Mobility-aware Handover Strategies in Smart Cities

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***Abstract*—Supporting the Internet of Things and Smart City applications is one of the most important goals in the ongoing design process of 5G cellular systems. Another trend is an increasing focus on data-driven optimization and Self-Organized Networking, in order to automate network deployments and increase performance and efficiency. This approach, however, does not fully take advantage of the data generated by the Smart City. In this work, we propose to process and use the information flowing through the network from the city sensors to increase the awareness of the network itself, improving the communication performance. We exploit vehicular traffic data from the Traffic for London (TfL) sensor network to infer mobility patterns and improve the efficiency of LTE handovers.**

I. Introduction

Self-Organized Networking (SON) techniques are expected to be a cornerstone of future mobile networks: due to the ever growing number of connected devices, the complexity and variety of functions of a 5G network can only be managed with self-adapting optimization techniques [1]. The rapid growth of the Internet of Things (IoT) is one of the major contributors to this complexity: the massive deployment of connected sensors and actuators generates a significant amount of traffic [2] that can put networks designed for human communications under strain.

Smart Cities are one of the most important IoT applications: the data generated by a network of sensors distributed all around an urban area [3] is processed to help define policies and provide new services to the citizens. The volume of data that has to be transmitted and processed is significant; however, Smart City sensors are not just a burden on cellular networks, as the information they generate can be used by the network to make smarter decisions based on a greater awareness of the environment. The promise of higher efficiency and reduced operating costs can be an incentive for the network operators to support ambitious Smart City projects with pervasive sensor deployments.

This mutually beneficial relationship between Smart Cities and cellular networks is at the core of the "SymbioCity" concept, originally proposed in [4]. This work builds on that paradigm, exploiting vehicular traffic data from the London Urban Traffic Control (UTC) sensor network to dynamically adjust the asymmetric handover range expansion bias [5] in Heterogeneous Networks (HetNets). In particular, this parameter can be adapted without manual tuning from the cellular network operator, according to the average speed of the vehicular traffic in the cell area, following a SON approach driven by big data analytics. Handovers are expected to be a major issue in ultra-dense HetNets, and the technique we propose will improve the communication performance without triggering the well-known ping-pong effect [6], [7].

The rest of this work is organized as follows. Sec. II presents an overview of state-of-the-art techniques in traffic data analysis, SON and handover management, while Sec. III describes the Transport for London (TfL) traffic sensor network, the available data, and our analysis of the vehicular mobility patterns. We provide the details of our handover optimization technique in Sec. IV, along with an example application using the London traffic data. Finally, in Sec. V we make our final remarks and suggest some possibilities for future research.

II. Related Work

Smart Cities have been a very active field of research in the past few years, and there is a burgeoning interest in their potential from companies and governments worldwide [8]. Smart City sensors can communicate using dedicated low power networks, such as LoraWAN, SigFox and IEEE 802.15.4 [9], or they can use the existing cellular networks, with lower infrastructure costs (place&play paradigm), but with a possibly significant impact on existing human communications [10].

The use of big data-driven optimization at various scales (e.g., fog computing [11]) is one of the main 5G guidelines [12], [13], but the integration of the data from the cellular network itself with those available in a Smart City is still theoretical. Combining the knowledge of the external world that a Smart City can give with SON techniques might represent a big step towards a real cognitive network [14].

One of the network procedures that Smart City integration might help optimize is handover: as cellular networks become denser in response to the growing traffic demand in urban areas, and micro-, femto- and even picocells [5] are deployed all over the world, smart and efficient handover strategies become fundamental to maximize throughput and reduce Radio Access Network (RAN) and Core Network (CN) signaling. The SON approach is one of the most promising candidates to address these complex issues [15], and mobility pattern information is one of the most valuable assets that a Smart City can provide to the cellular network.

