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Techno-economic framework for dynamic operator selection in a multi-tier heterogeneous network

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ABSTRACT

Tremendous growth of the mobile network market driven by technology evolution requires a corresponding paradigm shift of the economic aspects of mobile networks. The high heterogeneity and flexibility of 5G mobile networks have led operators to shift their business models towards an open spectrum market. In this paper, we first introduce a comprehensive techno-economic framework to investigate a heterogeneous network (HetNet) that consists of two operators: a macro cell operator and a small cell operator, operating in conditions of an open spectrum market. Both operators coexist in such a way that the small cell operator leases the spectrum from the macro cell operator. In contrast to other similar studies, in our framework, we apply the concept of evolutionary stable equilibrium (ESE), which provides some level of intuition to the behaviour of the operators. In addition, we implement the method of dynamic service selection by the end users based on a utility function, which is sensitive to both the service price and the expected throughput. To analyse the techno-economic performance of the system, we develop a real-world simulation model that encompasses a 3D urban environment using real network topology from the OpenCellID database; this model includes a large number of end users with realistic mobility patterns. The simulation results show that, from the user's perspective, the network switching mode provides better service at a lower price due to high market competition. From the view of the operator, the most profitable mode is the static contract because there is stable service demand regardless of the price. The multi-homing mode is a promising intermediate solution that can satisfy both the end users and the operators.

1. Introduction

The amount of broadband Internet data is increasing each year, and Cisco Visual Index projections claim that global mobile data traffic will reach 49 exabytes per month by 2021 [1]. To cope with higher service demand, operators are forced to massively enhance their infrastructure by overlaying several tiers of coverage within a single heterogeneous network (HetNet) [2]. However, straightforward extension of existing infrastructure requires massive capital expenditures and additional economic risk due to its low return on investment. This problem arises due to the natural phenomena of user mobility and nonuniform traffic demand. Therefore, to improve the overall utilization of network infrastructure and spectral resources, it is necessary to adopt user-oriented solutions such as dual connectivity, multi-homing (MH) and network switching. Recent research has shown that there are three aspects of mobile networks that affect their overall efficiency: whether they are user-oriented (price-performance ratio and service availability), technical aspects (spectral efficiency, peak data rate, etc.) and economic aspects (operator's profit, return on investment, spectrum price, etc.) [3–5].

The aim of this paper is to analyse the techno-economic factors of HetNet by adopting the dynamic service selection solutions, namely, MH and network switching, to further increase the network's performance. These user-driven solutions open up new and diverse options in terms of service provisioning for the end

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users. In general, both technologies are developed from conventional dual connectivity service provisioning through an X2 interface. However, conventional dual connectivity provides multiple simultaneous sessions operated by a single service provider [6]. Novel solutions allow end users to switch between operators (network switching) or even maintain multiple connections with different operators (MH). The important feature of these scenarios is that the end user should have full control over the situation and the operator should perform all the actions needed to satisfy user demand. Another aspect that should be considered is the capability of the user's equipment (UE). While for network switching, one active LTE stack is enough, MH requires at least 2 LTE stacks and the assistance of multipath TCP on transport layers [7]. To address this challenge, major chipset manufacturers such as MediaTek, Qualcomm and Spectrum have been working to develop active dual LTE support [8]. Moreover, embedded SIM cards (eSIM) have strong potential to decrease the switching costs for the end user and enable real time network switching and MH in the future. Thus, we are developing towards a completely democratized mobile network market where each user will be able to choose instantaneous connection by analysing its feasibility for particular conditions. Therefore, it is necessary to study possible scenarios that will be beneficial for both the end users and the operators.

Currently, there are some issues that prevent the adoption of interoperator network switching and MH. The existing business models of operators are very intrinsic and focus mostly on exclusive contracts with end users. The introduction of dynamic switching and MH will require a new paradigm of simplified operator switching for the end users. Nevertheless, leveraging dynamic switching will stimulate competition at the operator level, which would eventually be reflected by the enhanced network performance provided to end users. Moreover, interoperator MH allows operators to share revenue from the same end users, which adds more flexibility to the operators' behaviours in the market. The example of electricity and natural gas retail markets shows that liberalization resulted in the significant enhancement of the experience of all participating parties. Although the mobile communication market is very different from the energy market, there are still some similar features, e.g., it is impossible to accommodate spectral resources, variable spectrum utilization can occur over time and market imperfections are present (price discrimination, monopoly, cartel agreements, etc.) [9].

In this paper, we study a realistic scenario of a multi-operator HetNet with user-driven network selection. We propose an extensive computational model that reflects a dynamic and realistic system and compare it with the reference simulation model based on stochastic geometry. We distinguish between two different types of operators - a macro cell operator and a small cell operator. We assume that the HetNet layers are being operated by different operators in a way such that the small cell operator leases part of the spectrum from the macro cell operator. Similar coexistence is used in China, where China-Telecom and China Unicom lease TD-LTE capacity from China Mobile [10]. In such a scenario, the operators aim to optimize their profits by adjusting the service prices, while the end users are able to dynamically choose an operator for connection. Therefore, in this article, we study the technical and economical efficiency of MH and network switching for a multi-operator HetNet.

The major contributions of this paper are as follows:

- A new techno-economic framework for dynamic operator selection in a multi-tier and multi-operator HetNet is developed. The novelty of the proposed framework is that it allows several operators to share the same spectrum while considering not only the technical parameters but also the economic factors such as service price and operator profit.
- A real-world simulation model is developed to simulate realistic network deployment taking into account the technical, economic and user-oriented characteristics of the system. The novelty of the proposed model is that it combines a realistic three-dimensional environment and real locations of the cells within a target simulated coverage area.
- A new method of dynamic service selection by the end user is developed based on the corresponding utility functions for network switching and MH service modes. The novelty of this method is that it incorporates the techno-economical aspects while taking into account practical aspects of implementation according to 3GPP LTE specification.
- Extensive simulations are conducted including multiple technical and economic parameters of the system and an large number of end users by using Cuda accelerated computing.

The remainder of the paper is organized as follows. Section 2 reviews recent related works involving a techno-economic network analysis. Section 3 provides a detailed description of the proposed techno-economic framework for dynamic operator selection. The simulations and performance analysis are presented in Section 4. Section 5 provides the discussion and suggests future research topics. Finally, we conclude the paper in Section 6.

2. Related works

The problem of price dynamics and dynamic service selection in competing macro cell networks has been widely studied by industry and academia. The pioneering work in this area was introduced by Ileri et al. [11], who proposed a framework for modelling a scenario in which the operators compete for scarce spectrum resources and for potential customers (i.e., end users). The authors proposed the idea of demand-responsive pricing that is realized in real time and enables the operators to attract end users and stimulate competition. The interactions among the participating parties are regulated by the spectrum policy server, which is responsible for ensuring fair spectrum distribution in the system. Later, Duan et al. [12] conducted a comprehensive analytic study of competing operators and proved that dynamic competition results in a 25% decrease in the operator's profit. On the other hand, such a profit loss is compensated by an increase in the end user's throughput. Further, [13] proposed a new service selection paradigm called flex service (which is technologically very similar to the network switching discussed in this paper) and analysed the duopoly competition of LTE macro cell operators with flex service selection enabled in the system. They demonstrated that flex service adoption can enhance the end user's network experience (throughput, blocking probability, etc.). However, the analysis was limited to wireless spectrum markets with homogeneous operators and did not consider a HetNet that includes both macro and small cell operators. Notably, the abovementioned works assume full rationality of the operators, which is not common in reality [14]. To address this issue, Xing et al. [15] proposed various stochastic learning algorithms as good alternatives for operators to discover the optimal operating price.

The economic characteristics of networks - including competition and cooperation between the small cell operator and the macro cell operator - were originally investigated in [16]. The authors analysed the profits of the operators and the Nash Equilibrium pricing points under different conditions between the operators of both networks. The study considered a static pricing scenario with the presence of nonatomic end users (the end users' utility does not affect each other) and a dynamic pricing scenario with the presence of a negative externality in the system. Dynamic service pricing depends on the number of end users in each network, and additionally, each end user's utility depends on the utility of other end users. In general, the more end users that access the network, the less utility each of them can obtain. The motivation to lease the macro cell frequency spectra to the small cell operator in an Internet of Things (IoT) scenario is further considered in [17]. The authors introduced an auction procedure based on the Knapsack formulation problem between the macro cell operator and the small cell operator. The proposed auction mechanism provides the incentive to lease the spectra as both operators are capable of achieving higher profits. The joint network and user selection modelled by an evolutionary game theoretical approach is provided in [18]. Finally, Li et al. [19] analysed the interaction between two tiers using different small cell access policies with a focus on the economic perspective. They formulated a framework based on game theory, a one-leader multiple-follower Stackelberg game, and the optimal strategies for both tiers with different small cell access policies were identified.

Most of the referenced works use a framework based on game theory as the fundamental modelling tool. Despite its unique properties, there are several difficulties with game theory modelling; for example, this method limits, isolates or takes into account every set of factors and variables that influence the strategies and outcomes [20]. The solution concept of game theory, in terms of Nash equilibrium, is hard to compute because the system of equations used to define such an equilibrium might well be too complex. Due to the complexity of game theory, the investigated scenarios are often limited to either unrealistic cases, such as fewer end users and cells, or idealistic channel conditions. Moreover, classical game theory assumes full rationality of all game participants, which cannot be preserved in a real system. We believe that system dynamics approaches based on artificial intelligence with agent-based modelling show some promise in this area. Currently, there are several contributions that implement the system dynamics approach to analyse the techno-economic aspects of the interactions between the macro cell operator and the small cell operator. Gazda et al. [21] introduced a two-level agent-based model to analyse interactions in both wholesale and retail spectrum markets. To estimate the optimal spectrum volume for leasing on the wholesale market, the authors proposed a reinforcement-based learning mechanism. The established framework enabled the authors to link general conclusions from game theory models with the system dynamics approach. Nevertheless, this study assumed reduced agent decision space and a linear region with stationary end user positions. On the other hand, Basaure et al. [6] analysed the impact of transactions and switching costs on the efficiency of wireless spectrum markets. This research was later extended by Finley et al. [7]. However, the authors considered an artificial topology consisting of a square area and random-walk user mobility, without taking into account any economic aspects.

In the current paper, we develop a techno-economic framework that reflects the abovementioned conclusions and provides additional functionality based on the application of the system dynamic approach. Our model incorporates real radio access network (RAN) topology of a T-mobile operator in a 3D copy of the environment in the city of Košice (Slovakia). In contrast to the abovementioned research, we implement a realistic multipath propagation channel for both macro and small cell operators, a realistic mobility model with pedestrians and vehicular transport, and a much larger number of end users. We believe that the proposed framework will help us to simulate realistic scenarios, which can be useful for mobile network operators who make important decisions regarding future 5G communication systems with dynamic service selection capabilities.

