IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 17 April 2024, accepted 13 June 2024, date of publication 26 June 2024, date of current version 19 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3419216

SURVEY

# A Survey on NB-IoT Random Access: Approaches for Uplink Radio Access Network Congestion Management

**LOINI IIYAMBO**[1], (Graduate Student Member, IEEE), **GERHARD HANCKE**[1,2], (Fellow, IEEE), AND **ADNAN M. ABU-MAHFOUZ**[1,3], (Senior Member, IEEE)

[1]Department of Electrical, Electronic, and Computer Engineering, University of Pretoria, Pretoria 0028, South Africa
[2]Department of Computer Science, City University of Hong Kong, Hong Kong
[3]Council for Scientific and Industrial Research, Pretoria 0184, South Africa

Corresponding author: Loini Iiyambo (loinitsh@gmail.com)

**ABSTRACT** Narrowband Internet of Things (NB-IoT) is one of the most promising technologies for enabling reliable communication among low-power, and low cost devices present in massive machine-type communications (mMTC). In NB-IoT, random access (RA) is implemented in the medium access control (MAC) layer to resolve access contention among massive IoT devices. Efficient network access techniques are required to effectively solve the massive access issues in NB-IoT, guaranteeing increased throughput and high spectrum utilization. In this paper, we present a comprehensive overview of NB-IoT towards supporting mMTC, with focus on the NB-IoT coexistence with 5G, as well the design challenges and requirements of RA in NB-IoT. Moreover, available literature is reviewed to highlight the RA congestion control schemes proposed during the past few years to alleviate RA collisions. While existing RA approaches mainly focus on conventional contention-based techniques for performing RA, intelligent learning based and grant-free Non-Orthogonal Multiple Access (NOMA) have been identified as a potential candidates to increase the transmission efficiency of mMTC applications.

**INDEX TERMS** Narrowband Internet of Things, random access, radio access network congestion, grant-free non-orthogonal multiple access, machine learning.

## I. INTRODUCTION

Mobile devices and wireless communication have developed significantly over the past years. Fuelling to this growth is the demand for both high-speed wireless connections, faster and seamless Internet based services and applications, making 5G one of the most promising technologies for future applications. In most cases, the 5G cellular network is characterised by high bandwidth, large coverage, and low latency compared to cellular networks such as 3G and 4G.

Further development of the 5G architecture has facilitated the advancement in Internet of Things (IoT) where autonomous devices are interconnected using a combination of cellular, short range and long range wireless technologies. 5G based IoT enables multiple innovative applications between billions of low powered machine type devices (MTD), introducing massive Machine Type Communication (mMTC). mMTC span a wide range of application areas including home automation, industrial control, smart cities, and health care. It is expected that over 100 billion IoT devices will be connected to the mobile network in the year 2030 [1].

To better meet the demands of massive Machine Type Communication (mMTC), Narrowband Internet of Things (NB-IoT) was developed by the Third Generation Partnership Project (3GPP) to facilitate communication among large-scale deployments of IoT devices [2]. According to [3] and [4], NB-IoT is the most promising Low Power Wide Area Network (LPWAN) technology compared to technologies such as ZigBee, LoRa, and Ingenu. The main design requirements of NB-IoT are to provide deep coverage for massive connections at low cost and low power consumption [5].

The associate editor coordinating the review of this manuscript and approving it for publication was Min Jia.

© 2024 The Authors. This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License.
For more information, see https://creativecommons.org/licenses/by-nc-nd/4.0/

These requirements present numerous design challenges for NB-IoT development due to the need for new and improved techniques in terms of energy saving, enhanced coverage, and low data rates. Most of these improvements are achieved by reusing some of the design features of LTE, making it more suitable to accommodate a large number of devices with improved quality of services.

During the initial connection establishment of massive Machine Type Communication (mMTC) networks, a user equipment (UE), referring to the 3GPP standard naming for an NB-IoT node, initiates the random access (RA) procedure by sending an initial preamble sequence to the base station (eNB) using the uplink NB-IoT physical random-access channel (NPRACH). Due to the limited number of preambles, two or more UEs may transmit the same preamble simultaneously, resulting in a collision. The collided devices cannot transmit data until a successful preamble transmission is achieved. Successful preamble reception is made even more challenging since the UEs are placed in unreachable geographic locations, such as deep basements and underground environments, where the wireless signals may not easily penetrate.

NPRACH repetitions have thus been introduced to improve the reliability of RA by allowing collided devices to repeat preamble transmission several times, thus improving the signal reception of the preambles at the eNB. Taking into consideration that mMTC aims to support 1,000,000 devices per square kilometer (km$^2$), this means that numerous devices will concurrently perform RA over the shared channel causing severe radio access network (RAN) congestion as well as increased repetitions [6], [7]. The massive deployment of NB-IoT devices lead to increased latency, packet loss and severe packet delay during RAN congestion. Improved massive connectivity techniques controlling random access in NB-IoT are thus required to increase random access success, thereby reducing access delay, and lower power consumption of the UE.

To the best of our knowledge, this paper is the first to survey random access network congestion management in NB-IoT. In this paper, an in-depth discussion of the issues and requirements affecting random access in NB-IoT is provided. Due to the demand for efficient massive connectivity techniques, our thorough survey offers classification and discussion of the existing RA enhancement techniques proposed in NB-IoT as well as the potential of grant-free Non-Orthogonal Multiple Access (NOMA) schemes in addressing the shortcomings of grant-based RA techniques in supporting mMTC. Table 1 summarises existing surveys in comparison with ours.

## LIST OF FREQUENTLY USED ACRONYMS

| | |
|---|---|
| ACB | Access class barring |
| CE | Coverage enhancement |
| CRQ | Contention resolution queues |
| DL | Downlink |
| CFO | Carrier frequency offset |
| eNB | Evolved node base station |
| LPWAN | Low power wide area network |
| MAC | Medium access control |
| MCL | Maximum coupling loss |
| MTD | Machine type devices |
| mMTC | massive machine type communication |
| NOMA | Non-orthogonal multiple access |
| NPRACH | Narrowband internet of things physical random-access channel |
| NR | New radio |
| PD-NOMA | Power domain non-orthogonal Multiple Access |
| PHY | Physical layer |
| RL | Reinforcement learning |
| UE | User equipment |
| UL | Uplink |
| RACH | Random-access channel |
| RAN | Radio access network |
| SCMA | Sparse code multiple access |
| SIC | Successive interference cancellation |
| TA | Timing advanced |
| TOA | Time-of-Arrival |

**TABLE 1. A description of previous related surveys on NB-IoT.**

| Reference | Year | Key Contribution |
|---|---|---|
| [8] | 2017 | Surveys performance based theories and security requirements of NB-IoT. |
| [9] | 2018 | Surveys the evolution of NB-IoT, key technologies and identifies open issues. |
| [10] | 2019 | Surveys resource allocation techniques and energy efficient techniques of IoT |
| [11] | 2019 | Presents a comprehensive overview of Physical and MAC layers developments in NBIoT |
| [12] | 2020 | Surveys NB-IoT resource management focusing on data rate, energy efficiency and scalability enhancement. |
| [13] | 2020 | Surveys 5G NR coexistence with NB-IoT. |
| [14] | 2020 | Surveys downlink scheduling issues and potential solutions |

The major contributions of this review article can be summarized as follows.

NB-IoT is a new radio interface that is still at its initial stages of development thus there is still ongoing research to find optimal configurations to facilitate improvement in the system performance. RA optimization can easily be achieved once the RA requirements and challenges are clearly identified and understood. Therefore, this paper aims to provide an in-depth discussion on the technical design challenges and requirements of random access in NB-IoT.

Several researchers have studied and proposed novel solutions addressing random access congestion schemes in NB-IoT networks. Our study extensively reviews available literature and provides a classification of the existing random access congestion control schemes proposed for NB-IoT and mMTC in general. The RA schemes classification is beneficial to potential researchers who want to propose congestion control techniques for mMTC.

Most of the existing RA control techniques rely on contention-based RA for network access. With the tremendous growth of IoT traffic, these schemes are incapable of accommodating the traffic growth due to the signalling overhead and excessive latency. Our work review both grant-free NOMA and the intelligent learning approaches that are deployed to efficiently handle the massive connectivity of IoT devices in mMTC network and compares the performances of these newly proposed approaches.

The remainder of the paper is organized as follows. In Section II and III, we provide a general overview of NB-IoT and random access control in NB-IoT, followed by the design challenges and requirements of NB-IoT in section IV. Section V provide the schemes developed to address random access congestion control in NB-IoT. Lastly, we present the latest trends of grant-free NOMA and machine learning schemes that are proposed to address the RA challenges of mMTC.

## II. NB-IoT OVERVIEW

The evolution of 5G networks presents a huge potential for MTC by supporting short, infrequent, and heterogeneous traffic which may be attractive for delay insensitive IoT applications such as water meter readings and goods' tracking services. Envisaging this growth, the Third Generation Partnership Project (3GPP) carried out deliberate extensive research way back in 2005 focusing on improving existing wireless technologies. Since wireless networks serves network devices with varying resources and application needs, different UE categories were introduced to cater for this need. The differences between the 3GPP UE categories and the evolution towards NB-IoT are summarised in Table 2.

NB-IoT [2], [15] can coexist with networks such as GSM, LTE and general packet service (GPRS). This coexistence enables high utilization of the design features of existing cellular technologies, contributing immensely to the fast deployment of NB-IoT which is made possible by reusing existing hardware and spectrum without coexistence issues.

NB-IoT can be deployed in three different modes, namely, guard band, stand-alone and in-band. In stand-alone mode, NB-IoT uses a dedicated band, whereas in-band and guard-band uses a physical resource block (PRB) within LTE. In all these modes, NB-IoT is designed to provide low cost devices, low power consumption, massive connectivity, and deep coverage [2], [16].

The PHY and MAC layer design of LTE are redesigned and optimised to enhance NB-IoT performance as follows:

- Downlink and uplink channels utilises a bandwidth of 180 kHz
- Orthogonal frequency-division multiple access (OFDMA) is used in the downlink channel with 15 kHz subcarrier spacing over 12 subcarriers
- The frame structure used for transmission is 10 ms long uses slot duration of 0.5 ms.
- Single-carrier frequency-division multiple access (SC-FDMA)is used in the uplink channel with either 3.75 kHz or 15 kHz subcarrier spacing
- Uplink supports both single tone and multi-tone (i.e. 3, 6, 12 tones) operation.
- The physical layer uses forward error correction (FEC) using turbo coding techniques and Cyclic Redundancy Check (CRC)codes.
- Repetition of control signals and data transmission is used to achieve coverage enhancement in devices located in deep structures.
- Uses frequency division duplexing (FDD) half-duplex
- Quadrature phase-shift keying (QPSK) and binary phase-shift keying (BPSK)/QPSK modulations are utilised on the downlink/uplink subcarrier.

Both the uplink and downlink channels inherit their numerology from LTE. According to [17] and [18], the uplink channel bandwidth is shared between 15 subcarriers of either 3.75 kHz or 15 kHz spacing. In uplink transmission, single carrier frequency division multiple access (SC-FDMA) is used to transmit data. Both singletone and multi-tone are supported in uplink transmission. The physical channels used for uplink communication are:

1) Narrowband physical uplink shared channel (NPUSCH): carries control signals and actual data from the UE to the eNB. The data being communicated is differentiated using two different formats. Format 1 is used to send uplink data with maximum transmission block size of 1000 bits and format 2 is used for carrying signaling data.
2) Narrowband Random Access Channel (NPRACH): used to facilitate random access procedure which is normally performed before the data payloads can be send by the UE.

In the downlink transmission, orthogonal frequency division multiple access (OFDMA) is used by the 12 subcarriers with subcarrier spacing of 15 kHz. The physical signals/channels found in downlink communication are as follows:

1) Narrowband Downlink Shared Channel (NPDSCH): used to transmit data that is specific for UE.
2) Narrowband Downlink Control Channel (NPDCCH): contains donlink control information (DCI).
3) Narrowband Broadcast Channel (NPBCH): responsible for communicating the master information block (MIB) from the eNB to the UE.
4) Narrowband Primary Synchronization Signal(NPSS)/ (NSSS): used for establishing time-frequency synchronization between the UE and the eNB.

