A Layered and Grid-Based Methodology to Characterize and Simulate IoT Traffic on Advanced Cellular Networks

Filippo Malandra, Hakim Mellah, Abbas Dehghani Firouzabadi, Constant Wetté, and Brunilde Sansò

Abstract

With the advent of increasingly large smart-city and IoT deployments, meeting communication requirements in terms of throughput and delay becomes more and more challenging. Network performance analyses must be carefully addressed, usually through simulation software. Because of the large-scale nature of the IoT, traditional simulation methods do not scale well. Thus, in this article, we present two original contributions that provide scalability to network performance simulations. First, we introduce the concept of multi-layered analysis for large-scale networks and, second, we provide a method to quickly associate propagation measures to user equipment. The proposed concept is based on the de-coupling of the access and the user layer and the introduction of a so-called grid layer created by pre-computing propagation measures in the considered area. These propagation data are then ready to be used in the network performance simulation. To show the eficacy of the proposed approach, several realistic use cases are analyzed along with a comparison of the time needed to simulate with and without our grid-based methodology. Numerical results show that a significant reduction of computational time is achieved by employing our approach, especially in large-scale networks. Experiments were also performed to study the trade-off between grid granularity, RSS precision errors and computational time, showing that the method can be flexibly adapted to the planners' requests.

Introduction

Due to the rising number of people moving to large cities, the provisioning of services and resources, such as health, transportation, parking, and power, is becoming increasingly complex. To cope with this intricacy, cities are becoming *smart* and deploying a vast number of connected devices, such as smart meters, sensors, and actuators. The interconnection of those devices is commonly referred to as the Internet of Things (IoT). Cellular networks, such as LTE and 5G, are a favored solution due to their existing infrastructure, large bandwidth availability, and quasi-ubiquitous coverage. However, the massive introduction of smart devices can degrade the network performance and, consequently, not only jeopardize the quality of service experienced by human users but also the functions of the very smart systems they are supposed to support.

As a consequence, networks must be carefully calibrated for this new massive traffic. Therefore, network performance studies are needed to

- Characterize the type of trafic generated by smart devices
- Analyze their impact on the cellular networks supporting large-scale smart systems
- Study the impact on the applications using the network.

The most common approaches to analyze network performance are based on mathematical models, simulation software, or trafic traces provided by cellular operators [1].

The performance evaluation of IoT networks is a fairly recent topic as we can see in the following articles. Reference [2] implements the main functionalities of enhanced machine-type communications (eMTC) and narrow-band IoT (NB-IoT) in the NS-3 simulator [3]. Using energy consumption, latency, and scalability as criteria, the performance of both systems is compared. Reference [4] introduces a framework to simplify and systematize the evaluation of the performance of an IoT communication technology based on NS-3 simulation. This framework includes the definition of a scenario and its Key Performance Indicators (KPIs) and their evaluation. Although these studies simulate more than a thousand devices, they are still not scalable enough for large-scale applications throughout a city. A study of large-scale IoT networks using stochastic geometry tools has recently been published in [5]. The authors model the spatial distribution of homogeneous IoT devices and calculate the delay bound of transmissions for certain exceptional cases. Despite this, there is still a large gap between the performance in the real world and approximated theoretical expressions. In addition, stochastic geometry studies often ignore the mathematical model of dynamic processes such as mobility and handover.

To understand why it is so dificult to obtain realistic network level KPIs from very large-scale simulations we need to explore how propagation is treated. Indeed, the first step in performance studies consists in characterizing the propagation between each User Equipment (UE) and its serving antenna. To do so accurately, geographical data on the position of both IoT devices and network elements are needed. There exists a large body of literature that has proposed a comprehensive variety of propagation models to predict and characterize the quality of the signals transmitted from the UEs to the base stations and vice versa. A popular approach followed in state-of-the-art propagation models relies on ray-tracing-based techniques [6]. However, due to their complexity, these techniques cannot be easily scaled to the extremely large size of smart-city networks. Hence, numerous empirical models employ deterministic expressions. For instance, popular propaga-

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tion models are COST-231 [7] and 3GPP TR 38.901 [8], which are designed for different environments and scenarios. However, the complexity of these models makes it impractical to compute them *online* because they would slow down the network simulation and undermine its scalability. Even though most of these computations can be computed *offline* and then used in the simulation, this would not be suficient to reduce complexity. These propagation models rely on the position of UEs and base stations to operate, and changes in the network topology (such as in the presence of a base station failure) or the user placement (such as in a mobility scenario) would entail the need to re-compute the propagation between (some or all) UEs and their serving base stations.

