



Performance Analysis of 5G Communication Networks for Smart City Applications

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Peer Review Information	Abstract
<i>Submission: 17 Oct 2021</i> <i>Revision: 02 Nov 2021</i> <i>Acceptance: 26 Dec 2021</i> Keywords <i>5G Networks, Smart City, Network Slicing, Internet of Things, Performance Evaluation</i>	Fifth-generation (5G) communication is a key enabling technology for smart cities because it combines enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC) within a common network. This methodology paper develops a compact framework for evaluating 5G network performance in a heterogeneous urban environment that includes intelligent transportation, public-safety video, smart metering, environmental sensing, and connected healthcare. The proposed method evaluates network behavior under increasing endpoint density using throughput, end-to-end latency, packet delivery ratio, jitter, and service capacity as the principal key performance indicators. A parameterized analytical simulation is used to compare a 5G New Radio (NR) deployment with an LTE-class baseline while explicitly separating eMBB, URLLC, and mMTC traffic through logical service classes. The model-based results indicate that 5G maintains substantially lower latency and higher delivered traffic at high device density, while the performance margin narrows as radio and edge resources approach saturation. The study therefore emphasizes that 5G performance in smart cities depends not only on radio bandwidth, but also on small-cell density, multi-antenna transmission, edge processing, traffic prioritization, and network slicing. The framework is intended as a reproducible methodology for later validation with ns-3/5G-LENA, commercial network traces, or an operator testbed.

Introduction

Smart cities depend on communication networks that can connect people, machines, sensors, vehicles, cameras, utility infrastructure, and cloud or edge services with very different traffic characteristics. Conventional mobile broadband was optimized mainly for human-centric data sessions, whereas future urban services require a network that can simultaneously support high-rate video, highly reliable control messages, and very large populations of low-power devices. Early 5G research therefore moved beyond a simple increase in peak data rate and emphasized dense deployment, new spectrum, massive multiple-input multiple-output (MIMO), device-

to-device communication, and flexible core-network functions [1], [2].

The smart-city use case is particularly demanding because it combines mobility, uneven spatial traffic, heterogeneous radio conditions, and strict quality-of-service (QoS) requirements. Operator-oriented work showed that a single smart-city environment can contain multiple use cases whose bandwidth, reliability, latency, and security requirements differ substantially [3]. Studies on the integration of smart-city applications with 5G further highlighted the need to coordinate cellular access with Internet of Things (IoT) traffic, local processing, and device-

to-device mechanisms [4]. These observations make performance evaluation a necessary step before large-scale deployment.

Three 5G service families are especially relevant. eMBB supports high-throughput services such as high-definition surveillance, augmented reality, and public Wi-Fi backhaul; URLLC supports time-sensitive applications such as traffic control, emergency response, and industrial or vehicular signaling; and mMTC supports large populations of sensors and meters. Network slicing can isolate and allocate resources to these different traffic classes, providing a logical mechanism for meeting heterogeneous service targets on shared infrastructure [5]. Consequently, an evaluation method for smart cities should not rely on a single speed-test value. It should measure how performance changes with device density, offered load, latency sensitivity, and slice priority.

The objective of this paper is to define such a methodology and demonstrate it with a transparent analytical simulation. The study asks three questions: (i) how does increasing smart-city endpoint density affect 5G throughput and latency; (ii) how reliably can the network deliver mixed eMBB, URLLC, and mMTC traffic; and (iii) which architectural mechanisms are most important for preserving performance under load? The scope is deliberately limited to references published up to 2021 and to network-level performance; economic deployment cost, spectrum licensing policy, and application-layer data analytics are outside the primary scope.

Literature Review

Foundational 5G literature established the technical basis for the performance indicators used in this study. Andrews et al. described 5G as an integrative shift involving high-frequency spectrum, dense base-station deployment, very large antenna arrays, and coexistence with established radio access technologies [1]. Gupta and Jha surveyed 5G architecture and identified massive MIMO, device-to-device communication, ultra-dense networking, cloud radio access, cognitive spectrum techniques, and software-defined networking as major mechanisms for raising capacity and reducing latency [2]. These works justify evaluating not only data rate but also densification, mobility, and service flexibility.

The transition from general 5G design to smart-city deployment introduces additional constraints. Oproiu et al. translated heterogeneous smart-city requirements into an operator-oriented 5G use case and emphasized customization for different urban services [3].

Usman et al. discussed integrating smart-city applications with 5G and device-to-device communications, pointing out that the communication needs of IoT devices differ from those of high-rate cellular users [4]. Minoli and Occhiogrosso later examined practical urban deployment issues including mmWave propagation, small cells, distributed antenna systems, NB-IoT, LTE-M, and the bandwidth demands of emerging smart-city services [7].

