Quality of Service-aware 6G- Enabled NB-IoT for Health Monitoring in Long Distance High-Speed Trains

Bipasha Guha Roy, Deepsubhra Guha Roy*, *Member, IEEE*, Piyali Dutta, Surbhi Bhatia Khan*, Senior *Member, IEEE*, Fatima Asiri, Manel Ayadi

***Abstract*—Internet of Things connectivity in home health monitoring is a high-in-demand application area. The electronics industry and procedural researchers seek high-end, secured, on-time, cost-effective ways to build reliable quality of service (QoS) proved autonomous systems using existing wireless techniques. Also, the continuous availability of a traffic-free gateway, particularly in isolated places, is necessary for large-scale data gathering and real-time data update processes to function the sensor nodes in an Internet of Things (IoT) network. Improved Narrowband IoT (NB-IoT) is one of the most desirable networks offered by 6th generation (6G) connectivity in IoT-associated remote-monitoring proceedings. In this article, we propose a QoS-aware narrow bandwidth allocation-based prototype model for healthcare monitoring in long-distance high-speed trains during the patient transfer from home to the healthcare center or vice versa. This article demonstrates a possible enhancement in social aspects of cognitive IoT applications with large data systems in industrial informatics.**

***Index Terms*— Bandwidth allocation, Health-monitoring, Narrowband-IoT, QoS-aware, 6G standard.**

I. INTRODUCTION

IN a hugely populated country like India, a significant number of individuals keep some dedicated choices of healthcare destinations far from their residences. Due to their lower economic background, they depend enormously on long-distance high-speed trains compared to airlines. Research says most chronic conditions must be taken care of by doctoral check-ups at regular intervals. Unfortunately, transferring the patient without proper monitoring is highly risky, and the rapidly growing IoT industry, which has already developed several IoT healthcare monitoring models [4], sadly has not yet offered a competent system for long-distance trains. Moreover, a small part of the country has introduced a high-speed bullet train with sufficient IoT network connectivity facilities [1], yet it needs to be fine-tuned. Currently, the Indian railway utilizes 5th generation (5G) connectivity, which is an integrated part of the 3rd generation partnership (3GPP Rel-15/16/17) standards and offers narrowband Internet of Things (NB-IoT).

Meanwhile, the upcoming 6th generation (6G) network offers more reliable opportunities to develop intelligent autonomous transport systems that need real-time traffic management and control. This work concentrates on edge-centric, potential 6G-enabled NB-IoT connectivity standards. It aims to connect numerous intelligent NB-IoT devices, focusing on scalability, coverage, QoS matric, lower latency, and adaptive nature through massive Machine-Type Communications (mMTC) systems. Despite its vast potential, implementing IoT solutions in this discussed situation brings intimidating challenges like train velocity, random distance shift from the base station, bandwidth transformation, etc. Power consumption is also one crucial factor since new features mostly come with significant increments in energy usage, which can be resolved using a 6G standard network. Considering all the issues associated with India's rail connectivity length and diverse landscape, narrowband IoT (NB-IoT) is a perfect exposition for implementing IoT solutions associated with the 6G standard. With its improved coverage, lower power consumption, and low cost, NB-IoT technology possesses the potential to grow into a mainstream Indian technology. Two ways are there for quality control and request management to prevent workload surplus related to packet delay in the dynamic system: congestion management and congestion avoidance. The proposed methodology supports both of these. Novelties of our proposed prototype model are:

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- We adopted 6G-enabled NB-IoT connectivity in a dynamic healthcare monitoring facility traveling in a high-speed train.
- Our prototype emphasized the characteristics of NB-IoT network slicing, high connection, and low power consumption.
- The proposed decision-making module competently chooses available NB-IoT in-band and guard bands on demand.
- Offers a preventive data loss due to a probable cell handover and bandwidth crisis using data storage and transfer through dynamic queue.

