

The importance of spatio-temporal infrastructure assessment: Evidence for 5G from the Oxford–Cambridge Arc

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ABSTRACT

The roll-out of 5G infrastructure can provide enhanced high capacity, low latency communications enabling a range of new use cases. However, to deliver the improvements 5G promises, we need to understand how to enhance capacity and coverage, at reasonable cost, across space and over time. In this paper, we take a spatio-temporal simulation modeling approach, using industry-standard engineering models of 5G wireless networks, to test how different infrastructure strategies perform under scenarios of uncertain future demand. We use coupled open-source models to analyze a UK growth corridor, a system-of-cities comprising 7 urban areas, known as the Oxford-Cambridge Arc. We find that population growth has a marginal impact on total demand for 5G (up to 15%), as the main factor driving demand is the increase in per user data consumption resulting mainly from video. Additionally, the results suggest only limited justification for deploying 5G based purely on the need for more capacity. Strategies which reuse existing brownfield Macro Cell sites are enough to meet future demand for Enhanced Mobile Broadband, except in the densest urban areas. While spatio-temporal analysis of infrastructure is common in some sectors (e.g. transport, energy and water), there has been a lack of open analysis of digital infrastructure. This study makes a novel contribution by providing an open and reproducible spatio-temporal assessment of different 5G technologies at a time when 5G is starting to roll-out around the world.

1. Introduction

5G is mooted to revolutionize urban environments by providing higher capacity communications with lower latency. Mobile connectivity has already changed how we interact with our environment, and the resulting novel, often big, datasets have enabled advances in urban analytics and the science of cities (Chin, Huang, Horn, Kasanicky, & Weibel, 2019; Fan et al., 2018; Li, Gao, Lu, & Zhang, 2019; Li & Goldberg, 2018; Ríos & Muñoz, 2017; Semanjski, Gautama, Ahas, & Witlox, 2017; Tu et al., 2019; Wan et al., 2018; Yuan, Raubal, & Liu, 2012; Zhai, Wu, Fan, & Wang, 2018). Yet, there is a relative lack of analysis of the infrastructure which enables this data collection. Reliable digital connectivity, with increased capacity and reduced latency, can be used by a number of highly anticipated technologies, such as Intelligent Transport Systems (Aliedani & Loke, 2019; Gurumurthy & Kockelman, 2018) and massive real-time machine connectivity (such as the ‘Internet of Things’, ‘industry 4.0’ etc.) (Cao & Wachowicz, 2019). These technologies are proposed as solutions to a range of economic, social and environmental problems in cities (Bergés & Samaras, 2019).

Digital infrastructure can be defined as the technologies that deliver the internet, including fiber optic cable, legacy copper and coaxial

cable, as well as cellular (2G–6G), Wi-Fi and satellite broadband technologies. Demand for mobile data has been satisfied over the last decade with the fourth generation of cellular technology, known as 4G, which provided mass-market mobile broadband services to smartphone users, spurring the development of the digital ecosystem and creating vast amounts of user data. However, as data consumption has grown exponentially year-on-year since the Apple iPhone release in 2007, driven mainly by increased video consumption, mobile networks have struggled to keep up with demand. Consequently, the fifth generation (5G) of cellular technology provides significant improvements which are particularly needed in capacity-constrained urban areas (Rendon Schneir et al., 2019). Mobile Network Operators (MNOs) around the world have begun to roll-out 5G infrastructure and are offering enhanced mobile broadband, although it will likely be years before most users are covered.

5G has been seen by governments around the world as a cornerstone of a successful future industrial strategy (Lemstra, 2018), with the USA, China, Europe, South Korea as well as many others vying for leadership of this new group of technologies. While there has been significant engineering research on 5G, there has been little geospatial assessment of infrastructure needs. This is despite many computational urban and

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environmental researchers developing new technologies which need digital connectivity for a range of use cases including river monitoring (Ueyama et al., 2017), detection of forest fires (Aslan, Korpeoglu, & Ulusoy, 2012; Ballari, Wachowicz, Bregt, & Manso-Callejo, 2012), monitoring waste and surface water runoff (Rettig, Khanna, Heintzelman, & Beck, 2014; Sempere-Payá & Santonja-Climent, 2012), congestion analysis (Kan et al., 2019) and assessing urban movements (Kim, 2018).

Given that 5G will be needed to meet future data demand, and given the range of demand-side and supply-side factors affecting the roll-out of 5G infrastructure, two research questions are posed:

1. Under different scenarios of population growth, how will mobile telecommunication data demand be affected?
2. Which 5G infrastructure deployment strategies best meet future demand?

In order to answer these questions, a literature review is first carried out. A spatio-temporal technoeconomic method is then proposed in Section 3, with the strategies to be tested outlined in Section 3.5, before results are presented in Section 4. The findings are then discussed in relation to the research questions in Section 5, with conclusions provided in Section 6.

2. Literature review

This literature review first provides an introductory overview of 5G and its new technological capabilities, before reviewing the spatio-temporal modeling of digital infrastructure.

2.1. What is 5G?

Currently, the main use case justifying the roll-out of 5G is enhanced mobile broadband (eMBB), which is the first use case class supported by Release 15 of the 3GPP 5G specification (3GPP, 2019) (known as ‘Non Standalone’ 5G as it utilizes a 4G LTE core network). However, a variety of other use cases are proposed for 5G, including ‘massive machine type communications’ and ‘ultra-reliable and low latency communications’ (Martín, Pérez-Leal, & Navío-Marco, 2019). Data exchange is expected to take place between humans, between humans and machines, and between machines, as illustrated in Fig. 1.

An important feature of 5G is the ability to deliver connectivity to

specific uses via ‘slicing’ techniques, allowing different levels of Quality of Service (QoS) for specific applications including virtual and augmented reality (Erol-Kantarci & Sukhmani, 2018; Imottesjo & Kain, 2018), public safety (Naqvi, Hassan, Pervaiz, & Ni, 2018; Usman, Gebremariam, Raza, & Granelli, 2015), manufacturing (Rao & Prasad, 2018a), connected and autonomous vehicles (Giust et al., 2018; Ullah et al., 2019), health (Lloret, Parra, Taha, & Tomás, 2017) and utilities (Mouftah, Erol-Kantarci, & Rehmani, 2018; Rao & Prasad, 2018b).

A range of new engineering technologies associated with the supply of 5G enable this dramatic improvement in the quality of data access. These include technical 5G features such as network function virtualization, software-defined networks, use of millimeter wave spectrum and massive Multiple-Input Multiple-Output (mMIMO). These supply-side techniques are expected to have significant demand-side impacts by enabling digital transformation across vertical industrial sectors (Cave, 2018). In this review, which is focused on the spatial analysis of 5G, we will not provide a comprehensive engineering overview of different technologies, therefore interested readers should explore the many existing reviews available (Akyildiz, Nie, Lin, & Chandrasekaran, 2016; Andrews et al., 2014; Jaber, Imran, Tafazolli, & Tukmanov, 2016; Panwar, Sharma, & Singh, 2016).

One school of thought suggests that 5G will require increased densification of the network through the building of millions of Small Cells, particularly in crowded areas of very high demand (Paglierani et al., 2019). While Macro Cells may serve up to 30 km in remote rural areas, Small Cells are expected to serve anywhere from 1 to 2 km down to 200 m in the densest urban settings. As 5G technologies are still evolving, we lack analysis on the implications of Small Cell deployment strategies, and the associated policy ramifications. Fig. 2 provides a stylized example of a Macro Cell coverage area, with a high density of Small Cells operating within this area to provide local high capacity hot-spots.

There are a range of views on the potential impact of 5G, ranging from optimistic (International Telecommunication Union, 2015) to conservative (Webb, 2016). While impressive capacity can be achieved with 4G LTE and 4G LTE-Advanced technologies, the mobile industry will need to move to 5G and other technology generations over the long-term in order to help reduce the cost per bit associated with data transfer, as well as addressing a broader range of new use cases. However, since the Average Revenue Per User (ARPU) has either been static or declining in many major economies over the past decade, and even declining globally (GSMA, 2020), there is not a huge appetite for

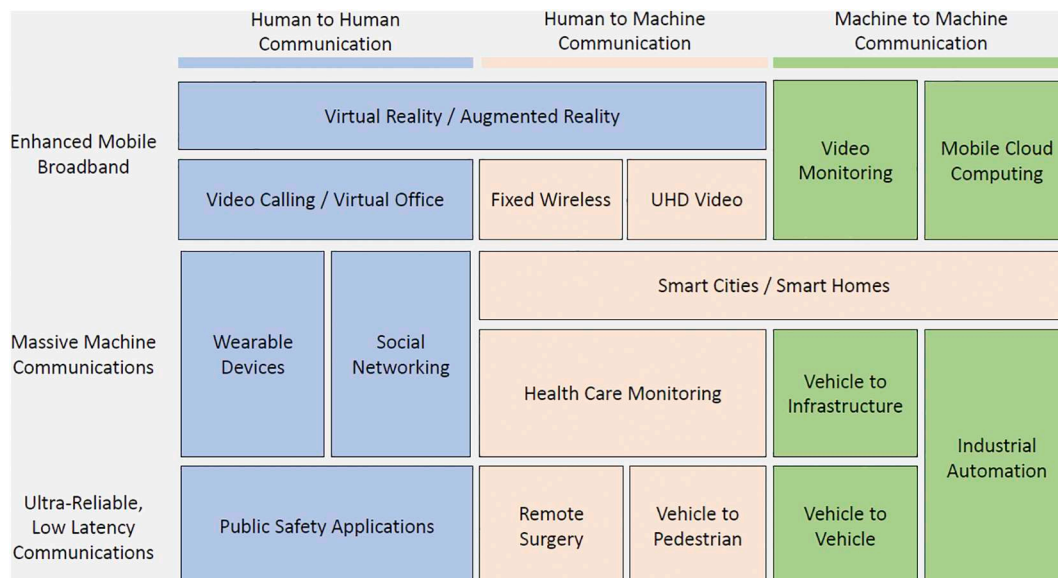


Fig. 1. 5G use cases (adapted from 5G Americas, 2017).