### A. COMPARISON OF NB-IoT WITH OTHER LPWAN TECHNOLOGIES

Existing wireless networks such as Bluetooth, Wi-Fi, and ZigBee are not suitable for IoT applications due to their limited coverage and high data rate offerings [19]. IoT applications, therefore, benefit more from LPWAN technologies

**TABLE 2.** Advancement of UE categories towards NB-IoT.

| | Cat. 1 | Cat. 0 | Cat. M1 | Cat. NB1 |
|---|---|---|---|---|
| **Downlink Peak rate** | 10 Mbps | 1 Mbps | 1 Mbps | 200 kbps |
| **Uplink peak rate** | 5 Mbps | 1 Mbps | 1Mbps | 144 kbps |
| **Antenna** | omnidirectional | omnidirectional | omnidirectional | omnidirectional |
| **Bandwidth** | 20 MHz | 20 MHz | 1.4 MHz | 200 kHz |
| **Transmit power** | 23 dBm | 23 dBm | 20 dBm | 20 dBm |
| **Duplex** | full duplex | half duplex | half-duplex frequency-division duplex (HD-FDD) | half duplex |
| **Coverage enhancement** | 140.7 dB | 164 dB, 154 dB | 155.7 dB | 164 dB |
| **Power Saving Method** | PSM, eDRX | PSM, eDRX | PSM, eDRX | PSM, eDRX |
| **Mobility** | low | low | high | low |
| **3GPP Rel Features** | Release 8<br>Support RF channel bandwidth 1.4 MHz-20 MHz, optimization of charging mechanisms, addressing, fixed location, low mobility and low activity terminals, handling large UE | Release 12<br>Power-saving mode (PSM), low-complexity device, relaxed RF requirements | Release 13<br>Reduction in device cost and complexity, extended DRX, reduced RF bandwidth, improved network coverage<br>Release 14<br>Multicast, enhancement for message segmentation and mobility, system access on non-anchor carriers<br>Release 15<br>Early data transmission, cell range and load control, power enhancements, development of 5G New Radio, Non-orthogonal Multiple Access<br>Release 16<br>Co-existence of NB-IoT with 5G NR, Preconfigured Uplink Resources, 2-step PRACH, multiplexing, traffic prioritization, Mobility enhancements, Multiple-input multiple-output(MIMO) enhancements, multiple grant-free uplink transmission configurations<br>Release 17<br>Extend 5G NR, NR-Light, NR multicast and broadcast, MIMO enhancement, Dual-connectivity enhancements, dynamic spectrum sharing, network automation, coverage enhancement, RAN data collection enhancements | |

due to their low cost and low data rates attributes. LPWAN technologies can be categorised as licensed and unlicensed frequencies, and each technology is differentiated in terms of security, power consumption, delay, coverage, and scalability. The different LPWAN technologies are described below.

LoRa [19] which stands for long range, is a physical layer technology developed by Semtec to provide long range communication. It operates in the unlicenced band of 868 MHz, 915 MHz, and 433MHz bands [20]. The media access control used in LoRa is referred to as LoRaWAN. In a typical LoRa network, LoRa nodes are connected to a LoRa gateway which further connects to the LoRa application server through the LoRa network server. LoRa networks can cover up to 2km, and this is made possible by the chip spread spectrum modulation, which also contributes to its low power consumption.

Founded in France by a company of the same name, Sigfox [21], [22] is a LPWAN technology with a physical presence in over 70 countries. The Sigfox technology transmits data packets to the Sigfox base station using ultra-narrowband (UNB), attributing to low interference and collisions. It operates at Industry, Scientific, and Medical (ISM) frequencies ranging between 862 MHz to 928 MHz. Sigfox uses the binary phase shift keying (BPSK) modulation technique, which benefits the technology in terms of spectrum efficiency, high receiver sensitivity and affordable hardware designs. It saves the energy consumption of the nodes by limiting the amount of data it can transmit in a day to 12 bytes and 4 messages for uplink and downlink channels respectively. Since the technology is able to cover between 30-50 km in open spaces and 3-10 km in a city, Sigfox is suitable for applications requiring low data transmission and large areas coverage [23].

Initially founded in 2008, Ingenu [24], [25] was developed to overcome limitations such as link capacity, and low data rate faced by LoRa and Sigfox. Ingenu tried to improve these limitations by using direct-sequence spread spectrum (DSSS) modulation and Random Phase Multiple Access (RPMA) technique within the 2.4 GHz ISM band. This way, UE are able to send data using high data rates up to 624 kbps on uplink and 156 kbps on the DL. Additional features of Ingenu includes receiver sensitivity up to 142dBm and it may easily suffer interference due caused by other wireless networks operating in the same spectrum.

The Weightless LPWAN protocol is created by the Weightless Special Interest Group (SIG) to operate in the TV white spaces. It defines three different standards, namely, Weightless-N, Weightless-W, and Weightless-P. The difference among the three specified protocols are: Weightless-N: the IoT devices connect to the base station through ultra-narrow band and it utilises the ISM spectrum which varies per region. Differential Binary Phase Shift Keying modulation (DBPSK). It supports data rates up to 100 kbps and is only able to send data in the uplink channel. This one way communication is not appropriate for most applications especially those that requires reliability because it does not guarantee receipt of data packets. The coverage area supported by weightless N is 5km in cities. Weightless-W operates in the 470-790 MHz spectrum aimed for TV white space. Its data rates ranges between 1kbps and 10Mbps. More than one modulation scheme is supported by the Weightless-W standard such as DBPSK and 16-QAM (16-Quadrature Amplitude Modulation). Successful deployment of Weightless-W is hindered by the limitation of hardware design and unavailability of TV white spaces. Weightless-P is the latest standard among the three standards. It provides data rate up to 100kbps and utilises Gaussian minimum shift keying (GMSK). It has a lower lifespan compared to weightless-N. It is able to cover around 2km in the city and offers more coverage in the village.

DASH7 Alliance Protocol (D7AP) is developed by the DASH Alliance to support wireless sensor and actuator network (WSAN) and radio-frequency identification (RFID) applications. It utilises a radio interface and network stack standardised by ISO/IEC 18000-7 in 433MHz, 868, and 915 MHz ISM bands. The wireless devices can be connected either in a star or tree topology using 2-GFSK and access the media using CSMA/CA. Traffic and operational features of DASH7 are considered to be bursty, light, asynchronous, stealth and transitive (BLAST). Mobile nodes within 2 Km can effectively communicate with each other offering data rates up to 167 kbps. Low power consumption is achieved through using pull and push communication technique between the wireless nodes and the base station, where by, nodes are kept in sleep mode most of their active time and only transmit data during a specific time. The key devices included in the DASH7 architecture are shown in the diagram below.

Initially a proprietary technology, Z-wave was developed in 2001 by Zensys in 2001 for home automation. A maximum of 232 home equipment used for cooking, security, lighting, etc are connected to one another using a mesh topology. These devices communicate a maximum message length of 256 bytes at radio frequencies of 908.4MHz, 868.4MHz, and 919MHz in USA, Europe, and Australia respectively, and are able to transmit data up to 100 kbps. The allocated frequency spectrum offers low interference due to the limited presence of devices connected within the spectrum. It utilises FSK modulation technique and the signal can cover a communication range between 30 meters up to 100 meters depending on the location density. Power is conserved by switching the nodes on and off during allocated time slots which prevents the nodes from continuous data transmission. Interoperability between devices is achieved through using a four layered architecture consisting of the application layer, MAC layer,routing layer and the transfer layer.

NB-IoT utilises a system bandwidth used of 180 Khz which is equivalent to one physical resource block (PRB) of LTE. Unlike other LPWAN technologies, NB-IoT utilises the licensed spectrum which offers numerous benefits in terms of reliability, high transmission power and reduced interference. It is against this background that NB-IoT received wide acceptance from major telecommunication operators such as Erickson, Nokia, Intel and Huawei [26] whose contribution towards NB-IoT is illustrated in [27]. Further NB-IoT enhancements are made in release 14, release 15 and release 16. The comparison of NB-IoT with other LPWAN technologies is presented in Table 3.

### B. NB-IoT IN 5G

The 5G new radio (NR) air interface, introduced by 3GPP in release 15, operates in both low and high frequency ranges. Utilising these two frequency ranges enables sufficient coverage among the three major 5G use cases, namely, enhanced mobile broadband (eMBB), ultra reliable low latency communications (URLLC), and massive machine type communication (mMTC) [28]. These use cases are identified to serve the diverse users and service requirements in the emerging Internet of Things (IoT). Specifically, eMBB targets applications demanding high data rates and low latency, whereas URLLC targets applications demanding extremely low latency and extremely high reliability. mMTC targets applications that are delay-tolerant and have low data rates.

Generally, mMTC is characterised by massive IoT devices, whose applications transmit sporadic, small volumes of data that is mainly uplink dominated. The NB-IoT standard is developed to satisfy various mMTC services with the below performance objectives:

1) Provide coverage equivalent to a maximum coupling loss (MCL) of 164 dB.
2) Support uplink (UL) and downlink (DL) data rates of at least 160 bits per second (bps).
3) Deliver data packets of 105 bytes within 10 seconds.
4) Achieve 10 years battery life while transmitting daily UL data of 200 bytes and 20 byte DL message.
5) Support 1,000,000 devices per square kilometer (km$^2$).

Utilising the NB-IoT architecture to accommodate mMTC requires smooth transitioning and support between legacy 4G and 5G NR. Efficient LTE to 5G migration techniques are required to guarantee seamless continuation of services and excellent coexistence between NB-IoT and NR. Coexistence

**TABLE 3.** Comparison of NB-IoT with other LPWAN technologies.

| Technology | Coverage | Modulation | Data rate | Packet size | MAC | Frequency Band | Topol-ogy | Physical Design Features |
|---|---|---|---|---|---|---|---|---|
| **LoRa** | Urban: 2 - 5 km Rural: 15 km | spread spectrum techniques (CSS) | 50 kbps | small | Unslotted aloha | 433/868/915 MHz | Star, Mesh | High receiver sensitivity Resilient to interference Low energy, low cost LoRa transceivers |
| **INGENU** | Rural: 5 - 10 km, Urban: 1 - 3 km | DSSS | UL: 624 kbps, DL: 156 kbps | small | Similar to cdma | 2.4 GHz | Star, tree | High tracking precision, Wider spectrum utilization, Increased transmission power |
| **Weigthless-P** | Urban: 3 km, Rural: ∼ 25 km | Quadrature Phase Shift Keying (QPSK) and Gaussian Minimum Shift Keying (GMSK) | 0.625 kbps to 100 kbps | 48 bytes | | 169, 433, 470, 780, 868, 915 and 923 MHz | star | Support existing Radio Frequency technologies with minimal interference, higher power consumption, support handover, roaming, and cell re-selection |
| **SIGFOX** | Urban: 3 - 10 km, Rural: 30 - 50 km | Differential binary phase-shift keying(DBPSK), Gaussian frequency shift keying (GFSK) | 100 bps | small | Unslotted aloha | 902MHz/ 868MHz | star | Inter-hardware compatibility, Longer battery lifespan |
| **DASH7** | Up to 5 km | 2-GFSK | 13, 55, 200 kbps | small | CSMA/CA | 433/868/915 MHz | Star, tree | Low cost, Low latency, High interoperability |
| **Z–Wave** | 100 m | GFSK Manchester | 40 - 100 Kb/s | small | CSMA/CA | 908.42 MHz/ 868.42 MHz | mesh | |
| **NB-IoT** | 10 - 15 km | QPSK and BPSK modulations | UL: 158.5 kbps, DL: 106 kbps | small | Ofdma, scdma | 7 - 900 MHz | star | reduced device cost, minimized battery consumption |

between NB-IoT and 5G NR is achieved by deploying NB-IoT carriers within the NR carrier. Unlike LTE, the 5G communication system presents several attractive features that makes its coexistence with NB-IoT possible. These features are:

- Scalable OFDM numerology: similar to NB-IoT, the 5G NR physical layer design uses OFDM modulation with support for 15-kHz subcarrier numerology. NR supports additional subcarrier spacing ranging between 15 kHz to 240 kHz. In addition, 5G NR supports two frequency bands, namely, FR1 and FR2 supporting frequency band from 0.45 GHz to 6 GHz and frequency band from 24 GHz to 52.6 GHz respectively. mMTC utilises below 2GHz bands.
- Flexible frame structure: there are various waveforms parameters which differs in terms of Sub-Carrier Spacing (SCS), slot duration, and slots per sub-frame thus enabling more than one 5G service to be offered within the same carrier.
- Ultra-lean design: regular transmission of the broadcast signals, synchronization signals, and reference signals are reduced to improve the energy efficiency of the NB-IoT devices as well as to avoid interference between the two wireless networks.

Appropriate positioning of NB-IoT within the NR carrier is achieved through proper alignment of subcarrier grids and resource blocks which guarantees subcarrier orthogonality and increases resource utilization [29].

A number of 5G technologies have been introduced to cater for the traffic growth introduced by the massive NB-IoT devices. The key 5G enabling technologies are indicated in Table 4.

