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Impact of information update generation on the radio access network of cellular Internet of Things

Marcelo E. Flores Vázquez[1,2] · **Luis Tello-Oquendo**[3,4] · **Vicent Pla**[5] · **Juan Aranda**[6] · **Juan V. Capella**[7] · **Andrea K. Guamo Morocho**[8]

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Abstract

Cellular Internet of Things (CIoT) is considered a suitable technology to provide connectivity to IoT devices and support machine-type communication (MTC). CIoT relies on cellular networks, such as 5 G, to handle the increased demand for data and avoid overload. However, the limited capacity of the Random Access Channel (RACH) in 5 G Radio Access Networks (RANs) represents a challenge for implementing real-time IoT applications. Information update generation and the Random Access (RA) protocol play a crucial role in ensuring timely updates. This paper presents a performance analysis of the impact of information update generation patterns on the RAN in CIoT when the number of IoT devices and information update frequency increase. An extensive simulation study was conducted, considering MTC and H2H (human-to-human) traffic with varying access request intensities. We determine the maximum information update frequency to provide a highly successful access probability over the RAN.

Keywords Cellular systems · Machine-type communications · Performance analysis · RAN slicing · Resource allocation

1 Introduction

Nowadays, we live in a world that is becoming more connected thanks to the new information technology known as the Internet of Things (IoT). IoT has been conceived to enable real-time applications with features such as local decision-making and remote monitoring using a network of devices with sensing capabilities, called IoT devices [1]. For example, in [2], an IoT device was proposed for real-time water quality monitoring. This device measures the level of residual free chlorine present in water using Oxidation-Reduction Potential (ORP), pH, and temperature sensors, which are processed, stored and then transmitted to a control center over

✉ Luis Tello-Oquendo
luis.tello@unach.edu.ec

Marcelo E. Flores Vázquez
mfloresv@ups.edu.ec

Vicent Pla
vpla@upv.es

Juan Aranda
juan.aranda@unisabana.edu.co

Juan V. Capella
jcapella@disca.upv.es

Andrea K. Guamo Morocho
aguamo@gts.uvigo.es

1 Cloud Computing Smart Cities and High Perfomance Computing Group, Universidad Politécnica Salesiana, Calle Vieja 12-30, 170517 Cuenca, Ecuador

2 Instituto Universitario de Automática e Informática Industrial, Universitat Politècnica de València, Camino de Vera, 46022 Valencia, Spain

3 College of Engineering, Universidad Nacional de Chimborazo, 060108 Riobamba, Ecuador

4 Facultad de Ingeniería en Electricidad y Computación, Escuela Superior Politécnica del Litoral, 090902 Guayaquil, Ecuador

5 Department of Communications, Universitat Politècnica de València, Camino de Vera, 46022 Valencia, Spain

6 Faculty of Engineering, Universidad de La Sabana, Campus del Puente del Común, Km 7 Autopista Norte de Bogotá, Chía 250001, Cundinamarca, Colombia

7 Information and Communication Technologies University Research Institute, Universitat Politècnica de València, Camino de Vera, 46022 Valencia, Spain

8 Signal Processing in Communications Group, Universidad de Vigo, 36310 Vigo, Pontevedra, Spain

the existing Internet infrastructure. Usually, real-time applications include a massive number of IoT devices within the same network where ubiquitous and automated interaction of information between IoT devices occurs without human intervention [3]. This interaction is known as machine-type communication (MTC).

Cellular IoT (CIoT) has become an enabling technology to provide connectivity to IoT devices and support MTC [4]. CIoT is based on cellular network technologies such as Long-Term Evolution (LTE), LTE-Advanced (LTE-A), and fifth-generation (5 G) [5]. These networks have experienced rapid growth, and the ubiquity of devices and different applications have greatly increased the demand for real-time information update messages [6]. Hence, these networks deal with the demand for increased load and surge in information update traffic, which can generate overload situations. These situations should be handled efficiently to avoid losing data or providing outdated information to the control center, where analysis and decision-making are performed [7].

The frequency of information update messages, following some generation patterns in the source (e.g., uniform, exponential, synchronized, and non-synchronized), and the Random Access (RA) protocol used in the radio access network (RAN) play an important role in providing timely updates. There is a trade-off between the capacity of the Random Access Channel (known as RACH) and the generation of information update messages. If the RACH would have infinite capacity, generating information update messages more frequently would imply better key performance indicators (KPIs), but since this is not the case in real deployments, a greater frequency of information update messages generation implies increasing the traffic load, which will translate into a greater delay in the RACH and even losses. However, decreasing the frequency could seriously deteriorate the freshness of the information, especially in real-time IoT applications [8].

To position our contributions in context, we first review some closer works related to information updating patterns in cellular IoT. Zhang et al. [8] proposed FRESH, an online uploading energy-efficient scheduler that allows IoT devices to transmit information update messages to a base station (BS) over a cellular network in an energy-efficient way. FRESH presented superior results regarding energy consumption and terminal activation rate for different update generation rates (following a Poisson distribution) and information freshness requirements (based on the age of information metric). However, the impact of FRESH in a cellular IoT was evaluated in a simulated NB-IoT scenario, but without considering the random access procedure in the RAN. Mankar et al. [1] provided a performance analysis of a cellular IoT that supports real-time applications and device-to-device communications, following a stochastic geometry-based approach. Regarding real-time applications, the authors assumed that IoT devices transmit update messages in a synchronized time-slotted fashion over a cellular network using a *generate-at-will* policy, that is, whenever their associated BS allows them to do so (scheduled transmission in a uniform random fashion). Co-channel access was considered for the underlay transmission and orthogonal channel access for the overlay transmission. The age of information metric was used to quantify the freshness of the update messages transmitted by the IoT devices to their associated cellular BS. A similar approach was followed in [9] for the information update pattern but under an ALOHA-like stationary random access policy. Regarding random services in wireless networks, such as cellular networks, in [10] it was studied how often a device should generate information update messages. It was shown that it was necessary to balance the update transmission rate against congestion.