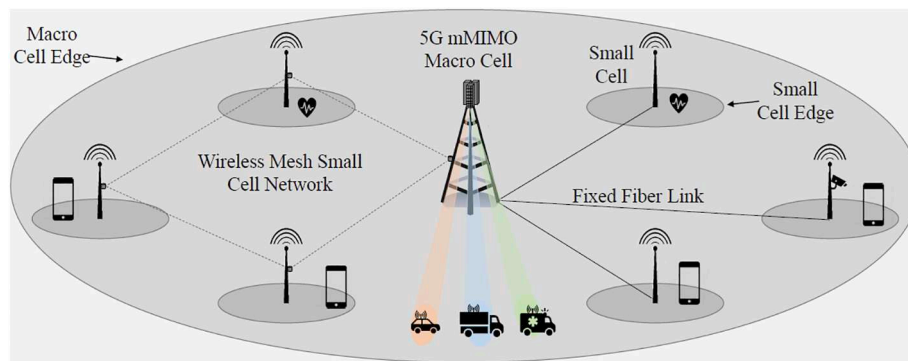


Fig. 2. A typical 5G Macro Cell containing many Small Cell hotspots.

mass infrastructure deployment due to capital constraints.

2.2. Review of digital infrastructure assessment

This section focusses on past analyses which have modeled the spatial and temporal aspects of digital communications infrastructure. All infrastructure assets exist in space and time, therefore are inherently subject to spatio-temporal dynamics (Kasraian, Maat, & van Wee, 2019; Makarchuk & Saxe, 2019; Pacsi, Sanders, Webber, & Allen, 2014; Peer, Garrison, Timms, & Sanders, 2016; Sanders, 2015; Serok, Levy, Havlin, & Blumenfeld-Lieberthal, 2019). As infrastructure is highly durable and becomes a sunk cost in an existing asset portfolio, these assets ultimately become subject to path-dependent lock-in effects, where migration away from a particular technological trajectory becomes costly due to increasing returns to scale (Arthur, 1994). These generic properties affect how we understand and model these complex adaptive systems in order to inform their future design, operation and maintenance (Chester & Allenby, 2019; Gilrein et al., 2019; Oughton, Usher, Tyler, & Hall, 2018; Saxe & MacAskill, 2019).

In other critical infrastructure systems, such as transportation, there is a well-established set of open-source spatio-temporal tools, methods and models that can be applied to answer questions pertaining to interactions between land use, transportation and the environment (Capelle, Sturm, Vidard, & Morton, 2019; Harvey et al., 2019; Kii, Moeckel, & Thill, 2019). Some private companies have developed their own internal capabilities to assess how the movement of people and vehicles may place new demand on the cellular network. However, these activities are not made openly available. Thus, in terms of open-source tools, methods and models accessible to the research community, there are a limited number available for the spatio-temporal analysis of digital infrastructure.

Spatial engineering approaches to wireless networks are frequently considered from a theoretical perspective, often using random processes to synthesize networks for assessment. Topology planning is essential for efficient capacity utilization and thus cost efficiency (Haddaji, Bayati, Nguyen, & Cheriet, 2018; Jaber et al., 2016; Lee & Murray, 2010; Taufique, Jaber, Imran, Dawy, & Yacoub, 2017). Models often use spatial point methods, where user location is treated as a stationary Poisson point process, base station locations as a stationary Poisson cluster process and connecting internet nodes as a stationary mixed Poisson process (Suryaprakash & Fettweis, 2014). Frequently, stochastic geometry is applied for system-level performance analysis with the network treated as a hierarchical process using a Poisson tree, given certain radio channel conditions and interference (Martin-Vega, Di Renzo, Aguayo-Torres, Gomez, & Duong, 2015). Wireless planning is often treated as an optimization problem, although most analyses focus on a single variable (e.g. cost) (Taghizadeh, Sirvi, Narasimha, Calvo, & Mathar, 2018), rather than considering the multiple objectives which are needed to reflect key performance parameters (Li et al., 2016). Spatial optimization techniques are well suited for wireless networks

because they can help define the maximum level of coverage, with the highest degree of reliability (Akella, Delmelle, Batta, Rogerson, & Blatt, 2010; Lee & Murray, 2010; Shillington & Tong, 2011). This includes using mixed integer programming approaches to help simultaneously solve problems such as basestation location, frequency channel assignment and the support of emergency communication services (Akella et al., 2005). Increasingly, natural language processing and machine learning is being combined with data mining social media to develop empirical geospatial analytics on wireless network performance (Du et al., 2018).

As well as assessing the spatial topological design of wireless networks, which is common in the engineering literature (González, Hakula, Rasila, & Hämäläinen, 2018), consideration also needs to be paid to temporal decisions. There can be significant implications for future upgrade costs, given the path-dependent nature of infrastructure assets. While spatio-temporal analysis is studied in detail using inductive statistical techniques on empirical data (Liu, Liu, Tang, Deng, & Liu, 2019; Montero-Lorenzo, Fernández-Avilés, Mondéjar-Jiménez, & Vargas-Vargas, 2013; Song, Zhao, Zhong, Nielsen, & Prishchepov, 2019), deductive spatio-temporal simulation approaches are still an emerging area of research (Xie, Yang, Zhou, & Huang, 2010; Yang, Yu, Hu, Jiang, & Li, 2017). National spatio-temporal assessment of 5G has been undertaken for the UK (Oughton & Frias, 2018; Oughton, Frias, Russell, Sicker, & Cleevely, 2018), but there has been little sub-national focus. In general, relatively little (openly accessible) spatio-temporal modeling has been undertaken for telecommunications when compared to the level of assessment in transportation networks. Much of the geospatial analysis of fixed and mobile broadband networks over the past two decades has relied on building an empirical statistical evidence base from inductive methods (Grubestic, 2006, 2008, 2010; Mack & Grubestic, 2014; Tranos, 2013; Tranos & Mack, 2015), in order to inform future decisions.

The standard approach for assessing the economics of cellular networks is in terms of the Total Cost of Ownership (TCO) under different deployment scenarios, including all infrastructure, energy and maintenance costs, as well as the potential leasing of both spectrum and fiber (Yaghoubi et al., 2018). There is a need to analyze a full range of deployment options, as a lack of planning prior to deployment can result in significantly higher costs, and greater inefficiency in energy consumption. Such an approach is common in the engineering literature (Cano, Carello, Cesana, Passacantando, & Sansò, 2019; Frias & Pérez, 2012; Giglio & Pagano, 2019; Yunas, Ansari, & Valkama, 2016), but these techniques are rarely applied spatially, for example at the sub-national level.

2.3. Infrastructure assessment and 5G

Infrastructure assessment provides a comprehensive overview of the future supply and demand of energy, transport, digital, water and waste services under different potential scenarios (Chester & Allenby, 2019;

Garcia et al., 2019; Hall et al., 2016; Saxe, Casey, Guthrie, Soga, & Cruickshank, 2015; Saxe, Miller, & Guthrie, 2017). This is essential evidence for making effective policy decisions given the huge challenges faced in delivering the infrastructure needed over coming decades. In infrastructure sectors such as energy or transportation one of the most pressing issues is environmental sustainability, whereas in digital infrastructure the two major issues are: connecting all users who are still yet to be connected (approximately 3 billion globally are yet to acquire basic internet access); and addressing the major disparities between basic broadband services (e.g. 2 Mbps) and those with high capacity connections.

One of the first infrastructure assessments of 5G was the UK Government's Connected Future report (National Infrastructure Commission, 2016) along with affiliated supporting evidence (Frontier Economics, 2016; LS telcom, 2016; Oughton & Frias, 2016; Real Wireless, 2016). Analysis has estimated it would take until 2027 for the majority of the population to be covered by 5G (Oughton & Frias, 2018), with the UK government now having adopted this target in both Ofcom's Connected Nation report and in the UK's Future Telecom Review (Department for Digital, Culture, Media, and Sport, 2018; Ofcom, 2018a). Currently we still lack quantified evidence of how this might be achieved in practice. Throughout the UK coverage issues still exist in many areas, with only 76% of premises receiving an indoor 4G signal from all operators, approximately 64% of the geographic area (Ofcom, 2018b). Past UK spectrum coverage obligations include 90% population coverage on the 3G bands including 900, 1800 and 2100 MHz, and then a 98% population requirement on the 4G LTE 800 MHz with 90% confidence at indoor locations with a downlink speed of not less than 2 Mbps (2600 MHz has no coverage obligation) (Cave and Nicholls, 2017). Having completed a thorough literature review on 5G infrastructure assessment, a method capable of answering the research questions will now be presented.

3. Method

A demand-led simulation modeling approach is taken to develop a high-resolution spatially explicit implementation of a telecommunication Long Run Incremental Cost (LRIC) model. A range of software development techniques have been used to develop the model, including unit testing, in-line documentation and open-source model code (Oughton & Russell, 2019, 2020), all of which aim to improve transparency, reproducibility and confidence in the results. The system model will now be described, followed by the demand and capacity assessment components. The upgrade strategies to the tested are outlined in Section 3.5.

3.1. System model description

Using a national multi-level network, assets are geographically nested in a spatial hierarchy enabling a spatio-temporal simulation model for the period 2020–2030. A Network Manager object contains all the necessary data and methods for simulating different deployment strategies and is operated via a model runner script, as illustrated in Fig. 3.

