Data-Driven Automatic Calibration of IoT Network Simulators: A Literature Review

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Abstract

Network simulators are widely used in Internet of Things (IoT) research and deployment planning, yet a significant gap often exists between simulated and real-world network behavior, stemming from default radio model parameters that fail to capture real propagation conditions. This work presents a state-of-the-art review of the theoretical foundations required to close this gap: WSN/IoT fundamentals and network simulation tools, radio propagation modeling, and existing calibration approaches, from empirical/manual methods to data-driven, Machine Learning (ML)-based inverse models and adaptive strategies capable of keeping a simulator, framed as a network digital twin, synchronized with a real deployment over time.

Introduction: The Simulation-to-Reality Gap

Wireless Sensor Networks (WSNs) and IoT deployments rely on simulators like Cooja to test protocols without costly physical deployment. Simulators, however, are only as trustworthy as their radio propagation model. Cooja executes the exact same firmware, including the same MAC-layer logic, as real hardware, so any divergence cannot come from the protocol logic itself.

1. Is it the hardware? Cooja's Z1 mote vs. the real M3 testbed node:

Table 1: *Comparison of CC2420 (Z1/Cooja) and AT86RF231 (M3/real) radio chip specifications.*

Parameter	CC2420 (Z1 / Cooja)	AT86RF231 (M3 / real)
Standard	IEEE 802.15.4	IEEE 802.15.4
RX sensitivity	−95 dBm	−101 dBm
TX power	0 dBm (typ.)	−17 to +3 dBm

Near-identical specs → hardware is not the primary variable.

2. Then what is it? Idealized vs. realistic reception boundaries:

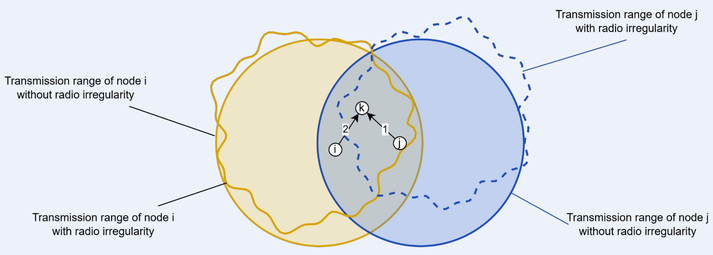


Figure 1: *Idealized (UDGM) vs. realistic reception boundaries (Dezfouli et al., 2015)*

Conclusion: the gap is a physical (PHY) layer model-fidelity problem, not a hardware mismatch. This is the strategy behind the review that follows: four themes of related work (right), moving from manual measurement toward a data-driven, adaptive calibration direction discussed at the end.

Review Framework

The literature is organized into four themes, spanning manual field-measurement approaches to fully automatic, learned calibration methods, reviewed column-by-column to the right.