Table 1 presents a qualitative comparison between this work and the closest related studies. Although the aforementioned studies used an information update pattern, they overlooked its real impact on the RAN under a specific RA procedure according to a standard, such as those proposed for 4 G/5 G cellular networks (e.g., the 3GPP standards, see Sect. 2.1). This paper aims to study the impact of different information update generation patterns on the CIoT RAN. Specifically, the study addresses the following questions: what is the impact of information update patterns on the RAN in cellular IoT when the number of IoT devices and the information update frequency increase? What should be the information update frequency to provide a highly successful access probability for the RAN? The main metrics considered were the probability of successful access, access delay, and the average number of preamble transmissions. A discrete-event simulator of the 5 G RAN was developed in C++ to evaluate the RAN performance. In addition, independent MATLAB simulations were performed to corroborate the results. Two types of traffic were employed in each simulation, MTC and human-to-human (H2H), with different access request intensities. This allowed for analyzing the impact of the information update patterns with different frequencies on the RAN performance in CIoT.

In brief, the main contributions of this paper are: (i) to analyze the impact of information update generation patterns on network performance metrics such as the probability of successful access, access delay, and the average number of preamble transmissions under different traffic conditions using a discrete-event simulation model; (ii) to compare the information update generation patterns considering the most suitable parameter configuration of the RACH for the different massive traffic scenarios evaluated; (iii) to determine the optimal range of information update frequency values through reliability conditions that will comply with the provisions of the 3GPP standards.

Table 1 Qualitative comparison of related work

Reference	Update information pattern	RA procedure	Communication technology
Mankar et al. [1]	Generate-at-will (synchronized UEs)	Generic random process	Not specified
Chen et al. [9]	Generate-at-will (synchronized UEs)	ALOHA-like	Not specified
Zhang et al. [8]	Poisson process	Not specified	NB-IoT
This work	Constant time between updates (synchronized & unsynchronized UEs)	Contention-based (3GPP standard)	4 G/5 G

The rest of the paper is organized as follows. The system model is presented in Sect. 2 jointly with the information update generation patterns. Section 3 presents the network configuration parameters and the KPIs considered in the study for evaluating the network performance. The results are presented and discussed in Sect. 4. Finally, the conclusions and future work are presented in Sect. 5.

2 System model

A scenario consisting of a BS simultaneously serving MTC and H2H user equipments (UEs) is considered. At the time $t < 0$, all UEs are idle and disconnected from the BS. At $t = 0$, the MTC UEs start generating information update messages with a certain frequency and at a random time determined by the frequency generation pattern, which is set as detailed in Sect. 2.3. Upon generating an information update message, the MTC UEs transition from idle to active state and establish the connection towards the BS (RA procedure detailed in Sect. 2.1). As for the background H2H traffic and to generate the most realistic environment possible within the cellular network, traces collected from the Call Detail Records (CDR) of the Italian operator Telecom Italia were used, which provided the data as part of a "Big Data Challenge" in 2014 [11–13].

The RA can operate in two modes: contention-free and contention-based. The former is used for critical situations such as handover, downlink data arrival, or positioning. The latter is the standard mode for network access, it is used by UEs to change the radio resource control (RRC) state from idle to connected, to recover from radio link failures, to perform uplink (UL) synchronization, or to send scheduling requests [14].

Random access attempts are allowed in predefined time/frequency resources, called random-access opportunities (RAOs). The BS broadcasts the periodicity of the RAOs using a variable referred to as the physical RACH (PRACH) Configuration Index (*prach-ConfigIndex*). The periodicity varies between a minimum of 1 RAO per frame (i.e., 1 RAO every 10 ms) up to 10 RAOs per frame (i.e., 1 RAO every 1 ms) [15].

The PRACH signals a connection request when a UE needs to access the RAN. It carries a preamble for initial access to the network. There are up to $R = 64$ orthogonal preambles available to the UEs per cell [15]. In contention-free mode, there is a coordinated assignment of preambles, so collision is avoided, but base stations (named gNBs in 5 G) can only assign these preambles during specific slots to specific UEs. Hence, UEs can only use these preambles if assigned by the gNB, and during specific slots. In the contention-based mode, preambles are selected randomly by the UEs, so there is a risk of collision; that is, there is a probability that multiple UEs in the cell pick the same preamble; therefore, contention resolution is needed. In the sequel, we focus on the contention-based random access mode. Table 2 shows a summary of the notations used in this paper.

2.1 Contention-based random access procedure

Figure 1 illustrates the random access procedure implemented, adhering to the 3GPP standard. This procedure entails the exchange of four messages between the UE and gNB. As observed, a UE initiates its access attempt by sending *Msg1* to the gNB. *Msg1* contains a preamble randomly chosen by the UE from a set of preambles. Due to preamble orthogonality, several UEs can access the gNB in the same RAO using different preambles. However, if two or more UEs transmit the same preamble, the transmitted preamble cannot be decoded by the gNB, i.e., an *Msg1* transmission collision occurs [16]. If *Msg1* has sufficient transmission power, it will be decoded by the gNB [16–18]. If it is not decoded, the UE will make a new attempt by increasing the transmission power.