Finally, the model skillfully fits the changes in the resource NB-IoT cell and stable/static access points available in the cell.

Apart from these, the adaptation beyond 5G/ 6G enhances the overall security and quality of service (QoS) measures to accumulate such delicate use cases.

We divided our work into the following phases. This section highlights the existing NB-IoT and improved relay-based proposal [17] with the summarization of associated assumptions. Section II introduces the proposed analytical model and assesses its novelty. Section III discusses the enhanced setup, performance improvement report, and gain over existing approaches. Section V concludes the paper with probable future directions in the discussed field.

A. Motivation and Service Selection

A modern train control system with LTE-based mobile train radio communication (MTRC) has been adopted by Indian railways to modernize the existing GSM-R and significantly improve safety, radio, and other applications [1]. According to the latest report published by Indian Railways, the adoption will improve communication support for the 450 pairs of super-fast trains. It will help utilize the unlimited convenience of bullet trains with a maximum speed of 350 km / h [3]. One thousand eight hundred ten crores INR has already been endorsed to implement LTE-based MTRC through the pilot project, which contains four works of the 640 KM route. Another authenticates effort [approved by NITI Aayog, extended board for railways (EBR) and sanction of CCEA] to modernize the existing signaling structure of the Indian railway comprises some provisions related to the adoption of LTE/5G to automate, like traffic control, electronic interlocking system, IoT-bases connectivity/security, train management, etc.

This article proposes a prototype model to continue IoT application for health monitoring using upcoming 6G enabled NB-IoT during travel on Indian long routed super-fast and bullet trains. Two key points must be considered before implementing the proposed solution into an existing real-time environment. First, the patient's data only belongs to the health monitoring center. Second, the network setup and gateways are not restricted (i.e., open for public usage). Existing terms and conditions of Indian railway healthcare ensure that each traveling person's health and medical records are available to the clinics, doctors, and particular medical practitioners to incorporate patient and clinic management via a dedicated channel. The availability and data sharing will be exclusively on-demand and online, considering adequate information security [2, 3]. This health management system can also be integrated with the National Population Register (NPR) and Unique Identification Authority of India (UIDAI) systems to increase data security. The proposed prototype model is intended to provide continuous quality service to Indian railways and other similar environments by implementing a 6G-enabled NB-IoT network.

II. QUALITY OF SERVICE FOR RAILWAY OVER NB-IOT

A method of preference assertion and preemption of dissimilar service requests are essential to distribute a mutual communication substructure for mission grave and non-mission critical railway applications. A quality of service (QoS) mechanism supporting 3GPP infrastructure has already been designed for railway communication [2, 5]. The method follows the Quality Control Index (QCI) designed for the individual type of railway solicitation. Traffic is established upon source and destination IP addresses. The LTE access layer scheduler confirms that traffic with top precedence QCI attains radio source chunks ahead of lower precedence traffic. The reasonable price, low power ingesting, competence to accommodate, enormous positioning of irregularly diffusing, and high communication assortment modules are the foremost necessities for developing IoT resolutions. These can be cooperatively mentioned as Low Power Wide Area Networks (LPWANs) [3, 4]. The two utmost widespread long-range LPWAN expertise are SIGFOX and LoRaWAN, standardized by IEEE, ETSI, and 3GPP [3]. Though the allied functioning ideologies are primarily different, both of the technologies function in sub-GHz license-exempt industrial, scientific, and medical crews and follow a cellular-like structure topologically. With ultra-narrow band signal operators, 100 Hz and 600 Hz [6, 7] are the frequencies of SIGFOX for uplink and downlink connectivity, respectively. SIGFOX comes with some restricted facilities like it has an approximate data rate of 100bit/sec. SIGFOX is capable of tracking 140 and 4 per device packets for uplink and downlink. The payload-frame of SIGFOX is less than 12 bytes each frame having one second maximum on-air time. In spite of the advantage like low battery consumption, SIGFOX is not comparatively desired for future opportunistic crowd-sensing applications. On the other side, another formula was introduced by the 3GPP family first, in LTE Rel. 12 with 1Mbit/s data rates and 20MHz bandwidth [8, 9]. It can be operated over 1.4MHz bandwidth and can reduce the maximum transmission power upto 20dBm. Another existing technology introduced for poor LTE penetration having countries is known as extended coverage GSM (EC-GSM). The ultimate solution deploying NB-IoT having 180 kHz narrowed bandwidth can be effortlessly cohesive into the existing networks and consequently empower user equipment with 20dB advanced while being around ten times less complex than that of Cat. 1 [9, 10, 13]. It can provision a numerous number of IoT devices and can equally divide into 12 sub-bands each of 15 kHz [11]. Uplink and downlink are up to 250Kbit/s and 227Kbit/s, respectively. It has the power to cover a range of 10km and 30km in urban and rural distributions accordingly. First time, in June 2016, NB-IoT had fundamentally been standardized and accomplished to include into LTE Rel. 13 officially [21].

