Technological Forecasting & Social Change 180 (2022) 121672

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

5G network deployment and the associated energy consumption in the UK: A complex systems' exploration

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A R T I C L E I N F O

Keywords:
5G network
Socio-technical systems
Energy consumption
Spatio-temporal evolution
Agent-based model

A B S T R A C T

Investing in the communication infrastructure transition requires significant scientific consideration of challenges, prioritisation, risks and uncertainties. To address these challenges, a bottom-up approach was used to demonstrate the future of wireless network transmission and deployment. This study developed an agent-based model to explore the future deployment of non-standalone 5G networks, synthesizing multi-dimensional data visualization. In particular, this research took the UK as an example to investigate the spatiotemporal dynamic characteristics of 5G evolution, and further analysed the energy consumption and carbon footprint of 5G networks, as well as the consequent change in the operating expenses pattern. The simulation results show that 700 MHz and 26 GHz will play an important role in 5G deployment in the UK, which allow base stations to meet short-term and long-term data traffic demands respectively. Furthermore, due to the geopolitical restrictions and embargos, telecommunications may face additional costs of £0.63bn to £1.19bn when deploying 5G radio access networks. Network densification may cause some environmental and economic problems. Take a medium demand scenario as an example, it is found that the electricity consumed by the 5G radio access network will account for more than 2.1% of the total electricity generation, and indirectly lead to 990,404 tonnes carbon emissions in 2030.

1. Introduction

Being connected has become a defining feature of the modern economy and a significant trend of the 21st century. Cisco forecasts that by 2023, nearly two-thirds of the global population will have Internet access, and the number of devices connected to networks will be more than three times the global population (Cisco, 2020). However, current internet speeds can only take us so far and severely restrict economic development. To unlock a digital data-driven economy, the UK Government has set an ambitious agenda for building world-digital infrastructure (UK Government, 2017). The fifth generation technology standard for wireless cellular networks, or 5G for short, is the next generation of wireless cellular network or mobile network, which is capable of ultra-fast data speeds, and low latency, and has been began deploying worldwide in 2019 (DCMS, 2017). Communication networks are generally composed of three key parts, core network, bearer network, and radio access network. Compared with early communication networks, 5G networks will require more antennas, greater bandwidth and higher base station density (Alsharif and Nordin, 2017). According to Metcalfe's law (Madureira et al., 2013), the value of a network is equal to the square of the number of nodes in the network, and the value of the network is proportional to the square of the number of connected users. Therefore, with respect to social impacts, 5G is not simply 4G plus 1G, but will more revolutionary and of higher value. It will not only provide infrastructure support for the deep integration of cross-domain, all-round, and multi-level industries, but also fully release the magnification, superposition, and multiplication effects of digital applications on economic and social development. However, the total power consumption of a single 5G base station is about four times that of a single 4G base station and considering the high density the overall power consumption of 5G networks may be 12 times that of 4G networks (Chih-Lin et al., 2020). Such energy consumption cannot be tolerated because it will cause corresponding environmental and economic problems. The construction of a new generation of wireless cellular networks is also costly, that often exceed billions of pounds. The technical complexity of 5G makes its implementation cost even higher. This also implies that upgrading the existing network to 5G will not be a once-off action, but a step-by-step evolutionary process, from a socio-technical perspective. The transition from 4G to 5G is not only a technological change, but also a competition for deployment and operations management. Countries who fail to adapt will likely lose first-mover

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https://doi.org/10.1016/j.techfore.2022.121672
Received 17 November 2020; Received in revised form 31 December 2021; Accepted 2 April 2022

Nomenclature

Abbreviations

4G	4th generation communication technology
5G	5th generation communication technology
ABM	Agent-based model
AR	Augmented reality
BB	Baseband
CapEx	Capital expenses
CIFUS	Committee on Foreign Investment in the US
eMBB	Enhanced broadband
GHG	Greenhouse gas
GHz	Gigahertz
ICT	Information and communication technology
IoT	Internet of Thing
LTE	Long term evolution
Mbps	Million bits per second
MHZ	Megahertz
MIMO	Multiple input multiple output
mmWave	Millimetre wave
MNO	Mobile network operator
MS	Mains supply
Ofcom	The Office of Communications
O&M	Operation and maintenance
OpEx	Operating expenses
PA	Power amplifier
PDF	Probability distribution function
RAN	Radio access network
RF	Radio frequency
TRX	Multiple transceivers
VR	Virtual reality

Symbols

A	active days per month, days
B	average busy hours per day, h
BW	bandwidth of the serving cell, MHz
C	spectral efficiency, bps/Hz
$D_{x,t}$	total population in postcode x in year t, Number of people
f	spectrum band, MHz
G_i	antenna gain of serving cell, dBi
G_m	antenna gain of inter cell, dBi
h	fading loss factor, MHz
I_m	total interference from the inter cells, W
N	average power of the noise and interference over the bandwidth, W
n	path loss factor, -
N_o	thermal noise at a receiver, dBm
N_{TRX}	number of transceivers, -
P	load-depend energy consumption, W
P_{BB}	BB power consumption, W
P_{full}	power consumption at full load, W
P_{idle}	power consumption at idle state, W
P_{out}	antenna element output power, W
P_{PA}	PA power amplifier, W
P_{RF}	RF power consumption, W
$P_{r,i}$	the desired received signal power by user, W
P_t	monthly data consumption per capita in year t, GB
$P_{t,i}$	transmit power from the serving cells, W
$P_{t,m}$	transmit power from the inter cells, W
P_0	power consumption at the minimum non-zero output power, W
r	distance from a receiver to serving cells, m
R_i	distance between the user and the serving cell, m
R_m	distance between the user and the inter cell, m
$R_{x,t}$	required data traffic rate in postcode x in year t, Mbps
S	average received signal power over the bandwidth, W
$SINR$	signal to interference and noise ratio, dB
S_t	smartphone penetration rate in year t, %
T	throughout, Mbps
U_t	required data traffic rate per capita in year t, Mbps/per-capita
Δ_p	slope of the load-dependant power consumption, -
η	bandwidth efficiency, %
η_{PA}	PA power efficiency, %
λ	base station density, -
σ_{cool}	loss factor incurred by active cooling, %
σ_{DC}	loss factor incurred by DC-DC power supply, %
σ_{feed}	feeder loss, dB
σ_{MS}	loss factor incurred by mains supply, %

advantage, while Mobile Network Operators (MNOs) who fail to adapt will likely lose market share. Currently, the deployment of 5G networks is about to transition from policy-led to technology-driven (Fig. 1). In the near future, it will experience a transition to business-led, and then a follow-up transition to market-driven.

Previous research topics on the diffusion of 5G network technology mostly focused on the relationship between policy incentives and the development of 5G technology, that is, transition from policy-led to business-led (in Fig. 1). They provided little understanding of the dynamics of 5G deployment from a socio-technical perspective. The 5G system is integral and hierarchical. There are interactions amongst its various components, and their behavioural relationship is nonlinear. Each component cannot be separated from the 5G system as a whole to study separately and then superimposed to get the whole, but must be studied using a complex system method. To investigate the future development and potential energy impact of 5G, this study focuses on modelling the development of 5G base stations in the UK in the next ten years by developing an agent-based model (ABM) and assess its economic and environmental impact. The specific advantages of using an ABM include the abilities 1) to model location, which is critical to end-users at a postcode level, the base stations interact (noise and interferences) in a spatial dimension; 2) to incorporate socio-political variables and technical mechanisms in simulation – which are essential to 5G deployment. Specifically, a novel 5G diffusion planning framework incorporating spatial interactions and socio-techno-political factors via an ABM is developed to answer the research questions:

- How does the deployment strategy need to change for best economic performance (i.e. cheaper energy)?
- What is overall cost to 5G deployment of geopolitical restrictions?
- What is the energy cost and carbon footprint of the UK's 5G deployment strategy?

The rest paper constructed as follows. Section 2 reviews the past literature and Section 3 introduces the research design and specific methods. In Section 4 simulation results are presented and in Section 5 their implications for policy are discussed. In the conclusion, the key points are summarised.

2. Literature review

Understanding the spatiotemporal dynamic characteristics of 5G deployment can greatly help decision-makers formulate strategic plans and recommend least-regrets configuration plans in different regions. To

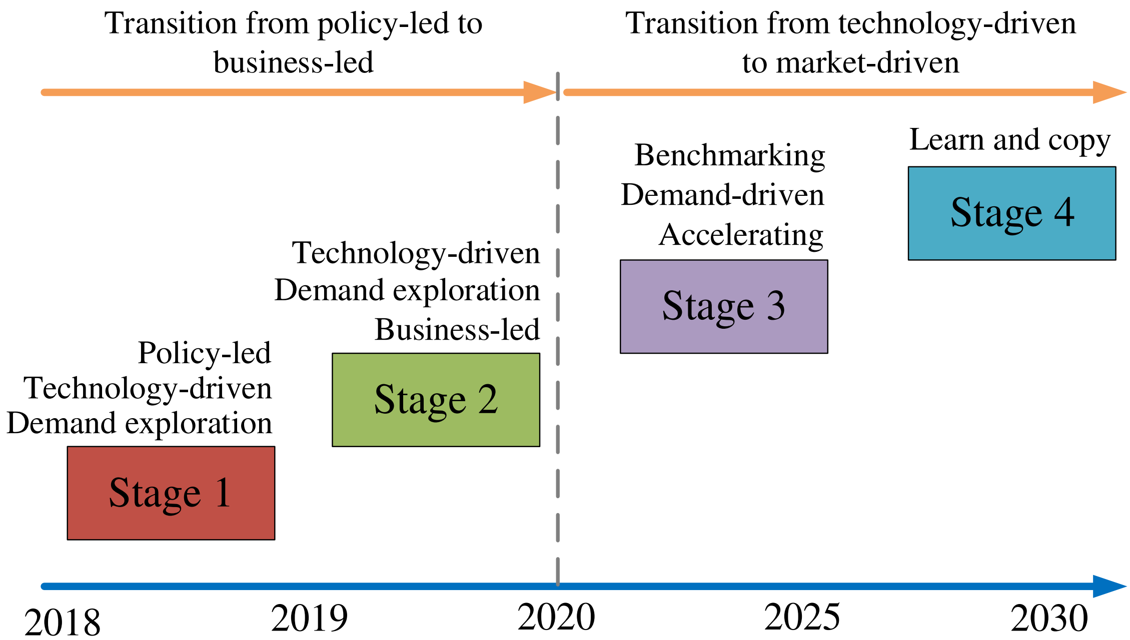

Fig. 1. The rollout rhythm of 5G networks.

this end, Oughton and Russell (2020a) developed a decision-support model which can quantify the performance of digital infrastructure strategies for mobile digital communications. Based on the model, they undertook a supply-driven and demand-driven investment analysis using a case study of the Netherlands, and estimated the traffic threshold delivered per user from integrating 5G spectrum bands on the existing Dutch macrocell network (Oughton et al., 2019); explored the cost, coverage and rollout implications of 5G networks across Britain, by extrapolating 4G characteristics for the period 2020–2030 (Oughton and Frias, 2018); conducted scenarios-based assessment of 5G infrastructure strategies in relation to mobile traffic growth using Britain as a case study example (Oughton et al., 2018); and particularly analysed the marginal impact of population growth on total demand for 5G in a UK growth corridor - the Oxford-Cambridge Arc (Oughton and Russell, 2020b). Furthermore, from a temporal perspective alone, Ghoul and Jia (Ghoul and Jia, 2017) proposed a new pricing model to be consistent with the growth of mobile broadband, and they found that the reuse of existing 4G base stations have a large impact on reducing costs when a denser 5G macro base stations deployed. However, this study did not explain how the evolution of changes of 5G deployment in spatial development. For a spatial perspective alone, Frias et al. (Frias et al., 2017) assessed the perceived value of a particular spectrum according to the impact that the spectrum could have in decreasing rollout costs. They found that adding spectrum with similar propagation characteristics to a coverage-constrained network is of no value. Apart from these research, other previous studies on 5G deployment were mainly conducted from either theoretical or non-spatiotemporal perspective, and random processes were usually used to construct networks for assessment. For example, Haddaji et al. (2018) proposed a novel method of 'BackHauling-as-a-Service' for 5G network planning and total cost of ownership analysis, in which they used a stochastic geometry model (Voronoi Tessellation) to define the backhauling zones within a geographical area. Not only that, given radio channel conditions and interference, stochastic geometric models can be also used for system-level performance analysis. Martin-Vega et al. (2015) analysing a hierarchical backhaul and the Radio Access Network of a Hyper-Dense Heterogeneous network, in which they used a stochastic geometry model (Poisson Tree) to define the traffic concentrators, base stations and users (i.e. nodes of Poisson Tree). In addition, machine learning and artificial intelligence can also be used in wireless cellular network planning. Aondoakaa et al. (2018) developed a meta-heuristic algorithm to provide an optimisation framework for the cost-effective design of 5G base station networks. However, this framework was mainly used to support the decisions about the optimal base station topology in a 5G mobile network, but it did not consider the changes in spatiotemporal development.

Besides technical aspects, the rollout rhythm of 5G networks is largely affected by exogenous factors, such as policies, the economy, and the market. For example, due to the trade war between China and the United State (US), the Committee on Foreign Investment in the US (CFIUS) has strengthened its measures to protect core semiconductors and 5G technology. Therefore, world-wide 5G rollout in the US could be slowed down by CFIUS regulations (Crabb, 2019). Following the US government's expressed concerns about the safety of its equipment, Huawei has been banned from competing for further UK 5G infrastructure contracts. Oxford Economics (Worthington, 2019) pointed out that restricting a key supplier of 5G infrastructure from helping to build a country's network would increase that UK's 5G investment costs by between 8% and 29% over the next decade. 5G deployment is not only expensive for equipment, but also for spectrum resources. In 2018, the UK completed the first auction of 5G spectrum bands, i.e. 2.3 GHz and 3.4 GHz. The four major mobile network operators (MNOs) (EE, Vodafone, O2, Three) spent a total of nearly £1billion (OFCOM, 2018). The UK is expected to complete the auction of 700 MHz and 3.6–3.8 GHz spectrum bands in 2021 (OFCOM, 2020), and the final transaction price will also be an astronomical figure. Therefore, MNOs participating in 5G deployment will bear huge investment risks. Affected by economics of scale (Katz and Berry, 2014), MNOs are often not keen to invest in low-income regions due to CapEx and OpEx as well as scarcity of electricity from the grid make these regions cannot make much profits. Therefore, this profit-orientated deployment pattern may cause 5G to be mainly deployed in urban areas (Chiaraviglio et al., 2017b). As a result, the positive aspects brought about by 5G technology may be 'urban' in nature (Rao and Prasad, 2018). Oughton and Frias (2018) found that 90% of the population is covered with 5G by 2027 if the business-as-usual, but coverage is unlikely to reach the final 10% due to exponentially increasing costs. Neokosmidis et al. (2017) assessed multi socio-techno-economic factors that affect the adoption and deployment of 5G networks and found that the weights of the criteria are the performance (0.36), business (0.2), acceptance (0.18), flexibility (0.17), and technology (0.09). With the transition of 5G deployment from service-driven to market-driven, market demand has been driving the development of mobile networks towards the ecosystem. More and more people completely rely on their mobile devices either for work or entertainment, and mobile broadband data traffic has also begun to explode (Trestian et al., 2017). This is mainly due to the rise of data-hungry applications on smartphones such as TikTok and YouTube. The launch of more similar applications in the future will further push customers to embrace the 5G technologies in the market. Apart from that, 5G is the foundation access technology for Internet of Things (IoT) (Borkar and Pande, 2016), the demand for some key services such as smart cities, smart medicine, augmented reality (AR) and virtual reality (VR), is accelerating the adoption and deployment of 5G.

