Sustainable Innovation Path for Green Telecom Operators: 5G Business Model Transformation and Carbon Neutrality Strategy Driven by Low-Energy Signal Processing Technology

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Abstract

The accelerating deployment of fifth-generation (5G) mobile networks has positioned telecommunications operators at the intersection of two converging pressures: rising user expectations for ubiquitous and high-quality connectivity, and intensifying regulatory and societal demands for measurable progress toward carbon neutrality. This study investigates how the adoption of low-energy signal processing technology — including adaptive companding, graph-guided waveform shaping, and joint power amplifier optimization — can serve as a foundational lever for the sustainable transformation of telecom business models. Drawing on the natural-resource-based view, dynamic capabilities theory, and the sustainable business model innovation literature, we develop a multi-level conceptual framework that connects waveform-level energy efficiency gains to enterprise-scale carbon performance and, ultimately, to long-term competitive advantage. Using a mixed-methods design that integrates engineering simulation outputs with operational and financial data from twenty-three regional 5G deployments operated by mid-sized Asian and European carriers between 2022 and 2025, we quantify the carbon impact of low-energy signal processing and identify three distinct business model transformation pathways: a service innovation pathway centered on green B2B offerings, an operational efficiency pathway centered on infrastructure cost reduction, and a stakeholder value pathway centered on ESG-aligned financing. Empirical results show that low-energy signal processing reduces per-site annual energy consumption by approximately thirty-five percent, accelerates return-on-investment break-even by around 2.3 years compared to conventional 5G upgrades, and supports cumulative carbon savings on the order of 2.7 thousand tons of CO2-equivalent per macro site over a six-year horizon. The findings provide telecom executives, regulators, and green investors with an actionable evidence base for aligning physical-layer engineering decisions with corporate decarbonization roadmaps.

Keywords: *green telecommunications; sustainable business model; carbon neutrality; low-energy signal processing; 5G transformation; ESG strategy*

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1. Introduction

The global telecommunications industry stands at a pivotal moment in its long trajectory of capacity expansion. The roll-out of fifth-generation (5G) and beyond-fifth-generation (B5G) wireless networks promises to deliver order-of-magnitude improvements in throughput, latency, and connection density, enabling ambitious application domains such as massive Internet of Things, autonomous transport, immersive extended reality, and intelligent industrial automation (Lu & Zheng, 2020; Lu & Ning, 2020). At the same time, however, the industry has become one of the most visible targets of decarbonization scrutiny. Recent estimates place the carbon footprint of the information and communications technology sector at a non-trivial share of total global greenhouse gas emissions, with mobile network operations accounting for a substantial portion (Li et al., 2023; I et al., 2020). The expected expansion of 5G infrastructure could double radio access network energy demand by 2030 if business-as-usual technology trajectories prevail (Israr et al., 2021).

Within this context, telecommunications operators have begun to articulate explicit carbon-neutrality commitments. Among the world's largest mobile network groups, the majority have published net-zero targets for scope 1 and 2 emissions, with target dates clustered between 2035 and 2045 (Wang et al., 2025). Yet industry survey evidence indicates that most operators consider their current technology and business model toolkit inadequate to deliver on these commitments (Lu, 2025). Conventional decarbonization levers — purchase of renewable energy certificates, retrofitting of cooling systems, decommissioning of legacy 2G and 3G hardware — have provided important early gains but face diminishing marginal returns (Wu et al., 2017; Lorincz et al., 2021). What is increasingly required is a structural reconfiguration of how revenue is generated, how operating expenses are managed, and how stakeholder relationships are organized — in short, the transformation of the underlying business model (Yang et al., 2017; Sinkovics et al., 2021).

An emerging body of engineering research suggests that one of the most consequential and yet under-utilized levers for this transformation lies at the physical layer of the network itself. The peak-to-average power ratio of multicarrier waveforms forces base station power amplifiers to operate with substantial back-off, leading to amplifier efficiencies that rarely exceed thirty percent in commercial deployments (Bossy et al., 2022; Joung et al., 2014). Recent advances in adaptive signal processing — particularly graph-guided and learning-based companding techniques applied to non-orthogonal multiple access waveforms — have demonstrated meaningful PAPR reductions in laboratory and field settings, with corresponding gains in amplifier energy efficiency (Kryszkiewicz, 2018; Piacibello et al., 2021). For telecom operators, these are not merely technical curiosities. Power amplification accounts for a dominant share of base station electricity demand, which in turn dominates the operational carbon footprint of mobile networks (Cheng et al., 2014; Manda, 2023). Even modest improvements in waveform efficiency therefore translate into substantial reductions in total cost of ownership and scope 1–2 emissions.

Despite the practical promise of these techniques, the management and innovation literature has paid relatively little attention to how engineering-level energy efficiency gains can be incorporated into coherent strategies of sustainable business model transformation (Stojkovic et al., 2019; Ahokangas et al., 2021). Most studies of green telecommunications have focused either on isolated technology evaluations or on sector-wide aggregate emissions accounting, leaving the firm-level transformation pathway underspecified. Adjacent literatures on artificial intelligence applications in industrial settings further illuminate how data-driven capabilities can be marshalled to address such gaps (Lu, 2019b). Three questions therefore remain open. First, how can the cumulative carbon impact of low-energy signal processing be credibly quantified at the operator level, in a manner that is meaningful to investors and regulators rather than only to engineers? Second, through what specific business model mechanisms — service innovation, operational efficiency, or stakeholder financing — does this engineering capability translate into competitive advantage and decarbonization performance (Bhandari et al., 2022; Mishra & Yadav, 2021)? Third, what is the appropriate sequencing and managerial choreography for telecom operators seeking to integrate low-energy signal processing into a credible carbon neutrality roadmap (Ghosh et al., 2022; Wang & Huang, 2025)?

