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An Open-Source Techno-Economic Assessment Framework for 5G Deployment

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ABSTRACT Optimal network planning is crucial to ensure viable investments. However, engineering analysis and cost assessment frequently occur independently of each other. Whereas considerable research has been undertaken on 5G networks, there is a lack of openly accessible tools that integrate the engineering and cost aspects, in a techno-economic assessment framework capable of providing geospatially-explicit network analytics. Consequently, this paper details an open-source *python simulator for integrated modelling of 5G* (pysim5G), that enables both engineering and cost metrics to be assessed in a single unified framework. The tool includes statistical analysis of radio interference to assess the system-level performance of 4G and 5G frequency band coexistence (including millimeter wave), while simultaneously quantifying the costs of ultra-dense 5G networks. An example application of this framework explores the techno-economics of 5G infrastructure sharing strategies, finding that total deployment costs can be reduced by 30% using either passive site sharing, or passive backhaul sharing, or by up to 50% via a multi-operator radio access network. The key contribution is a fully-tested, open-source software codebase, allowing users to undertake integrated techno-economic assessment of 5G deployments in a single geospatial framework.

INDEX TERMS 5G, techno-economic analysis, infrastructure sharing, open-source, software.

I. INTRODUCTION

How do we simultaneously assess (i) the engineering performance capabilities of different network deployments and (ii) the infrastructure deployment costs? The delivery of 5G is expected to lead to ultra-dense cellular networks due to efficiency gains designed to deal with increasingly large data traffic demands [1], driven predominantly by video traffic [2]. Existing capacity and coverage of mobile data services will be significantly expanded through a variety of means, including the introduction of new sub-6GHz and millimeter wave spectrum bands (>26GHz), increased network densification, the introduction of novel technologies including higher order MIMO and edge compute [3], in addition to fundamental network architecture changes.

Given that user demand for data continues to grow at a very fast rate, Mobile Network Operators (MNOs) are searching for new technologies which can help lower the cost per bit of delivering high-capacity data services. Unfortunately, in many telecommunications markets the Average Revenue Per User (ARPU) has either been declining or remained static in real terms, decreasing globally by 1% in 2018 [4]. Hence, it is desirable that 5G infrastructure investment is carried out within existing capital expenditure (capex) budgets. Recent solutions being proposed to help reduce costs range from passive infrastructure sharing between competitors [5] through to the use of a 'neutral host' business model [6], [7].

Considering these challenges, the motivation for this research is that (i) relatively little techno-economic assessment of 5G has taken place [8], [9], (ii) there are few open-source analytical frameworks available to address this problem, and (iii) we still lack quantified assessment of the cost savings resulting from infrastructure sharing strategies [10].

Three main classes of 5G use cases are envisioned: Enhanced Mobile Broadband (eMBB), Massive Machine

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Type Communications (mMTC), and Ultra-Reliable and Low Latency Communications (URLLC). Although 4G LTE and 4G LTE-Advanced technologies can provide impressive capacity, over the long-term 5G and further technology generations will be needed to help meet demand in a broader range of use cases and industries.

Whereas commercial deployments of 5G infrastructure have already started around the world, many MNOs have yet to begin. More importantly, 5G opens the opportunity for non-MNO roll-out of 5G infrastructure, in infrastructure sharing or private network deployments. Whilst MNOs will have their own integrated techno-economic analytical tools (in-house or through suppliers), many medium or smaller operators, and new entrants do not. They still rely on 'siloed' processes where engineering and cost assessment take place as distinctly separate phases. Better cellular planning tools are needed [11] and although many exist, they often focus more on either the engineering aspects [12]–[16], or the economic aspects of the planning stage [17], [18]. Furthermore, there is a need for such tools to be also available to the research community, to better connect the analysis of new technological advances to the engineering costs involved in deployment. Consequently, the conjecture of this paper is that integrated techno-economic assessment tools can help to reduce uncertainty and improve the efficiency of infrastructure investments.

Although there are many sequential steps to deploying new 5G infrastructure assets, including planning, design, migration, operation and maintenance, the planning phase is one of the most crucial steps to ensure viable investments which optimize capacity and cost, otherwise the network operator must resort to overprovisioning [19]. Thus, the key contributions of this paper include:

1. Creating a unified techno-economic assessment framework to evaluate the geospatial deployment of 4G/5G infrastructure coexistence in terms of capacity, coverage, and cost.
2. Developing a 4G/5G system simulator in Python, one of the most popular general-purpose programing languages, allowing engineers, business analysts and researchers to explore the open-source code, test the model and make their own additions to the software capability.
3. Applying this open-source assessment framework to test the cost efficiency of 5G infrastructure sharing strategies.

Having articulated the potential contribution, an initial overview of a system assessment framework will be presented in Section II, followed in Section III by a capacity assessment model, and the software architecture in Section IV. Finally, results are reported in Section V before conclusions are given in Section VI.

II. SYSTEM ASSESSMENT FRAMEWORK

Private or public infrastructure decisions need to be supported by quantitative analytics. Although Long Run Incremental Cost modeling approaches are frequently used in telecommunications [20], such approaches are usually spreadsheet-based, not spatially explicit and do not take advantage of data science techniques. Indeed, there has been surprisingly little analysis on the national assessment of digital communications networks, with only a few examples overcoming these limitations [21]–[23], despite growing needs in industry and government [24], [25]. Figure 1 illustrates a national system assessment framework capable of quantifying the impact of potential infrastructure decisions.

