A Bayesian Decision Architecture for Adaptive IoT Monitoring under Energy, Connectivity, and Measurement Uncertainty

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Abstract

Adaptive IoT monitoring systems require decision mechanisms that can operate under uncertainty, especially when deployed in rural environments with limited energy, intermittent connectivity, and noisy sensor measurements. In water-monitoring applications, fixed-threshold rules may trigger inadequate decisions because they usually ignore the interaction between domain conditions and operational constraints. This paper presents an emerging result from an ongoing research project that investigates Bayesian Networks as an interpretable decision layer for adaptive IoT monitoring. We propose an initial Bayesian decision architecture for rural cistern monitoring, integrating evidence about cistern level, measurement uncertainty, precipitation, communication-link quality, and battery status. The model infers water risk and transmission viability to support an operational decision. We conducted a preliminary evaluation using five simulated scenarios covering normal operation, water-supply risk, uncertain measurement, low transmission viability, and poor operational conditions. The results indicate that the model produces coherent inferences and can adjust the final decision when water-related urgency and system-level feasibility diverge. Although still preliminary, the architecture provides a structured basis for engineering adaptive decision mechanisms in constrained IoT systems. Future work will incorporate real sensor data, refine the conditional probability tables, adopt more granular states, and compare the Bayesian policy with fixed-threshold baselines.

Keywords

Bayesian Networks, Adaptive IoT, Decision Architecture, Rural Water Monitoring, Uncertainty, LoRaWAN

1 Introduction

Rural water monitoring systems are increasingly relevant in regions where water availability is affected by climatic variability, infrastructure limitations, and restricted access to communication networks. In the Brazilian semi-arid region, rainwater cisterns play an important role in domestic water supply, especially in communities where centralized monitoring infrastructure is limited or unavailable. However, the monitoring of cistern water levels is still often performed manually, through visual inspection or empirical estimates, which limits the ability to detect critical conditions, plan interventions, and support data-driven water management decisions [4, 9].

Internet of Things (IoT) technologies provide a promising basis for remote water monitoring in such contexts. Low-cost embedded devices, water-level sensors, and low-power communication technologies can enable periodic data collection even in areas with limited infrastructure. In particular, Low-Power Wide-Area Network (LPWAN) technologies, such as LoRaWAN, have been investigated as alternatives to cellular networks in rural and remote environments due to their long communication range and low energy consumption [1, 6, 12]. Nevertheless, deploying IoT systems in rural water monitoring scenarios involves more than collecting and transmitting sensor readings. These systems must operate under energy constraints, intermittent connectivity, environmental exposure, and uncertainty in the measurements produced by low-cost sensors.

A common strategy in monitoring systems is to trigger actions based on fixed thresholds. For example, an alert may be emitted whenever the estimated water level falls below a predefined limit. Although this approach is simple and practical, it may be insufficient when operational decisions depend on multiple uncertain and interdependent factors. A low water-level reading may be unreliable due to sensor noise or environmental interference; a critical storage condition may have different implications when recent or expected precipitation is considered; and the decision to transmit an alert may depend not only on the water risk itself, but also on the current communication-link quality and the available battery level. Therefore, adaptive IoT monitoring requires decision mechanisms capable of combining domain-related evidence and operational evidence under uncertainty [2, 5, 7, 11].

Bayesian Networks offer a suitable mechanism for this type of problem because they provide an interpretable probabilistic model for representing variables, dependencies, and uncertainty [8, 13]. Unlike opaque predictive models that usually require large training datasets, Bayesian Networks can be initially structured from domain knowledge and expert input, and later refined with empirical data. This characteristic is especially useful in early-stage IoT applications, where real-world datasets may not yet be available or may be costly to obtain. Previous studies have shown the usefulness of Bayesian approaches in water-resource management and decision support, particularly in scenarios involving scarce data, heterogeneous evidence, and uncertainty [3, 10, 14, 15]. However, there is still room to investigate how Bayesian decision models can be engineered as part of adaptive IoT architectures for small-scale rural monitoring systems.

This paper reports an emerging result from an ongoing research project that investigates the use of Bayesian Networks as a decision layer for adaptive IoT-based monitoring of rural cisterns. We propose an initial Bayesian decision architecture that integrates five types of evidence: cistern water level, measurement uncertainty, precipitation, communication-link quality, and sensor-node battery status. These variables are used to infer two intermediate conditions, namely water risk and transmission viability, which are then combined to support an operational decision. The proposed architecture is intended to support decisions such as whether to emit an alert, prioritize a message, request a new measurement, or keep the system in its regular monitoring mode.