**TABLE 4.** 5G enabling technologies for NB-IoT.

| NB-IoT Enabler | Benefits |
|---|---|
| Software Defined Network | - Isolate data plane from the control plane<br>- Allow network programmability by outside applications<br>- Provides flexibility, network management simplification and reconfigurable network |
| Millimeter-wave spectrum | - Low transmission signal strength loss<br>- Enabling the transmission and reception over the narrow-beam utilizing array of directional antenna for high gain |
| Massive MIMO | - Achieving higher spectral efficiency for cellular systems |
| Network function virtualization | - Provides core virtualization and centralized baseband processing within RANs<br>- Supports the network scalability mechanism, network slicing |
| Cognitive radios | - Utilise spectrum efficiently and intelligently<br>- Selecting the best available channel and allows spectrum sharing<br>- Provides spectrum mobility |
| Cloud radio access network | - Allows different radio access technologies to share the same physical network infrastructure<br>- Supports distributed antenna system (DAS) or femtocell type deployments<br>- Centralized processing of baseband signals from multiple remote radio units |
| Downlink and Uplink Decoupling | - Allows UE to transmit uplink traffic using a different base station from the one it receives downlink traffic<br>- Increase throughput and data reliability |
| Heterogeneous Networks | - Increase network access for a large number of IoT devices |
| Relay stations | - Extend the communication range of a base station improving throughput in the network |

## III. RANDOM ACCESS PROCEDURE IN NB-IoT

Random access is a media access protocol technique utilised by M2M to acquire access to the eNB. Generally, every user wishing to transmit data over the NB-IoT is expected to establish a network connection through the random access procedure in order to perform uplink synchronization required for data transmission. The distributed and simple operational design of the random access scheme makes it an attractive and preferred access control solution for M2M communication [30]. Random access schemes are classified into either grant-free or grant-based access, which essentially determines how UE accesses the radio resources during a data transmission demand. The grant-free scheme provides users with the flexibility of selecting resource blocks at any given time. Users accessing the spectrum through the grant-free scheme do not have to wait to be granted radio resources by the base stations. Slotted Aloha, a grant-based random access scheme commonly used in cellular networks, allows a UE to randomly select a traffic channel that they use to establish a connection with the network. All the UEs requiring data transmissions perform random access through sending messages to the NB-IoT physical random-access channel (NPRACH) which is a newly designed uplink physical channel for NB-IoT. NPRACH provides time-frequency resources required for data transmission and performs accurate preamble detection required to maintain uplink orthogonality among the various UE.

Three distinct NPRACH configurations indicating NPRACH repetition value, preamble transmission interval, NPRACH starting time, NPRACH periodicity etc, are specified for the coverage classes supported in NB-IoT [31]. The coverage classes, namely, a) CE level 0, b) CE level 1, and c) CE level 2 with MCL of 144 dB, 154 dB and 164 dB respectively [17], [32], serve UEs with varying path losses. The coverage enhancement classes are indicated in figure 2. The NPRACH subcarriers are shared by the three coverage classes in units of 12.

The random access procedure can be triggered by any of the following actions:

- UE originated initial access to the NB-IoT network.
- Network initiated response to a paging message.
- Transitioning from idle state to connected state.
- Random access re-attempt after random access failure.

Normally, the contention-based RA procedure includes four signalling messages that are exchanged between the UE and the eNB. The signalling messages are indicated in figure 1.

The steps used to achieve uplink connection are shown below:

*Step 1:* Upon successful initial synchronization with the eNB, a UE selects a CE level based on the measured reference signal receiving power (RSRP). It then chooses any random access preamble and transmit it over the NPRACH to establish a connection with the NB-IoT network.

*Step 2:* Since multiple UE transmits preambles, the eNB determines the source of the preamble and responds by sending a random access response (RAR) on the NPDSCH which contains information related to cell identification and uplink timing.

*Step 3:* Using the uplink resources allocated in step 2, a UE transmit its identification information to the eNB.

*Step 4:* The eNB responds with a contention resolution message including the identification of the permitted UE. The permitted UE can proceed with data transmission.

The successful exchange of the four messages symbolises the completion of the random access procedure. Since random access is facilitated by slotted ALOHA, more than one UE can transmit the same preamble sequence simultaneously resulting in either detectable collisions or undetectable collisions [33]. All the UE involved in collisions will enter a random back-off and reattempt the random access procedure in the next random access opportunity (RAO). The

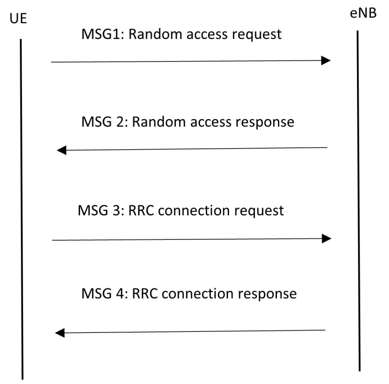


**FIGURE 1.** Random access procedure in NB-IoT.

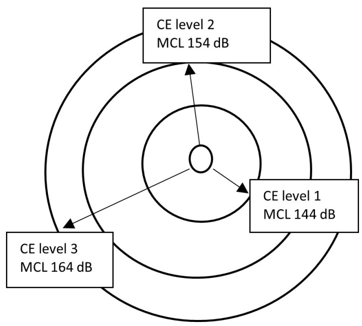


**FIGURE 2.** Coverage enhancement levels.

major drawback associated with the random access technique is the excessive preamble collisions and re-transmissions in the contention-based schemes which occur as a result of a UE choosing the same resource block to facilitate data transmissions.

## IV. DESIGN CHALLENGES AND REQUIREMENTS OF RANDOM ACCESS IN NB-IoT

Heterogeneous machine type devices (MTD), characterised by massive number of devices including cameras, actuators, and water meter readers determines when to access NB-IoT physical random-access channel (NPRACH) in a distributed manner. To achieve high NPRACH success opportunity among M2M in NB-IoT, the MTD require:

- Sufficient NPRACH spectrum resources
- Efficient preamble detection scheme
- Reliable preamble design
- Sufficient preambles to perform RA
- Correct identification of all the active UE
- Utilization of more channels
- Data transmission of massive connections
- Reliable repetition scheme

Achieving the above requirements is highly influenced by factors such as massive connectivity, control and signalling overhead, NPRACH repetitions, preamble misdetection, preamble collision, and limited spectrum resources, which degrade the random access performance of the MTD. These factors are discussed as follows:

### A. MASSIVE CONNECTIVITY

mMTC is characterised by a large number of low cost and energy constrained devices that send infrequent, bursty, low priority, and mostly uplink dominated traffic at different times of the day. For example, a fire alarm signal will generate a large amount of small data payloads at the time smoke is detected in a building. During the initial access on the network, IoT devices utilise the contention-based random access procedure to transmit preambles on the NPRACH to establish resource allocation with the NB-IoT network. Since mMTC aims to support 1000 000 devices per square kilometer, the massive simultaneous NPRACH access from these devices can easily congest the radio access network (RAN), causing intolerable access delay, packet loss, and even service unavailability [14].

### B. CONTROL AND SIGNALING OVERHEAD

Connection setup and connection release signalling packets are continuously exchanged between the UE and the eNB. The characteristics of MTC traffic, which are sporadic and predominantly uplink, significantly contribute to the overhead of connection establishment. Unlike in conventional mobile networks, UEs in the NB-IoT network do not consistently sense and transmit data. Normally, when a UE detects no activity on the network, it enters idle mode. However, upon detecting traffic activity, a UE switches back into transmission mode and begins sending uplink traffic to the eNB. Since a large number of UEs are deployed in 5G IoT, there is a massive exchange of small-sized control packets between the UEs and the eNB, compromising the quality of the link. Existing MAC layer techniques are not capable of efficiently handling the massive load of small-sized data control packets. Therefore, 5G approaches that can analyse the behaviour of sporadic traffic are required to alleviate the burden caused by signalling overhead.

### C. NPRACH REPETITIONS

Achieving coverage enhancement (CE) of +20dB (compared to GSM/GPRS) is one of the design objectives of NB-IoT. Improved coverage guarantees sufficient signal power to the 5G enabled IoT devices deployed in remote areas with high penetration losses such as basements. In NB-IoT, coverage enhancement is achieved through the use of tones, repetitions, modulation and coding schemes (MCS). NPRACH repetitions and data repetitions are employed in both uplink and downlink transmissions, enhancing the reliability of the random access procedure by repeating the preamble transmission up to 1024 and 2048 times in uplink and downlink, respectively [17], thus improving the received signal at the eNB.

These repetitions are performed across the three CE levels supported in NB-IoT. The number of repetitions increases with higher path loss, meaning that UEs located towards the network edge are likely to perform more repetitions than those closer to the eNB. Preamble repetition values differ for each coverage class based on path loss, with more repetitions in higher CE levels to compensate for signal attenuation. However, increased NPRACH repetitions can burden spectrum resources, leading to random access delays and higher energy consumption [34]. Additionally, UEs persist in the RA connection until the maximum number of repetition attempts is reached, at which point they transition to the next higher CE level for a new RA attempt. This can lead to an unequal distribution of UEs among CE levels, resulting in uneven traffic load across the three levels. The unique RA configurations for each CE level can also introduce network performance disparities. Further research is necessary to understand the impact of data repetitions on NPRACH success and to determine the optimal repetition value that ensures an acceptable distribution of UEs among CE levels.

### D. PREAMBLE MISDETECTION

Unlike LTE, which employs Zadoff-Chu (ZC) sequences, the newly designed NPRACH preamble is specifically intended to facilitate connections from multiple UEs for RA operations. During RA, the eNB monitors the time-frequency resources for the initial uplink preamble. Upon receiving the signal, the eNB estimates the time of arrival (ToA), Carrier Frequency Offset (CFO), and UE identity. It then generates and transmits the RAR to the UE. These estimated parameters are crucial for maintaining orthogonality with multiple UEs and scheduling data transmissions. Inefficient NPRACH receiver designs significantly impact the correct detection of the transmitting user, affecting parameter estimation between the UE and the eNB. This results in increased random access delay, reduced system throughput, and a higher packet error rate [35].

### E. PREAMBLE COLLISION

The NB-IoT cell can configure up to 48 subcarriers, equivalent to 48 preambles from which a user attempting to establish a connection selects one preamble at random. Considering the large number of IoT devices, this limited number of preambles available in the network causes multiple UEs to select the same preamble for performing the initial RA, resulting in NPRACH collision. When a collision occurs, the eNB fails to correctly detect the preamble, and it will not be able to respond with message 2 of the RA procedure. Preamble collision, more common in event-driven applications, leads to RACH failure, causing random access delay, packet loss, and under-utilization of radio resources [36]. While having more preambles can reduce collisions, it negatively affects the remaining uplink resources reserved for data transmission.

### F. LIMITED SPECTRUM RESOURCES

To better meet the IoT requirements, NB-IoT is designed to operate in a narrow system bandwidth of 180 kHz which is equivalent to one physical resource block (PRB) of LTE. Efficient utilization of the limited system bandwidth used by both NPRACH and NPUSCH for uplink transmissions is key in achieving maximum access success and data transmissions in the NB-IoT network. Although sufficient NPRACH resources reservation increases NPRACH repetitions which guarantees the successful reception and decoding of the preamble at the eNB, it may lower the NPUSCH resources required for data transmission. Adequate channel resources are thus required to ensure fairness among data transmission and random access.

Existing solutions designed to serve long sized packets lacks the sufficient capacity to accommodate the large amount of random access in MTC. Newer RA enhancement solutions are thus required to effectively deal with the massive uplink traffic while alleviating the aforementioned weaknesses. These solutions should particularly aim to reduce preamble repetitions, provide optimal RA configuration parameters, and improve preamble detection and at the base station.

## V. APPROACHES TO RANDOM ACCESS IMPROVEMENTS FOR mMTC

mMTC random access schemes are expected to provide simple and adaptive access to a multitude of user equipment contending for channel access. However, centrally coordinating the short, sporadic, and unpredictable traffic transmissions from massive IoT devices is a challenging task due to the obstacles outlined in the previous section.

Several random access enhancement schemes have been proposed in LTE networks to address the random access overload and congestion challenges, including access class barring (ACB) [37], [38], [39], slotted access [40], [41], [42], prioritized random access scheme [43], [44], [45], [46], group based [47], [48], [49], and Distributed Queueing [50], [51], [52], [53], [54].

### A. ACCESS CLASS BARRING

Access Class Barring (ACB) is the standardised access protocol adopted in LTE to facilitate access requests. The ACB mechanism classifies UEs into different access classes (ACs) depending on their requirements. To manage the PRACH overload issue, devices in the various ACs check their access eligibility by determining the barring status. The UE achieve this by generating a random number between 0 and 1 and compare it to the ACB probability barring factor. Network access is granted if the UE generated value is less than or equal to the barring factor, otherwise the transmitting node back off for some time. Both the ACB barring factor and the barring time are broadcasted in the system information block. In order to improve the overall system performance, it is critical for the eNB to select optimal barring factor and barring time values especially when the network is experiencing network overload. The optimal ACB value to reduce the congestion and access delay is determined in [37] and [55]. Generally, the ACB scheme is beneficial in scenarios where M2M devices consists of varying QoS requirements of which service differentiation is achieved by grouping M2M devices in different access classes. In such a scenario, RA is only granted to devices in the allowable classes with the rest of the devices barred from access. The limitation of the ACB scheme is that it trades-off access delay for high access success which can be attractive to applications that can withstand long access delay but not suitable for event based mMTC applications. Furthermore, the dynamic nature of mMTC traffic makes it difficult to obtain the exact number of devices attempting RA causing improper determination of the optimal ACB factor. There exist a number of proposals to improve the performance of ACB. For instance, dynamic ACB is proposed such that the eNB adaptively changes the ACB factor depending on the state of the network environment or the network parameters.

