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Adaptive Channel Coding with Semantic-Aware Error Protection for 6G Non-Terrestrial Networks

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Abstract

Non-terrestrial networks (NTNs) — comprising low-Earth-orbit (LEO) satellites, high-altitude platform stations (HAPS), and unmanned aerial vehicles (UAVs) — are increasingly regarded as a foundational layer of sixth-generation (6G) wireless systems, extending connectivity to rural, maritime, and disaster-affected regions that remain beyond the economic reach of terrestrial infrastructure. NTN links, however, present a uniquely hostile channel environment: long and time-varying propagation delay, large Doppler shifts induced by high relative platform velocity, deep fades from atmospheric and rain attenuation, and severe constraints on onboard power and computation. Conventional fixed-rate or classically-adaptive channel coding schemes, which react only to instantaneous signal-to-noise ratio (SNR), are poorly matched to this environment: they either over-provision redundancy, wasting scarce bandwidth and energy, or under-provision it and trigger the so-called cliff effect, in which a small SNR drop causes catastrophic decoding failure. In this paper we propose semantic-aware adaptive channel coding (SA-ACC), a framework that couples semantic importance estimation with rate- and redundancy-adaptive coding so that error-protection resources are allocated according to the task-relevant meaning of transmitted content rather than uniformly across all bits. We formalize the system model for a representative NTN scenario — a LEO downlink relayed through a HAPS node — define a semantic importance metric derived from task-gradient sensitivity, and design a two-stage adaptation control loop that jointly selects code rate, modulation order, and per-feature protection level under explicit delay and energy budgets. We further specify a complete evaluation methodology, comparing SA-ACC against fixed-rate LDPC/polar coding, conventional adaptive coding and modulation (ACM), and non-semantic deep joint source-channel coding (JSCC) across bit error rate, block error rate, semantic fidelity, throughput, latency, and energy metrics, and use this methodology to reason about SA-ACC's expected behavior ahead of full numerical validation. Our architectural analysis indicates that SA-ACC should be able to sustain task-relevant reconstruction quality at lower effective SNR than baselines optimized purely at the bit level, at the cost of additional encoder and decoder complexity that we discuss explicitly. We close by outlining the simulation and ablation study required to convert this design-and-methodology contribution into a fully validated result.

1. Introduction

1.1 Motivation

The shift from generation (5G) to sixth generation (6G) wireless systems is expected to formally bring in non-terrestrial platforms. Satellites, HAPS and UAVs. As top parts of the radio access network instead of just a backup for coverage gaps [3, 5]. The International Telecommunication Union's IMT-2030 framework calls out everywhere connectivity, supported by NTN integration as a 6G feature [3]. This change is already visible in the market: LEO constellations such as Starlink, OneWeb and Kuiper are growing fast. Direct-to-device satellite services from big mobile operators have gone from pilot to commercial rollout in the last two years [1, 6]. Reliable communication over NTN links however stays harder than, over terrestrial links. Following four characteristics dominate: Reliable communication over

NTN links, however, remains fundamentally harder than over terrestrial links. Four characteristics dominate:

1. **Long and variable propagation delay.** Even LEO links introduce tens of milliseconds of one-way delay, and delay varies continuously as the platform moves through its pass, complicating closed-loop adaptation schemes that assume near-instant channel state feedback.
2. **Large Doppler shifts.** A LEO satellite at ~ 600 km altitude moving at ~ 7.5 km/s induces Doppler shifts on the order of tens to hundreds of kHz depending on frequency band — one to two orders of magnitude larger than typical terrestrial mobile Doppler [97].
3. **Deep and correlated fades.** Rain attenuation, atmospheric scintillation, and shadowing from platform geometry produce fades that are both deeper and longer-correlated than typical terrestrial multipath fading.
4. **Constrained onboard resources.** Satellites and HAPS operate under strict power, mass, and thermal budgets, limiting the complexity of onboard coding and processing that can be deployed, particularly for regenerative (as opposed to transparent) payloads.

Classical channel coding — fixed-rate forward error correction (FEC) such as LDPC, turbo, or polar codes — is either over-conservative (wasting throughput when conditions are good) or brittle (failing catastrophically when conditions degrade below the design point). Adaptive coding and modulation (ACM), long used in DVB-S2 and subsequent satellite broadcast standards, mitigates this by switching among a discrete set of code rate/modulation pairs based on estimated channel quality [22, 25, 43]. However, ACM treats all transmitted bits as equally important: a corrupted bit in a semantically critical region of an image, sensor reading, or control message is penalized identically to a corrupted bit in a perceptually or task-irrelevant region.

Semantic communication has emerged over the past several years as a paradigm shift that targets the *meaning* or *task relevance* of transmitted content rather than its exact bit-level reconstruction [57, 61]. Deep joint source-channel coding (JSCC) approaches demonstrate that neural encoder-decoder pairs trained end-to-end can avoid the cliff effect that plagues separated source-channel coding, degrading gracefully as SNR drops rather than failing abruptly [68]. Extensions that explicitly weight features by task-relevant semantic importance show substantial gains in downstream task performance under bandwidth and channel constraints [72].

Despite this progress, the intersection of semantic-aware coding and the specific reliability challenges of NTN channels remains comparatively underexplored. A small number of very recent works (2025–2026) have begun to address semantic communication specifically within NTN contexts [86, 87], but — to the best of our knowledge — none proposes a concrete, jointly-optimized adaptive coding *mechanism* that couples semantic importance estimation with rate/redundancy adaptation under the specific delay, Doppler, and energy constraints of NTN links. This is the gap this paper addresses.

1.2 Contributions

This paper makes the following contributions:

1. We formalize a system model for semantic-aware adaptive channel coding in a representative NTN scenario (LEO downlink with optional HAPS relay), explicitly incorporating propagation delay, Doppler-induced SNR variation, and onboard energy constraints into the adaptation problem (§ 4).

2. We define a semantic importance metric for NTN payloads (imagery, sensor data, or control messages) based on task-gradient sensitivity, extending prior semantic-importance JSCC work [72] to the NTN setting (§ 5.2).

3. We design the SA-ACC adaptation control loop, which jointly selects code rate, modulation order, and per-feature semantic protection level subject to a latency and energy budget, and provide pseudocode for the adaptation algorithm (§ 5.3–5.4).

4. We define a comprehensive evaluation methodology — metrics, baselines, and simulation scenarios — for validating SA-ACC against fixed-rate coding, conventional ACM, and non-semantic deep JSCC (§ 6).

5. We provide a structured, falsifiable set of pre-simulation predictions grounded in the mechanism design and prior literature, and identify the specific simulation studies required to convert these predictions into publishable quantitative results, which we outline as immediate future work (Sections 7–8).

This paper extends our earlier work on adaptive coding for constrained wireless links [AUTHOR-CITE] by moving from purely channel-reactive adaptation to a jointly channel- and content-aware formulation suited to the delay and Doppler characteristics of NTN specifically. *(Full citation to be inserted once prior-work details are confirmed by the author.)*

1.3 Paper Organization

The rest of this paper is laid out in the way. Section 2 reviews related work that covers NTN architectures, channel coding for satellite links, adaptive coding and modulation semantic communication and how these areas connect. Section 3 shows the system model. Section 4 explains channel and mobility modeling that's specific to NTN. Section 5 presents the proposed SA-ACC framework. Section 6 describes the evaluation methodology that was built to validate SA-ACC. Section 7 discusses the expected behavior of SA-ACC with respect to this methodology before numerical validation. Section 8 highlights limitations. Section 9 wraps up with suggestions, for work.

2. Related Work

2.1 NTN Architectures for 5G/6G

Non-terrestrial networks bring together satellites of types GEO, MEO and more and more LEO, high-altitude platforms (HAPS) and unmanned aerial vehicles (UAVs) into an architecture that sits next to

normal ground infrastructure. This layered architecture is often called a space-air-ground integrated network or SAGIN [11, 12]. Recent studies show how this space-air-ground integrated network is moving toward 6G and they point out that software-defined and AI-native control planes will be needed to manage how non-terrestrial networks share resource allocation, between space, air and ground segments in time [13, 14]. HAPS in particular have drawn renewed attention as an intermediate layer bridging the coverage/latency trade-off between LEO satellites and terrestrial base stations, with recent work exploring HAPS-UAV cooperative architectures for both connectivity and integrated sensing [1].