Data inputs include spatially disaggregated demographic scenarios and scenarios of how per-user data demand may evolve in the future, which is a standard way to assess how future population change may affect demand for services (Mayaud, Tran, Pereira, & Nuttall, 2019). Geospatial information is required for site locations, as well as data on the available spectrum portfolio allocation by carrier frequency, bandwidth and technology generation.

3.2. Demand assessment

Predicting future demand is challenging because a key characteristic of the digital ecosystem is rapid innovation which can drive

technological change. The adoption of smartphones led to significantly increased per-user data demand resulting predominantly from augmented video consumption. Average per user data demand has risen from approximately 0.2 GB per month in 2012 to 1.9 GB per month in 2017 (Ofcom, 2018c).

The widely-used Cisco traffic forecast expects mobile traffic to continue to grow significantly over coming years, with mobile data traffic in the UK expected to grow at 38.5% Compound Annual Growth Rate (CAGR), from 2017 to 2022 (Cisco, 2017). The Cisco estimates are commonly used in the literature (Rendon Schneir et al., 2019), hence a set of data demand forecasts are created for Low, Baseline and High scenarios. One of the largest unknown factors is the adoption of unlimited data plans which could have a substantial impact on future data growth.

In this model, key demand drivers for cellular capacity include (i) the per user throughput rate and (ii) the number of users in an area. The average **User Data Rate** is determined from the scenario forecasts, providing estimated traffic demand in gigabytes per user per month in Britain (UD_i^{GBpm}) from which the busy hour individual demand in megabits per user per second (UD_i^{Mbps}) is estimated for the i^{th} user according to (1)

$$UD_i^{Mbps} = UD_i^{GBpm} \cdot \frac{1}{t} \cdot \frac{1}{b} \cdot 1024 \cdot 8 \cdot \frac{1}{3600} \quad (1)$$

Monthly traffic is converted to daily based on 30 days per month (t), and where 40% of daily traffic (b) takes place in the busy hour. The demand result is converted from gigabytes to megabytes, from bytes to bits, and finally from hourly demand to per second demand. Additionally, a minimum guaranteed user speed of 5 Mbps is applied as an evolution of the UK's 4G LTE coverage obligation of 2 Mbps.

The **Users Per Area** is estimated from the population (P_i) of residents per postcode sector using a set of demographic scenarios which use an open-source spatial interaction model, *simim* (Smith, Russell, & Usher, 2019). Variations to internal migration are then based on changing regional attractiveness, driven primarily by the dwelling scenarios described later in Section 3.5. Population is produced and validated for 380 Local Authority Districts using census data and Office for National Statistics projections, then disaggregated to 9000 national postcode sectors using a set of weights based on the share of domestic postal delivery points.

Given user demand changes through the day, as users move about dynamically in space, we consider the residential population estimates as representing a nighttime profile. To supplement the daytime users, employment data are taken from the UK Business Register and Employment Survey (Nomis, 2018) by Lower Level Super Output Area and are aggregated to the postcode sector level, to help capture this spatio-temporal dynamic. If the daytime employment exceeds the resident population, the resident population is augmented by the additional employment amount. This means each postcode sector broadly represents the busiest time of day based on population movement.

Market Share is defined as a scenario parameter used to model a 'hypothetical operator'. We use a market share ($share_i$) of 30% of users, broadly in line with the UK's Mobile Call Termination Market Review (Ofcom, 2018d). It is also reasonable to expect that not all users will simultaneously access the network at once, as is standard practice for network dimensioning traffic throughput (Holma & Toskala, 2012), and therefore an overbooking factor (OBF) of 20 is used. Smartphone penetration ($penetration_i$) in Britain is 80%, so only this proportion of the population will access high capacity wireless services such as 4G LTE or 5G.

The total number of active users (AU_i) accessing the cellular network in an area can therefore be estimated using eq. (3)

$$AU_i = \frac{P_i \cdot (share_i) \cdot (penetration_i)}{OBF} \quad (3)$$

Resulting in the total demand (TD_i^{Mbps}) for the i^{th} area as follows in

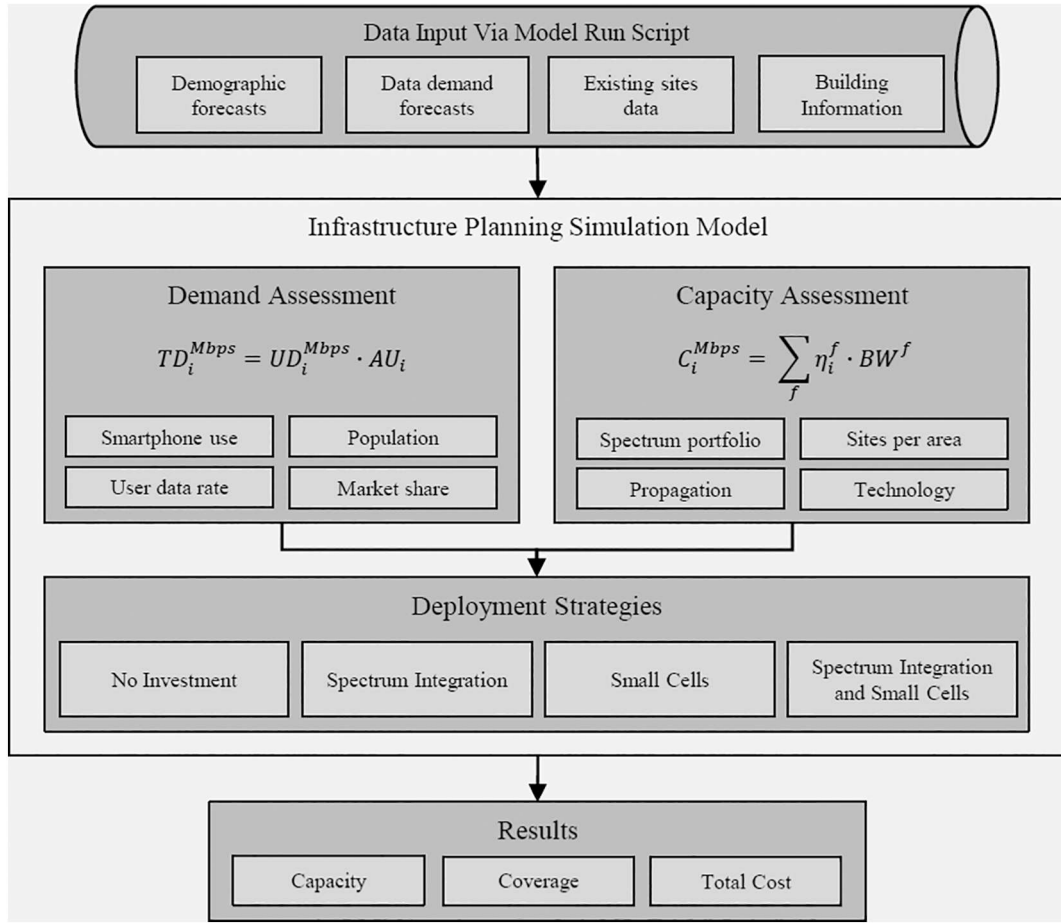


Fig. 3. Digital communications system-level evaluation framework.

eq. (4)

$$TD_i^{Mbps} = UD_i^{Mbps} \cdot AU_i \quad (4)$$

Having formally defined the demand assessment method, the capacity assessment method can now be articulated.

3.3. Capacity assessment

The capacity assessment module quantifies cellular capacity expansion using three methods: improving spectral efficiency via new technology generation (e.g. 4G–5G); the provision of new spectrum bands; and the deployment of new cells to densify the network.

The mean Network Spectral Efficiency (η_i^f) (bps/Hz/km²) is estimated per frequency (f) for the i th area, given a set number of cells (β_{cells}) per site, and the density of sites (γ_{sites}) in an area, as in eq. (5)

$$\eta_i^f = \beta_{cells} \cdot \gamma_{sites} \quad (5)$$

This is carried out using a stochastic geometry approach via the open-source python simulator for integrated modeling of 5G, *pysim5G* (Oughton, 2019; Oughton, Katsaros, Entezami, Kaleshi, & Crowcroft, 2019). First, *pysim5G* estimates the Signal to Interference plus Noise Ratio (SINR) in different urban and rural environments using industry-standard statistical propagation models. Next, the ETSI coding and modulation lookup tables for 5G are used to map received signal to SINR (European Telecommunications Standards Institute, 2018). The spectral efficiency for 8×8 Multiple Input Multiple Output (MIMO) antenna is mapped to the SINR (Tse & Viswanath, 2005). The estimated capacity per square kilometer can then be obtained (C_i^{Mbps}) for the i th area by multiplying the spectral efficiency (η_i^f) by the bandwidth of the

carrier frequency (BW^f), as in eq. (6)

$$C_i^{Mbps} = \sum_f \eta_i^f \cdot BW^f \quad (6)$$

Finally, to ensure a specific Quality of Service, the stochastic approach allows the 10th percentile value to be extracted from the distribution of simulation results for each frequency. This means that the network capacity is assessed for the cell edge user with 90% reliability.