Mobility affects ultra-dense network performance significantly, as handover strategies need to adapt to it. The research on mobility models [16], [17] and their integration in communication protocols (e.g., Medium Access [18] or interference coordination [19]) is already ongoing, and using real Smart

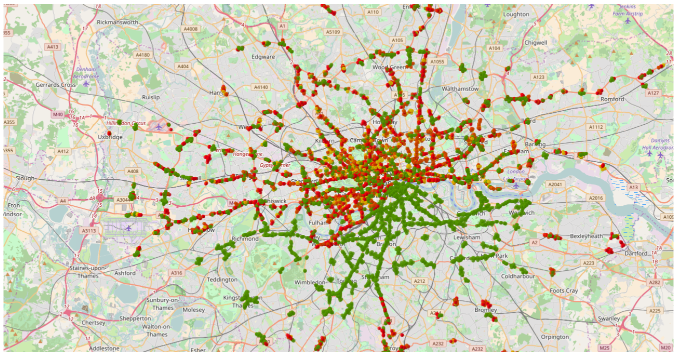

Fig. 1: Map of traffic in London from 12pm to 1pm on the 23rd of January, 2015. Free intersections are shown in green, heavily congested ones in red.

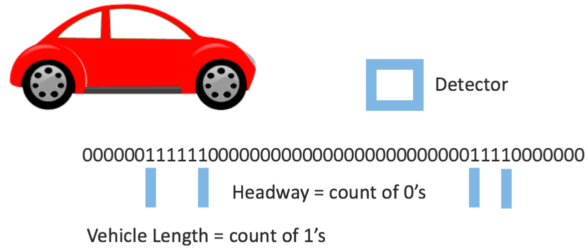

Fig. 2: Diagram of a traffic detector. Source: TfL.

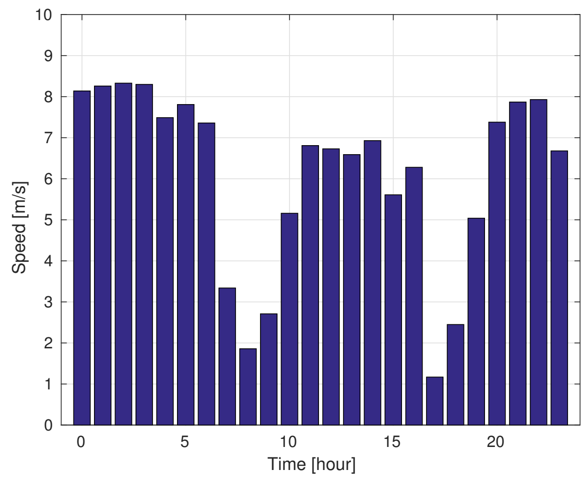

Fig. 3: Hourly average speed on the 23rd of January, 2015 at the intersection between Homerton High St. and Daubeney Rd.

City data as input for these techniques would reduce the uncertainty compared to purely statistical approaches.

While handover algorithms are well-studied and several decision criteria have been proposed in the literature [20], the most common ones are based on Received Signal Strength (RSS). 3GPP defines a baseline handover procedure for LTE in [21], and most studies focus on optimizing its parameters. The handover is triggered only if the difference between the serving and the neighboring cell RSSs is larger than a threshold value for the duration of the Time-to-Trigger (TTT) parameter. This is meant to avoid unnecessary handovers due to fluctuations caused by fast fading, but introduces a delay in the association with the optimal evolved Node Base (eNB), whose impact becomes more significant as the UE speed increases [22], [23]. An analytical model for optimizing the TTT is introduced in [7].

However, high handover delays might be just as damaging to the user experience as a strong ping-pong effect. In order to overcome this trade-off, we need to exploit other parameters, such as the hysteresis threshold. Biasing this threshold towards femtocells is already a standard practice to favor offloading from the Macro tier [5], and it is possible to adapt the bias based on the user mobility to reduce the handover delay problem caused by the TTT. In [24], the authors present a heuristic that reacts to late or early handovers and adapts the bias for each pair of neighboring cells. Another work jointly adapts the TTT and bias in a reactive manner [25]. In this paper we use real vehicular data from TfL in order to dynamically adapt the bias to the average speed of vehicles, avoiding the ping-pong effect and increasing the throughput.

III. Data Gathering and Analysis

The London UTC sensor network is composed of more than ten thousand sensors, buried in the road at critical junctions all across the city center. The Split Cycle Offset Optimization Technique (SCOOT) optimizer uses traffic data from the sensors to adapt traffic light waiting times dynamically, in order to reduce congestion. The raw sensor data of the first quarter of 2015 for the North and Central regions of London were publicly released by TfL. A sample map of traffic is shown in Fig. 1.