The objective of this study is to evaluate, at a preliminary conceptual level, whether a Bayesian decision architecture can produce coherent operational inferences under different combinations of water-related and system-related evidence. At this stage, all variables are represented using binary states, and the model is evaluated through simulated scenarios designed to represent typical monitoring situations, such as normal operation, water-supply risk under favorable communication conditions, critical water level with uncertain measurement, and water risk combined with low transmission viability. Rather than claiming a fully validated deployment, this paper presents an initial architecture and discusses its potential as a basis for adaptive decision-making in constrained IoT monitoring systems.

The main contribution of this paper is an early-stage, interpretable Bayesian decision architecture for adaptive IoT monitoring under energy, connectivity, and measurement uncertainty. By combining evidence about both the monitored resource and the operational state of the IoT node, the proposed architecture goes beyond fixed-threshold monitoring and provides a structured basis for future refinement with real sensor data.

The remainder of this paper is organized as follows. Section 2 presents the proposed architecture and the preliminary scenario-based evaluation. Section 3 discusses the current findings, limitations, and next steps of the research.

2 Bayesian Decision Architecture and Preliminary Evaluation

This section presents the proposed Bayesian decision architecture and the preliminary scenario-based evaluation conducted at this stage of the research. The purpose of this evaluation is not to provide a final validation of the architecture, but to examine whether the initial model produces coherent operational inferences under representative combinations of domain and system evidence.

2.1 Proposed Architecture

The proposed architecture is centered on a Bayesian Network used as an adaptive decision layer for IoT-based monitoring of rural cisterns. The architecture assumes that the IoT node collects or estimates evidence related not only to the monitored resource, but also to the operational conditions of the monitoring system itself. Thus, the decision layer combines water-related evidence, measurement reliability, communication conditions, and energy availability before recommending an operational response.

The initial Bayesian Network contains five input nodes: *Cistern_Level*, *Measurement_Uncertainty*, *Precipitation*, *Link_Quality*, and *Battery_Status*. These variables represent, respectively, whether the cistern is in a critical storage condition, whether the water-level measurement is uncertain, whether there is recent or expected precipitation, whether the communication link is adequate, and whether the sensor node has sufficient energy. From these input nodes, the network infers two intermediate nodes: *Water_Risk* and *Transmission_Viability*. The first captures the probability that the water situation requires operational attention, while the second captures the probability that the system is able to transmit data or alerts under the current communication and energy conditions. Finally, the output node, *Operational_Decision*, estimates whether the system should perform an action, such as sending an alert, prioritizing a message, requesting an additional reading, or changing its operating mode.

In this first version, all nodes are represented with binary states, *TRUE* and *FALSE*. This modeling choice reduces the complexity of the initial network, facilitates the elicitation of conditional probability tables, and enables a controlled conceptual evaluation before the incorporation of real sensor data. The structure of the network is organized into three levels: observed or estimated evidence, intermediate probabilistic inferences, and the final operational decision.

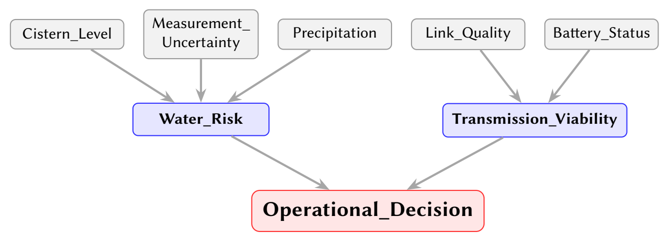

Figure 1: Initial structure of the proposed Bayesian Network.

The dependency structure follows the expected causal interpretation of the domain. *Cistern_Level*, *Measurement_Uncertainty*, and *Precipitation* influence *Water_Risk*. A critical water level increases the probability of risk, while measurement uncertainty reduces confidence in the observed level. Precipitation acts as an attenuating factor, since recent or expected rainfall may reduce the urgency associated with a low water level. Similarly, *Link_Quality* and *Battery_Status* influence *Transmission_Viability*, since both communication conditions and energy availability affect the capacity of the IoT node to transmit data or alerts. The final decision depends on both *Water_Risk* and *Transmission_Viability*, reflecting the assumption that an adaptive system should consider not only the urgency of the monitored condition, but also its ability to respond to it.

Table 1 summarizes the variables included in the initial model.

Table 1: Nodes of the initial Bayesian Network.