The gNB responds with an *Msg2* to each successfully decoded *Msg1*. The *Msg2* includes identification information for the detected preamble and the granting of reserved resources (UL Grant) for the *Msg3* transmission [16, 18]. The UEs that do not receive the *Msg2* within the W_{RAR} time window will raise their power and perform retransmission by randomly choosing a new preamble. All UEs that receive an UL grant through *Msg2* will be able to transmit *Msg3*. The transmission of *Msg3* is guaranteed through the hybrid automatic repeat request (HARQ) [16, 18].

Table 2 Summary of notations

Notation	Description
R	Available preambles for contention-based random access
W_{RAR}	RAR window size
U_{ID}	Device identification
ϕ	Offset for information update messages' generation patterns
$Phi1$	Constant time between updates with synchronized devices pattern
$Phi2$	Constant time between updates with unsynchronized devices pattern
T_u	Time between updates
U	Update arrival rate
K	Number of preamble transmissions per access attempt
P_s	Access success probability
η_A	Total number of attempts with successful access
η_T	Total number of preamble transmissions needed to complete the RA procedure
D	Access delay

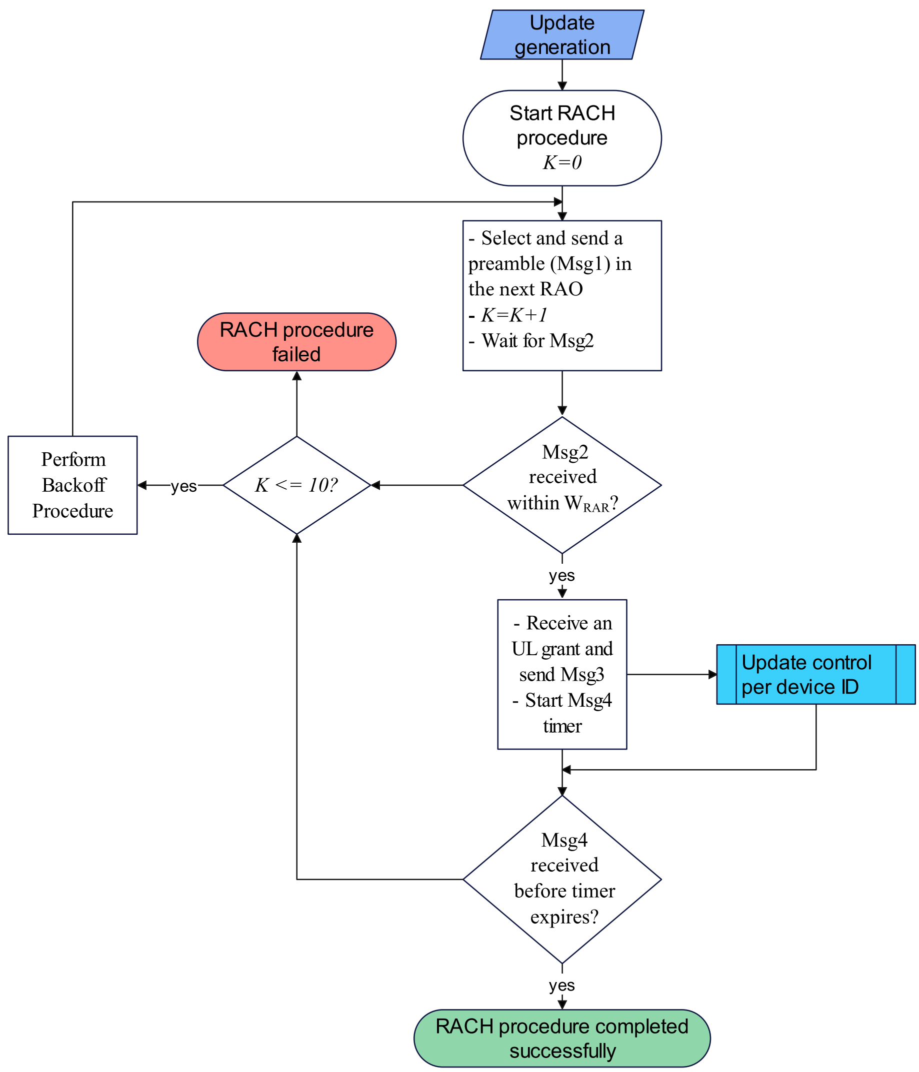

Fig. 1 Contention-based random access procedure

The gNB transmits *Msg4* in response to *Msg3*. *Msg4* also uses the HARQ process. If the UE does not receive *Msg4* within the contention resolution time, the connection is declared failed, and a new access attempt is planned by increasing the transmission power. If a UE reaches the limit of unsuccessful re-transmissions, the network is declared unreachable, terminating the RA procedure [16]. UEs that complete the RA procedure receive a block of time-frequency resources for communication. All UEs that fail their transmission must execute a backoff procedure, regardless of the reason for the failure or the slice to which they belong. In this procedure, the UE waits for a random time, $\mathcal{U}(0, BI)$ in milliseconds, before starting a new preamble transmission in a new RAO. BI is the backoff indicator, defined by the gNB and sent to the UEs in the *Msg2* [18, 19]. Finally, as shown in Fig. 1, a control process block for information update messages was created to ensure that the gNB receives accurate and fresh information generated by the devices, which are identified using the variable U_{ID}. The following section provides a detailed explanation of this process.