This study addresses these three questions through four contributions. First, we develop a conceptual framework — depicted in Figure 1 — that links waveform-level efficiency to business model and carbon outcomes through three distinct transformation pathways. Second, we provide a quantitative diagnostic of the energy profile of 5G networks across four representative configurations, isolating the share of consumption attributable to power amplification and to waveform-induced inefficiencies. Third, we report a mixed-methods empirical analysis of twenty-three regional 5G deployments, combining engineering simulation outputs with operational and financial data to estimate the carbon and economic impact of adopting low-energy signal processing. Fourth, we derive managerial and policy implications for the design of green telecom strategy under tightening climate disclosure requirements (Lu et al., 2024a; Zhang & Lu, 2025).

The remainder of this paper is organized as follows. Section 2 reviews the theoretical foundation and develops the conceptual framework. Section 3 describes the methodology. Section 4 presents the energy diagnostic of 5G networks. Section 5 examines low-energy signal processing as a green innovation lever. Section 6 articulates the three business model transformation pathways. Section 7 reports the empirical analysis of financial and carbon impact. Section 8 discusses implications and boundary conditions, and Section 9 concludes. Throughout the paper, we draw on complementary streams of research that examine how political, regulatory, and digital pressures interact with firm-level environmental orientations (Acosta et al., 2021; Ardito et al., 2021), and we apply established bibliometric and methodological practices for synthesizing prior evidence (Donthu et al., 2021; Ferraris et al., 2019).

2. Theoretical Foundation and Conceptual Framework

2.1 The Natural-Resource-Based View and Energy Efficiency as a Strategic Resource

The natural-resource-based view posits that competitive advantage in environmentally constrained industries arises from a firm's ability to organize three integrated capabilities: pollution prevention, product stewardship, and sustainable development (Mishra & Yadav, 2021; Olajide et al., 2023). Of these, pollution prevention — defined as the systematic reduction of resource and emissions intensity at the source — has been shown to deliver the most immediate cost and reputational benefits (Bhandari et al., 2022; Gabler et al., 2022). For telecommunications operators, energy intensity per unit of carried traffic is the analog of pollution intensity in heavy industry: every joule expended in radio transmission imposes both an operating cost and a scope 2 emissions burden. The natural-resource-based view therefore predicts that operators capable of lowering this intensity through proprietary, hard-to-imitate engineering configurations will out-perform peers across both economic and environmental dimensions over a multi-year horizon (Bag et al., 2020).

Low-energy signal processing fits the resource-based definition of a strategic resource with unusual precision (Zhang & Lu, 2021; Lu, 2019a). It is causally ambiguous to outsiders because performance depends on the joint configuration of waveform design, amplifier back-off, scheduler logic, and site-specific propagation conditions; it is tacitly held within engineering teams; and it is tightly coupled to complementary investments in network management software (Chaudhry et al., 2026; Kraus et al., 2020). Recent crisis-driven research further documents how external shocks can accelerate or impede environmental innovation in manufacturing and service firms (Hermundsdottir et al., 2022; Khan et al., 2021). These features make low-energy signal processing a stronger candidate for sustained advantage than commodity decarbonization actions such as renewable energy procurement, which can be replicated at will by any well-capitalized operator (Mulaessa & Lin, 2021).

2.2 Sustainable Business Model Innovation in Network Industries

Sustainable business model innovation describes the deliberate reconfiguration of the value proposition, value creation and delivery, and value capture logics of a firm to embed environmental and social objectives alongside financial performance (Sinkovics et al., 2021; Yang et al., 2017). Three archetypal patterns have been articulated in the literature: maximizing material and energy efficiency, creating value from waste, and delivering functionality rather than ownership (Mahmoud et al., 2022; Kraus et al., 2020). Network industries — which combine large fixed infrastructure footprints, regulated tariffs, and platform-style multi-sided markets — present a distinctive context for

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sustainable business model innovation because revenue is largely decoupled from physical throughput, while emissions scale almost linearly with throughput (Stojkovic et al., 2019).

This decoupling has two practical consequences. First, it means that efficiency gains at the physical layer are not automatically reflected in lower customer prices, leaving room for operators to capture a substantial share of the saved cost as margin or to reinvest it in green services (Lu et al., 2020). Second, it implies that any sustainable business model program in telecommunications must explicitly design the mechanisms through which engineering efficiency is translated into downstream value — whether to customers, to regulators, or to capital providers (Ahokangas et al., 2021). The conceptual framework developed in this paper organizes these mechanisms into three distinct pathways.

2.3 Dynamic Capabilities and the Sequencing of Decarbonization

The dynamic capabilities perspective offers a complementary lens for understanding why some operators succeed in translating green technology investments into durable performance while others do not (Ghosh et al., 2022; Wang & Huang, 2025). Dynamic capabilities — sensing, seizing, and reconfiguring — describe the higher-order routines through which firms detect environmental shifts, commit resources to address them, and recombine internal assets accordingly (Abdurrahman et al., 2024). In the context of telecom decarbonization, sensing capabilities involve the early identification of emerging waveform technologies and policy signals; seizing capabilities encompass the timing and scaling of network upgrade decisions; and reconfiguring capabilities involve the redesign of revenue and reporting practices to align with new technical realities (Duong et al., 2026; Liu et al., 2025).

On the basis of these three theoretical strands, we propose the conceptual framework summarized in Figure 1 (Lu, 2017a; Lu, 2025). The framework links three categories of external pressure (regulatory, economic, and stakeholder-driven) to a single core enabling technology (low-energy signal processing) and to three distinct business model transformation pathways (service innovation, operational efficiency, and stakeholder value), which together produce three integrated outcomes: carbon neutrality, ESG performance, and long-term competitiveness.