Currently, the information and communication technology (ICT) sector consumes about 4.7% of global electricity production (Gelenbe and Caseau, 2015) As 5G is envisaged as a key technology enabling IoT to address the challenge of rising mobile data demand, power consumption from the information and communication technology sector is forecast to increase significantly by 2030 (Mowla et al., 2017). When the 5G deployment transitions to commercial drive, the energy consumption problem will gradually become prominent. Many researches have been conducted to reduce the energy consumption of wireless cellular networks. Auer et al. (2011) proposed an evaluation framework to quantify the energy efficiency of a wireless cellular network and assess the power consumption of various base station types under different traffic loads. Base stations are considered to be the main source of energy consumption (Hasan et al., 2011). At present, the typical power and peak power of a base station are about 6 kW and 9 kW, respectively, and they will increase to 14 kW and 19 kW with the application of the millimetre wave and 5G new technologies in the existing frequency band (Huawei, 2020). Not only that, 5G base stations will also be deployed at a higher density (Andreev et al., 2019), which means the energy consumption of 5G networks will increase rapidly in the next decade. More importantly, the ever-increasing power consumption may challenge the future power infrastructure, so there is an urgent need to build a green 5G network to improve energy efficiency (Abrol and Jha, 2016). Many approaches have been proposed to improve the energy efficiency of 5G networks. Buzzi et al. (2016) grouped the approaches into four broad categories, including resource allocation (Zappone and Jorswieck, 2015), network planning and deployment (Niu et al., 2010; Oh et al., 2013), energy harvesting and transfer (Mukhlif et al., 2018), and hardware solutions (Han et al., 2011; Rost et al., 2014). More recently, Alamu et al. (2020) conducted a comprehensive review and outlook on energy efficiency techniques in ultra-dense wireless heterogeneous networks and introduced another two categories of approaches: optimisation of radio transmission process (Alamu et al., 2020), base station sleeping strategy (Chang et al., 2020). However, previous studies on energy consumption are either for local networks or for a single base station, so there is a lack of comprehensive analysis of the energy consumption characteristics of 5G networks at the national level.

3. Methodology

The ABM method was selected in the study, as it allows us to model the interactions between multiple and diverse participants, each of whom makes decisions based on their circumstances and what they are assumed to know (Grubic et al., 2020; Rinaldi et al., 2001; Varga et al., 2014). Furthermore, ABM is increasingly being used to model and simulate wireless cellular networks (Laghari and Niazi, 2016; Papazoglou et al., 2013). The deployment of a generation of telecommunication infrastructure usually spans a decade, where the combination of policy, technology and socio-economic uncertainty is highly dynamic and complex. In order to address these challenges, in this paper an ABM framework developed by Chappin and Dijkema) (2010) is employed to support our research, since it is specifically used for modelling infrastructure system transitions. The framework consists of five main elements: system representation, exogenous scenarios, transition assemblages, system evolutions and impact assessment (Fig. 2). Our previous work (Grubic et al., 2020) had described the connotation of each elements in detail which will not to be repeated here. The objectives of this study are to simulate spatio-temporal dynamics of 5G base station diffusion by replicating political and technical features of real world, and visualizing the related economic and environmental impacts over time. Section 3.1 to 3.4 mainly focus on the development of an ex-ante 5G ABM, and Section 3.5 explores how to employ the related ABM results to analyse the environmental impacts.

3.1. System representation

An ABM can be defined as a collection of heterogenous, intelligent and interacting agents which operate and exist in an environment, which in turn is made up of agents (Crooks and Heppenstall, 2012). In broad outline, the proposed ABM in this study is design-orientated instead of operational, which simulates the future deployment of 5G base stations to meet end-users' demand in the UK context. The whole system evolution starts from very urban to very rural areas. The investment agent implements the deployment strategies in each area under certain policies. The collective 5G system functionality depends on each individual base station's functionality, as well as the coupling dynamics in between. Due to the characteristics of base station agents, one base station agent capacity in one area is influenced by local base station agents as well as ones in the adjacent areas, because the surrounding base station agents can cause interferences. It means that deploying a new base station agent can influence all surrounding base station capacity (both for itself area and adjacent areas), which influences other areas' deployment decisions, then the whole year deployment pattern consequently changes as the budget is constrained. In each time step, the investment agent is responsible for calculating the demand per area, iteratively deploying UK base stations in turn. After characterizing ABM, this part introduces system areas and boundaries, investment agent characteristics, base station agent technical configurations.

3.1.1. System boundaries

In defining the system boundaries, the geomatics of legacy wireless cellular networks and the demographics in the UK, which covers England, Scotland and Wales of more than 9000 postcode areas, was followed. Northern Ireland is not included because its demographic information is not available at a postcode level. In order to analyse the regional characteristics of 5G deployment, such as local income level and population density, the UK's regions were classified into three geotypes (Analysis Mason, 2010): urban, suburban, and rural areas. Then the demographic information from the most recent UK Census ("UK Census Data," 2011) and the Administrative Division data ("UK Administrative Division," 2019) were embedded into each postcode to create a geodemographic database.

3.1.2. The base station agent

Each base station agent is a basic unit providing communication services for end-users, and its capacity not only depends on its own configuration but also the interactions from nearby base stations. This subsection firstly introduces the types of base station agent, spectrum frequency and UK coverage background, followed by elaborating capacity and dynamic interactions with nearby base stations.

Base station types: The most pertinent communication infrastructure, i.e. Radio Access Networks (RAN) (Auer et al., 2011), components considered in this study include Macrocells and Microcells. Unlike Picocells and Femtocells, these cells are the regular based stations that provide coverage to a large area with inter distance from hundreds of meters to several kilometres, as illustrated in Fig. 3. They are usually installed by the mobile network operator (MNO) in a planned manner to ensure and/or improve outdoor cellular coverage. More importantly,

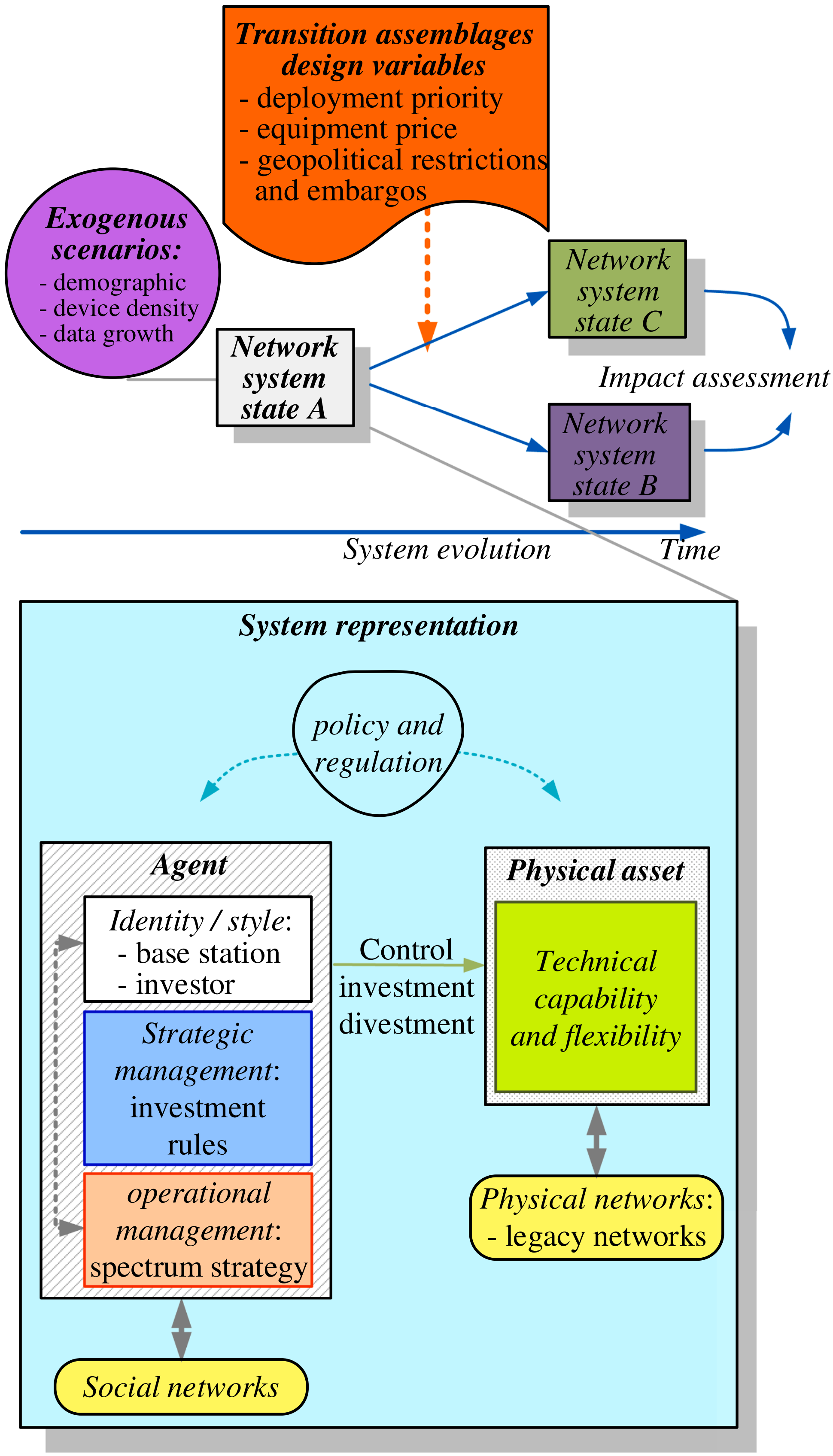

Fig. 2. A framework for evaluating 5G network system transitions with agent-based models (adapted from (Chappin and Dijkema, 2010)).

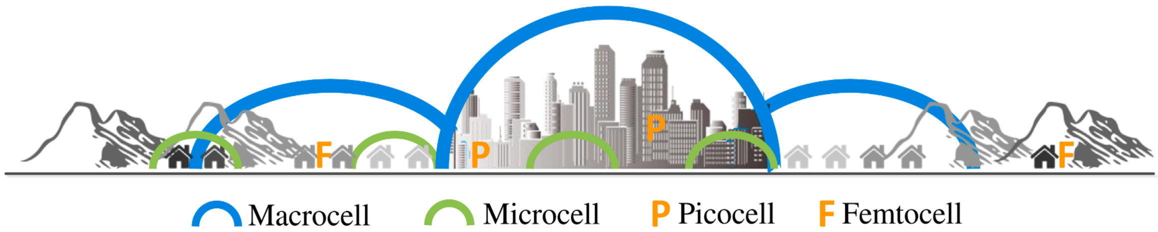

Fig. 3. Network architecture site types (5 G Infrastructure Requirements in the UK, 2016).

these base stations (also known as site, cell) consume approximately 80% of the energy required for cellular network operation (Fehske et al., 2011). Please see Table 1 for more specifications of different types of base stations.

Spectrum frequency: All mobile data travel through base stations on a frequency band, with characteristics that higher frequency bands could carry data further than others and lower frequency bands are better at passing through walls and other obstacles. The deployment of base stations and the selection of frequency bands often consider local geographical conditions and communication technologies to maximize coverage while considering cost performance, as illustrated in Fig. 3. The frequency spectrum used for civil communications is a limited resource, controlled by the government and licensed to major MNOs. In the UK MNOs strive to have frequency resources through bidding in order to deploy their own cellular networks. For example, as shown in Fig. 4, the frequency bands of 900 MHz, 1800 MHz and 2100 MHz, have primarily been using for 2G and/or 3G services; and 800 MHz, 1400 MHz, 2100 MHz, 2300 MHz and 2600 MHz have been using for 4G services. In general, low-frequency bands (<1000 MHz) mainly support improved coverage and user experience; mid-frequency bands (sub-6 GHz, usually between 1000 MHz and 6000 MHz) meet the increasing capacity demand for mobile services; and high-frequency bands (≥26 GHz, mmWave) make delay unnoticeable. Ofcom[1] has revealed its strategies to provide more spectrum resources to deployment 5G networks, that is, first 5G spectrum auction held in 2019 had licensed 3400 MHz to four major MNOs, and the planned second auction in early 2021 will open up to the much-anticipated frequency bands of 700 MHz.

UK coverage background: Approximately 144,000 base stations belonging to the four major MNOs (EE, Vodafone, O2 and Three) were mapped into the created geodemographic database (Boswarva, 2017). amongst these base stations, a total of 42,136 sectored Macrocells of 4G networks have screened out with detailed location and configuration information (Oughton and Frias, 2018), as visualised in Fig. 5, if needed they can be upgraded to 5G to save money and space. Therefore, the current distribution of Macrocells is likely to form the basis for 5G deployment. Furthermore, the detail geotype data characteristics are listed in Table 2.

Base station capacity and interactions: In reality mobile devices in an area will receive signals from different cellular cells, as shown in Fig. 6, and an interference signal (purple dash line) modifies a desired signal (green solid line) in a disruptive manner, as it travels along a communication channel between its source and received, thereby reducing spectral efficiency.

In quantifying the changes to communication capacity from 5G deployment, a theorem in information theory proposed by Shannon and Hartley (Gokhale, 2004) was applied in this study. The theorem establishes the channel capacity of a communication link (Eq. (1)), a bound on the maximum amount of error-free information per time unit that can be transmitted with a specified bandwidth in the presence of the noise interference.

$$C = \sum_{k=1}^{\min(n_T,n_R)} BWlog_2\left(1+\frac{S}{N}\right) \tag{Eq. 1}$$

Where C is a theoretical upper bound of the channel capacity, bits per second; n_T and n_R denote the number of transmit and receive antennas respectively (configuration details see Section 3.3 paragraph 1), BW is the bandwidth of the channel, Hz; S is the average received signal power over the bandwidth, W; N is the average power of the noise and interference over the bandwidth, W; therefor, $\frac{S}{N}$ is defined as the signal to interference and noise ratio (*SINR*). For a system with M cells, the SINR of the serving cell (i) can be expressed as follows (Eq. (2)):

$$SINR_i = \frac{P_{r,i}}{\sum_{m\neq i}^{M} I_m + N_o} \tag{Eq. 2}$$

Where N_o is the thermal noise at a receiver, 100 dBm ("Thermal Noise Power Calculator.," 2020); $P_{r,i}$ is the desired received signal power by user; I_m is the total interference from the inter cells. It should be emphasised that the interactions (interferences) from inter-cells in adjacent postcode also be considered, which means building new cells in one postcode inevitably influence nearby existing base station capacity, then further influence the deployment decisions of adjacent areas. Therefore, deploying dense cells may lead to a high noise level in a heterogenous network. $P_{r,i}$ and I_m can be further expressed as Eq. (3) and Eq. (4) (Ali et al., 2016):

$$P_{r,i} = P_{t,i}h_iG_iR_i^{-n} \tag{Eq. 3}$$

$$I_m = \sum_{m\neq i}^{M} P_{t,m}h_mG_mR_m^{-n} \tag{Eq. 4}$$

Where $P_{t,m}$ is the transmit power from the inter cells; R_i is the distance between the user and the serving cell; R_m is the distance between the user and the inter cell; n is the path loss factor, 2 assumed; G_i and G_m are the antenna gain of serving cell and inter cell (considering beamforming technology), respectively, 6 dBi (Matalatala et al., 2017); h is the fading loss depending on geotypes, which can be expressed as Eq. (5) (OFCOM, 2012):

$$h = \begin{cases} 4.2 + 1.3log_{10}(f), & urban \\ 3.5 + 1.3log_{10}(f), & other \end{cases} \tag{Eq. 5}$$

Note: the geotypes can significantly influence the fading loss, suburban and rural areas have less adverse impact on base station capacity.

Table 1
Specifications of different types of base stations.

