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AISR :A Protocol-Closed Architecture for Interference-Aware Channel-Mask Control in Industrial LoRaWAN

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Abstract

Industrial Long Range Wide Area Network (LoRaWAN) telemetry operates under variable propagation, contention, external interference, regional spectrum rules, and limited downlink capacity. An adaptive channel policy is useful only when the network can observe alternatives, predict a benefit over the time required to deliver control, issue a legal command that the device accepts, and verify that the realized transmissions improve application outcomes after sensing and reconfiguration cost. This paper reconstructs Adaptive Interference-Aware Spectrum Reallocation (AISR) as a protocol-closed network-side controller. A gateway or dedicated monitor supplies calibrated channel observations; a causal predictor estimates packet success, energy, and deadline risk; a constrained optimizer selects device-specific legal channel masks; and a verification layer records command acceptance, actual channel use, delivery, latency, and energy. The proposed architecture introduces control age, abstention, fallback, hysteresis, and auditability as first-class design variables. It also separates the evidential roles of the available harbor RSSI/SNR localization dataset from those of a genuine intervention trial. The harbor record can characterize observed link variation, but it lacks simultaneous counterfactual channel measurements, a complete attempted-packet denominator, MAC-command traces, application delivery times, and device-current measurements. No performance improvement is therefore claimed. A staged evaluation protocol compares fixed plans, configured Adaptive Data Rate (ADR), a valid history-based policy, published allocation families, and AISR under identical traffic, sensing budgets, channel conditions, and control authority. The resulting framework makes interference-aware LoRaWAN channel management falsifiable at the level of radio observation, protocol execution, and application benefit.

Keywords: Industrial long range wide area network, Channel-mask management, Interference prediction, Adaptive data rate, Packet delivery; Control age, Device energy, Reproducibility.

1 | Introduction

Low-power wide-area networks support periodic sensing and supervisory telemetry across ports, factories, utilities, and geographically distributed industrial assets. Long Range Wide Area Network (LoRaWAN) combines long-range LoRa modulation with a networked MAC architecture, but reliability is shaped by

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propagation, channel occupancy, spreading factor, transmit power, offered load, capture, gateway diversity, receive-window behavior, and regional duty or dwell restrictions. Surveys of LoRaWAN, comparative LPWAN design, and massive-IoT scalability have consistently identified collisions, interference, downlink scarcity, and resource allocation as coupled limitations [1–5].

The attraction of interference-aware adaptation is straightforward: when one legal channel becomes persistently unfavorable, a network may prefer another. The implementation is not instantaneous. LoRaWAN channel availability is represented through regional and device-specific rules, and network control may be conveyed through MAC commands such as LinkADRReq under the applicable specification [6], [7]. The command must wait for a downlink opportunity, respect gateway airtime constraints, reach the device, be accepted, and affect a later uplink. Consequently, an observation can be stale before the selected mask becomes active.

Prior research already covered multiple parts of this problem. Joint spreading-factor and channel assignment was optimized in multi-operator networks [8]; adaptive resource allocation was compared with optimization-based alternatives [9]; multi-armed bandit and learning-automata approaches selected channels and spreading factors [10], [11]; game-theoretic and decentralized reinforcement-learning methods considered channel competition [12], [13]; and channel allocation was studied under intra- and inter-system interference [14]. Adaptive Data Rate (ADR)research addressed convergence, mobility, fairness, reliability, and energy [15–19]. Thus, the scientific gap is not a lack of adaptive algorithms. It is the closure of the complete observation–prediction–actuation–verification loop under actual LoRaWAN authority and cost.

Adaptive Interference-Aware Spectrum Reallocation (AISR) is formulated around that closure. The contribution is fourfold. First, a control contract binds every decision to a named regional plan, device capability, protocol version, observation source, and command path. Second, a robust objective balances lower-confidence delivery, energy, deadline risk, and update cost while permitting abstention. Third, control age and acceptance are modeled explicitly rather than treating an intended mask as an executed action. Fourth, a staged evidence protocol distinguishes exploratory link variation from counterfactual channel benefit and industrial transfer. The work is a proposed design; it does not report a completed implementation or validate the numerical improvements stated in the source manuscript.