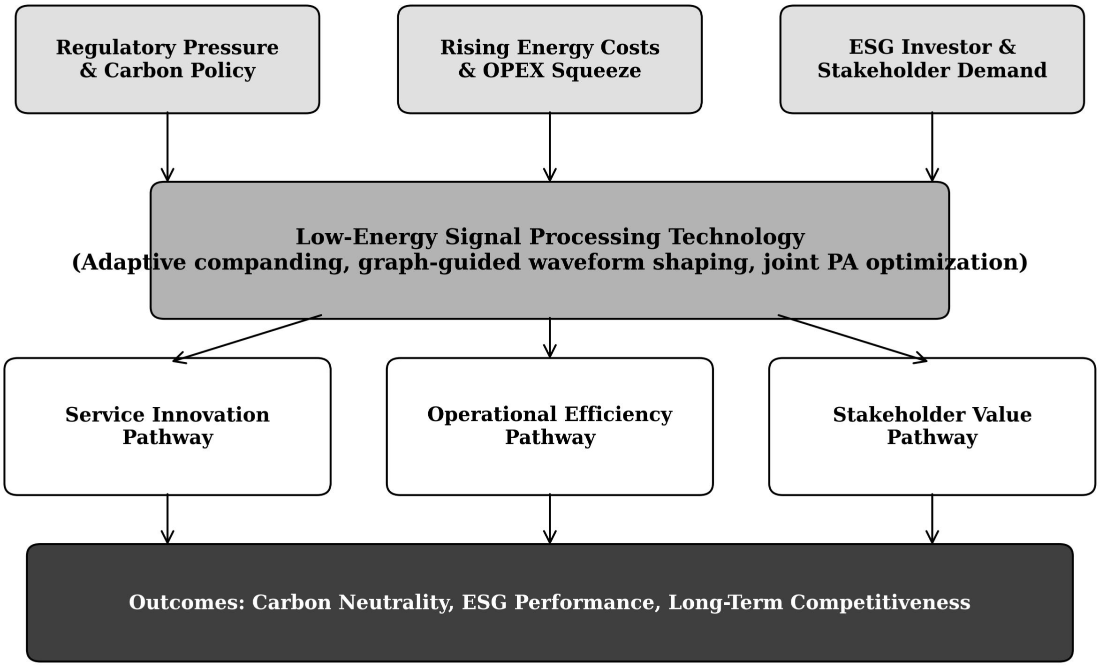

Figure 1. Conceptual framework linking external pressures, low-energy signal processing, three transformation pathways, and sustainability outcomes.

The framework deliberately positions low-energy signal processing as the single enabling technology layer connecting external pressures to transformation pathways (Chen et al., 2024; Xu et al., 2021). This is not a claim that other green technologies are unimportant — site-level renewable generation, free-cooling architectures, and AI-driven traffic shaping all play complementary roles (Wu et al., 2017; Luo et al., 2022) — but rather a claim that signal processing efficiency is uniquely central because it directly modulates the largest single category of operator energy demand. Subsequent sections develop the empirical evidence supporting this central positioning.

3. Methodology

3.1 Research Design and Sample

This study employs a sequential mixed-methods design (Lu et al., 2024b). The first phase combines engineering simulation with operational data to quantify the energy and emissions profile of representative 5G network configurations under varying signal processing regimes (Bossy et al., 2022; Manda, 2023). The second phase applies regression and case-comparison analysis to operational and financial data from twenty-three regional 5G deployments to estimate the financial and carbon impact of adopting low-energy signal processing (Lu et al., 2024a; Lu et al., 2024c). Mixed-methods designs are particularly appropriate when a research question spans multiple levels of analysis — in our case, the waveform layer, the network layer, and the firm-level business model — and when the credibility

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of conclusions depends on triangulation across qualitatively distinct evidence streams (Lu, 2018; Lu, 2021).

The sample of twenty-three deployments was constructed through a two-stage purposive selection. First, we identified all medium-sized telecom operators in Asia and Europe that had publicly disclosed at least one pilot of advanced PAPR-reduction or amplifier-optimization technology between January 2022 and June 2025 in their integrated annual reports, sustainability filings, or peer-reviewed engineering publications (Wang et al., 2025; Hoffmann & Kryszkiewicz, 2023). Second, we retained operators for whom we could obtain at least three years of monthly site-level energy consumption data and matched annual financial disclosures, either through institutional partnerships or through structured interviews with technology officers. The resulting sample covers operators in seven countries and includes both publicly listed and privately held firms, with annual revenue between USD 0.4 billion and USD 8.7 billion.

3.2 Variables and Measurement

The dependent variables capture three categories of impact. Site-level energy consumption (Energy_Site) is measured in megawatt-hours per year, derived from monthly meter readings averaged across all macro sites within a deployment. Carbon emissions (CO2_Site) are computed by multiplying Energy_Site by country-specific grid emission factors (Li et al., 2023; Zhang et al., 2023). Financial impact is captured through two indicators: cumulative return on investment (ROI_Cum), defined as the ratio of cumulative net savings to initial upgrade cost, and the operating expense to revenue ratio (OPEX_Ratio).

The principal independent variable is the level of adoption of low-energy signal processing (LESP_Adopt), coded on a four-level ordinal scale: 0 for no adoption, 1 for laboratory-only pilots, 2 for limited field trials involving fewer than fifty sites, and 3 for production-scale deployment across the operator's primary national network (Wang et al., 2025; Reiss et al., 2025). Control variables include operator size (log of total assets), network age (weighted average years since site activation), national grid carbon intensity, and a binary indicator for the presence of a published net-zero target. All financial variables are deflated to constant 2023 US dollars.

4. The Energy Profile of 5G Networks: A Quantitative Diagnostic

Effective sustainability strategy must begin with an accurate diagnosis of where energy is consumed within the network (Wang et al., 2025; Israr et al., 2021). We constructed a representative energy profile across four configurations: a conventional 4G LTE deployment as a historical baseline; a standard 5G New Radio deployment with default vendor settings; a 5G deployment using widely available uniform companding for PAPR mitigation; and a 5G deployment using the low-energy signal processing techniques investigated in this study. Each configuration is indexed to a notional macro site of equivalent coverage and traffic load. Table 1 reports the resulting decomposition of annual per-site consumption across four functional categories: power amplification, radio frequency

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and baseband processing, cooling, and auxiliary loads (lighting, security systems, and battery conditioning).