3. Techno-economic framework for dynamic operator selection in a multi-tier HetNet

3.1. System model of multi-operator HetNet

The concept of multi-tier HetNet has appeared to increase the capacity by using additional layers of coverage and leveraging higher frequency reuse factors. The advantage of HetNet is in literally unlimited capacity and area spectral efficiency. Nevertheless, there is one important bottleneck regarding spectrum scarcity. Each additional tier of coverage requires its own part of spectrum, which must not interfere with any other overlapping tiers of coverage. Therefore, each tier is usually composed by smaller cells, compared to the previous one, i.e. macro cells, micro cells, picocells and femtocells. Such architecture allows to reuse the same spectrum band within the coverage tier and among different tiers, as long as there is not any interference between neighboring or overlapping cells.

Within the scope of current paper, multi-tier HetNet provides a very convenient environment to study the techno-economic aspects of dynamic operator selection by the end user. To simplify the simulation model, our system is constrained by two tiers of HetNet coverage: macro cells and small cells. In addition, we limit our study to two mobile network operators, where first operator owns all spectrum and macro cells infrastructure, while second owns only small cells infrastructure. For convenience, further in this paper we call them macro cell operator and small cell operator. Thus, we simulate the system where end user can dynamically switch between operators to choose the best tradeoff between price and quality. On the other hand, both operators can negotiate the service price for end users, while keeping for simplicity fixed leasing price. Thus, macro cell operator is able to set up his profit margins from serving the end users and leasing the spectrum to small cell operators. Nevertheless, small cell operator is able provide better service quality for higher price for the end users, while paying less to the macro cell operator for the used spectrum. The overall diagram of the studied scenario is shown in Fig. 1. The RAN topology of the macro cell operator reflects the realistic conditions of a T-Mobile operator in the city of Košice. The RAN topology of the small cell operator is numerically optimized using intelligent coverage planning, which was proposed in [22]. The parameters for the air interface are chosen from the 3GPP specification [23]. Thus, the macro cell base station utilizes 20 MHz of spectrum in a 2100 MHz band (i.e., 100 Resource Blocks (RBs) in an LTE resource grid). For the small cell operator, we set the bandwidth at 4 MHz (i.e., 20 RBs), and the bandwidth is leased from the macro cell operator. Spectrum leasing contributes to the immediate revenue of the macro cell operator. The activities behind the spectrum leasing/payment are governed by the Spectrum Broker entity that controls the spectrum access. Eventually, both operators compete to attract end users by applying a dynamic spectrum pricing strategy. From the end user perspective, we define three different types of service selection for the end users:

- Static one-contract - end users are attached to the same operator throughout the whole simulation.
- Network switching - end users select the operator in real time based on the immediate service circumstances.
- MH - end users are attached to both operators simultaneously.

Finally, Table 1 provides a summary of the notation that will be utilized in this paper.

Now, let us present our principal assumptions and the system of analytical expressions used in our simulations. We consider N end users in the system; their instant locations are determined by the coordinates $\mathbf{x}_i(t) \in \mathbb{R}^2,\ i \in \{1, 2, \ldots, N\}$. Moreover, we also let macro cell operators to hold the following positions $\mathbf{y}_j \in \mathbb{R}^2$,

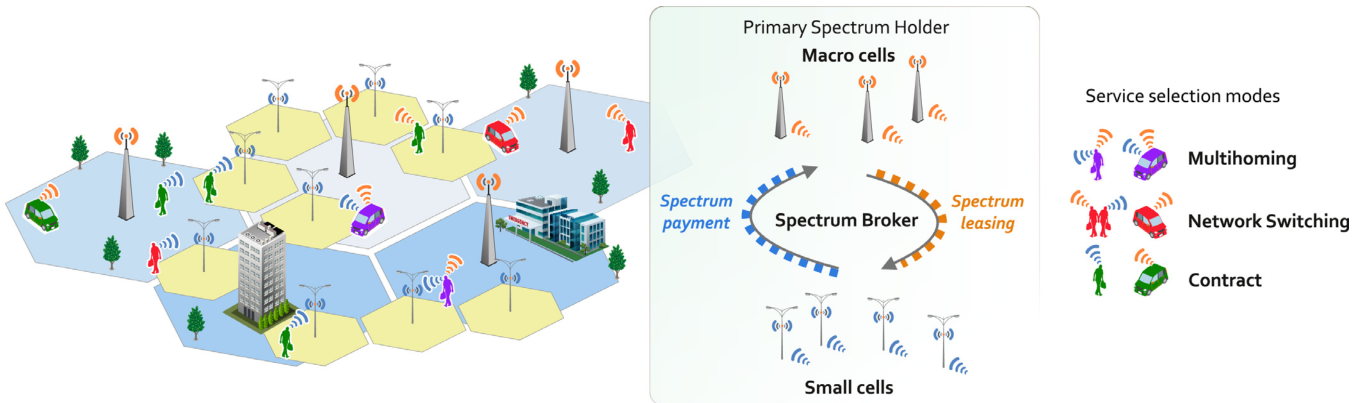

Fig. 1. Schematic diagram of a HetNet model with different strategies of end users: contract, MH, and network switching.

Table 1
The mathematical symbols used in the model listed in alphabetical order. In distinction to the main text, no detailed explanation of the indices is included.

Notation	Description
A_{ij}	antenna gain in the formula for channel gain
$\mathcal{A}_R$	space of the price level indices; strategic space of operator
FSPL(.,.)	free space path loss as a function of two arguments
I_{ij}	interference power that affects the signal received
I_{ij}^k	interference power perceived by the end user on kth RB
L_{ij}	path-loss coefficient
M	number of the positions of macro cells
N	number of end users in the system
$N^{\mathcal{M}}$	number of end users accessing the macro cell operator
$N^{\mathcal{S}}$	number of end users accessing the small cell operator
N^{RB}	number of resource blocks
P_j	base station power; present in γ_{ij} and q_{ij}
$\Phi^{\mathcal{M}}$	macro cell operator profit
$\Phi^{\mathcal{S}}$	small cell operator profit
$\Theta(\ldots)$	step function
R	number of the price levels involved in $\mathcal{A}_R$
$RACH_{\mathcal{M}}$	random access request for the small cell operator
$RACH_{\mathcal{S}}$	random access request for the macro cell operator
W	bandwidth per resource block
b_{ij}^k	indicator of the resource block scheduling
c	speed of light
$d_{ij}^{\mathrm{tran-rec}}$	separation distance of the respective transmitter/receiver
η	learning parameter of LR-I scheme
f	carrier frequency
g_{ij}	channel gain between end user and base station
$g_{\mathrm{fad},ij}(t)$	flat fading contribution that is function of time
γ_{ij}	SINR of ith user associated with jth base station
μ	parameter of ultility function indicating the quality - price sensitivity
n, $\chi_\sigma^{\mathrm{CI}}$	path-loss guiding parameters
$p^{\mathcal{M}}$	macro cell service price; $p^{\mathcal{M}} \in \mathcal{A}_R$
$p^{\mathcal{S}}$	small cell service price; $p^{\mathcal{S}} \in \mathcal{A}_R$
$p_{\max}$	maximum price that the end user is willing to pay present in $u(q_i^k, p_i^k)$ utility function
$\boldsymbol{\pi}^{k*}$	(equilibrium) fixed point of $\boldsymbol{\pi}^k$
$\boldsymbol{\pi}^k$	probability vector of the price distribution
q_i^k	expected throughput achieved by the end user
$q_{\min}$	minimum throughput that satisfies the end user
σ_γ^2	noise dispersion
$u_i^{\mathrm{DS}}(.,.)$	utility function for dynamic switching scenario
$u_i^{\mathrm{MH}}(.,.)$	utility function for multihoming scenario
w	spectrum leasing price, constant over the simulation

$j \in \{1, 2, \ldots, M\}$. We assume uncorrelated flat fading on each RB and an isotropic antenna transmission/reception pattern. We analyse the macro cell layer, with straightforward transformation to the small cell layer. Then, the channel gain between the ith end user and the associated jth base station can be expressed as:

$$g_{ij}(t) = A_{ij} g_{\mathrm{fad},\,ij}(t) L_{ij}, \tag{1}$$

where A_{ij} is the antenna gain, $g_{\mathrm{fad},\,ij}(t)$ represents the uncorrelated time-variant flat fading contribution and L_{ij} is the path-loss coefficient. We consider a close-in (CI) free space reference distance model that is used for the design of 5G wireless communication systems, especially for urban micro- and macro-cellular scenarios [24]. The path-loss for the CI model is given by:

$$L_{ij} = \mathrm{FSPL}(f,\ 1\,m) + 10n\log_{10}(d_{ij}^{\mathrm{tran-rec}}) + \chi_\sigma^{\mathrm{CI}}[\mathrm{dB}], \tag{2}$$

where f is the carrier frequency; FSPL(.,.) denotes the free space path loss in decades of distance starting at a distance of 1 m; $10n$ describes the path loss in dB in terms of decades of distance starting at 1 m; $d_{ij}^{\text{tran-rec}}$ is the separation distance of the respective transmitter/receiver i, j pair; $\chi_{\sigma}^{\text{CI}}$ is the auxiliary parameter. The FSPL(.,.) is defined as:

$$\text{FSPL}(f,\ 1\,m) = 20\log_{10}\left(\frac{4\pi f}{c}\right), \tag{3}$$

where c denotes the speed of light; the path-loss is strictly determined by two guiding parameters: the previously mentioned n and $\chi_{\sigma}^{\text{CI}}$. In [24], the authors define two modifications of the CI model: one for the open square geometry and one for the street-canyon case. In this paper, we consider a metropolitan area with high population density, which can be reflected by a street-canyon CI model for the macro cell operator. On the other hand, for the small cell operator, we assume that all users are within a line-of-sight (LOS) wireless link, so we can apply an open square propagation model. Thus, the parameters of the propagation model for the small cell operators are set as $n = 2$ and $\chi_{\sigma}^{\text{CI}} = 2.9$. Accordingly, for the macro cell operator, we set $n = 2.7$, and $\chi_{\sigma}^{\text{CI}} = 8.1$.