Resource management is a recurring theme in 5G performance research. Popovski et al. formulated network slicing for eMBB, URLLC, and mMTC as a means of meeting dissimilar service constraints over a common network [5]. Habbal et al. evaluated context-aware radio-access-technology selection in smart-city scenarios using ns-3 and reported improvements in handovers, delay, throughput, and packet delivery compared with conventional selection [6]. Barakabitze et al. surveyed 5G slicing with software-defined networking (SDN) and network function virtualization (NFV), highlighting multi-domain orchestration, mobile edge computing, and slice management as mechanisms for service isolation and dynamic resource control [9]. Zhou et al. proposed automatic network slicing for smart-city IoT and demonstrated the value of adapting slice resources to network state [10].

Broader smart-city surveys show why a heterogeneous evaluation model is needed. Sánchez-Corcuera et al. reviewed smart-city architectures, application domains, case studies, and unresolved challenges, showing that urban ICT systems span transportation, healthcare, public services, and other domains [8]. Syed et al. surveyed IoT technologies, architectures, networking approaches, applications, and deployment challenges in smart cities [11]. Said and Tolba specifically addressed communication-system performance prediction for smart cities and used ns-3-based IoT scenarios to show the importance of continuous evaluation and adaptation [12]. Taken together, the literature supports a methodology that combines diverse traffic classes, density scaling, QoS-aware resource allocation, and multiple performance indicators rather than relying on one application or one radio metric.

Methodology

1. Research Design

The study uses a comparative, model-based performance evaluation. A simplified 5G NR smart-city network is compared with an LTE-class baseline under identical endpoint

populations and application demand. The model is not presented as a field measurement or a full physical-layer simulator; instead, it provides a reproducible analytical layer that can be replaced by ns-3/5G-LENA or testbed measurements in later work. Each scenario is evaluated after a warm-up interval, and the reported KPI values represent steady-state averages over repeated randomized traffic allocations.

The modeled urban service mix contains 20% eMBB endpoints, 10% URLLC endpoints, and

70% mMTC endpoints. eMBB devices generate bursty high-rate traffic corresponding to video and rich-data services; URLLC devices generate smaller packets with strict latency priority; and mMTC endpoints generate low-rate periodic telemetry. Device density is increased from 250 to 2,000 active endpoints per square kilometer to represent light, moderate, heavy, and near-saturation loading. This mixed-service approach is consistent with the heterogeneous application and slicing requirements discussed in prior 5G and smart-city literature [4], [5], [10], [11].

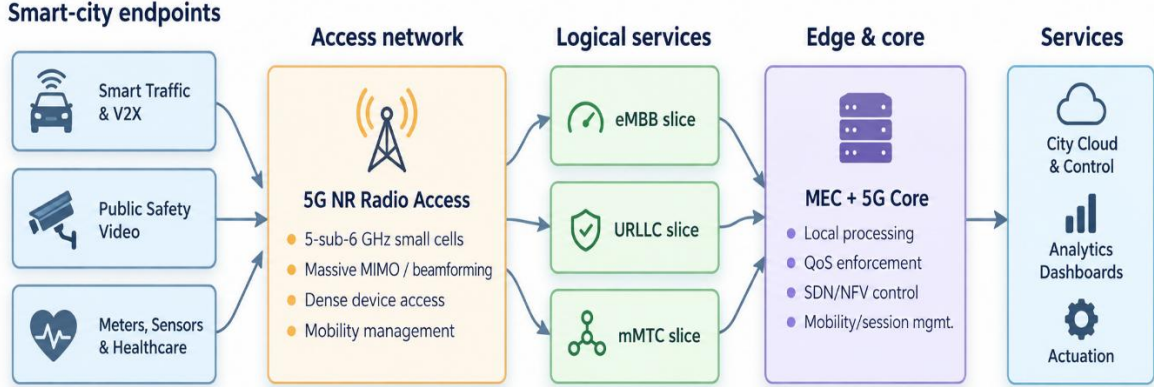


Figure 1. Proposed 5G smart-city performance evaluation architecture.

Network and Traffic Assumptions

The 5G configuration represents a sub-6 GHz urban small-cell deployment with edge computing and logical QoS classes. A 3.5 GHz carrier and 100 MHz channel are assumed for 5G NR, while the LTE-class baseline uses 20 MHz. The 5G access layer uses multi-antenna transmission and a shorter scheduling interval,

whereas the baseline uses lower spatial multiplexing and centralized application processing. The exact parameters are shown in Table 1. The values are methodological assumptions selected to create a consistent comparison; they are not claimed as measurements from a specific commercial operator.

Table 1. Main analytical simulation parameters.