Using the geographic area (a_i) in square kilometers, the resulting mean guaranteed capacity per active user (C_{AU}^{Mbps}) during the busiest hour can be calculated, as per eq. (7).

$$C_{AU}^{Mbps} = (C_i^{Mbps} \cdot a_i) / (AU_i \cdot a_i) \quad (7)$$

To obtain a set of **representative physical site assets** the Sitefinder data (Ofcom, 2012) is updated to be consistent with existing 4G coverage statistics released by Ofcom's Connected Nation report. In recent years, passive infrastructure sharing agreements have essentially created two physical networks in the UK, the first between Vodafone and O2 Telefonica ('Cornerstone') and the second between BT/EE and Hutchinson Three. We consider the Vodafone and O2 Telefonica ('Cornerstone') sites as the key supply-side input for (predominantly Macro Cell) sites. Representative site locations are obtained by taking latitude and longitude coordinates for individual cell assets, buffered by 100 m, with the polygon centroid of touching buffers forming a reasonably accurate location approximation. Due to site sharing, a single MNO has access to roughly 50% of sites, resulting in 22,589 national sites. The statistics are disaggregated by ranking the revenue potential of each postcode sector and calculating the cumulative geographic area covered using the expectation that MNOs rationally deliver 4G coverage to the highest revenue sites first. This approach is consistent with how

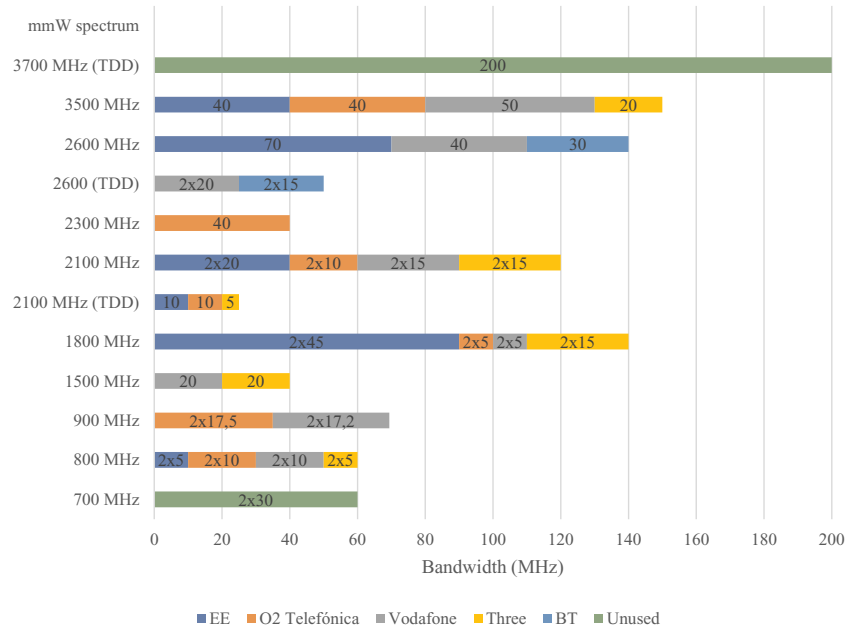


Fig. 4. Spectrum portfolio by carrier frequency, bandwidth and operator.

MNOs deploy new cellular generations.

Fig. 4 illustrates the UK's existing national spectrum portfolio below 6 GHz, broken down by carrier frequency, bandwidth and operator. For scaling purposes, millimeter wave was excluded, but includes 2GHz bandwidth at the 26 GHz frequency.

As the purpose of this assessment is to consider a 'hypothetical operator', representing a set of average operator characteristics. Hence, a set of representative 4G LTE and 5G New Radio (NR) carrier frequencies (f) and bandwidths (BW^f) are tested in either Frequency Division Duplex (FDD) or Time Division Duplex (TDD) mode. For each of the 700 MHz, 800 MHz, 1.8 GHz and 2.6 GHz bands, 10 MHz bandwidth is used, along with 50 MHz bandwidth for 3.5 GHz and 3.7 GHz, and 500 MHz bandwidth for 26 GHz. Table 3 provides a comprehensive description of how each of these bands is used in the different strategies.

3.4. Cost assessment

For each asset ($Asset_{NPV}$) the TCO is estimated by calculating the Net Present Value of the combined initial capital expenditure required in the first year of deployment (i) as a one-off cost (c_i), with the ongoing operating expenditure (opex) over the lifetime of the asset (o_t) (annual opex is treated as 10% of the initial capex value for all active components). Over a period (Y) of 10 years, a discount rate of 5% (r) is used, as illustrated in (7).

$$Asset_{NPV} = c_i + \sum_{t=0}^Y \frac{o_t}{(1+r)^t} \quad (7)$$

This calculation assumes a 10-year lifespan of for all assets and does not consider price trend changes. Guided by the data from Ofcom's Mobile Call Termination model (Ofcom, 2018e), Table 1 contains a set of comparable TCO costs which include (i) £316,147 for upgrading a 2G/3G site to a three-sectored 4G multicarrier site (including adding fiber backhaul), (ii) £121,422 to upgrade a 4G site with a 5G band, and (iii) £27,847 for a 5G Small Cell. The estimated annualized costs are comparable to other assessments (Wisely, Wang, & Tafazolli, 2018).

3.5. Upgrade strategies

A variety of different 5G deployment strategies are tested to assess

Table 1

Total Cost of Ownership by technology.

Cost Parameter	Upgrade to 4G LTE Macro (£)	Macro Carrier Upgrade to 5G (£)	Small Cell (£)
Basestation (8 × 8 MIMO)	40,900 (x3)	14,500 (x3)	2500
Civil works and installation	18,000	18,000	10,000
Fiber backhaul	20,000	–	1000
Metro & Core upgrade	7890	3250	1350
Capex	168,590	64,750	14,850
Opex	16,859	6475	1485
Total Cost of Ownership	316,147	121,422	27,847
Annualized cost	31,615	12,142	2785

performance in terms of capacity, coverage and cost, focusing mainly on deploying new 5G spectrum and network densification. A Distributed Radio Access Network (D-RAN) architecture is used for both macro and small cells. Macro cells utilize a fixed fiber backhaul, whereas small cells utilize a wireless microwave link. Traffic is transferred across a local metro access network and a metro-core aggregation network, before reaching the core, as illustrated in Fig. 5.

In terms of the upgrade evolution, if 4G LTE is not already present on a site, these spectrum bands are added first along with any necessary fiber backhaul upgrades. We expect that operators want to maximize the reuse of existing brownfield Macro Cell sites to reduce investment costs when densifying the existing network (Smail & Weijia, 2017).

The parameters used to estimate RAN capacity are reported in Table 2.

No Investment represents a case where no new infrastructure capacity is deployed to meet demand. **Spectrum Integration** enables the 'hypothetical operator' to add new frequencies (700 MHz and 3.5 GHz) to multi-carrier basestations on existing brownfield Macro Cell sites. **Small Cells** involves the deployment of greenfield Small Cell sites and associated backhaul. Finally, **Spectrum and Small Cell** allows the options involved in the Spectrum Integration strategy to be first deployed, followed by the options in the Small Cells strategy, should the capacity be required. This is known as a 'Heterogeneous Network', or 'Het Net' in the cellular industry, as there are multiple types of cells being deployed. Table 3 reports these technical options by strategy. Spectrum bands are

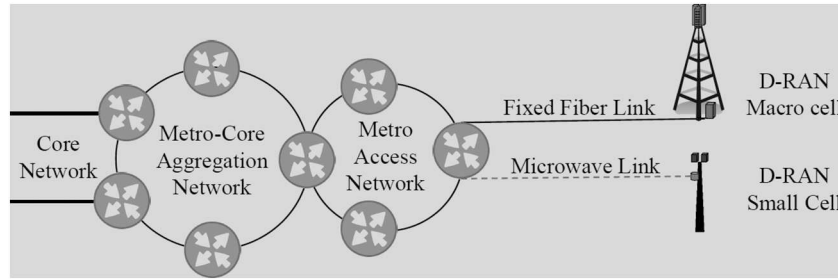


Fig. 5. Network architecture.

Table 2
RAN technical parameters.

Parameter	Description
Height	30 m (macro), 10 m (small cell), 1.5 m (UE)
Power	40 dB (macro), 24 dB (small cell)
Gain	16 dB (macro), 5 dB (small cell), 4 dB (UE)
Losses	1 dB (macro), 1 dB (small cell), 4 dB (UE)
Propagation model	ETSI TR 138901
Indoor users	50%
Line of Sight breakpoint	500 m
Log normal shadow fading	$(\mu, \sigma) = (0, \sigma)$
Log normal building penetration	$(\mu, \sigma) = (12, 8)$

deployed preferentially using the lowest frequencies first.

As infrastructure investment strategies by major mobile network operators are designed nationally, the simulation model is run for the whole of Britain, with those areas within the Oxford-Cambridge Arc extracted from the final model outputs. Given industry-wide mobile infrastructure investment (~£2 billion annually), and the market share of the ‘hypothetical operator’ (30%), annual investment decisions are constrained by allocating a maximum national investment (£600 million).

3.6. Case study area

The Oxford–Cambridge Arc is an area of high potential urban and economic development (National Infrastructure Commission, 2019). Around 1.3 million people live in a system of cities comprising seven urban centers of Oxford, Northampton, Milton Keynes, Bedford, Luton, Peterborough and Cambridge, and a further 2.4 million live in other towns and villages across the Arc. A combination of strategic road and rail investments have been proposed to improve connectivity across the Arc, including an Expressway (Highways England, 2018) and new, reinstated or upgraded rail lines and stations (Network Rail, 2018). For this study, we assumed routes for road and rail and location of new or relocated stations as shown in Fig. 6 below.

This transport infrastructure is part of a broader aim to significantly increase housing supply across the region. Several scenarios have been considered for completion of additional homes per annum across the Arc (Savills, 2016; Infrastructure Transitions Research Consortium 2020), including a ‘transformational’ scenario of 30,000 homes per

annum where 23,000 dwellings per annum meet internal needs and 7000 dwellings per year may be introduced to relieve pressure from elsewhere in London and the South East.

In this study we explore the impacts of four scenarios of development (shown in Fig. 7) which affect population density and hence mobile data demand. The Baseline scenario continues with average dwelling completions over 2004–2014, with no assumption of new transport infrastructure. The Unplanned scenario assumes a slightly higher rate of dwelling completion stimulated by the new transport infrastructure, but no focused policy of housing delivery. The Expansion and New Settlements scenarios both assume a rate of 30,000 dwellings per annum, but test different spatial patterns of development. Expansion focuses development in and around existing urban centers, whereas New Settlements introduces five new towns near new road junctions and rail stations, north of Bicester, south of Winslow, north of Cranfield, east of Sandy and north of Basingstoke.