Type	Coverage radius	Power consumption	Application scenario
Macrocell	1 – 10 km	3 kW – 10kW	Main wide area radio coverage
Microcell	300 – 1000 m	150 W – 300kW	Infill radio coverage and additional capacity (e.g. urban and suburban)
Picocell	Limited	15 W – 50W	Localised coverage (e.g. inside buildings)
Femtocell	Limited	10 W – 30W	Coverage improvement (e.g. home or small business premises)

[1] The Office of Communications, UK

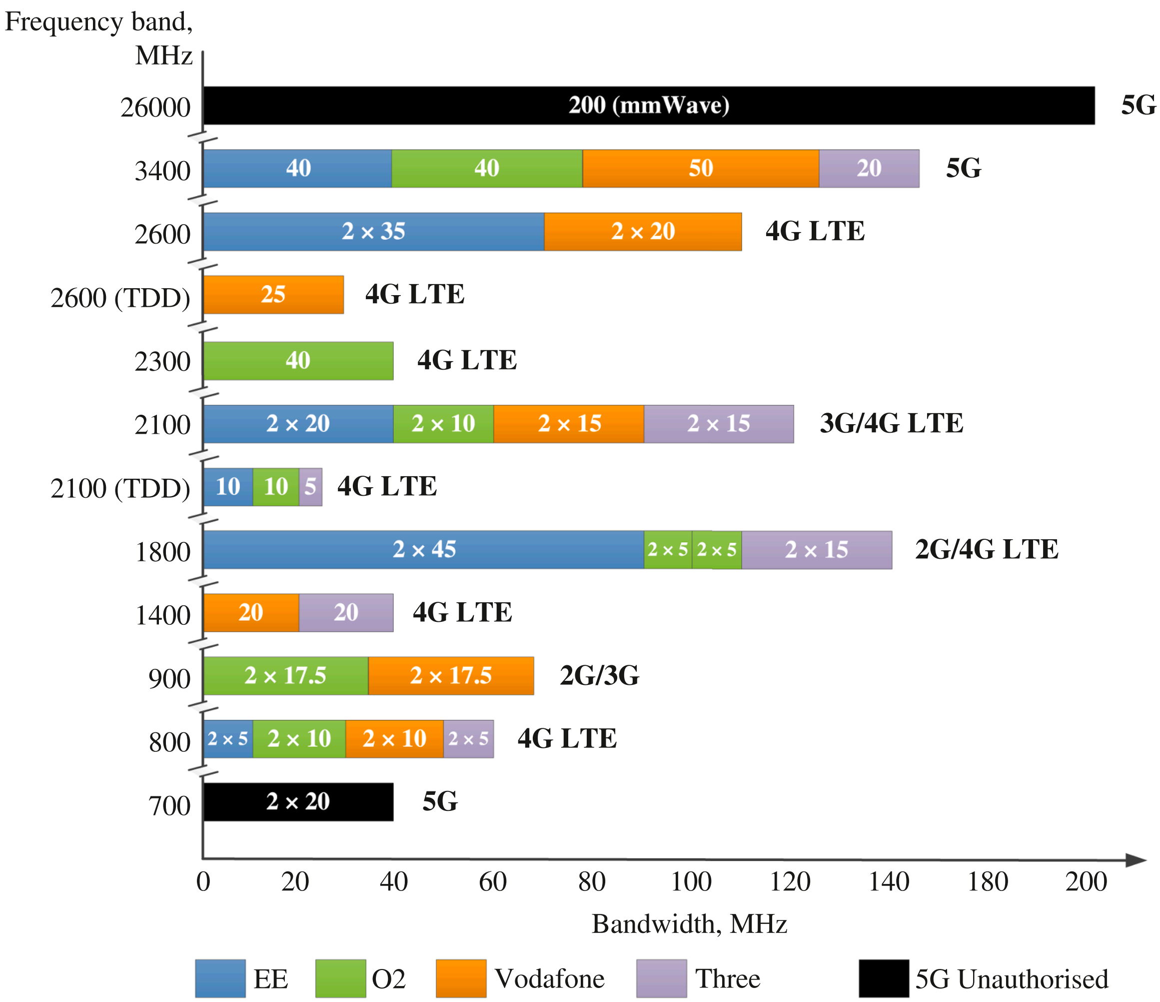

Fig. 4. Spectrum bands used by major MNOs in the UK.

Where f is the spectrum band, MHz. Assuming that mobile devices are randomly distributed in a postcode area, Eq. (6) was used to calculate the throughput (T, Mbps) of the serving cell (Ali et al., 2016):

$$T = \eta BW \int_{-\infty}^{+\infty} C_i f(r) dr \quad \text{(Eq. 6)}$$

Where η is the bandwidth efficiency, 90% assumed; and $f_R(r)$ is the probability distribution function, which can be further expressed as Eq. (7) (AlAmmouri et al., 2018):

$$f(r) = 2\pi\lambda r exp\left(-\pi\lambda r^2\right) \quad \text{(Eq. 7)}$$

Where r is the distance from a receiver to serving cells; λ is base station density. With network densification, the corresponding noise and interference are growing. To reduce the CapEx, the optimal (minimal) number of base stations in a postcode will be found. Therefore, the traffic capacity in postcode x can be abstracted as a function (Eq. (8)):

$$Traffic\ capacity\ (x) \ = \ F\ (\lambda,\ geotype,\ configurations) \quad \text{(Eq. 8)}$$

3.1.3. The investment agent

At present, UK MNOs are investing approximately £2bn per year ("UK spectrum usage and Demand" 2020) for upgrade and expand wireless cellular networks, excluding spectrum costs. Therefore, investment agent in year t can be expressed as follow (Eq. (9)):

$$Investment\ (t) \ = \ \begin{cases} x, & 0 < x < £2bn \\ & £2bn \end{cases} \quad \text{(Eq. 9)}$$

Investment (t) is the expense in year t, when x is less than 2 billion, it indicated the requirement of entire UK is satisfied; otherwise, it means the investment is insufficient.

3.2. Exogenous scenarios

An exogenous scenario is a collection of variables that influences system demand. More specifically, exogenous scenario parameters are those related to the data flow characteristics and wireless access devices. They were identified during the brainstorming discussions with experts and scholars from the telecommunications industry (see Acknowledgements).

3.2.1. Demographic change

The growing population is challenging the current mobile network capacity, which forces the MNOs to deploy the new-generation technology to improve wireless cellular networks. According to the estimates and projections of the Office for National Statistics ("Overview of the UK population," 2019; "UK Census Data," 2011), the UK population will grow steadily and reach over 70 million people by 2030 (see Fig. 7). However, population growth rates in different regions are not inconsistent. Fig. 8 shows the UK population growth rate by postcode. It is foreseeable that in the near future, there will be greater population growth in Greater London, Midlands, as well as the administrative and economic capital of Scotland and Wales. In order to reflect the impact of this factor in the analysis, the population growth rate of each administrative region was further embedded in the created geodemographic

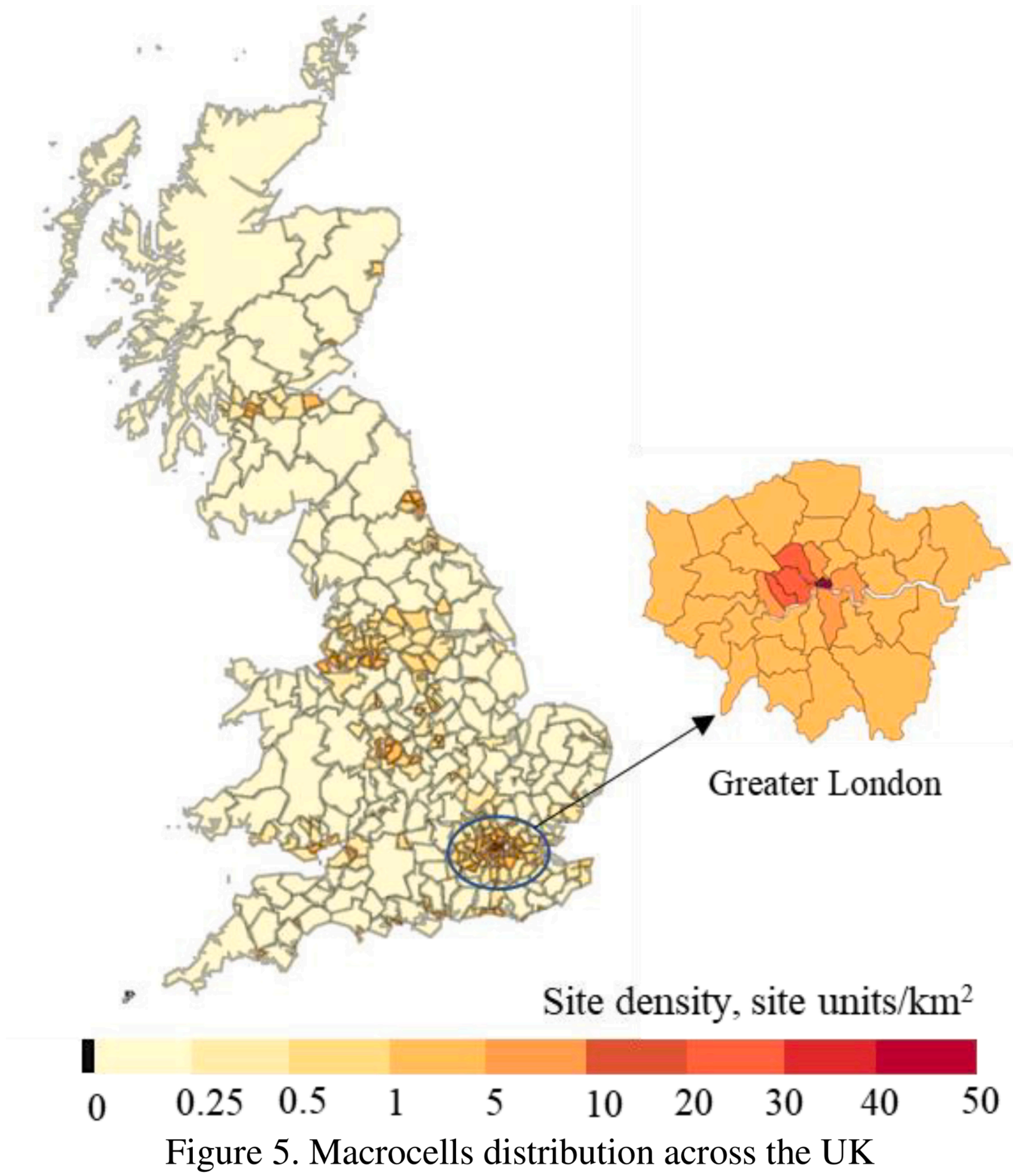

Fig. 5. Macrocells distribution across the UK.

Table 2
Geotype data characteristics.

Geotype	Criterion, people/km^2	Area, km^2	Population, %	4G coverage, %	Site count
Urban	> 7959	461	8.4	100	2888
Suburban	> 782	16,421	62.1	100	19,997
Rural	0 – 782	215,233	29.5	86.8	18,848

database to predict the current year's population as the systems evolves.

3.2.2. *Density of mobile clients*

With the rapid development of smart mobile technology, mobile devices and wireless terminals have greatly replaced the PC clients and become the core trend of the IT industry. It is foreseeable an explosive growth of mobile client Apps and the accompanying further popularity of mobile clients. amongst mobile clients, smartphone currently account for about 95% of mobile data consumption, and it is expected that this share will continue to increase in the coming decades. As shown in Fig. 9, after the rapid development of the smartphone penetration rate in the UK, the growth rate has slowed down in 2018, but it is expected to continue to grow steadily at a slow growth rate of about 1%, i.e. 64,000 people per year, and will exceed 90% by 2030.

3.2.3. *Mobile data growth*

Since 2010 Ofcom publishes an annual statistical survey of developments in the communications sector of a previous year (OFCOM, n.d.), including per-capita mobile data consumption as shown in Fig. 10. The 2019 edition is the most recently published statistical survey. Over the past eight years, per-capita mobile data consumption has been increasing more than 30 times. The rapid increase in data consumption

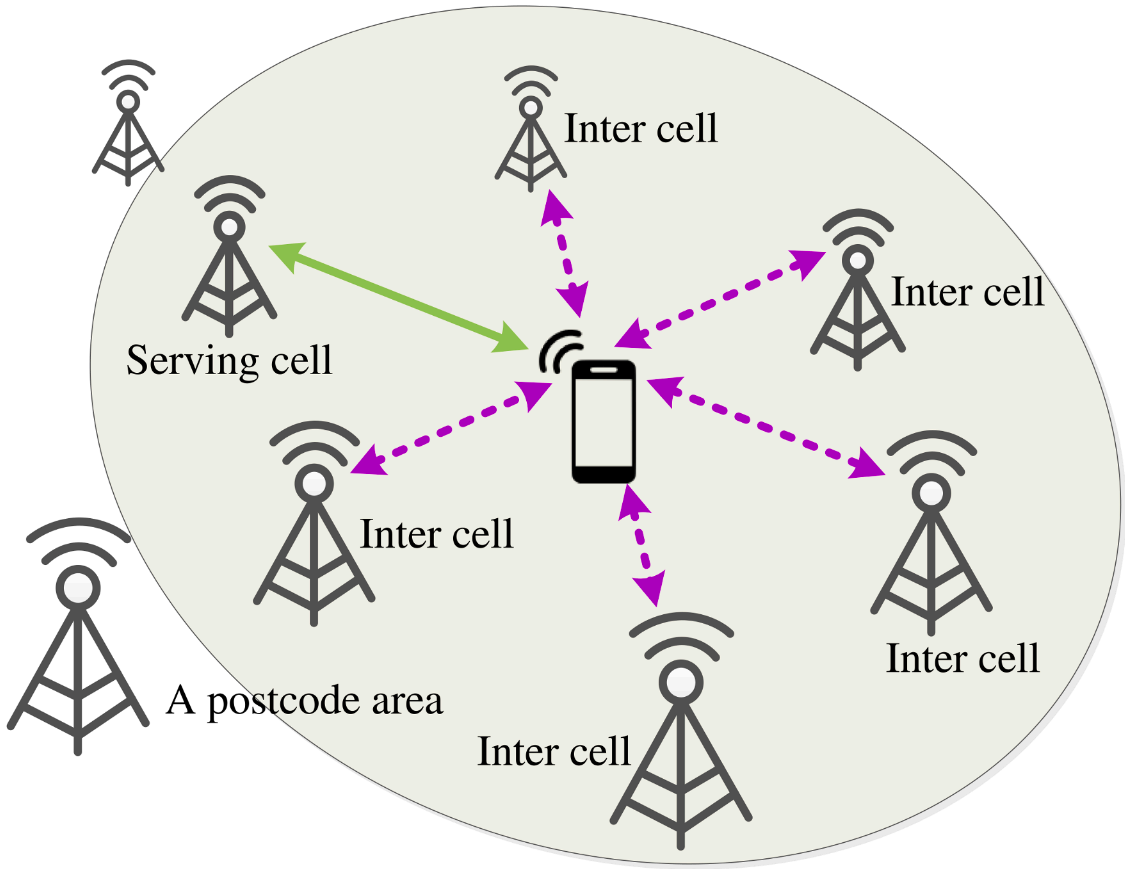

Fig. 6. Schematic diagram of noise and interference signal in a postcode area.