This effect appears evident in some of the most popular public simulators of the data plane of the Radio Access Network (RAN) and Evolved Packet Core (EPC), such as Simu5G [9], LTE-Sim [10], and NS-3 [3]. Even though details on how these simulators integrate the propagation computations have not been the object of publications, their public nature allowed us to dive into the code and realize that to update the user's received signal or the interference imposed on the user, the calculations related to the channel model are performed each time there is a change and for every single user and antenna. Comparative analysis of running time (using NS-3) for some propagation models has been presented in [11]. A key result that was found in this work is that *the simulation computational complexity grows quickly with the number of users and base stations*. Furthermore, in [12], the computational time for the different propagation models has been illustrated. It has been shown that the computation of path loss models takes about 5 μs to 10 μs per packet in NS-3 simulator. One possible solution could be to reduce the rate of path loss updates for every UE by assuming static (or slowly varying) scenarios. However, this would entail the storage of path loss information for every user in the system, which is impractical in scenarios with high user density such as in smart cities. As a result, it is too dificult for these tools to simulate the thousands of devices and hundreds of base stations that are needed for large-scale IoT urban systems.

To overcome these issues, the object of this article is to present a new methodology to study and characterize IoT traffic transported by a city-wide cellular infrastructure that involves a significant complexity reduction for the wireless channel modelling. The proposed methodology decouples the system in layers and makes use of a middle layer (between the network and the users), based on the offline grid-based computation of the wireless channel propagation. This structure permits an extensive use of parallel computing techniques thus reducing the computational time required to perform this task. Moreover, we also show how the results of this computation can be quickly associated to the large number of nodes in the user layer, exploiting known geographical properties to reduce the computational time. The modular structure of this methodology easily permits an integration with complex mathematical analysis models and with off-the-shelf network simulators.

Although its main advantage is the possibility to perform a considerable part of the computations *offline*, our methodology is well-suited for dynamic scenarios with local changes in the topology: examples of such scenarios, such as the failure of base stations or the mobility of users, have an impact on a limited geographical area within the area of interest. Therefore, the problem is circumscribed to a subset of the rectangles in the grid (hereafter referred to as *grid points*) thus requiring an *online* computation only on the affected geographic areas. A quick and computationally eficient method to associate UEs to grid points is also presented. The possibility to quickly retrieve propagation data and use them in *simulation runtime* is a key feature of the proposed methodology.

It is important to highlight that the proposed methodology purely focuses on *large-scale propagation effects*, such as path loss. While *small-scale propagation effect*s, such as frequency-selectivity (multi-path) and time-selectivity (Doppler), are extremely important and can severely degrade the propagation

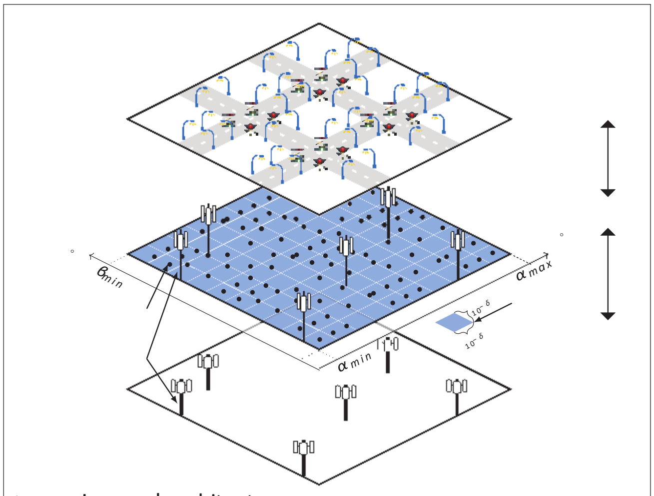

Figure 1 Layered architecture.

of a wireless signal, they mainly occur over very short distances (e.g., a fraction of a wavelength) and are not dependent on the geographical location of users. In fact, these small-scale phenomena are usually modelled by means of random distributions. In this study, we consider advanced cellular networks deployed over extended geographical areas, such as a *smart city*, with hundreds of thousands of base stations and users: therefore, accounting for small-scale effects in such scenarios would be impractical from a computational standpoint.

The remainder of this article is organized as follows. The overall layer-based architecture of our system is presented: details on the network access, user, and grid-based layers as well as the propagation characterization method and the network analytics component are included in dedicated subsections. A discussion on realistic use cases and numerical results on the computational eficiency of our approach are provided. Concluding remarks are drawn.