At each timestep in the simulation approach, postcode sectors are allocated a specific geotype, which groups areas into clusters with similar cost properties, primarily driven by population density. The population density bands for these geotypes follow Ofcom’s Mobile Call Termination model (Ofcom, 2018e) including Urban (>7959 persons per km²), Suburban 1 (>3119 persons per km²), Suburban 2 (>782 persons per km²), Rural 1 (>112 persons per km²), Rural 2 (>47 persons per km²), Rural 3 (>25 persons per km²) and Rural 4 (0 persons per km²).

Fig. 8 illustrates a range of metrics for the study area, from the allocated geotypes for postcode sectors, to the number and density of cellular sites, as well as the estimated area capacity in 2019. We can see that the Arc does not have many dense urban areas and is dominated by a low population density, mostly rural landscape. For the ‘hypothetical operator’ modeled here (with access to 50% of total sites), most areas have between 1 and 4 cellular sites. The density of sites is generally below 0.25 sites per square kilometer, except in denser urban and suburban areas, where this increased to between 0.25 and 1 sites per square kilometer. Hence, the average guaranteed 4G user connection at the cell edge is over 80 Mbps km² in urban areas, decreasing significantly in rural areas to below 10 Mbps km², based on the existing site density and level of 4G coverage, using capacity data generated with the open source software *pysim5G*.

Table 3
Upgrade strategies.

Generation	No investment	Spectrum integration	Small cells	Spectrum and small cell
Upgrade to 4G LTE (if not already available)	–	FDD 2 × 10 MHz at 800 MHz FDD 2 × 10 MHz at 2600 MHz Add fiber backhaul	–	FDD 2 × 10 MHz at 800 MHz FDD 2 × 10 MHz at 2600 MHz Add fiber backhaul
Upgrade to 5G	–	FDD 2 × 10 MHz at 700 MHz FDD 2 × 10 MHz at 3.5 GHz TDD 50 MHz at 3.7 GHz TDD 500 MHz at 26 GHz	TDD 50 MHz at 3.7 GHz TDD 500 MHz at 26 GHz	FDD 2 × 10 MHz at 700 MHz FDD 2 × 10 MHz at 3.5 GHz TDD 50 MHz at 3.7 GHz TDD 500 MHz at 26 GHz

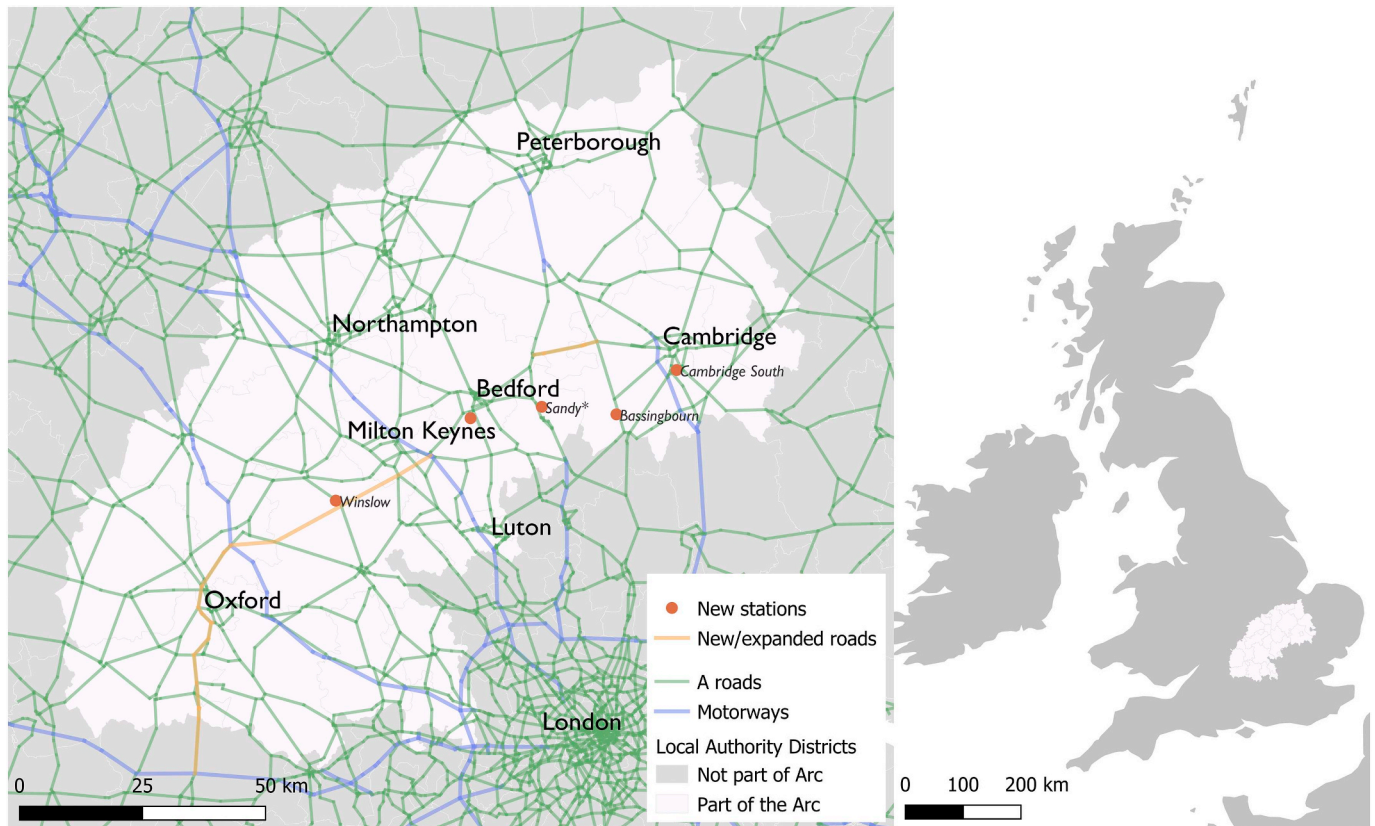


Fig. 6. Oxford–Cambridge Arc with major road network and future road/rail assumptions.

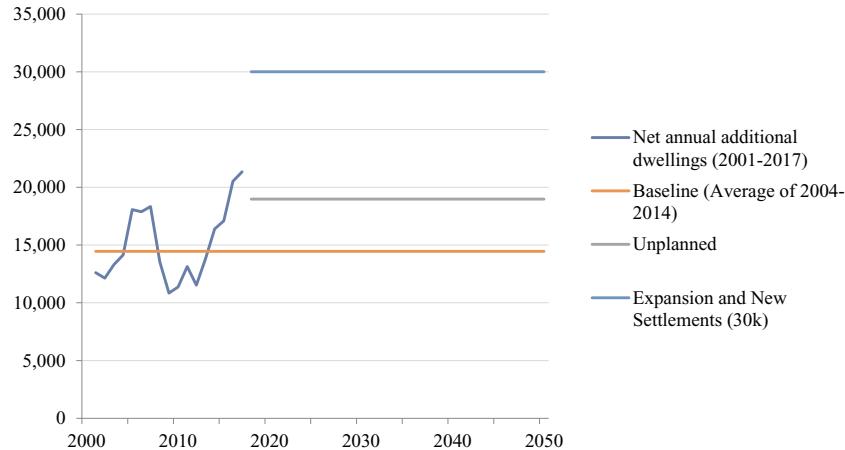


Fig. 7. New dwellings per annum across the Arc, showing 2001–2017 data and scenarios (Ministry of Housing, Communities and Local Government, 2019).

4. Results

The demand results by scenario will be presented first, then the supply-side infrastructure strategy performance. Fig. 9 illustrates the data demand results, beginning with the exogenous inputs including monthly per user data consumption (A) and population growth (B). Data consumption per user increases significantly over the time period because of the shift towards unlimited data plans which have now been introduced to the UK mobile telecoms market. Monthly consumption is approximately 5 GB per user in 2020, over 10 GB by 2023 and reaching almost 25 GB by 2030.

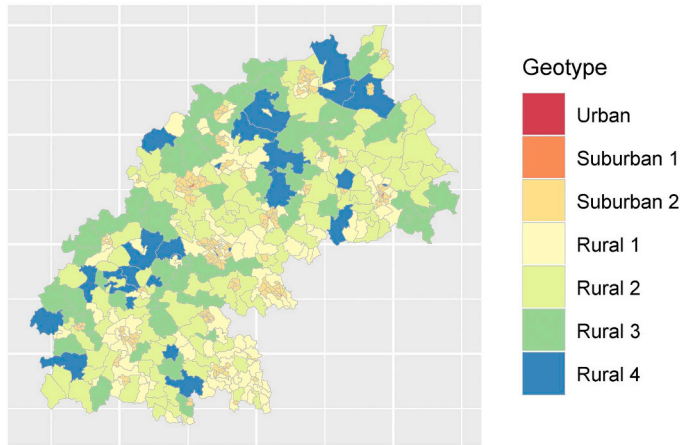
Population growth in the Arc corridor varies by demographic scenario, ranging from 4.2 million people in all scenarios in 2020, to almost 4.4 million in 2030 in the Baseline, and then up to 5 million by

2030 in the New Cities scenario. The Expansion scenario has similarly high growth, reaching 4.8 million people by 2030, followed by modest growth in the Unplanned scenario, with over approximately 4.5 million people by 2030.