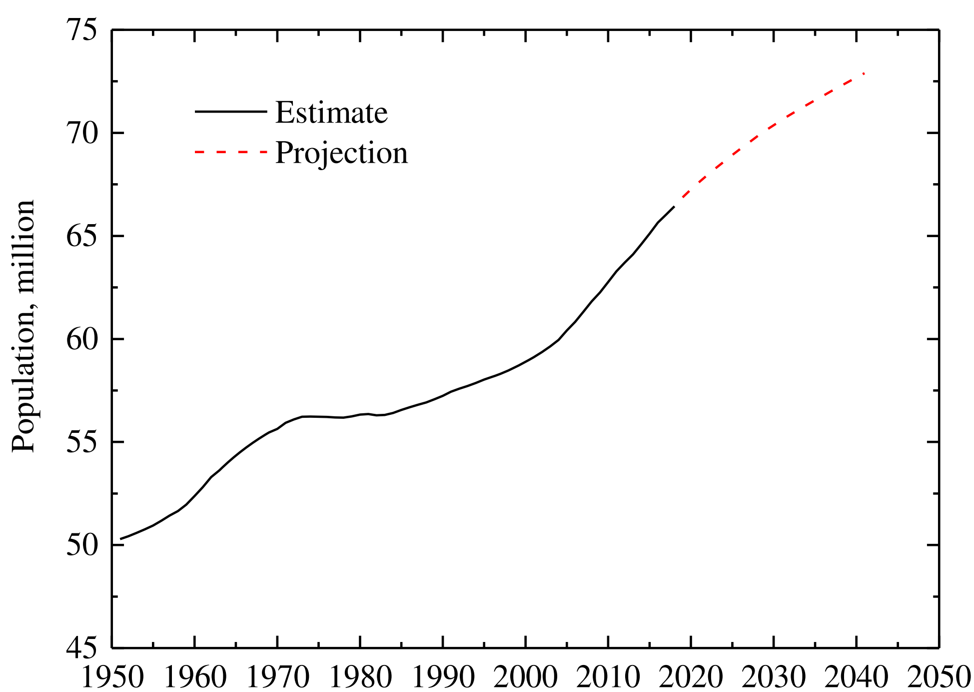

Fig. 7. UK population estimates and projections (source: ("Overview of the UK population," 2019)).

mainly benefits from the upgrading of communication infrastructure, especially 4G networks, and higher mobile broadband speeds, which has promoted the use of data killer applications (such as TikTok and YouTube) on smartphones. Due to the uncertainty of policy impact on Apps, we envisioned three mobile data growth scenarios, that is, high-demand, medium (business as usual), and low-demand. Considering that the growth rate of data demand conforms to the population growth (Alamu et al., 2020), a logistic curve (Eq. (10)) was used to forecast mobile data

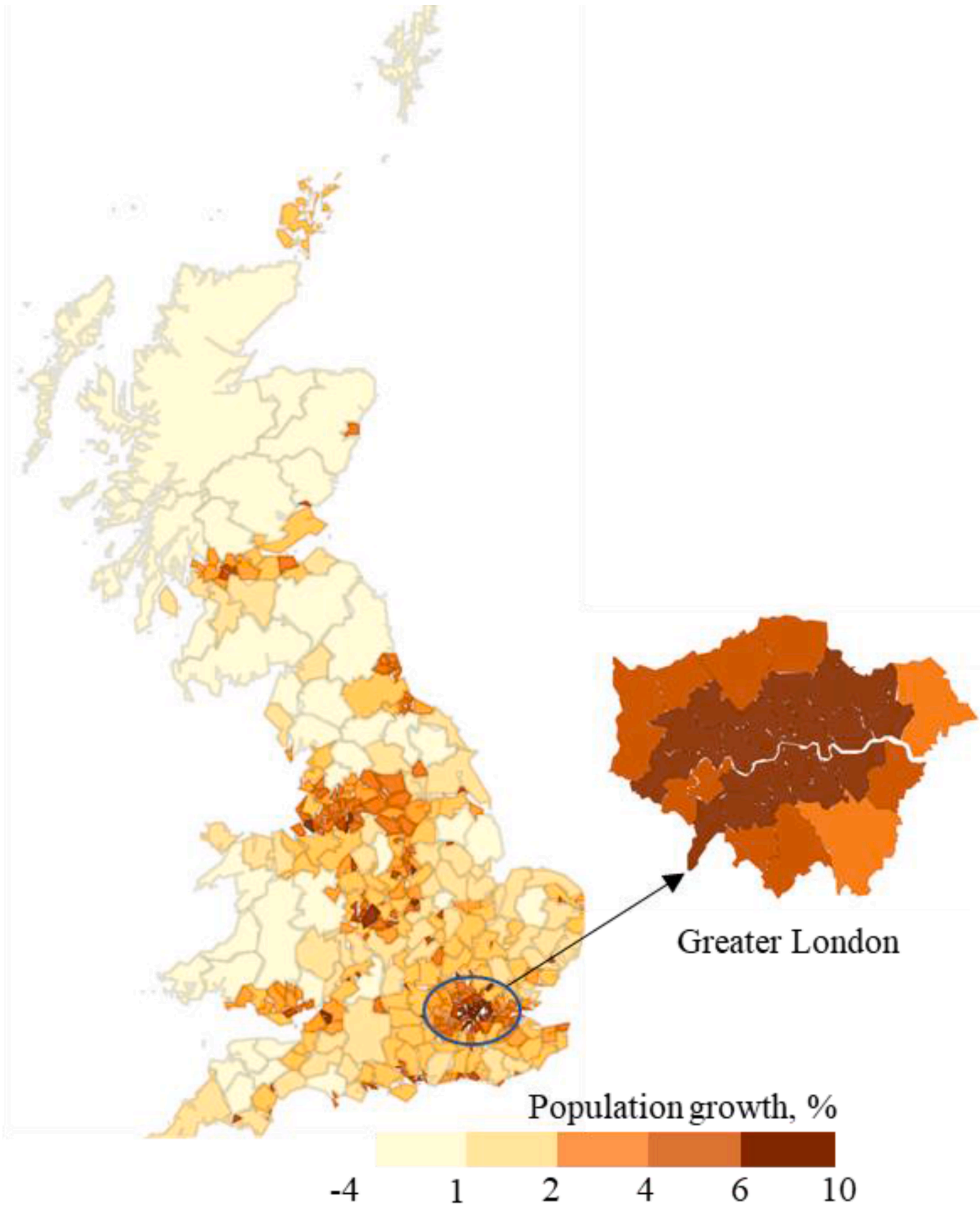

Fig. 8. UK population growth rate differs at a postcode level (source: ("Overview of the UK population," 2019)).

growth.

$$P(t) = \frac{KP_0e^{rt}}{K + P_0(e^{rt} - 1)} \quad \text{(Eq.10)}$$

where, t represents the number of years from 2010, and other coefficients are as follows:

	Low	Medium	High
K	15.5483	25.9011	44.767
P_0	0.1333	0.1432	0.1491
r	0.4675	0.4456	0.4329

When the curve changes from concave to convex, the rate of change of growth will change from positive to negative. The turning points of the three scenarios are in the 2024, 2026, and 2028. After determining the monthly per-capita mobile data consumption, Eq. (11) was further used to calculate the data traffic demand ($R_{x,t}$, Mbps) of a postcode area in year t.

$$R_{x,t} = D_{x,t} \times S_t \times U_t \quad \text{(Eq. 11)}$$

Where $D_{x,t}$ represents the total population of a postcode area x in year t; S_t represents the smartphone penetration rate (Fig. 9) in year t; U_t represents the peak data traffic demand (Mbps/per-capita) and can be calculated following Eq. (12).

$$U_t = P_t \times 1024 \times 8 \times \frac{1}{A} \times \frac{B}{24} \times \frac{1}{3600} \quad \text{(Eq. 12)}$$

Where P_t is the monthly data consumption per capita (Fig. 10); A and

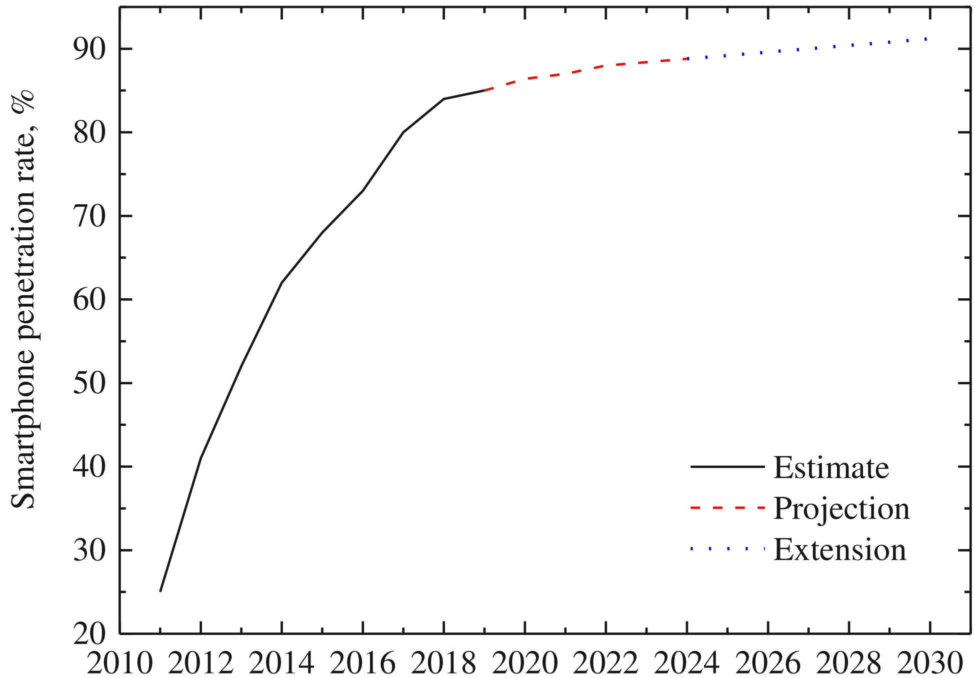

Fig. 9. UK smartphone penetration rate (source: estimate (Statista, 2018); projection (Statista, 2019); extension by linear interpolation).

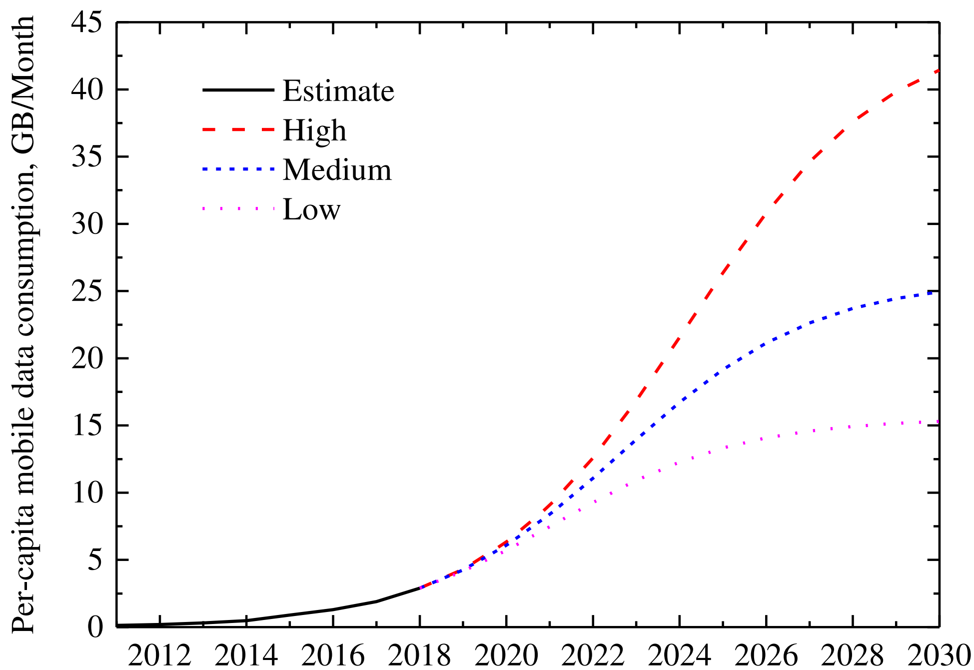

Fig. 10. UK mobile data growth (source: estimate (OFCOM, n.d.)).

B are the active days (30 days assumed) per month and average busy hour (4 h assumed) per day, respectively. Then, the total data traffic demand (Mbps) in year t can be expressed as Eq. (13), and will be further embedded into the geodemographic database.

$$Total\ Demand_t = \sum_{x=1}^{x} R_{x,t} \tag{Eq. 13}$$

3.3. Design variables for transition assemblages

A transition assemblage can be understood as investigation and design of technical configurations, policies, regulations, and investment strategies and their implementation, which will lead to infrastructure transitions (Chappin and Dijkema, 2010).

In this study, we mainly focused on the commercial 5G non-standalone networks,[2] and the configurations (transmit and receive antennas, spectrum frequency and bandwidth) defined in this part has a decisive impact on base station capacity (see Eq.1). In terms of key

[2] The non-standalone (NSA) mode of 5G NR refers to an option of 5G NR deployment that depends on the control plane of an existing 4G LTE network for control functions.

features of 5G, enhanced mobile broadband (eMBB) and multiple input multiple output (MIMO) were took into consideration, and an 8T8R (8 transmit antennas and 8 receive antennas) MIMO system was assumed to be used in all 5G base stations. From the current distribution of wireless cellular network base stations (Boswarva, 2017), it can be seen that some areas of the UK are still not covered by 4G services. In order to make full use of spectrum resources, the networks in these areas will first be upgraded with Macrocells integrated with two 4G frequency bands of 800 MHz and 2600 MHz. On the other hand, for those areas covered by 4G services, or after those uncovered areas being covered by 4G services, the newly available spectrum for the UK's MNOs (40 MHz @700 MHz and 150 MHz @3400 MHz, see Fig. 4) will be deployed on to the existing Macrocells, and then the same spectrum deployment to new Microcells where necessary if demand is not met. In the choice of available frequency bands, lower frequency bands are prioritised to ensure coverage while minimizing delivery costs.

On the other hand, the launch of the new spectrum will also significant affect 5G deployment progress. Due to the impact of the epidemic, the UK's original auction date for the new spectrum (700 MHz) in early 2020 has been postponed, maybe closer to November 2021 that Ofcom says ("Next UK 5 G spectrum auction is still 6 to 18 months away," 2020), though the specific date for the launch of the new spectrum remains uncertain. Furthermore, Europe has agreed to harmonise frequencies in the 26GHz band (mmWave) and it is believe to be the key enabler of future 5G services in capacity ("5 G Frequencies in the UK," 2020). Although there is no timetable to enable millimetre waves in the UK, the development of the digital economy will accelerate the arrival of mmWave has been widely accepted. In view of these information, in this study we assumed that 700 MHz band together with the licensed 3400 MHz band will be used first to upgrade 4G Marcocells; and the enabling of mmWave was driven by demand instead, for government decision-making reference.

3.3.1. Deployment priority

For the deployment of 5G by upgrading existing Macrocells, the four major MNOs in the UK have launched a deployment plan in 2019 (Jones and Comfort, 2019), and given priority to capital cities, i.e. London, Glasgow, and Cardiff, sorting by the population density of the city. The upgrade in this study is based on the principle that the higher the population density, the higher the priority. In addition, two infrastructure sharing agreements between the joint venture companies (O2 and Vodafone; EE and Three) were considered in the system evolution, it is assumed that each company domains the same market share. For Macrocells, they can be shared between the joint venture companies and the Microcells can be accessed by the four companies.

3.3.2. Equipment price trend

During the 5G deployment, the cost of purchase and upgrade 5G is dynamically changing with time. Table 3 was used as the annual budget for 5G deployment across the UK in this study and a 3% depreciation rate was assumed. It is worth to be noted that, in fact, the annual available budget of an MNO highly relies on its cash flow. Connecting the developed model to actual cash flow can further improve the accuracy of model predictions.

Table 3
Capital expense (CapEx) by deployment strategy*.

Cost description	Upgrade to 4G Macrocells, £	Upgrade 4G Macrocells to 5G, £	Set up 5G Microcells, £
Base station	122,700 (OFCOM, 2015)	15,000 (OFCOM, 2015)	2500 (5G-NORMA, 2015)
civil works and installation	18,000 (5 g-norma, 2015)	18,000 (5 g-norma, 2015)	13,300 (5 g-norma, 2015)
fibre backhaul	20,000 (oughton and frias, 2018)	–	20,000 (oughton and frias, 2018)
Metro & Core upgrade	7890 (Oughton and Russell, 2020b)	3250 (Oughton and Russell, 2020b)	1350 (5G-NORMA, 2015)

* Depreciation rate: 3%.

3.3.3. Geopolitical restrictions and embargo

Another important factor worth noting is that the UK government has withdrawn its decision to not restrict a key supplier from intervening in 5G networks. Therefore, MNOs may face additional costs of up to 2 billions of pounds and bear the consequences of lagging behind other European countries in 5G technology for three years (Assembly Research, 2020). Also considering that Oxford Economics' analysis (Worthington, 2019) that of a 8% - 29% increased investment costs in the next decade, we set a premium rate of 18.5% in the CapEx model (see Table 4) to reflect how the policy of restricting a key supplier will affect the CapEx.