To enable such a framework, different data inputs are required for local statistical areas at the level of spatial disaggregation desired. This includes geospatially-explicit demographic forecasts, cell sites data and building information. The capacity assessment module then requires data on the number of existing cell sites per area, along with the available spectrum portfolio. Demand assessment for an area considers the number of users, individual data demand, the quantity of data traffic offloaded to Wi-Fi and the market share of the hypothetical operator being modeled.

For each timestep, the demand assessment module estimates the required average busy hour demand needing to be met. Likewise, the capacity assessment module estimates the average capacity able to be provided based on the cell site density, available spectrum and present technology.

The impact of different decisions can then be simulated using the decision module, including (i) deploying new spectrum, (ii) adding new cellular sites, (iii) increasing infrastructure sharing, (iv) deregulating planning, (v) adapting the fiscal environment, (vi) reducing spectrum costs and finally (vii) testing the impact of coverage obligations. The results of such decisions provide explicit spatio-temporal results in terms of area capacity, coverage cost and energy efficiency. This paper specifically reports the design of the model in the capacity assessment module highlighted in red in Fig. 1.

III. CAPACITY ASSESSMENT MODEL

Generally, the further away a user is from a connecting site, the lower the data transfer rate the user will achieve. This results from increased path loss between the user and the site which degrades the level of received signal. Often this is due to a combination of the propagation characteristics of the carrier frequency, and the level of environmental clutter such as buildings, as well as interference and noise from other sources.

The method presented here concentrates on the key 5G use case of eMBB, which is the first use case class supported by the current 3GPP 5G specification [26].

The simulation approach accounts for the three main ways the capacity of a cellular access network can be enhanced, including (i) improving spectral efficiency (additional bits per Hz), (ii) increasing spectral reuse via network densification (building more sites), and (iii) adding new spectrum bands (augmenting the total amount of spectrum bandwidth).

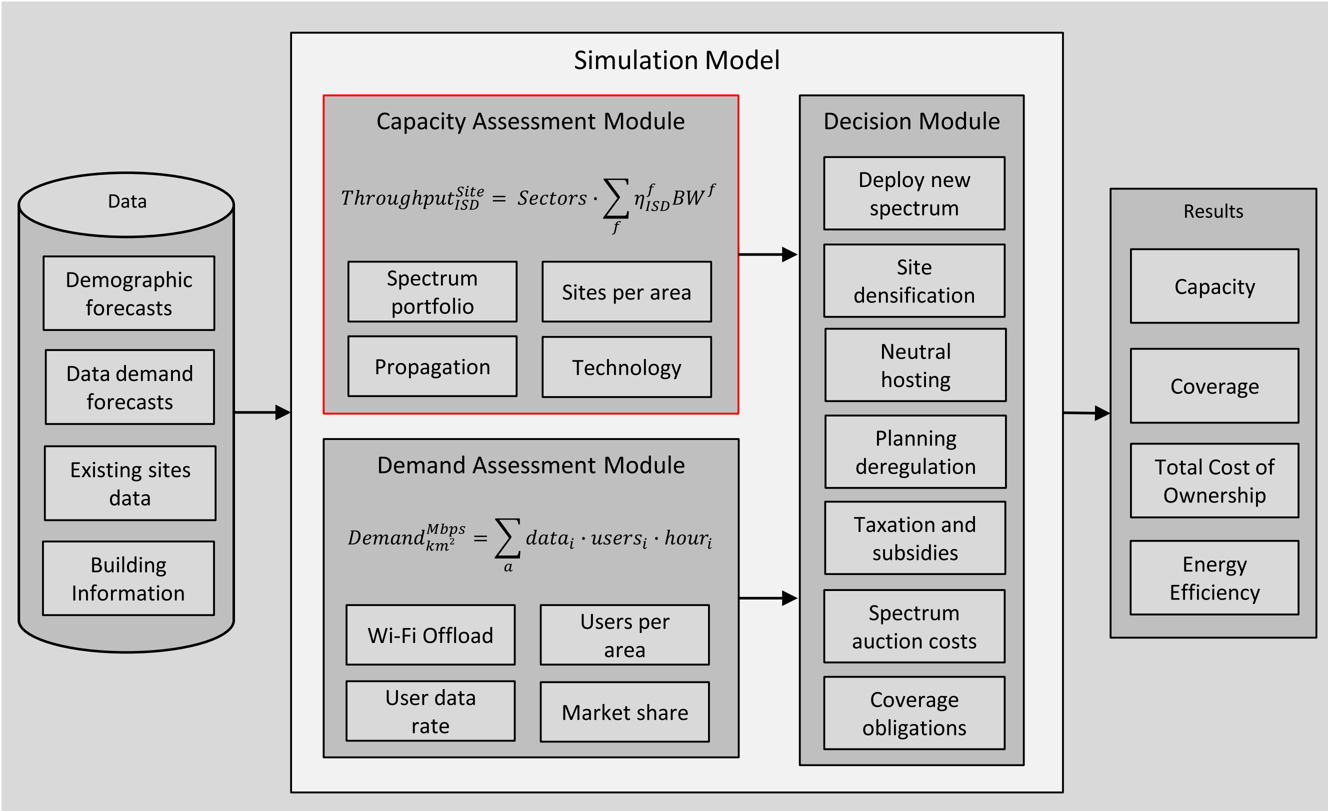

FIGURE 1. System assessment framework.