Node	Meaning
Cistern_Level	Critical water-level condition.
Measurement_Uncertainty	Water-level reading is unstable/unreliable.
Precipitation	Recent or expected precipitation.
Link_Quality	Communication link adequacy.
Battery_Status	Sensor node energy sufficiency.
Water_Risk	Water condition requiring operational attention.
Transmission_Viability	Ability to transmit data or alerts.
Operational_Decision	Recommended operational action.

The conditional probability tables were initially defined from the literature review and expert discussion. For *Water_Risk*, the highest risk probability occurs when the cistern level is critical, the measurement is reliable, and there is no precipitation. Conversely, risk is low when the cistern level is not critical, even if operational uncertainties exist. For *Transmission_Viability*, the best condition occurs when both the link and the battery are adequate, whereas viability decreases when either communication or energy is compromised. Finally, *Operational_Decision* encodes the central policy of the architecture: the system is more likely to act when water risk is high and transmission is viable, but it may adopt a restricted response when risk is high and operational conditions are poor.

2.2 Preliminary Scenario-Based Evaluation

The preliminary evaluation was conducted using simulated scenarios. Each scenario instantiates the five input nodes with *TRUE* or *FALSE* values and observes the resulting probabilities for *Water_Risk*, *Transmission_Viability*, and *Operational_Decision*. The scenarios were designed to represent typical situations in rural cistern monitoring, including normal operation, water-supply risk, uncertain measurement, poor communication, and low battery conditions.

The goal of this evaluation is to verify the logical consistency of the proposed network and to identify whether the model behaves according to the expected operational interpretation of each scenario. Therefore, the results should be interpreted as preliminary evidence of conceptual feasibility, not as a definitive experimental validation.

Table 2 summarizes the five scenarios and the probabilities inferred by the network.

In C1, the cistern is in an adequate condition, the measurement is reliable, the communication link is stable, and the battery level is sufficient. The network inferred low *Water_Risk* and high *Transmission_Viability*, resulting in a low probability of *Operational_Decision*. This behavior is consistent with a non-emergency situation in which the system can remain in regular monitoring mode.

In C2, the cistern level is critical, the measurement is reliable, there is no precipitation, and the system has adequate communication and energy conditions. This scenario produced the highest probability of *Operational_Decision*, suggesting that the system should prioritize alert transmission or another operational response. This result illustrates the expected behavior when both the domain condition and the system condition support immediate action.

C3 represents a critical water-level reading under measurement uncertainty. Although the cistern appears to be in a critical condition, the sensor readings are unstable or noisy. Compared with C2, the probability of *Operational_Decision* decreases from 82.48% to 62.81%. This difference reflects the role of *Measurement_Uncertainty* as a confidence modulator. Instead of treating every critical reading as an emergency, the network supports a more cautious response, such as requesting a new reading, issuing a lower-priority warning, or delaying a definitive alert until more reliable evidence is available.

C4 represents a high water-risk situation under poor operational conditions. Although the probability of *Water_Risk* is high, *Transmission_Viability* is low due to poor link quality and insufficient battery. As a result, the probability of *Operational_Decision* is lower than in C2, suggesting a restricted response, such as sending a minimal alert, storing data locally, or prioritizing energy conservation until communication conditions improve. This behavior illustrates how the proposed architecture avoids assuming that a high-risk domain condition automatically implies full operational action.

Finally, C5 represents a situation with adequate water level but poor communication and energy conditions. The network inferred low *Water_Risk*, low *Transmission_Viability*, and the lowest probability of *Operational_Decision*. This result is coherent with the expected behavior: since there is no relevant water risk, the system should not spend scarce energy or communication resources on non-urgent transmissions.

Overall, the preliminary results suggest that the Bayesian decision layer can distinguish between water-related urgency and operational feasibility. In particular, the model does not rely exclusively on water level as a fixed threshold. Instead, it modulates the decision according to measurement reliability, precipitation, communication quality, and battery status. This behavior is especially relevant for constrained IoT systems, where false alerts, unnecessary transmissions, and energy waste can reduce the long-term viability of the monitoring infrastructure.

2.3 Implications for Adaptive IoT Monitoring

The preliminary scenarios also suggest three design implications for adaptive IoT monitoring systems. First, the decision mechanism should separate domain urgency from operational feasibility. In the proposed model, *Water_Risk* captures the condition of the monitored resource, while *Transmission_Viability* captures whether the system is currently able to communicate under energy and link constraints. This separation is important because a critical domain condition does not necessarily imply that the system can perform a full communication action.