System Modelling

Layered Architecture

The basic architecture of the considered system is illustrated in Fig. 1, where it is possible to notice the 3 layers our analysis is based on. At the top of the figure we have the User layer. In this work, we predominantly focus on IoT devices but the analysis can be extended to other type of devices. This layer, as shown in the figure, contains all the systems that would make up a smart city, such as houses, smart buildings, street and traffic lights as well as other elements that may produce telecommunication traffic that is captured by the telco infrastructure (car, buses, trains, cameras, alarms, etc.). On the bottom we have the Network Access layer. This layer contains the base stations and antennas that are used to provide cellular connectivity to the users.

In classical simulation modelling, those two layers would be considered together as the first step in a simulation would be to evaluate the propagation between each user and a serving base station. However, when studying the quality of signal propagation at a given user, one not only needs to consider the serving base station, but also the neighbor base stations, as they generate disruptive interference. As a consequence, the complexity of the propagation analysis grows with the number of users and the number of antennas/base stations.

In our model, we introduce a grid-based layer, which is used as a middle layer between the user and network access layers. By way of this modelling detail, we can precompute the propagation quality at each point of the grid and then simply associate users to the closest grid point. A flowchart of the proposed methodology is illustrated in Fig. 2. The characteristics of each

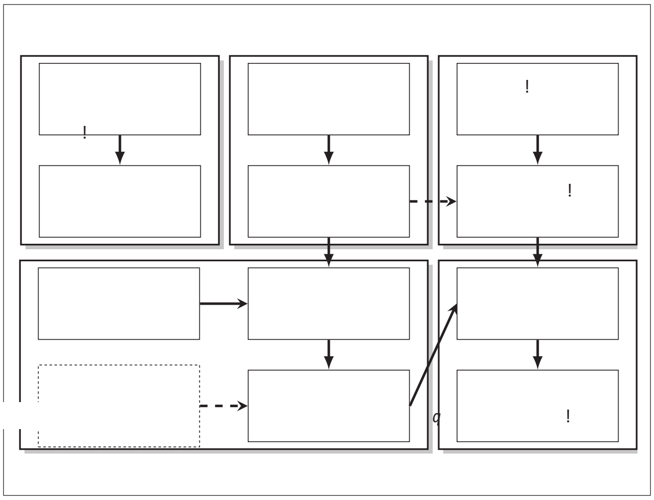

Figure 2. A flowchart of the proposed methodology.

step of the proposed grid-based methodology are presented in the remainder of this section.

Network Access Layer

The first layer in the analysis is composed of all the network elements that are used to provide radio access to UEs. In particular, we have a set B of base stations and the sets A_i of all the antennas installed at base station $i \in B$. In what follows, we will solely focus on the antennas.

Network Nodes Placement: The first step in this layer consists in the placement and characterization of the base stations and antennas. To perform this operation, we used real data from [13]. From this regularly updated database, it is possible to retrieve the GPS location of all the base stations and antennas installed in Canada as well as key features, such as the transmitted power, the height, the carrier frequency, the orientation and the tilt. These data are used to accurately characterize the network access layer.

Network Generation: Based on the database, it is possible to filter all the network elements that are operational within the area of interest. These nodes are allocated along with their features, which will be used to characterize the propagation in the grid.

Grid-Based Layer

Grid Parameter Definition: As also illustrated in Fig. 1, a grid is composed of a number of *grid points*. To create a grid we first need to identify the latitude and longitude bounds of the geographical area under study given by the tuples (α_{min}, α_{max}) and (β_{min}, β_{max}), respectively. Next, we have the grid granularity δ, that represents how small should be the area of each rectangle in the grid. Of course, this area depends on how finely we want the propagation precision to be and it is closely dependent on the type of antennas that are present in the study. The higher the frequency, the higher the precision needed. For example, a value of $\delta = 4$ entails that the generated grid is composed by grid points placed at an *angular distance* of 10^{-4} degrees. To compute the linear distance between two points on earth, we need other information, such as latitude and longitude, given the irregularities in earth surface, which is not a sphere. However, using a spherical approximation, we can easily show that the distance L (expressed in meters) between 2 points at an angular distance of $10^{-\delta}$ degrees is given by the formula $L = 1.119 \cdot 10^{6-\delta}$ (assuming an Earth radius of $6.371 \cdot 10^6$ m). Therefore, $\delta = 5$ yields grid points at a distance of roughly 1.1 m whereas with $\delta = 6$ we can estimate 11.1 cm between the centers of adjacent grid points. A larger grid granularity, despite its increased complexity, is necessary in high-frequency scenarios, such as 5G FR2 networks, where the signal quality can considerably differ even at a short distance.