2.2 Control process of information update messages

The control process of information update messages is conducted by the gNB during each RAO. In this process, every UE generates update messages indistinctly, resulting in two different scenarios. In the first scenario, a single packet from a UE arrives and is transmitted immediately. In the second scenario, multiple packets from a certain UE are received within the same RAO. In this case, an analysis must be carried out to purge the information and retain the freshest information update message on the UE side. The process of debugging and discarding information update messages involves the following sequential phases, illustrated in Fig. 2:

1. Discard according to the timestamp corresponding to *Generation Time*, thus leaving the most recent information update message.
2. Discard according to the number of preamble transmissions. Each device has up to a maximum of 10 attempts to send the preamble as indicated by [20]. When the first purge is passed, the amount corresponding to the indicated variable and the one with the least number of attempts is selected since a certain amount of time is added between each attempt to send the preamble, affecting the freshness of the information update message to be sent. In case more than two information update messages have passed the two previous debugging stages, the third one is proposed.
3. Discard based on the timestamp of each update message; this way, the one with the earliest timestamp will be selected, thus presenting the most current information.

Finally, if there is more than one information update message, only one is randomly chosen among those available for presentation.

2.3 Generation patterns of information update messages

Two different information update messages' generation patterns from the source were defined for MTC traffic, which uses different update frequencies. These are:

1. **Constant time between updates with synchronized devices (Phi1)**: All IoT devices generate information update messages at $\phi + k\,T_u$, $k = 0, 1, 2, \ldots$
2. **Constant time between updates with unsynchronized devices (Phi2)**: IoT device i generates information update messages at $\phi_i + k\,T_u$, $k = 0, 1, 2, \ldots$

Note that the time is slotted and the time between updates T_u is equivalent to the inverse of the update arrival rate, i.e., $T_u = \left(\frac{U}{1000}\right)^{-1}$; $0 \leq \phi, \phi_i < T_u$. The difference between these types of updates lies in selecting the opportune moment to generate an information update message.

3 Network configuration parameters and performance metrics

A discrete-event simulator of the 5 G RAN was developed to evaluate the proposals. The system accommodates MTC and H2H traffic in each simulation, with different access request intensities. The contention-based RA procedure described in Sect. 2.1 is replicated with the parameters listed in Table 3. Simulations were run j times until the average results from the jth differ from the $j-1$th simulation by less than 1%. The devised simulator provides the flexibility of choosing the parameters of interest, including the type of traffic, number of devices, timing, processing, and channel parameters such as the number of available preambles, priorities, and backoff window size, among others. The simulation runs considered the parameters listed in Table 4.

Regarding the performance metrics, three KPIs for RACH capacity evaluation with each updating policy are considered; these are the following [5, 20]:

1. Access success probability P_s. It is the probability of completing the random access procedure within the maximum number of preamble transmissions. P_s is defined by (1)

$$P_s = \frac{\eta_A}{\eta_T}, \tag{1}$$

Fig. 2 Flow diagram of the information update messages' control process per IoT device