A recurring theme across this literature is that NTN integration is not merely a coverage extension but requires fundamental re-engineering of physical- and link-layer mechanisms — synchronization, random access, and channel coding — that were designed under terrestrial delay and Doppler assumptions [2]. This motivates the physical-layer focus of the present paper.

2.2 Channel Coding for Satellite/NTN Links

Forward error correction for satellite links has a long history rooted in DVB-S2 and its successors, which standardized LDPC codes concatenated with BCH outer codes and, later, adaptive coding and modulation (ACM) to exploit favorable channel conditions [25]. Polar codes, adopted for 5G NR control channels, have since been proposed and analyzed for satellite and 6G contexts due to their capacity-achieving property and comparatively simple successive-cancellation decoding [32, 33]. Several works compare LDPC and polar code performance specifically under satellite channel conditions, including long propagation delay and Doppler-induced fading, generally finding complementary strengths: LDPC decoding parallelizes well, while polar decoding offers lower latency at short-to-moderate block lengths [39, 40]. Generalized code structures that hybridize LDPC and polar components (e.g., GLDPC-PC) have been proposed explicitly with 6G requirements in mind [31].

2.3 Adaptive Coding and Modulation (ACM)

Rate-adaptive coding for time-varying satellite channels predates the semantic communication literature by well over a decade. Early work established statistical channel-state-information-based adaptation to avoid the feedback overhead and delay-sensitivity of instantaneous CSI-based schemes, which are particularly problematic given satellite round-trip times [21, 43]. Standardized ACM for DVB-S2/DVB-RCS selects among a discrete set of modulation-and-coding pairs based on estimated channel quality indicator feedback [25]. More recent work replaces hand-tuned threshold-based MCS selection with reinforcement-learning (RL) agents that learn the SNR-to-MCS mapping directly from interaction with the channel, showing gains particularly under outdated or noisy CSI — a condition endemic to NTN links given their propagation delay [47, 52]. These RL-based approaches inform the adaptation-loop design in Section 5.3, though none of the surveyed work incorporates semantic importance as an adaptation signal.

2.4 Semantic Communication Foundations

Semantic communication reframes the communication objective from exact bit-level reconstruction (Shannon's classical framework) to accurate recovery of task-relevant *meaning* [57]. Deep-learning-based approaches, typically structured as trainable encoder-decoder pairs with a differentiable channel model in between, have been demonstrated across text (DeepSC), speech (DeepSC-ST), and image modalities [57, 59]. Recent surveys group this research into source and channel coding, resource allocation and multi-modal extensions. They always point out the cliff effect. The drop in quality when the SNR is below a certain level. As the main problem, with traditional source-channel coding. This is the issue that semantic JSCC methods are designed to fix [61, 64].

2.5 Joint Source-Channel Coding and Task-Oriented Communication

The use of communication in NTN scenarios is a new area that is growing quickly. Recent studies suggest that the special problems of NTN. Bandwidth deep signal drops and limited resources on board. Fit very well with what semantic communication can offer: strong focus on important tasks when compressing data, good performance even when signal strength is low and the ability to create good results from very little information that survives the signal issues [87]. Specific studies have looked at communication for sending images from low Earth orbit satellites when there is not enough bandwidth [88] using semantic awareness in O-RAN systems, for NTN [89] and creating video from satellites even when there are a lot of errors [92].

2.6 Semantic Communication in Non-Terrestrial Networks

The application of semantic communication specifically to NTN scenarios is a nascent but rapidly growing subarea. Recent work argues that NTN's characteristic constraints — bandwidth scarcity, deep fades, and onboard resource limits — are unusually well matched to what semantic communication offers: aggressive task-relevant compression, JSCC's graceful SNR degradation, and (increasingly) generative reconstruction from sparse cues that survive fading [87]. Application-specific studies have explored semantic communication for LEO Earth-observation downlink under bandwidth constraints [88], semantic-aware O-RAN integration for NTN [89], and generative semantic communication for satellite video under high error rates [92].

Positioning relative to closest prior work. A comprehensive 2026 survey [87] covers architectures, methodologies, and open challenges across semantic communication in NTN at a broad level, and should be read as the most directly related prior publication to the present paper. Where that survey maps the landscape, the present paper narrows in on a single, concrete question within it: how should the mapping from semantic importance to error protection change as the channel itself changes predictably across a satellite pass? SA-ACC answers this with a jointly-optimized coding mechanism — pairing semantic importance estimation with code-rate and modulation adaptation under an explicit delay and energy budget — together with a defined evaluation methodology for validating it, which the survey identifies as an open direction but does not itself propose.

2.7 Gap Statement

Synthesizing the above, three gaps motivate this paper: (i) classical ACM for NTN adapts to channel SNR but not to content-level semantic importance, wasting redundancy on task-irrelevant bits; (ii) semantic/JSCC approaches address the cliff effect and task relevance but have largely been validated on terrestrial or generic wireless channels, not under NTN-specific delay, Doppler, and energy constraints; and (iii) the small existing body of NTN-specific semantic communication work is predominantly architectural/survey-level rather than proposing and specifying an adaptive coding mechanism with a defined evaluation protocol. SA-ACC is designed to close this three-way gap.

Table 2
Distribution of the reviewed literature (106 sources, 2010–2026) across sub-areas and primary venue.

Sub-area (§)	**Ref. range**	**Count**	**Dominant venue(s)**
NTN architectures (2.1)	[1]–[20]	20	IEEE, Springer
Channel coding for satellite/NTN (2.2)	[21]–[42]	22	IEEE, MDPI
Adaptive coding & modulation (2.3)	[43]–[56]	14	IEEE
Semantic communication foundations (2.4)	[57]–[67]	11	IEEE
JSCC / task-oriented communication (2.5)	[68]–[85]	18	IEEE, MDPI, Elsevier
Semantic communication in NTN (2.6)	[86]–[93]	8	IEEE, Elsevier
6G physical layer: reliability/Doppler (2.7 background)	[94]–[106]	13	IEEE, MDPI
Total	[1]–[106]	**106**	—

3. System Model

3.1 Scenario

We consider a representative NTN downlink scenario consisting of a LEO satellite transmitting to ground user equipment (UE), optionally relayed through a HAPS node acting as an intermediate regenerative or transparent relay (Fig. 1). This scenario is chosen because it exercises the full set of NTN-specific channel impairments — long delay, large Doppler, deep fades — while remaining representative of near-term commercial 6G-NTN deployment patterns (direct-to-device LEO connectivity, with HAPS as an emerging complementary layer) [1].

Figure 1. *System architecture: LEO satellite, HAPS relay, and ground UE, showing the SA-ACC encoder at the transmitter, semantic-aware decoder at the receiver, and the feedback path carrying channel-state and semantic-relevance signaling back to the adaptation controller.*

3.2 Notation

Table 1
Notation and parameters.

Symbol	Description	Typical range / units
$h(t)$	Complex channel gain at time t	—
$\gamma(t)$	Instantaneous received SNR	dB
$f_D(t)$	Doppler shift at time t	kHz
τ	One-way propagation delay	ms
R_c	Channel code rate	1/3–8/9
M	Modulation order	2 (BPSK) – 64 (64-QAM)
s_i	Semantic importance weight of feature i	[0,1]
B	Available channel bandwidth	MHz
E_{tx}	Transmit energy budget per frame	J
L_{max}	End-to-end latency budget	ms
Q_{task}	Task-level reconstruction/inference quality metric	task-dependent

3.3 Semantic Communication Pipeline

The transmitter pipeline consists of: (i) a semantic encoder E_θ that maps source data x to a latent semantic representation $z = E_\theta(x)$; (ii) a semantic importance estimator that computes per-feature importance weights $s = \{s_i\}$ (Section 5.2); (iii) an adaptive channel encoder that maps (z, s) to channel symbols under a selected code rate R_c and modulation order M, allocating unequal error protection according to s; and (iv) transmission over the NTN channel. The receiver performs the inverse mapping, with a semantic decoder D_φ reconstructing either the source data itself (for reconstruction-oriented tasks) or a task-specific output (for inference/control-oriented tasks), depending on deployment.

