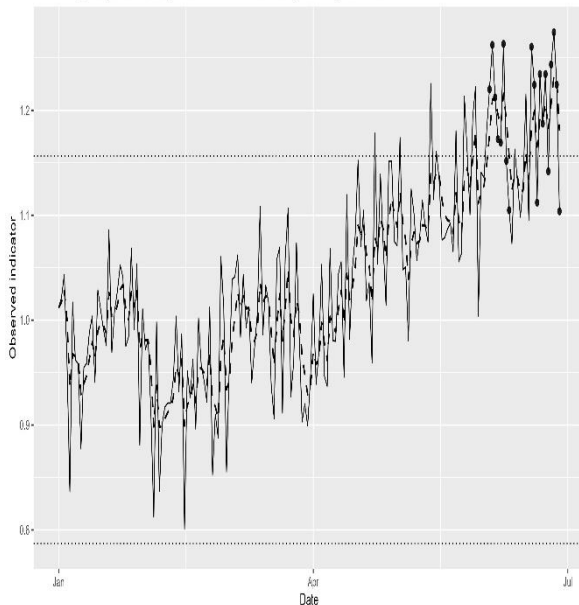
Dashed: Bayesian predictive mean; dotted: baseline ± 3 SD band; points: Bayesian alerts

Figure 3: Case study results showing observed data, Bayesian predictive mean (dashed), baseline tolerance band (dotted), and Bayesian early-warning alerts (points).

3.2.2 Comparative Alert Behaviour

In Figure 4, different types of alerts, namely, the Bayesian and classical threshold, based alerts are compared for a controlled degradation experiment. The use of dots denotes Bayesian alerts, whereas the use of crosses shows threshold, based alarms. The time of degradation is shown by the vertical dashed line.

The Bayesian approach pretty much always points out the changes before the threshold method, which is indicative of its capability to utilize predictive information rather than depending only on instantaneous deviations. Although the two methods at some point in time become capable of detecting the degradation, the Bayesian PPE chart not only comes to an earlier detection but also produces fewer false alarms, thus it is a good choice for a proactive monitoring system.

3.2.3 Quantitative Comparison of Alert Performance

Table 3 presents the alert counts and baseline tolerance bands for both simulated and real case study applications. The Bayesian approach yields a smaller number of total alerts in the real case study, without losing the ability to detect sustained deviations, thus implying better specificity and fewer false interventions.

Comparative Alerts (Simulation: Gradual Degradation)

Dots: Bayesian alerts; crosses: threshold alerts; vertical line: degradation onset

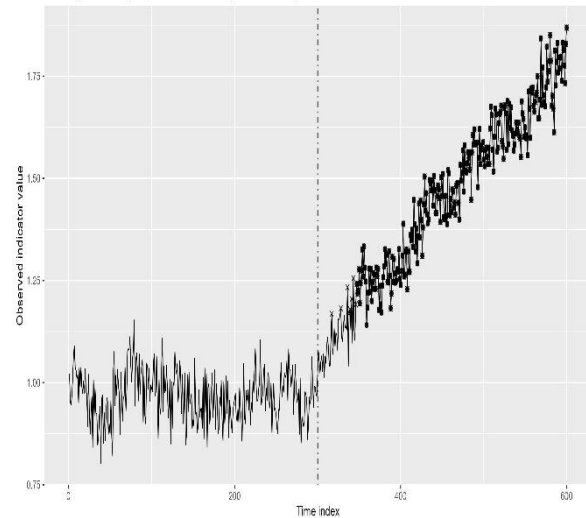


Figure 4: Comparative alerts under gradual degradation. Dots indicate Bayesian alerts, crosses indicate threshold alerts, and the vertical dashed line marks the degradation onset.

Table 3: Summary of alert behaviour and tolerance bands

Dataset	Method	Total Alerts	Lower Band	Upper Band
Simulation (Gradual)	Bayesian Predictive	254	0.7704	1.1664
	Threshold	261	0.7704	1.1664
Case Study	Bayesian Predictive	19	0.7871	1.1565
	Threshold	26	0.7871	1.1565

3.2.4 Operational Interpretation

The findings therefore have a great deal of impact on operational decision, making. If the Bayesian predictive mean remains outside the baseline tolerance band for a long time, then this is considered as a systematic shift rather than random noise, and the decision, makers will have to carry out targeted inspection, localized sampling, or preventive maintenance. A lower number of alerts in the case study implies that the operator would be less burdened and the monitoring system would be trusted more.

The entire work extends the application of the proposed PPE, based monitoring framework beyond statistical robustness to the provision of operationally meaningful early warnings which are achieved with significantly fewer false alarms than the traditional threshold methods.