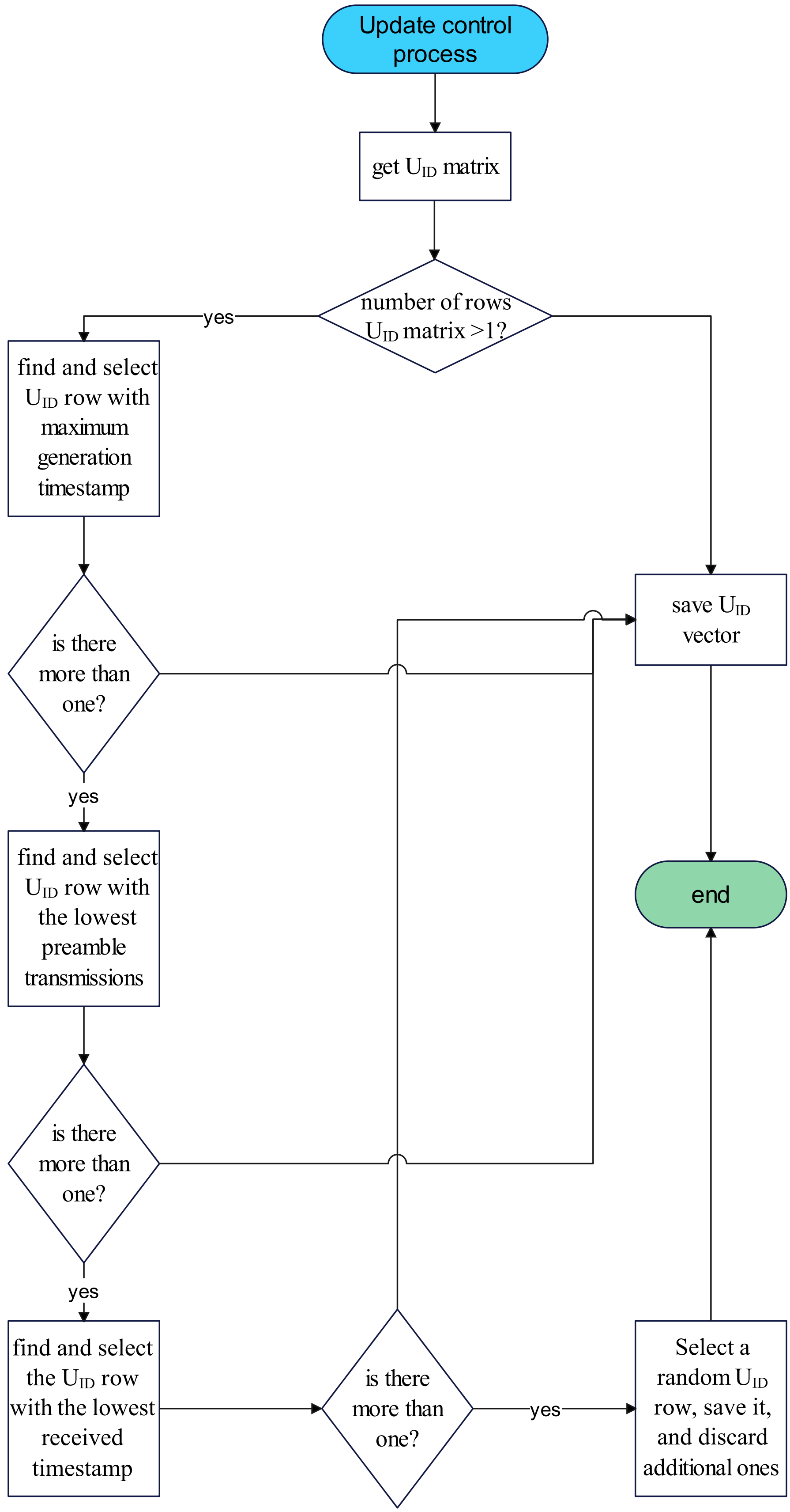

Table 3 RACH configuration

Parameter	Setting
PRACH configuration index	*prach-ConfigIndex* $= 6$
Periodicity of RAOs	5 ms
Subframe length	1 ms
Available preambles for contention-based random access	$R = 54$
Maximum number of preamble transmissions	*preambleTransMax* $= 10$
RAR window size	$W_{\text{RAR}} = 5$ subframes
Maximum number of uplink grants per subframe	$N_{\text{RAR}} = 3$
Maximum number of uplink grants per RAR window	$N_{UL} = W_{\text{RAR}} \times N_{\text{RAR}} = 15$
Backoff Indicator	$BI = 20$ ms
mac-ContentionResolutionTimer	48 subframes
Re-transmission probability for *Msg3* and *Msg4*	0.1
Maximum number of *Msg3* and *Msg4* transmissions	5
Preamble processing delay	2 subframes
Uplink grant processing delay	5 subframes
Connection request processing delay	4 subframes
Round-trip time (RTT) of *Msg3*	8 subframes
RTT of *Msg4*	5 subframes

Table 4 Simulation configuration

Parameter	Setting
Number of information update messages per second (U)	[5, 50]
Number of MTC devices (N)	[4, 100]
Simulation time (T)	1 min (fixed)
Stop criteria (error)	$< 1\%$

where η_A is the total number of attempts with successful access, and η_T is the total number of preamble transmissions.

2. Average number of preamble transmissions per access attempt $\mathbb{E}[K]$.
3. Statistics of access delay D. This indicator is defined as the number of access attempts that were successfully completed within a time D after the first preamble transmission.

4 Results

In the following, we detail the network performance results for MTC traffic according to the network configuration detailed in Table 3. These results were obtained using the discrete-event simulator of the 5 G RAN developed in Python and corroborated with MATLAB simulations independently. The simulations were run on a PC with Windows 10 OS (64-bit), an Intel Core i7-6600U CPU, 2.81 GHz, and 16 GB RAM, with a clock precision of 10^{-7} s.

We consider that the number of information update messages per second (U) for the MTC device ranges from 5 to 50. Also, the network's MTC devices (N) vary from 40 to 100. The H2H service is considered *background traffic* in each scenario. During the tests, the simulation time T remained fixed; that is, $T = 1$ minute, representing a sufficient time to obtain samples.

4.1 Information update messages pattern Phi1

Figure 3 illustrates the behavior of P_s as a function of the number of information update messages per device for several system loads. This analysis makes it possible to observe and determine that around a certain value of U, the deterioration of the system's performance is notorious ($P_s < 0.9$). Note that the decrease in P_s indicates the inflection point at which increasing U harms the system. For example, when the system is under low load, it is more tolerant to the increase of U (note $N = 50$, from $U = 45$, P_s starts to decrease), but when the system is overloaded ($N = 100$), it is expected that with values of $U > 20$ the delivery of the update to an application will be negatively affected.

Regarding K, under lower values of updates/s ($U < 10$), as shown in Fig. 4, the number of attempts made by the IoT devices that successfully access the network is toler-