3.4 Channel Model

The NTN channel combines large-scale path loss, Doppler-induced frequency offset, and small-scale fading with a Rician or shadowed-Rician model appropriate to the LOS-dominant character of satellite links [97]. The received signal at time t is modeled as (1),

$$y(t) = h(t) \cdot e^{j2\pi f D(t) t} \cdot x(t) + n(t) \qquad (1)$$

where $h(t)$ captures large- and small-scale fading, $f_D(t)$ is the time-varying Doppler shift driven by satellite ephemeris and ground-user geometry, $x(t)$ is the transmitted signal, and $n(t)$ is additive white Gaussian noise. Doppler shift magnitude for a LEO satellite at ~ 600 km altitude reaches tens to hundreds of kHz depending on carrier frequency band, roughly one to two orders of magnitude larger

than typical terrestrial mobile Doppler [97, 42]. § 4 details the specific Doppler and delay model adopted for simulation.

4. Channel and Mobility Modeling

4.1 Propagation Delay and Doppler Dynamics

For a LEO satellite in a circular orbit at altitude h_{sat}, the one-way propagation delay and Doppler shift vary continuously across a pass as a function of elevation angle $\theta(t)$, following standard orbital-geometry relations for the satellite–ground path length and its rate of change; we adopt the ephemeris-based formulation used in prior LEO downlink Doppler-compensation work [42] as the basis for our model. This time variation is central to the adaptation problem: unlike a terrestrial mobile channel, where Doppler is driven by comparatively slow and largely unpredictable user mobility, NTN Doppler is driven by fast but *predictable* platform motion. SA-ACC is designed to exploit this predictability through ephemeris-aware pre-compensation rather than purely reactive estimation, consistent with recent Doppler pre-compensation literature [99].

4.2 Fading and Shadowing

We model fading in this scenario using a shadowed-Rician distribution, which is well established as an appropriate representation of the line-of-sight-dominant, occasionally shadowed character of LEO and HAPS links [97]. The Nakagami and Rician limiting cases of this model allow it to represent both clear-sky and shadowed conditions within a single parametric family, which we use to sweep across representative NTN operating conditions in the simulation plan of Section 6.

4.3 Energy and Latency Budget Model

Onboard energy for a regenerative payload is modeled as a per-frame budget E_{tx} constraining the achievable transmit power and, indirectly, the sustainable code rate. The end-to-end latency budget L_{max} combines propagation delay τ, encoding/decoding processing time, and any HARQ retransmission overhead, and is treated as a hard constraint for latency-sensitive traffic classes (e.g., control messages) and a soft, quality-traded constraint for delay-tolerant traffic (e.g., Earth-observation imagery).

5. Proposed Method: Semantic-Aware Adaptive Channel Coding (SA-ACC)

5.1 Architecture Overview

Figure 2. *SA-ACC encoder–decoder pipeline: semantic encoding, importance estimation, and unequal-error-protection channel encoding at the transmitter; channel decoding and semantic decoding at the receiver; with the feedback path (CQI estimate, decode status) closing the loop back to the adaptation controller.*

SA-ACC extends the semantic-importance JSCC principle [72] by making the mapping from semantic importance to error protection *adaptive* to instantaneous and predicted channel conditions, rather than fixed at training time. This is the central methodological contribution: existing semantic-importance JSCC work fixes the protection allocation policy after training, whereas NTN channels vary too rapidly and too predictably (via known ephemeris) for a fixed policy to be optimal across an entire satellite pass.

5.2 Semantic Importance Estimation

Following [72], we compute the importance of encoded feature *i* as the magnitude of the gradient of a downstream task loss *L_task* with respect to that feature, as in (2),

$$si = \| \partial Ltask / \partial zi \| \quad (2)$$

normalized to [0,1] across the feature set. For reconstruction-oriented deployments (e.g., Earth-observation imagery where a human or downstream vision model consumes the reconstructed image), *L_task* is a perceptual or task-specific loss (e.g., a pretrained object-detection or classification loss evaluated on the reconstruction) rather than raw pixel MSE, consistent with evidence that MSE-optimized JSCC underperforms perceptually- or semantically-weighted variants at low SNR [74]. For control/inference-oriented deployments (e.g., telemetry or sensor data feeding an onboard or ground autonomy stack), *L_task* is the loss of the downstream control/inference model itself, in the spirit of task-oriented communication [82].

5.3 Adaptation Control Loop

The adaptation controller selects, per transmission frame, a code rate *R_c*, modulation order *M*, and a semantic protection profile *π(s)* — an allocation of unequal error protection strength across importance-weighted feature groups — by solving the constrained optimization in (3),

$$\max(Rc, M, \pi)\ Qtask(Rc, M, \pi \mid \gamma, fD) \text{ s.t. } Etx \le Ebudget, L \le Lmax \quad (3)$$

where *Q_task* is the expected task-level quality achievable under the current (or ephemeris-predicted near-future) channel state *(γ, f_D)*. Because exhaustive search over *(R_c, M, π)* is infeasible at frame timescale, we adopt a two-stage controller that approximates (3): (i) a coarse channel-quality-to-MCS mapping analogous to conventional ACM, updated at the pace of channel coherence time, informed additionally by ephemeris-predicted Doppler/SNR trajectory rather than purely reactive CQI feedback; and (ii) a fast semantic-protection allocator that redistributes redundancy across feature groups within the coding budget fixed by stage (i), updated per-frame based on the current content's importance distribution *s* from (2).

Figure 3. *Flowchart of the two-stage adaptation control loop: slow, channel/ephemeris-driven MCS selection (Stage 1) followed by fast, per-frame semantic importance estimation and protection allocation (Stage 2), closing with receiver feedback into the next frame's adaptation decision.*

5.4 Adaptation Algorithm (Pseudocode)

Algorithm 1

restates the two-stage control loop of Section 5.3 as an explicit procedure. The algorithm is split into two named subroutines that mirror the two adaptation timescales: CoarseMCSSelect, which runs slowly — once per channel coherence interval — and reacts to the ephemeris-predicted channel trajectory rather than a single instantaneous estimate; and FastSemanticAllocate, which runs once per transmission frame and distributes the redundancy budget fixed by the coarse stage according to the semantic importance of the current frame's content, computed via (2). The main loop simply calls the fast stage every frame and the coarse stage only when the coherence timer expires, so the two update rates never interfere with one another. Line numbers in the discussion below (e.g., L9–L12) refer to Algorithm 1.

Algorithm 1 SA-ACC Two-Stage Adaptation Loop

Require: channel estimate γ(t); ephemeris-predicted Doppler f_D(t);
energy budget E_budget; latency budget L_max;
coherence interval T_coh
Ensure: reconstructed output $\hat{x}$ (or task output) at the receiver,
for each transmitted frame x

1: procedure CoarseMCSSelect(γ(t), f_D(t)) ▷ slow stage, §5.3(i)
2: γ_pred ← PredictChannel(γ(t), f_D(t)) ▷ ephemeris-based
3: (R_c, M) ← argmax of (3) over the (R_c, M) grid,
4: evaluated at γ_pred subject to E_budget, L_max
5: return (R_c, M)
6: end procedure
7:
8: procedure FastSemanticAllocate(x, R_c, M) ▷ fast stage, §5.3(ii)
9: z ← SemanticEncoder(x) ▷ z = E_θ(x)
10: for each feature i in z do
11: s_i ← ‖ ∂L_task/∂z_i ‖ ▷ Eq. (2)
12: end for
13: s ← Normalize({s_1, …, s_n}) to [0,1]
14: π ← AllocateProtection(s, R_c, M) ▷ solves (3) for π
15: return (z, π)
16: end procedure
17:
18: ── Transmitter main loop ──
19: (R_c, M) ← CoarseMCSSelect(γ(t), f_D(t)) ▷ initialize, L1–L6
20: timer ← 0
21: for each outgoing frame x do
22: (z, π) ← FastSemanticAllocate(x, R_c, M) ▷ every frame, L8–L16

23: y ← ChannelEncode(z, π, R_c, M)
24: Transmit(y)
25: if timer ≥ T_coh then ▷ coherence timer elapsed
26: (R_c, M) ← CoarseMCSSelect(γ(t), f_D(t)) ▷ re-run slow stage
27: timer ← 0
28: end if
29: timer ← timer + 1
30: end for
31:
32: ── Receiver, per received frame ──
33: $\hat{y}$ ← Receive()
34: $\hat{z}$ ← ChannelDecode($\hat{y}$, π, R_c, M)
35: $\hat{x}$ ← SemanticDecoder($\hat{z}$) ▷ $\hat{x}$ = D_φ($\hat{z}$)
36: feedback ← (EstimateCQI($\hat{y}$), DecodeSuccess($\hat{y}$))
37: SendToTransmitter(feedback) ▷ closes loop, Fig. 3
38: return $\hat{x}$
———

Two design choices in Algorithm 1 are worth calling out explicitly, since they are easy to miss on a first read. First, the coherence timer at L25–L28 is what keeps the two stages from fighting each other: CoarseMCSSelect fixes the redundancy budget that FastSemanticAllocate is only ever allowed to *redistribute*, never expand, so a frame-rate semantic re-allocation can never accidentally destabilize the slower channel-tracking loop. Second, the receiver's feedback message at L36 carries both a channel-quality estimate and a binary decode-success flag rather than either alone; the coarse stage consumes the former, while a decode failure alone is sufficient to trigger a timer reset at L25 even before *T_coh* formally elapses, letting the controller react immediately to an unexpected channel excursion rather than waiting out the nominal coherence interval.