3.4. System evolution

By reacting to the exogenous scenarios and transition assemblages, the agents, the constituent elements of ABMs (e.g. postcode areas, technical systems, policies and regulations variables), drive the evolution of the system. Agents are modelled as interdependent and their aggregate behaviour emerges as the collective operation of the whole system from the interaction amongst many numbers of subsystems. In this study, the system evolution occurs as postcode area agents deploy 5G Macro- or Microcells, which in turn brings changes to infrastructure capacity and consumption. Therefore, understanding the system evolution entails answering the following questions, which will allow the designed ABM to run a virtual evolution of the system.

1) What factors determine deployment strategy?
2) How do they interact and influence each other?

3.4.1. Factors determining deployment progress

The ABM is a demand-driven model, which is significantly influenced by a combination of parameters listed in Table 5. The full evolution system and interactions amongst different elements is shown in Fig. 11. Exogenous factors initially determine the demand of each postcode, while transition parameters and control variables are some fixed parameters determine characteristics of postcodes, base station capacity, maximum investment budget. As can been seen from Section 3.1, investment agent will be responsible for upgrading and purchase 5G equipment, the UK policies has constrained the annual maximum investment within 2 billion pounds. While investing 5G deployment, the transition variables affected the annual price of Macrocell and Microcell strategies. The UK government has withdrawn its decision to not restrict a key supplier from intervening in 5G networks, the premium of the equipment will also be taken into account in the model. On the other hand, the policies regulated the spectrum frequency and bandwidth in base stations. 40 MHz @700 MHz, 20 MHz @800 MHz, 40 MHz @2600 MHz and 150 MHz @3400 MHz will be used in Macrocells, whereas 150 MHz @3400 MHz and 200 MHz @26 GHz will be approved to embed into Microcells. In actual deployment, the deployment priority is defined when investment is not sufficient for entire UK, postcodes with higher

Table 4
CapEx for unrestricted and restricted deployment strategies*.

	Upgrade to 4G LTE Macrocells, £	Upgrade 4G Macrocells to 5G, £	Set up 5G Microcells, £
Unrestricted	148,590	36,250	17,150
Restricted	176,079	42,956	20,323

* Market share of the key supplier: 35% ("UK Ban on Huawei's 5 G Equipment Increases Telecoms' Capex," 2020).

Table 5
Variables of the 5G ABM.

Type	Variable	Operational ranges / specifications
Exogenous scenarios	Demographic change	See Fig. 7 and Fig. 8 in Section 3.2.1
	Density of mobile clients	See Fig. 9 in Section 3.2.2
	Mobile data growth	See Fig. 10 in Section 3.2.3
Design	Deployment priority	Sorting by city population density (Section 3.3.1)
	Equipment price	See Table 3 in Section 3.3.2
	Geopolitical restrictions	Premium rate of 18.5% (Section 3.3.3)
Assessment	Energy consumption	
	Carbon footprint	
	Operating expense	

meeting a given criteria.

The ABM is a demand-driven model based on the bottom-up approaches, the model variables and details of algorithm has been shown in Table 5 and Table 6, respectively. More specifically, the model starts with building the UK postcode level visualised map database based on OpenStreetMap[3] and GeoJSON,[4] following by inputting the demographic information and legacy Macrocells, which is the descried geodemographic database above (see Section 3.1.1). At the same time, the exogenous factor which is created to CSV file also be appended to the geodemographic database (see Section 3.2). Next, the associated transition assemblages (technical system, spectrum policies, deployment priority, investment strategy, infrastructure sharing agreements and cost model) will be initialised (see Section 3.3), before the cellular network deployment. Macrocell and Microcell are used to meet the growing traffic demand during the system evolution, and the deployment strategy making coded into the model is a multi-choice decision-making

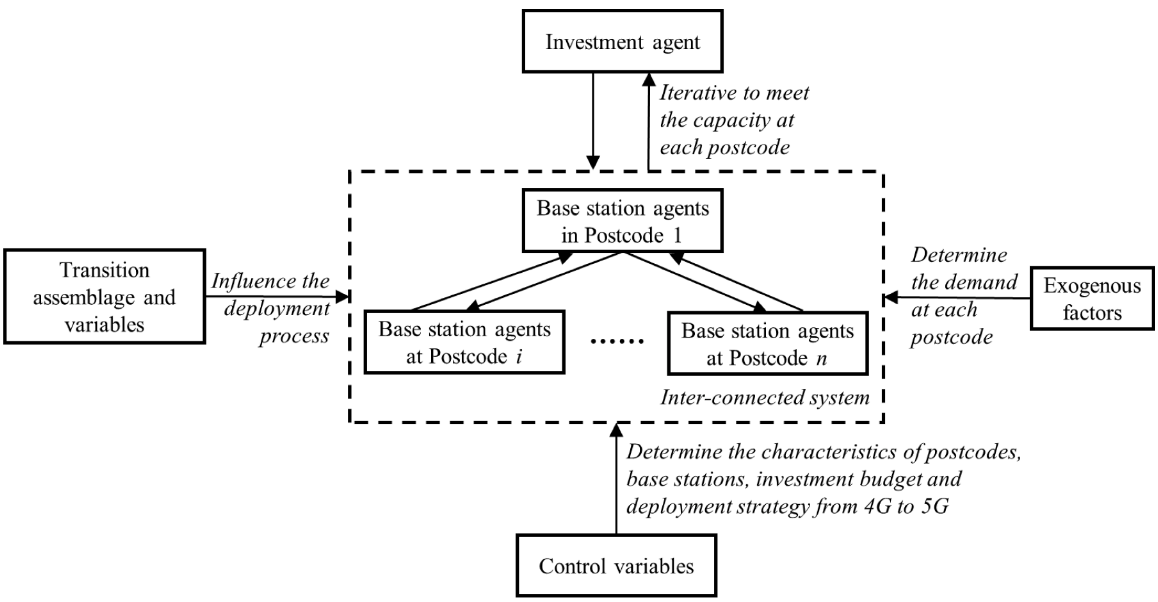

Fig. 11. Factors determining deployment progress.

population density will be firstly developed. In terms of behaviours of base station agents, it can be defined as follows:

- Upgrade existing Macrocell to 4G Macrocell. It is reported that there are 13.2% of rural areas across the UK (see Table 2) are not covered by 4G services, thus, the model will firstly check the area 4G coverage. The existing Macrocells in these areas will be installed with 20 MHz @800 MHz and 40 MHz @2600 MHz carriers if not fully covered with 4G.
- Upgrade existing Macrocell to 5G Macrocell (see Table 2 and Fig. 4). After ensuring ubiquitous 4G services in the local area, the legacy Macrocells will be embedded with new spectrum resources (40 MHz @700 MHz and 150 MHz @3400 MHz) to meet the increasing demand.
- Building new 5G Microcell. The newly built 5G Microcell (150 MHz @3400 MHz and 200 MHz @26 GHz) can be a supplement to the local capacity if the 5G Macrocell cannot meet the demand.

3.4.2. *Translating considerations into an ABM design*

The ABM in this study was developed via Python®. The deployment of base stations is following the pseudo-code as illustrated in Table 6. The flow charts are composed of transition and state elements. When certain conditions are met, a transition to a new state will be triggered. Triggering factors involve arrival of information, elapse of time and process, characterised in Section 3.4.1 base station behaviours. The annual deployment starts from the postcode with high population density. In each step, the newly built base station agents alter the capacity of in their local postcode spatial area, as well as cause interferences to nearby base stations on adjacent areas. In this way, the ABM updates the changed capacity of influenced areas. Even though the previous deployment has satisfied one area's demand, a new deployment can break the trade-off, then new base stations must be built to satisfy this unbalanced postcode in priority. The algorithm is a double loop structure: the first loop will run a ten-year deployment (ten times in total) between 2021 and 2030. The second loop is conditional, it ends until one of two situations is met: 1) all postcodes' demand are satisfied; 2) annual investment budget has run out. Once the network deployment completed at that year, the newly built base station information (coordinates, cost and capacity) will be exported for impact assessment. Meanwhile, the information will be synchronized to the geodemographic database for the program iteration, and each iteration can obtain the deployment details at that year. As a result, 5G deployment information can be visualized in both spatial and temporal dimension.

[3] An open source map library accessed at: https://github.com/openstreetmap
[4] GeoJSON is an open standard format designed for representing simple geographical features.

Table 6
The pseudo-code of 5G ABM.

Algorithm: 5G agent-based model

Input:
- mobile user density in each postcode matrix $X_{n\times4}$, // postcode, area, number of users, and mobile user density
- base station density in each postcode matrix $Y_{n\times4}$, // postcode, area, number of 4G base station, and base station density
- annual investment AI. // fixed to £2bn

Output: predicted postcode level base station density matrix $BS_{n\times3\ \times\ 10}$. // postcode, number of macrocells, number of microcells in a year from 2021 to 2030

Initialize local capacity of each postcode $C = (c_1, \ldots, c_n)$;
local demand of each postcode $D = (d_1, \ldots, d_n)$;
for $year \leftarrow 1{:}10$ **do**
sort the user density of each postcode, update the matrix $X_{n\times4}$
update all d_i $(1 \le i \le n)$ according to Eq. (11) to (12).
update all c_i $(1 \le i \le n)$ according to Eq. (1) to (7).
annual expense $e \leftarrow 0$
while $(e < AI$ or $\forall d_i < c_i)$ **do**
for $p \leftarrow 0$ **to** *length* $[X_{n\times4}]$
if $(d_p \le c_p)$ **then**
continue;
else
calculate *cost* by executing deployment strategy (see Section 3.4.1)
update the optimal number of base stations b_p (see Section 3.1.2)
$e \leftarrow e + cost$
update all c_i $(1 \le i \le n)$ according to Eq. (1) to (7)
end if
end for
end while
return $BS_{n\times3\ \times\ 10}$
end for

3.5. Impact assessment

The main objective of the impact assessment is to gain insights on the potential impact of 5G deployment on energy consumption and carbon footprint, and operating expense (OpEx) in the context of identified policies and scenarios.

3.5.1. Energy consumption

In general, a base station consists of composed of multiple transceivers (TRX), and each of them serves one transmit antenna element. A TRX comprises a power amplifier (PA), a small-signal radio frequency (RF) transceiver, a baseband (BB) unit, a DC-DC power supply unit, a mains supply (MS) unit, an active cooling system. Assuming that the power consumption of a base station is proportional to the number of transceivers (N_{TRX}) (Auer et al., 2011), the load-dependant energy consumption (P) can be can be calculated as follows (Eq. (14)):

$$P = N_{TRX}\frac{P_{PA} + P_{RF} + P_{BB}}{(1-\sigma_{DC})(1-\sigma_{MS})(1-\sigma_{cool})} \qquad \text{(Eq. 14)}$$

where σ_{DC}, σ_{MS}, and σ_{cool} represent the loss factors incurred by DC-DC power supply, mains supply and active cooling, respectively; P_{PA} can be expressed as (Eq. (15)):

$$P_{PA} = \frac{P_{out}}{\eta_{PA}\left(1-\sigma_{feed}\right)} \qquad \text{(Eq. 15)}$$

where η_{PA} represents the PA power efficiency; σ_{feed} represents the feeder loss; and P_{out} is the antenna element output power, which linearly changes with the actual data traffic load (Auer et al., 2011), varying between 0 and the P_{out} at maximum load (P_{max}). Therefore, Eq.15 can be rewritten in the form of a linear equation of P with respect to P_{out} (Eq. (16)):

$$P = \Delta_p P_{out} + N_{TRX}P_0, \ \ (0 < P_{out} \le P_{max}) \qquad \text{(Eq. 16)}$$

Where Δ_{p} is the slope of the load-dependant power consumption and can be determined by the power consumptions under full-load (P_{full}) and idle state (P_{idle}), respectively; and P_0 is the power consumption at the minimum non-zero output power. In reality, not all subscribers are always active, and P_{out} varies with data traffic load. The real-time P_{out} can be obtained by multiplying the P_{full} by a normalised data traffic load. A typical daily normalised data traffic load profile is shown in Fig. 12 and it was used in this study. Other base station technical parameters used in energy consumption calculation are listed in Table 7.

3.5.2. Carbon footprint

An industrial sector's carbon footprint can be measured by undertaking a carbon emissions assessment. Once the size of a carbon footprint is known, a strategy can be devised to reduce it, for example, by technological developments, energy efficiency improvements. However, calculating the carbon footprint of an industry sector is a complex task, and there is a set of standards for tracking greenhouse gas (GHG) emissions across scopes within the value chain (Greenhouse Gas Protocol, 2020). In this study, we focus on Indirect Emissions, from the generation of purchased electricity.

The energy mix for electricity generation in the UK has undergone tremendous changes in the past few decades. Since 2012, the share of coal has fallen sharply, and completely replaced by an increase in the consumption of natural gas and other renewable resources in 2020, such as wind, solar, and bioenergy (CarbonBrief, 2019). In order to quantitively assess the carbon footprint with 5G deployment, the projected UK electricity mix (Fig. 13) was used in this study. The associated CO_2 emission by fuel is listed in Table 8. It should be noted that most of the UK's imported electricity comes from France (CarbonBrief, 2019), via the 2 GW electricity interconnector between the two countries. The carbon intensity of electricity traded with France was taken into account to calculate the associated CO_2 emission of electricity excise.

In addition, energy taxes in UK are levied within the framework of the 2003 European Union Energy Tax Directive. Climate Change Levy (OECD, 2019), the one main taxes on energy use within this framework, applies to electricity supplied to businesses and the public sector. Although originally electricity generated from renewables other than hydro, including biofuels and waste was not taxed, but this exemption was phased out from 1 August 2015. According to Taxing Energy Use 2019, a nominal carbon tax rate is GBP 18.00 per tonne of CO_2. This means that MNOs of operating 5G networks not only need to pay high electricity bills, but they may also need to pay high electricity excise tax.

3.5.3. Operating expense (OpEx)

Generally, OpEx consists of the annual operation and maintenance (O&M) costs, site lease costs, the leased lines per backhaul link, and energy costs (Table 9). The annual O&M costs were assumed as to 10% of the CapEx of that year (Chatzimichail, 2014). Other data mainly came from Ofcom MCT model (Ofcom, 2020b) and 5G Norma (5G-NORMA, 2020). In terms of energy costs, the nominal price (£0.12/kWh) applicable to extra-large non-domestic consumers was used in this study ("Gas and electricity prices in the non-domestic sector," 2020).

4. Results and analysis

This study developed an ABM based communication infrastructure evolution framework and methods, synthesising multi-dimensional data visualisation with bottom-up approaches. By running the developed model, we obtained the quantitative results of the spatiotemporal evolution of 5G deployment in different scenarios, and further analysed the energy consumption and carbon footprint of the 5G network, as well as the subsequent change in the OpEx pattern.