The aim of the system model is to estimate the mean Network Spectral Efficiency ($\bar{\eta}_{area}$) (bps/Hz/km^2) [27]. The quantity of cells per site ($\bar{\eta}_{cells}$) and density of co-channel sites (ρ_{sites}) using the same spectrum frequency affects the Inter-Site Distance (ISD), as detailed in (1).

$$\bar{\eta}_{area} = \bar{\eta}_{cells} \cdot \rho_{sites} \tag{1}$$

For a set number of cells and sites, the Network Spectral Efficiency ($\bar{\eta}_{area}$) can be estimated using a stochastic geometry approach to provide an average value representing the number of bits per second per Hz (bps/Hz), given a certain traffic load and current radio channel and interference conditions. Such an approach overcomes the limitations of static interference assumptions [28], better accounting for potential interference constraints across space [29]. Decreasing the ISD, increases the density of network assets per square kilometer, allowing greater spectral reuse of carrier frequencies, resulting in capacity enhancements. The system model simulation process is illustrated graphically in Fig. 2.

Network planning has a significant impact on the achieved spectral efficiency as the level of useful signal obtainable by the User Equipment (UE), in relation to unwanted interference and noise, affects the Signal to Inferences plus Noise Ratio (SINR). The SINR (SINR_j) for the j^{th} user is estimated using the level of received signal from the best serving cell, treated here as a macrocell (S_j), given the sum of the background interference ($\sum_i I_{i,j}$) from the i^{th} interfering cell at the j^{th} receiver UE, plus the received background and receiver UE noise (N_j), as formalized in (2):

$$\text{SINR}_j = \frac{S_j}{\sum_i I_{i,j} + N_j} \tag{2}$$

The simulation software tests different spectrum portfolios depending on the user's preference. In this example, a broadly representative set of existing 4G LTE and 5G New Radio (NR) carrier frequencies are used operated in Frequency Division Duplex mode, consisting of 10 MHz bandwidth for each of the 700 MHz, 800 MHz, 1.8 GHz and 2.6 GHz bands, 40 MHz bandwidth for 3.5 GHz, and 100 MHz bandwidth for 26 GHz.

Geometry data for supply-side physical infrastructure assets is required. In this paper the software is demonstrated using a test dataset based on a hexagon cellular planning approach, for a single transmitter and six other interfering transmitters, generated automatically by the software. The *pysim5G* software can either produce GeoJSON hexagon objects for user defined ISDs or take advantage of real sites data.

The Monte Carlo simulation functions by generating a user-defined set of indoor and outdoor receivers, distributed across a site area. The distance is then calculated between each receiver and the serving site and used to estimate the potential path loss, including any building penetration loss if indoor. The same process is carried out between the receiver

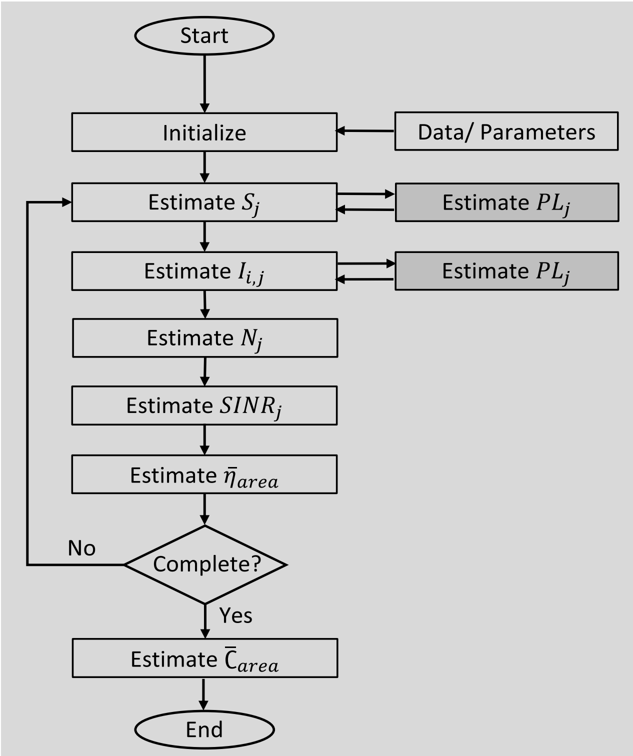

FIGURE 2. Simulation process.

and other interfering sites, to obtain the sum of the unwanted interference.

To reduce the general computational cost of looping in Python, pointer indirection and per-element dynamic type checking, the simulation efficiency is increased by utilizing NumPy arrays (capable of being directly implemented in C). Hence, the user can specify a set number of iterations to define for each random parameter, with the mean value of the NumPy array being used to improve loop efficiency.

Propagation effects are accounted for by a path loss module which utilizes the ETSI 5G channel model for frequencies from 0.5 to 100 GHz [30]. As the purpose here is to develop an integrated techno-economic assessment model, path loss estimation focuses on general parameters by using lognormal distributions to capture shadow fading from environmental clutter and building penetration losses. Thus, both received power and unwanted interference effects can be estimated.

Modulation and coding rates are calculated based on the SINR at the UE using 4G and 5G lookup tables [31], as defined by 3GPP. To statistically ensure certain Quality of Service (QoS) levels are achieved, the results generated via the Monte Carlo method for a specific set of simulation parameters can be extracted based on user-defined summary statistics. This could either be the mean capacity value for a network configuration (as demonstrated here), or a specific percentile value (e.g. 5th) to represent the cell edge rate. The approach taken focuses only on the downlink because it is generally the largest bottleneck.

TABLE 1. Simulation parameters.