2 | Related Work and the Closure Gap

2.1 | Scalability, Interference, and Resource Allocation

LoRaWAN scalability studies showed that pure-ALOHA approximations can omit capture, multi-channel reception, multiple spreading factors, and constrained downlinks. Empirical and simulation studies found that inter-network interference, device density, and downstream traffic can materially change delivery [20–22]. Broad surveys organized solutions around spreading-factor assignment, power, frequency allocation, gateway deployment, scheduling, and interference cancellation [1–4]. This literature established that a channel decision cannot be isolated from the other radio and MAC variables.

2.2 | Adaptive Data Rate and Adaptive Channel Selection

ADR studies primarily adjusted spreading factor and transmit power, with extensions for mobility, convergence, fairness, energy, capacity planning, and transmission-parameter selection [15–19], [23], [24]. Channel-specific work ranged from proportional-fair optimization and multi-operator games to reinforcement learning, bandits, and TinyML [8–14], [25]. These methods differed in who controlled the action, what observations were available, and whether they modeled LoRa devices or LoRaWAN network commands. A result for direct device-side selection cannot automatically serve as a network-server baseline; conversely, a server policy is ineffective when downlink control cannot be delivered.

2.3 | Data-Driven Prediction and Industrial Evidence

Industrial deployments confirm that nominal radio range does not remove application-specific constraints on throughput, energy, maintainability, and operational integration [26]. Consequently, a harbor trace can motivate hypotheses about link variation, but it cannot by itself demonstrate interference attribution, legal mask execution, or transfer to another industrial topology.

Machine-learning surveys documented growing use of supervised learning, reinforcement learning, and lightweight inference for LoRaWAN resource management [27], [28]. Experimental work also predicted packet delivery from observable link and interference conditions [29]. Yet prediction accuracy is not policy value: a predictor can be well calibrated while the chosen action is illegal, unavailable, delayed, or too costly. Industrial evidence additionally requires stable definitions of generated messages, deduplicated delivery, deadlines, current consumption, and surveillance duration. The ACOGA routing work in [30] concerns complementary network-layer energy management; its outcome cannot substitute for a LoRaWAN channel-mask comparator.

Table 1. Literature strands and the control-loop element they leave outside the claim.

Strand	Representative Sources	Primary Object	Closure Still Required
Scalability and surveys	[1–4], [20–22]	Network capacity, interference, topology, and resource taxonomies.	Executable device-specific control and post-command verification.
ADR optimization	[15–19]	Spreading factor, power, convergence, mobility, and energy.	Channel observation and legal mask-update path.
Channel allocation	[8–14]	Optimization, games, bandits, learning automata, and TinyML.	Equivalent observation budget, command authority, acceptance, and cost.
Data-driven prediction	[27], [28], [29]	Prediction of link or packet outcomes.	Counterfactual intervention and causal policy evaluation.
Industrial / harbor data	[26], [31], [32]	Observed RSSI/SNR and deployment-specific link variability.	Unchosen channels, attempted messages, control events, latency, and current traces.

3 | System Boundary and Control Contract

Consider N end devices, one or more gateways, a network server, and the region-valid channel set B_r. At decision epoch t, device i has an enabled-channel mask $m_{i,t}$, data-rate and power state, firmware-defined channel-selection behavior, and a next feasible downlink opportunity. The control contract K records the LoRaWAN version, regional parameters, device class, firmware, default and mandatory channels, supported mask commands, duty or dwell restrictions, gateway downlink capacity, monitoring hardware, clock synchronization, and logging boundary. An action outside K is infeasible even if it optimizes a radio score.

Observation also needs a boundary. Gateway packet metadata describe channels on which packets were successfully demodulated; they do not necessarily measure occupancy or interference on unchosen channels. Full channel sensing requires a calibrated receiver or monitor whose bandwidth, sampling schedule, detection threshold, coverage, and energy are documented. The policy must distinguish missing observation from a clean channel and must not infer the counterfactual response of an unobserved channel from RSSI alone.

