Towards Adaptive Wireless Networking for Energy-Free Sensor Networks in Structural Health Monitoring Applications

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***Abstract*—Long-term monitoring of critical infrastructure requires reliable wireless sensing solutions able to operate in harsh environments. Energy-free sensing technologies enable decades-long structural health monitoring (SHM), but collecting data from these highly constrained devices raises challenges related to intermittent communication, limited resources, and complex propagation conditions. This research investigates adaptive wireless networking strategies for energy-free sensor networks on bridges, combining propagation-aware modelling, adaptive medium access, and lightweight routing. Initial work addresses LoRa-based gateway placement optimisation; future work will integrate realistic bridge propagation models into network simulation to design adaptive architectures using mobile sinks and relays.**

***Index Terms*—Energy-free sensors; Wireless sensor networks; LoRa; Adaptive routing; Propagation modelling**

I. Introduction

Structural Health Monitoring (SHM) is becoming increasingly important as ageing infrastructure requires continuous assessment to ensure safety and optimize maintenance. Recent advances in energy-free sensing technologies offer the possibility of monitoring critical structures for decades without battery replacement. However, collecting data from these highly constrained devices remains challenging, particularly in large infrastructures where wireless communication is affected by complex propagation conditions, limited communication opportunities, and constrained network resources [1].

This document presents the research directions of ongoing work investigating adaptive wireless networking for energy-free sensor networks. The objective is to develop communication protocols that jointly consider radio propagation, sensor constraints, and application requirements to enable reliable and energy-efficient data collection. The research focuses on propagation-aware network modelling, adaptive communication strategies and lightweight adaptive routing mechanisms for long-term bridge monitoring.

II. Research Challenges and Objectives

The overall objective of this PhD is to develop adaptive wireless networking strategies enabling reliable and energy-efficient data collection from energy-free sensor networks deployed on large civil infrastructures. This requires jointly considering the physical characteristics of the monitored structure and the design of the communication network.

The first challenge is realistic propagation modelling. Wireless communication on bridges is strongly affected by geometry, construction materials, and non-line-of-sight conditions [4], while existing network simulators often rely on simplified path-loss models. This research investigates realistic bridge modelling to characterise infrastructure-specific propagation effects, building on multi-medium channel modelling approaches recently proposed for bridge sensor deployments [13]. Furthermore, bridge deployments introduce unique network constraints, as sensors are typically distributed along the deck in quasi-linear topologies [2]. Short-range multi-hop technologies may therefore require dense relay deployments, motivating the use of LoRa/LoRaWAN due to its long-range and energy-efficient communication capabilities [3].

The second challenge is integrating realistic propagation information into network simulation. Digital bridge models and their propagation characteristics will be incorporated into ns-3 [9], combining physical environment modelling with network-level evaluation. This propagation-aware framework will enable the design and optimization of efficient data collection strategies by considering environmental constraints, link variability, and deployment-specific characteristics.

The final challenge is to develop adaptive networking strategies that exploit propagation awareness to overcome communication limitations. This includes investigating mobile sinks and LoRa relay nodes [14] to mitigate communication gaps, improve reliability, and support long-term data collection.

III. Research Methodology

The research methodology follows a propagation-aware network modelling pipeline linking bridge characteristics to wireless communication performance, summarised in Fig. 1. It comprises three stages: (i) bridge-specific propagation modelling, (ii) integration of link characteristics into ns-3 simulations, and (iii) evaluation of adaptive communication architectures under realistic deployment conditions.