5.5 Complexity and Onboard Feasibility Considerations

Because FastSemanticAllocate (L8–L16) must execute within the latency budget on potentially resource-constrained onboard hardware — for a regenerative satellite or HAPS payload — or on ground-station/UE hardware, for a transparent payload where the semantic encoder resides at the ground segment, we anticipate that the importance-estimation step at L10–L12, a per-feature gradient computation, will be the dominant additional cost relative to conventional ACM. This cost is plausibly amortizable through lightweight importance-prediction networks distilled from the full gradient computation, an approach used in adjacent semantic-importance JSCC work [72]. Concrete complexity and latency figures for this step depend on the target onboard hardware profile and are among the quantities the simulation study in Section 6 is designed to produce.

6. Performance Metrics and Evaluation Setup

6.1 Metrics

• **Bit error rate (BER) and block error rate (BLER)** — conventional physical-layer reliability metrics, retained for direct comparability with classical FEC and ACM baselines.

• **Semantic fidelity / task accuracy** — reconstruction-oriented deployments use a perceptual similarity metric (e.g., LPIPS or a task-specific feature-similarity score) rather than raw PSNR/MSE, consistent with evidence that pixel-level metrics do not track task-relevant quality under aggressive compression [74]; inference/control-oriented deployments use downstream task accuracy or control-loop success rate directly.

• **Throughput** — effective information rate delivered under the adaptation policy, accounting for retransmissions.

• **Latency** — end-to-end delay from source frame availability to receiver reconstruction/decision, including propagation delay.

• **Energy** — transmit energy per successfully delivered task-relevant unit of information (a semantic-aware analogue of energy-per-bit).

6.2 Baselines

1. **Fixed-rate LDPC/polar coding** — A static code rate that is chosen for the worst-case design signal-to-noise ratio. This is similar to the satellite forward error correction.

2. **Conventional ACM** — A method that selects modulation and coding schemes based on the signal-to-noise ratio without using weighting. This is typical of DVB-S2 type systems [25].

3. **Non-semantic deep JSCC** — A learning encoder and decoder that is trained without giving more protection to important features. It provides the level of protection to all parts [68].

4. **(Ablation) SA-ACC without ephemeris prediction** — This version only adapts to the channel reactively. It helps to see how much the ephemeris prediction adds beyond the weighting.

5. **(Ablation) SA-ACC without semantic weighting** — his version becomes an adaptive JSCC that protects all parts equally. It shows how much semantic importance contributes when the rate control adapts.

Table 3
Baseline and ablation methods summary.

Method	Rate adaptation	Semantic weighting	Ephemeris-aware	Representative prior work
Fixed-rate LDPC/polar	No	No	No	[30], [35]
Conventional ACM	Yes (reactive)	No	No	[25], [43]
Non-semantic deep JSCC	Partial	No	No	[68], [78]
SA-ACC w/o ephemeris (ablation)	Yes (reactive)	Yes	No	—
SA-ACC w/o semantic weighting (ablation)	Yes	No	Yes	—
SA-ACC (full, proposed)	**Yes**	**Yes**	**Yes**	—

6.3 Simulation Scenarios

• **Scenario A — LEO direct-to-device, Earth-observation imagery downlink.** Bandwidth-constrained, delay-tolerant; evaluates semantic fidelity vs. coding rate trade-off.

• **Scenario B — LEO-HAPS relay, control/telemetry uplink.** Latency-sensitive, small-payload; evaluates BLER and latency under URLLC-like constraints [102].

• **Scenario C — Full-pass Doppler sweep.** A satellite pass from horizon to horizon, evaluating adaptation responsiveness as elevation angle (and thus Doppler and SNR) varies continuously.

Table 4
Simulation scenario parameters (values to be finalized during implementation; representative ranges shown).

Parameter	Scenario A (Earth obs.)	Scenario B (telemetry)	Scenario C (full pass)
Orbit altitude	~ 550–600 km (LEO)	~ 550–600 km (LEO) + HAPS at ~ 20 km	~ 550–600 km (LEO)
Elevation angle range	20°–90°	20°–90°	5°–90° (horizon-to-horizon)
Carrier frequency band	Ku/Ka-band	S/Ka-band	Ku/Ka-band
Payload type	Multi-band imagery	Telemetry / control vectors	Mixed
Latency budget *L_max*	Delay-tolerant (seconds)	Strict (tens of ms)	Variable across pass
Primary metric	Semantic fidelity vs. rate	BLER, latency	Throughput vs. elevation
Doppler regime	Full range across pass	Full range across pass	Full range, continuously swept

6.4 Statistical Validation Plan

At every SNR–Doppler operating point the proposed scheme and the baseline methods must be tested across hundred independent channel realizations. This will give performance estimates that're statistically reliable. Show the results as performance and include suitable confidence intervals. The importance of the gains that SA-ACC shows over each baseline can be checked with paired tests. A paired t-test or the Wilcoxon signed-rank test can be used, depending on what the data look like. Using the channel realizations, for all the schemes makes the comparison fair and consistent. This statistical analysis is a part of the simulation method and it should be finished as part of the overall validation of performance (see Section 8).

7. Expected Behavior and Pre-Simulation Analysis

We have not yet run the simulation study specified in Section 6, and we want to be explicit about that up front: none of the curves in this section are measured results. What we present instead is a structured, mechanism-grounded analysis of how we expect SA-ACC to behave once that study is run, reasoned from the design of the adaptation loop (Section 5) and from the reported behavior of the closest related mechanisms in the literature (Section 2). We use this analysis to motivate why the evaluation methodology in Section 6 is the right one, and to state falsifiable predictions that the simulation phase should confirm or overturn. Figures 4–7 are illustrative sketches of these predictions, not simulation output, and are labeled as such throughout.

7.1 Expected BER/BLER Behavior vs. SNR

The central mechanism-level claim behind SA-ACC is that decoupling error protection from a single scalar SNR threshold — and instead distributing it according to semantic importance — should soften the cliff effect that fixed-rate coding exhibits and that conventional ACM only partially avoids. Deep JSCC architectures are already reported in the literature to degrade gracefully rather than catastrophically as SNR drops [68], and semantic-importance weighting has separately been shown to improve task-relevant outcomes under a fixed bit budget [72]. SA-ACC combines both mechanisms, so we expect it to inherit the graceful-degradation property of JSCC while additionally outperforming a non-semantic JSCC baseline specifically in the SNR region where the redundancy budget is tight enough that *where* protection is spent starts to matter. Figure 4 sketches this expected qualitative shape.

Figure 4. *Expected qualitative BLER-vs-SNR behavior for SA-ACC against the three primary baselines, Scenario A. This is an illustrative sketch of the predicted trend, reasoned from the mechanism design and the cited prior work — it is not simulation output. The prediction to be tested is that SA-ACC and non-semantic JSCC both avoid the sharp knee visible in fixed-rate coding, and that SA-ACC separates from non-semantic JSCC in the low-to-mid SNR range specifically on semantically critical content.*

7.2 Expected Semantic Fidelity vs. Coding Rate

The paper's core claim rests less on raw BLER than on task-relevant semantic fidelity at a given coding rate — this is the comparison we consider most important to run first once simulation begins. Because SA-ACC concentrates protection on high-importance features rather than spreading it uniformly, we expect its fidelity-vs-rate curve to sit above a non-semantic JSCC baseline at low-to-moderate rates, where the choice of *what* to protect matters most, with the gap narrowing as the rate increases and redundancy becomes abundant enough that uniform protection is no longer a meaningful handicap.