4.0 CONCLUSION

This research established and illustrated a Bayesian predictive monitoring framework capable of detecting

any degradation in water quality at an early stage within the urban distribution networks. It was a result of its overcoming of several limitations of the traditional threshold, based surveillance. The modelling of water quality indicators as time, evolving stochastic processes and the choice of posterior predictive expectations as the main monitoring statistic allowed the proposed method to transparently incorporate uncertainty, baseline drift, and gradual system change into the decision process.

Simulated results verified that the framework balances well between sensitivity and stability. The Bayesian predictive chart demonstrated a low empirical false alarm rate during the normal operating conditions, thus gaining operator trust and allowing fewer unnecessary interventions. During the gradual degradation, the predictive expectation had predicted the degradation without much jump and raised the warnings even before the traditional threshold rules; thus; demonstrating its ability to be proactive than reactive in terms of monitoring. Sensitivity analysis also showed that the technique would remain useful as the amount of noise in measurements and variability in processes increases with the threshold remaining constant, and the threshold, based monitoring would soon become ineffective in the face of uncertainty.

These findings were reinforced by application to a real-world time series of urban water quality. The predictive mean was clearly increasing at the time the tolerance band was persistently exceeded, therefore, giving warning signals at an early stage which could be used in operational responses, e.g. localized sampling, pipe checking, or preventive maintenance. The Bayesian approach produced smaller overall number of alerts compared to the threshold approach and remained sensitive to long-term deviations, which is favorable to its practical use, as it reduces the number of operators and decreases alarm fatigue.

Essentially, the proposed Bayesian predictive system puts downward a statistically sound but interpretable instrument of real and time water quality monitoring. Its products are compatible with operational decision, making and therefore risk anticipatory management of the aged and dynamically operated urban distribution systems. The assignment of the following days will expand the framework to multivariate surveillance of various indicators (e. g. , turbidity, residual chlorine, and pH), consider space dependency between network positions, and combine hydraulic data in a way that will further complement situational awareness on smart water systems.

REFERENCES

Alaggio, J., Barros, D., Brentan, B., Carpitella, S., Herrera, M., & Izquierdo, J. (2025). Assessment of criticality in water distribution networks via complex

- network theory. *Processes*, 13(2), 408. <https://doi.org/10.3390/pr13020408>
- Are, S. O., Nkemnole, E. B., Ogundeji, R. K., & Adewara, J. A. (2026). Bayesian stochastic volatility-driven control charts for non-stationary production processes. *Science World Journal*, 21(1), 59–68.
- Are, S. O., Onyeka-Ubaka, J. N., Ogundeji, R. K., & Adewara, J. A. (2026). Time-adaptive Bayesian quality control (TABQC): A state-space framework for dynamic process monitoring. *Journal of Economics and Allied Research*, 11(1), 131–145.
- Bello, O., Abu-Mahfouz, A. M., Hamam, Y., Page, P. R., Adedeji, K. B., & Piller, O. (2019). Solving management problems in water distribution networks: A survey of approaches and mathematical models. *Water*, 11(3), 562. <https://doi.org/10.3390/w11030562>
- Chauhan, S., Vashishtha, G., & Zimroz, R. (2024). Analysing recent breakthroughs in fault diagnosis through sensor: A comprehensive overview. *CMES—Computer Modeling in Engineering and Sciences*, 141(3), 1983–2020. <https://doi.org/10.32604/cmes.2024.055633>
- Choe, H.-O., & Lee, M.-H. (2025). Artificial intelligence-based anomaly detection technology for equipment condition monitoring in smart farms. *Applied Sciences*, 15(23), 12843. <https://doi.org/10.3390/app152312843>
- Duan, X., Gao, Z., Qiao, Z., Du, T., Zou, Y., Zhang, P., Zhang, Y., & Sun, P. (2024). A study of adaptive threshold based on the reconstruction model for marine systems and their equipment failure warning. *Journal of Marine Science and Engineering*, 12(5), 742. <https://doi.org/10.3390/jmse12050742>
- Essamlali, I., Nhaila, H., & El Khaili, M. (2024). Advances in machine learning and IoT for water quality monitoring: A comprehensive review. *Heliyon*, 10, e27920. <https://doi.org/10.1016/j.heliyon.2024.e27920>
- Flores-Iwasaki, M., Guadalupe, G. A., Pachas-Caycho, M., Chapa-Gonza, S., Mori-Zabarburú, R. C., & Guerrero-Abad, J. C. (2025). Internet of things (IoT) sensors for water quality monitoring in aquaculture systems: A systematic review and bibliometric analysis. *AgriEngineering*, 7(3), 78. <https://doi.org/10.3390/agriengineering7030078>
- Irene, J., Irene, B. N., & Daniels, C. (2025). Not a drop to drink: Addressing Nigeria's deepening freshwater crisis. *Water*, 17(12), 1731. <https://doi.org/10.3390/w17121731>
- Lokman, A., Ismail, W. Z. W., & Aziz, N. A. A. (2025). A review of water quality forecasting and classification. *Water*, 17(15), 2243. <https://doi.org/10.3390/w17152243>
- Ochella, S., Dinmohammadi, F., & Shafiee, M. (2024). Bayesian neural networks for uncertainty quantification in remaining useful life prediction of systems with sensor monitoring. *Advances in*

