

A Model for Minimizing Packet Loss Probability Considering the Environmental Coefficient in Observation Wells

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Received: 22 Mar 2026 | Received Revised Version: 18 Apr 2026 | Accepted: 06 May 2026 | Published: 31 May 2026

Volume 08 Issue 05 2026 | Crossref DOI: 10.37547/tajas/Volume08Issue05-40

Abstract

Reliable, low-loss delivery of data packets is one of the basic requirements for any LoRa-based remote monitoring network installed at groundwater observation wells. This paper looks at what actually governs packet transmission efficiency in such networks, paying particular attention to the physical environment inside the observation well itself — the well casing, the burial depth of the sensor, the water column above it, and the condition of the cap all attenuate the radio signal in ways that a generic outdoor LoRa link does not experience. The links between signal attenuation, background noise, signal-to-noise ratio (SNR), packet loss and transmission reliability are analyzed, and a simplified model is proposed that adds an observation-well environment coefficient, K_q , to the standard distance-based path-loss equation. To see whether the coefficient actually helps in practice, network reliability was compared for two cases over twelve ten-day observation periods between December 2025 and March 2026: a baseline case that ignores the well environment (R_0) and the proposed case that accounts for it (R_1). In every one of the twelve periods, R_1 came out roughly 2.0–2.5 percentage points higher than R_0 , with packet loss falling by a comparable margin. This gives a concrete, measurable basis for reducing packet loss in LoRa-based observation-well monitoring networks by taking the well environment into account rather than treating every deployment as if it were the same.

Keywords: LoRa technology, observation well, groundwater monitoring, packet transmission, environment coefficient, SNR, packet loss probability, network reliability, wireless sensor network.

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Cite This Article: Memonova Gulrukh Nazrikulovna. (2026). A Model for Minimizing Packet Loss Probability Considering the Environmental Coefficient in Observation Wells. *The American Journal of Applied Sciences*, 8(5), 292–298. <https://doi.org/10.37547/tajas/Volume08Issue05-40>

Introduction

Low-power, long-range wireless communication has become almost indispensable over the last few years for remote monitoring, precision agriculture, industrial control, environmental observation and telemetry — groundwater-level monitoring through observation wells being one clear example. Among Low-Power Wide-Area Network (LPWAN) technologies, LoRa and LoRaWAN are the ones most often chosen for such Internet of Things applications, largely because of their wide coverage, low energy consumption and relatively simple

infrastructure requirements [1], [2]. The chirp-spread-spectrum modulation used at the LoRa physical layer is what makes long-range links possible in the first place, but how efficiently packets actually get through still depends heavily on network density, channel load and the chosen transmission parameters [1], [3] — and, once the device sits inside an observation well, on the physical condition of that well as well.

Distance alone does not decide packet transmission efficiency in a LoRa network. Delivery probability, network capacity, transmission time, energy use and

packet collisions all play a part. Where many end-devices share one gateway under access rules close to plain ALOHA, packet loss and network congestion grow quickly. Large-scale modeling of LoRaWAN networks bears this out: transmission success falls as the network grows, and the effect is worse still when confirmed traffic and downlink resources are limited [1], [2], [4].

A further complication is that the different spreading factors (SF) used in LoRa are not perfectly orthogonal to one another, so devices transmitting at the same time on different SFs still interfere. In a real, dense deployment this measurably lowers the chance that a given packet is received correctly. Judging transmission efficiency by signal strength alone is therefore not enough — inter-SF interference, channel bandwidth and the strategy used to choose parameters all matter [3], [5]. How spreading factor, bandwidth, coding rate and transmit power are balanced against one another jointly decides a network's energy efficiency, capacity and reliability [6].

Adaptive Data Rate (ADR) is the main mechanism LoRaWAN uses to keep this balance under control. It does not always work as well as it should, though: several studies report that standard ADR algorithms adapt too slowly or land on a suboptimal setting, and that the end-device and the network server can end up disagreeing about which parameters to use [7]. This has pushed later work toward collision-aware ADR, flexible link-margin schemes and scheduling-based approaches, all of which have been shown to cut the packet error rate, raise throughput and use network resources more efficiently [4], [8], [9].

Related analytical work on other communication networks has looked at how packet switching and routing choices affect the reliability of a data-transmission network, in one case combined with neural-network-based prediction [11], and at how the reliability of an IoT-aided remote monitoring system can be evaluated once its sensing devices sit on real physical infrastructure exposed to field conditions — low-voltage overhead transmission lines, in that particular case, rather than observation wells [12]. The problem taken up here belongs to that same broader tradition, applied to a deployment setting — an enclosed, partly water-filled well — that does not appear to have been treated this way before.