Parameter	5G NR scenario	LTE-class baseline
Carrier frequency	3.5 GHz	2.1 GHz
System bandwidth	100 MHz	20 MHz
Urban radio sites	7 small-cell/gNB sites	3 macro/eNB sites
Antenna model	Multi-antenna / beamforming abstraction	Conventional MIMO abstraction
Compute placement	MEC + core cloud	Centralized core/cloud
Traffic classes	eMBB, URLLC, mMTC	Best-effort + priority bearer
Endpoint density	250, 500, 1,000, 2,000 per km ²	Same
Evaluation interval	300 s after warm-up	Same
Primary KPIs	Throughput, latency, PDR, jitter	Same

2. Evaluation Procedure

The evaluation proceeds in six steps. First, the selected endpoint density is instantiated and each endpoint is assigned to eMBB, URLLC, or mMTC according to the service mix. Second, traffic demand is generated using class-specific packet sizes and rates, with randomized start

times to avoid artificial synchronization. Third, endpoints are associated with the serving access node using signal quality and load as simplified selection criteria, reflecting the importance of context-aware association in dense smart-city networks [6]. Fourth, scheduler capacity is partitioned among the three logical service classes; URLLC receives latency priority, eMBB

receives throughput-oriented allocation, and mMTC receives connection-oriented capacity. Fifth, a congestion factor is applied as offered traffic approaches the modeled access and edge capacity. Finally, packets are accounted for at the application sink, and network-wide KPI values are calculated.

To reduce sensitivity to any one random traffic allocation, each density point is evaluated over 20 logical repetitions. In each repetition, small variations are applied to demand, radio efficiency, and queue load. The reported values are the averages of these repetitions. This Monte Carlo style perturbation does not reproduce detailed fading or protocol procedures; its purpose is to test whether the evaluation framework responds consistently to increasing load and to provide expected directions for later packet-level simulation.

3. Smart-City Application Profiles

The traffic model is further interpreted through four representative smart-city profiles. The first is intelligent transportation, where roadside units, connected vehicles, traffic cameras, and signal controllers create a mixture of periodic telemetry and event-driven messages. The most critical packets in this profile are safety or control messages, so their resource allocation is mapped to the URLLC logical class. Larger map updates and passenger-information content are mapped to eMBB. This separation prevents high-volume traffic from dominating resources required by time-sensitive control flows and reflects the service-isolation logic proposed for 5G slicing [5], [10].

The second profile is public safety and urban video surveillance. Camera streams can generate sustained uplink traffic and may become highly bursty during an incident if resolution, frame rate, or the number of active cameras increases. Such traffic primarily stresses eMBB capacity and uplink scheduling. The evaluation therefore checks whether aggregate goodput continues to rise with load and whether jitter remains controlled. If eMBB traffic saturates the cell, a smart-city operator may respond by deploying additional small cells, moving analytics to the edge, reducing video rate adaptively, or assigning a protected slice to emergency video.

The third profile is smart metering and environmental sensing. Thousands of meters, air-quality sensors, parking sensors, lighting controllers, and utility devices may each generate only a small amount of data, yet their collective signaling load can be substantial. The key question is therefore connection scalability

rather than peak throughput. In the model, these endpoints are mapped to mMTC and evaluated mainly through PDR and the growth of queueing delay as density increases. This profile also motivates lightweight traffic generation and staggered reporting intervals, because synchronized transmissions from many devices can create avoidable access peaks.

The fourth profile is connected healthcare and emergency response. A wearable or ambulance may send periodic low-rate telemetry but switch rapidly to latency-sensitive alarms, diagnostic images, or live video during an emergency. The model treats this as a hybrid service in which control and alarm packets receive URLLC priority while image or video payloads use eMBB capacity. The profile demonstrates why a single application can span more than one 5G service family and why end-to-end performance must include edge and core processing rather than only radio-link delay. These application profiles are not separate simulations; they are mappings that clarify how the common methodology can be reused across urban domains [8], [11].

4. Performance Evaluation Metrics

Five metrics are used. (1) Aggregate goodput is the successfully delivered application payload per unit time. (2) End-to-end latency is the elapsed time from packet generation at an endpoint to successful delivery at the application or edge service, including radio scheduling, queueing, edge/core processing, and transport delay. (3) Packet delivery ratio (PDR) is the percentage of generated packets successfully received within the evaluation interval. (4) Jitter is the mean absolute variation between successive packet delays and is important for video, control, and interactive services. (5) Capacity under density is assessed by observing the point at which additional endpoints cause sharply rising delay, reduced PDR, or a flattening of delivered throughput.