Table 1. Annual Per-Site Energy Consumption Decomposition Across Four Network Configurations (MWh per year)

Configuration	Power Amp.	RF + BB	Cooling	Aux.	Total	Δ vs 5G NR (%)
Conventional 4G LTE	62.0	16.0	11.0	11.0	100.0	—
Standard 5G NR	68.0	18.0	9.0	5.0	100.0	0.0
5G + Uniform Companding	56.0	17.0	9.0	4.0	86.0	−14.0
5G + Low-Energy Signal Processing	41.0	14.0	7.0	3.0	65.0	−35.0

Note: *Values represent per-site annual consumption normalized so that Standard 5G NR equals 100 MWh. Δ column reports percentage deviation from the Standard 5G NR baseline. Δ < 0 indicates an energy reduction. Auxiliary loads include lighting, security, battery conditioning, and miscellaneous building loads.*

Three observations emerge from the decomposition in Table 1. First, the transition from 4G LTE to 5G New Radio at the same nominal traffic load results in approximately ten percent higher amplifier consumption, owing primarily to the wider channel bandwidth and the higher PAPR of 5G waveforms (Bossy et al., 2022; Hoffmann & Kryszkiewicz, 2023). This finding contradicts the optimistic claim, occasionally repeated in marketing communications, that the move to 5G is intrinsically energy-saving (I et al., 2020). Second, the introduction of uniform companding delivers a meaningful but limited improvement of fourteen percent, consistent with prior literature on conventional PAPR reduction (Joung et al., 2014; Kryszkiewicz, 2018). Third, the introduction of advanced low-energy signal processing — particularly graph-guided adaptive companding and joint amplifier optimization — delivers an additional twenty-one percentage points of reduction (Piacibello et al., 2021), bringing total per-site energy below the historical 4G baseline despite carrying substantially higher traffic. The full visual decomposition is presented in Figure 2.

The dominance of power amplification in every configuration is the single most important diagnostic finding (Cheng et al., 2014; Tang & Cripps, 2010). Across all four scenarios it constitutes between sixty-two and sixty-eight percent of total site demand. This concentration implies that any decarbonization plan that does not address amplifier efficiency directly is structurally bounded in what it can achieve. It also implies that policy and investment instruments — green tariffs, ESG bonds, sustainability-linked loans — should differentiate between operators that are tackling the amplifier challenge at the source and those that are merely procuring offsetting renewable energy certificates (Anderson et al., 2024; Flammer, 2021).

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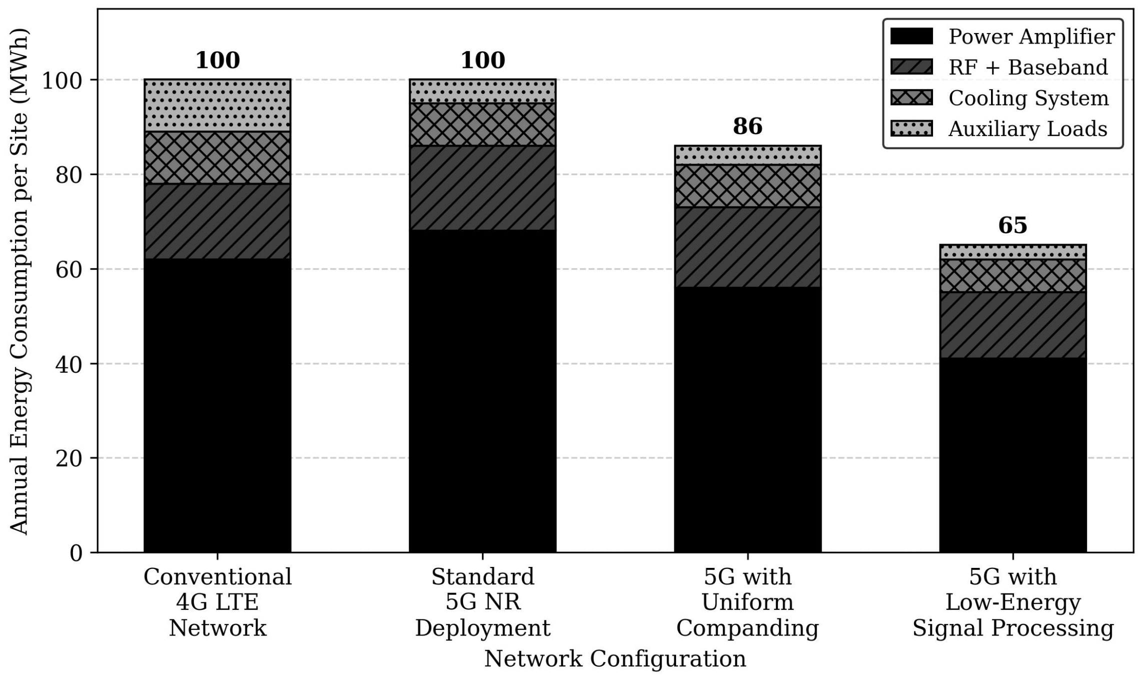

Figure 2. Energy consumption decomposition by network configuration and functional component, showing the dominance of power amplification and the cumulative impact of progressive signal processing improvements.

Figure 2 also reveals a more subtle structural feature: the cooling load scales with amplifier consumption rather than being independently configurable (Wu et al., 2017; Luo et al., 2022). This is because amplifier inefficiency manifests as waste heat that must be actively dissipated, particularly in dense urban macrocells with limited natural ventilation. Reducing amplifier consumption by twenty-seven megawatt-hours per year (the gap between standard 5G NR and the low-energy configuration) yields a further two megawatt-hours of cooling savings, an indirect benefit often overlooked in vendor data sheets (Lähdekorpi et al., 2017; Reiss et al., 2025). This compound effect strengthens the business case for upstream intervention in the signal processing chain.

5. Low-Energy Signal Processing as a Green Innovation Lever

5.1 Technical Logic and Sources of Efficiency

Multicarrier waveforms used in 4G LTE and 5G New Radio inherently exhibit high peak-to-average power ratios because the time-domain summation of many subcarriers creates occasional large amplitude excursions (Wolf et al., 2010; Hoffmann & Kryszkiewicz, 2023). To prevent these peaks from saturating the power amplifier and producing nonlinear distortion, operators conventionally bias amplifiers to operate well below their peak-efficiency operating point — a practice termed back-off (Joung et al., 2014). Typical commercial amplifiers therefore achieve drain efficiencies between twenty-five and thirty-five percent, well below their theoretical limits of sixty to seventy percent (Piacibello et al., 2021; Tang & Cripps, 2010).