Figure 5. *Expected task-relevant semantic fidelity vs. effective coding rate, Scenario A — an illustrative prediction, not simulation output. We treat this comparison as the priority result to obtain once the simulation environment (*Section 6*) is implemented, since it most directly tests the paper's central claim.*

7.3 Expected Throughput Behavior Across a Satellite Pass

Because NTN Doppler is driven by predictable orbital motion rather than random user mobility, we expect the ablation that removes ephemeris-aware prediction (reactive-only adaptation) to lag the full SA-ACC controller specifically during the fast-changing portions of a pass — near acquisition and loss of signal at low elevation angles — where a purely reactive controller's channel estimate is systematically stale by the time it acts. We expect the two variants to converge near peak elevation, where Doppler and SNR change slowly enough that reactive estimation is no longer a meaningful handicap.

Figure 6. *Expected throughput across a full satellite pass (elevation angle as a time proxy), Scenario C, comparing ephemeris-aware vs. reactive-only adaptation. Illustrative prediction, not simulation output.*

7.4 Expected Energy Efficiency

Energy per successfully delivered semantic unit folds together two effects we expect to compound in SA-ACC's favor: fewer retransmissions from avoiding the cliff effect, and less redundancy spent on task-irrelevant content. We expect this to place SA-ACC below the non-semantic JSCC baseline, which in turn should sit below conventional ACM and fixed-rate coding, though the magnitude of this ordering — and whether it holds under a tight rather than generous energy budget — is an open empirical question we have not yet tested.

Figure 7. *Expected energy per successfully delivered semantic unit, Scenario B, across all baselines. Illustrative prediction, not simulation output.*

7.5 Ablation Plan

Table 5 specifies, rather than reports, the ablation study we intend to run once simulation is implemented: isolating the individual contributions of semantic weighting and ephemeris-aware prediction by comparing the two partial variants introduced in Section 6.2 against the full SA-ACC controller across each primary metric. We expect both ablated variants to underperform the full system, but the paper's contribution claim depends on confirming this rather than assuming it, and Table 5 exists to make that confirmation concrete and checkable rather than left implicit.

Table 5
Planned ablation comparison (to be populated with simulation output). Columns record the expected direction of each delta from the design analysis above; values are placeholders pending measurement.

Metric	Full SA-ACC	w/o semantic weighting (expected delta)	w/o ephemeris prediction (expected delta)
BLER (Scenario A, mid-SNR)	baseline	expected increase	expected increase (near horizon)
Semantic fidelity (Scenario A)	baseline	expected decrease	minimal expected change
Throughput (Scenario C, low elevation)	baseline	minimal expected change	expected decrease
Energy per semantic unit (Scenario B)	baseline	expected increase	expected increase

7.6 Comparison with Related Work

Table 6
Qualitative comparison of SA-ACC against baselines and the closest related NTN semantic communication work (Section 2.6). NTN-validated and energy-metric columns for SA-ACC reflect design intent, not completed validation.

Method	Semantic-aware	Channel-adaptive	Ephemeris-aware	NTN-validated	Energy metric reported
Fixed-rate LDPC/polar	No	No	No	Partial	Rarely
Conventional ACM (DVB-S2-class)	No	Yes	No	Yes	Rarely
Non-semantic deep JSCC	No	Partial	No	Partial	No
Semantic-importance JSCC (terrestrial)	Yes	Partial	No	No	No
NTN semantic communication (survey-level, Section 2.6)	Yes	Partial	Partial	Yes	Partial
SA-ACC (proposed)	**Yes**	**Yes**	**Yes**	*Planned*	*Planned*

8. Limitations

This paper presents SA-ACC at the level of system model, mechanism design, and evaluation methodology. It does not yet include the numerical simulation results required to confirm the predictions laid out in Section 7, and we treat that gap as the paper's central open limitation rather than a minor caveat. Specific limitations and open items, to be resolved before submission to a Q1/Q2 venue, are as follows.

1. **No simulation results yet.** All quantitative comparisons in Section 7 are predictions, not measurements. A Q1/Q2 reviewer will expect, at minimum, Scenario A and B results with statistical validation as specified in Section 6.4 before considering this a complete contribution.

2. **Semantic importance estimator validated only on image/vision tasks in prior work** [72]; its extension to NTN telemetry/control payloads (§ 5.2, second case) is proposed but not yet empirically validated in this or prior work.

3. **Ephemeris-aware prediction assumes accurate, low-latency ephemeris availability** at the adaptation controller; robustness to ephemeris staleness or error is not yet characterized.

4. **Onboard complexity claims in § 5.5 are qualitative**; a concrete complexity/latency profiling study on representative onboard hardware (or a realistic proxy) is needed.

5. **Single relay topology considered.** Multi-hop or multi-satellite relay scenarios, and their interaction with the adaptation loop, are out of scope for this paper.

9. Conclusion and Future Work

This study presents SA-ACC, a semantic-aware link-adaptation framework designed to make 6G non-terrestrial communications more reliable. Unlike adaptive coding schemes that only react to the current channel quality SA-ACC takes semantic importance into account when choosing the code rate the modulation order and the protection of feature-level data. The model explicitly includes the challenges of non-terrestrial networks, such as long propagation delays, Doppler shifts, fading and limited energy and computing power. To handle both channel changes and quick link and semantic updates a two-stage ephemeris-aware control system was created. The authors also set up an evaluation approach that lets them compare SA-ACC with standard LDPC/polar codes, usual ACM and non-semantic JSCC baselines on metrics like reliability, semantic fidelity, throughput, latency and energy use. This new view of link adaptation goes beyond bit-level reliability and looks at how useful the recovered information really is.

Future extensions may investigate multimodal semantic traffic, imperfect channel and ephemeris knowledge, adaptive protection under highly dynamic mobility conditions, and cooperative operation across LEO, HAPS, and multi-satellite relay configurations. The proposed framework therefore provides a practical foundation for developing adaptive communication strategies in which semantic relevance and channel conditions are considered jointly for more efficient and reliable 6G NTN operation.

Declarations

Disclosure

During the preparation of this manuscript, the author used ChatGPT (OpenAI) to assist with language refinement, improvement of readability, organization of selected sections, and presentation of technical content. All AI-assisted outputs were critically reviewed, edited, and verified by the authors.

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Author Contribution

Ambar Bajpai solely conceptualized the study and carried out the analysis, interpretation, visualization, and overall development of the manuscript.