1) Data congestion control
2) Regular data up gradation
3) Data security
4) Stable connectivity
5) Continuous monitoring
6) Seamless compatibility between IoT sensor node and connectivity
7) Real time complexity measurement

A. Proposed Analytical framework for Health Monitoring Network into Train

The fabricated prototype model represents the opportunistic crowd-sensing of IoT data over NB-IoT to support real-time health monitoring while traveling by train. Indian railway offers GSM-R to the travelers and currently, has declared to introduce LTE-based Future Radio Mobile Communication (FRMC). Our motivation is to utilize the NB-IoT structure to carry forward a compassionate data-processing IoT application where dynamically hands-off is taking place. Our clear goal is superfast expresses and bullet trains offering the facility of enhanced network connectivity to accomplish satisfied IoT-integration into a running train. The proposed framework extends the quality of service of existing facilities regarding healthcare IoT connectivity. Also, it assures the relay-based IoT data delivery from the trackside antennas [15, 16] to the core base stations. Specifically, it provides time and cost-effective quality service through enhancing instant network connectivity.

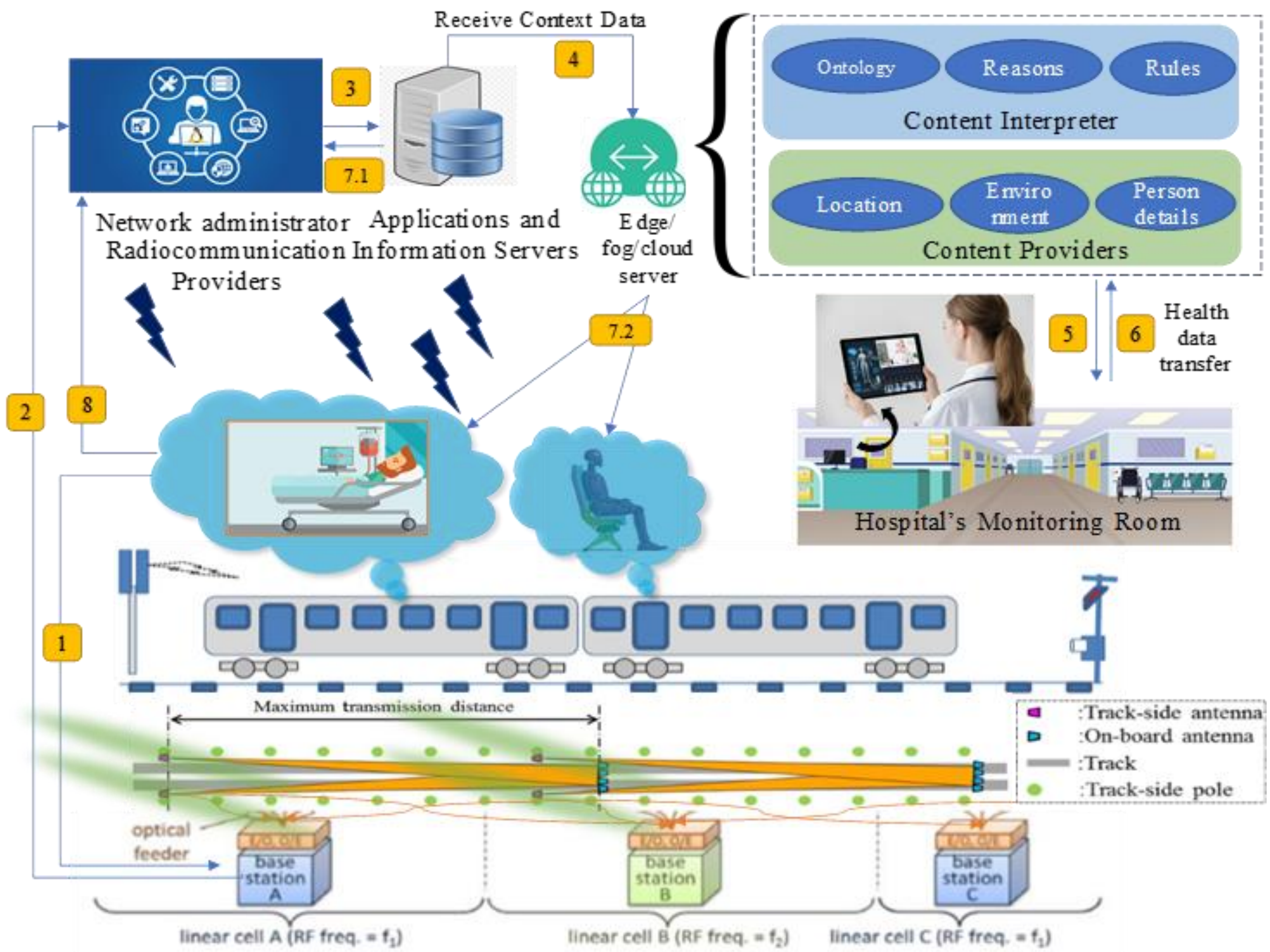

Fig. 1. A prototype model of NB-IoT network for IoT-healthcare monitoring into speed train.