Parameter	Value	Unit
Iterations	100	Samples per receiver (n)
Spectrum bands	0.7, 0.8, 1.8, 2.6, 3.5, 26	GHz
Respective spectrum bandwidths	10, 10, 10, 10, 40, 100	MHz
ISD	0.25 - 5	km
Transmit power	40	dBm
Transmitter antenna type	Directional	-
Transmitter antenna gain	16	dBi
Sectors	3	Sectors
Transmitter height	30	Meters
UE antenna gain	4	dBi
UE losses	4	dB
UE misc. losses	4	dB
UE height	1.5	Meters
Propagation model	ETSI TR 138 901	-
Shadow fading log normal distribution	(μ, σ) = (0, σ)	dB
Building penetration loss log normal distribution	(μ, σ) = (12, 8)	dB
Frequency reuse	1	Factor
Shadow fading	Log normal	dB
Indoor probability	50	%
Line of Sight	<250	Meters
Transmission method	Single-In, Single-Out (SISO)	-

The propagation environment is represented by ETSI-defined urban and rural clutter types, leading to use of different propagation model parameters. Additionally, users can specify the probability of a UE being indoor, leading to further building penetration losses, which are modelled using a lognormal distribution, as per the simulation parameters in Table 1.

The Total Cost of Ownership (TCO) is estimated for each asset ($Asset_{NPV}$) by calculating the Net Present Value (NPV) of the initial capital expenditure required in the first year of deployment (i) as a one-off cost (c_i), combined with the ongoing operating expenditure (opex) over the lifetime of the asset (o_t) (with opex being 10% of the initial capex value for all active components, annually). A discount rate of 3.5% (r) is used over a period (Y) of 10 years, as illustrated in (3).

$$Asset_{NPV} = c_i + \sum_{t=0}^{Y} \frac{o_t}{(1+r)^t} \tag{3}$$

This calculation does not consider price trend changes and assumes a 10-year lifespan of macrocells. As shown in Fig.2, the total cost ($\bar{C}_{area}$) per square kilometer for different network configurations can then be calculated based on the density of assets by area. The costs per asset item are stated in Table 2,

TABLE 2. Equipment costs by deployment strategy.

Category	Equipment	Capex ($USD)	Opex ($USD)	Quantity required	Equipment sharing by strategy			
					Baseline	Passive site sharing	Passive backhaul sharing	Active MORAN
RAN	Single sector antenna	1,500	150	3	-	-	-	x
	Single remote radio unit	4,000	400	3	-	-	-	x
	Single baseband unit	10,000	1,000	1	-	-	-	x
Site	Tower	10,000	-	1	-	x	-	x
	Civil materials	5,000	-	1	-	x	-	x
	Transportation	10,000	-	1	-	x	-	x
	Installation	5,000	-	1	-	x	-	x
	Site rental	-	9,600	1	-	x	x	x
Power	Power/generator/battery system	5,000	500	1	-	x	x	x
Backhaul	High-speed backhaul hub	15,000	1,500	1	-	-	x	x
	Router	2,000	200	1	-	-	x	x

approximately based on the Mobile Call Termination model released by UK Ofcom [20].

GSMA has described three types of infrastructure sharing strategies [5], shown in Table 2. Thus, shared infrastructure assets take place between 2 MNOs, according to the following strategies:

1. **Baseline** where no sharing takes place and a dedicated network is built for a single MNO.
2. **Passive site sharing** involves sharing a tower, civil materials, transportation, installation, site rental and a power system supply (connection, generator and battery).
3. **Passive backhaul sharing** involves sharing high-speed fibre backhaul, an on-site router, site rental and a power system (connection, generator and battery).
4. A **multi-operator radio access network (MORAN)** involves sharing all equipment including three sector antennas, a single remote radio unit, a single baseband unit, a tower, civil materials, transportation, installation, site rental and a power system (connection, generator and battery), as well as high-speed fibre backhaul and an on-site router.

IV. PYSIM5G ARCHITECTURE

An object-oriented approach is utilized in Python 3, combined with the use of gold-standard software design principles including test-driven development and in-line documentation. An online repository hosts the pysim5G [32] source distribution, example data and documentation allowing any user access to run the model described here. Unit tests provide certainty to current and future model users that the code carries out the intended purpose, allowing enhanced validation of individual modules.

A meta-class object called the 'SimulationManager' holds all other asset objects and contains a set of methods for budget estimation. The 'Transmitter', 'Receiver' and 'Interfering-Transmitter' objects have a set of attributes required for the simulation, specifically latitude and longitude coordinates, and necessary inputs for propagation and system capacity modeling (including those listed in Table 1, such as power, gain and height for receivers and transmitters). Additionally, the 'SiteArea' object contains the geometry for the area being modeled. Fig. 3 illustrates how these classes exist within a set of interconnected software modules enabling a reproducible data pipeline.

The software is operated using the simulation runner script ('run.py') which is capable of reading in all required data and writing out all necessary results and utilized data layers. The simulation manager ('simulation_manager.py') contains the main model code and is capable of instantiating each of the required objects. For specific steps in the link budget estimation process, the simulation manager can call the path loss module ('path_loss.py') to help estimate received power and received interference. Once the engineering simulation model has been run, the results are passed to the cost module ('costs.py'), which calculate the NPV of capital and operational expenditure for each network configuration, with the results being passed back to the simulation runner script for writing to desired file formats.

