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COMPUTER SCIENCE | RESEARCH ARTICLE

Verification of performance degradation in a telecommunications system due to the uncertainty of human users in the loop

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Abstract: The intensive use of new technologies that cause more interactions between systems and the daily activities of human users is changing the focus on how network re- sources should be managed. However, these changes can create challenges related to the level of uncertainty that people introduce to the system. In this context, this research study seeks to determine whether people's uncertainty influences network performance and how significant its impact is. For these purposes, a simulated case study of a Vehicle for Hire application designed to run over a network slicing of a fifth-generation (5G) network. The simulations compared call drop rates in several settings configured to represent different levels of uncertainty, introducing random alterations to free channel planning reserved for the handover process. The simulation results reveal that the uncertainty specifically introduced by people exerts a high negative impact on network performance, evidencing the need to develop an algorithm that considers this uncertainty when managing resources within the 5G network core.

Subjects: Management of IT; Systems & Computer Engineering; Networks

Keywords: Network performance; uncertainty; crowdsensing; 5G; resource management; human behavior

ABOUT THE AUTHOR

In this research line we propose to bring together elements of Psychoanalysis with advanced Computer Networks Technologies concepts, towards a deeper understanding of the individual as well as the collective behaviour of people, when generating data in socially interactive media. Computer Networks Technologies provide the formal tools and rigorous mathematical methods while psychoanalysis gives a fundamentally different insight in human behaviour and decision-making processes. This must provide a new technology paradigm, in which user data in social applications can be understood and analysed in a robust way by the interaction of the two Sciences.

In this sense, in this research it was found that there is a high impact on the performance of communication networks due to the uncertainty that people introduce into the system.

PUBLIC INTEREST STATEMENT

In this paper, to demonstrate that the daily actions of people can affect the performance of communication networks, a use case of an application such as Uber on a 5G network was designed. The simulations measure the impact that is generated when Uber drivers, for personal reasons, deviate from the routes generated by the application. The results clearly show that the uncertainty introduced by drivers has a negative effect on the performance of the 5G network.









1. Introduction

Technological advances that allow faster connectivity to a larger number of devices, Cyber-Physical convergence and the increasing use of mobile crowdsensing applications (MCSA) are driving emerging paradigms in communications networks to evolve from a focused infrastructure approach toward a human-centered approach. These factors increase network traffic by enabling multiple interactions between human users in real time with sensors embedded in both technological gadgets and mobile devices (Agiwal et al., 2019). As a result, there is a vast spatial-temporal data diversity and quantity that reflect both individual user behavior and the behavior of society as a whole (Zheng et al., 2021). From the perspective of Infrastructure Providers (InPs), this data analysis can serve as feedback to improve the dynamic management of network infrastructure resources. However, the reliability of these data may become compromised given that, in several contexts, human perceptions are susceptible to emotional biases. This often-neglected inherent uncertainty in human behavior increases the complexity of resource management activities, which have traditionally been based on highly simplified demand models.

MCSA are an important factor in this evolution, because it pave the way to provide decentralized ubiquitous the data collection from different fields to address problems, such as critical infrastructure management, natural disasters, and intelligent transportation systems (Kong et al., 2019), (AbualSaud et al., 2019) and (Phuttharak & Loke, 2019).

Among the technological advances to support MCSA fifth-generation (5G) network stands out for its features, furthermore, will increase hyperconnectivity by supporting high densities of interconnected devices in reduced-size coverage areas under high performance parameters (Gupta & Jha, 2015), thus accelerating the integration between human processes and communication networks. Moreover, 5G core programmability enables the rapid creation, deployment, and management of new applications focused on satisfying basic needs, as well as the development of new resource management methods with an emphasis on real-time data analysis.

Several studies have approached these new phenomena from a wide range of perspectives. For example, in (Luu et al., 2021), they developed a integer linear programming formulation for allocating resources within a network slice where the number of users is partially unknown and their resource demands are uncertain. In (Wan et al., 2019), they studied the real-time navigation of vehicles in urban areas with mobile crowdsourcing data, developing two algorithms that process the trajectories according to the maximum areas that the vehicles can cover during a period. Although they obtain good results taking into account the quantitative uncertainty, they do not study the human uncertainty related to this problem. In (Arooj et al., 2020), developed a framework to process in real time crowdsourcing data from machines and people for the solution of mobility in smart cities, although several sources of information supported by 5G technologies are used in decision-making, the impact of human uncertainty is not analyzed in this work either. The study in (Mazied et al., 2019) proposes using reinforcement learning from the SDN control plane to manage uncertainty intelligently in 5G networks. However, this method lacks a way to quantitatively assess wireless control plane performance. Furthermore, (Moltafet et al., 2019) proposes allocating resources based on an integer linear programming method with uncertain channel state information, considering only quantitative data uncertainty. The study in (Silva et al., 2019) presented an extensive research on location-based social networking challenges and opportunities within the context of the EMBRACE project, addressing the topic of designing efficient solutions for 5G networks considering human behavior, uncertainty, and networking resource heterogeneity. Even when its results are not focused on infrastructure resource allocation, but rather on making better urban computing decisions, (Ismail et al., 2021) studied and classified different uncertainty sources for Self-Adaptive Software Systems by discussing an Internet of Things (IoT) use case. Still, the authors fail to address the impact from uncertainty on network performance. In (Alzate-Mejia et al., 2021), the uncertainty introduced by humans to different scenarios was explored by analyzing different sources of uncertainty. The scenarios assessed were presented in the IoT field. Some of the uncertainty scenarios studied include citizen security under