This segment confers about the working principle of resourceful crowd-sensing as portrayed in Fig. 1, consuming our novel logical framework over NB-IoT. At first, a reference point has been stated with modeling, and immediately after that, it has been extended into the dynamic message transmission progression towards the discussed issue, assuming the package-progression of sensor traffic as a network of queues. The scheme is fundamentally a modified version of non-preemptive priority handling with higher priorities of bandwidth allocation in terms of constant data drift [4]. Already originated data-channel to the specially treated passengers are occupied in the meantime and act as a separate queue of tasks constantly. The network monitor has to allocate specific bandwidth to the special queue each time as the packet delivery rate and the available bandwidth is dynamically varying in every timespan. Initially, the message delay distribution is attained by solving the parameterized formulas. In continuation of the above scenario, the required energy to distribute the message delivery procedure as well as the lifetime of the sensors is also measured by smearing this delay distribution. Recall that according to the 3GPP Rel. 13 specifications, the radius of the coverage-area (R_2) in the rural zone is possibly up to 30km. Moreover, taking into the justification that the sensor density (σ) is relatively higher than the message generation intensity (R_2), the Palm's superposition theorem can be applied [5]. The subsequent cumulative procedure will proximately be Poisson while superimposing numerous independent points into a single process. It is also noted that the regular interval of message generation of each statically allocated sensor node towards the access point is not equal to the aggregated result intensity, since it also holds some inter-arrival messages as well [18].