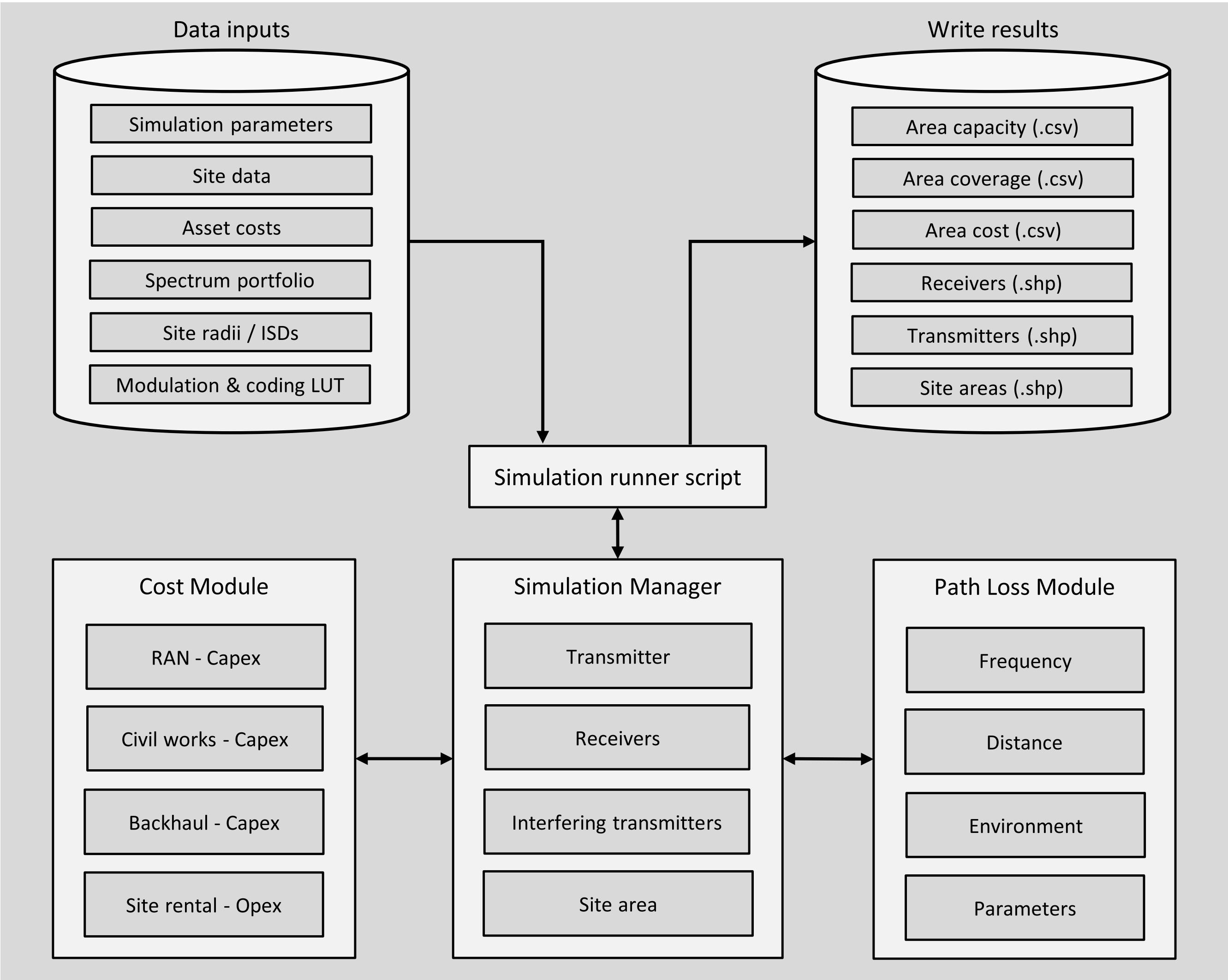

FIGURE 3. **Model architecture.**

The software takes advantage of the Geospatial JavaScript Object Notation (GeoJSON) data standard defined by the Internet Engineering Task Force (IETF), which enables both spatial and non-spatial information to be simultaneously stored for an entity in a single dictionary [33]. GeoJSON differs from other formal (and often proprietary) Geographic Information System standards, in that it is open-source and is maintained by the internet engineering community. As transmitter and receivers are loaded into the model, they are converted to a GeoJSON format to store all necessary spatial and non-spatial information.

The results produced can be written in many ways, including (i) a set of shape files (.shp) containing all transmitters, receivers, site area boundaries, and associated results, for geospatial plotting, (ii) individual files (.csv) for each simulation run for every engineering parameter, and (iii) an aggregated lookup table containing a single set of engineering and economic results for each simulation run (given a desired QoS level such as 50% or 95% cell edge reliability).

The full results contain a row for each receiver latitude and longitude position, as well as the environment, ISD, site area (km^2), site density (km^2), carrier frequency (GHz), carrier bandwidth (MHz), the number of site sectors, the technology generation, antenna height (m), path loss (dB), received power (dBm), interference (dBm), SINR (dB), spectral efficiency (bps/Hz), link capacity (Mbps) and area capacity (Mbps/km^2). The aggregated results contain the same metrics but for a specific reliability level (minus coordinates). Similarly, the cost results contain a single row for each iteration based on reliability level, deployment strategy, the environment, ISD, site area (km^2), site density (km^2), total deployment cost ($/$km^2$), and the cost for each individual component ($/$km^2$). Results will now be presented.