Grid Generation: Once the size of the grid and the rectangles are established, propagation models should be put in place for every user in the grid. However, all the users inside a particular grid point are assumed to receive the same power, that is equivalent to the power received in a particular point of the rectangle (the center or a corner). Because the grid rectangle will have the lowest calculation granularity, we equate it to a point and call it a *grid point*. In the subsections below, we will provide more details on propagation modelling as well as the UE and the grid association.

Propagation Characterization

Choice of A Propagation Model: The coverage area of a cell depends on various factors such as the transmit power of the base station, antenna directivity, antenna tilt, and path loss (including characteristics of environment). As a result, the received signal strength (RSS) from an antenna $a \in A$ to a grid point $g \in G$, hereafter denoted with RSS , is defined as a function of the above mentioned elements. For sake of simplicity, we can generally state that $RSS = f(d, \theta)$, where d is the Euclidean distance between antenna a and grid point g, θ represents the angle between the antenna direction θ and the segment between a and g. Finally $q \in Q$ is the chosen propagation model.

There are several well-known propagation models in the literature that are specific for some type of environment and level of frequency, such as COST-231 [7]. A recent popular propagation model introduced for cellular networks is 3GPP TR 38.901 [8]. Different scenarios are considered for modeling various environments: RMa, UMa, UMi, Indoor, Backhaul, D2D/V2V, etc. For each scenario, a set of equations that account for features recreating the environment are considered, both in the Line-of-Sight and Non-Line-of-Sight cases.

It is worth mentioning that our framework does not need to function exclusively with propagation models. In fact, real measurements could very well be incorporated in the grid assessment: for instance, if a statistically significant sample of i real measurements of the RSS in a given grid point $g \in G$ (denoted by $RSS(i)$) is available, the theoretical RSS value RSS can be replaced by the average of the sample $E(RSS(i))$.

Propagation Computation: The first objective of the proposed propagation computation method, described in Algorithm 1, is to compute RSS , which represents the received signal strength from antenna a at grid point g. In this algorithm, the propagation model (Cost, Hata, 3GPP, …), environment (urban, rural, …), the area of interest $\mathcal{Z}$, receiver height, cutoff threshold γ and granularity δ are considered as inputs. Given an antenna a and a grid point, to limit the complexity of the algorithm, we introduce the parameter γ as the minimum signal strength for an antenna to cover a grid point. The distance where RSS equals γ represents the maximum range of antenna a, i.e., Δ .

As described in Algorithm 1, the first step in the process is to generate grid points g considering an area of interest $\mathcal{Z}$ and a granularity δ. Afterwards, for each antenna a, we can calculate the maximum range Δa depending on the chosen propagation model q and the cutoff threshold γ (in the direction of maximum radiation strength). Then, for each point of the grid, we calculate the distance d to the antennas *in range*. If the distance is less than the maximum range of the antenna, we compute the angle between the point and the BS. Next, we get the antenna gain at the angle θ using the antenna patterns, usually provided by the antenna manufacturers. After that, we compute the path loss between each point and the antennas based on the chosen propagation model. Subsequently, we compute $RSS \ \forall a \in A, \forall g \in G$.

Grid-Based Propagation Map: Once the values for RSS are computed for all grid points and all antennas, we need to create the lists ξ of *serving antennas* at each grid point g. A toy example to illustrate the way to generate the list of serving antennas ξ for all the grid points $g \in G$ is provided in Fig. 3. This list, especially in crowded urban scenario, can be utterly large because of the short distance between antennas. To reduce complexity, we have limited the size of the lists ξ_g to k elements. These lists are sorted by decreasing values of $RSS_{a,g}$. This computation completes the characterization of the grid-based propagation map of the area of interest $\mathcal{Z}$.

User Layer

After allocating the network, generating the grid, and characterizing the propagation, the following step is to model the user layer in Fig. 2. The two main operations are the *UEs placement* and the *UEs-grid association*, described below.

UEs Placement: The location of UEs may be random, fixed or pre-established, depending on the type of system and application. For instance, if we assume smart-city sensors and actuators as UEs, they will probably be located at the premises of some city buildings, urban signs or urban furniture (trafic lights, pedestrian crossings, city lights, cameras, etc.). UEs can also be mobile, with a random mobility (i.e. trafic watches for joggers) or mobile with pre-established mobility, such as buses or bicycles in a bicycle path.