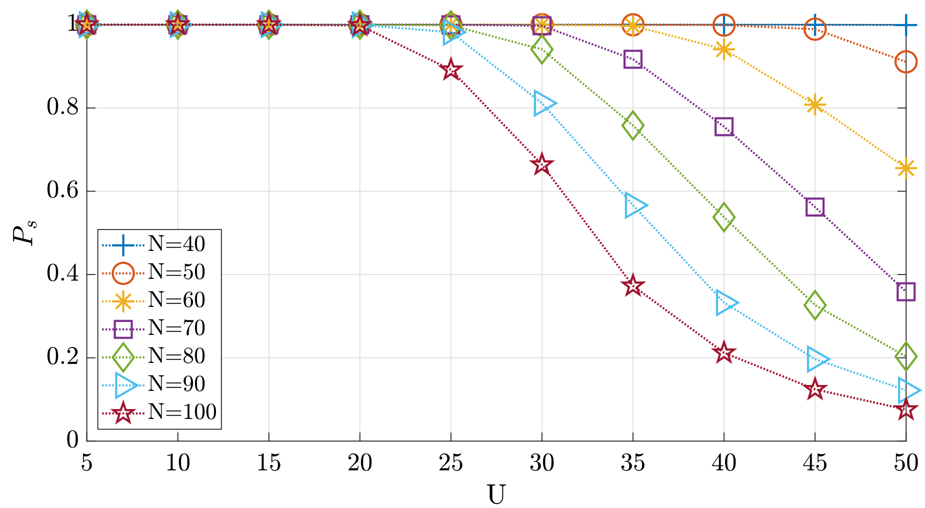

Fig. 3 Update pattern Phi1. Successful access probability P_s

ant but greater than two for all the scenarios except for $N = 40$. In an overload situation ($N = 100$) and higher update frequency ($U = 50$), the IoT devices should perform at least five attempts to complete the RA procedure. Therefore, the higher the information update messages' intensity U, the higher the average number of preamble transmissions K, which is expected in cellular IoT. Similar behavior is shown in Fig. 5 for the access delay based on the 95 th percentile; that is, the information update messages frequency is directly proportional to the delay generated after $U > 15$ and $N > 70$. Hence, for real-time IoT applications with access delay requirements of less than 90 ms, in an overload situation, the information update messages' frequency is recommended to be $U \leq 15$.

4.2 Information update messages pattern Phi2

Regarding the successful access probability, the Phi2 information update message pattern presents a behavior similar to the first pattern analyzed; that is, the lower the system loads, the better the P_s in all scenarios for a higher number of information update messages per second. The inflection point at which the system's performance (P_s) is expected to be negatively affected by the frequency of information update messages, under overloaded, is also $U > 20$ (Fig. 6).

Some minor differences but not negligible with the Phi1 pattern can be seen in the K (Fig. 7) and D_{95} (Fig. 8) metrics. The Phi2 generation pattern provides better performance for $U \leq 25$ and $N \leq 100$ compared to Phi1 ($U \leq 20$) regarding the K metric. When the system is overloaded, the Phi2 generation pattern allows up to 20 information update messages per second with access delay generated less than 100 ms , better than the Phi1 generation pattern ($U \leq 15$).

5 Conclusion

We conducted an evaluation study to analyze the impact of information update message generation patterns on RAN performance in cellular IoT. We evaluated network performance metrics such as the probability of successful access, access delay, and the average number of preamble transmissions under different MTC traffic conditions, considering H2H service as background traffic, using a discrete-event simulation model.

It is evident that increasing the number of information update messages per IoT device affects the successful access probability and has implications for the number of preamble transmissions a device requires for successful access, resulting in an increased access delay or obsolescence of information at the destination. Generating a short number of information update messages for a given number of users would ensure that system performance is not affected, bandwidth usage is not compromised, and fresh information is delivered at the destination, but it would not be a realistic real-world scenario and may not be an optimal solution. The opposite scenario suggests that excessively increasing the frequency of the generation of updates would compromise all three metrics and the information state of the system. We conclude that the successful access probability serves as a good indicator of how many updates an IoT device must report to not degrade the system's performance. Hence, achieving a proper balance between information update frequency and successful access probability is essential for optimal CIoT operation.

The proposed update control process is able to adjust the information update frequency, enabling a significant number of IoT devices to successfully access the RACH, even during overload situations. However, it currently operates in scenarios where the UEs load remains constant in the channel, which might not always be the case. For instance, during

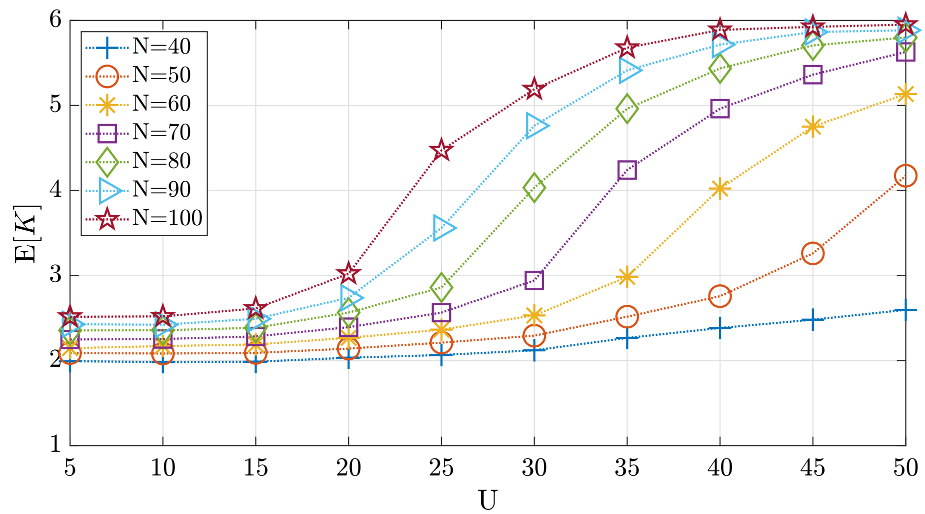

Fig. 4 Information update message pattern Phi1. Average number of preamble transmissions required for successful access $\mathbb{E}[K]$