a mobile wireless sensors network, a telemedicine case study within the Smart Space context, and a call center case study within Industry 4.0. For this research study, a new 5G scenario is created to explore the effects from human uncertainty on network performance. Through an exhaustive literature review, different computational methods were studied to deal with uncertainty from the classic multiple criteria decision methods to different machine learning methods. In addition, a novel proposal under development was presented to address the uncertainty introduced by humans. This proposal was grounded both on computational and psychoanalysis methods. However, this work failed to respond whether the uncertainty introduced by humans is an important factor in network performance degradation, which is the purpose of this work.

This research study seeks to determine whether human uncertainty affects performance in communication networks and, that being the case, to verify the significance of its impact. This paper seeks to fill the gap found in the literature by discussing, from the InP standpoint, how network performance is affected. In addition, this work will only consider the uncertainty associated with humans through the simulation of a given 5G network process.

The rest of the paper is organized as follows: Section 2 presents an introduction to 5G standardization, some challenges faced by the handover process, and a review of the concepts and functional entities relevant to this research. A description of the case study assessed by means of an example is presented in Section 3. Next, Section 4 details system configurations and the simulation methodology. Section 5 discusses the results from the simulations. Finally, in Section 6, our conclusions are presented.

1.1. Network

The 5G design is based on three use cases that will group the possible applications to be deployed, as well as the parameters that are considered as fundamental 5G capabilities, as presented in Figure 1 below. Massive Machine-Type Communications (mMTC) are aimed at the deployment of a large number of affordable, high-energy autonomous devices that, due to their characteristics, do not transmit large amounts of data. Enhanced Mobile Broadband (eMBB) is intended for human-centric applications that make heavy use of data consumption. Ultra-Reliable and Low-Latency Communications are set to enable availability and latency capabilities with strict limits.

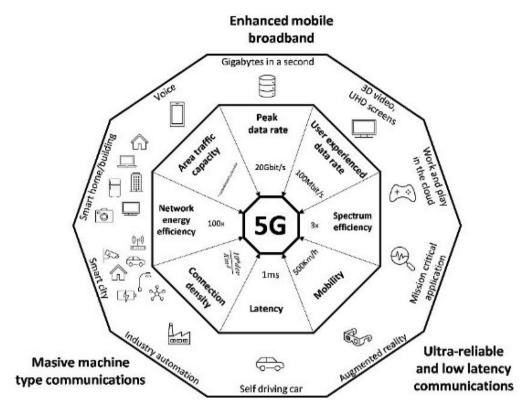
On the other hand, anticipating the appearance of new 5G use cases and applications, the technical specifications of its fundamental capabilities have been established. For example, for connection density, up to 10 million connections per km2 are defined, thereby tripling energy efficiency with respect to IMT-Advanced, increasing traffic densities up to 10 Mbps/m2, and establishing a maximum data rate of 20Gbit/s under ideal conditions, a user-perceived data rate of 100Mbps at the coverage area edge, latency times of up to 1 millisecond, and mobilities of up to 500 km/h.

These capabilities enable the massive implementation of IoT applications well as the deployment of Industry 4.0 (Agiwal et al., 2016). However, to achieve this, large infrastructure investments are required. From a business perspective, this leads to the generation of a massive application ecosystem that accelerates the return on investment. Although there are foreseeable use cases, such as fixed wireless access, or the deployment of mass broadcast services, such as mobile television, it is expected that the intensive use of infrastructure will be in new services that have not even been imagined. Therefore, guaranteeing the availability of resources for the demand of the different services offered is an important task for obtaining larger profits.

A main 5G deployment resource is the radio spectrum. This resource is vital since it is the means used to conduct communications between devices. Within the 5G operational processes, the handover reserves certain spectrum channels, and the Quality of Service (QoS) and Quality of Experience (QoE) metrics depend largely on its correct operation.



Figure 1. Usage scenarios and key capabilities for 5G. Adapted from ITU-R M.2083–0.