UEs-Grid Association: The last step consists in associating a UE to a grid point in the area of interest. The pre-computation of the lists ξ_g (as described earlier) permits retrieving the antennas that can serve each UE as well as the quality of the link (dependent on the *RSS*). This association needs to be performed anytime a UE generates trafic as it is used to determine the throughput, the delay and other network KPIs. Thanks to the way the granularity parameter δ is defined, the association of a UE u (with GPS coordinates lat_u and lon_u) can be complet-ed by simply rounding lat_u and lon_u to δ decimal places. This operation permits to quickly identify the grid point g (to which UE_u is mapped) and retrieve the list of serving antennas ξ_g. The success of the proposed methodology lies in the fact that it can be applied to both static and dynamic scenarios. When UEs are moving, the UEs-grid association needs to be updated more or less frequently depending on the UEs speed and trajectories, on the number and distance of antennas, and on the granularity.

Network Analytics

Network Simulator: Once the user layer is completely defined and the grid-based mapping is put in place, we have all the necessary elements to perform with ease any large-scale simulation. Different IoT applications can be assigned to different UEs and we can play with the intensity as well as with the statistical behaviour of those applications to extract information about a current system, or about "what-if" scenarios (failures, extreme congestion, security attacks, etc.). Further details on the simulator used in this research are provided earlier.

Performance Analysis: The simulation produces very detailed KPIs related to the networking performance of the application for all the scenarios that can be considered. These KPIs can then be used for data analysis and Machine Learning (ML) methods both for situational detection as well as for event forecasting. It is worth mentioning that the networking data do not only provide information about the network but, with smart modelling, can also indicate what is happening with the system (smart-grid, tele-medicine, etc.) that is relying on the infrastructure.

Use Cases and Numerical Results

To show the effectiveness and usefulness of the proposed methodology, in what follows, we compare the execution time of the same network simulation software with or without the grid-based middle layer. We have also devised 3 real-world scenarios to present possible use cases for the proposed method.