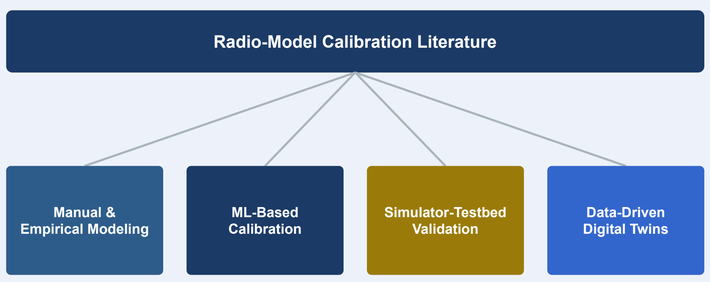


Figure 2: *Taxonomy of the reviewed calibration literature.*

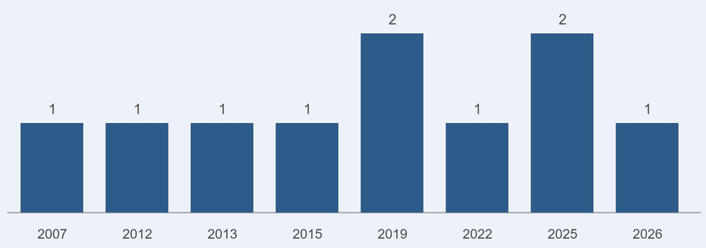


Figure 3: *Reviewed works by publication year.*

References

- Dezfouli et al. (2015) — Modeling low-power wireless communications
- Dash et al. (2025) — Experimental propagation analysis in the CBRS spectrum
- Adeogun (2019) — Calibration of stochastic radio propagation models using ML
- Bharti et al. (2022) — A general method for calibrating stochastic radio channel models with kernels
- Zinonos & Vassiliou (2012) — Radio propagation in industrial WSN environments
- Kanaris et al. (2019) — On the realistic radio and network planning of IoT sensor networks
- Ivanov et al. (2007) — Experimental validation of the ns-2 wireless model
- Miranda et al. (2013) — Path loss exponent analysis in wireless sensor networks
- Tarafder et al. (2026) — Calibrating the digital twin channel
- Si-Mohammed & Théoleyre (2025) — Per-link data-driven network replication towards self-adaptive digital twins

Manual & Empirical Channel Modeling

Types of Radio Propagation Models

The literature broadly groups models into deterministic, statistical, and empirical categories. Empirical models, the category simulators like Cooja rely on, trade some physical precision for ease of calibration.

Deterministic

Ray Tracing

$$E = \Sigma(E_{dir} + E_{ref} + E_{dif})$$

Two-Ray Ground

$$PL = 40\log_{10} d - 20\log_{10}(h_t h_r)$$

Statistical

Rayleigh Fading

$$p(r) = \frac{r}{\sigma^2} e^{-r^2/2\sigma^2}$$

Rician Fading

$$p(r) = \frac{r}{\sigma^2} e^{-(r^2+s^2)/2\sigma^2} I_0\left(\frac{rs}{\sigma^2}\right)$$

Empirical ✓

Log-Distance/Shadow *

$$PL(d) = PL(d_0) + 10n\log_{10}\frac{d}{d_0} + X_\sigma$$

Okumura-Hata

$$PL = 69.55 + 26.16\log_{10} f + \ldots$$

Figure 4: *Example models per category (* = used in this work).*

Dezfouli et al. (2015) · Dash et al. (2025) · Miranda et al. (2013)

These works derive radio propagation parameters, path loss exponent, shadowing deviation, directly from field measurements by hand, across regimes from low-power IEEE 802.15.4 networks to 3.5 GHz CBRS links.



Figure 5: *Manual field-measurement calibration process (Dezfouli et al. (2015), Miranda et al. (2013)).*

\+ Direct experimental confirmation that default parameters diverge from measured reality, no ML infrastructure required.

– Derived once from a fixed campaign; no repeatable procedure; must be redone for every new deployment.

Relevance: *motivates calibrating model's parameters rather than relying on Cooja's generic defaults.*

Machine-Learning-Based Calibration

Adeogun (2019) · Bharti et al. (2022)

Manual measurement is accurate but does not scale, can this itself be learned? An ML regressor (a multilayer perceptron or kernel-based estimator) learns the inverse mapping from channel statistics to parameters, bypassing manual multipath extraction.

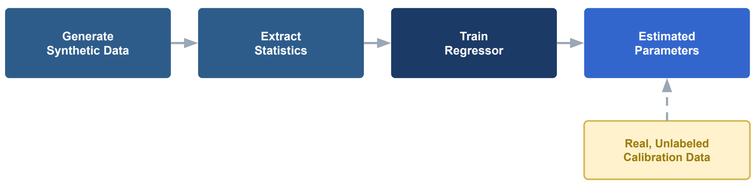


Figure 6: *Calibration pipeline, adapted from Adeogun (2019).*

\+ Fully automatic, learned calibration; validated with two complementary strategies.

– Targets general stochastic models, not simulator radio mediums like LogisticLoss; static, no adaptation.

Relevance: *the closest methodological precedent, this work extends the same inverse-mapping strategy to network-simulator KPIs.*

Simulators Validated Against Physical Testbeds

Zinonos & Vassiliou (2012) · Kanaris et al. (2019) · Ivanov et al. (2007)

Learned calibration is promising in principle, but has it been checked end-to-end against a real network? These works validate against real hardware, but not open IoT testbeds: an industrial oil refinery, a proprietary platform (TruNET), and a custom network.

Testbed	Open?	IoT-Specific?	Multi-Site?
Oil Refinery (Zinonos)	✗	✗	✗
TruNET (Kanaris)	✗	✗	✗
Custom Net. (Ivanov)	✗	✗	✗
FIT IoT-LAB (this work)	✓	✓	✓

Figure 7: *Testbed comparison, openness, IoT-specificity, and multi-site coverage.*

\+ Direct precedent for simulator-testbed validation; legacy models fail to match real environments.