2. 5G Handover challenges

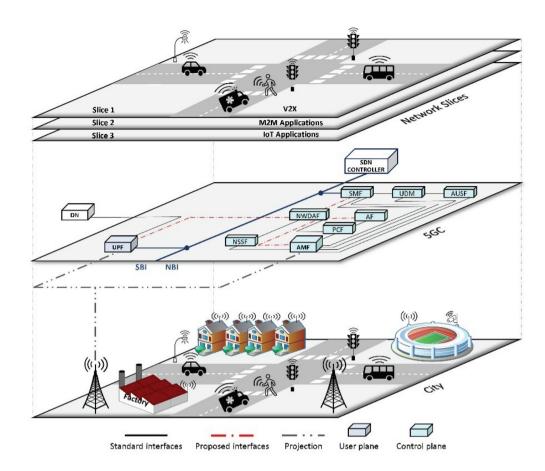
The HO is produced to transfer mobile device allocation from its base station to another that will continue to support it. This procedure is performed when signal conditions reach a limit or from providing other services such as load balancing or QoS Flow enhancement for voice. With 5G, new technical challenges are presented that make the HO procedure more complex. Some of these challenges are listed below. Frequency Harmonization. A particular case of these challenges is the need for 5G to use new harmonized frequencies for mobile services. Particularly with the use of millimeter waves that hinder precision in signal measurements due to fading problems, either due to environmental factors or their low diffraction around obstacles (Polese et al., 2017). As a result of abrupt fading, the measurement signal will have some degree of error, which can lead to unsuccessful or unnecessary HO.

Support systems for ultra-high density. Another challenge is the high density of equipment that 5G is intended to support. For this, different coverage areas have been designed, such as femtocells, picocells, microcells, and metrocells (Arshad et al., 2016). For example, picocells are designed for coverage of approximately 10 meters, being useful in urban areas with a high public influx such as shopping centers, airports, or metro stations, among others. These environments would produce high HO rates given the density of devices and short-coverage distances (Arshad et al., 2017), (Zhang et al., 2019) and (Merwaday & Güvenç, 2016).

The first technical challenges may be associated with quantitative parameters. However, for this research, there will be more focus on the third type of parameter because it is more sensitive to human uncertainty. Therefore, the following section will present a series of proposals and standards to improve resource management in 5G, which supports the feasibility of the case study presented in Section 3.



Figure 2. Softwarization and virtualization in logical 5G architecture.



3. 5G concepts and functional entities

The third Generation Partnership Project (3GPP) in collaboration with several organizations has been working on 5G system standardization. Its specifications are delivered through a Release system operating in parallel, thus facilitating the addition of new functionalities in subsequent Releases.

In Figure 2, an example to review some concepts and functions of the 5G-network core (5GC) is presented to facilitate the implementation of network slicing, as well as software-based improvements for the handover process. The example is divided into three sections. The lower section is a physical representation of a city, and the middle and upper sections are logical abstractions of the 5GC and networks slicing, respectively.

In the lower section, five sectors or dimensions of a city are represented: industrial, residential, recreational, telecommunications, and mobility. Its intention is to illustrate the diversity of use cases and applications that can exist and interact in a city through a 5G infrastructure.

The middle section is a logical projection of the 5GC functional entities grouped from the SDNs perspective and their corresponding communication interfaces. Among the interfaces indicated, those in red are interfaces that were proposed for data analysis and exchange, which in a real implementation of the case study would help find possible solutions. The functional entities presented in Figure 2 are explained below.



Network Data Analytics Function (NWDAF). NWDAF is a new centralized network function created for data collection and analysis and its use is defined by operators (Vidhya et al., 2020). NWDAF will prepare the way for using machine learning techniques in applied analytics on user computer data, whether statistical or predictions (Ghosh et al., 2019).

- Access and Mobility Management Function (AMF). AMF provides the control plane functions for User Equipment (UE) mobility management. It performs this function with the data generated by the UEs, and if it works in conjunction with NWDAF, these data can generate characterizations of the UEs to make predictions that optimize mobility support.
- Network Slice Selection Function. This network function selects the network-slicing instance to which the requesting UE's service belongs.
- User Plane Function. It is responsible for packet routing and forwarding and QoS management, among other functions.
- · Session Management Function. Its main function is related to session management.
- · Authentication Server Function. Authenticates servers and provides encryption keys.
- Unified Data Management. Manages data for access authorization, user registration, and data network profiles.
- Policy Control Function. Proportional, under policies, real-time control of network resources consumption.
- Application Function. Supports interaction with other functions to influence services, such as routing or policy control.
- Data Network. Represents a data network. For example, the operator's network or the internet.
 Due to high density of devices that can be connected in 5G, and the several types of services that can be offered, a manner to efficiently manage limited network and radio frequency resources is needed.

In this sense, 3GPP proposes using Reconfigurable Radio Systems (RRS). The RRS concept is based on the self-adaptation of dynamic environments for the optimization of these resources. These tasks are supported through technologies such as cognitive radio and software reconfiguration radio applications.

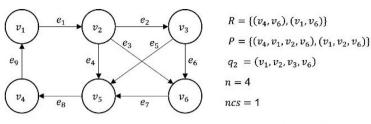
For this reason, the ETSI TR 103587 V1.1.1 document establishes a Radio Interface Engine. Its function is to deliver a defined method for exchanging relevant context information to some functional network entity, using iterative data processing. This data can be originated from different entities and will be used for decision making based on key performance indicators.