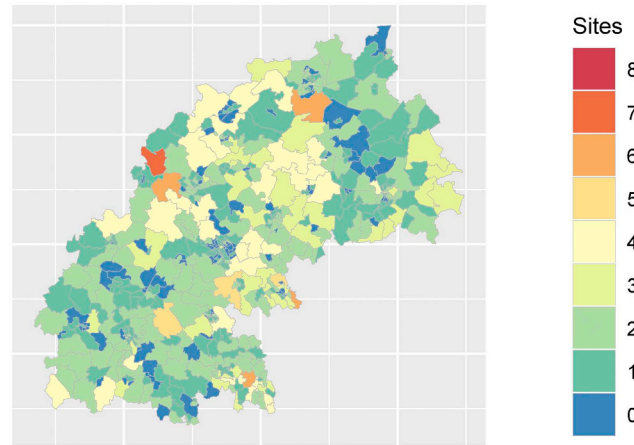
The total data demand in the busiest hour of the day is visualized by scenario in (C), where the Baseline evolved from below 0.25 Tbps in 2020, to over approximately 0.26 Tbps in 2030. In the most extreme growth New Cities scenario, demand increased to 0.3 Tbps in 2030. The minor differences between the per month data consumption rates indicate the minimum quality of service level of 5 Mbps is driving total demand, rather than the volume of monthly traffic needing to be served.

In Fig. 9, (D) shows the evolution of spatial demand for each scenario. In 2020, demand is generally below 30 Mbps per km², except in

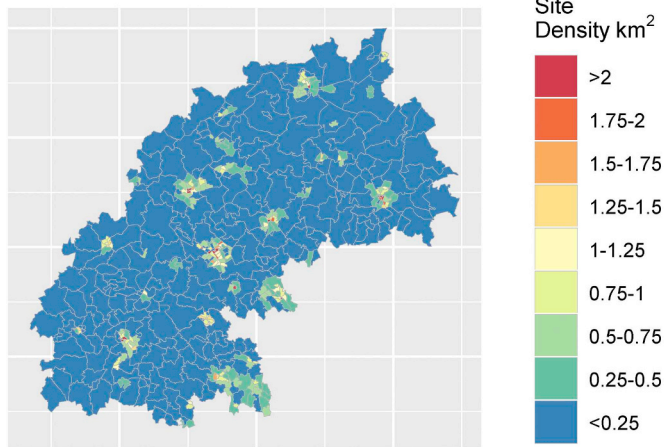
Postcode sector by geotype



Sites per postcode sector



Site density per postcode sector



Postcode sector by mean cell edge capacity

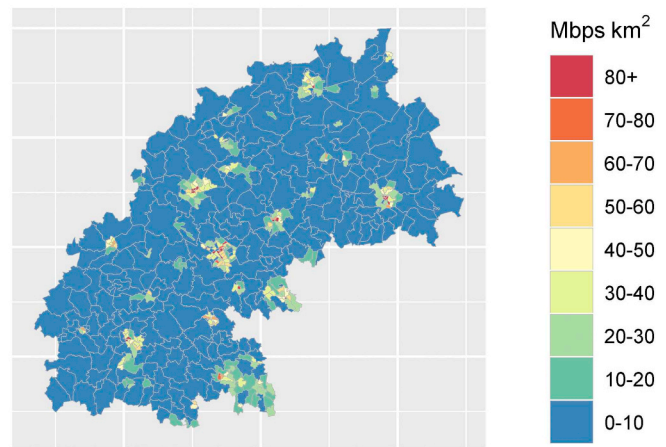


Fig. 8. Study area by geotype and existing capacity.

urban areas such as Luton (>30 Mbps per km^2) and Cambridge (>15 Mbps per km^2). In the Baseline, by 2030 all urban areas exceed 80 Mbps per km^2 and many less populated rural areas see demand increase above 10 Mbps per km^2 . In contrast to the Baseline, the largest spatial difference is in the New Cities scenario, reflecting the spatial development patterns provided by the upstream models. Increased demand takes place to the North and East of Oxford in Cherwell and Aylesbury Vale respectively, as well as North of Luton in Central Bedfordshire.

In terms of the supply-side performance of different infrastructure strategies, Fig. 10 visualizes the results for user capacity and cost. The mean cell edge user capacity represents the data transfer rate a user is guaranteed to achieve 90% of the time at the furthest point away from the closest cell site. We see minimal change under the No Investment and Spectrum Integration strategies, and more substantial per user capacity enhancements with the Small Cells and mixed Spectrum and Small Cells strategies. For example, the guaranteed per user capacity in the Baseline is only 1 Mbps in the No Investment strategy by 2030 and 20 Mbps in the Spectrum Integration strategy. This contrasts with 150 Mbps with Small Cells and 50 Mbps in the mixed Spectrum and Small Cells strategy.

The difference from the Baseline is then presented by scenario and strategy. The largest changes in capacity take place in the New Cities and Expansion scenarios. Again, we see very little difference with the No Investment and Spectrum Integration strategies. With Small Cells a dynamic is at play with more capacity being deployed between 2025 and 2028, especially in the New Cities and Expansion variants,

contrasting with a more gradual decline in the Spectrum and Small Cells strategy.

In terms of the Total Cost of Ownership, the Spectrum Integration strategy was approximately £150 million for a single hypothetical operator, with the Spectrum and Small Cells strategy being the second most costly at £300 million. In contrast, the Small Cells strategy was much more costly, with all scenarios costing at least £600 million to cover the Arc, roughly six times more than the least expensive strategy. When comparing the difference across scenarios, the New Cities variant had the largest difference where, for example, the estimated cost exceeded £40 million under the Small Cell strategy. This results from the need to deploy a lot more infrastructure to cover new settlements.

Fig. 11 breaks down these costs based on the type of urban-rural settlement pattern. While we do not see a vast difference between the scenarios, there are larger differences between the strategies. Spectrum Integration can cover suburban and rural areas more cheaply, whereas with Small Cells or Spectrum and Small Cells, we see large investment costs occurring in these lower population density areas.

The Spectrum Integration strategy delivers upgrades in urban, suburban and rural areas early in the study period. This results from the incremental deployment approach of the modeling method, where new capacity is only delivered to areas where demand is exceeding supply. This contrasts with the Small Cell strategy, where investment targets less dense rural areas, particularly in the middle to later periods of the assessment horizon. This reflects the fact that Small Cells can have tiny radii and therefore are more expensive per square kilometer than

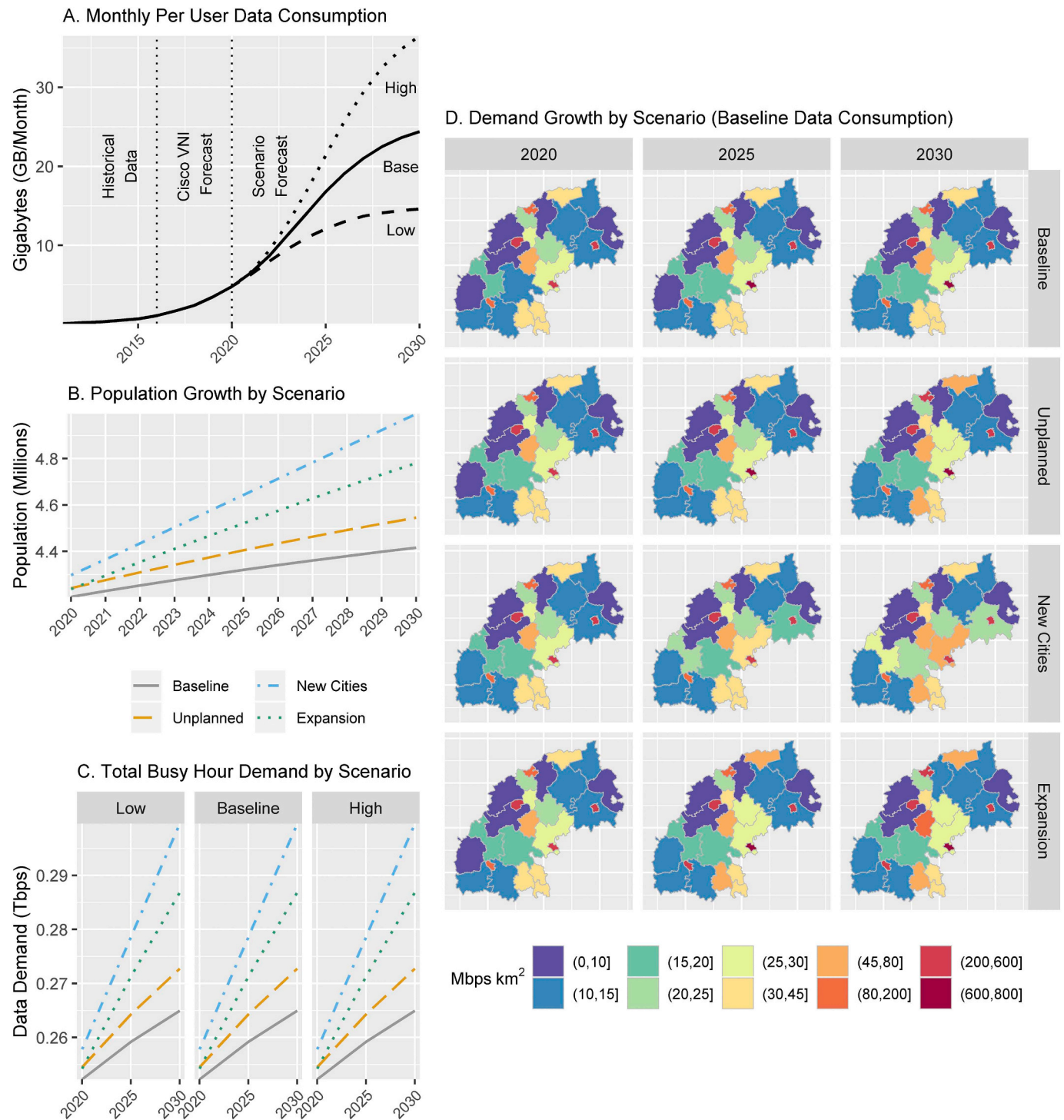


Fig. 9. Demand results.

merely adding spectrum to existing brownfield sites, so it takes longer for Small Cell deployments to reach these areas. On the other hand, enough capacity is delivered in urban and suburban areas that once they have small cell deployments, capacity far outstrips demand, therefore the model does not need to return to carry out further upgrades (unlike in other strategies).