### B. SLOTTED ACCESS SCHEME

The slotted access scheme is a common cellular network standard used for accessing the random access channel in LTE, NB-IoT and GSM. The slotted access scheme utilises time slots to coordinate the transmission of devices by assigning M2M devices to dedicated RA slots in which they can transmit without restricting the number of devices transmitting in a specific time slot. If two or more devices access the same channel in a given time slot, then there is a collision and the receiver is unable to obtain any transmitted information. To reduce the collision probability, each user is limited to transmit at the beginning of each time slot. Any device wishing to transmit data will therefore wait for the next available time slot so that it can transmit its data. Although time-slot synchronization simplifies collision detection, the massive and infrequent number of access requests leads to increased collisions and reduced efficiency potentially reducing the overall throughput. Moreover, as the number of devices in the network increases, the contention for time slots also increases.

### C. PRIORITIZED RANDOM ACCESS

Most of the access request schemes do not take into consideration the QoS requirements of the UE during random access. Moreover, the fixed access priorities present in the conventional ACB scheme lack the flexibility of changing during the random access procedure. To satisfy the QoS of the various mMTC, prioritized access schemes are proposed to provide maximum resource utilization by pre-allocating random access resources to the UE depending on their requirements. Typically, prioritized random access schemes categorises the UE in different classes based on their priorities then it assigns varying channel resources to the devices in the various classes. Specifically, delay-sensitive devices such as emergency alarms are allocated higher priority thus utilising more resources than the delay-tolerant devices which are assigned low priorities. Although all the classes are assigned different resources, the limited PRACH resources may not be sufficient for all devices, especially when there's a sudden increase in the number of heterogeneous devices accessing the network.

### D. GROUP-BASED

In the Group-Based Scheme, M2M devices are grouped based on their geographic location or application requirements, and they access the random access channel based on this grouping. Instead of all M2M devices contending simultaneously, group based schemes allow only one group or a specific number of devices from a particular group to access the channel at a given time, thus reducing the collision in the network. Depending on the application requirements, certain groups can be prioritised, ensuring improved QoS for those applications. Some group based access schemes can dynamically adapt to changing network conditions, which is beneficial in networks with fluctuating traffic load.

### E. DISTRIBUTED QUEUING

Distributed Queuing (DQ) organizes contending mMTC devices into logical queues to perform RA. During RA, a device select a RA slot and wait for the RAR for it to know about the success or failure of its preamble. Since more than one device can choose the same preamble, a dedicated contention resolution queue (CRQ) is assigned to the devices that selected the same preamble. Devices entering the CRQ become aware of their position in the queue through the RAR, and utilises their position to connect to the base station. The positions are continuously updated using internal counters. On the other hand, devices that did not experience collision enters the data transmission queue (DTQ) to proceed with sending their data. Devices wishing to perform random access for the first time are only accommodated once the CRQ is empty. Unlike ACB and slotted-ALOHA that do not scale well with bursty traffic, the DQ solutions are stable when there is a sudden increase in traffic. furthermore, a low probability of collision is achieved through the distribution of the collided devices in their own queues. The drawback of the DQ schemes is that an increase in preamble collisions escalates the CRQ resulting in higher access delay.

The NB-IoT random access procedure which adopts both the ACB scheme and slotted access is significantly challenged with the NPRACH overload issue caused by the simultaneous initial access requests of the massive M2M devices. To cope with these issues, novel random access congestion control techniques are studied to efficiently handle the massive access issue while meeting the performance requirements under insufficient spectrum resources. Although NB-IoT has inherited LTE design functionalities, the unique characteristics of NB-IoT such as repetitions, three CE levels, and the new random access preamble design presents challenges that requires improved RA congestion control solutions.

Several MAC and PHY performance models have been implemented to investigate RAN congestion issues in NB-IoT, focusing on 1) performance analysis [6], [40], [56], [57],

2) optimization [58], [59], [60], and 3) NPRACH receiver design [6], [35], [61], [62], [63], [64], [65], and 4) collision resolution [66]. A summary of the RA schemes proposed for NB-IoT is shown in Table 5.

The performance analysis of multi-channel slotted ALOHA system under heavy load is investigated in [42]. The authors derived approximation formulas to determine the number of users who successfully complete the random access procedure during the random access slot. Since NB-IoT is designed to use three CE levels, the work in [42] is not suitable for NB-IoT, hence the model presented by [40] and [56], which determines the access success probability and average access delay specific for each CE level. Similarly, the authors in [57] also analysed the RACH by considering the repetition values that were introduced to achieve coverage enhancement in NB-IoT. Performance analysis schemes are essential in providing in depth understanding of RA that is useful in determining optimal network parameters.

Random access can be effectively measured by the number of UE that successfully complete the four-way handshake. RACH optimization parameters such as backoff window, number of contending users, and repetition values should be carefully tuned to improve network throughput. In [60], the authors aim to increase the access success probability through joint optimization of preamble and CE levels based parameters. The work in [58] merged cognitive radio (CR) and NB-IoT to allow UE to access empty radio channels thus maximising throughput for RA. In [59], the authors proposed a reinforcement learning-based approach which dynamically allocate uplink resources thus maximising the network throughput. A distributed queuing based RA scheme is proposed in [66] to increase access success probability by employing contention resolution queues (CRQ).

Successful preamble transmission using NPRACH is critical for resource reservation in NB-IoT. NPRACH collision, which is commonly caused by concurrent transmission of multiple preambles, can be mitigated by developing efficient NPRACH receiver designs schemes focusing on preamble detection [61], [64], [65], [67], preamble increase [62], and efficient ToA estimation [35], [68].

Generally, NPRACH receiver schemes consist of preamble detection and timing delay estimation [33]. Preamble detection algorithms are employed at the eNB to efficiently detect the presence of preambles transmitted by the UE using the single-carrier frequency hopping OFDM symbol. A typical preamble detection approach utilises stochastic geometry to model and analyse the spatial distribution of IoT devices following a Poisson Point Process (PPP) arrangement. Stochastic geometry and Poisson Point Process are both powerful tools for modeling the random deployment of base stations characterised by random and temporal arrival of packets which is the case in NB-IoT networks. Since stochastic geometry generally perform very poorly with the increase in traffic demand among the various interactive queues at each eNB [69], it is often combined with queuing theory to derive spatiotemporal network parameters that are useful for preamble detection. To guarantee successful preamble detection at the eNB, preamble repetition is performed several times depending on the CE level of the UE. The accumulated signal power of the repeated preamble transmissions are compared against a detection threshold to determine the presence of a preamble. Optimal preamble detection threshold ensures increased detection probability and reduced false alarm status, which are both crucial for NB-IoT performance. In, the Neyman–Pearson criterion is used as a preamble detection threshold.

Upon preamble detection, the timing delay is estimated from the received preamble sequence. ToA estimation, which is obtained through inner and outer pseudo-random preamble hopping among the various subcarriers, is useful for achieving uplink synchronization and ensuring orthogonality between the UE. The NPRACH receiver algorithm proposed in [61] is based on a 2-D Fast Fourier transformation (FFT) to estimates the ToA and RCFO from the received preamble signal. The FFT has high computational complexity making it unsuitable to be deployed in NB-IoT. In [65], a low computation iterative scheme is proposed to determine residual carrier frequency offset (RCFO) and timing advanced (TA), thus avoiding the high computational complexity present in the 2-D FFT method. Another low complexity scheme [64] decouples ToA estimation from preamble detection by exploiting the phase of the received signal. Incorrect preamble and Time-of-Arrival (ToA) detection causes poor network performance and unavailability of services [70].

The preamble reuse technique proposed in [62] alleviate preamble collisions by enabling UE to transmit a partial preamble sequence (PPS). PPS is a smaller chunk of the long preamble sequence. A drawback of this scheme is the high detection performance degradation at the expense of reduced collisions. Kim et al. increase RA preambles by utilising the non-orthogonal preamble structure. These structure increases the amount of preambles through using various ZC sequences providing an opportunity for a large number of UE to attempt RA with guaranteed minimal collisions.

The authors in [66] proposed a collision resolution queue based on Distributed Queue (DQ) mechanism. In the proposed study, NB-IoT devices are assigned to the three contention resolution queues (CRQ) which are mapped to the three CE levels available in the NB-IoT network. All the colliding devices wait in the CRQ according to the fashion in which they should allowed to perform RA. Simulation results of the proposed model indicate reduced access delay.

## VI. NEW TRENDS IN mMTC RA CONTROL

### A. INTELLIGENT RA SCHEMES

Over the past years, RA enhancement techniques have focused on reducing the RAN overload issue in mMTC networks by integrating intelligent schemes into the traditional schemes. When applied to RA, learning-based algorithms

**TABLE 5.** RA congestion control schemes for NB-IoT.

| RA Focus | Protocol | Objectives | Findings |
|---|---|---|---|
| Performance Analysis | [40] | Estimates metrices of RACH access success and average access delay in NB-IoT | Devices in the lower CE level have the highest access success probability compared to the devices in the lower CE levels |
| | [56] | Modelling the probability of successful random access to analyse the system throughput. The work also model the queue length and retransmission time based on Markov chain. | The amount of UE, queue length, retransmission times, and packet generation rate affects the system throughput |
| | [57] | Evaluate the effect of NPRACH preamble repetition on random access success probability | Preamble re-transmissions improves the random access success rate |
| | [6] | Developed a mathematical framework for analysing RACH access considering the preamble repetition. | Obtained increased RACH access in the three CE levels Increasing the repetition value increases RACH success. |
| Throughput Optimization | [58] | Designed a narrowband cognitive radio IoT with random access to increase network throughput | Achieves high network throughput when optimal sensing parameters are used. |
| | [59] | Dynamically configure uplink resources to obtain optimal UE that can be served. | Obtain increase throughput compared to traditional approaches |
| | [60] | Developed a joint optimization model to increase access success of UE | The proposed model can determine optimal parameters in various conditions. |
| NPRACH receiver | [61] | Designed an algorithm to efficiently detect and estimate synchronization parameters of preambles used in uplink communication | The UE is properly detected and the synchronization parameters can be successfully estimated. |
| | [62] | Proposed the partial preamble transmission bearing in mind the impacts of collisions | Increased the number of orthogonal random access opportunities and reduces collision probability at the cost of preamble sequence detection. |
| | [63] | Utilises random geometry and collision probability to design a preamble detection model. Determine the impact of repetitions and retransmission on the access delay. | There is an improvement in the preamble detection with an increase in repetitions. |
| | [64] | Used Neyman–Pearson technique to determine the detection threshold and perform a detection analysis. | Obtained maximum coupling loss under additive white Gaussian noise (AWGN) and Rayleigh fading channels |
| | [65] | Designed a low complexity algorithm to estimate residual carrier frequency offset (RCFO) and timing advanced (TA) | The results indicate increased signal detection probability as well as improved timing advance. |
| | [35] | Designed an NPRACH reception method to detect preamble and measure the timing of arrival. | Simulation results indicate that the proposed scheme meets the 3GPP requirements. |
| Collision resolution | [66] | Proposed a resource grouping mechanism to increase access success | Obtained increased access probability, reduced access delay and improved RA attempts when compared to ACB schemes |

alleviate RAN congestion by enhancing RACH configuration, optimizing parameters, and predicting traffic patterns which increases the network throughput as well as the success probability of the UE attempting channel access [71], [72], [73]. For example, a huge volume of data related to random access parameters sensed from the surrounding environment can be analysed using intelligent schemes to create new behaviour patterns that can predict traffic load thus reducing the probability of concurrent random access collisions. Such issues could not easily be tackled using traditional approaches due to the complexity and volume of data involved. The effectiveness of intelligent learning approaches in optimizing random access is compared to non-learning based approaches in [74].

According to [75] and [76], reinforcement learning (RL) protocols are more suitable for modelling multiple access in wireless communications due to their model-free characteristics and their ability to enable a UE to adapt to the dynamic wireless network. Furthermore, the low processing complexity of RL algorithms makes them more suitable for battery-constrained MTDs. Therefore, RL is highly utilized in 5G applications to support various network functions and services.

The application of machine learning (ML) in effectively managing RA congestion has gained popularity over the past few years as indicated in Table 6. Specifically, queue-learning (Q-learning), a sub-category of reinforcement learning (RL), have been extensively studied in RA congestion control for dynamic ACB parameter adjustment in LTE [75], [77], [78], [79], [80], [81], [82], [83].

#### 1) ACCESS CONFIGURATION

In the ACB scheme, random access attempts are limited by the ACB factor broadcasted to the UE by the eNB, thus delaying the start of RA for numerous UEs. To alleviate congestion and improve the random access process, the ACB factor should be adapted based on the traffic load. This adaptation helps avoid the underutilization of resources while increasing the number of preamble transmissions. Different RL based ACB tuning schemes consider traffic control for multiple classes of MTC devices during the tuning of ACB barring factor. For example, in [78], the authors aim to optimize machine-to-machine (M2M) traffic over human-to-human (H2H) traffic. Since M2M applications are associated with distinct levels of QoS requirements, the work in [83], [84], and [82] adjust the ACB factor in a network consisting of heterogeneous traffic priorities ensuring that different ACB factors are assigned to the various traffic classes. Similar to [83], the authors in [81] consider the priority classes of the UE and assigns high ACB factor to devices experiencing high access delay. Unlike the traditional schemes which considers the lone tuning of ACB factor to optimize performance, the authors in [79] adjust both the barring factor and the barring time improving the energy and delay of the UE. The key performance metrics used to evaluate the capability of the introduced RL-based ACB schemes are defined in terms of the probability to successfully complete the RA procedure as well as the access delay. Experimental results show improved success access probability and lower average delay even in situations where there is an increase in the number of MTC devices. Although dynamic ACB control significantly improves the success probability of mMTC, the constant ACB updates cause increased energy consumption, affecting the performance of the low powered UEs.