In addition to the above functional entities, signalling is another critical component for the integration between 5G Radio Access Technologies (RAN) and SDN. For this purpose, the Framework of signalling for SDN in force at ITU-T Suppl.67 presents how a network controller enables the functionalities of the RAN using the SDN bounds application programming interfaces. Moreover, specifically for handover processes, in recommendation ITU-T Q.3229 are defined the protocol for the interface between different entities and the signalling requirements to information exchange between the transport location management physical entity and the handover decision and control physical entity.

Finally, the top section denotes network slicing. A slice is a logical network created, managed, and eliminated by administration functions on a physical infrastructure of the 5G network. This functionality will offer new services through the implementation of current and future use cases for the different scenarios proposed by 3GPP. The first slice shows a Vehicle-to-Everything (V2X) communication scenario, the second represents a Machine-to-Machine (M2M) communications scenario, and the third slice belongs to IoT scenario. Although these slices share the same physical infrastructure, they are independent virtual networks.



Figure 3. Simplified representation of the scenario and simulations.



(a) Simplified case study representation

	t_1	t_2	t_3	t_4
p_1	v_4	v_1	v_2	v_6
p_2	v_1	v_2	v_6	

(c) Optimal solution

(b)	Examp	ole	parameters
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	t_1	t_2	t_3	t_4
p_1	v_4	v_1	v_2	v_6
q_2	v_1	v_2	v_3	v_6

(d) Results with uncertainty introduced

4. Simulation environment

4.1. Description of transportation applications

Vehicle for Hire (VFH) applications offer the integration of two urban transportation players: users who need to mobilize, and drivers with vehicles available at the time the service is requested. Some applications of this type are, for example, Uber, Indriver, Cabify, or DiDi.

These services are offered in real time, and the application works on smartphones, where they must be installed on both user devices. In general, the operation principle of these applications is as follows: a user first selects a point of departure and a destination in the application. The application then generates a route (departure-destination route) that the driver who agrees to provide the service may follow. This type of task assignment is known as requester-centric mobile crowdsensing (RCMCS). However, as there is no application penalty to the driver for not following the routes, the assignment of the task remains at the discretion of the driver, leaving the application with a worker-centric mobile crowdsensing (WCMCS) type assignment of tasks (Zhao et al., 2021).

Therefore, human uncertainty arises when the path defined by the application is altered. These route alterations can occur for several reasons, on the part of either the user or the driver. For example, users can request changing the route to pass by a touristic place. In addition, the driver can change the route to increase profits or to prevent traveling through dangerous areas. These route changes change the planning of the resources assigned, which consequently can have an impact on the network. This resource allocation is what we intend to be assess with the simulations.

4.2. Problem formulation

This case study can be represented as a weighted, directed graph G=(V,E), where V is the set of nodes v that represent the 108 sectors of the scenario and E is the set of edges e where each has an associated weight. A e edge in E represents the path between two nodes, as shown in the reduced example in Figure 3(a). A v can have up to three outdegrees; therefore the weight associated with each outgoing e is related to the probability ρ to continue the road through any of the alternatives. In any case, the possibilities of following an alternate e from the same v are equal, and that, when added, a probability of $\rho=1$ is obtained.

In this problem, there are m VFH application requests denoted as $R = \{r_1, r_2, \dots, r_m\}$, and each r is symbolized as a pair of origin and destination points (o, d); therefore, a set of optimal routes



 $P = \{p_1, p_2, \dots, p_m\}$ must be allocated. To determine the optimal routes of the vehicles, the Dijkstra algorithm is used. Beside, the simulations are run in a set of time intervals $T = \{t_1, t_2, \dots, t_n\}$, where n is equal to the number of v that are in the longest p of P, as can be deduced from the example shown in Figure 3(b). Nevertheless, the solution must not exceed the restriction of the number of channels that there are for each sector ncs, as illustrated in the Figure 3(c). Hence, in every v used at each moment t, the $VFH \le ncs$; otherwise, the handover process fails and the call drop rate increases, which is the metric selected to determine if the simulated uncertainty negatively affects network performance.

In order to simulate the human uncertainty that the driver can introduce into the system, some routes p are replaced by alternative routes q, the details of the simulation procedures are expanded in section 3.4. As a consequence, if the results exceed the allowed limit of ncs, as evidenced in the Figure 3(d), the objective of this research is achieved by putting in evidence that the impact of uncertainty is important and, therefore, it is a problem that must be faced.

4.3. Simulation scenario description

The scenario is set in a highly commercial and tourist urban area. As denoted in Figure 4, the scenario is conformed of 9 blocks, 4 streets, 4 avenues, and 108 cell phone sectors.