4.1. Spatiotemporal evolution

The 5G deployment was carried out under three hypothetical data demand scenarios, i.e. low-demand, medium-demand (business-as-usual), high-demand. Therefore, before analysing the spatiotemporal deployment characteristics of base stations, we first predicted the

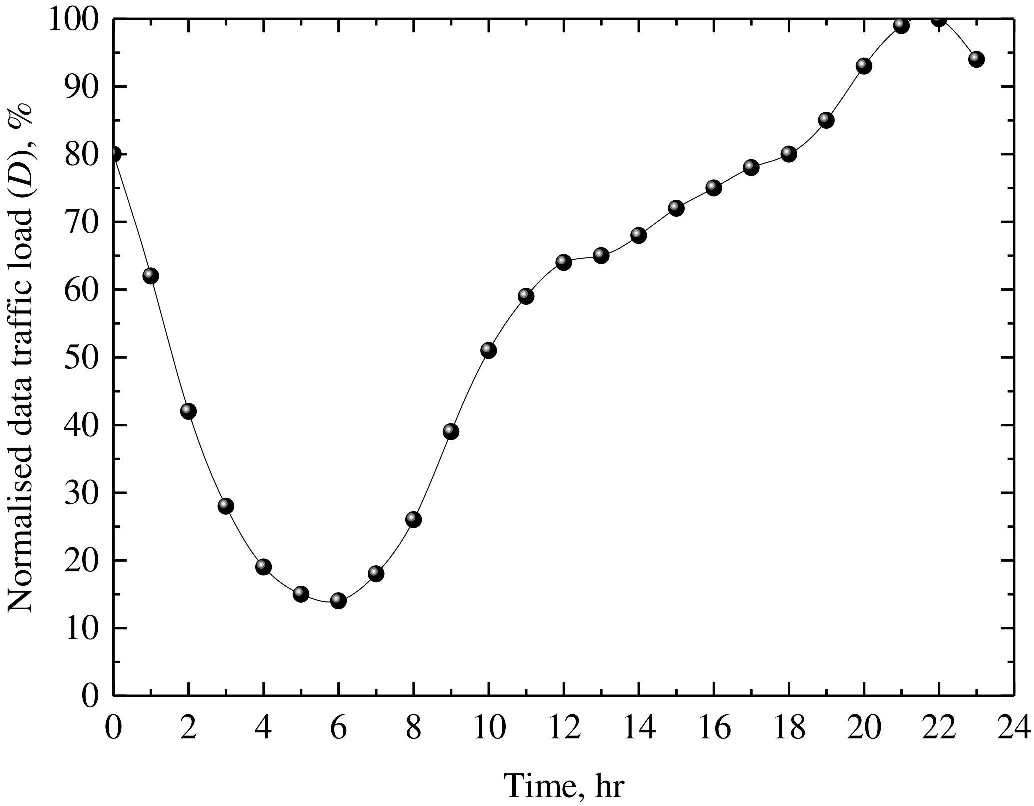

Fig. 12. Daily normalised data traffic load profile.

Table 7
Base station technical parameters.

Technical parameter	Macrocell	Microcell
PA power efficiency (η_{PA}),%	31.1	22.8
Feeder loss (σ_{feed}), dB	−3.0	0.0
RF power consumption (P_{RF}), W	12.9	6.5
BB power consumption (P_{BB}), W	29.6	27.3
Loss factor incurred by DC-DC power supply (σ_{DC}),%	7.5	7.5
Loss factor incurred by mains supply (σ_{MS}),%	9.0	9.0
Loss factor incurred by active cooling (σ_{cool}),%	10.0	0.0
Number of sectors per cell	3	1
Number of antennas per cell	8T8R	8T8R
Number of carriers per cell	2	2
Power consumption at full load (P_{full}), W	10,800	1157
Power consumption at idle state (P_{idle}), W	6000	864

demand for data capacity.

4.1.1. Demand for data traffic rate

Fig. 14 shows the growth in total demand for data capacity over the next ten years in the UK. If business-as-usual (medium), demand will grow from less than 5 Tbps in 2021 to more than 16 Tbps in 2030. In a high-demand scenario, the demand is even reach 24 Tbps; even in a low-demand scenario, the demand will still be 8.8 Tbps. It can be seen from Eq. (12) that the exogenous scenario parameters of population size, smartphone penetration rate and monthly data consumption are all first-power variables of the total demand function of data capacity. Comparing Fig. 7, Fig. 9 and Fig. 10, monthly data consumption has a decisive effect on demand growth as the magnitude of its variation is significantly larger than that of other exogenous scenario parameters.

In general, these predictions are consistent with Oughton's predictions for the region of Oxford–Cambridge Arc (Oughton and Russell, 2020b). For example, in their study in medium scenario the demand for Oxford, Luton, and Cambridge are expected to reach 400 Mbps/km^2, 700 Mbps/km^2, 400 Mbps/km^2 in 2030, respectively. However, it should be noted that they only considered 30% market share, but this study considered 100% market share. If as pro-rata prediction, our results are 340 Mbps/km^2, 740 Mbps/km^2, 510 Mbps/km^2 in these areas, respectively. Fig. 15 completely shows the data traffic density distribution across the UK, and locally enlarged shows the Greater London area, in three scenarios reflecting the underlying demographic characteristics of each postcode area. In all scenarios, the higher demand regions are mainly concentrated on the south and midlands of England, whereas the demand of Scotland and Wales is not significant. This can be primarily attributed to the relative low population density in Scotland and Wales. Compared to low-income rural areas, there is a higher demand in administrative and economic capital areas, e.g. Greater London, Glasgow, Edinburg and Cardiff. This tendency can be particularly magnified in the low-demand scenario. In addition, the demand density for inner London is significantly higher than outside, and it noted that three boroughs – Westminster, Islington and Tower Hamlets which possess the highest density, especially for the Tower Hamlets, its demand even exceeds 5000 Mbps/km^2 in the high-demand scenario. These results are of vital importance to decision-makers, as MNOs who fail to satisfy customers' demand will be likely to lose market share.

4.1.2. Spatiotemporal rollout of base stations

In terms of deployment, no doubt the newly deployed base stations increase consistently with the demand in each year. As shown in Fig. 16, the number of Microcells is significantly larger than that of Macrocells in all scenarios. It is projected that in the low, medium and high demand scenarios, the deployment of 360,000, 550,000, and 790,000 microcells will need to be completed respectively by the end of 2030. In general, most of the capacity is provided by the Microcells in the 5G network, with a limited number of Macrocells only as a supplement. Take the medium scenario (business-as-usual) as an example, it is found that all areas in the UK will be fully covered with 4G services after 2025, and the upgradation of vast majority of 4G Macrocell to 5G. Furthermore, 700

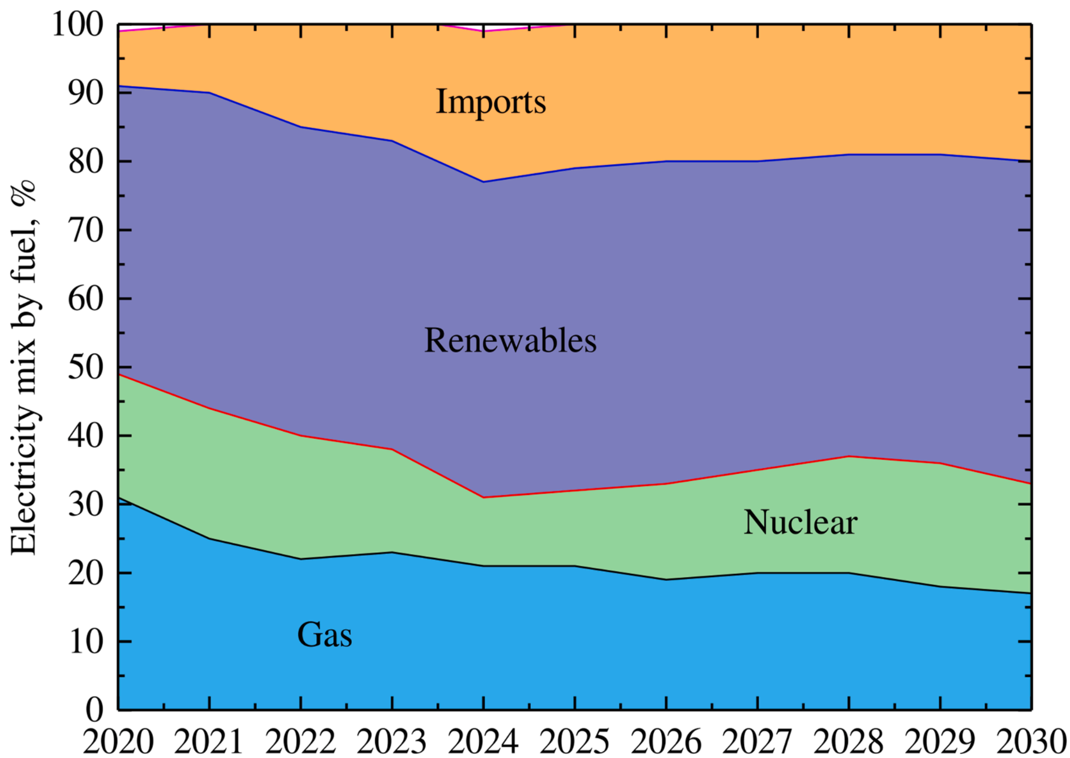

Fig. 13. Shares of the UK electricity mix by fuel between 2020 and 2030 (CarbonBrief, 2019).

Table 8
CO_2 emissions from electricity generation by fuel (source: (Moro and Lonza, 2018)).

Fuel type	CO_2 emission, g/kWh
Gas	500
Nuclear	29
Renewables	26
Import	93

Table 9
Operating expense by deployment strategy*.

Cost description	Upgrade to 4G LTE Macrocells, £	Upgrade 4G Macrocells to 5G, £	Set up 5G Microcells, £
O&M costs	17,607	4295	2032
Site rental costs	5000	5000	5000
Leased lines per backhaul link	1000	1000	1000
Energy costs	£0.12/kWh		

* Depreciation rate: 3%.

MHz and 3400 MHz spectrum resources can play an important role at the beginning of the deployment, because the basic demand at that time can be met by upgrading Macrocells. Due to the limited number of legacy Macrocells, ultra-large demand can be achieved by deploying Microcells embedded in 3400 MHz and 26 GHz.

Fig. 17 shows the annual CapEx on base stations delayed by geotype. Overall, to complete 5G deployment, if business as usual (medium-demand) UK needs to invest £13.1 bn in the next ten years, and it needs to invest £9.9 bn and £16.8 bn in low- and high-demand scenarios respectively. It is expected that more than 90% of the total CapEx of MNOs will go to suburban and rural areas to meet growing demand, while the total investment in densely populated urban areas is much less. By the end of 2021, the demand for data capacity will be met in urban, suburban and some rural areas. However, due to budget limitation on CapEx, 5G deployment in many rural areas will be delayed. Noted that in 2022, due to relatively mild demand growth in 2021 those regions where 5G have been deployed still have capacity margin. Therefore, most of the CapEx will go to rural areas. As shown in Fig. 17, rural areas without 5G coverage by 2022 will be highly dependant on Microcells, because legacy Macrocells are poorly deployed in these areas. For the areas with Macrocells, the local demand can be met by upgrading them to 700 MHz. In the next few years, considering that due to the decline in equipment prices, the annual budget can meet the 5G deployment needs across the UK. Regarding the political restrictions on key suppliers mentioned in Section 3.3, UK MNOs would face additional cost of £0.63 bn to £1.19 bn in 5G deployment. Compared with suburban and urban areas, rural areas that rely heavily on high investment intensity will be very likely suffer severely delays.

Fig. 18 shows the spatiotemporal distribution of Microcell density across the UK by scenario, which is an indicator of underlying demand density. In the next decade, the spatial distribution of Microcell density across the UK will change dramatically over time, but the Macrocell density will remain static (Fig. 5). The high density of Microcells will be mainly located in densely populated urban areas, while the low density will be primarily concentrated in small towns and rural areas. The reason for the high density of base stations in urban areas is not only due to high demand, path fading loss is also an important factor (see Eq. (5)), because the dense buildings will severely affect the signal power transmission, especially for the high and mid frequency bands. Take the high-demand scenario as an example, the Microcell density in most areas is between 1 unit/km^2 and 5 units/km^2. In the future 5G network, Microcell has characteristics of large capacity but limited coverage radius, which usually leads to excessive resource reservation in areas with low-demand density, which may be economically inefficient.

4.2. Energy consumption

In the next ten years, the power consumption of cellular network will increase with the densification of Microcell and upgrading of Macrocell. In terms of the aggregate energy consumption, as shown in Fig. 19, it

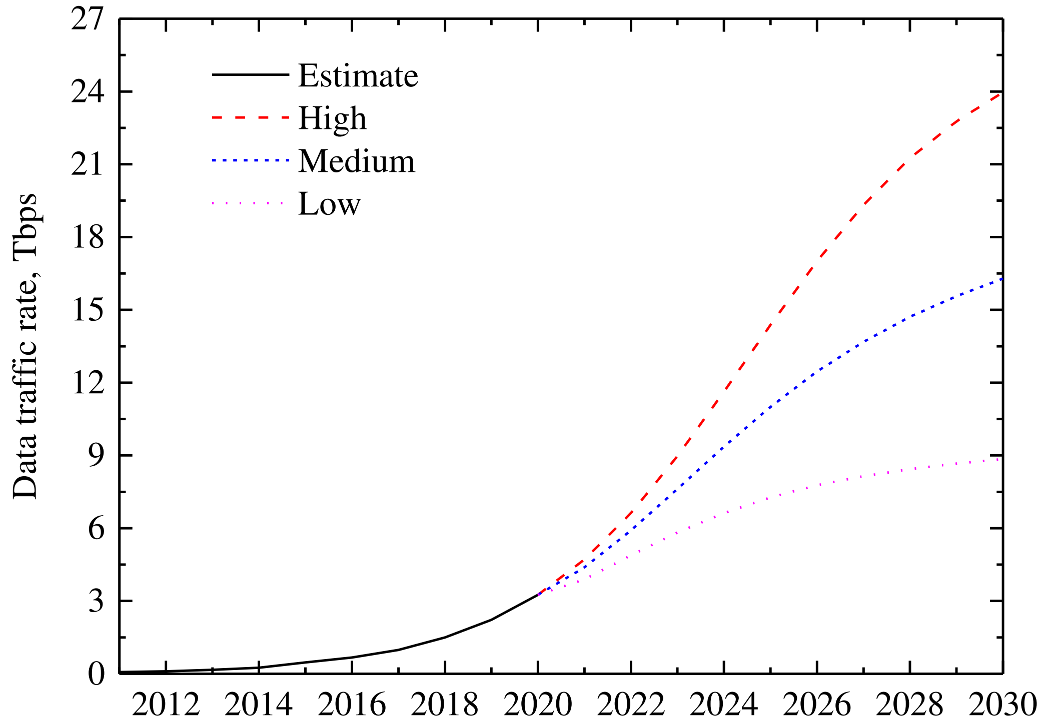

Fig. 14. Total demand for data capacity.

grows from 1.8 TWh in 2021 to 8.4 TWh in 2030 in the business-as-usual scenario (medium-demand), accounting for approximately 2.1% of the total electricity generation in the UK.[5] The energy consumption in 2030 in the low- and high-demand scenarios are 6.6 TWh and 10.5 TWh, respectively. The potential increase in energy consumption is not only due to the increase in the number of base stations, but also due to the increased energy consumption of operating a single base station with multi-frequency bands. It is expected that by 2030, most legacy Macrocells will be embedded in more than 4 frequency bands, and those frequency bands will coexist for a long time to achieve continuity of mobile services. In the early-stage deployment, most of the energy will be consumed by the upgraded Macrocells. With the densification of the network, the energy consumption caused by Microcell operation will gradually exceed that of the Macrocells.

Fig. 20 further shows the evolution of daily power consumption distribution across the UK and the Greater London area in the business-as-usual scenario (medium-demand). It can be seen that, the power consumption in rural (low-income) areas will increase dramatically over time across the UK; in contrast, the power consumption in urban (administrative and economic capital) areas will increase dramatically in the first two years but no obvious increase in the following years, taking Greater London for instance. The reason behind this phenomenon is that the mobile network deployment was poor in low-income areas before 2020, very few legacy Macrocells were deployed in those areas (Fig. 5). Thus, a large number of Microcells need to be built in order to meet the traffic demand. As a result, the energy consumption will be significantly promoted.

In addition, to reflect fluctuations in hourly power demand with the data traffic rate, visualization was performed. Still taking the business-as-usual scenario (medium-demand) for instance, Fig. 21 shows the variation in the distribution of power demand for one day across the UK and Greater London areas in 2030. The result shows that the minimum and maximum power demands will appear at 6AM-9AM and 9PM-0AM, respectively. However, large cities with ultra-dense base stations (e.g. Greater London) maintain a high-level power demand all the time. Specifically, some regions in London Zone 1 reach over 200 kW/km^2, which will likely pose a threat to the local power infrastructure. Similar results can be observed in other densely populated urban areas, such as Birmingham, Manchester, and Glasgow.