Each sensor is a simple presence detector: it senses whether a vehicle is above it every $T_s = 250$ ms, and returns a boolean output as depicted in Fig. 2. The resulting binary signal is packetized and delivered to a central server through different communication technologies.

In this work, we analyze the TfL dataset to extract the average vehicular speed at any crossing. Vehicle speed is not directly provided by TfL, but can be estimated using the detector output. If a vehicle of length L passes over a sensor at speed v, the detector will generate $n = \lfloor \frac{L}{vT_s} \rfloor$ ones in a row, followed by zeros when the vehicle has completely passed the sensor.

Therefore, assuming a reference vehicle length of $L = 4$ m, it is possible to get an estimate of the vehicle speed as:

$$v = \frac{L}{nT_s}. \tag{1}$$

Fig. 3 shows the evolution of the average speed measured by a single sensor over a whole day (namely, January 23, 2015): as expected, the speed of the vehicles is higher at night because of the lighter traffic, while during rush hour (from 8am to 9am

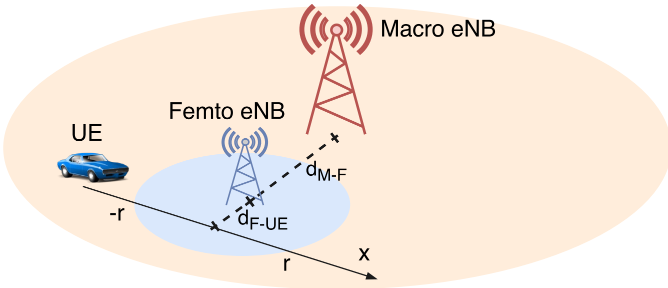

Fig. 4: UE trajectory in the considered scenario.

and from 5pm to 6pm) the average speed drastically decreases (the spatial distribution of traffic is shown in Fig. 1).

IV. Asymmetric Handover Bias Optimization in HetNets

After processing the sensor data as described in Sec. III, we use the vehicular speed to optimize the handover range expansion bias in a HetNet. This parameter is a constant, broadcast by the eNBs, that each User Equipment (UE) adds to the estimated Signal to Noise Ratio (SNR) of the neighboring eNBs when considering whether to handover or not [21]. We present a technique to dynamically adapt this parameter in Macro and Femto eNBs (MeNBs and FeNBs, respectively) in order to increase the capacity available to the UE.

In our scenario, one MeNB with transmission power P_{TX}^M and one FeNB with transmission power P_{TX}^F are placed at distance d_{MF} from each other. The two eNBs transmit at different carrier frequencies (off-band HetNets) to avoid cross-tier interference [26]: f_0^M for the MeNB and f_0^F for the FeNB. Following this assumption, we do not consider interference in the remainder of this paper, thus the SNR is used as the handover metric. Both tiers have equal bandwidth B. All the parameters of the simulations are summarized in Table I and are taken from [27], [28].

We consider a channel model with Friis path loss and log-normal shadowing. Denoting by P_{RX}^H the power received by the UE from the HeNB, with $H \in \{M, F\}$, and by P_{TX}^H the transmission power of the HeNB, we get

$$P_{RX}^H(t) = P_{TX}^H(t)\Psi_{SH}\alpha(t)h(f_0, \beta, d); \qquad (2)$$

Parameter	Value	Description
P_{TX}^M	46	MeNB transmission power [dBm]
P_{TX}^F	26	FeNB transmission power [dBm]
f_0^M	900	MeNB carrier frequency [MHz]
f_0^F	1800	FeNB carrier frequency [MHz]
B	20	Bandwidth [MHz]
d_{M-F}	40	Distance between MeNB and FeNB [m]
d_{F-UE}	10	Distance between FeNB and UE [m]
σ_M^2	8	MeNB log-normal shadowing variance
σ_F^2	4	FeNB log-normal shadowing variance
β_M	4.28	MeNB pathloss exponent (NLOS)
β_F	3.76	FeNB pathloss exponent (LOS)

TABLE I: Parameters used in the simulation.