By combining g_{ij} values and the respective base station powers P_j, we can define the signal-to-interference-plus-noise ratio (SINR) of the ith end user associated with the jth base station as:

$$\gamma_{ij}(t) \equiv \frac{P_j g_{ij}(t)}{\sum\limits_{s=1,\, s\neq j}^{M} P_s g_{is}(t) + \sigma_{\gamma}^2} = \frac{P_j g_{ij}(t)}{I_{ij}(t) + \sigma_{\gamma}^2}, \tag{4}$$

where σ_{γ}^2 is the noise dispersion. In the above formula, we emphasize the interpretation that all system noise is included in the value of the interference power I_{ij}, which affects the signal received at position i. To address the efficiency of the HetNet, we define the throughput value of the ith end user as following:

$$q_{ij}(t) = W\sum_{k=1}^{N_{\text{RB}}} \log_2\left(1 + \frac{P_i g_{ij}^k(t) b_{ij}^k}{I_{ij}^k(t) + \sigma_{\gamma}^2}\right), \tag{5}$$

where $b_{ij}^k = 1$ if the kth RB is scheduled for ith end user and $b_{ij}^k = 0$, otherwise. W denotes the bandwidth per RB ($W = 180$ kHz for LTE); g_{ij}^k denotes the channel power gain of the wireless link between the ith end user and the associated jth base station for kth RB; and I_{ij}^k denotes the interference perceived by the end user on the kth RB. In other words, the throughput experienced by the end user is affected by the signal's propagation characteristics, interference between neighbouring cells and the total number of end users. Note that in contrast to most other research (with the exception of [16]), in our model, we assume that the utilities of the end users (e.g., throughput) are closely related because the overall capacity of the base station is shared among all scheduled users. Thus, the larger number of end users associated with the dedicated base station results in lower end user utility, i.e., the effect of a negative externality. Since conventional static pricing schemes cannot cope with the negative externality, in our model, we develop a dynamic pricing scheme to improve the tradeoff between cost and performance for the end users.

3.2. Techno-economic analysis of a multi-operator HetNet

In conventional LTE networks, the number of end users associated with the base station is based on the measured values of reference signal receiving power (RSRP) or reference signal received quality (RSRQ). However, these criteria are reliable only for the case when the users have a static contract with one operator. The new functionality of our model RSRP remains relevant only when the users connect to a network for the first time. Notwithstanding the complexity of the model design, our goal is to include the economic-oriented aspects of MH and networks switching scenarios. Therefore, in addition to considering the RSRP parameter, we also consider the actual service price when determining the utility of the end users.

Joint consideration of technical and economical aspects is a challenging task, which requires a definition of the user's utility function, which can be used as a metric to support decision making process. Such utility function must incorporate the tradeoff between service price and experienced throughput in a way that value of utility function is directly proportional to the throughput and inversely proportional to the service price. The complexity of such decision making process is in the possibility that several utilities with equal values may have opposite parameters. For example, an option with high throughput for the high price will have the same value of utility function as an option with low throughput for the low price. Such uncertainty, requires an additional parameter of sensitivity, which will define the preferences of each user, i.e how much user is willing to pay for the service. Therefore, we use the utility function proposed by Xing [15], which allows to incorporate two required metrics (throughput and price) and additional calibration parameter, which defines the importance of each metric:

$$\begin{aligned} u(q_i^k, p_i^k) = \Big[&\mu\big(q_i^k - q_{\min}\big) + (1-\mu)\big(p_{\max} - p_i^k\big)\Big] \\ &\times \Theta\big(p_{\max} - p_i^k\big)\Theta\big(q_i^k - q_{\min}\big), \end{aligned} \tag{6}$$

where $\mu \in (0,\ 1)$ is a user-specific parameter indicating the quality - price sensitivity - of the end user; q_i^k is the expected throughput achieved by connecting to the kth operator ($k \in \{\mathcal{S}, \mathcal{M}\}$, where $\mathcal{M}$ denotes the macro cell operator and the small cell operator is denoted by $\mathcal{S}$); and $q_{\min}$ is the minimum throughput that satisfies the end user. Similarly, p_i^k is the price to be paid for the service offered by the kth operator to the ith end user; $p_{\max}$ is the maximum price that the end user is willing to pay. To fulfill some minimum requirements, the step function $\Theta(\ldots)$ with the properties $\Theta(Y) = 1$, if $Y > 0$ and $\Theta(Y) = 0$, if $Y \leq 0$ is used for the separate domains. The proof of the concordance between the preference relation and the Xing's utility function is given in the Appendix.

For the dynamic switching (DS) scenario, the end user's utility can be expressed as follows:

$$u_i^{\text{DS}} = \max_{k\in\{\mathcal{S},\mathcal{M}\}} u(q_i^k, p_i^k). \tag{7}$$

When considering MH scenario, the end user has additional "degrees of freedom", due to the ability to simultaneously connect to both operators (facing different prices and throughputs if compared to (Eq. (7))):

$$u_i^{\text{MH}} = u(q_i^{\mathcal{M}}, p_i^{\mathcal{M}}) + u(q_i^{\mathcal{S}}, p_i^{\mathcal{S}}). \tag{8}$$

After describing the demand side of the market, we step forward to present its supply side. The small cell operator $\mathcal{S}$ first leases the spectrum capacity from the macro cell operator $\mathcal{M}$ to use it for serving the end users. At the same time, the macro cell operator competes with the small cell operator in the market while offering its spectrum capacities to the end users, too. The macro cell operator, selling its spectrum capacities both to the small cell operators and to the end users, is expected to stabilize its income.

If considering the providers economy, let us denote $N^{\mathcal{S}}$ and $N^{\mathcal{M}}$ the number of the end users accessing the small cell network operator and the macro cell network operator, respectively. Here, an additional assumption is that the small cell operator's profit is determined by the service price $p^{\mathcal{S}} \in \{0, 1, \ldots, R-1\}$, the number of accessing users $N^{\mathcal{S}}$ and the spectrum leasing price w, which is constant. First, we introduce the profit of the small cell operator as:

$$\Phi^{\mathcal{S}} = \big(p^{\mathcal{S}} - w\big)N^{\mathcal{S}}. \tag{9}$$

Then, the macro cell operator's profit can be expressed as:

$$\Phi^{\mathcal{M}} = wN^{\mathcal{S}} + p^{\mathcal{M}}N^{\mathcal{M}}, \tag{10}$$

where $p^{\mathcal{M}} \in \{0, 1, \ldots, R-1\}$ is the service price of the macro cell operator.

The end users present the demand side of the spectrum trade. On the other hand, the operators disposing with their independent price policy form the supply side of the market.

Recall that $\mathcal{M}, \mathcal{S}$ are distinguishing marks of the macro cell and the small cell operator, respectively. Then the operators ' / players ' permanent characteristics can be described as follows:

1. The set $\mathcal{A}_R \equiv \{0, 1, \ldots, R-1\}$ is a discrete price strategy space of the cardinality R. This is the common characteristics available for future price-value modifications for both $\mathcal{M}$ and $\mathcal{S}$.
2. The players $\mathcal{M}$ and $\mathcal{S}$ differ in the respective payoffs (profit functions) $\Phi^{\mathcal{S}} = (p^{\mathcal{S}} - w)N^{\mathcal{S}}$ and $\Phi^{\mathcal{M}} = wN^{\mathcal{S}} + p^{\mathcal{M}} N^{\mathcal{M}}$.

With these objects in mind, we can build the tuple

$$\left[\underbrace{\{\mathcal{S}, \mathcal{M}\}}_{\text{players}} \longrightarrow \underbrace{\{p^{\mathcal{S}}, p^{\mathcal{M}}\}}_{\text{strategies}} \in \mathcal{A}_R \times \mathcal{A}_R \,; \quad \underbrace{\Phi^{\mathcal{S}} : \mathcal{A}_R \times \mathcal{A}_R \to \mathbb{R}^+ ; \quad \Phi^{\mathcal{M}} : \mathcal{A}_R \times \mathcal{A}_R \to \mathbb{R}^+}_{\text{profits}} \right]$$

which formally embodies the game in the *normal form* by mapping the strategic space to the players' respective profits. It should also be explicitly rendered, although profits are dependent on end users (their numbers $N^{\mathcal{M}}$, $N^{\mathcal{S}}$) accessing services, the end users are not deemed players in the game. They constitute only the kind of assets available to $\mathcal{M}$ and $\mathcal{S}$.

Let us focus for the moment on our subgoal, which is to analyse price dynamics, preferably if it tends towards stable conditions. Suppose that the statistical effects of a large number of moving end users along frequent communication lines do not significantly change the local demand for services, which in this way has a constantly fluctuating but rather stable character. This is one of the important reasons to believe that other demand-derived variables such as prices could fluctuate around steady-state values and thus be consistent with the idea of balance, albeit stochastic. On the other hand, we also assume that demand (exogenous) variability is important to our design of adaptive and learning pricing strategies that should be successful, attractive to practice, computationally feasible while explaining asymptotically produced stochastic game equilibrium.

We believe that the application of the automata principle game has great potential in this scenario. In our case, the automata are operating in the shared environment in a competitive way. Our goal is to study the implications of the interactions between a pair of automatons (the macro cell operator and the small cell operator), where each operator determines the price from its available strategic space in the process of gaming. To overcome the problem with achieving the complete or partial rationality of the operators, we consider the operators within a different paradigm as independent learners. The basic assumption is that after playing a game round, the operators are not informed of the actions (i.e., actual prices) chosen by their opponents. We define the probability vector $\pi^k = \left[\pi^k_\iota\right]_{\iota=0}^{R-1}$, assigning a probability to each price defined in the price strategy vector for each operator $k \in \{\mathcal{S}, \mathcal{M}\}$. In the course of the evolution, the probability vector is expected to evolve in the way of achieving maximal profits for the provider. In this respect, an evolutionary stable equilibrium (ESE) may be a more appropriate concept for a given system than Nash equilibrium.

Running the above given game in its iterative form, we employ the linear-reward-inaction (LR-I) algorithm to adjust the mixed strategies probabilities as follows:

1. **Step - initial conditions:** We set the initial probability vector $\boldsymbol{\pi}^k$ equal to $[1/R, 1/R, \ldots, 1/R]$, which means that the probability of the use of respective price candidates are set equal at the time of initialization.
2. **Step - prices, actions:** Based on probability vector $\boldsymbol{\pi}^k$, operator $k \in \{\mathcal{S}, \mathcal{M}\}$ chooses randomly its offer price $p^k \in \{0, 1, \ldots, R-1\}$.
3. **Step - profits:** The end users perform their actions based on the announced offer prices p^k ($p^{\mathcal{S}}$ and $p^{\mathcal{M}}$). The profits of the operators depend on the admissible actions. Formally, the profit of the kth operator in the case of offering price $p^k = \iota$ is Φ^k_ι.
4. **Step - learning.** Operator k plays according to the price ι. Its instantaneous profits serve to update the respective components of the probability vector $\boldsymbol{\pi}^k$ according to

$$\pi^k_j \leftarrow \pi^k_j - \eta \pi^k_j \Phi^{k,\text{rescaled}}_\iota \quad \text{if} \quad j \neq \iota \tag{11}$$

$$\pi^k_\iota \leftarrow \pi^k_\iota + \eta \left(\sum_{z \neq \iota} \pi^k_z \right) \Phi^{k,\text{rescaled}}_\iota , \tag{12}$$

where $\eta \in (0, 1)$ is the learning parameter. After calculation of the profit, it is rescaled to the (0,1) interval: $\Phi^{k,\text{rescaled}}_\iota = (\Phi^k_\iota - \min_{\iota'} \Phi^k_{\iota'})/(\max_{\iota''} \Phi^k_{\iota''} - \min_{\iota'} \Phi^k_{\iota'})$.