#### 2) RACH RESOURCE ALLOCATION

In addition to access configuration schemes, other studies solve the congestion in random access channel through RACH resource allocation using ML [59], [85], [86], [87], [88], [89]. Resource allocation techniques are specifically suitable for controlling access to the shared random access channel by guaranteeing specific resources to certain devices at the time of random access. For instance, when mMTC devices co-exist with highly reliable, low-latency devices, the eNB will separate the preamble resources and assign more resources to the low latency devices, thus improving access and data transmission. Utilising intelligent learning schemes for resource assignment is useful during the initial assessment of random access as it can quantify whether the available resources can sufficiently meet the demand of the various traffics in the network. Moreover, dynamic resource allocation approaches ensure equal distribution of RACH resources for both data transmission and RA procedure guaranteeing high success access. In [85], the authors consider the QoS of both M2M and H2H and implement a Q-learning approach which separates the preambles between H2H and M2M MTC devices. Similarly, [86] also proposes an intelligent preamble allocation scheme, dividing the available preambles between MTC and URLLC devices. In [87], a different resource allocation algorithm is proposed, allowing MTC devices to intelligently select the less congested base station based on its QoS performance. The application of RL in managing RACH resources is also proposed in [59], in which the authors dynamically allocate NPRACH resources to the various CE levels in NB-IoT. Reference [88] and [89] address RAN congestion by proposing Q-learning techniques to determine unique time slots for their transmissions.

#### 3) PREAMBLE DETECTION

Although access configuration and resource assignment schemes significantly reduce preamble collisions, the retransmissions of multiple UE can still increase the collision, impairing the access delay as well as uplink resources. In the conventional random access procedure, collision detection occurs when the UE fails to correctly decode the received preamble and fails to send the random access request response to the UE. Additionally, when two or more UEs select identical preambles and their preambles are correctly decoded, both UEs will receive the same message 2 and transmit their message 3 using similar resources resulting in a collision. Thus, efficient preamble detection schemes are required to correctly recognize the collided preambles to improve the performance of random access procedure. The work in [90] implements deep neural network to detect random access collisions. In [91], [92], and [93], intelligent approaches are proposed to predict active UEs and other synchronization parameters in NB-IoT. Simulation results indicate that the proposed schemes achieve better accuracy in estimating the ToA and CFO of the preamble structure.

### *B. GRANT-FREE NON-ORTHOGONAL MULTIPLE ACCESS (NOMA) RA*

In the conventional cellular networks, the grant-based four-step handshaking procedure adopted for establishing the connection between the base station and the MTC devices is a source of significant signalling overhead and excessive latency [94], [95]. The control signalling exchanged to facilitate the provision of resources prior to data transmission makes grant-based RA inefficient for mMTC. Novel channel access techniques such as grant-free RA effectively accommodate mMTC, lowering the signalling overhead and access delay. During grant-free RA, each UE randomly chooses resource blocks and transmits its packets to the eNB without waiting for a transmission grant from the base station. Most existing grant-based schemes are utilised in orthogonal multiple access (OMA), whereas grant-free RA schemes are combined with non-orthogonal multiple access (NOMA) to support massive connectivity in 5G mobile systems. OMA enables multiple users to share orthogonal resources simultaneously by dividing resources in time, frequency, or code. As an example, in code division multiple access (CDMA), a unique orthogonal code is assigned to every user sharing the same frequency. The assignment of unique codes allows multiple devices to share the same frequency without causing interferences, as their signals can be distinguished by their unique codes. Additionally, the receiver employed in OMA may implement interference mitigation techniques to reduce the impact of co-channel interference from other users. Since users operate in orthogonal resources, the interference mitigation schemes are typically simpler compared to non-orthogonal schemes. Although OMA schemes allocate orthogonal resources to various users, ensuring that their transmissions do not overlap in time, frequency, or code, they are inefficient for massive connectivity since they only allow each subcarrier to be accessed by one device at a time. Furthermore, the high traffic volume present in mMTC disadvantages OMA schemes from fully meeting the requirements in terms of spectral efficiency and power utilization.

On the other hand, NOMA [96], [97], [98] allows multiple users to simultaneously transmit data over a single subcarrier through non-orthogonal resource allocation in the power domain. NOMA allows for overlapping resource usage, offering more flexibility and higher spectral efficiency, but at the cost of increased decoding complexity and sophisticated interference management. Although NOMA has not been utilised in earlier cellular technologies such as 1G, 2G, 3G and 4G, it can easily be adopted in modern wireless systems due to its compatibility with technologies such as OFDMA, which is used in older cellular systems. According to [99], NOMA provides 30% more throughput than traditional OMA schemes. NOMA has been extensively studied in recent literature to improve spectral density in IoT based 5G wireless networks, supporting both data transmission and random access procedure. Utilising NOMA in RA significantly improves random access by allocating more uplink resources that can be utilised for the initial random access procedure. Furthermore, different users have access to various subcarriers, and one subcarrier can be accessed by multiple users attempting the random access procedure. The variants of NOMA, namely power domain non-orthogonal multiple access (PD-NOMA) [99], [100], [101], [102] and sparse code multiple access (SC-NOMA) [103], [104], [105], [106], multiplexes multiple users in power-domain and code-domain respectively. Specifically, in power domain, superposition coding (SC) is employed at the transmitter to allow multiple users to share the same resource by superposing multiple signals onto a single carrier in frequency domain. Prior to superposition coding, a power allocation strategy is adopted to allocate power levels to the users. Specifically, users are assigned power levels through centralized power allocation technique, distributed power control, or a combination of the two [107]. In the centralised power allocation technique, the base station assigns transmission power to the users based on their channel conditions, such that the users located in close proximity with the transmitter are assigned low power whereas users located further from the transmitter are allocated high power. On the other hand, in distributed power control, all the users assign themselves with transmission power. To address the inter-user interference that occurs as a result of multiple users sharing the same subcarrier, NOMA employs successive interference cancellation (SIC) at the receiver to decode the different signals. SIC first decodes the message with the highest transmission power followed by the message with the second-highest power. SIC can efficiently increase performance by utilising the signal to noise ratio (SNR) disparity between users caused by multipath signal transmission. Optimal uplink power allocation control is critical for detecting the desired signals, which can increase the system throughput [108], [109]. In PD-NOMA, it is important for transmitting devices to set their transmission power according to the channel conditions of users to ensure successful decoding at the SIC receiver. Hence, the studies in [110] developed an analytical model aimed at determining the optimal power transmission probabilities for UEs to guarantee maximum network throughput.

On the other hand, code-domain NOMA (CD-NOMA) supports massive connections of radio devices by allowing multiple users to share radio frequency resources. Sparse code multiple access (SCMA), a type of code-domain NOMA, maps the input bits directly to a multi-dimensional complex codeword by assigning distinctive codebooks to individual users. The codebooks are designed using operations such as interleaving, phase rotations, and permutations, which assist the correct functioning of the message-passing algorithm (MPA) during interference cancellation. SCMA is characterized by a number of attributes that make it suitable for massive connectivity. Firstly, SCMA provides non-orthogonal multiple-user access by assigning different codebooks to users, guaranteeing high coding gain at the receivers. Secondly, SCMA supports uplink grant-free multiple access, where users do not need to wait for a transmission grant from the base station. In SCMA grant-free access, users are pre-configured with resources such as time slot, frequency sub-band, preamble, and codebook that they use to perform random access. Thirdly, the SCMA codebooks can dynamically scale to accommodate a high number of users so that the superimposed signals are greater than the orthogonal resources. Lastly, the MPA receiver can decode each user's signals with reasonable complexity due to the sparsity of SCMA codewords.

Both CD-NOMA and PD-NOMA guarantee enhanced fairness and high spectral efficiency by allowing concurrent spectrum access for multiple users regardless of their channel conditions and QoS requirements [128], [129]. Several grant-free CD-NOMA and PD-NOMA schemes have been developed in recent studies to reduce the collision probability in random access in mMTC, focusing on power assignment, subcarrier allocation, as well as SIC receiver optimization. Some of these schemes integrate traditional congestion control schemes such as ALOHA and ACB with NOMA. The recent NOMA-based RAN schemes are provided in 7.

In [112], [113], [114], and [115], the authors investigated the hybrid of ALOHA-NOMA as potential MAC protocols for IoT devices. The proposed protocol takes full advantage of the high throughput of NOMA and low complexity of ALOHA to accommodate the increase in IoT applications in 5G networks. ALOHA-NOMA resolves collisions by utilizing multiple power levels as well as SIC, which minimizes retransmissions and achieves improved energy efficiency at the receiver. In [114], the authors proposed a dynamic frame structure in ALOHA-NOMA adapting to the

**TABLE 6. Machine learning approaches for random access congestion in mMTC.**

| Reference | Use Case | Considered parameters | Performance metrics | | |
|---|---|---|---|---|---|
| | | | Access success probability (%) | Access delay (seconds) | Others |
| [75] | ACB control | Traffic load, Number of UE in a slot | 58 | | |
| [78] | | Traffic load | 99.99 | 19.924 | |
| [79] | | UE energy | | 1.01759 | 0.5010[a] |
| [83] | | UE priority | Range between 79.2 and 98.5 | Range between 0.077 and and 3.937 | |
| [81] | | | 75 | 0.025 | |
| [82] | | | | | |
| [84] | | Differentiated QoS | 100 | 0.029 | |
| [85] | Resource separation | H2H/M2M traffic | 90 | 0.050 | |
| [86] | Preamble allocation | Low latency mMTC devices and URLCC devices | 85 | | |
| [89] | RA slot assignment | H2H/M2M traffic | 75 | 0.01 | |
| [88] | | Congestion level of RA slots | 70 | | |
| [90] | RA collision detection | random access preambles, collision-detection accuracy, back-off parameters | 41 | | 60[b] |
| [59] | Resource configuration | Network load | | | 31.50[c] |
| [92] | Estimation of ToA and CFO | | | | ToA 0.1 CFO 0.2 |
| [91] | | Colliding devices | | | ToA 0.99 $\mu s$ RCFO 1.61 $Hz$ |
| [93] | | | | | ToA $\leq$ 3.64 $\mu s$ RCFO $<$ 10 $Hz$ |

[a] Energy (mJ)
[b] RACH throughput (%)
[c] Served IoT devices per (transmission time interval)

**TABLE 7. NOMA based RAN enhancement schemes.**

| Reference | NOMA Domain | Use case | Network domain | Performance metrics | | |
|---|---|---|---|---|---|---|
| | | | | Throughput (%) | Success Probability | Others |
| [111] | PD-NOMA | Tuning access parameters | IoT | 42 | | |
| [112] | | Combines Aloha protocol with NOMA | | 80 | 5[a] | |
| [113] | | | | 48 | | |
| [114] | | | | 52 | | |
| [115] | | | Wireless sensor network | 90 | | |
| [116] | | Resource Allocation | IoT | 90 | | |
| [117] | | | | 85 | | |
| [118] | | | | 58 | | |
| [119] | | | | 98 | | |
| [107] | | | | | 90 | 0.0004[b] |
| [120] | | | | 98 | 73 | 2.5[c] |
| [121] | | | | | 85 | |
| [122] | | | NB-IoT | | 97 | |
| [123] | | | | | | 87[d] |
| [124] | CD-NOMA | Mitigation of preamble collision | MTC network | 90 | 100 | 0.0925[e] |
| [125] | | Time slot allocation, codebook assignment | IoT | 98 | | |
| [126] | | | | 97 | | 0.1[f] |
| [127] | | Analysis of grant-free NOMA | NB-IoT | | 99 | 0.0289[g] |

[a] Transmission power (in dB)
[b] Energy (in Joules)
[c] Power consumption (in dB)
[d] Connection density (devices/ slot)
[e] Access delay
[f] Packet loss
[g] Energy (in Joules)

total number of IoT devices present in the network. The active devices continuously change their transmission power to improve the quality of the SIC receiver, thus improving the system throughput. In [112], a NOMA-based RA scheme with multichannel ALOHA has been proposed in which UEs select their transmission power from a set of predefined power levels.

The selection of subchannel and power level is highly dependent on the channel gain, which yields an improvement in energy efficiency. In [113], the authors proposed a Slotted ALOHA-NOMA (SAN) receiver scheme aimed at correctly identifying active IoT devices. Such information is useful in determining appropriate power levels for the IoT devices as well as providing relevant channel-based information, i.e., users transmitting on a specific channel at a certain time. In [115], the authors propose two protocols based on the combination of slotted-ALOHA and uplink NOMA to minimize collisions in wireless sensor networks (WSNs). The proposed scheme prohibits collisions from occurring by deploying two NOMA detection schemes, namely successive interference cancellation (SIC) and joint decoding (JD). Although ALOHA-NOMA techniques improve spectral density and system throughput, an increase in the number of IoT devices can easily result in poor system performance as the devices compete for resources.