$$\gamma_H(t) = \frac{P_{RX}^H}{N_0 B}, \qquad H \in \{M, F\}; \qquad (3)$$

where Ψ_{SH} is the shadowing gain, which is distributed as $\mathcal{N}(0, \sigma)$ when measured in dB, $\alpha(t)$ is the multipath fading gain, and $N_0 = -143.82$ dBW/MHz is the noise power spectral density. The channel gain $h(f_0, \beta, d)$, which accounts for the path loss attenuation with exponent β, is given by

$$h(f_0, \beta, d) = A\left(\frac{c}{4\pi f_0}\right)^2\left(\frac{d}{d_0}\right)^{-\beta}, \qquad (4)$$

where c is the speed of light, d_0 is the reference distance of the far field model [29], and A is a constant. The parameter β is chosen from [28] in order to model respectively Line of Sight (LOS) and Non Line of Sight (NLOS) channels for the FeNBs and the MeNBs. We assume indeed that the FeNBs are deployed on the streets, and thus have a direct path to the UEs, while MeNBs are on top of buildings [30]. Finally, $\gamma_H(t)$ denotes the SNR at time t for the HeNB and is given by Eq. (3).

For the sake of simplicity, we assume that one UE is attached to the MeNB, moving as in Fig. 4 with constant speed v following a straight trajectory X. The UE speed at any time is derived from the TfL data as explained in Sec. III. We consider the UE to move at the average speed of the traffic around it. The data provided by the TfL sensors, indeed, does not allow to track the speed of a single vehicle. Moreover, the handover bias is a common parameter for all the UEs in the area. Finally, the time scale at which it is possible to update the handover bias does not allow to track the acceleration and deceleration of vehicles at crossing lights.

The SNR at the UE while moving depends on the distance from the Macro and Femto eNBs. As we can see in Fig. 5, the SNR from the FeNB is higher than that from the MeNB when the UE is close to the FeNB. The coverage area of the FeNB is defined as the area in which its SNR is higher than any other cell's.

In this scenario, the UE has to start a handover procedure towards the FeNB when the condition

$$P_{RX}^F(t) + \gamma_{th} > P_{RX}^M(t) \qquad (5)$$

holds for a period of time equal to the TTT, as specified in [31]. Note that in the simulation we have assumed $\gamma_{th} = 0$ for the sake of simplicity. We hence set TTT $= 512$ ms [21], which is high enough to avoid the ping-pong effect but small enough to get a reasonable handover delay.

This TTT value improves the performance of the system considerably when the traffic is moving slowly, but reduces the Theoretical Spectral Efficiency $\nu = \log_2(1+\gamma)$ when the UE speed is too high. This is because a fast-moving UE exploits the advantages of the FeNB for just a short time, while it remains in the FeNB for TTT seconds after the condition (5) is reversed.

To make sure that the UE starts the handover towards the FeNB as soon as (5) is verified, an asymmetric handover bias can be applied to P_{RX}^F. When the handover is towards the

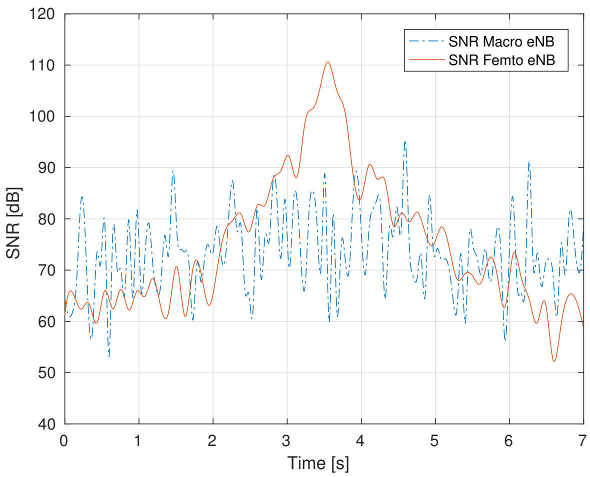

Fig. 5: $\gamma_M(t)$ (dash-dotted) and $\gamma_F(t)$ (solid) with a UE speed of 16 m/s. Multipath fading is not considered in this figure for the sake of visual clarity.