Performance IoT Simulator

In this study, we used the Performance IoT Simulator (PIoT), which is designed to analyze the performance of large-scale IoT networks in smart cities [14, 15]. In particular, PIoT permits simulating the data plane of the LTE RAN and EPC using real geographical data on the positions of both IoT users and network elements. PIoT — available at http://www.piotsimulation.com — also features grid-based calculations, random access, packet generation, packet transmission, while providing users with the possibility to simulate failures and user mobility. An array of KPIs are available to better study the network performance when using PIoT.

```
Inputs:
  • Antennas a ∈ A
  • Chosen propagation model q
  • Cutoff threshold γ
  • Granularity δ
  • Area of interest Z: (α_min, α_max, β_min, β_max)
  • Other params (e.g., Environment, receiver height, and
    transmitted power)
Outputs:
  • Grid points g ∈ G
  • ∀g ∈ G, ∀a ∈ A, RSS_a,g from antenna a to g
  • ∀g ∈ G, ordered list ξ_g of antennas covering g
Initialization:
  • Given δ, generate grid points g in area Z •
    ∀g ∈ G, ξ_g = {}
for all Antennas a ∈ A do
    Given q, find the maximum range Δ_a of antenna a
    for all Grid points g ∈ G do
        Calculate distance d_a,g
        if d_a,g ≤ Δ_a then
            Compute the angle θ_a,g
            Find antenna gain at θ_a,g
            Compute RSS_a,g = f_q (d_a,g, θ_a,g)
            Add the pair (a, RSS_a,g) to ξ_g
        end if
    end for
end for
Sort ξ_g by decreasing values of RSS_a,g
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ALGORITHM 1 Proposed grid-based Method.

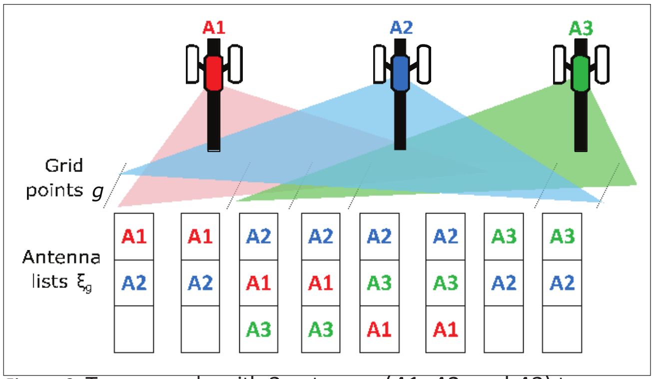

Figure 3. Toy example with 3 antennas ($A1$, $A2$, and $A3$) to illustrate how lists of serving antennas ξ_g are selected.

Simulation Results

We performed the simulation for an LTE cellular network in a selected area of the city of Montreal. In the following scenarios, we considered an application with more than 330000 residential addresses in Montreal as UEs and an average density of 1000 users/km^2. Data on the location and on the characteristics of the antennas and base stations are retrieved from [13]. For our simulation, we selected the LTE base stations of a specific provider in Montreal. We considered 5 different scenarios with 1,4,16,64,256 km^2 simulation areas, 10,24,47,95,221 base stations and 2000,8000,43000,119000,174000 users, respectively.

Only uplink trafic is considered in this scenario with packet interarrival times exponentially distributed with mean λ (ms). The packet length is also exponentially distributed with mean 1000 bytes. The overall number of available resource blocks is

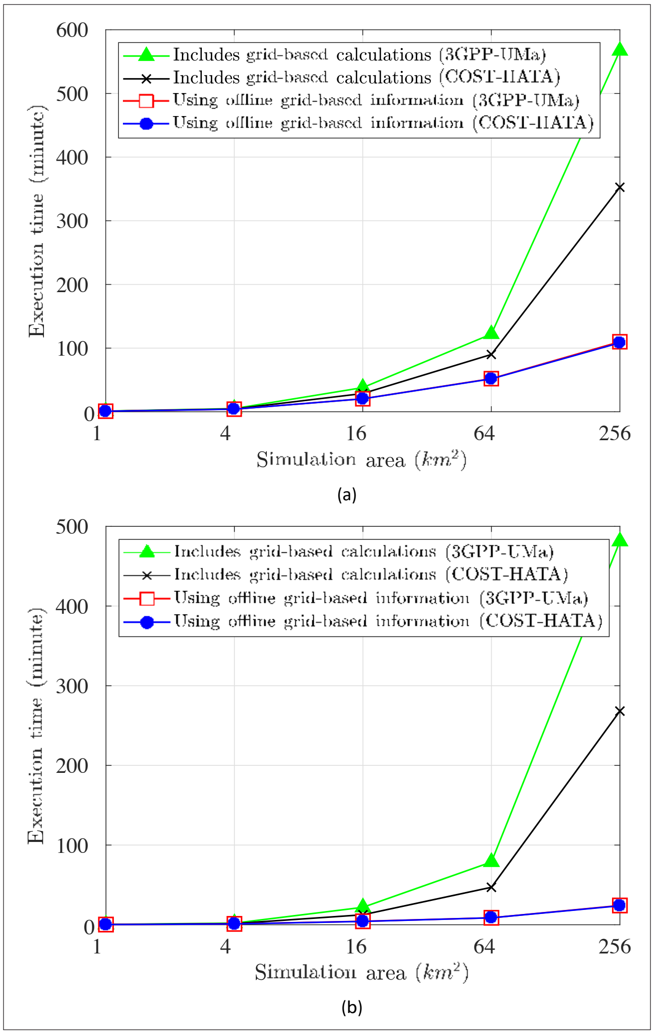

Figure 4. Comparison of the execution time with/without gridbased layer with different mean packet inter-arrival time λ: a) λ = 50 ms; b) λ = 1 s

50 (corresponding to a 10 MHz bandwidth). The simulator is performed on an Intel(R) Core(TM) i7 CPU at 3.40 GHz, with 32 Gb of RAM, a Linux Red Hat 4.8.5 operating system. We ran the smart city simulator for a duration of 10 seconds (equal to 10000 subframes of LTE).

First, we compute the coverage map of the simulation area using our grid-based program. We assume the grid granularity δ = 4 and minimum signal strength γ = –100 dBm. Two propagation models are considered: COST-HATA model and 3GPP model in the UMa Scenario. Then, when the coverage information is computed, we utilize it offline in the smart city simulator.

Figure 4 shows simulation results for high trafic (top figure) and low traffic (bottom) with mean packet interarrival times of λ = 50 ms and λ = 1 s, respectively. The figure depicts the execution time (expressed in minutes) versus the simulated area (km^2) in two cases:

1. When the middle layer is not used and the propagation characterization is performed online
2. When the simulator uses the pre-computed grid-based data to avoid excessive online computation. The two cases were run each with the 3GPP-UMa and the COST-HATA propagation models.