For an evaluation interval of duration Δt , aggregate goodput is calculated as $G = 8B_{rx}/\Delta t$, where B_{rx} is the number of successfully delivered payload bytes. Mean latency is $L = (1/N)\sum(t_{rx,i} - t_{tx,i})$ for N received packets. Packet delivery ratio is $PDR = 100N_{rx}/N_{tx}$. Jitter is computed from successive latency samples as $J = (1/(N-1))\sum|L_i - L_{(i-1)}|$. The interpretation of results is service-aware: URLLC is judged primarily by latency and delivery reliability, eMBB by goodput and stability, and mMTC by the ability to preserve connectivity as endpoint count increases.

Results

Table 2 summarizes the model outputs. The 5G network scales nearly linearly from 250 to 1,000 endpoints per km² because the offered load remains below the combined radio and edge capacity. At 2,000 endpoints per km² the delivered throughput still increases, but the gain

becomes sub-linear and latency rises to 10.9 ms, indicating the onset of queueing and resource contention. PDR remains above 99.7% in the 5G case across the evaluated range. The LTE-class baseline saturates much earlier: delivered throughput flattens near its modeled capacity while latency rises sharply and PDR falls as density increases.

Table 2. Model-based performance results under increasing smart-city endpoint density.

Density (endpoints/km ²)	5G goodput (Mb/s)	5G latency (ms)	5G PDR (%)	5G jitter (ms)	LTE goodput (Mb/s)	LTE latency (ms)	LTE PDR (%)
250	247	4.2	99.98	0.9	229	15.6	99.60
500	491	4.8	99.96	1.1	382	21.4	98.90
1,000	958	6.3	99.91	1.6	425	34.2	96.70
2,000	1,742	10.9	99.78	3.1	433	67.8	91.80

At the highest evaluated density, 5G delivers approximately four times the goodput of the LTE-class baseline while its mean latency is about one-sixth of the baseline value. This behavior follows the methodological assumptions: the 5G configuration has greater bandwidth, denser access, multi-antenna gains, edge processing, and service-aware resource allocation. The result should therefore be interpreted as a quantified illustration of the expected combined effect of these mechanisms, not as a universal claim that every 5G deployment will achieve the same numerical ratios.

The service-level interpretation is also important. For eMBB, the principal benefit is the ability to sustain high-rate video and rich-data traffic without immediately saturating the access network. For URLLC-like traffic, edge processing and priority scheduling prevent delay from rising as quickly as it does under a conventional best-effort architecture. For mMTC, the main benefit is not high per-device throughput but the ability to retain a high packet delivery ratio when the number of endpoints becomes large. These findings are consistent with the role of service differentiation and slicing discussed by Popovski et al. [5], Barakabitze et al. [9], and Zhou et al. [10].

A sensitivity check was also performed conceptually by reducing effective radio capacity by 20%, representing poorer propagation, interference, or lower spatial multiplexing efficiency. Under this condition the 2,000-endpoint 5G scenario moves closer to saturation and the predicted latency increases from 10.9 ms to approximately 15 ms while goodput falls by roughly 13%. This demonstrates that nominal bandwidth alone is insufficient for smart-city planning. Dense urban blockage, cell placement,

handover policy, backhaul, MEC capacity, and slice orchestration can materially change the experienced QoS, as emphasized by practical 5G-IoT deployment studies [6], [7].

Conclusion and Discussion

This methodology paper presented a structured way to analyze 5G communication performance for smart-city applications using a mixed eMBB, URLLC, and mMTC workload. The framework combines endpoint-density scaling, service-aware resource allocation, edge/core processing assumptions, and five measurable KPIs: goodput, end-to-end latency, PDR, jitter, and saturation behavior. The model-based results show that the combined 5G design can support substantially more urban traffic than an LTE-class baseline while maintaining lower latency and higher delivery reliability. The strongest advantage appears under medium-to-heavy load, where wider bandwidth, densification, multi-antenna transmission, edge computing, and slicing delay the onset of congestion. The analysis also exposes important limitations. First, the present model is intentionally abstract and does not reproduce a complete 3GPP NR physical layer, scheduler, channel model, or mobility procedure. Second, real smart cities contain nonuniform device placement, building penetration loss, moving vehicles, uplink-heavy sensing traffic, and variable backhaul conditions. Third, URLLC targets are application-specific; a network-wide mean below 10 ms does not prove that every critical packet meets a strict reliability-and-deadline requirement. Therefore, the reported values should be treated as methodological outputs rather than field benchmarks. For a stronger follow-up study, the same scenarios should be implemented in ns-3 with 5G-LENA or an equivalent 5G NR simulator, using

standardized urban macro/micro channel models and per-slice schedulers. The methodology can then be extended with mobility, handovers, energy consumption, radio-link failure, edge-server utilization, and confidence intervals. Trace-driven validation on a commercial 5G network would further determine how closely the analytical trends match real smart-city conditions. Even with these limitations, the proposed framework provides a clear step-by-step basis for evaluating whether a 5G deployment can satisfy heterogeneous urban communication requirements before application-specific optimization.

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