Among the scenario element characteristics, each block is numbered and represented in gray. Each block side is 100 meters long. The road direction in which vehicles will transit is indicated with a blue arrow in each street and avenue. The two streets and avenues at the center of the scenario are double lane, whereas far-end streets are single lane. Each sector covers half a block (50 meters) and one lane in width. The dimensions of the vehicles that will provide the service are set at 4 meters long and 1.8 meters wide. Dotted sectors cannot be used as a point of origin or departure because there is no sidewalk where the vehicle can park. Given the dimensions of the roads, in a case of maximum traffic, a sector can host up to eight vehicles at the same time (leaving a 1-m gap between them).

4.3.1. Simulation conditions for all scenarios

In the simulations, the following conditions are established: At the beginning of each simulation, all vehicles start from a departure sector, and each vehicle follows its route to its destination sector, where it comes to a complete stop. The minimum path defined for the simulations has at least one step from one sector to another. The reason is that at least one handover process must be counted for the measurements. When the simulation starts, all mobile devices will have guaranteed access to the network. Simulations are developed in discrete time intervals; the maximum number of intervals for each simulation is equal to the number of nodes between the origin and destination of the longest route. All vehicles advance to the next sector in each interval of the simulation; there are no additional conditions that may prompt the vehicle to stop, such as collisions or traffic lights. At no point in the simulation, new vehicles enter the scenario. Finally, the simulation ends when the vehicle on the longest route reaches its destination.

4.4. Explanation of a scenario simulation through an example

In each simulation, after adjusting the input parameters, two processes are performed. In the first process, the optimal routes are determined for each vehicle that fulfills the condition of not generating any failure due to the lack of handover channels. In the second process, alternate routes are generated for some vehicles, and the impact on the available handover channels is assessed.

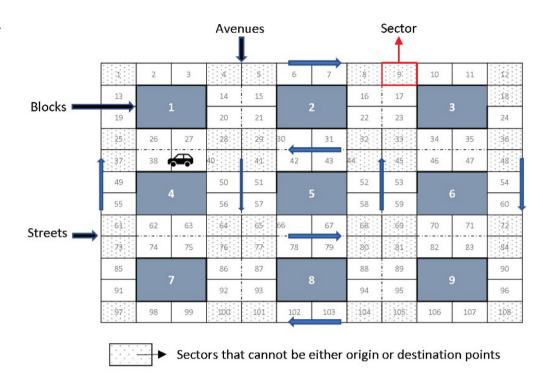
Below, an example is developed to explain the two simulation processes, and how the results are obtained. The explanation of each variable is performed in Section 4.1.

4.4.1. First simulation process

To illustrate the first simulation process, two channels have been defined for each sector as input parameters, and three vehicles are defined as load. For each vehicle, the following sectors have been



Figure 4. Simulation scenario.



chosen as an origin and destination point (o,d): For vehicle 1 (2, 99), for vehicle 2 (35, 86), and for vehicle 3 (99, 71). These data are the input parameters for the Dijkstra algorithm that determines the optimal route for each vehicle. For the example, the routes are drawn in colors, as denoted in Figure 5.

As it can be seen in Figure 6, although at the t_6 , t_7 , t_8 , t_9 , t_{10} and t_{11} times, sectors 40, 50, 56, 64, 76, and 86 were occupied by the vehicles traveling though routes 1 and 2, no failed handover were recorded since they did not exceed the two channels assigned to each sector. It can also be seen that this simulation has 15 time intervals because that is the number of sectors between the origin and destination of the longest route. It should be noted that the handover problem would be completely solved with a reserve of three channels since there cannot be more than three vehicles per sector. However, as it can be deduced from Figure 6(a) scenario configured so that two or more vehicles do not coincide at the same time and sectors during their routes would be a solution that saves important resources while maintaining QoE and QoS.

4.4.2. Second simulation process

To validate the hypothesis that human-introduced uncertainty alters the network performance, in the second simulation process, an optimal route is changed for an alternate route. For the example, we decided to change route 3. As denoted in Figure 7, the vehicle on route 3 has followed the optimal route to sector 73. However, in this sector, the route may be changed, directing the vehicle to sector 61 or to sector 62. As there are only these two possibilities, both have a probability of being chosen of $\rho=0.5$. For the example, the vehicle takes the route to sector 61.

With this new scenario, represented in Figure 8, where two vehicles follow the optimal route and the other takes an alternative route, the percentage of dropped calls due to the lack of sufficient channels for the handover process is again evaluated.

From Figure 9, until time t₅, there are no changes with respect to the first process simulation. However, from time t₆ onwards, the sectors through which the route 3 vehicle will pass to its



Figure 5. Representation of the first simulation process.

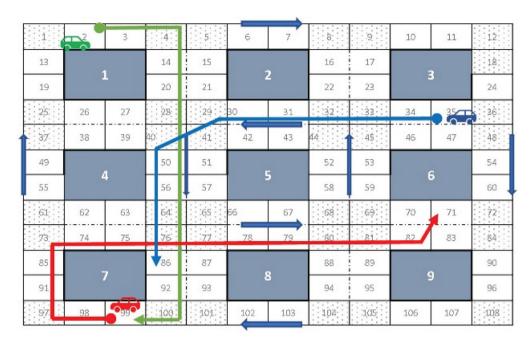


Figure 6. Data from the first simulation process.