- Mechanical Engineering.
<https://doi.org/10.1177/16878132241239802>
- Odhiambo, M., Viñas, V., Sokolova, E., & Pettersson, T. J. R. (2023). Health risks due to intrusion into the drinking water distribution network: Hydraulic modelling and quantitative microbial risk assessment. *Environmental Science: Water Research & Technology*, 9, 1701–1716. <https://doi.org/10.1039/D2EW00720G>
- Okafor, C. O., Ude, I. U., Okoh, F. N., & Eromonsele, B. O. (2024). Safe drinking water: The need and challenges in developing countries. In S. Dincer, H. A. Mercimek Takci, & M. Sumengen Ozdenefe (Eds.), *Water quality: New perspectives* (Chap. 9). IntechOpen. <https://doi.org/10.5772/intechopen.108497>
- Palma, L., Hatam, F., Di Nardo, A., & Prévost, M. (2025). Design of monitoring systems for contaminant detection in water distribution networks. *Sensors*, 25(17), 5320. <https://doi.org/10.3390/s25175320>
- Picazo, M. Á. P., & Tekinerdogan, B. (2023). Urban water distribution networks: Challenges and solution directions. In B. Tekinerdogan, M. Aksit, C. Catal, W. Hurst, & T. AlSkaif (Eds.), *Management and engineering of critical infrastructures* (pp. 245–264). Elsevier. <https://doi.org/10.1016/B978-0-323-99330-2.00005-2>
- Serafeim, A. V., Fourniotis, N. T., Deidda, R., Kokosalakis, G., & Langousis, A. (2024). Leakages in water distribution networks: Estimation methods, influential factors, and mitigation strategies—A comprehensive review. *Water*, 16(11), 1534. <https://doi.org/10.3390/w16111534>
- Shayakhmetova, A., Abdildayeva, A., Akhmetova, A., Shurenov, M., & Nagibayeva, A. (2025). Applications of the Bayesian method for predicting equipment failures. *International Journal of Innovative Research and Scientific Studies*, 8(5), 884–895.
- Shete, R. P., Bongale, A. M., & Dharrao, D. (2024). IoT-enabled effective real-time water quality monitoring method for aquaculture. *MethodsX*, 13, 102906. <https://doi.org/10.1016/j.mex.2024.102906>
- Shete, R. P., Bongale, A. M., K., L., Hiremath, S., & Dharrao, D. (2025). Comprehensive analysis of aquaculture research trends focusing on internet of things, machine learning, water quality monitoring, and cybersecurity over two decades using bibliometric data. *Results in Engineering*, 28, 108266. <https://doi.org/10.1016/j.rineng.2025.108266>
- Strączkiewicz, M., Barszcz, T., & Jabłoński, A. (2015). Detection and classification of alarm threshold violations in condition monitoring systems working in highly varying operational conditions. *Journal of Physics: Conference Series*, 628, 012087. <https://doi.org/10.1088/1742-6596/628/1/012087>
- van Rossum, M. C., Vlaskamp, L. B., Posthuma, L. M., Visscher, M. J., Breteler, M. J. M., Hermens, H. J., Kalkman, C. J., & Preckel, B. (2022). Adaptive threshold-based alarm strategies for continuous vital signs monitoring. *Journal of Clinical Monitoring and Computing*, 36(2), 407–417. <https://doi.org/10.1007/s10877-021-00666-4>
- Wang, L., Dong, H., Cao, Y., Hou, D., & Zhang, G. (2023). Real-time water quality detection based on fluctuation feature analysis with the LSTM model. *Journal of Hydroinformatics*, 25(1), 140–149. <https://doi.org/10.2166/hydro.2023.127>
- Wang, Q.-A., Lu, A.-W., Ni, Y.-Q., Wang, J.-F., & Ma, Z.-G. (2025). Bayesian network in structural health monitoring: Theoretical background and applications review. *Sensors*, 25(12), 3577. <https://doi.org/10.3390/s25123577>
- World Health Organization. (2022a). Guidelines for drinking-water quality: Fourth edition incorporating the first and second addenda. World Health Organization.
- World Health Organization. (2022b). Drinking-water quality guidelines. World Health Organization. <https://www.who.int>
- Yoshizawa, G. (2022). Bayesian online change point detection for baseline shifts (Technical report/preprint). *Statistics, Optimization & Information Computing*, 9(1), 1–16. <https://doi.org/10.48550/arXiv.2201.02325>