Second, measurement uncertainty should be treated as part of the decision process, not only as a preprocessing issue. In C3, the model reduces the probability of operational action even though transmission viability remains high. This behavior indicates that the system can avoid treating every critical reading as equally reliable, opening space for adaptive responses such as requesting a new measurement, delaying a definitive alert, or issuing a lower-priority warning.

Third, adaptive monitoring requires decisions that are interpretable and revisable. Since the Bayesian Network explicitly represents the variables and dependencies used to reach an operational decision, domain experts can inspect, discuss, and refine the model as real sensor data become available. This is particularly relevant in early-stage rural IoT deployments, where data may be scarce and expert knowledge is still necessary to define initial decision policies.

2.4 Current Limitations

This evaluation is still preliminary. First, the current network uses binary states, which simplifies the domain and may not capture intermediate conditions such as low, medium, and high water levels or different degrees of link degradation. Second, the conditional probabilities were initially elicited from expert discussion rather than learned from real sensor data. Third, the scenarios are simulated and manually instantiated, so they do not yet represent the full variability of a deployed rural IoT environment. Finally, the architecture has not yet been compared with a baseline based on fixed thresholds.

Despite these limitations, the results provide an initial indication that the proposed architecture is a plausible decision mechanism for adaptive IoT monitoring under uncertainty. The next stage of the research will incorporate real sensor readings, precipitation data, LoRaWAN communication metrics, and energy measurements to refine the network parameters and evaluate the architecture in a controlled or real-world setting.

Table 2: Preliminary results from simulated scenarios.

ID	Scenario Description	$P(WR = T)$	$P(TV = T)$	$P(OD = T)$
C1	Normal operation	8.00%	92.00%	9.94%
C2	Water-supply risk with favorable operational conditions	90.00%	95.00%	82.48%
C3	Critical water level with uncertain measurement	65.00%	95.00%	62.81%
C4	Water risk with low transmission viability	90.00%	5.00%	38.92%
C5	No water risk with poor operational conditions	5.00%	5.00%	8.33%

3 Conclusion and Next Steps

This paper presented an emerging result from an ongoing research project on adaptive IoT monitoring under uncertainty. We proposed an initial Bayesian decision architecture for rural cistern monitoring, designed to combine water-related evidence and operational evidence in a single interpretable decision model. The architecture integrates five input variables, namely cistern level, measurement uncertainty, precipitation, communication-link quality, and battery status, and uses them to infer water risk, transmission viability, and an operational decision.

The preliminary scenario-based evaluation suggests that the proposed model can produce coherent inferences under different combinations of evidence. In normal conditions, the model assigns low probability to operational action. When water risk is high and transmission conditions are favorable, the probability of action increases substantially. In contrast, when the water level is critical but the measurement is uncertain, or when high water risk occurs under poor transmission conditions, the model moderates the final decision. These results indicate that the Bayesian decision layer can go beyond fixed-threshold monitoring by explicitly considering uncertainty, communication constraints, and energy limitations. These findings suggest that separating domain risk from operational feasibility, and explicitly modeling measurement uncertainty, can support more nuanced decision policies in constrained IoT systems.

At the current stage, the work should be interpreted as a conceptual and exploratory contribution. The model still uses binary states, and the conditional probability tables were defined from domain interpretation and expert discussion rather than learned from empirical data. In addition, the evaluation was based on simulated scenarios and does not yet capture the full variability of a deployed rural IoT environment. Therefore, the results do not constitute a final validation of the architecture, but rather an initial indication of its feasibility as a decision-support mechanism for constrained IoT monitoring systems.

The next steps of the research include collecting real sensor data from cistern monitoring, incorporating precipitation records, communication metrics from LoRaWAN, and energy measurements from the sensor node, and mapping these data to the Bayesian Network variables. We also plan to refine the conditional probability tables, evaluate whether binary states should be replaced by more granular representations, and compare the Bayesian decision policy with fixed-threshold approaches. These steps will allow us to assess whether the proposed architecture remains coherent and useful under real or controlled experimental conditions.

Artifact Availability

The conditional probability tables (CPTs), prior probabilities, Bayesian Network specification, and evidence configurations for the simulated scenarios C1–C5 reported in Table 2 are publicly available at https://github.com/josejeffersonpiresgoncalves/bayesian-iot-cistern-monitoring. The repository also provides documentation describing the network structure, variable semantics, model parameterization, and current limitations. No real sensor data were used in this preliminary study.

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