4.3. *Indirect carbon emissions*

Fig. 22 shows the annual indirect carbon emissions of 5G network operations. By 2030, in the low-, medium- and high-demand scenarios, the indirect carbon emissions from 5G network operations will be 795,347, 990,404 and 1260,532 tonnes respectively. From 2021 to 2028, carbon emissions will increase with the densification of the network. However, due to reduced gas use for electricity generation, there will be some decline after 2028. Although the UK's electricity structure is expected to be dominated by renewable energy, but in the next ten years, the carbon emissions caused by natural gas will still be in a leading position. These indirect carbon emissions will require UK MNOs to pay up to £15–25 million per year in climate change levy (Fig. 23), which may adversely affect their profits. With the increasing emphasis on sustainability, reducing the use of dirty electricity may be an effective way to reduce carbon emissions and related climate change taxes.

4.4. *Operating expenses (OpEx) pattern*

Fig. 24 breaks down annual operating expenditures by scenario based on the four expenditure types. In all scenarios, the overall trend of OpEx is to increase with the increase in traffic demand. By 2030, mobile operators in the UK will spend 3.4 - 6.5 billion pounds a year to operate 5G base stations. Due to the deployment of dense microcells, site leasing costs account for about half of operating expenses. Compared with 4G networks, the ratio of site rental costs, fibre backhaul, and O&M costs may not change much. However, as a single base station integrates multiple frequency bands, energy consumption costs will increase significantly. As shown in Fig. 25, site rent, O&M and energy

[5] The total electricity generation in 2030 in the UK is estimated to 393 TWh (OFCOM, 2012)

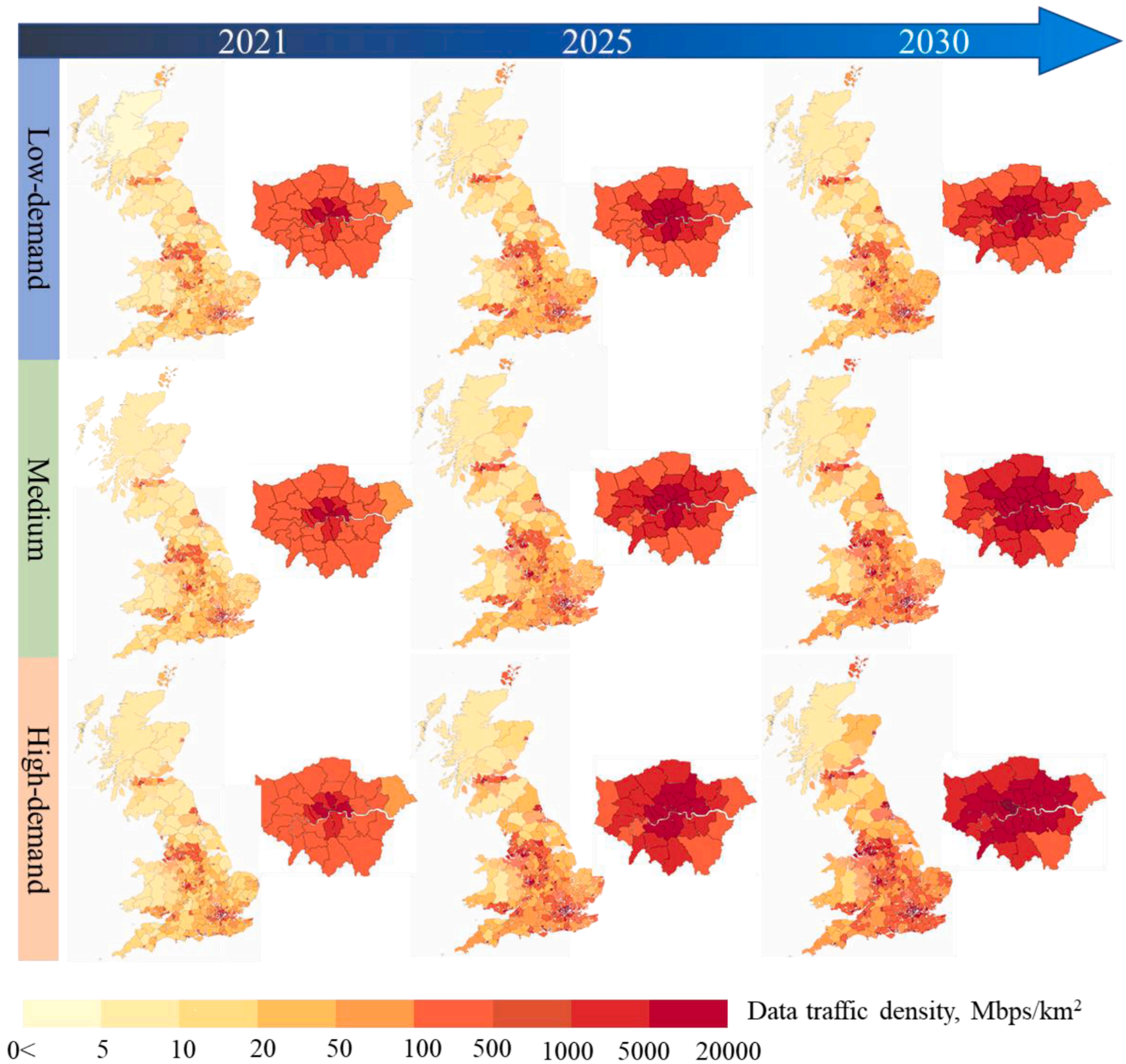

Fig. 15. Data traffic density distribution across the UK and the Greater London area.

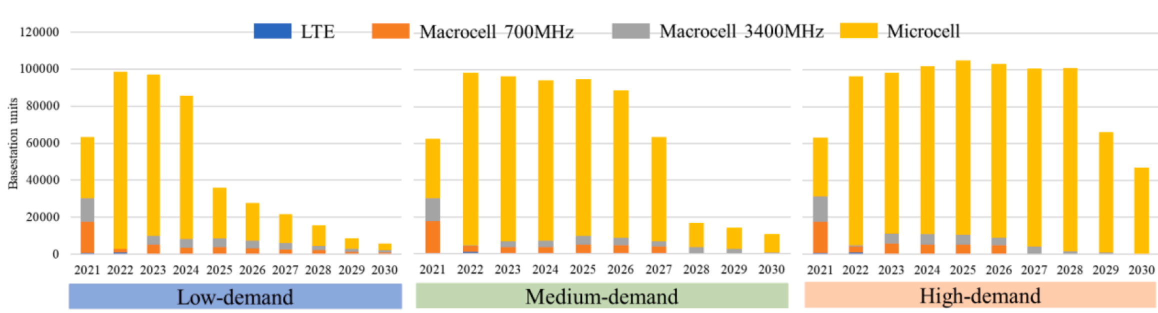

Fig. 16. Annual number of base stations deployed by type.

consumption account for approximately 50%, 23%, and 20% of OpEx, respectively. In contrast, fibre backhaul expenditure is less than 10% of total operating expenditure.

5. Discussion based on the above results

5.1. The significance of spectrum resources for 5G deployment

Both 700 MHz and 26 GHz will play an important role in 5G deployment in the UK, because they will enable base stations to meet short-term and long-term data traffic demands respectively. For example, due to the relatively low data traffic demands in the initial stage of deployment, the 700 MHz frequency band can be integrated into the Macrocell to meet the primary demands of many regions (see Fig. 16). The use of this frequency band is considered to be a cost-effective way to maximize the coverage of 5G services due to its good propagation characteristics. MNOs should tend to adopt this strategy in the initial stage, because the low frequency band allows them to cover more areas with fewer base stations. Under normal circumstances, by the end of 2022, more than 50% of Macrocells in the UK will be

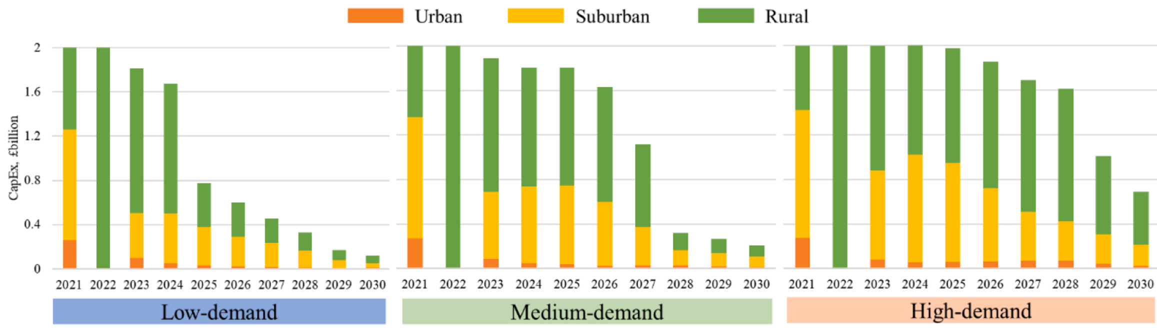

Fig. 17. Annual CapEx on base stations deployed by geotype.

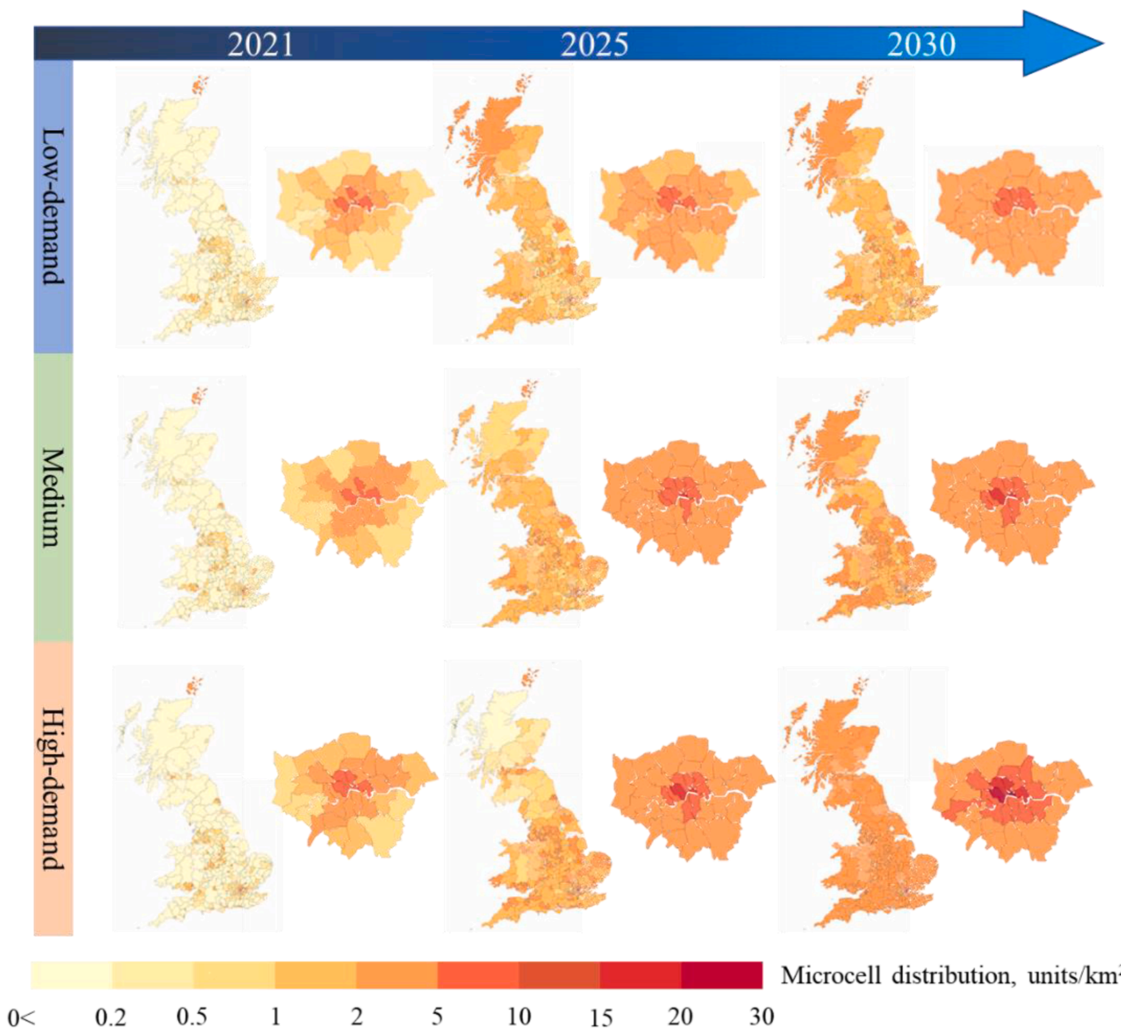

Fig. 18. Microcell density distribution across the UK and the Greater London area.

upgraded. A study conducted by Kassem and Marina (Kassem and Marina, 2015) also pointed out that it is possible to achieve wider coverage and less investment by using the 700 MHz frequency band in rural areas, roads and railway lines, because lower frequency bands require fewer base stations to be deployed. Taking into account the growth of data traffic demand in the next few years, only upgrading the Macrocell cannot meet all local needs, especially for ultra-densely populated urban areas. Therefore, it is necessary to build a new type of Microcell embedded in 26 GHz mmWave to achieve ultra-fast speed and negligible latency. These features will help unlock the digital economy (Vu et al., 2017). Therefore, the early arrival of new spectrum resources can greatly accelerate 5G deployment in the UK.

5.2. 5G network deployment regional priority

For business- and profit-driven MNOs, they are reluctant to invest in low-income areas because of small profits but huge investments. The population density in rural areas is low, and the establishment of ubiquitous 5G networks in rural areas generates very little income per square kilometre (Chiaraviglio et al., 2017a). In contrast, the profits in urban areas are more considerable, so it is more in the interest of MNOs to prioritise the deployment of 5G in urban areas. First, only 30% of the

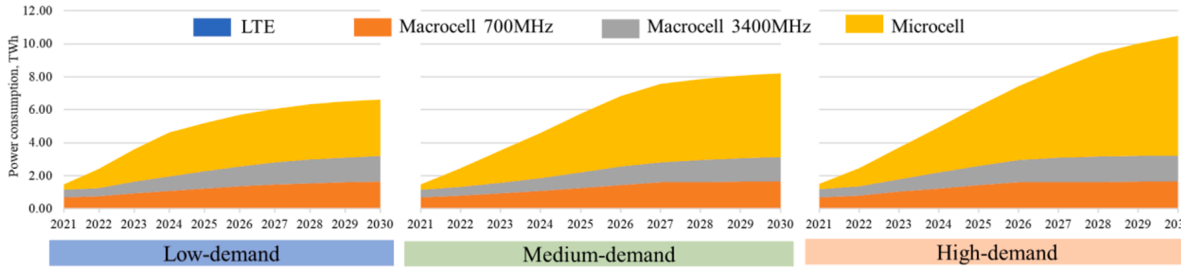

Fig. 19. Annual energy consumption of 5G networks across the UK.