The application of Sparse Code Multiple Access (SCMA) in Random Access, referred to as SCMA-Applied Random Access (SARA), has been proposed in several studies, including [124], to support the massive IoT connectivity of 5G wireless networks. SARA allows IoT devices that select the same preamble sequence to successfully connect to the network, which is not the case with the conventional Random Access procedure in LTE/LTE-A. In [124], the authors proposed an SCMA-based Random Access scheme to alleviate preamble collision among IoT devices in 5G wireless networks. The proposed scheme modifies the four-step Random Access procedure by employing the SCMA technique in the third step of the procedure, ensuring no preamble collision among IoT devices selecting the same preamble.

To further reduce random access channel congestion in mMTC networks, the application of Machine Learning (ML) in Non-Orthogonal Multiple Access (NOMA) is gaining momentum as a leading solution. The implementation of Q-learning in NOMA was first proposed in [117]. In their proposed scheme, a decentralized Q-learning algorithm allows each User Equipment (UE) to select appropriate transmission power and time slots by interacting with the network environment. Upon the transmission of packets, the eNB decodes the messages using Successive Interference Cancellation (SIC) and notifies the transmitting device of the outcome of the decoding. Simulation results comparing the proposed algorithm with non-NOMA-based schemes indicate improved throughput, especially when the number of devices increases. However, the increase in the number of devices affects the computation time in which the devices determine the access slots and transmission power. The authors in [116] investigated a NOMA based MTC system transmitting short data packets and proposed an adaptive Q-learning (AQL) algorithm for power allocation and time-slot assignment for the short packets [116]. Similar to [116] and [117], the work in [119] considers the coexistence of eMBB and mMTC devices in a NOMA based system, and utilise the deep reinforcement learning (DRL)algorithm to guarantee reliable packet transmission of mMTC devices in the available RA slots while ensuring improved throughput of eMBB devices. In [118], the authors proposed a deep reinforcement learning NOMA based optimization scheme in MTC that allows devices to choose their transmission power. Depending on the power levels, the base station derives the transmission probabilities and shares it with the IoT devices which uses it to determine its own transmission power. To achieve ideal decoding in uplink PD-NOMA, SIC requires diverse received power to successfully distinguish UE that share the same resource element. The authors in [107] proposed a power level pool optimization model which employs a Multi-Agent Reinforcement Learning (MARL) to study the power levels between Human-Type Communications (HTC) and MTC. Competing MTC devices are allocated subchannels after performing ACB access control then NOMA power levels are assigned using centralized power allocation and distributed power control. In [125], a Q-Learning based SCMA scheme to improve RA by assigning the best SCMA codebooks and time-slots to MTC devices is proposed. In the proposed scheme, the Q-learning technique minimises the codebook collision which often occurs when two IoT devices select the same codebook. Reference [126] proposed a distributed Q-Learning (DQL) throughput maximization scheme which select the optimal subframes and codebooks for MTC devices in SCMA based RA networks. The subframe and codebook selection is performed according to the congestion level and codebook indexes. Reference [121] proposed a Q-learning-assisted grant-free non-orthogonal RA (NORA) scheme to minimise RA collision by determining optimal transmission power and subchannel for the MTC devices. In [120], the authors proposed a RA enhancement scheme where the Q-learning technique is applied for power level selection for the IoT devices. While majority of the existing literature focuses on addressing RA challenges in mMTC systems with minimal literature focusing on NB-IoT, in [122], the authors propose a DRL based NB-IoT resource allocation mechanism, allocating time, frequency, and power resources to devices in the NB-IoT network. Another resource allocation scheme for NB-IoT is proposed in [123] in which transmission power and subcarrier assignment is performed. The scheme assigns devices to the subcarrier using NOMA and aims to increase the number of devices on a single subcarrier with minimal power consumption. In [127], the authors proposed a grant-free scheme integrating code-domain NOMA into NB-IoT, which considers the noise and channel conditions during preamble detection.

## VII. CONCLUSION

NB-IoT, designed to support massive machine devices, has gained popularity as a leading LPWAN solution. A large number of low rate, low cost, and delay tolerant IoT devices are supported in the NB-IoT network enabling services such as asset tracking, smart city, environment monitoring, industrial automation, etc. In order to cope with the demand for massive access presented by 5G, random access procedure is employed to provide initial connection to the NB-IoT network. The limited number of preambles as well as the presence of preamble collision and repetitions affects the performance of random access, decreasing the chance of successful preamble reception at the base station. In this study, recent work related to random access congestion control in NB-IoT has been surveyed and discussed. Most of the existing studies utilise access control schemes such as access class barring, slotted access, prioritized access, etc to develop congestion alleviation schemes focusing on throughput optimization, random access channel receiver designs, performance analysis, and collision resolution. Moreover, our review paper highlights the potential of adopting grant-free NOMA and intelligent learning schemes in addressing the signaling overhead and access delay issues brought forth by the massive connectivity of mMTC. Based on the comparisons we made between the existing literature focusing on random access enhancement in mMTC, it is evident that there is a need to develop more intelligent learning schemes to address the challenges of massive access emerging from MTC applications. Our review paper have also demonstrated the key performance indicators used to evaluate the performance of RAN enhancement schemes and provided the quantitative results of the various approaches.

## REFERENCES

[1] G. Liu and D. Jiang, "5G: Vision and requirements for mobile communication system towards year 2020," *Chin. J. Eng.*, vol. 2016, pp. 1–8, Apr. 2016.

[2] Y.-P. E. Wang, X. Lin, A. Adhikary, A. Grovlen, Y. Sui, Y. Blankenship, J. Bergman, and H. S. Razaghi, "A primer on 3GPP narrowband Internet of Things," *IEEE Commun. Mag.*, vol. 55, no. 3, pp. 117–123, Mar. 2017.

[3] T. V. Pasca, S. Dama, V. Sathya, and K. Kuchi, "A feasible cellular Internet of Things: Enabling edge computing and the IoT in dense futuristic cellular networks," *IEEE Consum. Electron. Mag.*, vol. 6, no. 1, pp. 66–72, Dec. 2017.

[4] N. Mangalvedhe, R. Ratasuk, and A. Ghosh, "NB-IoT deployment study for low power wide area cellular IoT," in *Proc. IEEE 27th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Sep. 2016, pp. 1–6.

[5] K. F. Muteba, K. Djouani, and T. O. Olwal, "Opportunistic resource allocation for narrowband Internet of Things: A literature review," in *Proc. Int. Conf. Electr., Commun., Comput. Eng. (ICECCE)*, Jun. 2020, pp. 1–6.

[6] Y. Liu, Y. Deng, N. Jiang, M. Elkashlan, and A. Nallanathan, "Analysis of random access in NB-IoT networks with three coverage enhancement groups: A stochastic geometry approach," *IEEE Trans. Wireless Commun.*, vol. 20, no. 1, pp. 549–564, Jan. 2021.

[7] *Study on RAN Improvements for Machine-Type Communications (Release 11)*, document 3GPP TR 37.868, 2011. [Online]. Available: http://www.qtc.jp/3GPP/Specs/37868-b00.pdf

[8] M. Chen, Y. Miao, Y. Hao, and K. Hwang, "Narrow band Internet of Things," *IEEE Access*, vol. 5, pp. 20557–20577, 2017.

[9] J. Xu, J. Yao, L. Wang, Z. Ming, K. Wu, and L. Chen, "Narrowband Internet of Things: Evolutions, technologies, and open issues," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1449–1462, Jun. 2018.

[10] S. Popli, R. K. Jha, and S. Jain, "A survey on energy efficient narrowband Internet of Things (NBIoT): Architecture, application and challenges," *IEEE Access*, vol. 7, pp. 16739–16776, 2019.

[11] C. B. Mwakwata, H. Malik, M. M. Alam, Y. Le Moullec, S. Parand, and S. Mumtaz, "Narrowband Internet of Things (NB-IoT): From physical (PHY) and media access control (MAC) layers perspectives," *Sensors*, vol. 19, no. 11, p. 2613, Jun. 2019.

[12] E. M. Migabo, K. D. Djouani, and A. M. Kurien, "The narrowband Internet of Things (NB-IoT) resources management performance state of art, challenges, and opportunities," *IEEE Access*, vol. 8, pp. 97658–97675, 2020.

[13] S. A. Gbadamosi, G. P. Hancke, and A. M. Abu-Mahfouz, "Building upon NB-IoT networks: A roadmap towards 5G new radio networks," *IEEE Access*, vol. 8, pp. 188641–188672, 2020.

[14] B. Rubbens and C.-W. Huang, "Adaptive congestion control for massive machine type communications in cellular network," in *Proc. IEEE Int. Conf. Consum. Electron. Taiwan (ICCE-Taiwan)*, Sep. 2020, pp. 1–2.

[15] *5G; Study on Scenarios and Requirements for Next Generation Access Technologies*, document 3GPP TR 38.913, Version 15.0.0, 2018.

[16] A. Hoglund, X. Lin, O. Liberg, A. Behravan, E. A. Yavuz, M. Van Der Zee, Y. Sui, T. Tirronen, A. Ratilainen, and D. Eriksson, "Overview of 3GPP release 14 enhanced NB-IoT," *IEEE Netw.*, vol. 31, no. 6, pp. 16–22, Nov. 2017.

[17] L. Feltrin, G. Tsoukaneri, M. Condoluci, C. Buratti, T. Mahmoodi, M. Dohler, and R. Verdone, "Narrowband IoT: A survey on downlink and uplink perspectives," *IEEE Wireless Commun.*, vol. 26, no. 1, pp. 78–86, Feb. 2019.

[18] B.-Z. Hsieh, Y.-H. Chao, R.-G. Cheng, and N. Nikaein, "Design of a UE-specific uplink scheduler for narrowband Internet-of-Things (NB-IoT) systems," in *Proc. 3rd Int. Conf. Intell. Green Building Smart Grid (IGBSG)*, Apr. 2018, pp. 1–5.

[19] A. Zourmand, A. L. Kun Hing, C. Wai Hung, and M. AbdulRehman, "Internet of Things (IoT) using LoRa technology," in *Proc. IEEE Int. Conf. Autom. Control Intell. Syst. (I2CACIS)*, Jun. 2019, pp. 324–330.

[20] J. So, D. Kim, H. Kim, H. Lee, and S. Park, "LoRaCloud: LoRa platform on OpenStack," in *Proc. IEEE NetSoft Conf. Workshops (NetSoft)*, Jun. 2016, pp. 431–434.

[21] A. Lavric, A. I. Petrariu, and V. Popa, "SigFox communication protocol: The new era of IoT?" in *Proc. Int. Conf. Sens. Instrum. IoT Era (ISSI)*, Aug. 2019, pp. 1–4.

[22] A. I. Petrariu and A. Lavric, "SigFox wireless communication enhancement for Internet of Things: A study," in *Proc. 12th Int. Symp. Adv. Topics Electr. Eng. (ATEE)*, Mar. 2021, pp. 1–4.

[23] L. Qiao, Z. Zheng, W. Cui, and L. Wang, "A survey on Wi-Fi HaLow technology for Internet of Things," in *Proc. 2nd IEEE Conf. Energy Internet Energy Syst. Integr. (EI2)*, Oct. 2018, pp. 1–5.

[24] Q. M. Qadir, T. A. Rashid, N. K. Al-Salihi, B. Ismael, A. A. Kist, and Z. Zhang, "Low power wide area networks: A survey of enabling technologies, applications and interoperability needs," *IEEE Access*, vol. 6, pp. 77454–77473, 2018.

[25] J. P. Queralta, T. N. Gia, Z. Zou, H. Tenhunen, and T. Westerlund, "Comparative study of LPWAN technologies on unlicensed bands for M2M communication in the IoT: Beyond LoRa and LoRaWAN," *Proc. Comput. Sci.*, vol. 155, pp. 343–350, Jan. 2019, doi: 10.1016/j.procs.2019.08.049.

[26] S. Agnes. (Oct. 2015). *Intel, Nokia and Ericsson Collaborate on NB-LTE Wireless for IoT*. Capacity Mag. [Online]. Available: https://telecoms.com/441951/intel-nokia-and-ericsson-collaborate-on-nb-lte-wireless-for-iot/

[27] E. Rastogi, N. Saxena, A. Roy, and D. R. Shin, "Narrowband Internet of Things: A comprehensive study," *Comput. Netw.*, vol. 173, May 2020, Art. no. 107209, doi: 10.1016/j.comnet.2020.107209.

[28] D. K. Rath and A. Kumar, "A primer on Internet of Things ecosystem and 5G networks," in *Proc. Int. Conf. Inf. Technol. (ICIT)*, Dec. 2018, pp. 233–238.

[29] M. Mozaffari, Y. P. Wang, O. Liberg, and J. Bergman, "Flexible and efficient deployment of NB-IoT and LTE-MTC in coexistence with 5G new radio," in *Proc. IEEE Conf. Comput. Commun. Workshops (INFOCOM WKSHPS)*, May 2019, pp. 391–396.