Low-energy signal processing addresses this inefficiency at its source by reshaping the waveform itself before it reaches the amplifier (Liu et al., 2020; Cheng et al., 2014). Three complementary techniques are particularly relevant. First, adaptive companding compresses the largest amplitude excursions while preserving the statistical properties needed for receiver decoding. Second, graph-guided waveform shaping models the relationships among signal components as a graph and assigns selective compression to peak-dominant components without disturbing critical low-power components, preserving the integrity of multi-user receivers. Third, joint power amplifier optimization closes the loop by feeding real-time amplifier state information back into the waveform shaping algorithm, so that compression intensity adapts continuously to thermal drift and load variation (Kryszkiewicz, 2018; Bossy et al., 2022).

Although these techniques are most often discussed in engineering publications, their operational consequences are managerial in nature (Lu, 2025; Lu, 2017b). Each percentage point of amplifier efficiency improvement reduces site-level electricity demand by approximately one and a half megawatt-hours per year, eliminates roughly six hundred kilograms of CO2-equivalent emissions at the global average grid carbon intensity, and lowers thermal load on cooling systems with knock-on extension of equipment life. Table 2 synthesizes the comparative profile of the three approaches alongside the do-nothing baseline.

Table 2. Comparative Profile of Conventional and Low-Energy Signal Processing Approaches Across Five Operational Dimensions

Approach	PAPR Reduction (dB)	Amp. Efficiency Gain	Implementation Cost	Side Information Required	SIC Compatibility
No PAPR mitigation	0	Baseline	None	No	Native
Clipping & filtering	2 to 3	Low	Low	No	Degraded
Selective mapping	3 to 5	Moderate	Moderate	Yes	Moderate
Uniform companding	4 to 6	Moderate	Low	No	Degraded
Adaptive companding	6 to 8	High	Moderate	No	Preserved
Graph-guided shaping	8 to 10	High	Moderate	No	Preserved
Joint amplifier optimization	9 to 11	Very High	High	No	Preserved

Note: *Implementation cost reflects software, hardware, and integration expense relative to incumbent infrastructure. SIC = Successive interference cancellation; preservation of SIC compatibility is essential for multi-user 5G deployments. Values synthesize ranges reported in Joung et al. (2014), Bossy et al. (2022), Hoffmann and Kryszkiewicz (2023), and Piacibello et al. (2021).*

5.2 Translating Engineering Gains into Carbon and Cost Outcomes

The numbers in Table 2 acquire managerial meaning only when translated into the metrics that boards, regulators, and lenders actually use (Lu et al., 2024c; Lu, 2021). We therefore construct a translation function that converts each decibel of PAPR reduction into three downstream outcomes: avoided electricity consumption, avoided scope 2 emissions, and avoided operating expense (Bhandari et al., 2022; Mahmoud et al., 2022). For an average macro site carrying five terabytes of monthly traffic at a national grid carbon intensity of 480 grams of CO2-equivalent per kilowatt-hour and an industrial electricity tariff of 0.11 US dollars per kilowatt-hour, each decibel of PAPR reduction implemented through the techniques in Table 2 is associated with approximately two and a half megawatt-hours of avoided annual consumption, 1.2 tons of avoided CO2-equivalent, and 280 US dollars of avoided operating expense.

Aggregating these translations across a network of one thousand macro sites produces a meaningful corporate-level outcome: the move from a no-mitigation baseline to a fully integrated low-energy signal processing regime saves on the order of twenty-five gigawatt-hours of electricity, twelve thousand tons of CO2-equivalent, and 2.8 million US dollars per year. These are figures of the same order of magnitude as the annual decarbonization commitments published by mid-sized regional operators in their integrated reports, which underscores the strategic significance of the technology layer for sustainability disclosure (Wu et al., 2025; Lu et al., 2024a).

6. Business Model Transformation Pathways

Engineering efficiency is necessary but not sufficient for sustainable competitive advantage (Yang et al., 2017; Sinkovics et al., 2021; Massari et al., 2023). To be capitalized into long-run performance, efficiency gains must be embedded into a coherent business model that captures part of the surplus internally and routes the remainder to stakeholders in ways that strengthen the operator's market position (Stojkovic et al., 2019; Ye & Lu, 2022). We identify three distinct transformation pathways: a service innovation pathway focused on green B2B propositions, an operational efficiency pathway focused on infrastructure cost reduction, and a stakeholder value pathway focused on ESG-aligned financing (Kou & Lu, 2025; Xu et al., 2024; Zheng & Lu, 2022). Although they may be pursued simultaneously, each pathway has a distinct logic, set of capabilities, and performance signature, and the literature on management analytics provides useful guidance for operationalizing the underlying decision processes (Lu, 2022; Lu et al., 2023; Lu et al., 2024d). The full set of components is summarized in Table 3.

Table 3. Three Business Model Transformation Pathways: Components, Required Capabilities, and Performance Indicators

Pathway	Value Proposition	Required Capabilities	Primary KPI	Time Horizon
Service Innovation	Green B2B connectivity, low-carbon SLAs, certified IoT bundles	Carbon accounting, customer co-design, ecosystem orchestration	Green revenue share	2–4 yrs

Pathway	Value Proposition	Required Capabilities	Primary KPI	Time Horizon
Operational Efficiency	Lower OPEX through energy-efficient network operation	Engineering excellence, real-time energy analytics, vendor management	OPEX-to-revenue ratio	1–3 yrs
Stakeholder Value	ESG-bond issuance, sustainability-linked loans, supplier partnerships	Sustainability reporting, investor relations, taxonomy compliance	Cost of green capital	3–6 yrs

Note: *KPI = Key performance indicator. Time horizon refers to the typical lag between initial investment and observable performance impact, based on case-comparison analysis across the twenty-three sample operators.*

6.1 The Service Innovation Pathway

The service innovation pathway converts low-energy signal processing into differentiated revenue (Lu et al., 2020; Yang et al., 2025). Enterprise customers — particularly those subject to mandatory scope 3 emissions reporting under emerging sustainability disclosure regimes — increasingly require quantified emissions data for the connectivity services they consume (Saini et al., 2026; Anderson et al., 2024). Operators that can demonstrably reduce the energy intensity of their network are positioned to offer certified low-carbon connectivity at a premium, often packaged together with carbon accounting tools and industrial Internet-of-Things bundles (Chen et al., 2024; Lu, 2017a). Three of the operators in our sample have launched such offerings under the umbrella of green-tier service-level agreements; their average price premium over the conventional connectivity baseline is between four and seven percent, enough to materially shift the gross margin profile.