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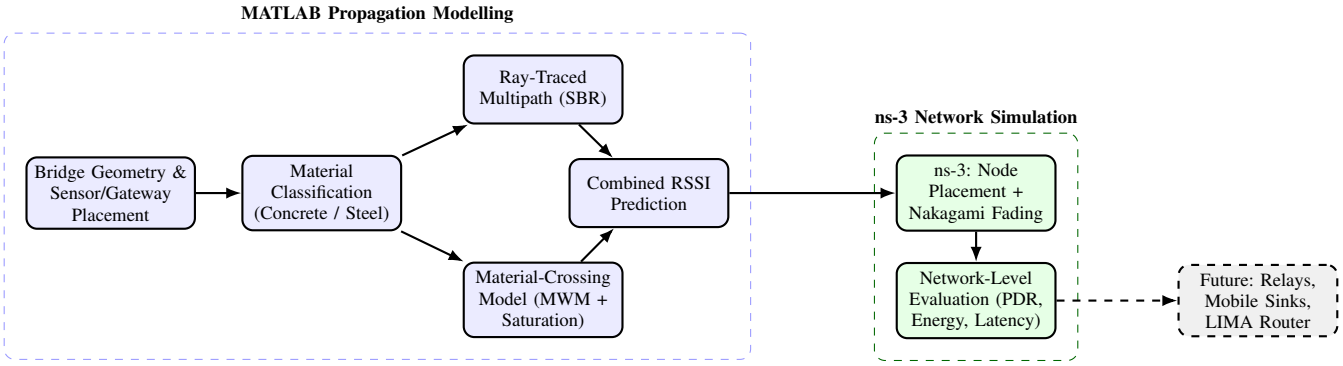


Fig. 1. Propagation-aware pipeline: MATLAB predicts per-sensor RSSI, driving ns-3 network simulation and, in future, adaptive relay strategies.

A. Structural Geometry, Sensor and Gateway Placement

The bridge geometry is represented as a triangulated surface mesh, generated from a finite-element model of a deep-beam bridge structure using MATLAB [10] and rescaled to a target real-world span. Sensor locations are distributed across five structural groups, i.e. upper deck, lower deck, web-beam (diagonal) members, and two pillars, chosen to span the range of exposure conditions a real deployment would need to characterise, from largely unobstructed deck-mounted sensors to heavily embedded web-beam and pillar sensors. The gateway is positioned above and beyond one end of the deck, consistent with typical LoRaWAN gateway placement practice of maximising elevation and minimising obstruction on the gateway side of the link. Multiple bridge typologies, such as beam, arch, cable-stayed, suspension, steel, and reinforced concrete bridges, will be modelled following the same principle to represent diverse geometry and material characteristics.

B. Material Classification and Ray-Traced Multipath Estimation

Each triangular mesh face is classified as either concrete (deck plates and pillar shafts) or steel (diagonal and vertical web members) based on its centroid position, and the two material subsets are exported as separate surface meshes. This split is necessitated by a tooling limitation: standard triangulated-mesh formats cannot encode more than one material per scene for ray-tracing purposes, so a true single-pass mixed-material ray trace is not directly available in the toolchain used here.

To recover multipath information despite this limitation, two independent shooting-and-bouncing-ray (SBR) passes are run: one against the concrete-only geometry and one against the steel-only geometry, each permitting up to two reflections and one diffraction event. The two resulting RSSI estimates are combined conservatively, taking the weaker of the two per sensor. This is an approximation, since a real signal traversing the bridge may encounter both materials jointly along a single multipath route, which two separate single-material scenes cannot jointly capture. The overall approach, deriving a semi-analytical multi-material path loss estimate and treating it as one input to a broader link-budget model, follows the same two-stage pattern used in [13], where a multi-medium (soil-water-air) channel model is derived for a river bridge pillar monitoring WSN and validated against a real LoRa deployment.

C. Material-Crossing Path Loss Model

As a second, independent estimate of link degradation, the direct sensor-to-gateway ray is intersected against both material meshes, with each distinct crossing assigned a fixed attenuation penalty based on material type. This follows the COST-231 Multi-Wall Model (MWM), which represents obstructed path loss as free-space loss plus a fixed attenuation factor per obstruction, extended here from building walls to bridge structural materials.