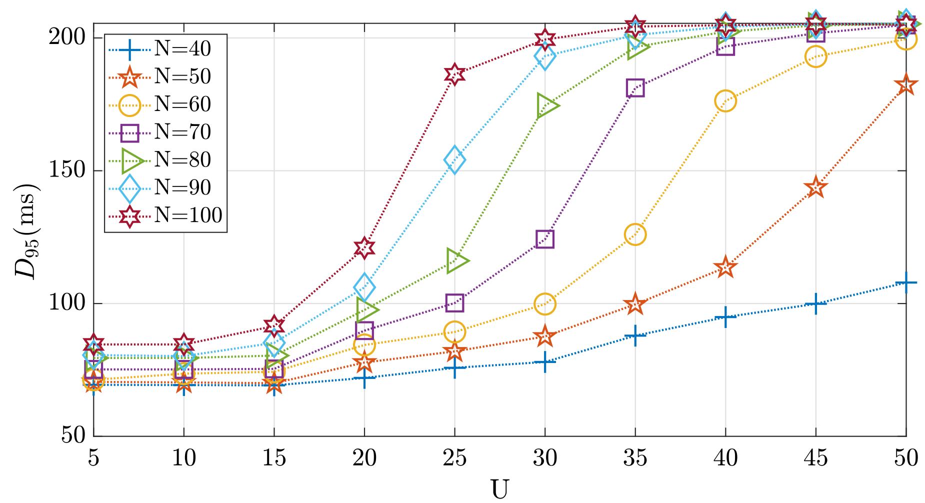

Fig. 5 Information update messages pattern Phi1. 95th percentile of access delay D_{95}

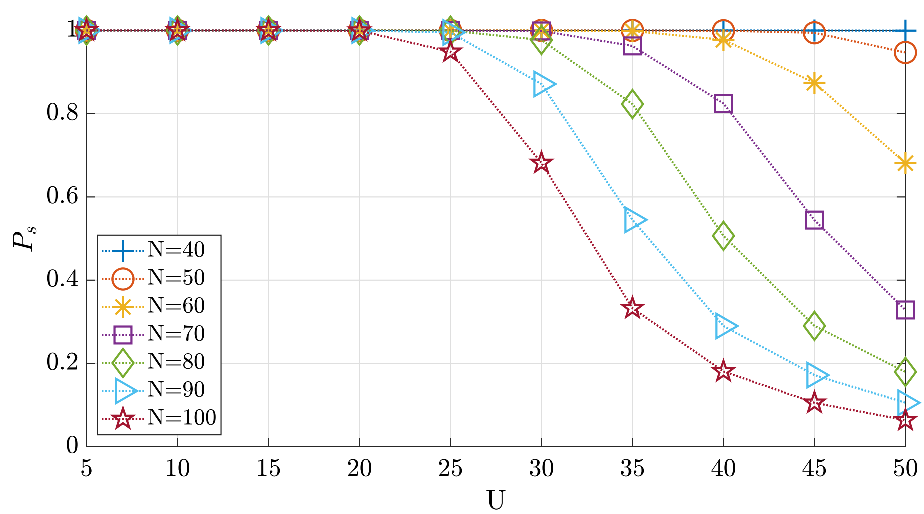

Fig. 6 Information update messages' generation pattern Phi2. Successful access probability P_s

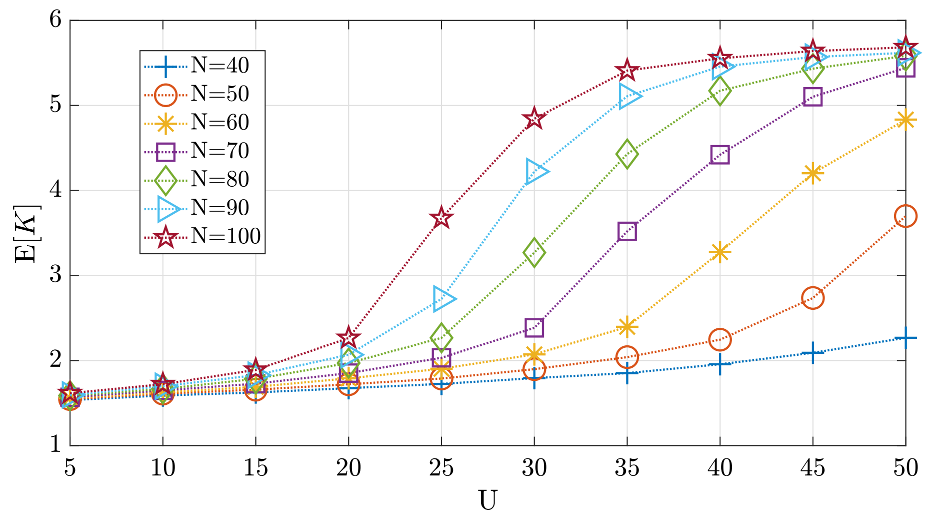

Fig. 7 Information update messages' generation pattern Phi2. Average number of preamble transmissions required for successful access $\mathbb{E}[K]$

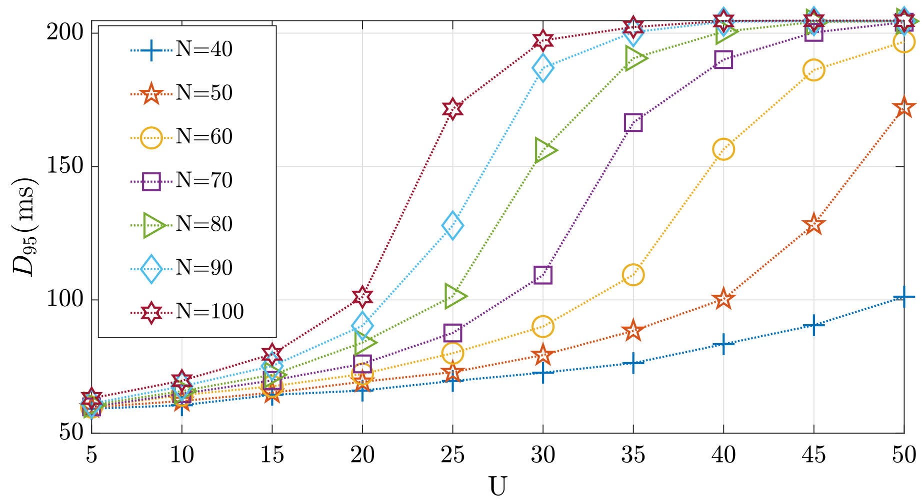

Fig. 8 Information update messages' generation pattern Phi2. 95th percentile of access delay D_{95}

emergency situations like environmental catastrophes, IoT devices typically handle different information update frequencies [21], leading to varying loads in the channel. To address this limitation, we plan to develop an adaptive mechanism based on reinforcement learning tools. This mechanism will dynamically and autonomously adjust the information update messages' frequency according to the load introduced by H2H and MTC users in the RACH.