Increasing the area of interest $\mathcal{Z}$ causes an increase in the computation time with both techniques, however, in the case of online propagation computation, we can observe a steeper increase in the time required to complete the simulation. Note that, for the pre-computed grid scenarios, the execution time of the simulation using the 3GPP-UMa and the COST-HATA models are almost identical. The modification of propagation models only changes the users serving base station and the scheduling of packets. Therefore there is just a small change on the simulation time that cannot be seen in the figure.

It can be inferred that the introduction of the middle layer has reduced the dependency of the computational time on the number of network elements. This is a very important result because it allows scaling up the size of the considered networks, which is a key feature when it comes to the analysis of large-scale networks, such as in a smart city.

Accuracy Analysis of the Grid-based Methodology

To verify the accuracy and performance of our proposed grid-based approach, we have analyzed two parameters:

1. The Root Mean Square Error (RMSE) of the RSS observed in the grid-based simulation with respect to a simulation without grid
2. The execution time to perform a grid-based simulation.

We have plotted these parameters in Fig. 5, where a straight black curve represents the RSS-RMSE and a green dashed line represents the execution time. The grid size was variable with the granularity parameter δ ranging from 2 to 6. We have conducted simulations using the Cost-HATA propagation model in a 4 km^2 area with 8000 users. Figure 5 illustrates the trade-off between execution time and accuracy. On the one hand, when δ is increased, the RSS-RMSE decreases as the size of the grid points becomes smaller. In particular, the RSS-RMSE tends to 0 when δ = 6. However, the execution time is significantly increased as the RSS computation needs to be performed for a larger number of grid points in the considered simulation area. On the other hand, one can sacrifice accuracy to reduce the execution time. Therefore, the user carrying out the grid-based simulation study can select the best granularity parameter depending on the network size and the accuracy and computation requirements.

Use Cases

In what follows, we study three different scenarios characterized by

1. Static UEs
2. Mobile UEs
3. Failures and congestion in the network.

Static Devices: This is the case in which all devices are fixed. Each type of device may belong to a particular application (i.e alarms, cameras, traffic lights, etc.) and, therefore, will create a specific type of trafic. To characterize the trafic distribution (in particular, packet arrivals and packet length), several mathematical distributions can be used, such as Poisson, exponential, log-normal, and Gaussian.

In this case, the propagation is characterized only once and its results (i.e., $RSS_{g,a}$ and ξ_g, see an earlier section for additional details) are used throughout the whole simulation process. It is important to remark that the grid-based layer with embedded information on the signal strength and the list of antennas covering each grid point can be used with several user scenarios in the same area of interest. In fact, thanks to the proposed layered approach, changes in the user layer have no impact on the propagation characterization nor on the other layers of the architecture.

Mobile Devices: In the scenario with mobility, the IoT devices can move at different speeds, such as cars, buses, pedestrians smart watches, and bikes. This is one of the use cases that greatly benefits from the adoption of a grid-based approach for the RSS computation. In fact, as the mobile nodes move from one grid point to another, it is quite easy to determine which base station will serve them at any point in time simply by examining the list of antennas associated to a grid point, as depicted in Fig. 6a.

Failures and Congestion: In the above use cases we assumed that all elements were functional and correctly operating. However, both base stations and devices can fail, thus degrading the performance of the IoT application and, in some cases, triggering handovers. When a UE fails, nothing changes with respect to the previously described grid-based methodology with the exception that there is a reduced load at the anten-na and base station serving the failing UE.