Number of channels = 2 Intervals t_1 t_2 t_3 t_4 t_6 t_7 t_8 t_9 t_{10} t_{11} t_{12} t_{13} t_{14} t_{15} Optimal route 1 2 3 4 40 50 56 64 76 86 100 99 14 20 28 92 Optimal route 2 35 33 32 31 30 29 40 50 76 64 99 98 97 85 77 71 Optimal route 3 91 73 74 75 76 78 79 80 81 82

destination in sector 71 change. However, at time t₉, the three vehicles coincide in sector 64, causing the call to drop on the mobile with the VFH application inside a vehicle. The simulation randomly selects to which mobile phone is the dropped call is accounted.

It is also observed that when the optimal route is altered, the number of time intervals assessed in the simulation increases, which becomes one more element to analyze in the results discussion.

Although, in principle, this test confirms the initial hypothesis, a sufficient number of simulations are conducted, as explained in Section 4.3, to secure statistical reliability.

5. Simulation methodology

The simulations are designed to reproduce the conditions of measurements conducted in motion. In other words, the mobile device inside a vehicle making trips within the urban area at a constant speed. The proposed diversity of routes aims to cover a wide range of possibilities in a real scenario.

5.1. Simulation variables

The metric defined to assess and evaluate the simulations is the Call Drop Rate. The Call Drop Rate is the probability that a call will end without user action. This parameter is the base parameter to evaluate the simulations. By definition, the percentage of dropped calls cannot exceed 3%.



Figure 7. Alternative paths in the second simulation process.

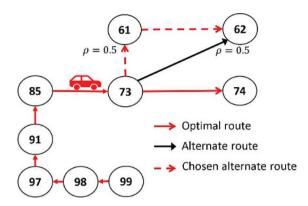


Figure 8. Representation of the second simulation process.

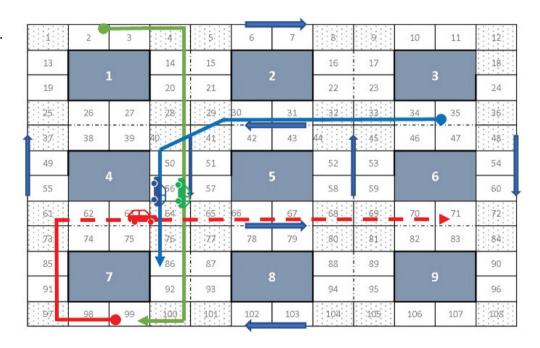


Figure 9. Data from the second simulation process.

	Number of channels = 2																
Intervals	t_0	t ₁	t_2	t_3	t_4	t_5	t_6	t ₇	t_8	t ₉	t ₁₀	t ₁₁	t ₁₂	t ₁₃	t ₁₄	t ₁₅	t ₁₆
Optimal route 1 🚗	2	3	4	14	20	28	40	50	56	64	76	86	92	100	99		
Optimal route 2	35	33	32	31	30	29	40	50	56	64	76	86					
Optimal route 3	99	98	97	91	85	73	61	62	63	64	65	66	67	68	69	70	71

For the case study, the Load, Load Distributions, Route Types, and Route Set Composition variables have been selected to closely represent the different conditions of a real scenario. Each variable is explained in detail below.

5.1.1. Load

The Load is related to the number of mobile devices with the application enabled in the simulation scenario. For each vehicle, only one mobile device is considered. Due to this direct relationship



between the number of mobile devices and vehicles, from this point, there is no distinction between mobile devices and vehicles. The simulations are conducted with the highest loads that obtain a valid solution for each route distribution. To be a valid solution, the routes must be optimal and have 0% dropped calls. Empirically, through the simulations conducted, it has been found that the highest load number is 25 vehicles per scenario.

5.1.2. Load distributions

According to their load, the total number of vehicles are distributed among scenario blocks, as illustrated by the example in Table 1.

Simulations are conducted with five types of load distributions by blocks: a homogeneous distribution, wherein vehicles are evenly distributed throughout the nine blocks; a centralized distribution, wherein vehicles are only distributed throughout Blocks 4–6; a border distribution, wherein vehicles are distributed in Blocks 1, 3, 7, and 9; a combined center and border distribution, wherein vehicles are distributed in Blocks 1, 3, 5, 7, and 9; finally, a random distribution, wherein vehicles are randomly distributed throughout the nine blocks. For the simulations, two random distributions are generated. For each block, with the defined number of vehicles per block, vehicles are randomly distributed among the eight possible sectors that can act as points of departure for each route. The destinations for each point of departure are randomly generated considering the route type.