In this scheme, the algorithmic steps 2, 3, and 4 are repeatedly applied either according to the number of repetitions or according to the predetermined stopping criteria (e.g., see Fig. 2 for obtaining intuition). By summing both sides of (11-12) in the iterative scheme, we can simply verify that the iterations automatically guarantee the normalization of the probability distribution, without, however, the satisfaction of the rather obvious constraint $0 \le \pi^k_\iota \le 1$. Moreover, as the method name indicates, the complexity requirement grows only linearly with the set of the price candidate options, i.e., $\mathcal{O}(R)$.

Let us focus on the selected dynamic properties of pricing strategies in terms of probability. Now, with the concept of evolutionary stability as a possible scenario, there is a much more compelling reason to perform numerical relaxation tests to study convergence to the state(s) of equilibrium, which are given by the fixed point(s) π^{k*}. The only scenario observed for $\boldsymbol{\pi}^k$ was the one in which a single component of this vector gradually approaches one while the remaining components are reduced to zero during a characteristic relaxation time, which is essentialy different for the small cell and macro cell cases. The outputs of two alternative simultaneous experiments are provided in Fig. 2 to demonstrate a unique equilibrium situation in the framework of different randomness implementation or stochastic disturbances by end users on the move. Altogether, 100 simulated stochastic paths (only two are analyzed in the respective figure) indicate almost the same final equilibrium prices. If we identify the duration of a tic with a second, as an estimate of a typical real time scale of the gaming and learning, then we can say that total relaxation to equilibrium requires about a third of the day.

Simulation makes it possible to reveal differences in the price of operators' services. Our conclusion is that the equilibrium price of the small cell operator is higher, which strengthens the aforementioned theoretical expectations. The numerical results can be considered as being partially in line with analytical expectations [26]. Obviously, however, these are only indirect indications of pure ESE, as it is difficult to demonstrate the existence of ESE in the context of factors such as variable environment and realistic urban geometry.

3.3. Method of dynamic operator and service selection by end users

In this section, we summarize our framework by proposing the method of dynamic service selection by the end users. As men-

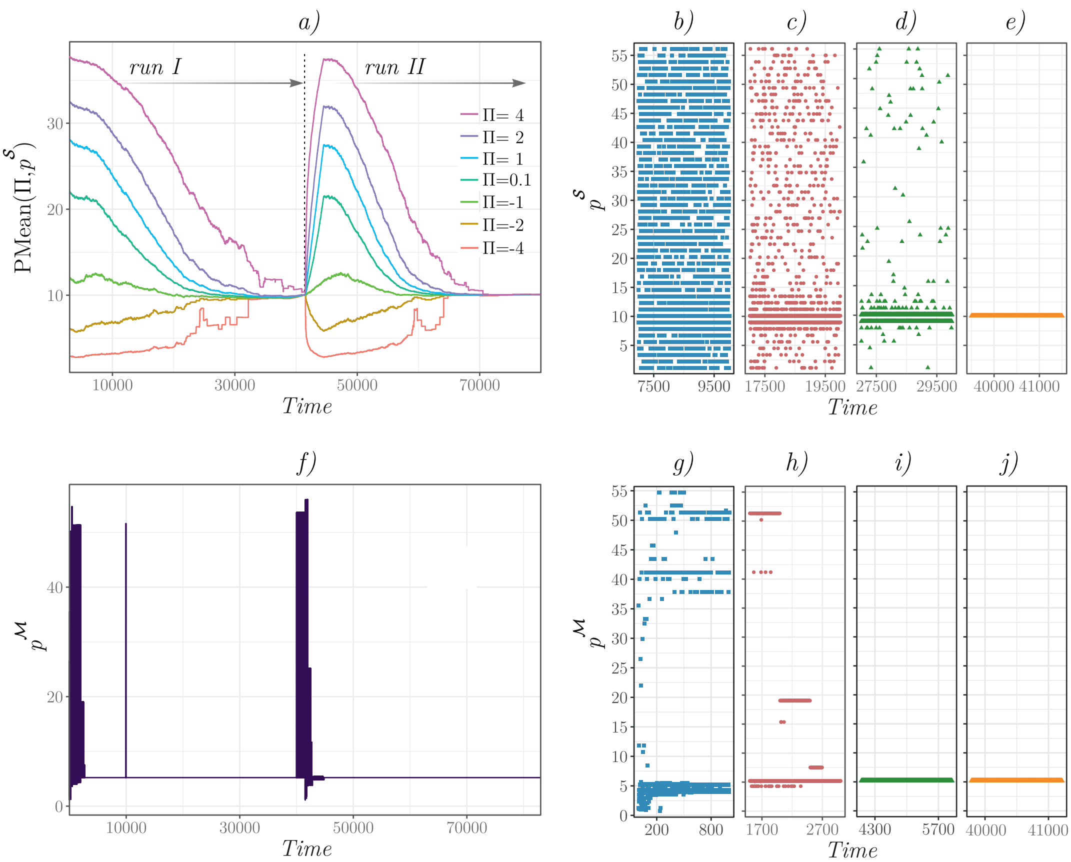

Fig. 2. The illustration summarizing the convergences of the numerical experiments of price formation (labels: run I, run II) to the equilibrium seen from the standpoint of the small cells (panels a, b, c, d, e) and macro cells (panels f, g, h, i, j). The closest neighbourhood of equilibrium is depicted in (e), (j). Exceptional numerical processing has been dedicated to the fluctuations in the $p^{\mathcal{S}}$ price - see panel (a). Here are the power averages (Minkowski means [25]) labeled by PMean(Π, $p^{\mathcal{S}}$) that are constructed for the list of the exponents $\Pi \in \{-4, -2, \dots, 2, 4\}$ and the prices corresponding to the sliding time window of the extent of 3000 tics. In (g), (h) we display the gradual stabilisation of the equilibrium (j) from several meta-stable candidates of $p^{\mathcal{M}}$.

tioned above, we incorporate two service options for the end user: MH and network switching. The workflow of the proposed method in our framework can be divided into four stages as follows:

1. **Request phase**: The UE i requests the connection by sending a random access request (RACH) (naturally, it splits into $RACH_{\mathcal{S}}$ and $RACH_{\mathcal{M}}$ variants) to small cell operator and/or the macro cell operator. From the practical point of view, the request phase can be easily implemented by existing means of the 3GPP standard for LTE networks. In particular, all requests will go to MME (Mobility Management Entity), which is responsible for handling a mobility of users and assignment of corresponding EPS (Evolved Packet System) bearers to the target users.
2. **Offering phase**: The macro/small cell operators collect channel state information on all desired connection and interference links and calculate the expected achievable UE throughput for the ith UE, small cell operator $\mathcal{S}$: $q_i^{\mathcal{S}}$ and macro cell operator $\mathcal{M}$: $q_i^{\mathcal{M}}$. Then, the operators send back the tuple offer, consisting of the expected throughput and updated service price based on (Eq. (11)), i.e., $\langle q_i^{\mathcal{S}}, p^{\mathcal{S}}\rangle$ and $\langle q_i^{\mathcal{M}}, p^{\mathcal{M}}\rangle$. From the practical point of view, the integration of service price and throughput into one offer for users will require coordination between the MME and LTE billing system before creation of EPS bearers.
3. **Admission phase**: Based on the connection mode:
   - *Network switching*: The UE i evaluates the utility function u_i^k and calculates whether the conditions in the utility function [see (Eq. (6))] can be satisfied. If they can, the UE i will connect to the operator with the highest calculated utility, as shown in (Eq. (7)). If not, the UE i will stay idle. This option can be easily implemented based on the conventional roaming procedure between different operators, which is defined in existing LTE standards. The only difference is that in our method, the user will actually influence the spectrum allocation between operators, while in conventional roaming, the spectrum of different operators is statically separated by commercial licenses.
   - *MH*: The UE i evaluates the utility function u_i^k and calculates whether the conditions in the utility function given by (Eq. (6)) can be satisfied. If they can, the UE i will connect to the operators with positive calculated utility based on (Eq. (8)). If both calculated utilities are positive, (small cell operator $\mathcal{S}$ and macro cell operator $\mathcal{M}$ at the same time) the UE i will connect to both operators. If the conditions in (Eq. (6)) are not fulfilled, the UE i will stay idle. This is the most complicated option in terms of practical implementation, as it requires complete coordination between two (or more) operators in terms of spectrum allocation and service price. The complexity can be decreased by using the shared evolved packet core (EPC) for all operators, so that the MME and LTE billing system will be able to create EPS bearers with corresponding prices by taking into account all available resources of all operators.

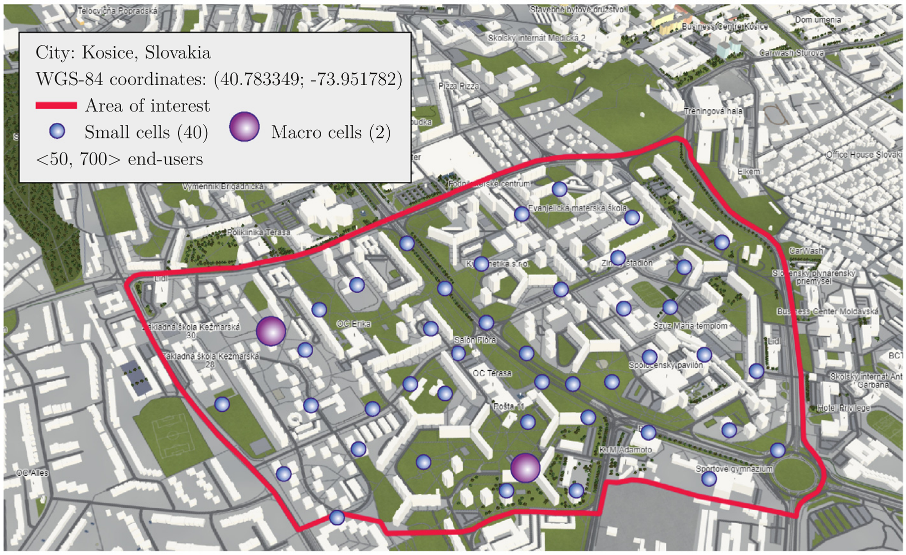

Fig. 3. Simulation environment based on a 3D urban model with real RAN topology of the city of Košice, Slovakia.