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Data availability All the data, models, and scripts used to make this paper are available upon request to the authors.

Declarations

Conflict of interest The authors have not disclosed any competing interests.

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Marcelo E. Flores Vázquez received an Engineering degree in Electronics and an Industrial Technologist degree from the Salesian Polytechnic University (Ecuador), he has a Master's Degree in Automation, and Industrial Informatics obtained from the Polytechnic University of Valencia (Spain), aMaster's Degree in Education, and a Higher Diploma in Socio-educational Research. He is currently a Ph.D. candidate in the Automatic Robotics and Industrial Informatics doctoral program at the Polytechnic University of Valencia (Spain). He has 10 years of experience in automation projects in the industry. He is a member of the Research Group in Cloud Computing Smart Cities & High-Performance Computing. He was a professor of PC Architecture and Embedded Systems in the master's programs of Mathematical Methods and Numerical Simulation and of Engineering in Electronics and Automation. He was a Fellow of the National Secretary of Science and Technology. Currently, he works as a Professor and Head of the Professional Sciences area at the Salesian Polytechnic University. He has several scientific publications on topics related to vision and sensor networks.

Luis Tello-Oquendo received the electronic and computer engineering degree (Hons.) from Escuela Superior Politécnica de Chimborazo (ESPOCH), Ecuador, in 2010, the M.Sc. degree in telecommunication technologies, systems, and networks, and the Ph.D. degree (Cum Laude) in telecommunications from Universitat Politécnica de Valéncia (UPV), Spain, in 2013 and 2018, respectively. From 2013 to 2018 he was Graduate Research Assistant with the Broadband Internetworking Research Group, UPV. From 2016 to 2017 he was a Research Scholar with the Broadband Wireless Networking Laboratory, Georgia Institute of Technology, Atlanta, GA, USA. He is currently an Associate Professor with the Universidad Nacional de Chimborazo. His research interests include MTC, wireless SDN, 5G and beyond cellular systems, IoT, machine learning. He is a member of the IEEE and ACM. He received the Best Academic Record Award from the Escuela Técnica Superior de Ingenieros de Telecomunicación, UPV, in 2013, the Extraordinary Doctoral Thesis Award from the Escuela de Doctorado, UPV, in 2019, and the Best Researcher Award from the Ecuadorian Corporation for the Development of Research and the Academy (CEDIA), in 2021.

Vicent Pla received the Telecommunication Engineering (B.E. & M.E.) and Ph.D. degrees from the UPV in 1997 and 2005, respectively, and the B.Sc. in Mathematics from the Universidad Nacional de Educación a Distancia (UNED), Spain, in 2015. In 1999, he joined the Department of Communications at the UPV, where he is currently a Professor. His research interests lie primarily in the area of modeling and performance analysis of communication networks. During the past few years, most of his research activity has focused on traffic and resource management in wireless networks. In these areas he has published numerous papers in refereed journals and conference proceedings, and has been an active participant in several research projects.

Juan Aranda received a B.S. degree in Electronic Engineering and a M.Sc. degree in Electronics Engineering (Cum Laude) from Universidad de los Andes, Colombia, in 2010 and 2012, respectively. The Ph.D. degree (Magna Cum Laude) in Engineering from the Pontificia Universidad Javeriana, Colombia, in 2020. Since 2021, he has been an Associate Professor with the Facultad de Ingeniería, Universidad de La Sabana, Colombia. His current research interests are wireless networks and connectivity on Internet of Things (IoT) applications, TinyML and Industry 4.0 applications.

Juan V. Capella is Area Director (attached to the vice-chancellor) of the Universitat Politécnica de Valéncia (UPV) and Director of UPV Science Park. He received the Eng. degree in Computer Science, MS degree in Computer Engineering and Ph.D. by the Universitat Politécnica de Valéncia (UPV) in 1998, 2002 and 2010. He is an associate professor of the Department of Computer Engineering (DISCA), UPV. Formerly Deputy Director of Research of DISCA-UPV (2016-2021) and Head of HP Institute ETSINF (2013 - 2015). He is visiting professor at ESIGELEC French engineering school, where he teaches in an international master degree. He has been involved in different innovation projects in higher education since 2002. He has published six books and more than 70 scientific papers in refereed international journals and conferences, and has taken part in 20 research projects funded by the EU or the Ministry of Education, being the principal investigator in several of them. He is member of the editorial committee of four international journals, and he has been reviewer, organizer, and member of the program committee of several international conferences organized by IEEE and ACM. He has received a number of recognitions including several best paper awards, research impact awards form ITACA institute and Excellence Teacher.

Andrea K. Guamo Morocho received the B.S. in Electronic and Telecommunications from the University of Loja, Ecuador, and her M.S. degree in Telecommunication Technologies, Systems and Networks from Universitat Politécnica de Valéncia. She is currently pursuing a Ph.D. degree in Signal Processing at the University of Vigo, Spain. Her interests include full-duplex, mmWave, and MIMO communications.