V. RESULTS

This section presents both the engineering and economic results for a single set of example simulations. Fig. 4 graphically illustrates the site capacity (ISD=1 km),

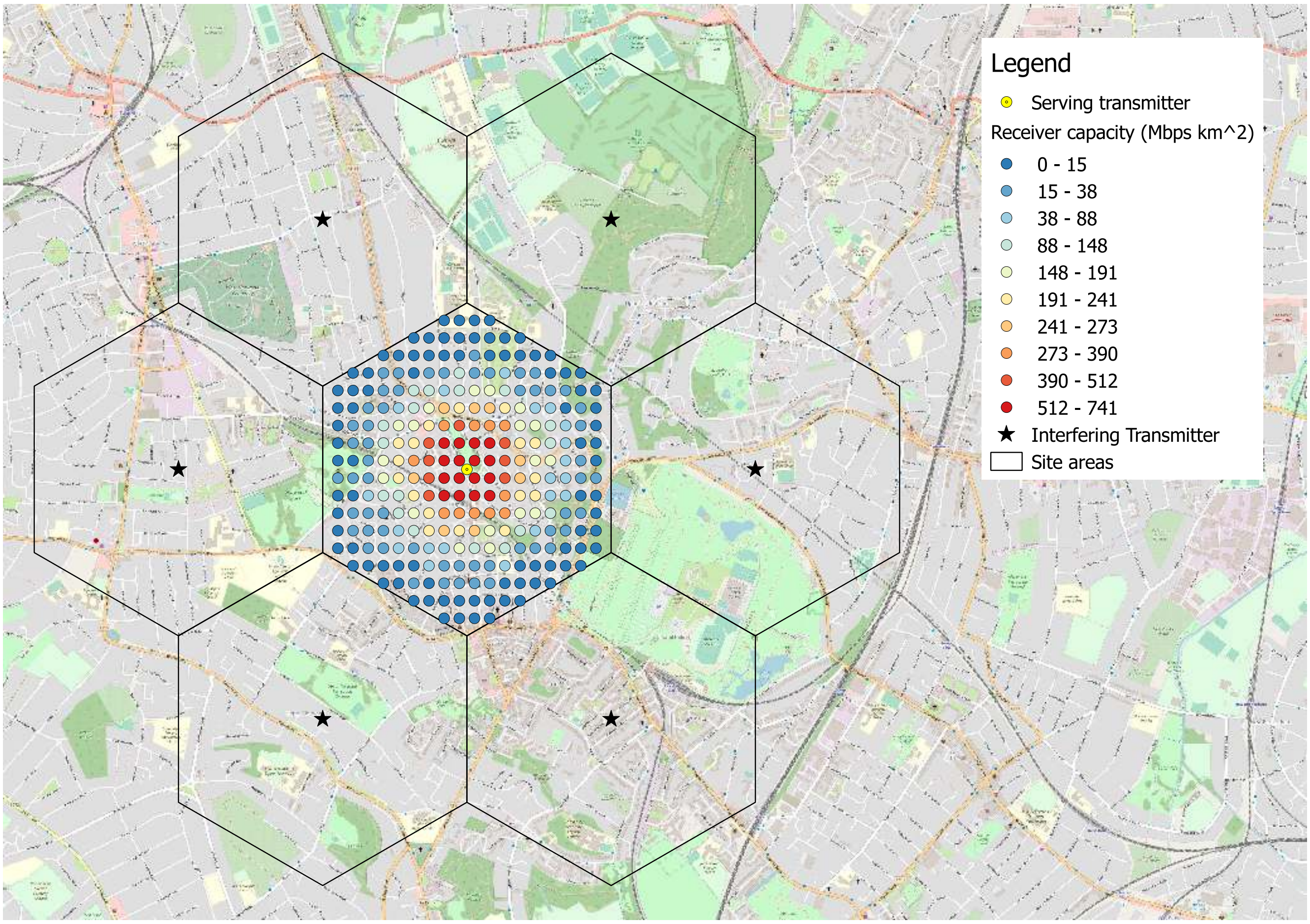

FIGURE 4. Simulation results (ISD=1 km) for Crystal Palace, South London.

for Crystal Palace, South London. The area in the immediate vicinity to the site has much higher capacity, driven by the availability of millimeter wave, although this capacity decreases rapidly moving away from the site.

For accurate estimation of network deployment costs, it is essential that the software produces accurate and coherent engineering metrics. Thus, Fig. 5 visualizes the average area results involved in the link budget estimation process, by frequency band and ISD. Then for each plot, multiple y-axis values for each single value of x are aggregated, allowing an estimate of the central tendency and suitable confidence intervals (bootstrapped at 95%), using the default parameters available in the Python visualization tool Seaborn.

The results presented are logical and coherent with existing theory. For example, higher building density in urban locations leads to greater path loss, whereas in contrast rural environments experience less path loss, leading to higher received power for comparable ISD values. Mean path loss ranged from approximately 100-160 dB over the ISDs tested and increased with (i) higher carrier frequencies and (ii) at greater distances from the transmitter. This pattern is reflected in the estimated received power and interference results, as would be expected.

The highest SINR recorded is approximately 20 dB in the densest scenarios, falling beyond the minimum channel quality threshold (−6.7 dB) after 2.5 km (for 26 GHz). Other bands, particularly the 3.5 GHz band function above this threshold, beyond the maximum ISD tested here.

Spectral Efficiency (SE) results are affected by interference, as well as the cellular technology generation deployed in each frequency. Hence, the highest mean SE results are at 0.7, 3.5 and 26 GHz (∼4.5 Bps/Hz) for the smallest ISD values (<1 km) due to the 5G NR interface. Depending on the band, these 5GNR mean SE values decrease below this level as the ISD increases. In contrast, legacy 4G resulted in lower mean SE values (∼3 Bps/Hz) at the smallest ISD values tested (<1 km), dropping to ∼2.5-3 Bps/Hz as the ISD increases.

For very small ISD values, capacity is, as expected, highest in the 26GHz band due to its much wider bandwidth (100 MHz), followed by 3.5 GHz (40 MHz), where a single user could achieve maximum link capacity of almost 2 Gbps and 1 Gbps respectively in line of sight near the serving cell. However, average capacity decreased quickly, particularly for millimeter wave, as the ISD increased.