5.1.3. Route types

This variable is configured to simulate different trip types within the simulations. All the routes used in the simulations were previously generated and are stored in a file, which is queried to extract the necessary data from the routes selected in the simulations. To avoid unrealistic situations in the simulations, routes with a loop of more than one block turns were excluded. In total, the simulations use 5112 routes. These routes were grouped into three sets of routes: long routes, medium routes, and short routes. Table 2 shows the distribution of grouped routes.

The routes are conformed in relation to simulation scenario distances, and we decided to group routes by the number of sectors that they cross from the point of departure to the destination. The grouping parameters are as follows:

- Long Route Set (Crl): routes that cross 24 or more sectors.
- Medium Route Set (Crm): routes that cross between 12 and 23 sectors.
- Short Route Set (Crc): routes that cross between 2 and 11 sectors.

For each of the generated routes, through a brute force method, we identified alternate routes that meet the same criteria of excluding routes with loops. This method works on 700 iterations for each route. For this reason, the number of alternate routes is not homogeneous. There are even cases of optimal routes without alternate routes. The number of iterations is selected after performing different tests to find the balance between results and execution times of each simulation.

Based on these route types, other sets of routes were generated to simulate more realistic simulation environments since normally the different routes will have different distances in their routes. These route groupings are called Mixed Route Set 1 (Crm1), Mixed Route Set 2 (Crm2), and Mixed Route Set 3 (Crm3). The grouping parameters are those presented in Table 3:

Hence, the simulations have six sets of routes, the sets of long, medium, short, mixed 1, mixed 2, and mixed 3 routes.



Table 1. Loads per block									
	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8	Block 9
Number of Vehicles	4	3	2	4	2	2	4	3	1

Table 2. Route grouping					
Types of Routes	Quantity				
Long	797				
Medium	2855				
Short	1460				
Total:	5112				

Table 3. Composition of mixed routes								
	Long Routes (%)	Medium Routes (%)	Short Routes (%)					
Crm1	50	40	10					
Crm2	40	50	10					
Crm3	40	40	20					

5.1.4. Percentage of routes with uncertainty

This simulation configuration seeks to compare the number of dropped call when the VFH application uses the calculated optimal routes (free of uncertainty) against the alternate routes that represent uncertainty. The uncertainty percentages for the total routes have been defined as 20%, 40%, 50%, 60% and 80%. As explained in subsection 4.1.1, the Load is associated with the number of routes that will be simulated in the scenario. This set of routes is generated for each type of route, except when evaluating the scenario with only optimal routes. As an example, Table 4 describes how the set of routes would be conformed with a load of 25. When adding the optimal routes plus the alternate routes for each scenario, there is always the same number of routes. In this case, there are 25 routes.

Hence, the six types of routes are evaluated with six different scenarios in terms of the uncertainty that exists in the set of routes. This variety of scenarios brings the results closer to possible real conditions conducted in this type of measurements.

5.2. Metrics

The parameter assessed through the simulations is the percentage of dropped calls, and the interruption marker is the lack of free channels to conduct the handover. The percentage of dropped calls must be less than or equal to $3\%.^1$ Eq. (1) indicates how the parameter used to confirm the hypothesis is evaluated. The equation is defined in the recommendation of the Telecommunications Standardization Sector ITU-T E.807: Definitions, associated measurement methods and orientation objectives of user-centered parameters for call handling in cellular mobile voice service.²

$$Drop \ Rate [\%] = \frac{Number \ of \ calls \ terminated \ unwillingly}{Total \ number \ of \ MOC \ call \ attempts} \times 100\% \tag{1}$$

MOC: Mobile Originating Call



Table 4. Cor	Table 4. Composition of scenarios with uncertainty									
	Percentages of Uncertainty									
	0%	20%	40%	50%	60%	80%				
Optimal Routes	25	20	15	13	10	5				
Alternate Routes	0	5	10	12	15	20				

5.3. Number of simulation samples

The calculation of the sample size uses the equation provisioned in Appendix C of the ETSI EG 202057–4³ recommendations as reference. Eq. (2) is configured for universes in which the hypothesis of infinite populations is accepted. In other words, universes with more than one hundred thousand elements. For the case under study, the universe (city) being measured has more than one hundred thousand users of the VFH application

$$N = \frac{\sigma(\alpha)^2 \times \rho(1 - \rho)}{(\Delta)^2}$$

$$N = \frac{1.75^2 \times 0.5(1 - 0.5)}{(0.06)^2} \tag{2}$$

N = 212

where,

- N = is the sample size that would be obtained if the infinite population hypothesis is accepted.
- $\sigma(\alpha) = 1.75$ (to achieve a confidence level of 94%).
- $\rho=$ Population proportion. The population is as diverse as possible, $\rho=$ 0.5.
- $\Delta = \text{ Margin of error set at } 6\%$.

The simulations of our use case are conformed by six sets of simulations defined by the load distributions in the scenario. For each of these distributions, 36 simulation configurations are generated, which result from the combinations between route types and uncertainty percentages. In total, for the simulation of the use case, 216 samples are then generated from which the consolidated results are obtained.