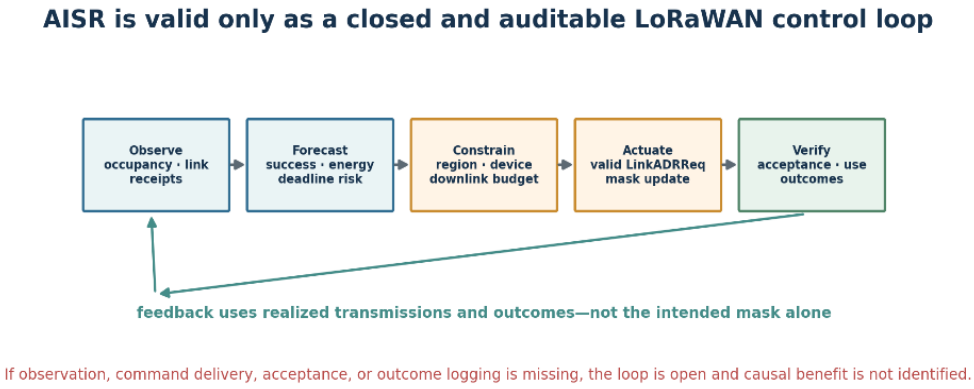


Fig. 1. Protocol-closed AISR loop.

Observation, forecasting, constraint screening, MAC actuation, and realized-outcome verification form one auditable cycle. A missing stage opens the loop and prevents a causal policy claim.

The harbor dataset in [31], [32] contains timestamps, device identity, location, and RSSI/SNR observations from three gateways for one mobile and two fixed nodes. The campaign used a stated physical configuration and is valuable for exploring temporal, spatial, device, and gateway variation. It does not record simultaneous outcomes on alternative channels, all generated messages and losses, MAC updates and acceptance, application delivery time, or current traces. It can support observation-model development and split design, but not a direct estimate of AISR policy value.

Table 2. Evidence boundary for the harbor record and an intervention trial.

Question	Harbor Record Supports	Intervention Evidence Required
Observed link variation	Exploratory RSSI/SNR variation by time, position, device, and receiving gateway.	Calibration, missing-reception treatment, held-out sessions, and monitoring coverage.
Alternative-channel response	Not identified from a fixed collection configuration.	Simultaneous sensing or randomized/probing actions with legal masks.
Packet benefit	Received records without a guaranteed generated-message denominator.	Application sequence IDs, all attempts, deduplicated receipts, retries, and deadlines.
Control execution	No complete command and acceptance trace.	Downlink opportunity, LinkADRReq fields, answer/acceptance, active-mask version, actual transmit channel.
Energy benefit	No complete device-current boundary.	Sensing, MCU, TX, RX windows, retries, command reception, and update energy.

4 | Adaptive Interference-Aware Spectrum Reallocation Decision Architecture

4.1 | Forecasts with Uncertainty

For candidate channel c and device i, a causal model estimates a lower-confidence packet-success probability $\underline{q}_i^{c,t}$, expected routine device energy $\hat{E}_i^{c,t}$, and expected end-to-end latency $\hat{L}_i^{c,t}$ over a forecast horizon H. Features use only observations available before t and include channel occupancy, recent delivery, RSSI/SNR summaries, data rate, power, payload, traffic, gateway diversity, device state, and time context. Calibration and prediction intervals are evaluated on held-out acquisition periods; point forecasts alone are insufficient for a controller that must abstain under uncertainty [33].

4.2 | Feasible Masks and Normalized Objective

Let $\pi_i^c(m_i)$ denote the implementation-specific probability that device i transmits on channel c under mask m_i. For joint mask m, one candidate robust objective is $\min_m \Sigma_i w_i\{\alpha[1 - \Sigma^c \pi_i^c(m_i) q_i^c(m)] + \beta \hat{E}_i(m)/E_0 + \gamma \hat{L}_i(m)/L_0\} + \lambda \Sigma_i C_u^{pdate}(m_i, m_{i,pr}^{ev})$. The weights are prespecified; E_0 and L_0 provide units; Cupdate includes incremental downlink airtime, receive-window energy, processing, and switching risk. Predictors depend on the joint action because concentrating devices on one channel may move rather than remove congestion.