Finally, Fig. 12 illustrates investments made by deployment decision. The shape of the investment curves is the same as in Fig. 11, however, the breakdown of cost by item can be read in tandem, helping us to understand infrastructure decisions by spending category. For example, across the strategies, some 4G LTE upgrades still need to take

place. In the Spectrum Integration strategy, this is in 2022–2023, but in the other strategies this takes place throughout the assessment horizon. The most interesting result is that the model deploys 700 MHz almost ubiquitously across urban, suburban and rural locations. A small number of higher density areas require upgrading to 3.5 GHz to meet very high demand.

In the Small Cell strategy, some 4G LTE upgrades still take place, but mainly spending is dominated by the deployment of greenfield 5G small cells. In contrast, the Spectrum and Small Cell strategy is like the Spectrum Integration strategy, but with a small number of Small Cells being deployed in areas where existing spectrum has not met demand.

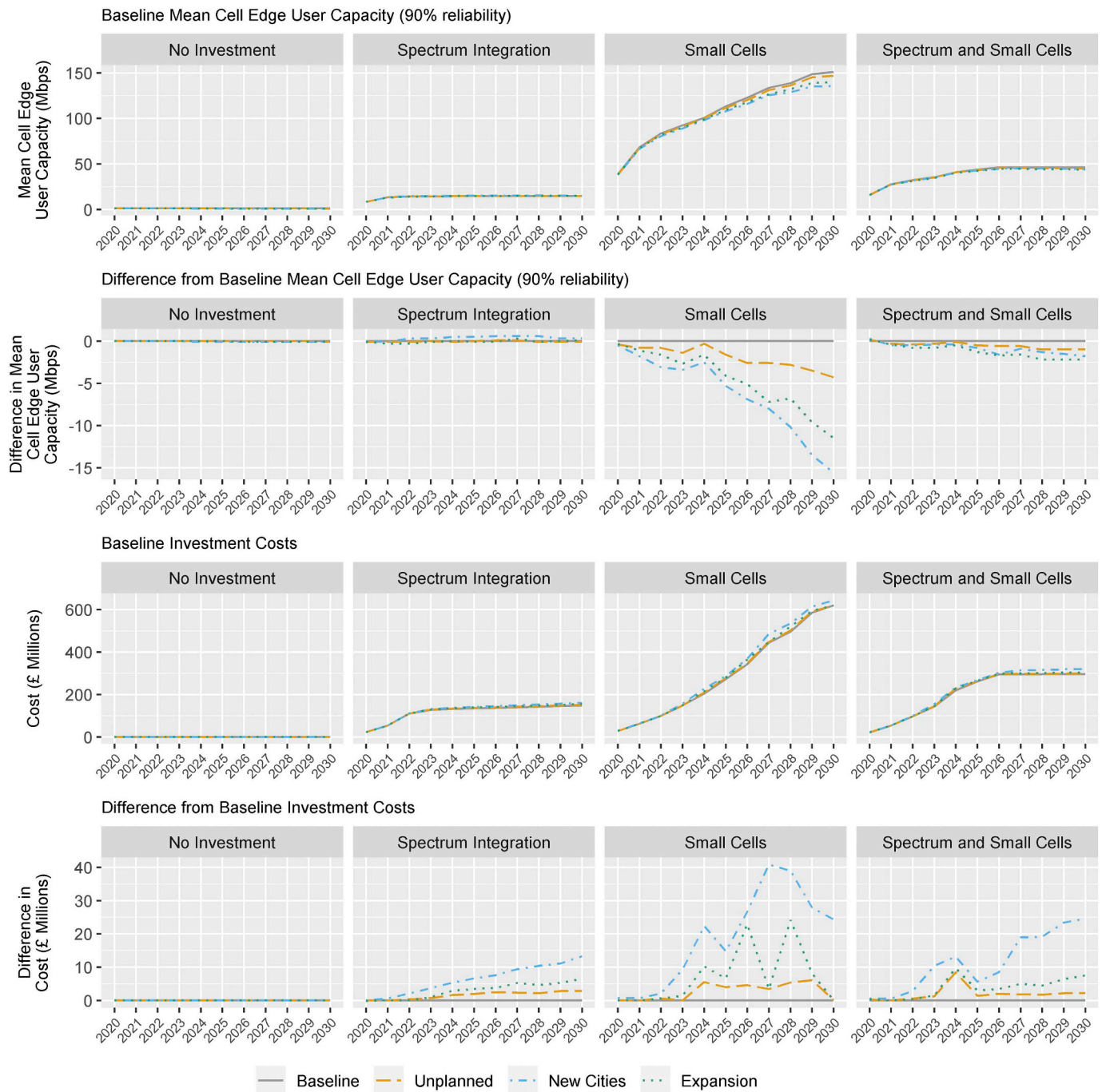


Fig. 10. Performance of 5G infrastructure deployment strategies.

These results are important as it suggests demand can generally be met by deploying 700 MHz spectrum onto existing brownfield Macro Cell sites.

5. Discussion

The results will now be discussed in relation to the two research questions articulated in the introduction of this paper.

1. Under different scenarios of population growth, how will mobile telecommunication data demand be affected?

We find that population growth has a moderate impact on the total amount of data demand within the Arc corridor. For example, the most

extreme New Cities scenario gave rise to an increase in data demand over the baseline of approximately 15% over the study period which would need to be met. However, putting this into context, baseline per user demand resulting from the consumer desire for streaming increasing quantities of on-demand video at increasingly high quality, could be many times higher than this (e.g. > 100% increase over the study period). The spatial variance which arose resulted from the heterogeneous settlement patterns of different scenarios. For example, the New Cities scenarios saw greenfield development between the existing urban settlements within the Arc, which would require new infrastructure to be deployed to meet future demand.

Additionally, although the simulation model utilized here was sophisticated in many aspects, the model focused on average demand, meaning spikes in congestion from users clustering in space was not a

Annual Investment Over The Study Period

Results reported by scenario, strategy and geotype

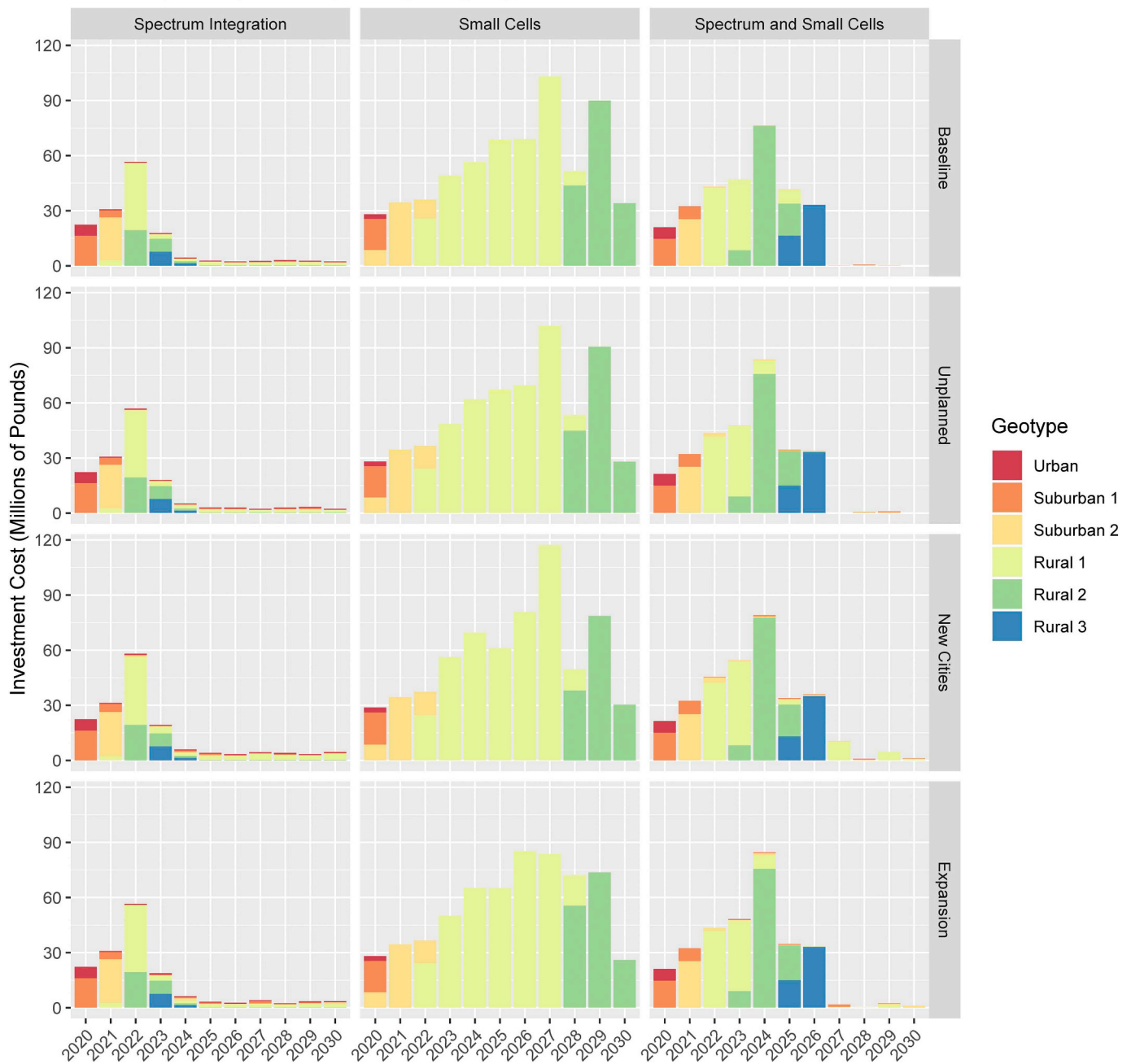


Fig. 11. Investment broken down by settlement type.

focal point of the analysis, though these events can often be the cause of the main Quality of Service issues experienced by MNOs.