On the other hand, when a base station fails, the performance of all the devices that are associated with the failed base station are degraded, triggering a handover to a different antenna or base station. Dealing with this type of events is largely simplified by the presence of the grid-based middle layer and by the list of *k* best antennas for each grid point. In particular, the grid points impacted by a failure can simply update their antenna list by removing the failing network elements. Therefore, during the simulation, the occurrence of failures does not have a severe impact on the user layer (as changes are managed by the grid-layer) nor on the overall simulation performance. Note that a similar situation can happen in case of congestion at a network element. An antenna or base station, following an increase in their load (for instance, due to a special event such as a power failure in the region, accidents or special circumstances) cannot be able to accommodate incoming trafic and can be treated in the simulator as failing nodes. Therefore, the proposed grid-based approach is also useful to simulate such scenarios characterized by network congestion as displayed in Fig. 6b.

Conclusion

With the advent of increasingly large IoT systems, the need for scalability in the computational assessment of network performance simulation is an important concern. This article presented a new simulation modelling concept that consists in the de-coupling of the access and user layer and the creation of a middle layer that allows the creation of a propagation middle-grid. This, alongside with the methodology to quickly assess the UE propagation information are fundamental contributions that allow a drastic reduction in computational time and permit the effective simulation performance evaluation of networks with hundreds of base stations and several hundred thousands UEs. This type of scalability is currently not available with traditional simulation methods.

The article numerical results show that the offline computation of the propagation, which is possible because of the grid-based middle layer, brings a large reduction in computational time. This is a direct consequence of the fact that, under static network conditions, there is no need to perform the computationally hungry propagation characterization *online*.

Given that a key element of the method is the grid granularity, experiments were performed to assess the trade-offs between granularity, propagation errors and computational time, showing that the planner can adjust the method to her desired propagation precision. On the one hand, the pre-computation of the path loss in the grid points does not seem to be justified in scenarios with low density of users as it would require the use of large grid points (low values of δ), as shown in Figure 5. On the other hand, it would bring about considerable advantages in terms of computation and scalability for large-scale scenarios with hundreds of thousands of users and network elements.

Moreover, the novel methodology is highly flexible and can be used with different datasets, different propagation models, as well as with any network simulator tool. It also proved useful when considering scenarios characterized by node mobility or by the presence of failures and congestion in the network. Future studies may focus on the integration of small-scale fading effects, on the extension of the approach to other type of wireless networks, such as mesh networks, and on the study of hybrid grids with variable density to accommodate the simulation of different areas with a heterogeneous distribution of users and network elements.

Additional Information

Please refer to http://www.piotsimulation.com for more information about our IoT simulator. Also, more information about residential addresses in Montreal can be found at https://donnees.montreal.ca.

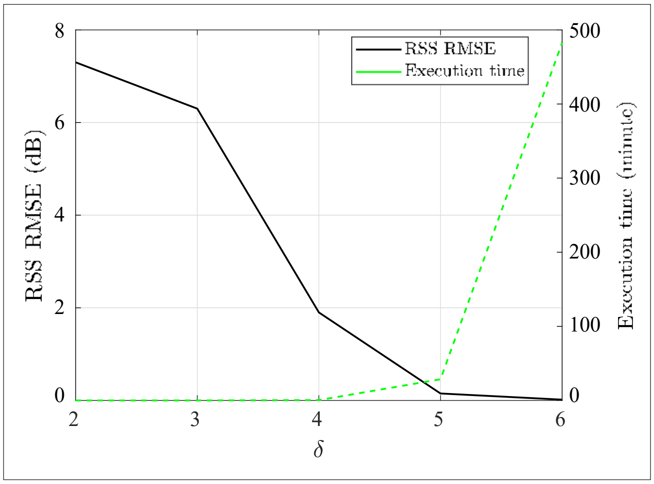

Figure 5. RSS RMSE and execution time as a function of granularity.

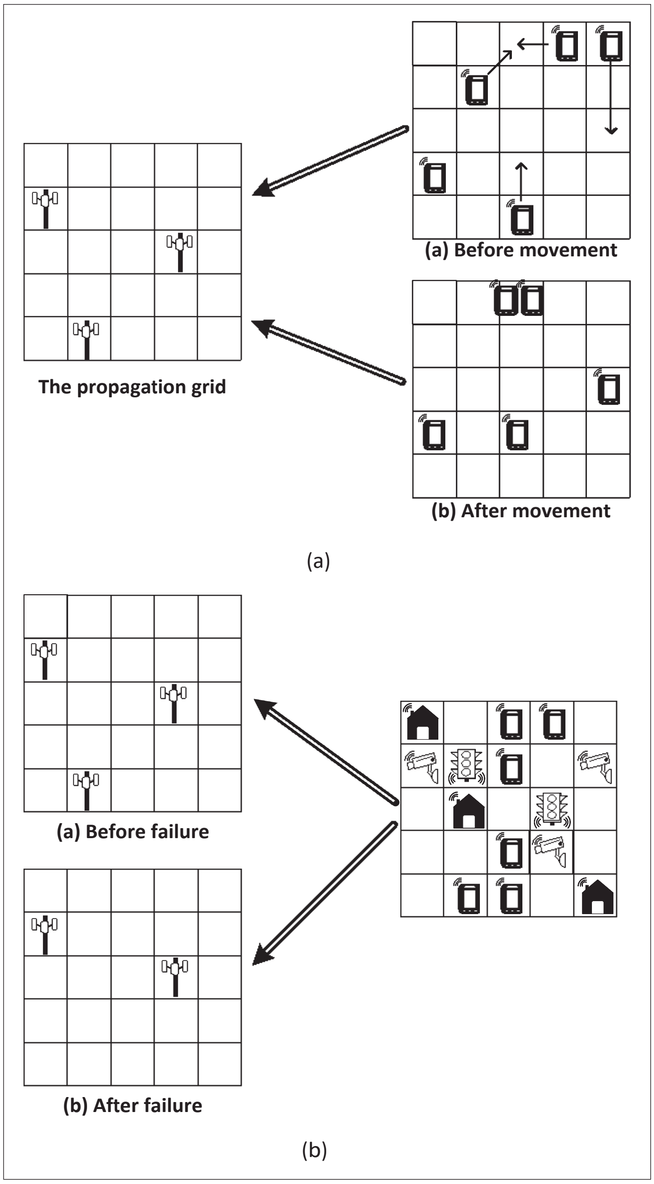

Figure 6. Some of the proposed use cases to test the grid-based methodology: a) use case 2: mobile UEs; b) use case 3: failures and congestions.

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