LoRa is by now deployed widely in practical systems, yet efficient packet transmission is still not a solved problem

— parameter selection, interference and packet loss all remain open questions. The stakes are arguably higher for groundwater observation-well monitoring specifically, because the sensing device sits inside a partially enclosed structure — the casing and the cap — that an above-ground LoRa node never has to contend with, and because the whole point of the system is defeated if level, temperature or salinity readings arrive late or not at all. Studying efficient packet transmission for LoRa-based observation-well monitoring is therefore worth pursuing on both theoretical and practical grounds [1], [6], [7].

LoRa- and GSM-based groundwater monitoring system built and field-tested in [13] a diver sensor placed 150 m below ground measured water level, temperature and salinity and transmitted the readings through a LoRa link to a gateway; depending on the network topology used, measured packet loss ranged from 4.7% to 12.8% . A related deployment of LoRa for monitoring reservoir level, temperature, rainfall and salinity likewise confirmed the technology's suitability for this kind of remote water monitoring, while noting that its potential for such applications remains comparatively underexplored [14]. Neither study, however, tied the packet loss actually observed in the field to the physical condition of the well or reservoir installation itself — the specific gap this paper takes on.

This study sets out to identify the main factors that govern packet transmission efficiency in LoRa-based observation-well monitoring networks, and to examine, on that basis, a way of cutting packet loss and raising reliability that explicitly accounts for the physical condition of the well. The paper works through the relevant physical- and network-layer parameters, the effect of the transmission environment, the role of adaptive-rate mechanisms, and the efficiency-improving approaches already reported in the literature [2], [4], [8], [9], before introducing an observation-well environment coefficient, K_q , built directly into the path-loss and reliability model.

1. Theoretical foundations of packet transmission efficiency in LoRa-based observation-well monitoring

LoRa is built for long-range, low-power transmission, but how well it performs in practice depends on more than distance — delivery probability, channel bandwidth, transmission time and the number of active

nodes all matter [1], [2]. Because LoRaWAN's uplink access is organized close to the ALOHA principle, packet collisions become more likely as node density rises, and packet loss rises with them; this is particularly relevant for a monitoring network made up of many scattered observation wells sharing a limited number of gateways [1], [4]. Efficient packet transmission is, for this reason, one of the central problems in LoRa-based networks generally, not just a detail of implementation [1], [2].

Four parameters mainly decide transmission quality in a LoRa network: spreading factor (SF), bandwidth (BW), coding rate (CR) and transmit power (TP). Get the balance between them wrong and coverage may improve while transmission time stretches out, the channel stays occupied longer, and packets collide more often [3], [6]. Raising SF, for instance, improves receiver sensitivity but shrinks network capacity, because time-on-air goes up as a direct consequence [3], [6]. High reliability and high throughput are, in other words, not usually available from the same parameter setting at once.

Because different SF values are not ideally orthogonal, packets from different devices interfere with one another in a real network, which lowers the probability of successful reception [5]. Assessing transmission efficiency therefore has to look beyond signal strength to interference, the reception threshold, SNR and channel load as well [5], [6].

2. Factors affecting transmission efficiency in observation-well monitoring networks

The transmission environment is the first thing that decides packet transmission efficiency in a LoRa network. Inside an observation well, the sensing device is enclosed by a casing, sits partly or fully below a water column of varying height, and is covered by a well cap — none of which an open-field, industrial or urban deployment has to deal with. Each of these adds its own source of attenuation. Received power falls, noise has a larger relative effect, and packet loss becomes more likely [1], [6]. Building this well-specific attenuation into the LoRa channel model as a dedicated coefficient is, on that basis, a reasonable and fairly direct step to take.

A second factor is simply how many devices are active and how often they transmit. More nodes means a higher chance that several of them transmit in the same, or a closely spaced, time window using similar parameters — which raises the collision probability and lowers the

successful-reception rate [2], [4]. Reynders et al. found that a lightweight scheduling scheme can improve both the reliability and the capacity of LoRaWAN networks, which suggests that simply managing network resources in a more orderly way already buys a measurable improvement [4] — relevant here because a national-scale network of observation wells will typically share gateway infrastructure across many wells.