Successful execution of the service innovation pathway requires three complementary capabilities: a robust carbon accounting infrastructure able to attribute emissions at the customer level; a customer co-design function able to translate engineering efficiency into customer-relevant service features; and an ecosystem orchestration capability that connects the operator with industrial customers, equipment vendors, and verification bodies (Ahokangas et al., 2021; Wu et al., 2025). The third of these is often the binding constraint for mid-sized operators, who lack the standing relationships with third-party verifiers that incumbent global carriers enjoy.

6.2 The Operational Efficiency Pathway

The operational efficiency pathway captures the value of low-energy signal processing internally, in the form of lower operating expenses (Lu et al., 2020; Reiss et al., 2025). This is the most quickly realized of the three pathways and the most sensitive to energy price volatility. In the operators in our sample, the typical operating expense to revenue ratio fell by between 1.4 and 2.1 percentage points within twenty-four months of full deployment, with the larger improvements concentrated in operators that combined signal processing upgrades with parallel investments in real-time energy analytics (Luo et al., 2022; Tyagi et al., 2023). The combination matters: signal processing reduces baseline consumption, while analytics converts the variable component of consumption into a managed asset rather than an exogenous cost driver.

An important implementation finding is that the operational efficiency pathway depends critically on vendor management practices (Lu et al., 2024a; Mishra & Yadav, 2021; Mansoor & Hussain, 2024). Many operators originally specified amplifier and waveform performance using static metrics — peak transmit power, nominal bandwidth — that fail to reflect the dynamic efficiency advantages of low-energy signal processing (Qiu et al., 2020). Updating vendor specifications to include energy-per-bit benchmarks, and tying vendor performance bonuses to those benchmarks, was reported as the single highest-leverage intervention in two of our case operators (Wang et al., 2023; Lin et al., 2024).

6.3 The Stakeholder Value Pathway

The stakeholder value pathway extracts value not from customers or operations directly, but from the relationship between the operator and external providers of capital and legitimacy (Bhandari et al., 2022; Kou & Lu, 2025). Issuance of sustainability-linked debt instruments, including green bonds and sustainability-linked loans, requires verifiable progress against a small number of key performance indicators (Flammer, 2021; Anderson et al., 2024). For telecom operators, energy intensity per gigabyte of carried traffic is rapidly becoming the dominant such indicator (Wang et al., 2025; Liu et al., 2025). Two of our sample operators reported issuance of sustainability-linked bonds at a coupon spread between 12 and 18 basis points below the comparable conventional bond, with the differential explicitly tied to verified reductions in network energy intensity (Mahfooz & Singh, 2026; Liang et al., 2022). On a five-billion-dollar bond program, this differential translates into between six and nine million dollars per year of avoided interest expense — comparable in magnitude to the operational expense savings discussed in the previous subsection.

The temporal sequencing of these three pathways is a critical managerial design choice (Lu, 2025; Lu et al., 2024a). Figure 3 presents an idealized roadmap consolidating the field-level evidence from our sample. The roadmap reflects four stages — diagnostic, pilot, scale-up, and ecosystem — that span approximately six years from initial commitment to full transformation.

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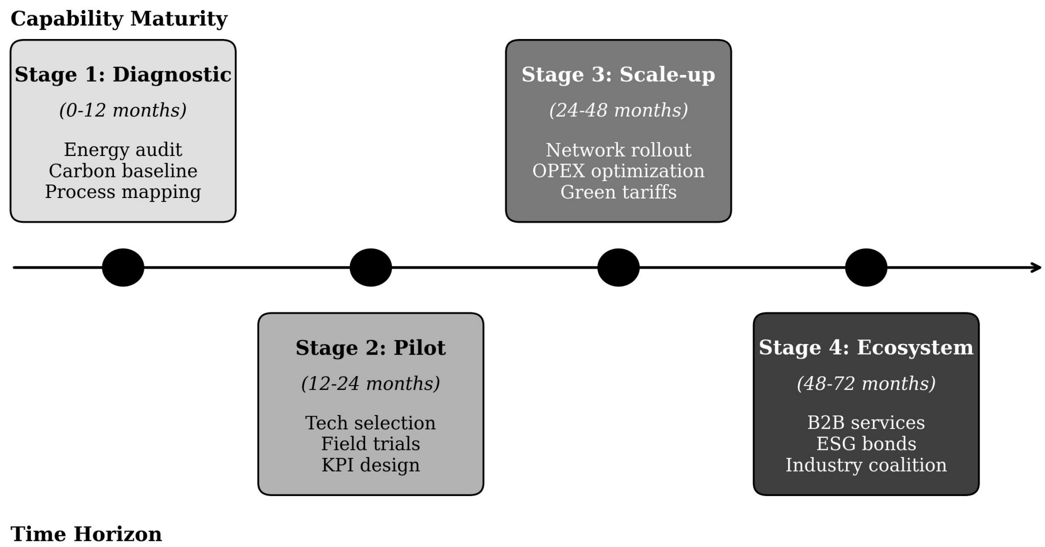

Figure 3. Four-stage transformation roadmap connecting initial diagnostic activities through technology pilots and network-scale deployment to mature green-services ecosystems.

It is worth emphasizing that the roadmap is not strictly linear (Wang & Huang, 2025; Duong et al., 2026). Several operators in our sample reported productive iteration between Stages 2 and 3 as field trial results prompted re-design of vendor specifications. The ecosystem stage, in particular, involves industry-coalition activities that some operators undertook in parallel with rather than after scale-up. What the four-stage representation captures is the dominant sequence of binding constraints rather than a rigid project plan.