[30] E. Paolini, C. Stefanovic, G. Liva, and P. Popovski, "Coded random access: Applying codes on graphs to design random access protocols," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 144–150, Jun. 2015.

[31] *LTE; Evolved Universal Terrestrial Radio Access (E-UTRA); Physical Channels and Modulation*, document 3GPP TS 136 211, Version 15.3.0, Release 15, 2018.

[32] B. Martinez, F. Adelantado, A. Bartoli, and X. Vilajosana, "Exploring the performance boundaries of NB-IoT," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 5702–5712, Jun. 2019.

[33] J. Zhang, D. Xie, and X. Wang, "TARA: An efficient random access mechanism for NB-IoT by exploiting TA value difference in collided preambles," *IEEE Trans. Mobile Comput.*, vol. 21, no. 3, pp. 1110–1123, Mar. 2022.

[34] N. Živic, "Improved up-link repetition procedure for narrow band Internet of Things," in *Proc. Int. Conf. Comput. Sci. Comput. Intell. (CSCI)*, Dec. 2017, pp. 1284–1289.

[35] H. Chougrani, S. Kisseleff, and S. Chatzinotas, "Efficient preamble detection and time-of-arrival estimation for single-tone frequency hopping random access in NB-IoT," *IEEE Internet Things J.*, vol. 8, no. 9, pp. 7437–7449, May 2021.

[36] Y. Wang, T. Wang, Z. Yang, D. Wang, and J. Cheng, "Throughput-oriented non-orthogonal random access scheme for massive MTC networks," *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1777–1793, Mar. 2020.

[37] Z. Wang and V. W. S. Wong, "Optimal access class barring for stationary machine type communication devices with timing advance information," *IEEE Trans. Wireless Commun.*, vol. 14, no. 10, pp. 5374–5387, Oct. 2015.

[38] S. Duan, V. Shah-Mansouri, Z. Wang, and V. W. S. Wong, "D-ACB: Adaptive congestion control algorithm for bursty M2M traffic in LTE networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9847–9861, Dec. 2016.

[39] H. He, P. Ren, Q. Du, L. Sun, and Y. Wang, "Traffic-aware overload control scheme in 5G ultra-dense M2M networks," *Trans. Emerg. Telecommun. Technol.*, vol. 28, no. 9, Sep. 2017, Art. no. e3146.

[40] R. Harwahyu, R.-G. Cheng, and C.-H. Wei, "Investigating the performance of the random access channel in NB-IoT," in *Proc. IEEE 86th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2017, pp. 1–5.

[41] C.-H. Wei, R.-G. Cheng, and Y.-S. Lin, "Analysis of slotted-access-based channel access control protocol for LTE-advanced networks," *Wireless Pers. Commun.*, vol. 85, no. 1, pp. 9–27, Nov. 2015.

[42] C.-H. Wei, R.-G. Cheng, and S.-L. Tsao, "Modeling and estimation of one-shot random access for finite-user multichannel slotted ALOHA systems," *IEEE Commun. Lett.*, vol. 16, no. 8, pp. 1196–1199, Aug. 2012.

[43] T. Kim, K. S. Ko, and D. K. Sung, "Prioritized random access for machine-to-machine communications in OFDMA based systems," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2015, pp. 2967–2972.

[44] C. A. Astudillo, T. P. C. de Andrade, and N. L. S. da Fonseca, "Allocation of control resources with preamble priority awareness for human and machine type communications in LTE-advanced networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2017, pp. 1–6.

[45] T.-M. Lin, C.-H. Lee, J.-P. Cheng, and W.-T. Chen, "PRADA: Prioritized random access with dynamic access barring for MTC in 3GPP LTE-A networks," *IEEE Trans. Veh. Technol.*, vol. 63, no. 5, pp. 2467–2472, Jun. 2014.

[46] Y.-J. Chen, L.-Y. Cheng, and L.-C. Wang, "Prioritized resource reservation for reducing random access delay in 5G URLLC," in *Proc. IEEE 28th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Oct. 2017, pp. 1–5.

[47] K. Lee, J. Shin, Y. Cho, K. S. Ko, D. K. Sung, and H. Shin, "A group-based communication scheme based on the location information of MTC devices in cellular networks," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2012, pp. 4899–4903.

[48] T.-H. Chuang, M.-H. Tsai, and C.-Y. Chuang, "Group-based uplink scheduling for machine-type communications in LTE-advanced networks," in *Proc. IEEE 29th Int. Conf. Adv. Inf. Netw. Appl. Workshops*, Mar. 2015, pp. 652–657.

[49] A. H. Tsai, L. C. Wang, J. H. Huang, and T. M. Lin, "Overload control for machine type communications with femtocells," in *Proc. IEEE Veh. Technol. Conf.*, Sep. 2012, pp. 1–5.

[50] A. Laya, L. Alonso, and J. Alonso-Zarate, "Contention resolution queues for massive machine type communications in LTE," in *Proc. IEEE 26th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Aug. 2015, pp. 2314–2318.

[51] C. Yoon, "Distributed queuing with preamble grouping for massive IoT devices in LTE random access," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2016, pp. 103–105.

[52] A. H. Bui, C. T. Nguyen, T. C. Thang, and A. T. Pham, "A comprehensive distributed queue-based random access framework for mMTC in LTE/LTE-A networks with mixed-type traffic," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 12107–12120, Dec. 2019.

[53] A.-T.-H. Bui, C. T. Nguyen, T. C. Thang, and A. T. Pham, "A novel effective DQ-based access protocol with load estimation for massive M2M communications," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Dec. 2017, pp. 1–7.

[54] W. Wu, Y. Li, Y. Zhang, B. Wang, and W. Wang, "Distributed queueing-based random access protocol for LoRa networks," *IEEE Internet Things J.*, vol. 7, no. 1, pp. 763–772, Jan. 2020.

[55] S. Duan, V. Shah-Mansouri, and V. W. S. Wong, "Dynamic access class barring for M2M communications in LTE networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2013, pp. 4747–4752.

[56] Y. Sun, F. Tong, Z. Zhang, and S. He, "Throughput modeling and analysis of random access in narrowband Internet of Things," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1485–1493, Jun. 2018.

[57] N. Jiang, Y. Deng, M. Condoluci, W. Guo, A. Nallanathan, and M. Dohler, "RACH preamble repetition in NB-IoT network," *IEEE Commun. Lett.*, vol. 22, no. 6, pp. 1244–1247, Jun. 2018.

[58] T. Li, J. Yuan, and M. Torlak, "Network throughput optimization for random access narrowband cognitive radio Internet of Things (NB-CR-IoT)," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1436–1448, Jun. 2018.

[59] N. Jiang, Y. Deng, A. Nallanathan, and J. A. Chambers, "Reinforcement learning for real-time optimization in NB-IoT networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 6, pp. 1424–1440, Jun. 2019.

[60] R. Harwahyu, R.-G. Cheng, C.-H. Wei, and R. F. Sari, "Optimization of random access channel in NB-IoT," *IEEE Internet Things J.*, vol. 5, no. 1, pp. 391–402, Feb. 2018.

[61] X. Lin, A. Adhikary, and Y.-P. Eric Wang, "Random access preamble design and detection for 3GPP narrowband IoT systems," *IEEE Wireless Commun. Lett.*, vol. 5, no. 6, pp. 640–643, Dec. 2016.

[62] T. Kim, D. M. Kim, N. Pratas, P. Popovski, and D. K. Sung, "An enhanced access reservation protocol with a partial preamble transmission mechanism in NB-IoT systems," *IEEE Commun. Lett.*, vol. 21, no. 10, pp. 2270–2273, Oct. 2017.

[63] J. Xing, W. Xue-Dong, W. Xiao-Wei, P. Dan, L. Cai-Hua, and L. Long-Ya, "Performance analysis of narrow-band IoT coverage enhancement based on repetition and retransmission," in *Proc. IEEE 6th Int. Conf. Comput. Commun. (ICCC)*, Dec. 2020, pp. 916–920.

[64] J.-K. Hwang, C.-F. Li, and C. Ma, "Efficient detection and synchronization of superimposed NB-IoT NPRACH preambles," *IEEE Internet Things J.*, vol. 6, no. 1, pp. 1173–1182, Feb. 2019.

[65] Q. Wu, P. Wu, W. Wen, T. Yang, and M. Xia, "An efficient NPRACH receiver design for NB-IoT systems," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 10418–10426, Oct. 2020.

[66] S. Xing, X. Wen, Z. Lu, Q. Pan, and W. Jing, "A novel distributed queuing-based random access protocol for narrowband-IoT," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2019, pp. 1–7.

[67] H. Q. Ta, Z. Wang, S. W. Kim, J. J. Nielsen, and P. Popovski, "Preamble detection in NB-IoT random access with limited-capacity backhaul," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2019, pp. 1–6.

[68] X. Yang, J. Yuan, Y. Zhou, and J. Shi, "An efficient ToA estimation technique based on phase correction for 5G mMTC system," in *Proc. IEEE 93rd Veh. Technol. Conf. (VTC-Spring)*, Apr. 2021, pp. 1–7.

[69] M. Gharbieh, H. ElSawy, H.-C. Yang, A. Bader, and M.-S. Alouini, "Spatiotemporal model for uplink IoT traffic: Scheduling and random access paradox," *IEEE Trans. Wireless Commun.*, vol. 17, no. 12, pp. 8357–8372, Dec. 2018.

[70] H. Chougrani, S. Kisseleff, W. A. Martins, and S. Chatzinotas, "NB-IoT random access for nonterrestrial networks: Preamble detection and uplink synchronization," *IEEE Internet Things J.*, vol. 9, no. 16, pp. 14913–14927, Aug. 2022.

[71] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, and H. Zhang, "Intelligent 5G: When cellular networks meet artificial intelligence," *IEEE Wireless Commun.*, vol. 24, no. 5, pp. 175–183, Oct. 2017.

[72] S. K. Sharma and X. Wang, "Toward massive machine type communications in ultra-dense cellular IoT networks: Current issues and machine learning-assisted solutions," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 1, pp. 426–471, 1st Quart., 2020.

[73] R. M. Sandoval, S. Canovas-Carrasco, A.-J. Garcia-Sanchez, and J. Garcia-Haro, "Smart usage of multiple rat in IoT-oriented 5G networks: A reinforcement learning approach," in *Proc. 10th ITU Academic Conf. Kaleidoscope, Mach. Learn. 5G Future (ITU K)*, Nov. 2018, pp. 1–8.

[74] N. Jiang, Y. Deng, and A. Nallanathan, "Traffic prediction and random access control optimization: Learning and non-learning-based approaches," *IEEE Commun. Mag.*, vol. 59, no. 3, pp. 16–22, Mar. 2021.

[75] J. Moon and Y. Lim, "Access control of MTC devices using reinforcement learning approach," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2017, pp. 641–643.

[76] X. Wang, X. Li, and V. C. M. Leung, "Artificial intelligence-based techniques for emerging heterogeneous network: State of the arts, opportunities, and challenges," *IEEE Access*, vol. 3, pp. 1379–1391, 2015.

[77] A. Turan, M. Koseoglu, and E. A. Sezer, "Reinforcement learning based adaptive access class barring for RAN slicing," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops)*, Jun. 2021, pp. 1–6.

[78] L. Tello-Oquendo, D. Pacheco-Paramo, V. Pla, and J. Martinez-Bauset, "Reinforcement learning-based ACB in LTE-A networks for handling massive M2M and H2H communications," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–7.

[79] A. H. Bui and A. T. Pham, "Deep reinforcement learning-based access class barring for energy-efficient mMTC random access in LTE networks," *IEEE Access*, vol. 8, pp. 227657–227666, 2020.

[80] D. Pacheco-Paramo and L. Tello-Oquendo, "Adjustable access control mechanism in cellular MTC networks: A double Q-learning approach," in *Proc. IEEE 4th Ecuador Tech. Chapters Meeting (ETCM)*, Ecuador, Nov. 2019, pp. 1–6.

[81] M. R. Chowdhury and S. De, "Delay-aware priority access classification for massive machine-type communication," *IEEE Trans. Veh. Technol.*, vol. 70, no. 12, pp. 13238–13254, Dec. 2021.

[82] Y. Sim and D.-H. Cho, "Performance analysis of priority-based access class barring scheme for massive MTC random access," *IEEE Syst. J.*, vol. 14, no. 4, pp. 5245–5252, Dec. 2020.

[83] Z. Chen and D. B. Smith, "Heterogeneous machine-type communications in cellular networks: Random access optimization by deep reinforcement learning," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–6.

[84] H. Y. Ali, S. Goulin, and A. M. Seid, "Autonomous RACH resource slicing for heterogeneous IoT devices communication using deep reinforcement learning," in *Proc. Int. Conf. Inf. Commun. Technol. Develop. Afr. (ICT4DA)*, Nov. 2021, pp. 125–130.

[85] A. S. A. El-Hameed and K. M. F. Elsayed, "A Q-learning approach for machine-type communication random access in LTE-advanced," *Telecommun. Syst.*, vol. 71, no. 3, pp. 397–413, Jul. 2019, doi: 10.1007/s11235-018-0509-2.