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Figures

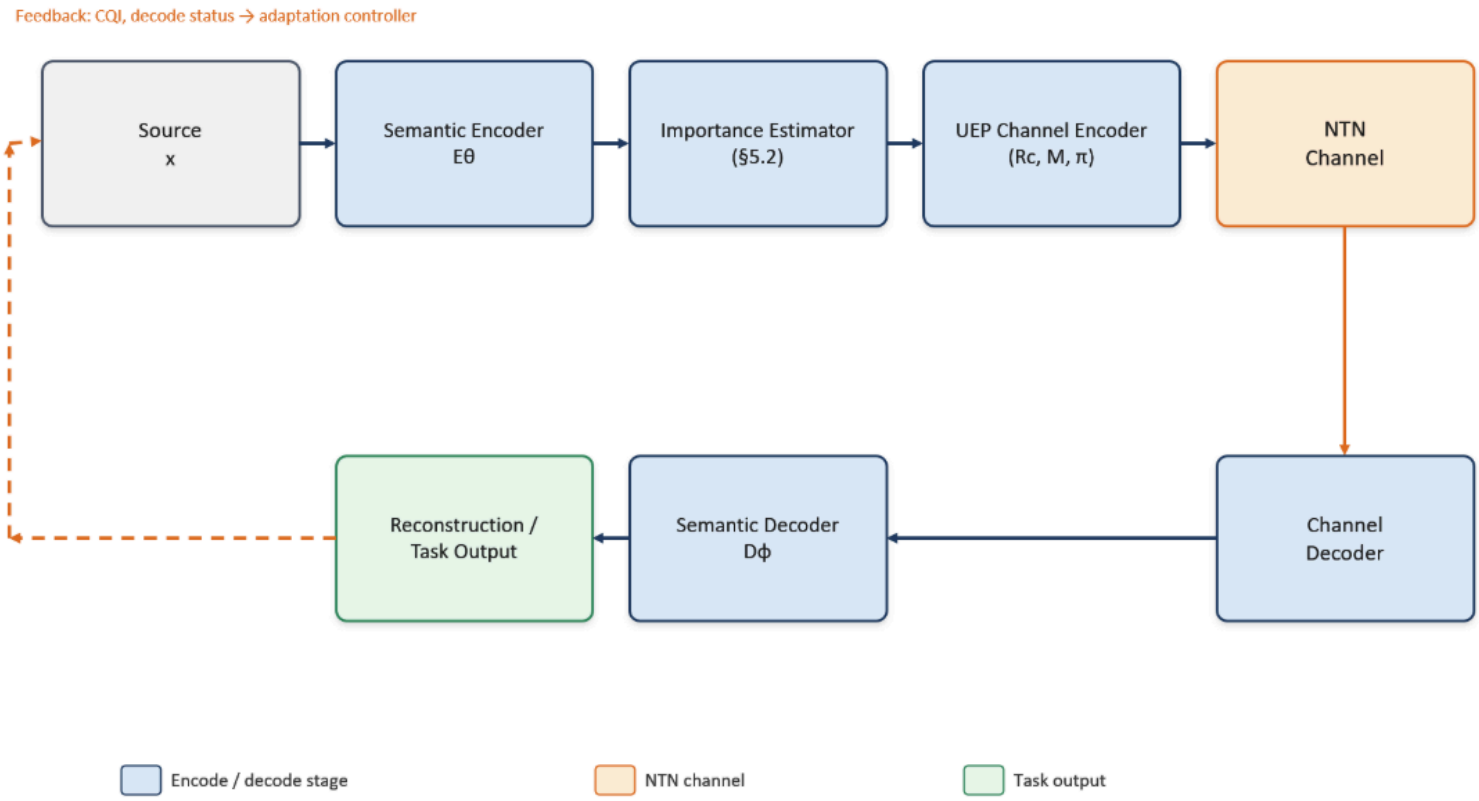


Figure 1

System Architecture

System architecture: LEO satellite, HAPS relay, and ground UE, showing the SA-ACC encoder at the transmitter, semantic-aware decoder at the receiver, and the feedback path carrying channel-state and semantic-relevance signaling back to the adaptation controller.

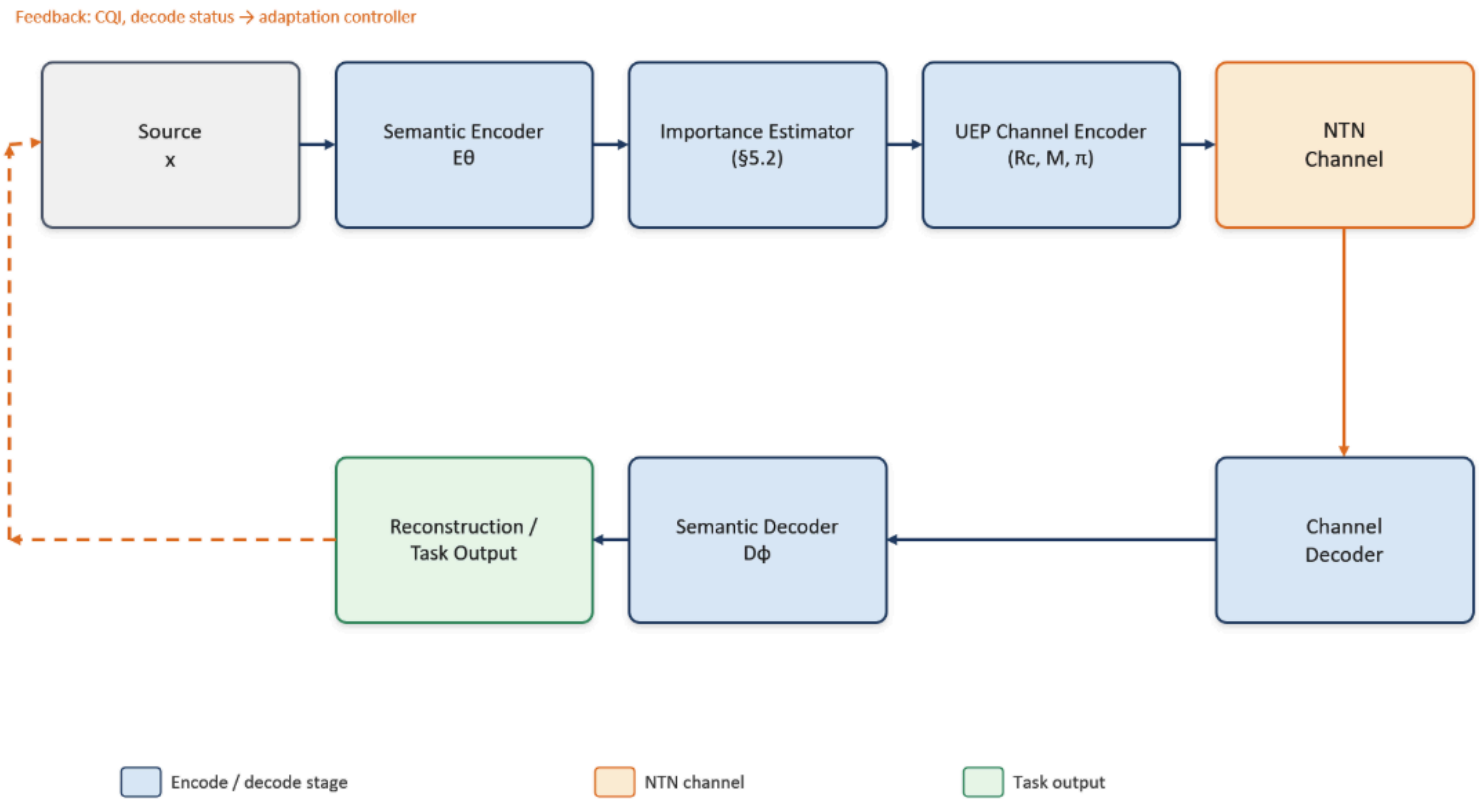


Figure 2

SA-ACC Encoder-Decoder Pipeline

SA-ACC encoder–decoder pipeline: semantic encoding, importance estimation, and unequal-error-protection channel encoding at the transmitter; channel decoding and semantic decoding at the receiver; with the feedback path (CQI estimate, decode status) closing the loop back to the adaptation controller.