The feasible set F_r contains only masks allowed by regional parameters, mandatory-channel rules, device capability, protocol state, and available downlink budget. Additional constraints can enforce minimum channel diversity, fairness, deadline-risk limits, and a maximum update rate. The controller sends an update only if its conservative expected advantage exceeds a hysteresis margin δ and the forecast remains valid through the expected control age.

4.3 | Control Age, Abstention, and Fallback

Define control age Δ_t^{tl} as the elapsed time from the final observation used by the decision to the first uplink actually affected by an accepted mask. It includes sensing, feature construction, inference, optimization, wait for a legal downlink, command delivery and acceptance, and wait for the next uplink. A policy optimized for horizon H must abstain when $\Delta_t^{tl} > H$ or when acceptance is uncertain. The active state changes only after logged acceptance; until then, the previous legal mask remains authoritative. A fallback mask preserves mandatory channels and service continuity.

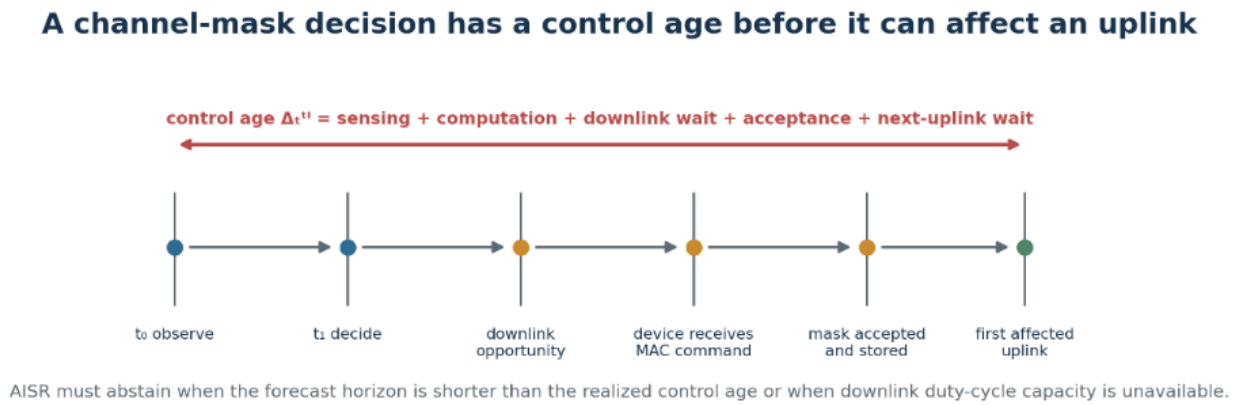


Fig. 2. Control age of a LoRaWAN mask update.

The decision cannot affect traffic until a valid downlink is received and accepted and a later uplink uses the new state.

The prospective algorithm is therefore: observe; timestamp and validate data; form causal features; forecast with uncertainty; enumerate legal masks; solve the robust objective; apply the hysteresis and control-age tests; transmit a valid command when capacity exists; verify acceptance; and score only subsequently affected traffic. Failed or stale updates are outcomes, not rows to be silently removed.

5 | Reproducible Evaluation

5.1 | Experimental Stages and Comparators

Stage A tests monitoring calibration and prediction without adaptation. Stage B conducts controlled counterfactual probing or replay in which alternative channels are observed under matched conditions. Stage C activates protocol-valid mask updates and logs their full lifecycle. Stage D repeats the study at an independent industrial site. Comparators are a fixed legal plan, the network server's configured ADR

behavior, a simple history-based legal-mask policy, and AISR. Published allocation families in [8–14] are added only when their observations and action authority can be made equivalent.

All policies receive the same offered traffic, channel conditions, sensing budget, gateway set, device firmware, retry behavior, and evaluation horizon. The ADR configuration, including margin and update fields, is archived. The experiment logs generated application IDs, actual uplink channel/data rate/power, every gateway receipt, network-server deduplication, acknowledgments, downlinks, mask versions, acceptance, deadlines, monitor samples, and synchronized current traces. Train, validation, and test periods are split by session or time block before feature scaling or model selection.