[86] J. Wang, C. Xing, and J. Liu, "Intelligent preamble allocation for coexistence of mMTC/URLLC devices: A hierarchical Q-learning based approach," *China Commun.*, vol. 20, no. 8, pp. 44–53, Aug. 2023.

[87] A. H. Mohammed, A. S. Khwaja, A. Anpalagan, and I. Woungang, "Base station selection in M2M communication using Q-learning algorithm in LTE-A networks," in *Proc. IEEE 29th Int. Conf. Adv. Inf. Netw. Appl.*, Mar. 2015, pp. 17–22.

[88] S. K. Sharma and X. Wang, "Collaborative distributed Q-learning for RACH congestion minimization in cellular IoT networks," *IEEE Commun. Lett.*, vol. 23, no. 4, pp. 600–603, Apr. 2019.

[89] L. M. Bello, P. Mitchell, and D. Grace, "Application of Q-learning for RACH access to support M2M traffic over a cellular network," in *Proc. 20th Eur. Wireless Conf. (EW)*, May 2014, pp. 1–6.

[90] C. Zhang, X. Sun, W. Xia, J. Zhang, H. Zhu, and X. Wang, "Deep learning based double-contention random access for massive machine-type communication," *IEEE Trans. Wireless Commun.*, vol. 22, no. 3, pp. 1794–1807, Mar. 2023.

[91] M. H. Jespersen, M. Pajovic, T. Koike-Akino, Y. Wang, P. Popovski, and P. V. Orlik, "Deep learning for synchronization and channel estimation in NB-IoT random access channel," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2019, pp. 1–7.

[92] F. A. Aoudia, J. Hoydis, S. Cammerer, M. Van Keirsbilck, and A. Keller, "Deep learning-based synchronization for uplink NB-IoT," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2022, pp. 1478–1483.

[93] Y. R. Kumar and N. M. Balasubramanya, "Deep learning based random access preamble detection for 3GPP NB-IoT systems," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2022, pp. 1689–1694.

[94] J. Choi, J. Ding, N.-P. Le, and Z. Ding, "Grant-free random access in machine-type communication: Approaches and challenges," *IEEE Wireless Commun.*, vol. 29, no. 1, pp. 151–158, Feb. 2022.

[95] H. Zhou, Y. Deng, L. Feltrin, and A. Höglund, "Analyzing novel grant-based and grant-free access schemes for small data transmission," *IEEE Trans. Commun.*, vol. 70, no. 4, pp. 2805–2819, Apr. 2022.

[96] L. Lei, D. Yuan, C. K. Ho, and S. Sun, "Joint optimization of power and channel allocation with non-orthogonal multiple access for 5G cellular systems," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2015, pp. 1–6.

[97] Z. Xiao, L. Zhu, J. Choi, P. Xia, and X.-G. Xia, "Joint power allocation and beamforming for non-orthogonal multiple access (NOMA) in 5G millimeter wave communications," *IEEE Trans. Wireless Commun.*, vol. 17, no. 5, pp. 2961–2974, May 2018.

[98] L. P. Qian, Y. Wu, H. Zhou, and X. Shen, "Dynamic cell association for non-orthogonal multiple-access V2S networks," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2342–2356, Oct. 2017.

[99] A. Benjebbour, Y. Saito, Y. Kishiyama, A. Li, A. Harada, and T. Nakamura, "Concept and practical considerations of non-orthogonal multiple access (NOMA) for future radio access," in *Proc. Int. Symp. Intell. Signal Process. Commun. Syst.*, Nov. 2013, pp. 770–774.

[100] Y. Saito, Y. Kishiyama, A. Benjebbour, T. Nakamura, A. Li, and K. Higuchi, "Non-orthogonal multiple access (NOMA) for cellular future radio access," in *Proc. IEEE 77th Veh. Technol. Conf. (VTC Spring)*, Jun. 2013, pp. 1–5.

[101] S. M. R. Islam, N. Avazov, O. A. Dobre, and K.-S. Kwak, "Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 721–742, 2nd Quart., 2017.

[102] J.-B. Seo, B. C. Jung, and H. Jin, "Performance analysis of NOMA random access," *IEEE Commun. Lett.*, vol. 22, no. 11, pp. 2242–2245, Nov. 2018.

[103] L. Yu, Z. Liu, M. Wen, D. Cai, S. Dang, Y. Wang, and P. Xiao, "Sparse code multiple access for 6G wireless communication networks: Recent advances and future directions," *IEEE Commun. Standards Mag.*, vol. 5, no. 2, pp. 92–99, Jun. 2021.

[104] A. Sultana, I. Woungang, A. Anpalagan, L. Zhao, and L. Ferdouse, "Efficient resource allocation in SCMA-enabled device-to-device communication for 5G networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 5, pp. 5343–5354, May 2020.

[105] J. Zeng, T. Lv, R. P. Liu, X. Su, M. Peng, C. Wang, and J. Mei, "Investigation on evolving single-carrier NOMA into multi-carrier NOMA in 5G," *IEEE Access*, vol. 6, pp. 48268–48288, 2018.

[106] D. Duchemin, J.-M. Gorce, and C. Goursaud, "Code domain non orthogonal multiple access versus ALOHA: A simulation based study," in *Proc. 25th Int. Conf. Telecommun. (ICT)*, Jun. 2018, pp. 445–450.

[107] Z. Shi and J. Liu, "Massive access in 5G and beyond ultra-dense networks: An MARL-based NORA scheme," *IEEE Trans. Commun.*, vol. 71, no. 4, pp. 2170–2183, Apr. 2023.

[108] D. Keerthi, P. Sreelakshmi, and P. P. Deepthi, "Optimum power allocation for power efficient NOMA," in *Proc. IEEE Int. Conf. Electron., Comput. Commun. Technol. (CONECCT)*, Jul. 2022, pp. 1–6.

[109] S. Sreenu and K. Naidu, "Intelligent energy-efficient power allocation for uplink NOMA systems," in *Proc. IEEE Int. Symp. Smart Electron. Syst. (iSES)*, Dec. 2022, pp. 57–61.

[110] Z. Chen, Y. Liu, L. X. Cai, Y. Cheng, R. Zhang, and M. Han, "Performance study of random access NOMA with truncated channel inversion power control," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2021, pp. 1–6.

[111] Y. Hu, L. Peng, and Y. Liu, "Design and analysis of a dynamic access class barring NOMA random access algorithm," *IEEE Commun. Lett.*, vol. 26, no. 12, pp. 3054–3058, Dec. 2022.

[112] J. Choi, "NOMA-based random access with multichannel Aloha," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 12, pp. 2736–2743, Dec. 2017.

[113] M. Elkourdi, A. Mazin, and R. D. Gitlin, "Slotted aloha-NOMA with MIMO beamforming for massive M2M communication in IoT networks," in *Proc. IEEE 88th Veh. Technol. Conf. (VTC-Fall)*, Aug. 2018, pp. 1–5.

[114] E. Balevi, F. T. A. Rabee, and R. D. Gitlin, "ALOHA-NOMA for massive machine-to-machine IoT communication," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–5.

[115] S. A. Tegos, P. D. Diamantoulakis, A. S. Lioumpas, P. G. Sarigiannidis, and G. K. Karagiannidis, "Slotted Aloha with NOMA for the next generation IoT," *IEEE Trans. Commun.*, vol. 68, no. 10, pp. 6289–6301, Oct. 2020.

[116] D.-D. Tran, S. K. Sharma, and S. Chatzinotas, "BLER-based adaptive Q-learning for efficient random access in NOMA-based mMTC networks," in *Proc. IEEE 93rd Veh. Technol. Conf. (VTC-Spring)*, Apr. 2021, pp. 1–5.

[117] M. V. da Silva, R. D. Souza, H. Alves, and T. Abrão, "A NOMA-based Q-learning random access method for machine type communications," *IEEE Wireless Commun. Lett.*, vol. 9, no. 10, pp. 1720–1724, Oct. 2020.
[118] Z. Chen, R. Zhang, L. X. Cai, Y. Cheng, and Y. Liu, "A deep reinforcement learning based approach for NOMA-based random access network with truncated channel inversion power control," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2022, pp. 1835–1840.
[119] X. Zhu, J. Wang, J. Li, H. Lu, Q. Lai, and X. Luo, "A scheme for uplink NOMA communication with intelligent resource allocation for mMTC traffic over eMBB traffic," in *Proc. IEEE 95th Veh. Technol. Conf. (VTC-Spring)*, Jun. 2022, pp. 1–5.
[120] A. Balci and R. Sokullu, "Grant free NOMA with deep learning for massive IoT applications," in *Proc. Int. Balkan Conf. Commun. Netw. (BalkanCom)*, Jun. 2023, pp. 1–6.
[121] Z. Shi, W. Gao, J. Liu, N. Kato, and Y. Zhang, "Distributed Q-learning-assisted grant-free NORA for massive machine-type communications," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2020, pp. 1–5.
[122] R. Ren, J. Wang, J. Yu, X. Zhu, X. Luo, and H. Lu, "Deep reinforcement learning for connection density maximization in NOMA-based NB-IoT networks," in *Proc. 8th Int. Conf. Comput. Commun. Syst. (ICCCS)*, Apr. 2023, pp. 357–361.
[123] A. E. Mostafa, Y. Zhou, and V. W. S. Wong, "Connection density maximization of narrowband IoT systems with NOMA," *IEEE Trans. Wireless Commun.*, vol. 18, no. 10, pp. 4708–4722, Oct. 2019.
[124] S. Moon, H.-S. Lee, and J.-W. Lee, "SARA: Sparse code multiple access-applied random access for IoT devices," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 3160–3174, Aug. 2018.
[125] D.-D. Tran, S. K. Sharma, S. Chatzinotas, and I. Woungang, "Q-learning-based SCMA for efficient random access in mMTC networks with short packets," in *Proc. IEEE 32nd Annu. Int. Symp. Pers., Indoor Mobile Radio Commun. (PIMRC)*, Sep. 2021, pp. 1334–1338.
[126] J. Su, G. Ren, Q. Wang, and B. Zhao, "An SCMA-based decoupled distributed Q-learning random access scheme for machine-type communication," *IEEE Wireless Commun. Lett.*, vol. 10, no. 8, pp. 1737–1741, Aug. 2021.
[127] H. G. Srinath, S. Jha, and N. M. Balasubramanya, "An efficient NB-IoT compatible GF-NOMA PHY mechanism for mMTC," *IEEE Internet Things J.*, vol. 10, no. 20, pp. 17949–17963, Oct. 2023.
[128] Z. Ding, X. Lei, G. K. Karagiannidis, R. Schober, J. Yuan, and V. K. Bhargava, "A survey on non-orthogonal multiple access for 5G networks: Research challenges and future trends," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2181–2195, Oct. 2017.
[129] S. Timotheou and I. Krikidis, "Fairness for non-orthogonal multiple access in 5G systems," *IEEE Signal Process. Lett.*, vol. 22, no. 10, pp. 1647–1651, Oct. 2015.

**LOINI IIYAMBO** (Graduate Student Member, IEEE) received the B.Sc. degree in computer science from the University of Namibia, Namibia, in 2011, and the M.Sc. degree in electrical engineering from the University of Cape Town, South Africa, in 2017. She is currently a Lecturer with Namibia University of Science and Technology and a Graduate Research Fellow with the Department of Electrical, Electronic, and Computer Engineering, University of Pretoria. Her research interests include the narrowband Internet of Things (NB-IoT), fifth-generation mobile networks, sensor networks, and software defined networking.

**GERHARD HANCKE** (Fellow, IEEE) received B.Eng. and M.Eng. degrees in computer engineering from the University of Pretoria, South Africa, in 2002 and 2003, respectively, and the Ph.D. degree in computer science from the University of Cambridge, U.K., in 2009. He is currently a Professor with the City University of Hong Kong, Hong Kong. Previously, he was a Researcher with the Smart Card and IoT Security Centre and a Teaching Fellow with the Department of Information Security, Royal Holloway, University of London. He also volunteers as an Extraordinary Professor with the University of Pretoria. His research interests include system security, reliable communication, and distributed sensing for the industrial Internet of Things.

**ADNAN M. ABU-MAHFOUZ** (Senior Member, IEEE) received the M.Eng. and Ph.D. degrees in computer engineering from the University of Pretoria, Pretoria, South Africa, in 2005 and 2011, respectively.

He is currently a Chief Researcher and the Centre Manager of the Emerging Digital Technologies for 4IR (EDT4IR) Research Centre, Council for Scientific and Industrial Research, Pretoria; an Extraordinary Professor with the University of Pretoria; a Professor Extraordinaire with Tshwane University of Technology, Pretoria; and a Visiting Professor with the University of Johannesburg, Johannesburg, South Africa. His research interests include wireless sensor and actuator networks, low power wide area networks, software-defined wireless sensor networks, cognitive radio, network security, network management, and sensor/actuator node development. He is a member of many IEEE technical communities. He is the Section Editor-in-Chief with *Journal of Sensor and Actuator Networks*, an Associate Editor of IEEE INTERNET OF THINGS, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON CYBERNETICS, IEEE ACCESS, and *Frontiers in Plant Science*.