The next section presents the results of the simulations.

6. Results and discussion

The simulations were run with two free handover channels, and with a maximum percentage of dropped calls of 3%. The configurations for each simulation with respect to the load and distributions of the routes are presented in Table 5.

The consolidated results presented in Table 6 and Figure 10. Consolidated results of the simulations are the average percentage of dropped calls obtained from all the scenarios with their different distribution types. These results reveal that when the optimal routes are chosen, the percentage of dropped calls is 0 %.



Table 5. Load distributions								
Route Distributions	Block Distribution	Load/Vehicles						
Homogeneous distribution	[3 3 3 3 3 3 2 2 3]	25						
Centralized distribution	[0 0 0 7 8 7 0 0 0]	22						
Border distribution	[5 0 6 0 0 0 5 0 6]	22						
Combined distribution between center and borders	[6 0 4 0 7 0 4 0 4]	25						
Random distribution 1	[1 2 3 3 5 4 2 5 0]	25						
Random distribution 2	[6 2 3 7 2 3 1 0 1]	25						

Table 6. Percentage of dropped calls											
		Percentages of Routes with Uncertainty									
	0%	20%	40%	50%	60%	80%					
Crl	0	19	23	27	31	33					
Crm	0	13	20	27	27	19					
Crc	0	9	11	15	15	18					
Crm1	0	10	17	18	23	25					
Crm2	0	18	22	19	25	27					
Crm3	0	10	16	14	19	15					

However, when the route is altered under any percentage of uncertainty, the percentage of dropped calls increases above the 3% threshold set as the maximum allowed value for the QoS metric. The dropped call increase trend is also clear as route uncertainty increases. However, in medium and mixed 3 route sets, the percentage of dropped calls decreases in some routes with high uncertainty.

Although this seems contradictory, one explanation for this phenomenon is that since the optimal routes are calculated using the Dijkstra algorithm, most routes are destined to pass through the interior sectors of the scenario, due to the direction of the streets and their centrality. Therefore, as optimal routes are changed to alternate routes that most likely do not go through central intersections (locations with larger vehicle congestion), the number of dropped calls decreases as vehicle loads decrease in these sectors.

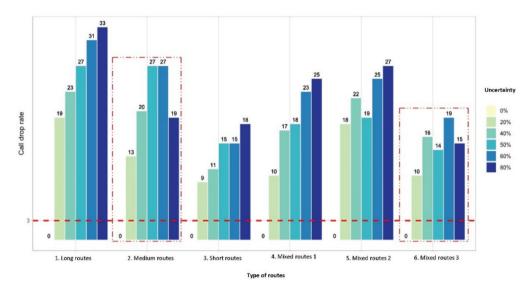
Among the sets of long, medium, and short routes, the set of long routes generally presents the highest percentage of dropped calls. This result is a consequence of the larger number of handover processes involved in the simulation. While in the mixed 1, mixed 2, and mixed 3 route sets, which represent combinations of routes closer to reality, the highest percentage of dropped calls is reported for the mixed 2 route set.

7. Conclusions

The simulation results from the VFH transportation application use case implemented in a 5G network slicing revealed that uncertainty introduced by humans affects network performance. Based on the results, it can be concluded that as uncertainty increases, network performance drastically decreases. A future line of research that can help expand our understanding of uncertainty for these scenarios is to analyze these results under the theory of networks. Approaches such as node centrality with its metrics of betweenness centrality and closeness centrality, and spectral node centrality with the Katz centrality metric, can offer clues or explanations to possible nodes that generate more congestion (Rueda et al., 2017), and that would require dynamic resource management.



Figure 10. Consolidated results of the simulations.



Although the human uncertainty was analyzed by measuring the call drop rate with the location data of the VFH application in a reduced simulation scenario, in order to take advantage of this kind of MCSA, future works should consider crowdsourced data sources, such as social media data, points of interest data, and collaborative websites.

As it is evidenced that human behavior influences the performance of communication networks, and since new technological paradigms are currently being incorporated to foster more dynamic resource management through software, a new methodological proposal is necessary to deal with human uncertainty as a key factor in network resource management. Therefore we propose that the problem that the problem of people subjectivity must be further explored in an interdisciplinary manner, as it has been raised in (Alzate-Mejia et al., 2021), wherein a new theoretical framework that combines psychoanalysis with computer calculations is proposed to address uncertainty. Specifically, the adoption of concepts introduced in The Four Discourses theory of the Lacanian theory is proposed for their suitability to be formally expressed in mathematical terms, which allows qualitative characteristics that harbor human uncertainty to be quantified. This proposal will be assessed and developed in our following research studies.

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Endnotes

- Recommendation ITU-T E.807, Section 7.4.5, (02/ 2014).
- Recommendation ITU-T E.807, Section 7.4.3, (02/ 2014).
- 3. ETSI Guide 202,057-4, Annex C, (10/2005).



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