We followed Algorithm 1 to search for a cell and further estimate a stable NBIoT uplink channel, primarily focusing on radio-controlled configurations (RC). The entire procedure starts with a set of checks on the existence of necessary information on device configuration from the Master Information Block (MIB). If each parameter value is satisfactory, the system checks Radio Controlled (RC) values and proceeds with cell searching. A sub frame counter also gets active with a block counter. If the user equipment (UE) receives the acknowledgment of the 11th sub frame, it states that the previous ten numbers of sub frame have been received successfully by the other end. Next, the network originates a synchronized search between the UE and the gNodeB (next-generation Node B or base station). Once the procedure detects a suitable narrowband cell, the device ensures efficient communication through a smooth uplink channel. Further, the estimation task repeatedly happens to increase precision.

TABLE I
TABLE FOR ABBREVIATION

Abbreviation /Symbol	Full Form	Value
MIB	Master Information Block	-
RC	Radio Configuration	R.NB.5, R.NB.6
SF	sub frame	50
UE	User Equipment	100
G_NODE_B	Next Generation Node B	-
SSS_DETECTION	Secondary Synchronization Signal detection	-
FFT	Fast Fourier Transform	128, 256, 512
NN_CELL_ID	Narrowband Cell ID	125 (0 to 503)
R_CELL	Cell radius	2 km
F_TX	carrier/ Transmission frequency	900e6 Hz
F_DOPPLER_THRESHOLD	Doppler threshold	100 Hz
ENODEB	base station	-
RSSI_CURRENT	received signal strength indicator from the current cell	-30 dBm (strong signal) to -120 dBm (weak signal)
RSSI_NEIGHBORING	received signal strength indicator from the neighboring cell	-30 dBm (strong signal) to -120 dBm (weak signal)
NRS_BASE_STATION	Narrowband Reference Signal	-
NPSS	Narrowband Primary Synchronization Signal	-
NSSS	Narrowband Secondary Synchronization Signal	-
NPBCH	Narrowband Physical Broadcast Channel	-
PER	Packet Error Rate	< 0.1 (10%)
NPUSCH	Narrowband Physical Uplink Shared Channel	180 kHz
NPDSCH	Narrowband Physical Downlink Shared Channel	180 kHz
HARQ	Hybrid Automatic Repeat Request	up to 4-8 retransmission attempts
MCS	Modulation and Coding Scheme	16QAM (QPSK)

Algorithm 1 Cell Searching and Channel Estimation

Initialization: Check for Master Information Block (MIB) data: radio controlled (rc)=R.N.B.5/ R.N.B.5/ R.N.B.6

```
Start {
1. Check for Master Information Block
{
if (RC==R.N.B.5) then do {
        config. device = active;
        block_count=frame_count×time;
        read sf from [0, …11]
        if sf==11 true do {
            start cell search;
            }
        }
end
}
2. Start Cell Search
do for (UE and g_node_b){
        active sss_detection;
        call fft;
        set max_cell_count=1;
        check nn_cell_id, offset;
        validate offset ;
        }
if offset && peak=true do{
        nn_cell_id=detect_cell_id
        }
        end cell search
  }
do nbiot uplink channel estimation;
do nbiot uplink channel estimation;
}
End
```

To manage IoT data dynamically, we consider the NB-IoT system setup with M number of straddling relays which will help to deliver real-time instrument messages. Conferring to the random directional model prototype, each relay-base station cooperates with the compartment-based IoT-AP modules and travels by ensuring the runs and tumbles mechanism. Therefore, it selects an arbitrary direction α among the uniformly distributed points from 0 to 2π and travels lengthwise to the conventional line in search of exponentially dispersed time t with a changing velocity v. Our system is being designed to make it an equilibrium. It is acknowledged that a circular area comprises a base station anywhere distributed over πR^2having a radius R. In the steady state it is irrespective of other relay base stations with the edge conquest effects. We propose to model the existing wireless sensor network over a changing velocity of IoT sensor devices [12, 14] i.e. the proposed analytical prototype is modified over static allocation of sensor devices with a turn of assorted allocation of resources. The train is in its running position, therefore, the distance and angle between the base station and APs are fluctuating continually, though the network is bound to give quality service to the prioritized IoT modules related to healthcare monitoring. Fig. 2 depicts the scenario where the data packets reach their desired destination gateway with the probability of $P_{i,j}$ using the available narrow bandwidth resource $B_{i,j}^{v}$. The search of a new base station is started when α becomes >150◦, to maintain the assured flow of data in-between the source and the destination. α is the angle between the packet delivery route of AP and the base station.