5.2 | Measures and Statistical Analysis

Packet-delivery ratio is the number of distinct generated messages delivered within the declared window divided by all generated messages. End-to-end latency runs from application generation to application delivery; undelivered messages and deadline misses are reported separately. Device energy is integrated over a declared boundary that includes sensing, MCU, transmit, receive windows, retries, and control, consistent with explicit LoRaWAN energy-model boundaries [34]. Goodput is delivered payload bits per time. Control overhead records command count, downlink airtime, acceptance, time to effect, failed updates, and incremental energy.

Repeated experiments report absolute outcomes, paired policy differences, uncertainty intervals, and failure cases. Time blocks or independent runs, rather than packets, are the resampling unit when temporal dependence is material. Calibration is assessed with reliability curves and proper scores [33]. Multiple algorithms are compared through predeclared omnibus and corrected pairwise procedures rather than isolated significance tests [35], [36]. Results are stratified by offered load, device count, mobility, channel occupancy, gateway diversity, distance, payload, and interference regime.

Table 3. Measures and raw material required to support them.

Measure	Operational Definition	Archived Material
Packet delivery	Distinct generated messages delivered within a stated window / all generated messages.	Generated IDs, attempts, gateway and server receipts, deduplication, deadlines, failures.
Latency and deadlines	Generation-to-application delivery distribution; misses and non-delivery separate.	Synchronized timestamps and application receipt log.
Device energy	Integrated joules per generated and delivered message at the stated boundary.	Current/power traces covering sensing, MCU, TX, RX, retries, and control.
Control efficacy	Accepted updates that become active; time-to-effect; paired post-update benefit.	Command fields, answers, mask versions, actual channels, control age.
Fairness and scalability	Per-device outcomes and degradation as devices and load increase.	Device-level metrics, load scenarios, compute, memory, and downlink ledger.
Net value	Radio/application benefit minus sensing, command, and switching cost.	Matched outcomes and every incremental resource term.

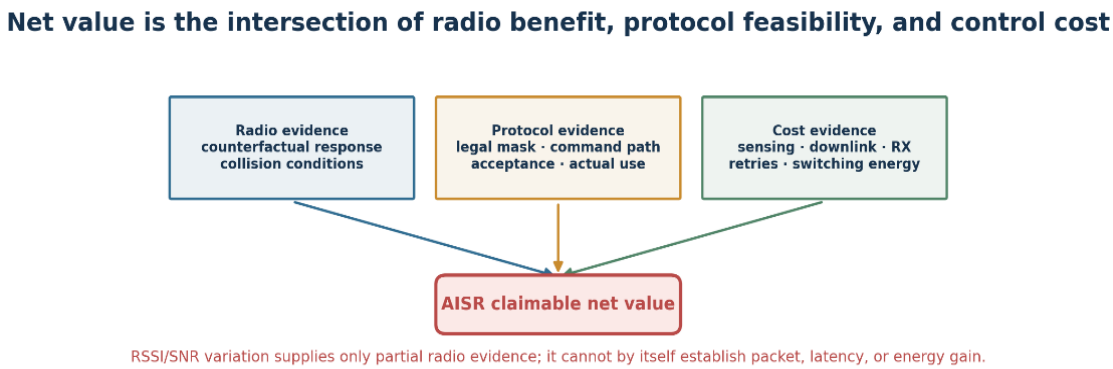


Fig. 3. Evidence intersection for an AISR claim.

Radio variation, protocol execution, and complete control cost must be observed together; any one component alone is insufficient.

5.3 | Ablation and Stress Testing

Ablations remove the predictor, lower-confidence bound, joint congestion term, update cost, hysteresis, and abstention rule separately. Stress tests vary external interference, burst duration, mobility, missing monitor samples, clock error, gateway downlink saturation, command loss, firmware heterogeneity, and sudden channel-regime shifts. An oracle with future knowledge may be shown only as an upper bound. The main comparison remains causal and must include monitoring and control latency.

Table 4. Prespecified failure modes and safe controller responses.