2. Which 5G deployment strategies best meet this future demand?

In terms of capacity alone, the Small Cell strategy provided the highest overall cell edge gain in per user 4G and 5G data access rates, at almost twice the provided capacity over other strategies, reaching an average of 150 Mbps per user by the end of the study period in 2030. The Spectrum Integration strategy by 2030 only achieved a guaranteed data rate of 20 Mbps per user in comparison. The Spectrum and Small Cell strategy was only marginally better in comparison however, delivering roughly 50 Mbps guaranteed per user by 2030. It is important to

remember however that users inside the cell would likely receive significantly higher capacities, as this analysis used a conservative modeling method focusing on the bottom end of the speed distribution.

The cost of delivering this capacity is a different matter. For example, the Small Cell strategy might have provided the largest uplift in user capacity, but the deployment approach was more than six times more expensive when compared to other options, cumulatively spending up to ~£600 million by the end of the study period in certain scenarios. In comparison, the Spectrum Integration strategy only reached a cumulative cost of ~£150 million by 2030.

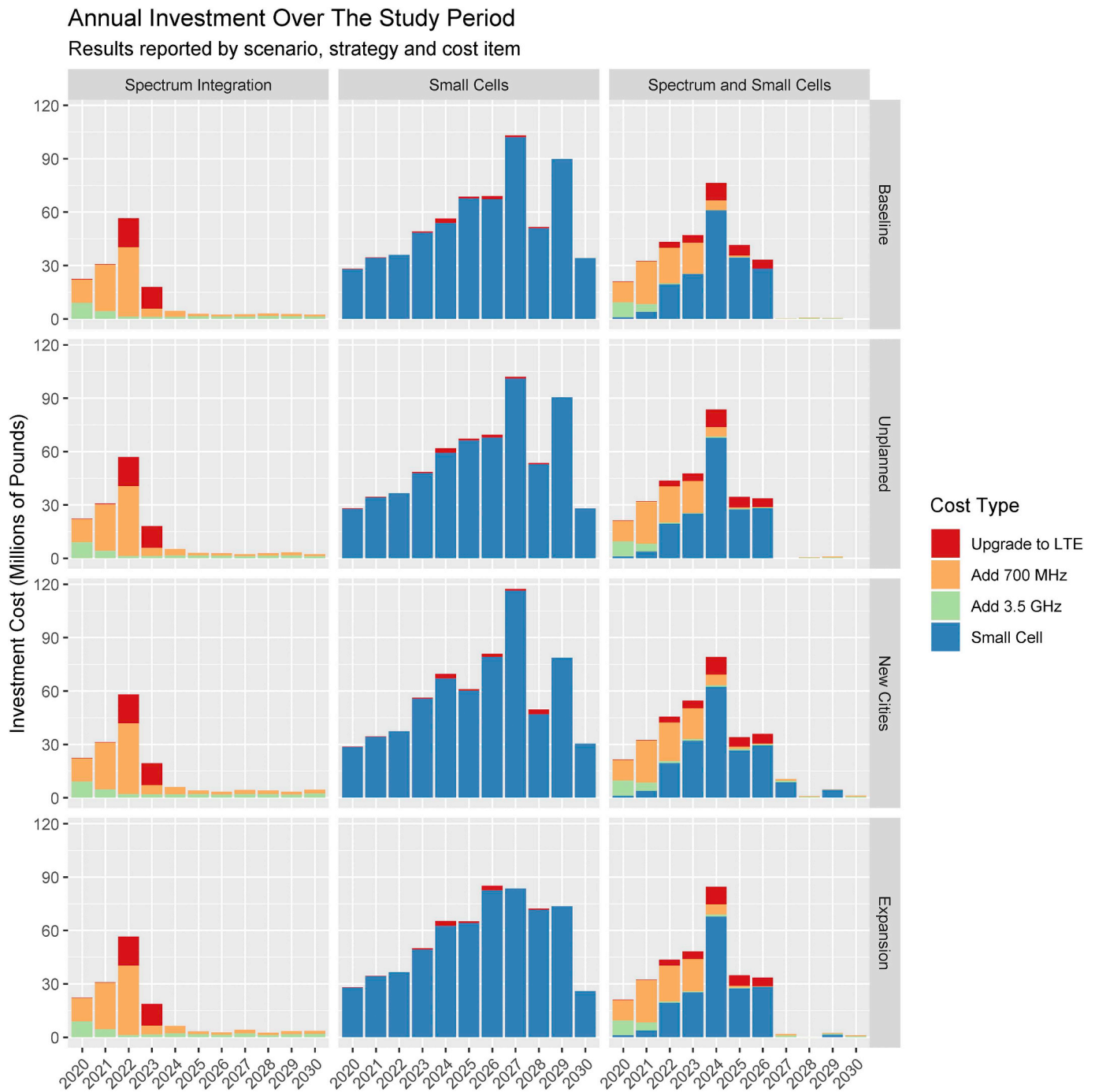


Fig. 12. Investment broken down by deployment decision.

5.1. Limitations

The assessment presented in this paper has several limitations which future research needs to address. Firstly, the focus of this 5G (Non Standalone) assessment was on the delivery of Enhanced Mobile Broadband (eMBB) which is not a radical change from the main use case for 4G LTE. A key promise of 5G relates to use cases which require Ultra Reliable Low Latency Communications (URLLC), which is expected to be addressed on the 3GPP Release 16. This assessment does not account for latency which will be an important factor in enabling the 5G ecosystem. Therefore, future analysis should consider both how lower latency may enable new activities, particularly resulting from the decentralization of information storage ('edge computing'), and how

spatio-temporal simulation may include latency metrics as part of the assessment of quality of service alongside capacity. Secondly, the method used here did not consider overall Quality of Service levels in terms of different guaranteed user data rates (a 'supply-driven' assessment). To attempt to gain more customers MNOs want to move towards delivering a minimum rate, for example 20 Mbps, to any user regardless of location or time of day. To assess this, a supply-driven methodology would be more appropriate for dimensioning this higher traffic demand. With the numerous scenarios and strategies tested in this paper, this was outside of the scope of the analysis, but is a key area for future research. Importantly, the existing 4G LTE spectrum and number of sites available in the study area could already support quite high traffic demand, meaning 5G was not always needed to meet existing demand.

This reflects the mainly suburban and rural areas assessed in the Arc corridor.

Finally, there are a variety of new 5G technologies that should be included in future assessments. For example, this analysis considered 8×8 MIMO base stations when estimating spectral efficiency, but it would also be important to consider massive MIMO technologies and how they can help to meet demand in the densest urban areas. Additionally, the network architecture assessed within this analysis was based on a Distributed Radio Access Network (D-RAN) which is common in existing 4G and 5G Non Standalone networks. However, over the next decade Cloud Radio Access Networks (C-RAN) will become more prevalent as this can provide both new services and important cost savings. The analysis presented here also does not include spectrum sharing or re-farming, which are possible options for enhancing capacity and coverage.

6. Conclusions

In this paper, we presented a general introduction to 5G infrastructure for spatial scientists interested in infrastructure planning for sustainable economic development. The key contribution was to apply a spatio-temporal scenario simulation modeling approach based on industry-standard engineering models of wireless networks. The method was used to develop an evidence base to help answer two key research questions pertaining to the uncertain future demand for 5G, and the performance of different supply-side infrastructure strategies in meeting future demand. Such evidence can be used to inform decisions taken by both network operators and by governments.

We found that different scenarios of population change have a marginal relative impact on the total demand for 5G infrastructure of up to 15%, as the main factor driving demand is the increase in per user data consumption, driven predominantly by on-demand video and unlimited data bundles. However, different spatial scenarios of urban development do affect the locations of infrastructure roll-out and the overall costs of the different strategies.

There has been very limited assessment of 5G infrastructure strategies in suburban and rural areas in the literature, therefore this assessment focused on a new transport corridor in areas with relatively low population density. Interestingly, we find these areas have significantly lower demand than busy urban areas, therefore there is limited motivation to deploy 5G frequency bands (e.g. 3.5 GHz), other than the low frequency 700 MHz band. Hence, an approach that reuses brownfield Macro Cell sites is generally satisfactory in meeting data demand over the study period.

In contrast, the deployment of Small Cells proved only suited to very dense urban areas, of which there are only a few in the Arc corridor. While Small Cells provided significant capacity enhancement, they were much more expensive to deploy in settings with lower population densities. However, there is a long-term future proofing argument for deploying Small Cells in the densest urban areas, especially as this will help not only with providing necessary cellular capacity, but also in meeting the strict latency requirements of the 5G standard.

Future research needs to examine the infrastructure requirements for other 5G use cases, particularly those with lower latency requirements, and could also explore the application of the simulation method to other regions.

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Data availability

Data required to reproduce the results of the case study are available online at <https://doi.org/10.5281/zenodo.3525286>

Code availability

The Cambridge Digital Communications Assessment Model (cdcam) is open-source, MIT-licensed and available online at <https://github.com/nismod/cdcam> and archived at <https://doi.org/10.5281/zenodo.3525286>

Author statement

All reviewer comments have now been addressed in the revised manuscript.

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