- *One-contract*: The UE i is attached to a specific operator; thus, no additional dynamics are allowed. This option is completely in line with the existing LTE standard.

4. **Scheduling phase**: Both the small cell operator $\mathcal{S}$ and the macro cell operator $\mathcal{M}$ schedule the corresponding RBs to the associated end users. From a practical point of view, for all created EPS bearers, the corresponding radio bearers should be assigned for each particular user. After that, each base station should schedule the target amount of RBs for each radio bearer. All functionality of this step is available in the current LTE standard, so that not many changes are required for implementation.

Although our proposed method is practically doable without massive changes in the existing mobile network infrastructure, there are some important aspects that should be taken into account. The general procedure of user admission and resource allocation should consider the user priority, service priority, handover configuration, UE capability and many other technical constraints for the proper scheduling of the RBs among multiple users. In the current paper, we have simplified all these factors and limit our model to the round-robin scheduling with equal priority of users. The reason for this limitation is that our aim in this paper is to study the impact of economical aspects such as service pricing and operators' profit, which requires the unification of the above mentioned variables. Nevertheless, in our further research in this direction, we will continue to extend the current model in order to simulate more realistic use cases of heterogeneous mobile networks.

4. Simulation and performance analysis of a multi-operator HetNet

4.1. Simulation environment and parameters

To study the joint effect of the operator's (dynamic pricing) and user-driven (dynamic service selection) actions, we develop a complex environment consisting of real city construction, streets and RAN infrastructure for the macro cell operator. The mobility of users is simulated using software developed for Python using the OSMnx package [27] with the OpenStreetMap database [28]. This new model is able to simulate a large number of pedestrian and vehicular end users by using Cuda acceleration. Data on the locations of the base stations are collected from OpenCelliD, which is the world's largest open database of cell towers and includes information on their locations and heights [29]. By using such a combination of open source databases, our model is able to simulate literally any place in the world with infrastructure. However, currently, there is not a database for small cell operators, so we apply the unsupervised machine learning algorithm introduced in [22] to find the optimal small cells topology for a given mobility pattern of end users and target coverage area. Moreover, to double-check the adequacy of our framework, we use a stochastic geometry model, namely, Matern's hard core point process (Matern's HCPP), which has been shown to be a good reflection of real-world small cell deployments [30]. The proposed model is the most suitable for designing small cell coverage and provides the most realistic distances between cochannel transmitters [30,31]. Fig. 3 presents the considered simulation environment for part of the city of Košice and Fig. 4 shows the main components of the modelling framework.

In our simulation, we assume that the macro cell operator is a one-way infrastructure network, so that only the downlink spectrum is shared with the small cell operator. The price of the spectrum unit (i.e., RB) is fixed at w. We set $w = 0.5$ to ensure that both operators have positive profit. The competition between the macro cell operator and the small cell operator is conducted in real time. Both operators aim to attract more end users to increase their profit. Each operator has unique advantages. Small cell operators are, in general, characterized by higher throughput because of better link quality and the spectrum reuse factor. The advantage of the macro cell operators is that they can provide more stable service for users with high mobility, i.e., vehicular users. Moreover, the macro cell operator can adjust the spectrum leasing price to increase his profit, which will eventually force the small cell operator to increase his service price for the end users. We assume that the end users are equally sensitive to price and throughput ($\mu = 0.5$) and can be connected in all three scenarios: MH, network switching and static connection. In case of the one-contract service selection, the users are split equally between the operators. Further, we assume that 1/4 of the end users are vehicular users with a velocity of 30 km/h.

Regarding the parameter selection, we use a 2.1 GHz frequency bandwidth, in which the primary spectrum holder (macro cell operator) obtains primary access rights to a given spectrum band in a similar way to the traditional exclusive licensing and is incen-

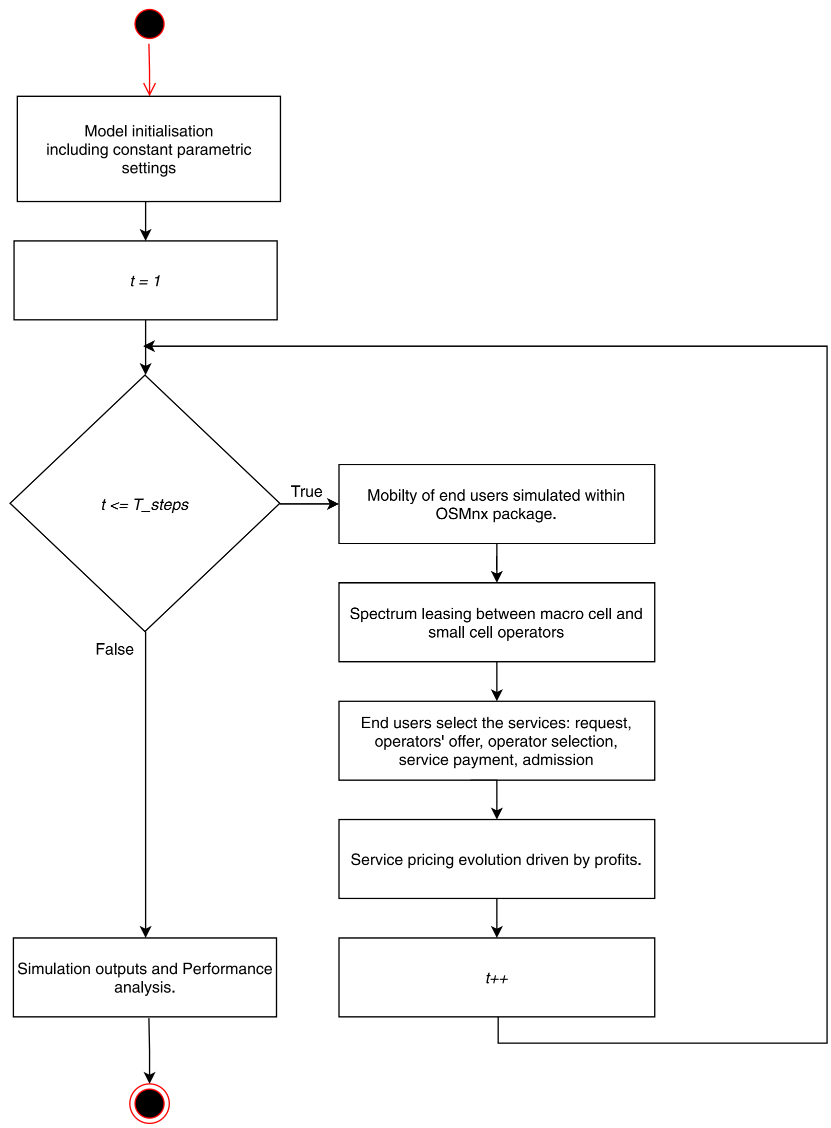

Fig. 4. Schematic holistic flow chart diagram of the model interactions.

tivized to admit secondary access use (small cell operator). The pros and cons of this scenario are discussed in detail in, e.g., [32]. The numerical simulations were conducted using the 3GPP LTE-A specification, and small cell parameters are as described in [33]. All simulation parameters are summarized in Table 2.

4.2. Simulation results and performance analysis

Highly structured dynamic simulation models, which generally produce large amounts of output data, are usually much clearer to understand from the point of view of equilibrium and stability. The existence of a stable ESE has its specific implications for the evaluation methodology related to the averages. Thus, for numerical simulations, the averages of the respective variables are first determined by equilibrating the dynamics of the system. The process requires some initial relaxation steps depending on the parameters as well as random factors; 1000 steps were used to create a data file. This record was used to calculate the averages.

We conduct all our simulations to determine how the number of end users influences the technical and economic efficiency of the network for both the operators and the end users. Let us start with the throughput, since it is the most common parameter of network performance (Fig. 5). In our implementation, average throughput values per user were calculated for each simulation time step, which were then averaged, to obtain a single average throughput value, for all observed time steps T_{steps} as:

$$\bar{q} = \frac{1}{N} \sum_{t_{\text{step}}=1}^{T_{\text{steps}}} \sum_{i=1}^{N} q_i(t_{\text{step}}) \, . \tag{13}$$

We observe that the throughput results for the stochastic geometry topology (Fig. 5a) and for the realistic-use case (Fig. 5b) are very close, so that both models yield almost optimal topology. This result confirms the conclusion in [30] regarding the feasibility of estimating realistic network parameters using stochastic geometry modelling based on Matern's HCPP.

When comparing different service types, we observe that network switching provides the highest throughput for a small number of users, while the static contract performs better for a large number of end users. Thus, we divide the discussion into two different scenarios: non-saturated network and saturated network. For the non-saturated scenario, the small cell operator can offer better throughput for a lower price (for price comparison, we refer the reader to Fig. 7), so that more end users are likely to

Table 2
Parameters of the simulation model.

Parameter	Value
Model (Monte Carlo)	Time steps used for averages T_{steps}: 1000 Number of trials: 100
Coverage area	Size: 1 km^2 Location: Košice, Slovakia WGS-84 coordinates: (40.783349; −73.951782)
Radio Access Network	
Macro cell operator	Transmit power: $P = 40.3$W Height & position: OpenCellID data for T-mobile operator System bandwidth: 20 MHz Carrier frequency: 2.1 GHz RB bandwidth: 180 kHz Antenna pattern: 0 dBi (isotropic)
Small cell operator	Small cell power: $P = 6.3$W Height & position: 3 m and positions determined by the algorithm in [22] Number of small cells: 40
Path-loss model	Close-in; (non-line-of-sight for macro cells) Close-in; (line-of-sight for small-cells)
Link scheduling	Round-robin
End user parameters	
Pedestrians	Antenna height: 1 m Number: $N \in (50, 700)$ Velocity: 5 km/h Mobility pattern: Random start/end point with the shortest path Utility constant $\mu = 0.5$ Minimum throughput $q_{\min} = 300$ kbit/s Maximum tolerated service price $p_{\max} = 40$ monetary units
Vehicles	Antenna height: 1 m Velocity: 30 km/h Other characteristics: see Pedestrians
Economic parameters	
Price	Spectrum leasing price per RB: $w = 0.5$ Service price; LR-I parameter: $\mu = 0.001$