Failure Mode	Detectable Symptom	Required Response
Stale forecast	Realized control age exceeds forecast horizon.	Abstain; retain the active legal mask; refresh observation.
Unavailable downlink	Gateway airtime or receive-window opportunity absent.	Queue only within validity limit; otherwise cancel update.
Command rejection	Negative/missing acceptance or incompatible mask.	Keep previous state; log reason; remove infeasible action.
Monitor blind spot	Missing or uncalibrated channel observation.	Increase uncertainty; do not label absence as low interference.
Congestion displacement	Target channel deteriorates after coordinated moves.	Use joint predictions, diversity/fairness constraints, and rollback.
Model shift	Calibration or residual error exceeds guardrail.	Fall back to fixed/ADR policy and trigger retraining review.

6 | Interpretation, Security, and Deployment Boundaries

The source manuscript reported gains in packet delivery, latency, and energy without the missing result table, generated-message denominator, synchronized event traces, current measurements, simulator definition, or uncertainty intervals required to reproduce them. Those percentages are not retained as findings. Likewise, plots of unexplained scores under unrelated technical labels cannot stand in for the defined communication outcomes. The rebuilt manuscript preserves the architectural hypothesis while returning efficacy to an open empirical question.

Security belongs inside the control boundary. A forged monitor stream can make a healthy channel appear occupied; a modified channel mask can deny service; replayed acceptance can create false state; and compromised model or threshold files can bias allocation. Production studies should authenticate management traffic, version and sign models/configurations, record actor and timestamp for each state transition, rate-limit changes, and maintain a recoverable legal fallback. The controller must not disable mandatory channels or convert a monitoring optimization into an availability attack.

Industrial generalization also remains bounded. A harbor localization campaign demonstrates harsh-environment link variability but does not represent every factory layout, interference source, traffic mix, or regulatory region. Periodic telemetry results should not be narrated as closed-loop safety control. Independent site replication, long negative-exposure periods, maintenance behavior, gateway failure, and firmware diversity are necessary before deployment claims.

7 | Limitations and Research Program

AISR is not yet an implemented predictor, optimizer, firmware feature, or field-tested system. The mask-to-channel probability π_i^c depends on device behavior and must be measured. Counterfactual channel response

is only partially identifiable without randomized probing or simultaneous monitoring. Joint action optimization can become combinatorial at scale. Downlink scarcity can dominate any radio advantage, while monitoring energy may lie outside the end-device budget but still inside the system boundary.

The strongest next program has four linked studies. First, reproduce the harbor observation analysis with session-wise splits and calibrated forecasts, making no policy claim. Second, construct a controlled multi-channel testbed with attempted-message, monitor, MAC, and current traces. Third, evaluate fixed, ADR, history-based, published channel-allocation, and AISR policies under identical authority and load. Fourth, repeat a frozen controller at an independent industrial site. Each stage should preserve raw events, configuration, code, seeds, firmware hashes, and table-generation scripts so later evidence extends rather than replaces the earlier record.

8 | Conclusion

AISR is recast as a protocol-closed controller rather than an unconstrained channel-ranking algorithm. A valid decision requires observable alternatives, causal and calibrated forecasts, a region- and device-legal mask, a deliverable MAC command, explicit acceptance, actual use of the new state, and a net application benefit after sensing and control cost. Control age, abstention, hysteresis, fallback, and an event-level audit trail connect these requirements into a testable architecture. The cited harbor data can support link-variation analysis but cannot establish counterfactual delivery, latency, or energy gains. Those claims require a new intervention record or a calibrated simulator followed by independent field validation. The paper therefore offers a rigorous route to evidence while leaving performance superiority deliberately unresolved.

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Author Contributions

R. R. A.: Conceptualization, methodology, investigation, and writing—original draft.

M. H.: Technical analysis, theoretical development, and critical review.

Kh. S.: Supervision, validation framework, and writing—review and editing.

All authors reviewed and approved the final manuscript.

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Data Availability

The data supporting this study include previously published research and an existing harbor RSSI/SNR localization dataset. No new experimental dataset was generated. The limitations of the available dataset and the requirements for further validation are discussed in the manuscript.

Conflicts of Interest

The authors declare that they have no financial, professional, or personal conflicts of interest that could have influenced the research, its interpretation, or the publication of this article.

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