Calibration identified two issues requiring correction and one further simplification. First, finite-element meshes represent flat surfaces as many small triangles, so a single ray may produce several near-coincident intersections; these are clustered within a small tolerance into one logical crossing before penalties are applied. Second, linearly summing fixed penalties over many crossings tends to overestimate path loss, consistent with the empirical correction recommended for COST-231 MWM [15] and consistent with published multi-wall models, where a flat, averaged per-wall model is shown to specifically degrade when many walls of the same material are crossed in sequence [12] — though that work's concrete/drywall-specific correction factors do not directly extend to the steel members considered here. A two-tier saturation is therefore adopted: the first few crossings per material receive the full penalty, while subsequent crossings receive a reduced marginal penalty. The thresholds remain to be calibrated against measured data. Finally, an earlier incidence-angle weighting was removed because the literature-derived penalties – including the 20.8 dB steel-obstruction loss measured at 868 MHz [11] – were obtained under varying realistic incidence angles, making an additional angle multiplier liable to double-count this effect.

Fig. 2 shows the resulting sensor-to-gateway link map for a steel deep-beam bridge scenario, colour-coded by the number of structural members crossed, which will support gateway placement, relay selection, and adaptive routing.

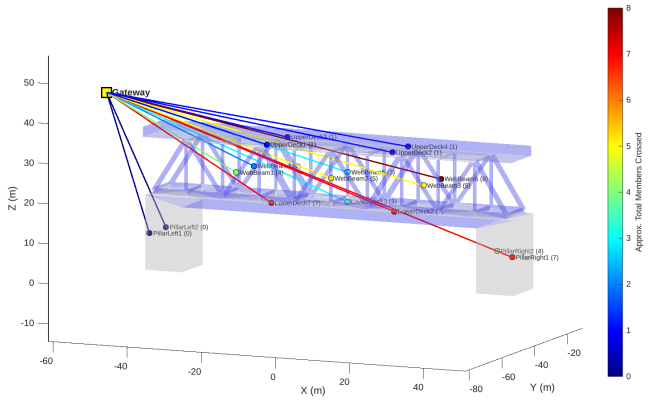


Fig. 2. Sensor-to-gateway links for a 100 m deep-beam bridge scenario (17 sensors across five structural groups), colour-coded by the number of concrete/steel members crossed along the direct path.

D. Combined RSSI Prediction

The material-crossing estimate and the ray-traced multipath estimate are treated as two independent, individually incomplete estimates of the same excess path loss rather than additive effects. The framework therefore allows the two estimates to be combined in several ways: by selecting the more conservative of the two, by considering only the material-crossing estimate, by considering only the ray-traced estimate, or by taking their average as a less pessimistic alternative. The conservative combination is used as the default, while the different strategies can be compared against RSSI-based expectations to determine which best represents the propagation characteristics of the considered bridge scenario. This follows the general principle of combining complementary structural and environmental propagation estimates rather than relying exclusively on a single model, consistent with [16], where an improved log-distance path loss and shadowing model incorporating wall-material obstructions and environmental factors outperforms a structural-only baseline for LoRaWAN indoor prediction. Stochastic fading and shadowing are deliberately excluded from these deterministic excess-loss estimates: small-scale fading is applied once, downstream in the ns-3 simulation through a Nakagami fading model layered on the resulting base path loss, thereby avoiding double-modelling of the same stochastic process.

E. ADR-Based Spreading Factor Assignment

For each sensor, the predicted RSSI is additionally used to compute a reference spreading factor and transmit power following standard LoRaWAN Adaptive Data Rate (ADR) logic [17]: the lowest spreading factor that still clears a target device margin above the relevant per-SF receiver sensitivity is selected, with any remaining margin used to reduce transmit power rather than further reduce spreading factor. This simplifies the network-side algorithm, which formally operates on measured SNR using per-SF demodulation floors rather than an RSSI-versus-sensitivity margin. This MATLAB-derived assignment is not used to configure the ns-3 simulation directly; the simulation instead relies on ns-3's own SNR-based ADR implementation, and the two are compared post hoc as a cross-check between the bridge-specific material model and ns-3's propagation-model-driven configuration.

F. Integration into network simulations

The material-crossing and ray-traced multipath estimates are treated as two independent, individually incomplete estimates of the same excess path loss rather than additive effects. They can therefore be combined by selecting the more conservative result, using either estimate alone, or taking their average as a less pessimistic alternative. The conservative combination is used by default, while the alternatives can be compared against RSSI-based expectations to identify the most representative approach for the considered bridge scenario. This follows the principle of combining complementary structural and environmental propagation estimates, consistent with [16], where incorporating wall-material obstructions and environmental factors outperforms a structural-only baseline for LoRaWAN prediction. Stochastic fading and shadowing are excluded from these deterministic estimates and applied only once downstream in ns-3 through a Nakagami fading model, avoiding double-modelling of the same stochastic process.