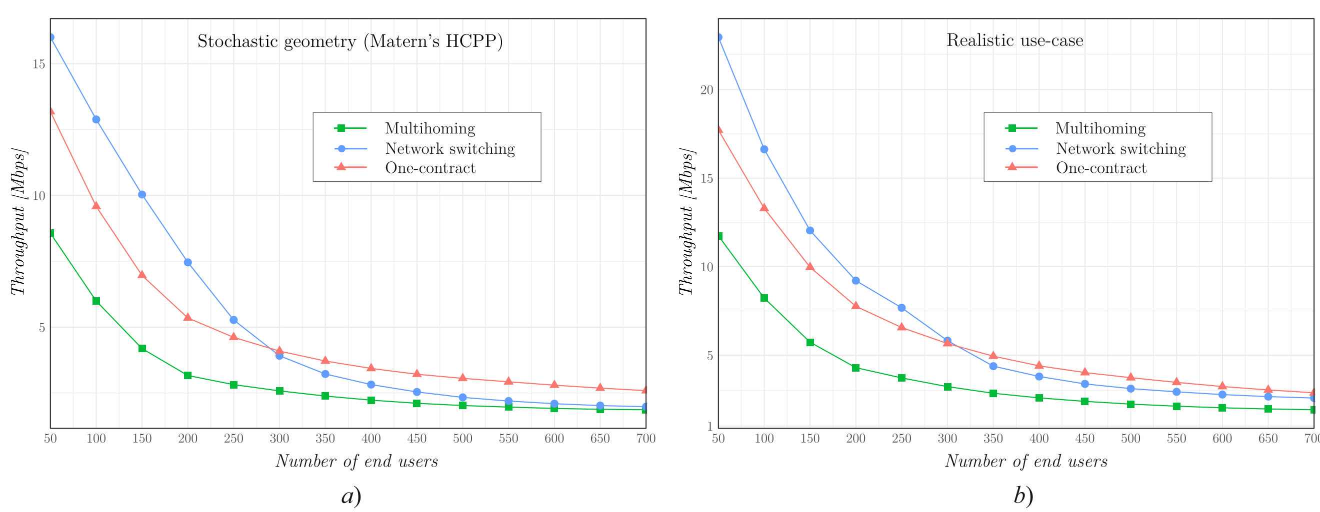

Fig. 5. Average throughput of the different service modes for the (a) stochastic geometry topology and for the (b) realistic topology.

be connected with higher throughput in the network switching mode. In contrast, the static contract does not allow end users to change their connection, so that a significant number of end users is still connected to the macro cell operator with lower throughput. Therefore, the average throughput for the non-saturated scenario is better for the network switching mode. For the saturated scenario, the situation is slightly different. In the network switching mode, the lower price of the small cell operator attracts more end users, so that users of small cells experience significantly lower throughput. In case of a static contract, the absence of competition prevents overwhelming the small cells, so that throughput for small cell end users is higher than in the network switching mode. Even though the macro cell operator is completely overloaded for both modes, the average throughput value among all end users is slightly higher in the static contract mode than in the network switching mode.

Interestingly, the MH mode performs worse than the other two methods regardless of the number of end users. This result can be explained by the fact that MH end users request low portions of bandwidth from each operator, with the hope that the aggregated

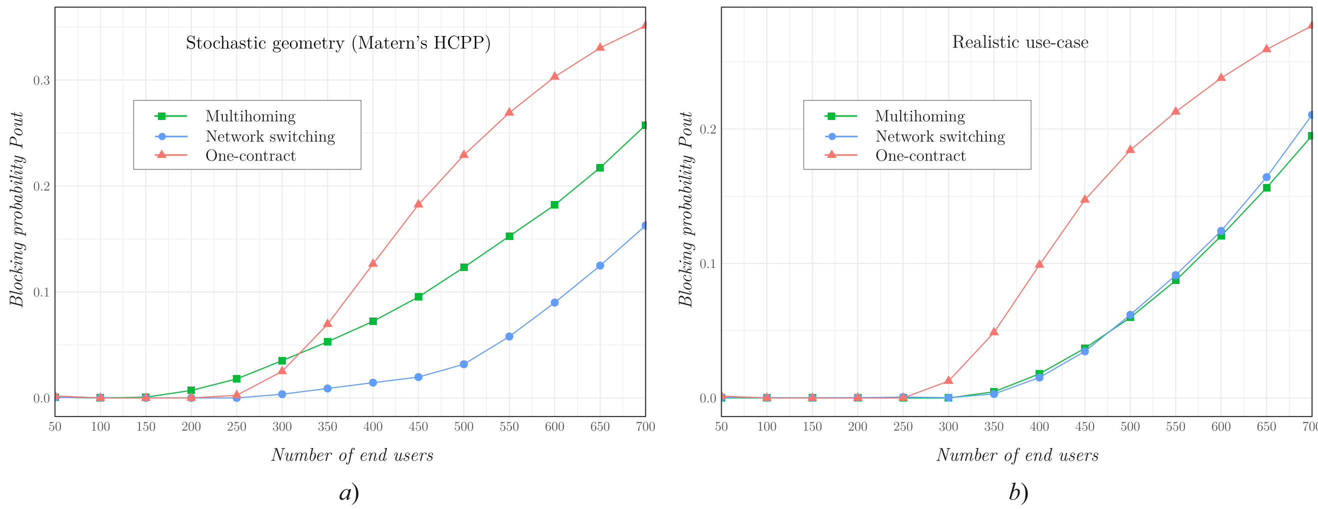

Fig. 6. Blocking probability of different service modes for the (a) stochastic geometry topology and for the (b) realistic topology.

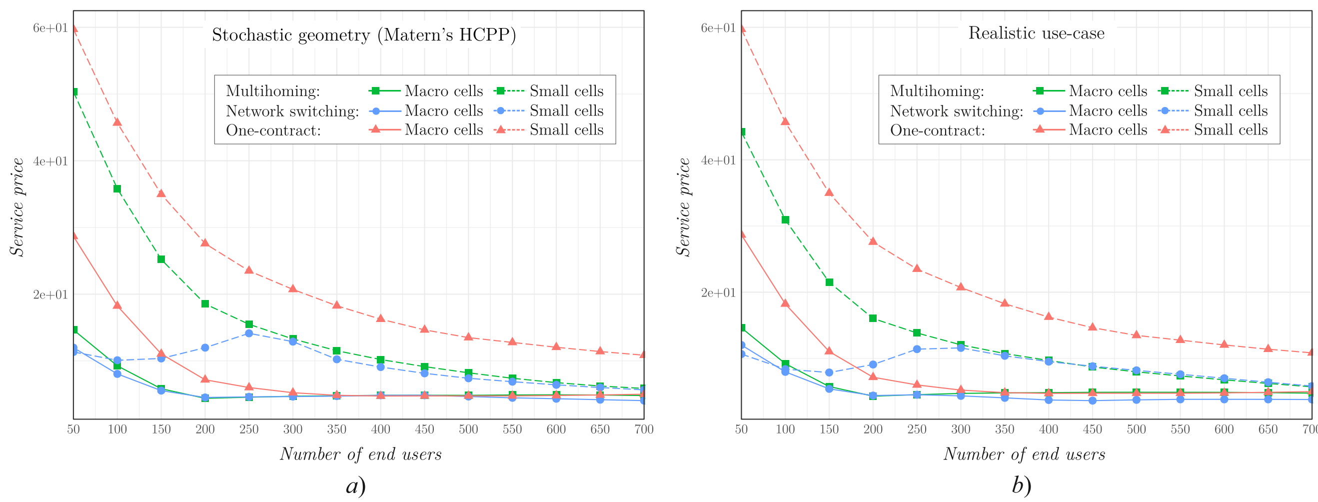

Fig. 7. Price of different service modes for the (a) stochastic geometry topology and for the (b) realistic topology.

bandwidth will be large enough. However, our model still lacks the important functionality of higher levels, so the network operators are not able to distinguish MH and network switching end users to properly allocate resources for them. Although some "lucky" MH end users can obtain high aggregated throughput, most of them suffer from a lack of resources, resulting in lower average throughput. Nevertheless, MH is a very promising technology, which is worth studying in further research.

Another important factor, in addition to throughput, is the service availability. This parameter ensures that the end users will receive service with the expected throughput whenever they want it and wherever network coverage exists. To assess service availability, we evaluate the blocking probability of the network (Fig. 6). The blocking probability is the probability that an operator will not be able to satisfy the request of an end user at some specific time due to network congestion. Note that we have set an acceptable throughput threshold of 300 kbits/s, in order to avoid misleading results, such as when some user will formally receive the service with almost zero throughput. The blocking probability P_{Out} is calculated by comparing all end user expected throughput values over time to one of the throughput thresholds $q_{\min}$ introduced in utility function [see (Eq. (6))]. The end user is considered to perceive blockage with respect to a given threshold when throughput is below the predetermined throughput threshold q_{min} and his contribution is counted as 0 kbit/s. The ratio of the number of end users that perceive blockage to the total number of end users can be repeatedly calculated for many time steps of the simulation (T_{steps}). The estimated blocking probability may be expressed as:

$$P_{Out} = \frac{1}{T_{\text{steps}}N} \times \sum_{t_{\text{step}}=1}^{T_{\text{steps}}} \sum_{i=1}^{N} \tilde{\delta}_{\text{thr}}[q_i(t_{\text{step}}), q_{\min}], \tag{14}$$

where q_i indicates the experienced throughput of ith user at time t_{step}.

The threshold effect is produced by the indicator:

$$\tilde{\delta}_{thr}[X, X_{\min}] \equiv \begin{cases} 1 & \text{if } X < X_{\text{thr}} \\ 0 & [\text{otherwise}] \end{cases}, \tag{15}$$

where X represents a general argument of this function. The second argument of $\tilde{\delta}_{\text{thr}}[., \bullet]$ is reserved for a certain threshold constant X_{thr} (specifically $q_{\min}$) with regard to which the blocking probability is calculated.

Similar to Fig. 5, we observe a clear change in the system behaviour as the number of end users increases. For up to 250 end users, the blocking probability is almost zero due to the vast amount of spectrum resources. With additional increases in the number of end users, we observe that blocking occurs more frequently. When comparing the different service modes, we can see that the static contract is less reliable because the end users have only one possible operator choice. In this case, network switching and MH perform better because they rely on both operators. However, the difference is not significant from the perspective of all end users. The largest observed difference between network switching and static contract modes is approximately 15%, while almost 80% of end users experienced an acceptable throughput. Note that end users under blockage have been counted in the calculations of average throughput in (Eq. (13)) as users with throughput equal to 0 kbit/s. Nevertheless, the number of such users is quite low, so that they did not affect the throughput results significantly. Even though the static contract mode contributes more “zeros” to the average throughput value, it also has many small cell users with quite high throughput. On the other hand, network switching decreases “zeros” but provides much more of the lowest threshold values, with 300 kbits/s throughput, due to the overload of the small cell operator.