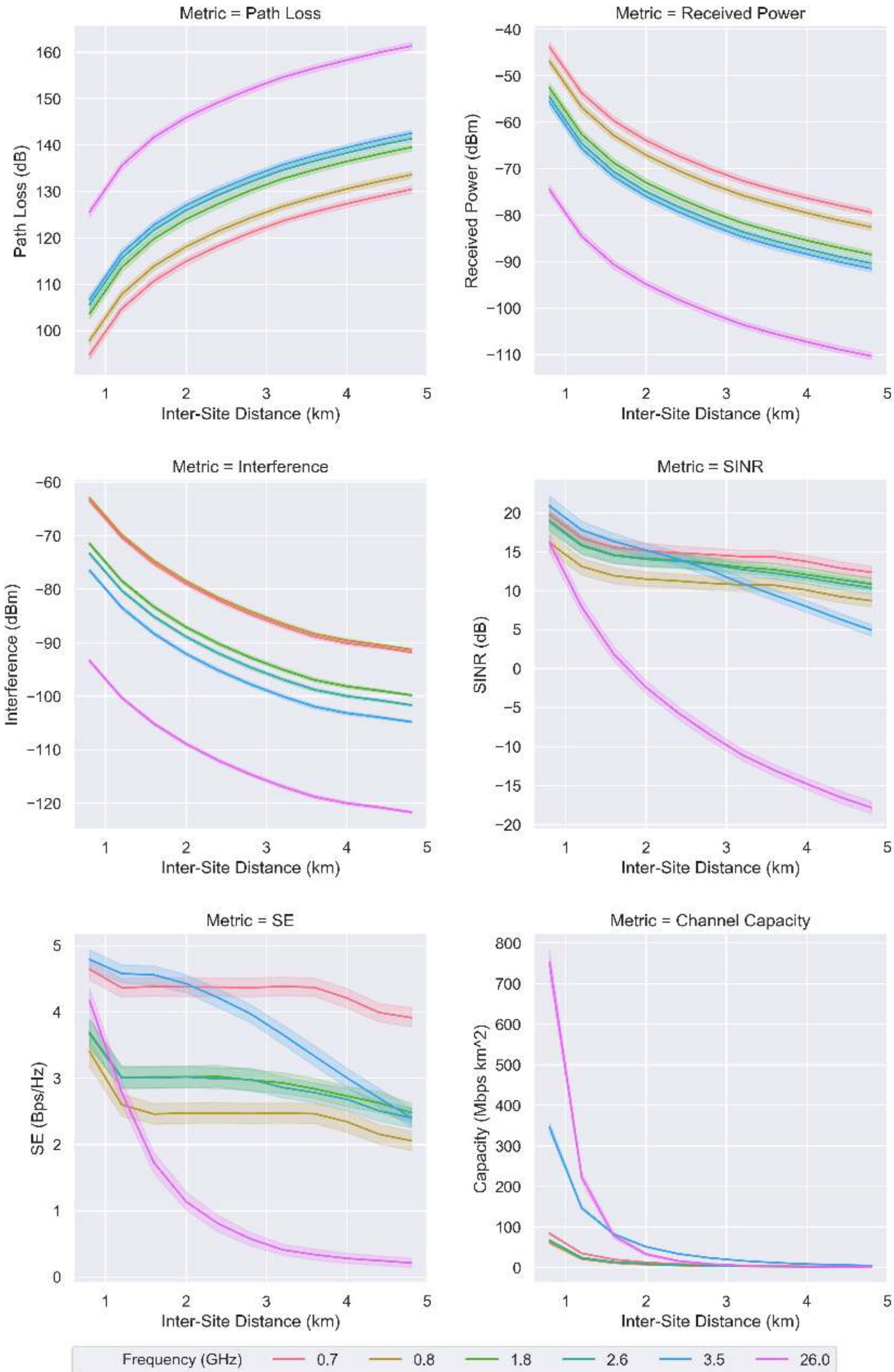

FIGURE 5. Engineering results by ISD and frequency band.

Fig. 6 illustrates the cost results per operator by area for the single set of simulation runs, focusing purely on the different infrastructure sharing strategies.

The mean cost results are discussed focusing on a 1 km ISD. In the baseline, the mean TCO of \$366,000 km^2 was dominated by site rental, accounting for approximately 41%