G. Adaptive communication architectures

Using the propagation-aware simulation framework, this research will investigate adaptive networking strategies to overcome communication gaps in complex bridge environments. Approaches including mobile sink data collection and LoRa relay-assisted communication [14] will leverage propagation knowledge to improve connectivity, reduce packet loss, minimise energy consumption, and support reliable long-term data collection.

IV. Preliminary Results

Initial work addressed gateway placement optimization for large-scale LoRaWAN bridge SHM networks, one of the key open problems for such deployments. A two-step Fuzzy C-Means (FCM) clustering framework was proposed: the optimal number of gateways is first selected using the Xie-Beni validity index [6] – well suited to the quasi-linear sensor distributions found on bridges – after which FCM computes the corresponding gateway locations. Two variants were compared: Euclidean-distance Gateway Placement Optimisation (EGPO), and Propagation-Aware Gateway Placement Optimisation (PAGPO), which replaces Euclidean distance with a cost derived from Radio Mobile [8] coverage predictions and link margins, in the spirit of prior FCM-based gateway placement work [5]. This preliminary propagation-aware approach provides an earlier, computationally simpler representation of the propagation environment, which is subsequently refined in this work through the material-aware MATLAB/ns-3 propagation pipeline.

The two strategies were evaluated on two realistic bridge scenarios exported to ns-3.44 LoRaWAN simulations: a 3.36 km water bridge with open propagation conditions (25–200

nodes) and a 1.5 km mountainous bridge with strong shadowing and NLoS effects (25–100 nodes). Results show that PAGPO consistently requires fewer or the same number of gateways as EGPO while maintaining comparable or better uplink delivery ratio, and reduces average per-node energy consumption, with the largest gains observed in sparser deployments on the water bridge and at higher node densities on the mountain bridge, where irregular propagation conditions penalize purely geometric placement. These results are detailed in [7], accepted at the 12th European Workshop on Structural Health Monitoring (EWSHM 2026).

In parallel, a material-aware propagation pipeline was developed and evaluated on a 100,m instrumented deep-beam bridge scenario with 17 sensors and a single gateway (Fig. 2). The pipeline combines base distance-dependent path loss with summed structural obstruction losses based on the steel and concrete members intersected along each sensor-to-gateway path. A second, independent correction based on ray-traced multipath simulations can optionally be layered onto this model. Initial evaluations showed that literature-derived attenuation values [11] required appropriate scaling: correcting for mesh-tessellation overcounting and applying a saturating penalty for paths crossing multiple members [12] produced plausible link margins across the deployment. This provides a modular basis for future calibration against measurement data, incorporation of environmental effects and antenna polarisation, and explicit quantification of propagation-model uncertainty before integration into ns-3.

V. Expected Contributions and conclusion

As a conclusion, building on the propagation-aware pipeline described in Section IV, this research is expected to deliver the following contributions:

- A material-aware bridge propagation model predicting per-sensor RSSI beyond conventional distance-only path-loss models.
- A propagation-aware gateway placement framework has been initiated and evaluated in ns-3 simulations, showing reduced gateway requirements and per-node energy consumption compared with purely geometric placement across bridge scenarios with contrasting propagation conditions.
- Integration of bridge-specific propagation predictions into ns-3, enabling network-level evaluation of packet delivery, latency, and energy consumption under realistic structural attenuation.
- Evaluation of wireless performance across diverse bridge typologies, including steel, reinforced concrete, beam, suspension, and cable-stayed structures, to characterise how structural design affects link quality.
- Adaptive communication strategies, including relay-assisted and mobile-sink architectures, targeting the structurally obstructed regions identified by the propagation model.
- Deployment guidelines for energy-free wireless sensor networks on large infrastructures, derived from propagation-aware network simulation results.

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