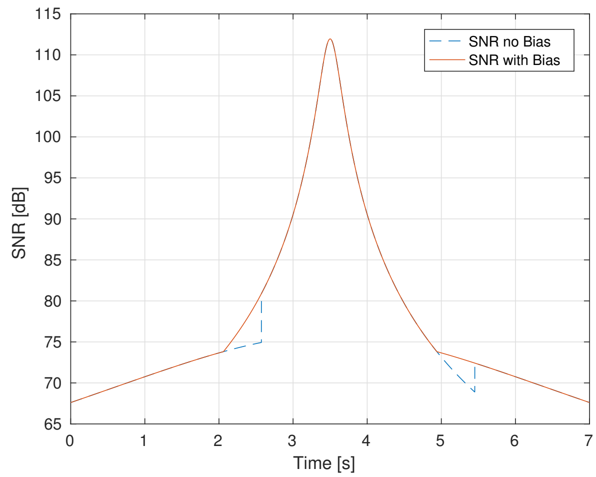

Fig. 6: $\gamma_M(t)$ and $\gamma_F(t)$ with a UE speed of 16 m/s. Multipath fading and shadowing are not considered in this figure for the sake of visual clarity.

FeNB, the bias needs to be positive to anticipate the beginning of the procedure, while when the handover is from the FeNB to the MeNB, the bias must be negative. We define the SNR difference in position x along the trajectory as

$$\Delta(x) = \bar{\gamma}_F(x) - \bar{\gamma}_M(x); \tag{6}$$

where $\bar{\gamma}_F(x)$ and $\bar{\gamma}_M(x)$ are the average SNRs from the two eNBs when the UE is in position x. Moreover, the trajectory of the UE draws a chord within the coverage area of the FeNB, with linear coordinates $-r$ and r with respect to the central point of the chord, as shown in Fig. 4. The optimal value of the bias is then given by

$$B_1 = \Delta(-r - vTTT) \tag{7}$$

$$B_2 = -\Delta(r - vTTT). \tag{8}$$

If the FeNB uses the optimal bias, the handover will be performed exactly on the edge of its coverage area.

By applying B_1 and B_2 to P_{RX}^F, (5) becomes

$$P_{RX}^F(t) + B_1 > P_{RX}^M(t) \tag{9}$$

while the condition to leave the FeNB is

$$P_{RX}^M(t) + B_2 > P_{RX}^F(t). \tag{10}$$

The difference between $\bar{\gamma}(x)$ with or without bias can be viewed in Fig. 6. Since the Theoretical Spectral Efficiency ν depends logarithmically on $\bar{\gamma}(x)$, using this asymmetric handover bias will increase ν, fully exploiting the FeNB. This improvement can be seen in Fig. 7. This figure is obtained calculating the average ν over 100 Monte Carlo simulations with independent shadowing and fading for a UE speed from 4 m/s to 20 m/s.

In the simplest case, in which there is no FeNB and the UE is always attached to the MeNB, ν_{MeNB} is essentially independent of the UE speed. The second case is a legacy handover

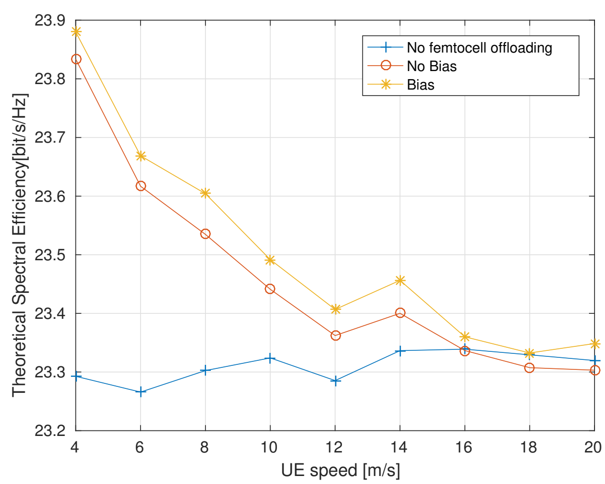

Fig. 7: Theoretical Spectral Efficiency as a function of the vehicular traffic speed v.