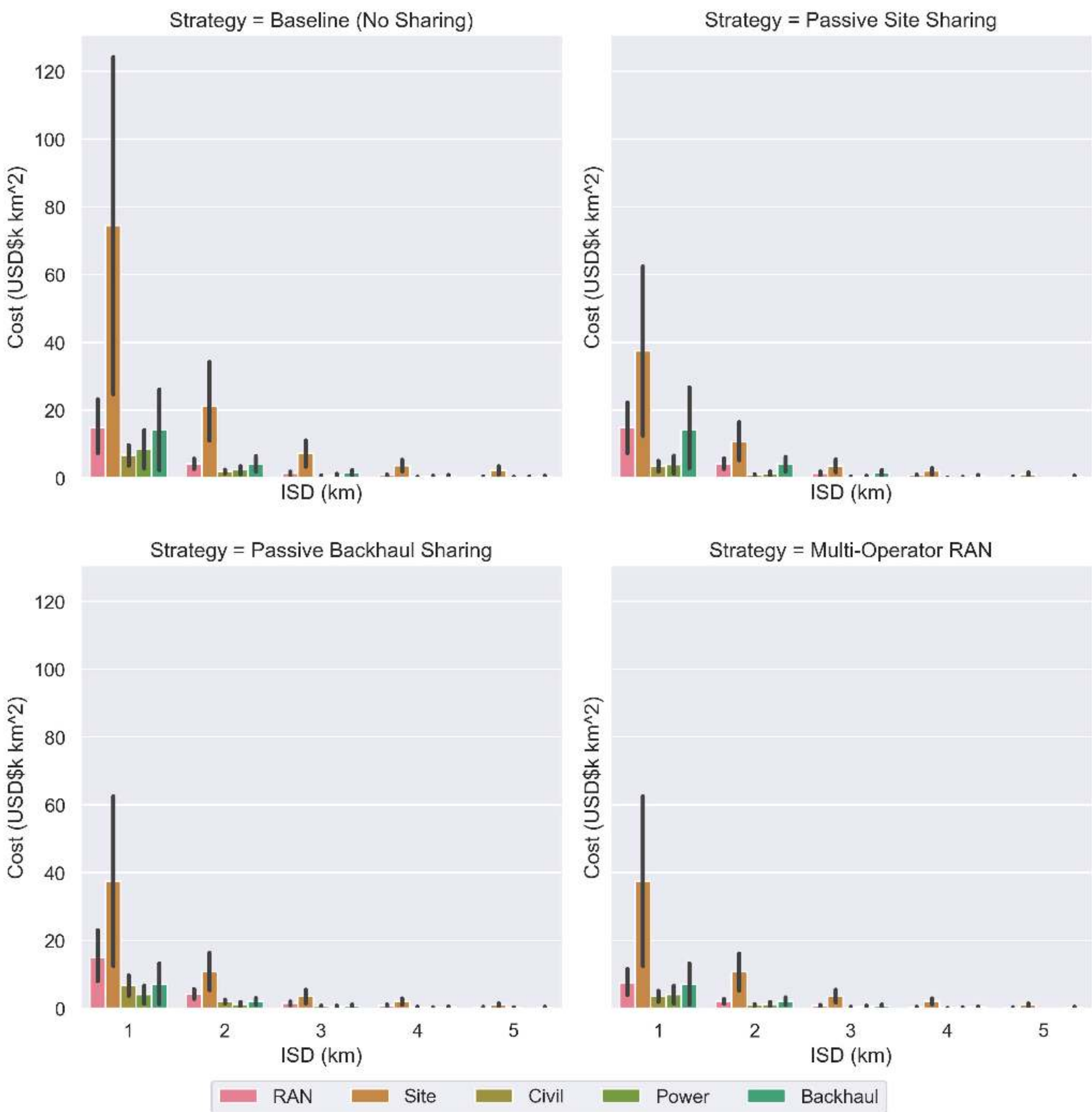

FIGURE 6. Cost results per operator by ISD and infrastructure sharing strategy.

(\$149,090 km^2) of required investment over the 10 year horizon, with the rest of the TCO made up by 24% RAN (\$88,967 km^2), 15% civil works (\$54,127 km^2), 5% power equipment (\$16,786 km^2) and 15% backhaul (\$57,073 km^2).

In contrast, the passive site sharing strategy was able to reduce the TCO (\$256,041 km^2) by approximately 30% below the baseline, with the site rental and civil works dropping to 29% and 11% of the cost composition respectively.

Similarly, the passive backhaul sharing strategy also saw the TCO (\$254,568 km^2) reduced by approximately 30% against the baseline, albeit by sharing different equipment. In this strategy, the site rental was also reduced to 29% of the TCO, with the shared backhaul dropping to only 11% of the total cost on average.

Finally, in the multi-operator RAN strategy all passive and active items were shared leading to an approximate 50% cost saving and a TCO of \$183,021 km^2. The percentage composition of the TCO is the same as in the baseline, but the raw monetary values per square kilometer dropped to only \$44,483 km^2 for RAN, \$74,545 km^2 for site rental, \$27,063 km^2 for civil works, \$8,393 km^2 for power and $28,536 km^2 for backhaul. Conclusions will now be provided.

VI. CONCLUSION AND FURTHER RESEARCH

Delivering 5G will require enhanced network planning methods to take advantage of improvements in the radio network and its flexibility, while simultaneously reducing the cost per bit of data transfer. Frontier MNOs often have their own integrated network planning tools developed in-house, however many operators (especially smaller ones, or new entrants) do not, and often rely on 'siloed' network planning, where engineering assessment and cost evaluation take place as separate steps.

Motivated by this problem, the general framework presented and applied in this paper introduces an integrated techno-economic assessment approach for evaluating the capacity and cost of 5G deployment strategies simultaneously, known as the *python simulator for integrated modelling of 5G* (pysim5G). Importantly, the codebase is open-source and available from an online repository [32], with comprehensive test coverage, and documentation. Hence, pysim5G is available for immediate use by engineers, business analysts or researchers, either in industry or academia.

Having applied this framework to assess different infrastructure sharing strategies, we were able to simultaneously present integrated engineering metrics and equipment costs from a single unified framework. The capacity, coverage and cost results also accounted for all 4G and 5G co-existing spectrum bands, including millimeter wave. Findings suggested that passive site sharing, and passive backhaul sharing strategies, could independently reduce total cost by 30% based on two MNOs, when compared to a baseline of a single dedicated network. A multi-operator RAN had the best cost reduction potential of approximately 50% against the baseline.

Due to the popularity of Python, and the open-source codebase offered here, users can relatively easily take advantage of the *pysim5G* software, as well as utilize other software packages for additional development opportunities.

Future research applications can build on the *pysim5G* framework. Useful developments include expanding the number of 5G technologies able to be tested, including beamforming and higher order MIMO for enhanced capacity, and the use of edge compute for low latency application planning. Optimization techniques could help to maximize capacity, coverage and cost, informing future investment decisions.

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