An interesting contradiction is observed for MH end users. As seen in Fig. 6a, network switching performs better than MH for stochastic geometry, while in Fig. 6b, network switching and MH have the same blocking probability. This can be explained by the fact that all Poisson point processes (stochastic geometry) share the feature of complete randomness, so that the user's association with the small cell operator is completely independent of the user's association with the macro cell operator [30]. Since stochastic geometry fills the whole target area with small cells, all end users are able to use the resources of both operators, resulting in a higher blocking probability. On the other hand, the realistic model in [22] takes into account the end users' mobility patterns for small cell coverage planning. Therefore, the results in Fig. 6b are caused by the fact that part of the area remains uncovered by the small cell operator, so the end users in such areas cannot use the resources of both operators. Nevertheless, we expect that for the realistic model, the blocking probability of the MH case will be higher than that of the network switching case as the number of end users increases.

Now, let us move to the economic parameters of the studied service selection modes. For a qualitative explanation of economic efficiency, we can consider the averages of the profits and service prices. Nonaveraged prototypes [see (Eq. (6))] are expressed using two independent thresholds: $p_{\max}$, $q_{\min}$, which can influence the shape of the average plot. Taking into account that our model is intuitively incomprehensible, it is necessary to conduct simulations for the target economic parameters.

First, we assess the evolution of the service prices (Fig. 7), which follow the basic reinforcement rules introduced in (Eq. (11)). The service prices are averaged over the price series generated according to the studied cases. The pricing mechanism can be explained by the synergy between the depreciated quality of services and the growing demand of end users. In Fig. 7, we separate the prices of the macro cell and small cell operators to provide a better understanding of the intrinsic market trends. Because of dynamic service selection, the price of the macro cell service tends to reduce compared to that for the conventional one-contract with no dynamic service selection. This is in accordance with basic market rules, as minimization of the switching costs stipulates that competition is followed by a decreased service price. In addition, the same observation is valid for the small cell operator's evolution. The small cell operator charges the highest prices for the static contract, followed by the MH mode. Naturally, the network switching mode is the most competitive scenario and is featured by the lowest service price. Hence, we can claim that the small cell operator charges higher prices because he provides a higher data rate than the macro cell operator and is obligated to pay the spectrum leasing price w to the macro cell operator.

Now, let us consider the profit of the operators, which has been defined explicitly in Eqs. (9) and (10). When analysing the results in Fig. 8, we observe that the profit of the macro cell operator is slightly decreased with the adoption of the network switching mode. The MH and one-contract modes provide very similar results in terms of the macro cell operator's revenue. On the other hand, the results for the small cell operator are completely different. The revenue of the small cell operator is strongly affected when network switching is enabled in the system, regardless of network utilization. For under- and mid-utilized networks, MH provides the highest profit for the small cell operator when the number of users is not very large. As the number of users increases, the static contract mode becomes the most profitable solution for the small cell operator. Overall, we can claim that for a given spectrum leasing price, both operators obtain positive profit. For mid- and high-utilization rates, the small cell operator's profit is significantly higher because of the large number of end users, which allows them to take advantage of the better frequency reuse factor and the higher capacity of the small cell operator.

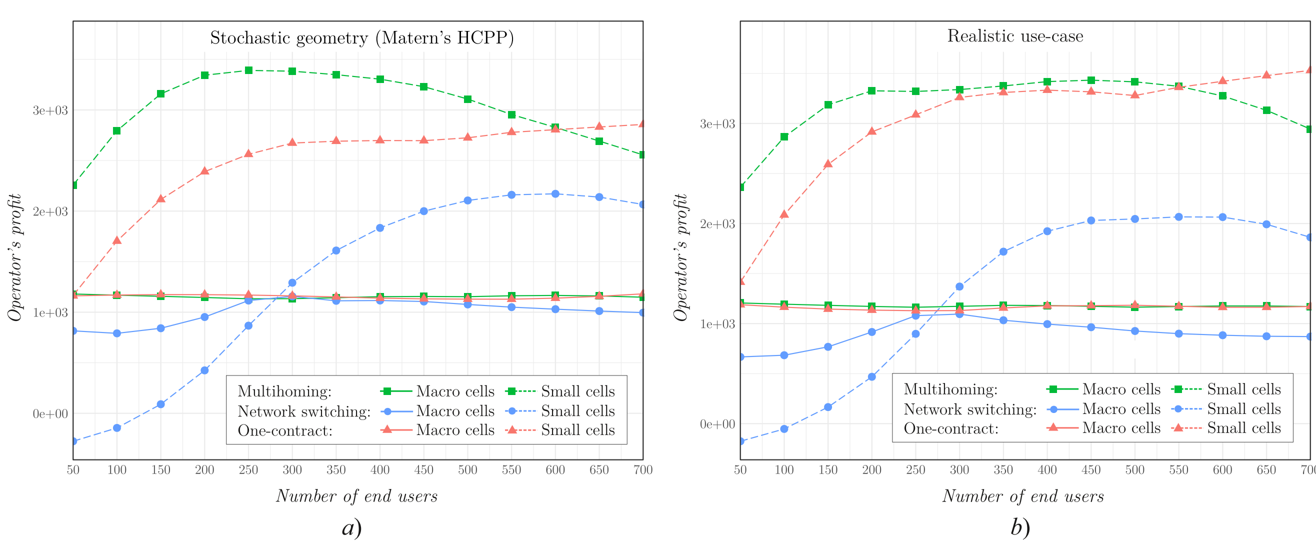

Fig. 8. Operator's profit from different service modes for the (a) stochastic geometry topology and for the (b) realistic topology.

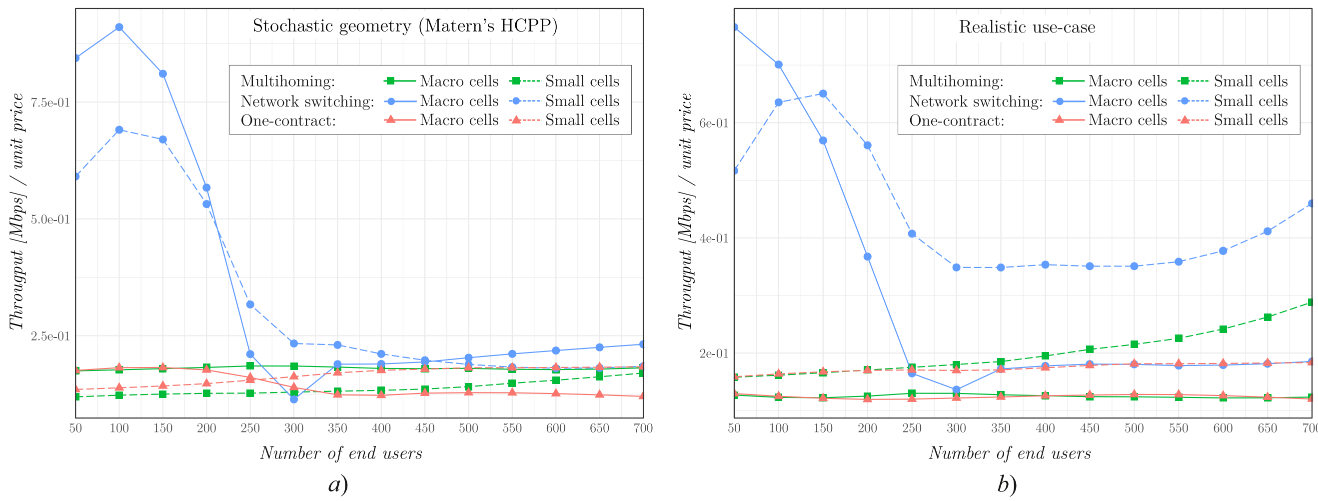

Fig. 9. Average throughput normalized to the unit price for different service modes (a) stochastic geometry topology and for the (b) realistic topology.

Finally, average throughput per unit price is of special importance to the end users in the network (Fig. 9). As we can see, the numerical results provided for this metric are completely in line with our previous results, as network switching provides ultimate performance in terms of achieved profit per unit price for all investigated numbers of end users in the system. It is noteworthy that in the realistic-use case, the end users particularly benefit from the optimized RAN topology of the small cell operator, which is reflected in the absence of a small decay for a higher number of end users, as seen in the stochastic geometry model.

5. Discussion and future research topics

The recent stagnation of the mobile communications market requires us to rethink the future of mobile networks considering the aspects of overall governance, the operators' strategies and user behaviour. The current business model used by operators is obsolete because stagnating revenues cannot cover the increasing expenditures of an infrastructure upgrade [34]. Although we observe the tremendous 5G development by R&D and academic institutions, in reality, 5G is still just used for advertising in some local areas rather than representing a completely reliable network. This occurs because the operators are not willing to invest in hardware infrastructure that will be outdated in a few years. If we compare the current state and the situation 20 years ago when the development of 2G and 3G networks began, we see that the average hardware cycle was approximately 10 years, while service prices were several times higher than current prices. Currently, we have decreased operation cycles of hardware, which, combined with reduced service prices, does not allow the operators to obtain a quick return on investments or meaningful profit. Such a situation forces the operators to extend the lifetime of old infrastructure as long as users are willing to pay for the services they receive. All efforts of network improvement, such as the transition from 3G to 4G or from 4G to 5G, eventually end up in significantly increasing the service price for the end users.

On the other hand, the number of end users is increasing rapidly, driven by the overall growth in the number of applications, services and hardware capabilities. In addition, we should note that the IoT concept has exploded the mobile network market with the millions of small devices that are capable of communicating over the Internet. These factors require significant improvement in network capacity and performance. As a promising solution, the HetNet concept has been introduced to improve both the frequency reuse factor and the overall capacity of the radio access network infrastructure [35]. HetNet assumes that there is an additional layer (or layers) of small cells, which aims to improve network capacity by reusing the spectral resources. In this paper, we have introduced the HetNet model, where macro cells and small cells are owned by different operators. Moreover, the entire spectrum band is owned by the macro cell operator. The small cell operator leases the spectrum from the macro cell operator for a given price. Such a relationship between the macro cell operator and the small cell operator can be considered as a coopetition; i.e., the operators compete for end users and simultaneously cooperate by trading the spectrum. Such a relationship has been observed in the real world, when a traditional mobile network operator, who has purchased the license for a spectrum band, leases part of his spectrum to virtual network operators. This concept was studied in [36], where the spectrum was divided and shared among multiple cells; the profits of both operators were maximized by offering competitive prices to the end users. Their approach converges to an economically efficient equilibrium, where the service providers offer more competitive prices and a high data rate for the end users, so that both operators are able to increase their profits. Although, in this paper, we have studied a different scenario, when the macro and small cell operators coexist in a single HetNet, our results and conclusions are similar to the aforementioned research.