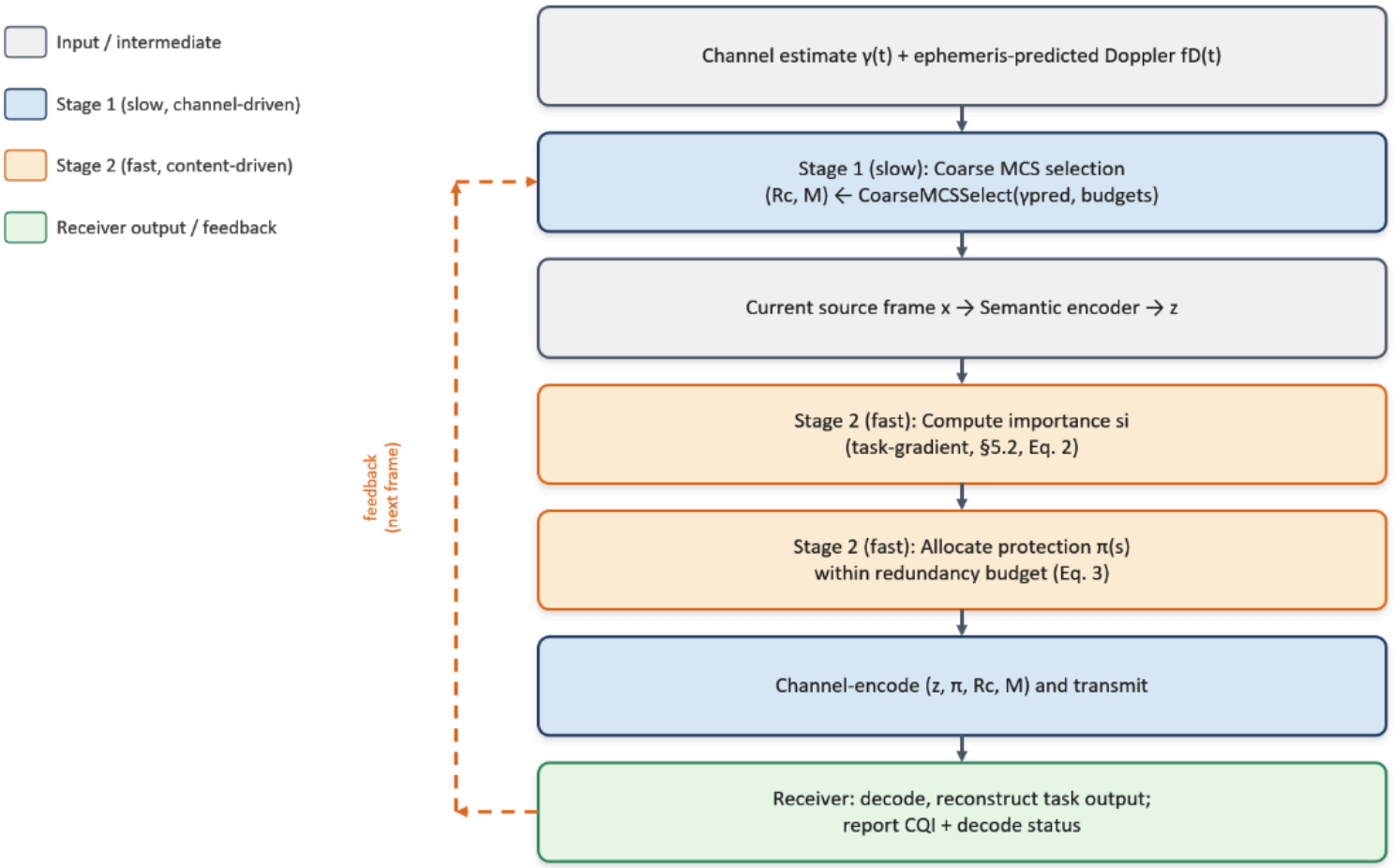


Figure 3

Adaptation Control Loop Flowchart

Flowchart of the two-stage adaptation control loop: slow, channel/ephemeris-driven MCS selection (Stage 1) followed by fast, per-frame semantic importance estimation and protection allocation (Stage 2), closing with receiver feedback into the next frame's adaptation decision.

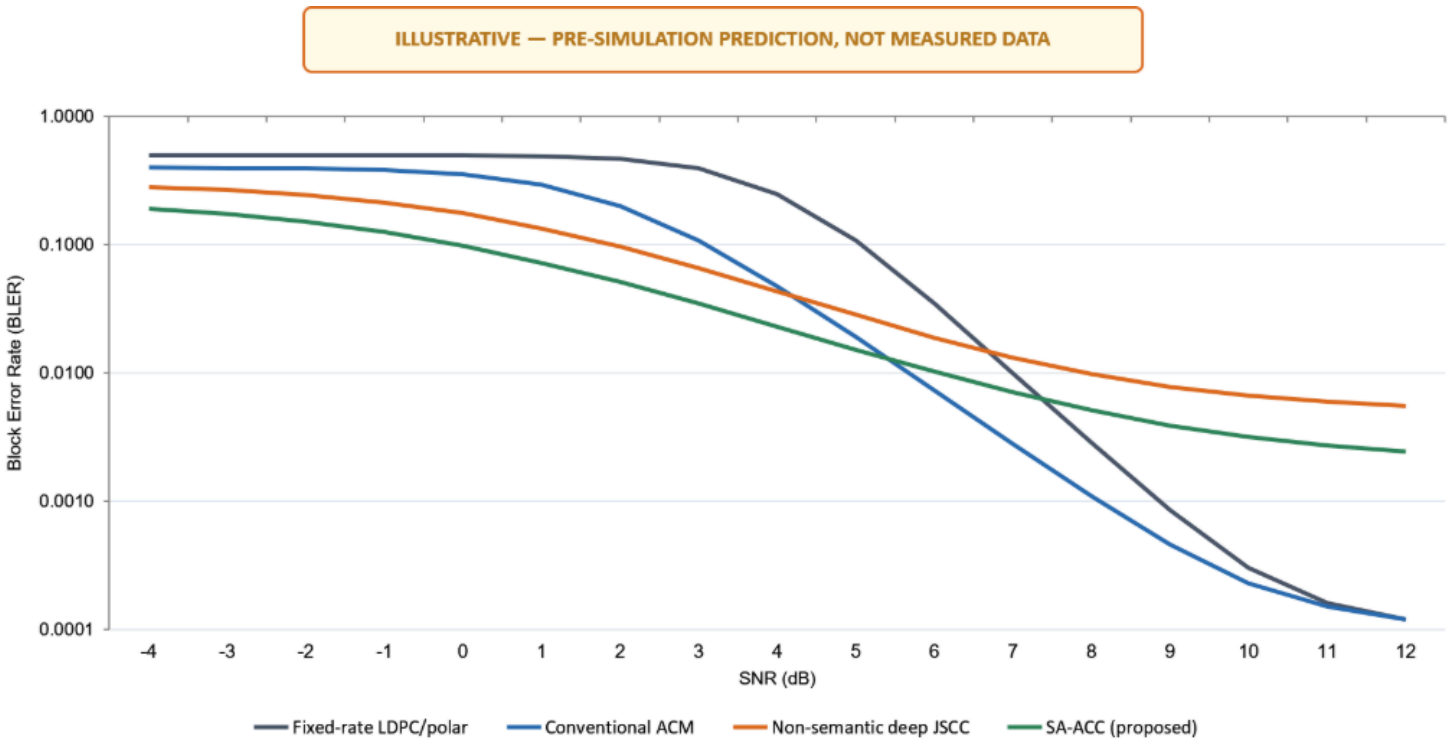


Figure 4

BLER vs SNR

Expected qualitative BLER-vs-SNR behavior for SA-ACC against the three primary baselines, Scenario A. This is an illustrative sketch of the predicted trend, reasoned from the mechanism design and the cited prior work — it is not simulation output. The prediction to be tested is that SA-ACC and non-semantic JSCC both avoid the sharp knee visible in fixed-rate coding, and that SA-ACC separates from non-semantic JSCC in the low-to-mid SNR range specifically on semantically critical content.

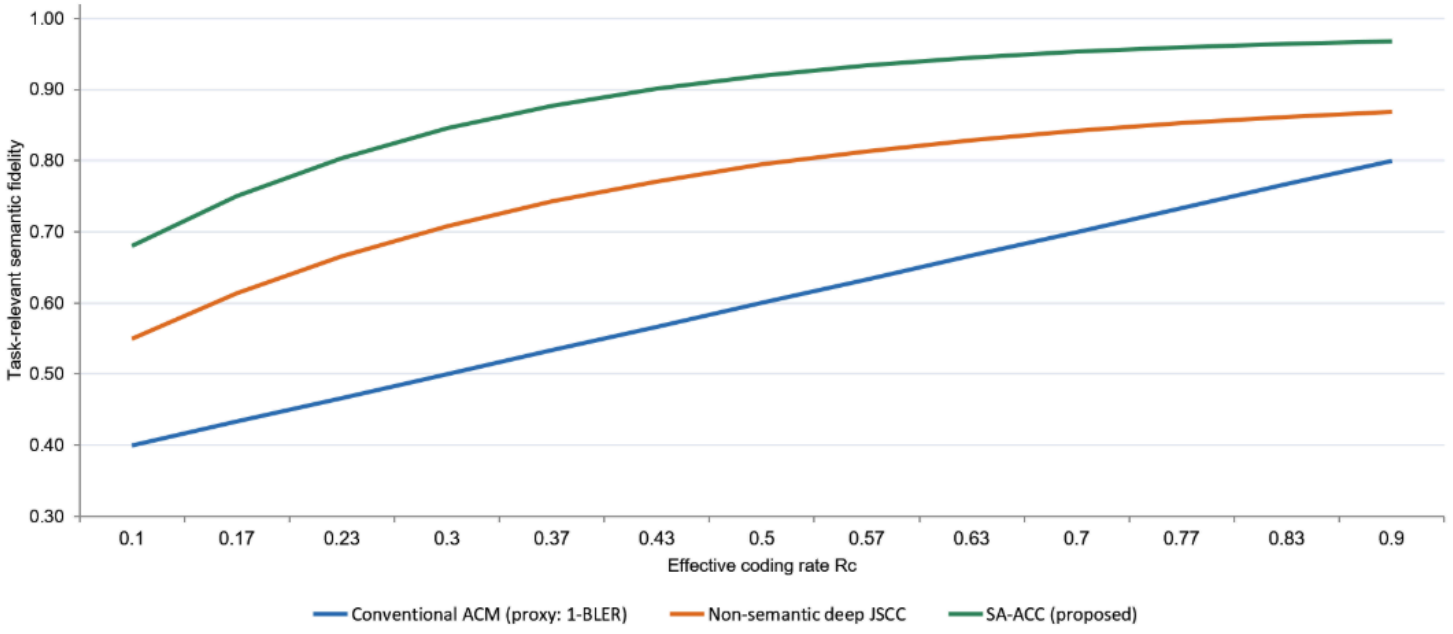


Figure 5

Semantic Fidelity vs Coding Rate

Expected task-relevant semantic fidelity vs. effective coding rate, Scenario A — an illustrative prediction, not simulation output. We treat this comparison as the priority result to obtain once the simulation environment (Section 6) is implemented, since it most directly tests the paper's central claim.