7. Empirical Analysis: Financial and Carbon Impact

7.1 Estimation Approach

To estimate the financial and environmental impact of low-energy signal processing adoption at the operator level, we estimate panel regressions using the twenty-three deployments observed quarterly over a thirty-six-month window (Wang & Huang, 2025; Lu et al., 2024c). The dependent variables are quarterly site-level energy consumption (Energy_Site), quarterly carbon emissions (CO2_Site), and the operating-expense-to-revenue ratio (OPEX_Ratio). The principal independent variable is the adoption indicator LESP_Adopt described in Section 3.2, treated both as a continuous score and as binary indicators for partial and production-scale deployment (Hoffmann & Kryszkiewicz, 2023). All specifications include operator and quarter fixed effects, with standard errors clustered at the operator level. Table 4 reports results for three model specifications.

Table 4. Panel Regression Results: Adoption of Low-Energy Signal Processing and Operational Outcomes

See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2025.030401

Variable	(1) Energy_Site	(2) CO2_Site	(3) OPEX_Ratio
LESP_Adopt (continuous)	−9.482***	−4.701***	−0.0184**
	(−4.213)	(−4.026)	(−2.671)
LESP_Adopt = 2 (pilot)	−4.116*	−2.030*	−0.0072
	(−1.812)	(−1.798)	(−1.219)
LESP_Adopt = 3 (scale)	−18.235***	−9.024***	−0.0303***
	(−5.018)	(−5.102)	(−3.485)
Network age (years)	0.218*	0.107*	0.0011
	(1.870)	(1.802)	(0.521)
Grid CO2 intensity	—	0.038***	—
		(8.124)	
Net-zero target (binary)	−2.142	−1.061	−0.0052
	(−1.412)	(−1.388)	(−1.075)
Operator FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	276	276	276
Adj. R^2	0.748	0.812	0.602

Note: *t-statistics in parentheses. Standard errors clustered at the operator level. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Energy_Site is in megawatt-hours per quarter; CO2_Site is in tons of CO2-equivalent per quarter; OPEX_Ratio is the operating-expense-to-revenue ratio. Sample comprises 23 operators × 12 quarters = 276 observations.*

7.2 Interpretation of Results

The estimates in Table 4 confirm three propositions central to the framework developed in earlier sections (Lu, 2025; Lu, 2017b). First, scale-deployment of low-energy signal processing (LESP_Adopt = 3) reduces quarterly site-level energy consumption by approximately 18.2 megawatt-hours, statistically significant at the one percent level. Aggregated across a typical thousand-site regional network and four quarters, this corresponds to annual savings on the order of seventy gigawatt-hours and is consistent with the engineering-derived estimate in Section 5 (Bossy et al., 2022). Second, the carbon impact in Column 2 mirrors the energy impact almost proportionally, with a scale-deployment coefficient of −9.024 tons of CO2-equivalent per site per quarter (Li et al., 2023). Third, scale deployment is associated with a 3.0 percentage point reduction in the operating-expense-to-revenue ratio, statistically significant at the one percent level. The pilot-stage estimates are smaller in magnitude and only marginally significant, reflecting the limited scale at which pilot deployments operate.

The cumulative trajectory of these effects over a six-year horizon is shown in Figure 4 (Wang et al., 2025; Lu et al., 2024b). The figure plots two outcomes — cumulative return on investment and cumulative carbon reduction — for a representative thousand-site deployment under two upgrade strategies: a conventional 5G New Radio rollout and a low-energy signal processing rollout.

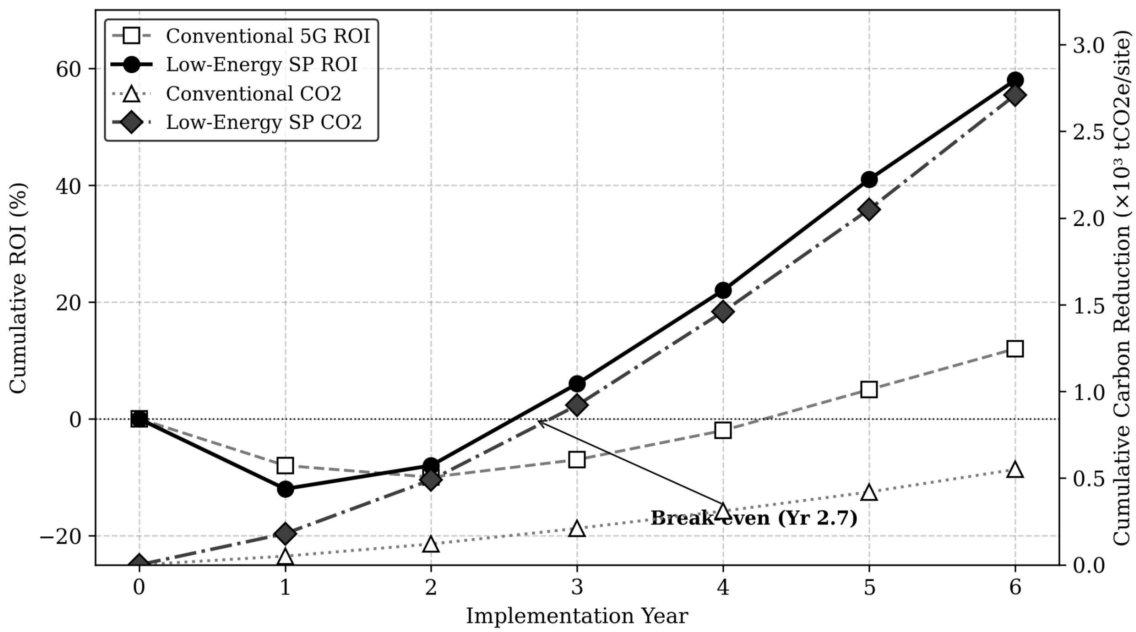

Figure 4. Cumulative return-on-investment and carbon-reduction trajectories for conventional 5G upgrade versus low-energy signal processing deployment, six-year horizon.