A third factor is the mechanism used to adapt transmission parameters on the fly, which in LoRaWAN mainly means Adaptive Data Rate. Standard ADR, however, does not perform equally well under all conditions — it struggles in particular when channel conditions change quickly or the network becomes dense [7]. This has led to collision-aware ADR, flexible-link-margin schemes and power-optimization approaches in later work, each shown to improve packet delivery ratio and overall network efficiency to varying degrees [8], [9], [10].

Using more than one gateway is a further way to raise the probability of successful reception. Work on gateway diversity shows that decoding can be improved either by receiving the same packet at several gateways or by reconstructing a signal from partially corrupted copies [10] — an approach that matters more, not less, in environments where signal attenuation is already high, such as observation wells.

3. Proposed model for minimizing packet loss probability

The model adopted here is deliberately simple, and its purpose is to capture the effect of the transmission environment when evaluating — and reducing — packet loss in LoRa-based observation-well monitoring. Total signal loss at distance d is written as:

$$L_{um}(d) = L_0 + 10n \cdot \log_{10}\left(\frac{d}{d_0}\right) + K_q \quad (1)$$

where $L_{um}(d)$ is the total signal loss at distance d (dB); L_0 is the signal loss at the reference distance (dB); n is the path-loss exponent, which depends on the environment; d is the transmission distance (m); d_0 is the reference distance (m); and K_q is the observation-well environment coefficient (dB). K_q is what carries the additional attenuation from sensor burial depth, water-column height, casing material and cap condition into the model — the less favorable the well, the larger K_q and the greater the resulting signal loss.

Received signal power follows directly:

$$P_r = P_t + G_t + G_r - L_{um}(d) \quad (2)$$

where P_r is the received power (dBm), P_t the transmit power (dBm), and G_t , G_r the transmit and receive antenna gains (dBi) respectively.

The signal-to-noise ratio is then:

$$SNR = P_r - N \quad (3)$$

with N the noise power (dBm).

Four indicators are used here to judge packet transmission efficiency: the probability of successful delivery, the packet loss rate, the change in SNR, and overall communication reliability. Packet loss and reliability are two sides of the same coin, reliability being defined as:

$$R = 1 - P_{loss} \quad (4)$$

where R is transmission reliability and P_{loss} is packet loss probability.

None of this points to a single fix. Raising reliability in a LoRa-based observation-well network in practice means managing several things together — an appropriate SF/TP combination, less channel load, a better ADR mechanism and, where it is warranted, reception at more than one gateway [4], [7], [8], [9], [10]. What this paper adds to that picture is the well environment coefficient itself: K_q is built into the relationship between signal loss, SNR, packet loss and reliability, and its effect is then checked against measured data rather than left as a theoretical add-on. Network reliability was worked out twice for the same twelve ten-day periods — once as a baseline, R_0 , that leaves K_q out, and once with K_q folded into the model, giving R_1 . Table 1 sets out both sets of values for the period from 1 December 2025 to 25 March 2026.

Table 1. Packet transmission indicators over ten-day periods, December 2025 – March 2026

Period	Date range	Average SNR (dB)	Packet loss (%)	Reliability R_0 (baseline)	Reliability R_1 (proposed model)
1	01–10 Dec 2025	7.86	8.5	0.915	0.937
2	11–20 Dec 2025	8.04	8.1	0.919	0.941
3	21–30 Dec 2025	7.71	8.7	0.913	0.935
4	31 Dec 2025–9 Jan 2026	7.40	9.4	0.906	0.929
5	10–19 Jan 2026	7.11	10.2	0.898	0.922
6	20–29 Jan 2026	6.87	10.9	0.891	0.916
7	30 Jan–8 Feb 2026	6.96	10.6	0.894	0.919
8	9–18 Feb 2026	7.24	9.7	0.903	0.926
9	19–28 Feb 2026	7.59	8.9	0.911	0.933
10	1–10 Mar 2026	7.94	8.1	0.919	0.941
11	11–20 Mar 2026	8.30	7.4	0.926	0.948
12	21–25 Mar 2026	8.48	7.0	0.931	0.952

Figure 1 shows the same comparison as a radar chart, with each of the twelve ten-day periods forming one axis and the R_0 and R_1 values traced as two overlapping polygons:

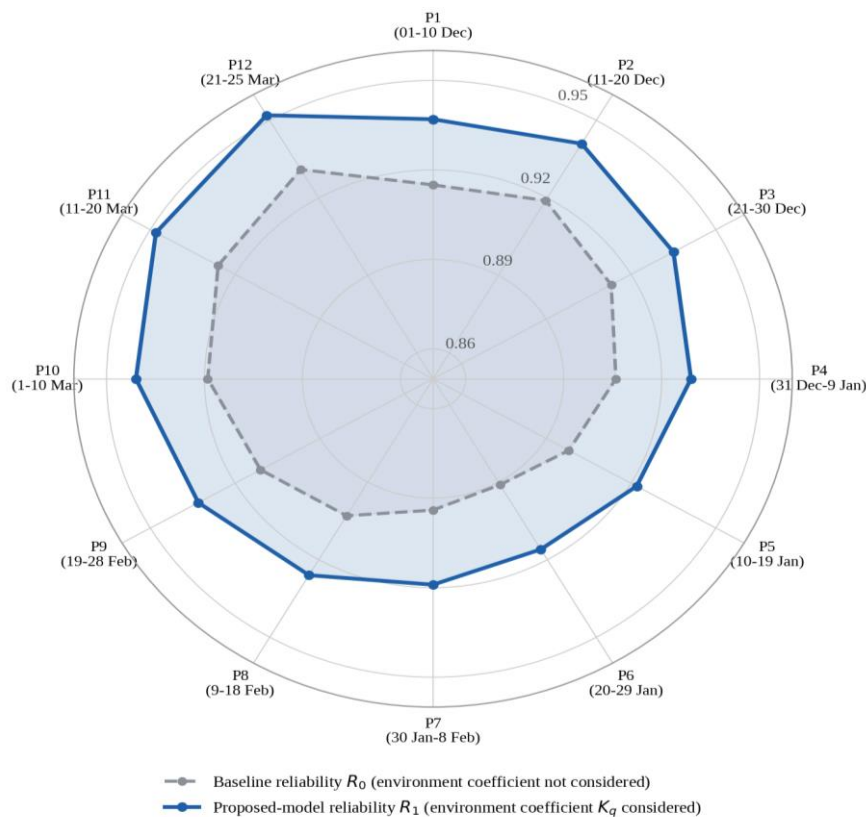


Fig. 1. Network reliability across twelve 10-day observation periods (Dec 2025 – Mar 2026): baseline vs. proposed environment-coefficient model

The baseline curve, R_0 , is not flat — it dips through late January before recovering by March, tracking the same stretch where average SNR is lowest and packet loss highest. Once K_q is folded in, R_1 sits above R_0 in every single period, typically by 2.0 to 2.5 percentage points, with packet loss down by a comparable amount. Figure 1 is really just this same pair of numbers drawn twice, but the radar layout makes the gap between the two profiles easy to see across the whole four-month window at once.

Put together, the twelve periods support a fairly simple relationship: as the well environment coefficient grows, total signal loss grows with it, SNR falls, packet loss increases, and reliability falls in turn — a chain that a model without K_q has no way of representing. Writing this relationship out analytically, and then checking it against real measurements, gives a practical way of picking better transmission settings for LoRa-based observation-well networks, and of clawing back some of the reliability an unfavorable well would otherwise cost.

Conclusion

This paper worked through the problem of efficient data-packet transmission in LoRa-based observation-well monitoring networks, both on paper and against measured data. The main factors at play — signal attenuation, background noise, signal-to-noise ratio, packet loss and communication reliability — were examined together rather than in isolation, since in practice none of them moves independently of the others.

Successful packet delivery in a LoRa-based observation-well network turns out to depend on more than distance to the gateway — network density, the chosen transmission parameters, the physical condition of the well, and the level of interference all have a direct effect.

Adopting a signal-loss model that includes an observation-well environment coefficient, and checking it against twelve ten-day periods of data, shows the mechanism plainly: as total signal loss rises, received

power and SNR fall, packet loss rises, and reliability falls with it — while simply accounting for K_q recovers roughly 2.0–2.5 percentage points of reliability across every period examined. That is a fairly strong indication that ignoring the physical characteristics of the well is not a safe simplification for LoRa-based groundwater monitoring and telemetry systems.

The results also point to where the practical gains are: choosing spreading factor, transmit power and channel parameters sensibly, and using adaptive control mechanisms, all matter. Collision-aware scheduling, improved ADR algorithms and multi-gateway reception each reduce packet loss and raise reliability in LoRa networks, to different degrees depending on deployment density.

Taken as a whole, efficient packet transmission over LoRa remains a problem that needs several things addressed at once rather than a single parameter tuned in isolation. The approach set out here — evaluating signal loss, SNR, packet loss and reliability together, with the well environment coefficient K_q built in from the start — gives both a way of quantifying that interdependence for observation-well monitoring networks and a reasonably concrete basis for choosing transmission settings that minimize packet loss in practice.

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