with no bias: as the plot shows, ν_{noBias} decreases drastically as the speed increases, as the delay in the handover caused by the TTT wastes most of the performance improvement from the FeNB. If the UE speed is higher than 16 m/s, the handover is so late that the UE would do better to disregard the existence of the FeNB completely: as soon as the UE finishes the handover process, it has to start it again since it has already moved outside of the FeNB coverage area. In the last case, in which the optimal asymmetric handover bias is applied, ν_{Bias} decreases when the speed increases, since the time in the FeNB coverage area becomes shorter, but the FeNB is always fully exploited. Since any moving UE spends a small fraction of its time close to the border between two cells, the gain in terms of absolute capacity is not large; however, the smart policy can prevent capacity drops before and after handovers, which

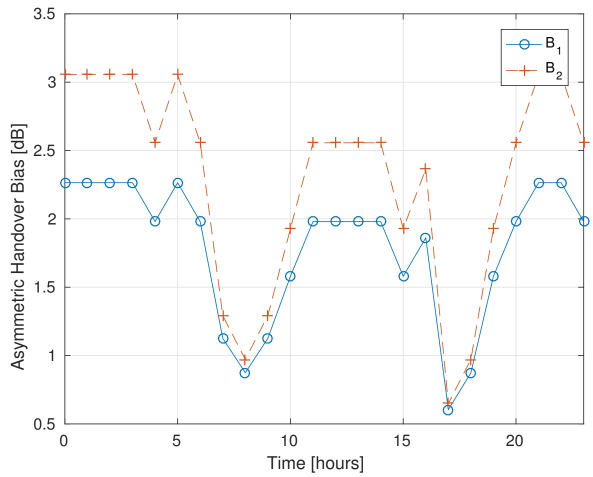

Fig. 8: Optimal handover bias throughout the day on the 23rd of January, 2015.

already imply a possible hiccup in the connection.

The presence of the FeNB is detrimental to vehicular UEs in the legacy scenario (no handover bias) if the speed of traffic exceeds 16 m/s, since $\nu_{\text{noBias}} \leq \nu_{\text{MeNB}}$. However, setting the optimal asymmetric handover bias allows network operators to keep the FeNB switched on, benefiting both pedestrian and vehicular UEs, in any situation, since $\nu_{\text{Bias}} \geq \nu_{\text{MeNB}}$ at any speed.

The optimal asymmetric handover bias over the course of a day for a specific intersection can be calculated from the TfL data as explained in Sec. III; the speed evolution shown in Fig. 3 results in the bias shown in Fig. 8. As expected, the handover bias is higher at nighttime, as the average speed of traffic is far higher than during the day. For this reason we can fix a threshold for the handover bias beyond which FeNB can be shut down in order to save energy, leaving all traffic to the MeNB. If we fix this threshold to 3 dB, then the FeNB will turn off only in the middle of the night, when the load on the MeNB is very light.

V. Conclusion And Future Work

In this work, we presented an optimization method that exploits road traffic data to adapt the handover range expansion bias in a heterogeneous cellular network. We showed that knowledge of the traffic on each road and of its speed can be used to improve the handover performance, and argued that a tighter integration between the smart city and the cellular network that serves it might be one of the most promising approaches towards Self-Organized Networks.

In particular, we exploit our knowledge of the speed of the traffic at any intersection to adapt the femtocell range expansion bias and mitigate the inefficiency caused by the TTT without incurring in the ping-pong effect; since the calculation is simple, this can be easily implemented in real time. An extended version of this paper with additional results and discussions can be found in [32].

The technique we used in this work is just an example of the possible benefits that the SymbioCity paradigm can bring to cellular networks: in the future, we plan to systematize this approach and integrate existing and new SON techniques along with data analysis from different Smart City sensors, studying and optimizing their interactions using data from both the cellular network itself and the smart city around it. For example, if there existed sensors that track the movement of each single vehicle, the handover process could be further improved by optimizing the relevant parameters for each user. Moreover, the possibility to adapt proactively to predicted changes in the speed of the traffic flow is also worth investigating; machine learning and regression methods, fed with past data and traffic control information as input, are a possible tool to accomplish this. Another challenge for future systems of this kind is the integration with novel technologies such as mmWave, which requires intelligent mobility management.

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