– Calibration entirely manual, hand-fitted once per environment; none use an open, purpose-built IoT testbed; no adaptive mechanism.

Relevance: *same validation spirit, but extended to FIT IoT-LAB. An open, multi-site IoT testbed platform, unlike the ad-hoc/proprietary ones above.*

Data-Driven Digital Twins

Tarafder et al. (2026) · Si-Mohammed & Théoleyre (2025)

All the above assume a one-time calibration, but real deployments change. The most recent works reframe this as a live digital twin; Si-Mohammed & Théoleyre notably use the same FIT IoT-LAB platform as this work.



Figure 8: *Physical network ↔ digital twin synchronization.*

\+ Recent evidence that data-driven digital twin research is active; one work targets self-adaptivity.

– Operate in a different regime (mmWave), or, even on the same FIT IoT-LAB platform, predict link quality directly rather than calibrate a reusable physical model.

Relevance: *this work adds fully adaptive, physical radio-model calibration, on the same open FIT IoT-LAB platform as the closest related work.*

Table 2. Synthesis of Reviewed Work

Work	Testbed	KPI(s)	Method	Adapt.?
Dezfouli et al. (2015)	Measurement campaign	RSSI, path loss	Manual fitting	No
Dash et al. (2025)	Live CBRS network	Path loss, RSRP, SINR	Manual, experimental	No
Adeogun (2019)	Synthetic + measured	PDP moments	ML (MLP) inverse mapping	No
Bharti et al. (2022)	Synthetic + 60 GHz	PDP statistics	Kernel-based (ABC)	No
Zinonos & Vassiliou (2012)	Oil refinery	RSSI	Manual, environment-specific	No
Kanaris et al. (2019)	TruNET wireless	Packet Reception Ratio	Cross-layer accuracy analysis	No
Ivanov et al. (2007)	Real wireless network	PDR, connectivity, latency	Manual calibration	No
Tarafder et al. (2026)	W-band OFDM lab	PDP, delay spread	Statistics-alignment	No
Si-Mohammed & Théoleyre (2025)	Real wireless network	Packet Delivery Ratio	Data-driven, KPI-based	Partially
This work	**FIT IoT-LAB**	**RSSI, loss rate, throughput, delay**	**ML inverse mapping**	**Yes**

Limitations Identified

- No existing work combines Cooja and FIT IoT-LAB specifically
- No work combines automatic, learned calibration with an adaptive mechanism
- ML/kernel calibration methods are validated on channel data, not on network-simulator KPIs
- Manual calibration does not scale across deployments or environments

Conclusion & Future Work

This review identifies a clear, unaddressed gap: no prior work combines data-driven, adaptive calibration of a network simulator's radio model against a physical low-power IoT testbed, particularly for the Cooja / FIT IoT-LAB pairing.

Our Direction: Calibration as an Inverse Problem

Rather than manually tuning parameters, calibration can be framed as an inverse problem: given real KPIs observed on a network, infer the parameters a simulator needs to reproduce them, extended with adaptive concept-drift detection (e.g., Page-Hinkley) to trigger recalibration as conditions change.

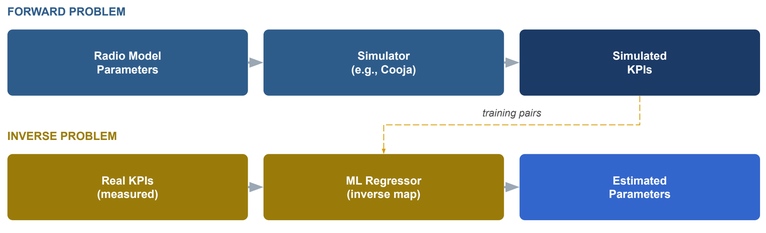


Figure 9: *Calibration reframed as an inverse problem.*

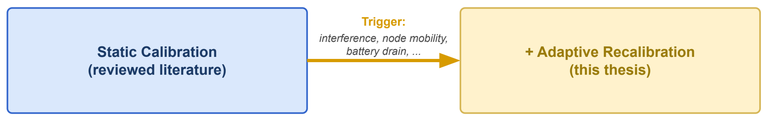


Figure 10: *From static calibration (reviewed literature) to adaptive recalibration (this work).*