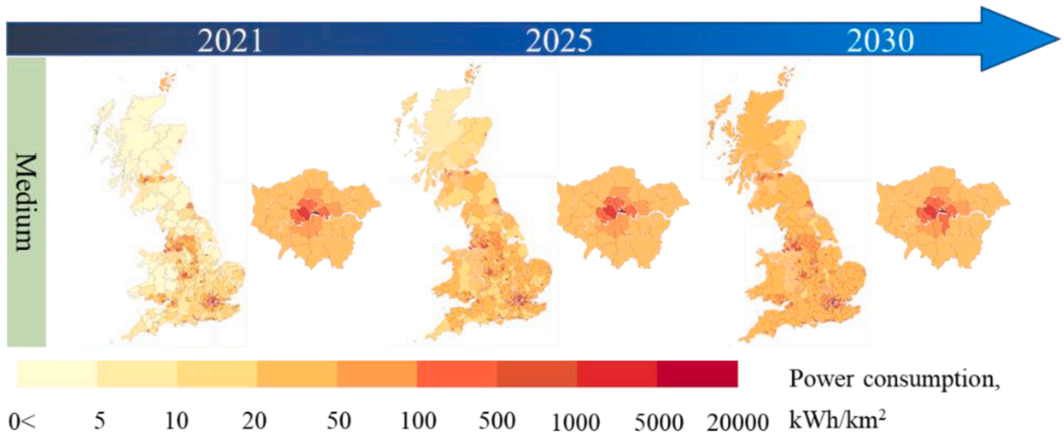

Fig. 20. Daily power consumption distribution across the UK and the Greater London area.

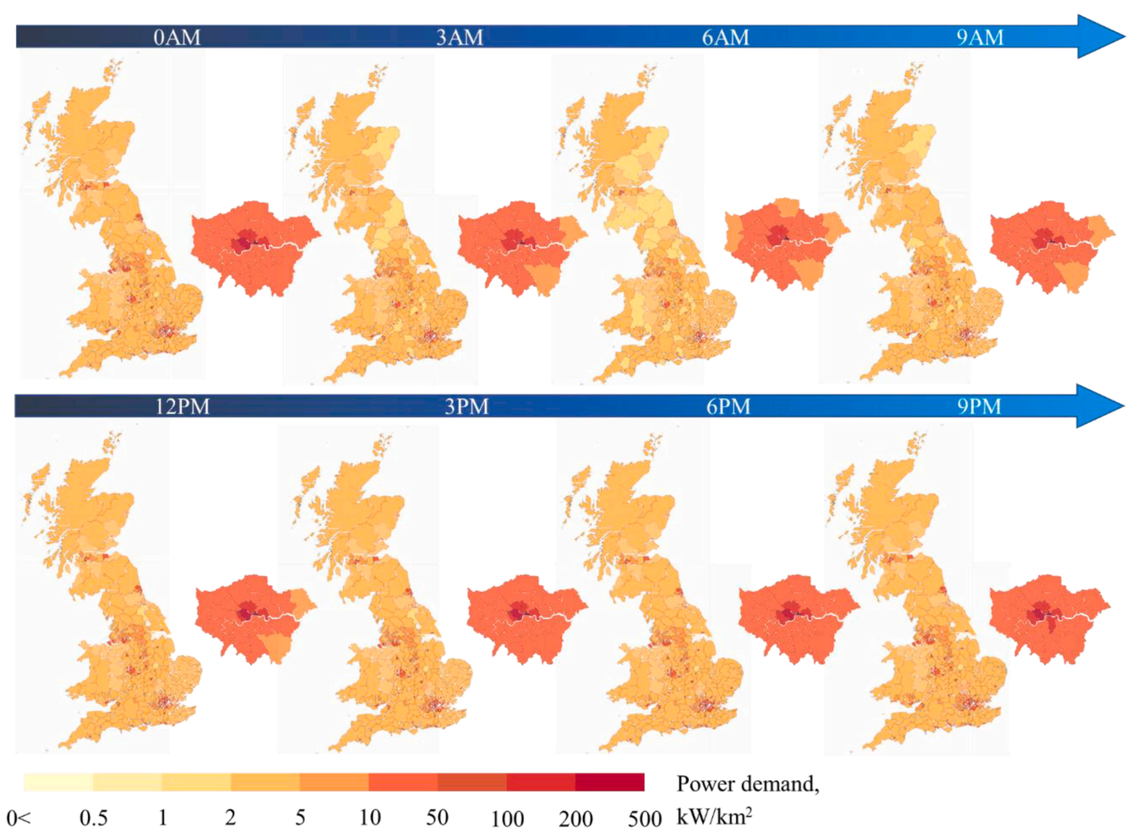

Fig. 21. Power demand variation in a day across the UK and the Greater London area in 2030.

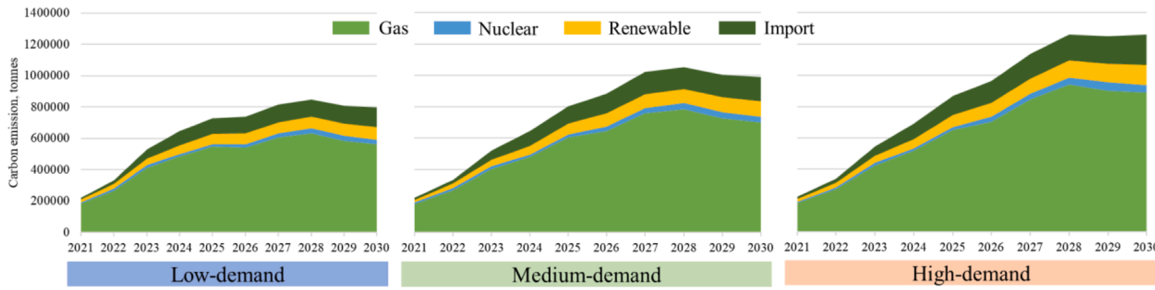

Fig. 22. Annual indirect carbon emissions.

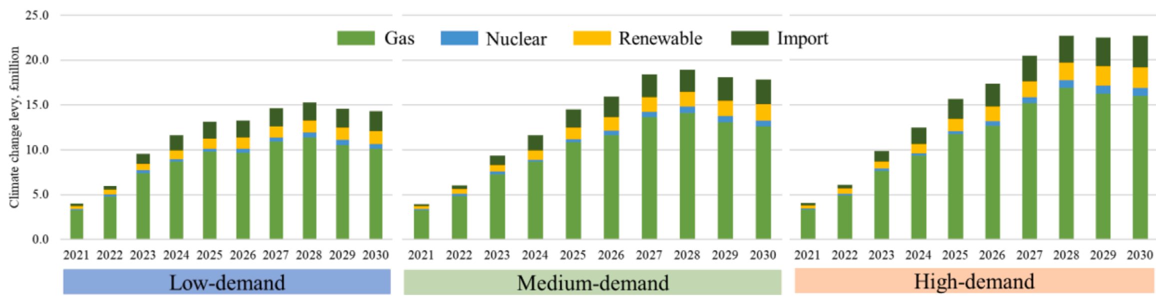

Fig. 23. Annual climate change levy.

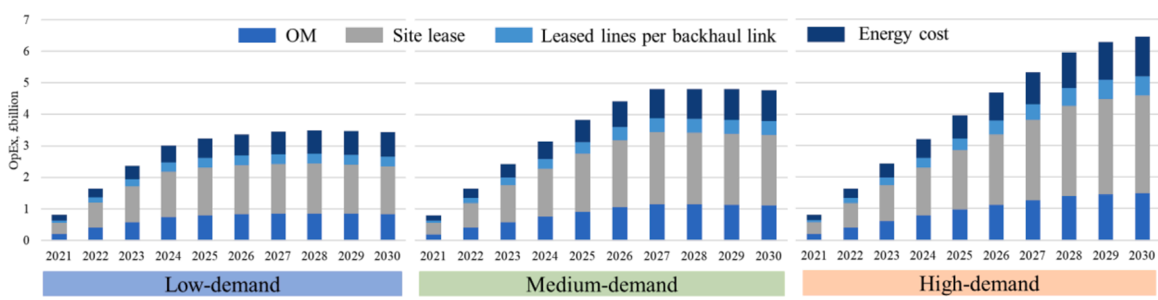

Fig. 24. Annual operating expenses (OpEx).

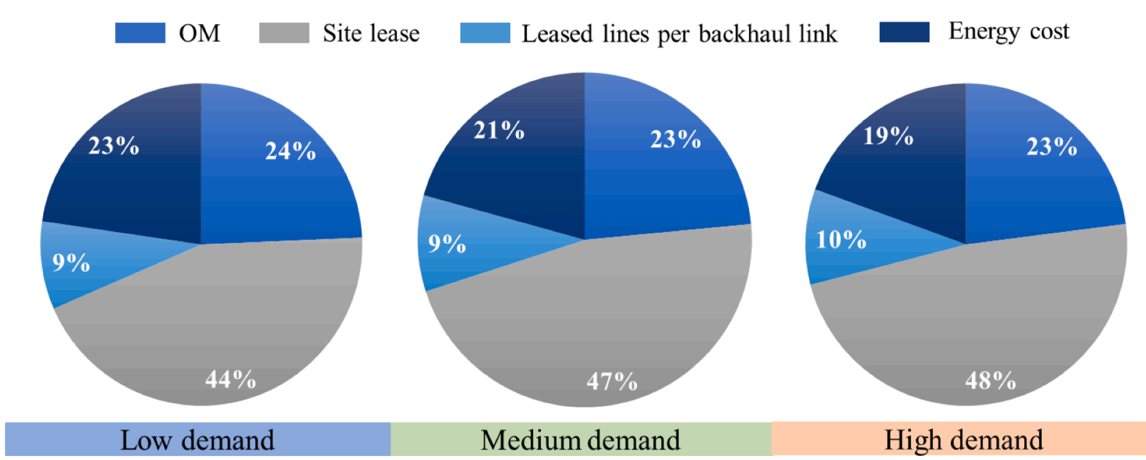

Fig. 25. Breakdown of operating expenses in 2030.

UK population lives in rural areas, but these areas account for more than 90% of the total area of the UK (see Table 2). In order to provide a ubiquitous mobile service, a dense 5G cellular network is required. However, the poor deployment of 4G networks in rural areas has been reflected in the legacy Macrocell density distribution (see Fig. 5). Therefore, only by upgrading the Macrocell cannot meet the data traffic demand of these areas, it needs to build a large number of Microcells to increase local capacity. Microcells embedded with high-frequency and mid-frequency bands can usually only cover a small area (the maximum radius of 5G Microcell is 200 m), which leads to overprovisioning in rural areas. As a result, due to economic inefficiencies, mobile network operators will be reluctant to invest in these areas. On the contrary, due to the large number of legacy 4G Macrocells that can be directly upgraded to 5G, it may be more cost-effective to deploy 5G in urban areas. The demand in these areas is relatively concentrated, so the installation of 5G Microcell may be more suitable for the demand distribution model in urban areas (see Fig. 18).

Furthermore, the 5G equipment will be more expensive than before due to the expulsion of the key supplier, and this effect can be significantly magnified in high-demand scenario (£1.19 bn extra cost). Small towns and rural areas across the UK will be severely affected as those areas account for most of CapEx. Due to the economic recession caused by the pandemic, the budget for 5G deployment may drop in the next few years. If MNOs want to build a ubiquitous cellular network in a short time, then the sudden increase of CapEx will challenge their cash flow. Therefore, MNOs might need to cherry-pick some major urban areas to deploy 5G but put other areas on the waiting list. In addition, 5G technology is actually 'urban' in nature. The high performance of 5G relies on an extremely complex architecture (Chiaraviglio et al., 2017a; Palattella et al., 2016), which consists of Macrocells, Microcells, fibre backhaul, computing nodes and large data centres. Therefore, high-performance deployment in rural areas at this stage is unviable economically and technologically. Also, this study did not consider the radical change – ultra-reliable low latency of 5G, because the technology is still under development. However, low latency communications will allow a series of new use cases that are closely related to 'urban' rather than 'rural', such as smart cities, autonomous driving, and telemedicine.

5.3. The challenges associated with high energy consumption

The 5G power consumption across the UK is expected to rise dramatically (see Fig. 19), which may bring about some economic and environmental issues. Therefore, there is an urgent need to improve the energy efficiency of 5G networks. In order to meet the high energy demand in the future, the distribution network requires significant investment, as its original design principles make it unable to meet the largest peak demand in the future (5 G Infrastructure Association, 2020). Distribution network operators should give priority to the upgrade of distribution networks in large cities, because since the initial stage of 5G deployment, the demand for electricity there will be high.

Nevertheless, the overall energy usage by 5G base stations needs to be reduced as it will account for approximately 2%−3% of total UK's energy consumption in 2030. Energy costs account for 19% - 23% of RAN OpEx, which will seriously affect MNOs' mainstream profits. GSMA (2020) also came up with a consistent estimate and pointed out that the future 5G energy cost will account for 20%−40% of the network OpEx. Due to the large number of base stations, maintaining 5G networks will bring potential growth in energy. The improvement of energy efficiency can not only alleviate the pressure on the power infrastructure, but also reduce the OpEx in terms of energy consumption.

5.4. To use green electricity to reduce indirect carbon emissions

The 5G specification of 3GPP requires that energy consumption be reduced by 90% (3GPP, 2020). Although the use of natural gas has been reduced in the past decade, carbon emissions are still mainly from gas-fired power generation (see Fig. 22). Substituting renewable energy for natural gas in electricity production can significantly reduce carbon emissions, which is obvious from 2028 to 2030. Therefore, MNOs should increasingly shift their energy procurement from carbon sources to green renewable technologies and alternative energy sources. For example, IRENA (International Renewable Energy Agency, 2018) found that renewable energy is currently the cheapest source of power generation in many parts of the world, and investment in renewable energy can be more cost-effective than conventional energy. At the meantime, the cost of wind turbines has fallen by 37% to 56%, and the cost of solar photovoltaics (PVs) has decreased significantly in the past ten years, and it is expected that the cost will be further reduced by 50% in the next five years (International Renewable Energy Agency, 2017).

6. Conclusion

This study took the UK as an example to study the spatiotemporal deployment of 5G networks in the next ten years, as well as the associated energy consumption from economic and environmental perspectives. A novel agent-based model was developed based on digital infrastructure evolution framework, synthesizing multi-dimensional data visualisation with bottom-up approaches. The simulation results show that high-demand regions are mainly concentrated in urban areas, but most of the capital expenses (CapEx) are spent on suburban and rural areas. As far as the political ban on major suppliers is concerned, the additional costs faced by mobile operators in the UK in 5G deployment are as high as 630 million pounds to 1.19 billion pounds, which will seriously affect 5G deployment in rural areas. In addition, most of the power consumption in 5G networks is contributed by Microcells rather than Macrocells, and those increasing base stations will challenge the local power infrastructure. The ever-increasing energy costs brought about by 5G networks pose a huge challenge to the profitability of MNOs. Based on these results four implications for decision-makers were identified.

The first argues that 700 MHz and 26 GHz frequency bands will play an important role in 5G deployment in the UK, which enables base stations to meet short- and long-term demand. In order to accelerate the 5G development, the launch of the two spectrum resources should be actively promoted. The second implication is that MNOs cannot tolerate the cost of establishing a ubiquitous 5G cellular network in a short period of time. Hence, Therefore, 5G networks should be deployed first in administrative and economic capital areas. The third meaning of the policy indicates that the traditional power distribution network cannot meet future electricity demand. At the meantime, the ever-increasing energy costs of 5G networks will seriously affect MNO's profits. Therefore, there is an urgent need to improve the energy efficiency of base stations. The fourth implication for policy states that compared with traditional fuel sources, the use of renewable technologies in 5G networks is not only environmentally friendly, but also cost-effective.

7. Author statement

I would like to resubmit the attached manuscript, "5G network deployment and the associated energy consumption in the UK: A complex systems' exploration" for consideration for possible publication in the Technological Forecasting & Social Change.

This paper is the result of the original co-work by X. Cheng, Y. Hu, L. Varga. All of the authors mutually agreed to send the paper to the Technological Forecasting & Social Change. This paper has not been published or accepted by any other journals.

Declarations of Competing Interest

None

Data statement

The input data used in the 5G ABM can be accessed via Mendeley Data Repository (Cheng et al., 2021).

Acknowledgements

The valuable discussion and comments by Dr Edward Oughton at University of Oxford and Mr Kai Zhu at Ericsson are acknowledged. Varga kindly acknowledges support of the Data Analytics for National

Infrastructure (DAFNI) EPSRC grant ref EP/R012202/1 and Centre for Complex Policy Evaluation (CECAN) ESRC grant ref ES/N012550/1.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2022.121672.

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