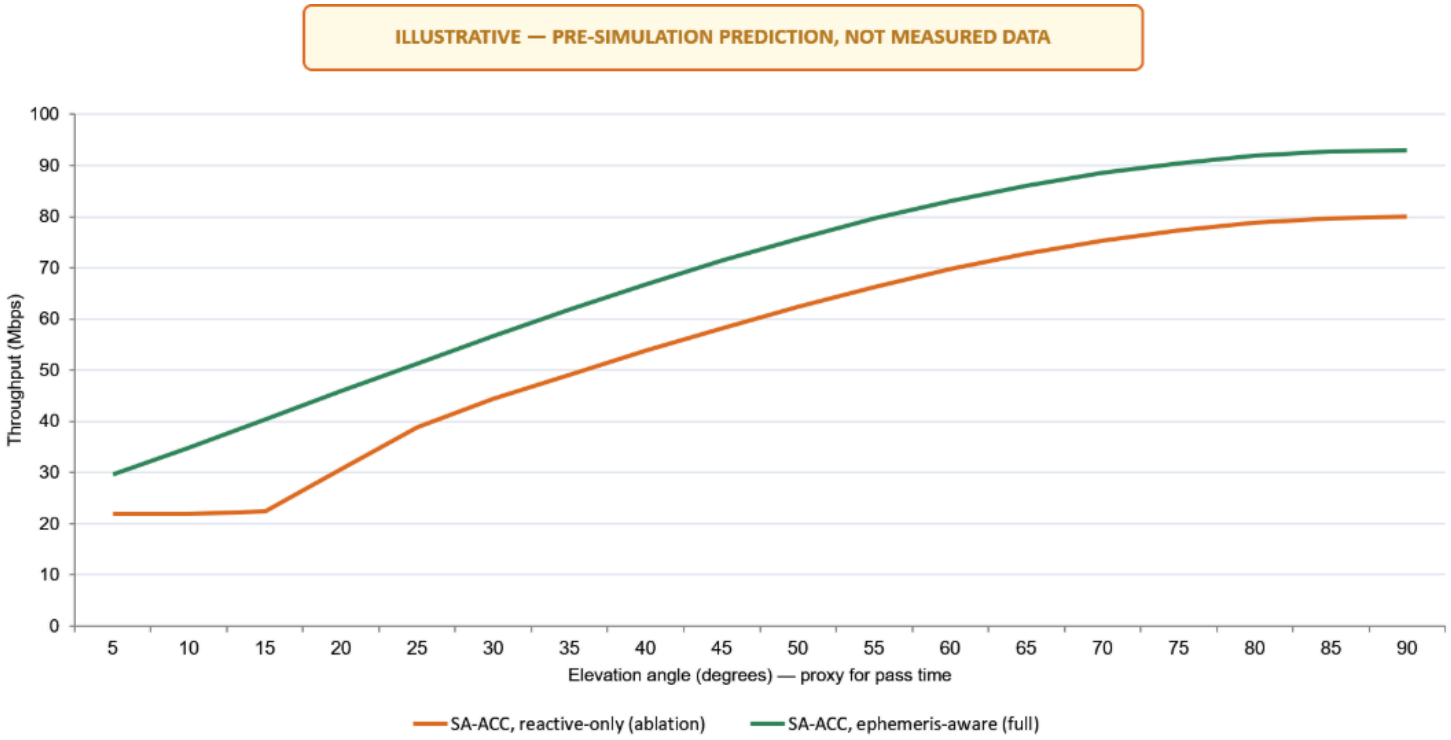


Figure 6

Throughput over a Satellite Pass

Expected throughput across a full satellite pass (elevation angle as a time proxy), Scenario C, comparing ephemeris-aware vs. reactive-only adaptation. Illustrative prediction, not simulation output.

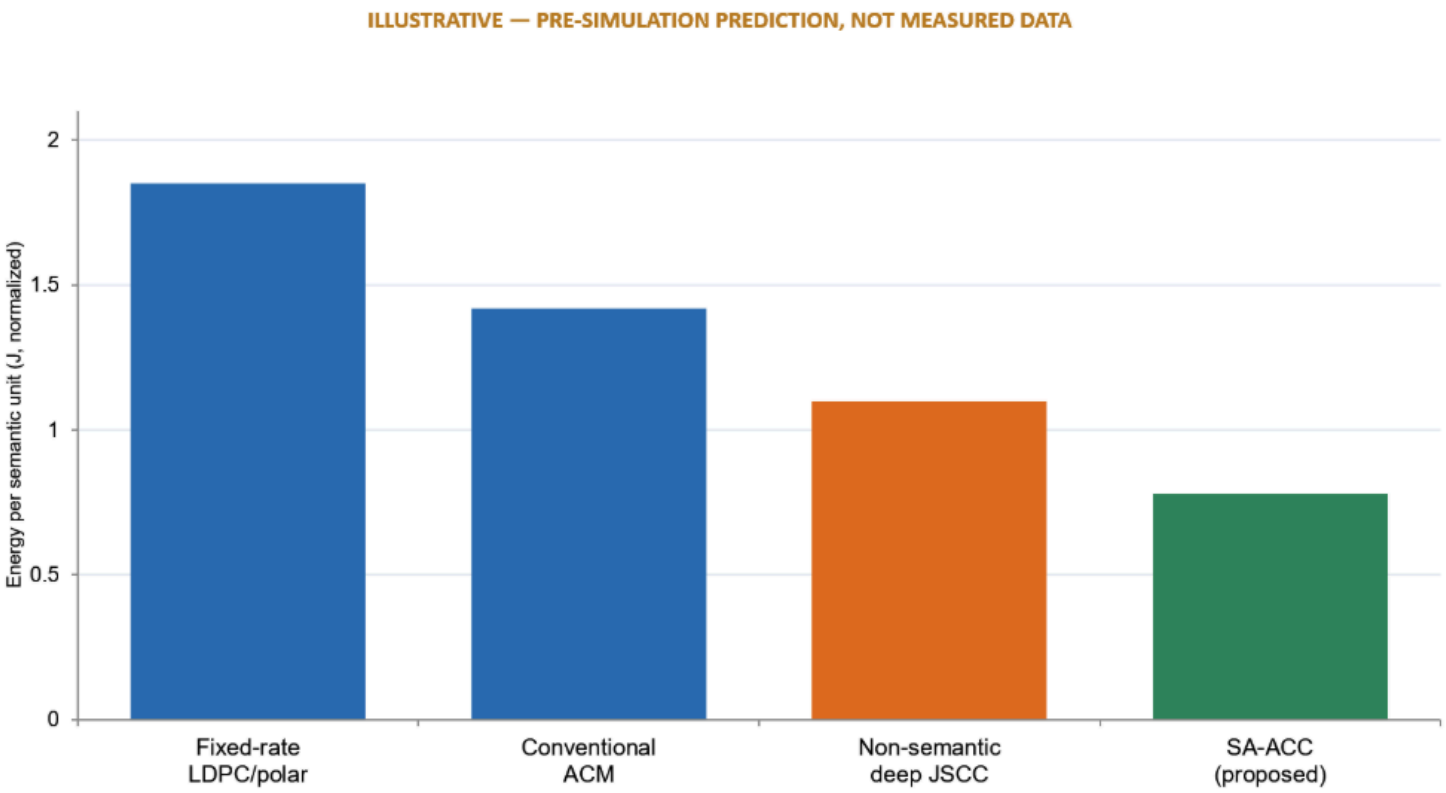


Figure 7

Energy Efficiency Comparison

Expected energy per successfully delivered semantic unit, Scenario B, across all baselines. Illustrative prediction, not simulation output.