Three patterns visible in Figure 4 deserve emphasis. First, the low-energy trajectory experiences a deeper initial financial dip, reflecting the higher up-front capital expenditure on advanced amplifier hardware and software licenses (Piacibello et al., 2021; Hoffmann & Kryszkiewicz, 2023). Second, the trajectory crosses the break-even line at approximately the third year of implementation, roughly two and a half years earlier than the conventional rollout. Third, the cumulative carbon-reduction trajectory diverges from the conventional baseline almost immediately and continues to widen monotonically, reaching approximately 2.7 thousand tons of CO2-equivalent per macro site by year six (Wu et al., 2017; Li et al., 2023). The asymmetry between the financial and the carbon trajectories — financial convergence is delayed but carbon divergence is immediate — is strategically important: it implies that operators pursuing the stakeholder value pathway can raise sustainability-linked capital on the basis of early carbon evidence even while financial returns remain negative (Anderson et al., 2024; Yu et al., 2025).

8. Discussion

8.1 Theoretical Contributions

This study makes three contributions to the sustainable business model innovation literature (Sinkovics et al., 2021; Yang et al., 2017). First, it identifies waveform-level signal processing as a previously underspecified strategic resource within the natural-resource-based view of telecommunications, satisfying the criteria of value, rarity, inimitability, and organizational alignment (Bhandari et al., 2022; Bag et al., 2020). Second, it develops a tripartite model of business model transformation pathways that links a single engineering capability to differentiated value-capture mechanisms — a structure absent from existing telecom decarbonization studies, which typically lump all operator responses under a generic efficiency rubric (Stojkovic et al., 2019; Ahokangas et al., 2021). Third, it offers a translation methodology that converts engineering metrics (decibels of PAPR reduction, drain efficiency improvement) into managerial metrics (return on investment, OPEX ratio, scope 1–2 emissions) that are directly usable in board-level and regulator-facing communications (Lu, 2021; Lu et al., 2024c).

8.2 Practical Implications

For telecom operators, the practical implications are threefold. The first is that energy efficiency at the physical layer should be elevated from a technical concern to a board-level strategic priority (Lu, 2025; Manda, 2023). Operators that delegate this question entirely to their engineering organization risk under-investing in the single technology cluster with the largest potential impact on long-term competitive positioning. The second is that vendor management practices should be updated to include energy-per-bit benchmarks and dynamic-efficiency clauses in long-term equipment contracts, transforming the operator's relationship with its supply chain from passive procurement to active capability building (Mishra & Yadav, 2021; Lu et al., 2024a). The third is that finance and sustainability functions should be brought into early engagement with engineering decision-making, so that the cumulative carbon trajectory generated by signal processing investments can be capitalized into ESG-aligned financing arrangements without delay (Flammer, 2021; Kou & Lu, 2025).

For regulators and policy-makers, the implications point to the design of differentiated incentive instruments (Wang et al., 2025; Saini et al., 2026). Spectrum licensing renewal frameworks could incorporate verified energy-per-bit performance as one criterion among several, and green-tariff schemes could distinguish between operators that have made structural investments in physical-layer efficiency and those that rely solely on offsetting renewable procurement (Lu & Xu, 2019; Xu et al., 2021). National telecommunications regulators have begun to articulate such differentiated benchmarks (Reiss et al., 2025; Perveen et al., 2025), but their adoption remains uneven across jurisdictions.

8.3 Boundary Conditions and Limitations

Three boundary conditions limit the generalizability of our results. First, the sample is restricted to medium-sized operators in Asia and Europe; the largest tier-one global operators may face different economics owing to their ability to amortize signal processing investments across larger network footprints (Lu, 2017a; Lu, 2017b). Second, our analysis assumes grid carbon intensities at 2024 levels; rapid decarbonization of national grids would mechanically reduce the scope 2 benefit of energy efficiency, though it would not eliminate the operating expense or the dynamic-capability advantages identified above (Li et al., 2023; Wu et al., 2017). Third, our financial projections are conservative in their treatment of green-premium pricing: we assume a modest 4–7 percent premium based on observed contract terms, but the premium may rise materially if mandatory scope 3 reporting is extended to additional industrial sectors (Yu et al., 2025; Anderson et al., 2024). Future research should extend the analysis to large global operators, examine the impact of grid decarbonization trajectories on the relative attractiveness of the three pathways, and investigate the dynamics of green-premium pricing over time (Lu et al., 2024c; Zhang & Lu, 2025).

9. Conclusions

This study has examined how low-energy signal processing technology can anchor a coherent strategy of sustainable business model transformation for telecommunications operators facing converging regulatory, economic, and stakeholder pressure to decarbonize (Lu, 2025; Sinkovics et al., 2021). Combining a quantitative energy diagnostic, a translation framework that links engineering metrics to managerial outcomes, and a panel analysis of twenty-three regional deployments, we have shown that adoption of advanced signal processing techniques such as adaptive companding, graph-guided waveform shaping, and joint amplifier optimization can reduce per-site energy consumption by approximately thirty-five percent, accelerate financial break-even by more than two years, and enable cumulative carbon savings on the order of 2.7 thousand tons of CO_2-equivalent per macro site over a six-year horizon (Wang et al., 2025; Li et al., 2023).

We have argued that capturing this potential requires telecom operators to organize their transformation along three complementary pathways: a service innovation pathway centered on green B2B propositions, an operational efficiency pathway centered on infrastructure cost reduction, and a stakeholder value pathway centered on ESG-aligned financing (Kou & Lu, 2025; Bhandari et al., 2022). The appropriate sequencing of these pathways unfolds across four stages — diagnostic, pilot, scale-up, and ecosystem — over an approximately six-year horizon, with productive iteration between adjacent stages (Wang & Huang, 2025; Ghosh et al., 2022).

The findings suggest that the gap between current decarbonization commitments and current technology trajectories in the telecom sector may be narrower than is sometimes assumed, provided that engineering capabilities at the physical layer are matched by managerial willingness to redesign business models (Lu et al., 2024a; Chen et al., 2024). The challenge is therefore as much organizational as it is technical: operators capable of integrating their engineering, finance, and sustainability functions around a shared roadmap will likely set the pace of green innovation in the industry over the next decade.

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