To reflect the different economic models of the HetNet, we have defined three service modes: one-contract, MH and network switching. The one-contract mode resembles a pure monopoly with static user assignment to a single operator. The MH mode operates as an oligopoly, with some competition in the retail market. Finally, network switching represents pure market competition, where a small price change can significantly affect the behaviour of the end users. Another factor that may influence market competition is the switching cost. In general, lower switching costs intensify price competition in the market and facilitate the emergence of the new operators. The implementation of mobile number portability with diminishing switching costs has resulted in lower retail prices for mobile services in many countries [37]. In this paper, we confirm the assumption that increased competition results in decreased prices.

Furthermore, in our proposed framework, we consider not only the competition in price but also competition in service quality (i.e., throughput and blocking probability). This factor is important because more users are willing to pay more for better service. Our results are consistent with those of previous studies and confirm that small cells are able to provide better throughput, due to their higher spectral efficiency. In terms of price, the small cell operator tends to ask more than the macro cell operator and, in the end, will set his prices higher than the macro cell operators, regardless of the service mode.

When combining the service quality and service price, we observed an interesting effect of network saturation. In general economic theory, a higher service demand leads to a higher service price, while preserving the same level of quality. However, in our framework, a larger number of end users causes service quality to decrease due to the limited spectrum resources. Such an effect forces the operators to discount the service to keep the utility of the end users at an acceptable level. Such a decrease in service quality prevails over the increasing demand in the overall service price determination. A comparison of the different service modes shows that the implementation of network switching improves overall resource allocation, which results in better service quality, which is consistent with previous studies [6,7].

A further analysis of the economic effect on the operators shows that the most profitable solution is the static one-contract mode because it provides stable service demand without competition, which obviously increases the prices. On the other hand, the overall network performance is rather low due to the high blocking probability and ineffective spectrum utilization. When comparing dynamic modes such as MH and network switching, we observe that MH is a better option for the operators because it allows them to keep some of the profit from the end users, even though they are connected to other operators as well. For example, in [38], the authors showed that MH does not introduce a profit loss for the operator. In contrast to MH, network switching is the least attractive option for the operators because it forces them to negotiate the prices to attract more end users, which results in lower profit. On the other hand, from the end users' perspective, the network switching mode provides the highest utility because the end users can dynamically switch between the operators and choose the best price-quality tradeoff. The MH and static contract modes both have advantages. While a static contract can provide higher throughput, MH has better reliability and a lower service price.

We envision that in the future, the mobile communications market will be democratized due to spectrum and infrastructure sharing by the operators. This will enable a situation in which the network infrastructure and spectrum may be owned by different companies, while the network operator can be a third party that does not own a spectrum and infrastructure. Such a model is driven by the rapid growth of the various IoT and web-services provided through the mobile network. Maintaining all these services requires a significant extension of the human resources of network operators, which may not be feasible for some of them. Therefore, we expect that in the future, the mobile communications market will be split into raw telecommunication companies, spectrum owners (probably the government) and many small service providers that will rent the spectrum and infrastructure to provide some specific services. The recent breakthrough of blockchain technology will definitely facilitate such type of relationships in mobile communication market by leveraging the power of smart contracts and cryptocurrencies. The features of blockchain will allow many small players to enter the market by using ICO (Initial Coin Offering) to acquire funding and develop their own network infrastructure. Thus, instead of few bulky network operators, we can have hundreds of small and agile network operators. Such a model will promote competition and speed up the development of technology, from which the end users will obviously benefit. Nevertheless, many additional solutions have to be developed to reach a completely democratized market. First, spectrum regulation should be completely reconsidered for both licensed and unlicensed bands to avoid speculation of the license price and ensure electromagnetic compatibility. Second, network management solutions should be improved significantly to avoid congestion and interference, as well as provide convenient mechanisms for ensuring the end-to-end quality of the user's experience. Third, several business models for the mobile communications market need to be established so that each company can decide whether to build its own hardware infrastructure and sell bits per second per square kilometre or rent the network infrastructure and sell specific user-oriented software applications. Finally, the mobility of users need to be reconsidered in order to ensure smooth autonomous handover between operators in real time without complex and expensive roaming procedures. Summarizing all aforementioned aspects, we envision that in the future, mobile communications will be driven by software-defined networks and network function virtualization, with wide adoption of blockchain technology and artificial intelligence.

6. Conclusion

Continuous growth in mobile networks and various network-based services results in the significant complexity of the wireless communications market. In this paper, we first introduce a comprehensive techno-economic framework, which takes into account network efficiency from the perspectives of both the end users and the network operators. In our context, the system lacks comprehensive information about the game, which is closer to the evolutionary profits acquired a posteriori, and therefore we have preferred the interpretation of simulation results through the ESE stability, which, unlike the traditional approach of Nash, seems more realistic. We have created a model in light of the many genuine technical and economic characteristics of the network with a particular focus on those game-theoretical features. Based on the developed model, we propose the method of dynamic service selection by end users, which allows the end users to choose between MH and network switching service modes. To study the performance of the proposed framework, we developed a simulation model that combines the real radio access network topology from the OpenCellID database, a real 3D model of an urban environment and realistic user mobility data from OpenStreetMap database. Using the developed model, extensive simulations were run to study the technical and economic parameters of the HetNet. The simulation results show that the network switching service mode provides the best performance for the end users but yields the lowest profit to the network operators. On the other hand, the static contract mode is the best in terms of the operators' profit but provides the worst performance for the end users. The golden mean can be found in the MH mode, which is an intermediate solution for both the end users and the operators. However, this mode is much more complex in terms of implementation and will be further investigated in our future research. We believe that the contributions of this paper are fundamental for future research that intends to conduct a comprehensive analysis of a techno-economic network. Additional research in this area will be always welcomed.

Declaration of Competing Interest

None.

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Appendix A

In the Appendix, we would like to discuss the specifics of Xing's utility function [see (Eq. (6))] considered throughout the paper. The preference relation is a standard tool that is used in the decision making of independent agents. We consider the decision space

$X = \{[p_i^k; q_i^k] |\ q_i^k \text{ is a throughput; } p_i^k \text{ is a price}\} \subseteq \mathcal{R}_{0+}^2$

of the ith end user when contacting the kth operator ($k \in \{\mathcal{S}, \mathcal{M}\}$). In the following, let us economize the math notation, and let us denote decision $\left[p_i^k; q_i^k\right]$ by tuple $\mathbf{x}$, ($\mathbf{y}$, $\mathbf{z}$).

The preference relation $\succeq$ is a binary relation defined on decision space X, which is:

- *reflexive*, i.e., $(\forall \mathbf{x} \in X)(\mathbf{x} \succeq \mathbf{x})$,
- *complete*, i.e., $(\forall \mathbf{x}, \mathbf{y} \in X)(\mathbf{x} \succeq \mathbf{y} \vee \mathbf{y} \succeq \mathbf{x})$,
- *transitive*, i.e., $(\forall \mathbf{x}, \mathbf{y}, \mathbf{z} \in X)((\mathbf{x} \succeq \mathbf{y} \wedge \mathbf{y} \succeq \mathbf{z}) \Rightarrow (\mathbf{x} \succeq \mathbf{z}))$.

We should propose a utility function $u : X \to \mathcal{R}$ capable of modelling the above given preference properties, i.e.,

$$(\forall \mathbf{x}, \mathbf{y})(u(\mathbf{x}) \geq u(\mathbf{y}) \Leftrightarrow \mathbf{x} \succeq \mathbf{y}).$$

The utility function has the form:

$$u(q_k^i, p_i^k) = \left[\mu\left(q_i^k - q_{\min}\right) + (1-\mu)\left(p_{\max} - p_i^k\right)\right] \times \Theta\left(p_{\max} - p_i^k\right)\Theta\left(q_i^k - q_{\min}\right).$$

Function u_i^k is capable of modelling the preference relation:

- *Reflexivity*, i.e., $(\forall \mathbf{x} \in X)\left(u_i^k(\mathbf{x}) \geq u_i^k(\mathbf{x})\right)$; the property is fulfilled by the function definition (function associates each element x of its domain to a **single** element u in its codomain, i.e., $u(\mathbf{x}) \geq u(\mathbf{x})$).
- *Completeness*, i.e., as a domain of the utility function is X, any pair of tuples from the decision space can be mutually compared, i.e.,

  $$(\forall \mathbf{x}, \mathbf{y})\left(u_i^k(\mathbf{x}) \geq u_i^k(\mathbf{y}) \vee u_i^k(\mathbf{y}) \geq u_i^k(\mathbf{x})\right),$$

  while function u_i^k is defined for every $p_i^k, q_i^k \geq 0$.
- *Transitivity*, i.e.,

  $$(\forall \mathbf{x}, \mathbf{y}, \mathbf{z} \in X)\left(u_i^k(\mathbf{x}) \geq u_i^k(\mathbf{y}) \wedge u_i^k(\mathbf{y}) \geq u_i^k(\mathbf{z}) \Rightarrow u_i^k(\mathbf{x}) \geq u_i^k(\mathbf{z})\right)$$

  that is given by the linear ordering property of the real numbers set (as a co-domain of u_i^k) function.

The utility function disposes with some extraordinary properties, which favour its application in the Machine-to-Machine communications. Its main predisposition is that it contains only the parameter μ that enables rather simple calibration. On the other hand, the existence of this single parameter has some impacts we should respect in its application.

- The interpretation of the parameter can be derived from the total differential definition:

  $$du_i^k = \frac{\partial u_i^k}{q_i^k} dq_i^k + \frac{\partial u_i^k}{p_i^k} dp_i^k, \quad q_i^k > q_{\min}, p_i^k < p_{max}.$$

  Equating the total differential equal to zero and providing some elementary manipulation, we obtain relation:

  $$\frac{dq_i^k}{dp_i^k} = -\frac{\frac{\partial u_i^k}{p_i^k}}{\frac{\partial u_i^k}{q_i^k}} = \frac{1-\mu}{\mu}$$

  that describes how large the increase of the throughput is if the prices are increasing by one monetary unit to preserve the end user satisfaction at the same level.
- Marginal utility MU (utility change echoed by the unity increase of the throughput / price) is given by:

  $$MU(p_i^k) = \frac{\partial u_i^k}{\partial p_i^k} = -(1-\mu) < 0$$

  and

  $$MU(q_i^k) = \frac{\partial u_i^k}{\partial q_i^k} = \mu > 0.$$

The above given results show that the price increase leads to the decrease of the end user utility, and the throughput increase implies the increase of the end user satisfaction. This is what is intuitively expected and shows that the utility function u_i^k conforms to the theory of economic decisions. On the other hand, the law of diminishing marginal utility does not work if Xing's utility function is applied, but it is assumed that in the case of the automated machine decisions, it can be neglected and the pros of the single parameter calibration outperform this disadvantage.

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