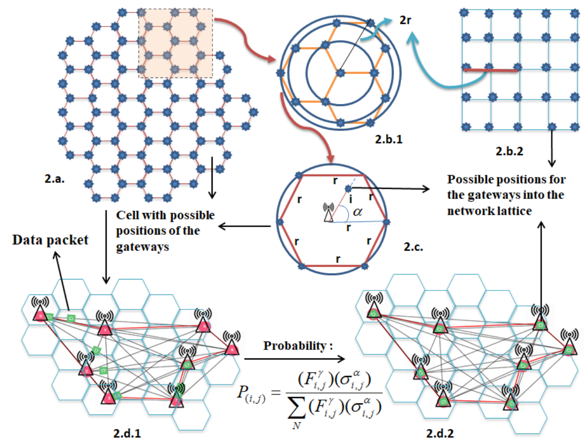

Fig. 2. 2a: Basic hexagonal lattice architecture considered for base station discovery, within the wireless sensor network; 2.b: Comparative cell architecture with another possible lattice construction: Rectangular cell architecture (2.b.1) and our analysis approach: Hexagonal collective cell architecture (2.b.2); 2.c: Unit cell architecture representation with angular analysis; 2.d.1: Simulation scenario1: Data packets are wondering for destination gateway; 2.d.2: Simulation scenario2: Data packets have reached to their desired destination gateway.

Hereafter, the cumulative influx progression of messages is Poisson where the intensity is $\lambda = S\lambda_i$. Now, we focus on the message serving the base station (BS). LTE resource administration changes for NB-IoT to serve the predictable handlers; meanwhile, expected N virtual channels are allocated to the sensors within the individual scheduling interval. A 180 kHz NB-IoT band can classically be fragmented into 12 separated 15kHz sub-bands, having six transmission occasions, respectively. Here, N = 6×12 = 72. Each slot of messages is being proceeded into a batch so that each message has to wait into the virtual buffer until the queue of a single transmission is not ready to be continued. Therefore, a discrete-time queuing model has been recognized with constant message service time. Meanwhile, λ is the intensity of the entire message arrival process and follows the Poisson distribution. Similarly, the message arrival number per slot also ensues the Poisson distribution over the parameter λ. Fig. 2 depicts the considered discrete-time queuing system.

Designing an algorithm to match high-speed train velocity in India using an NB-IoT (Narrowband IoT) in 6G network requires careful consideration of the following factors:

- Network Architecture and Standards
- Train Velocity
- Throughput and Data Rates
- Device Density

- Doppler Effect
- Latency
- Channel Estimation
- Energy Efficiency
- Coverage and Connectivity
- Handover Management
- Spectrum Efficiency
- Automation using Artificial Intelligence (AI)

The proposed "High-Speed Train Velocity Matching in 6G Enabled NB-IoT Network" (Algorithm 2) is designed to sustain connectivity and match the train's velocity. It ensures data transmission via the NB-IoT 6G network among medical UEs and monitoring centers.

Algorithm 2 High-Speed Train Velocity Matching in 6G Enabled NB-IoT Network.

Initialization:

- Initialize Parameters for the Network and Train
- Define train velocity (v_train) = 0 to 300 km/h.
- Initialize NB-iot network parameters:
- (R_cell) = r
- (f_tx) = $\frac{v}{\lambda}$
- Carrier BW = $B_{i,j}^{v}$
- f_doppler_threshold = $\frac{\pi}{4}$
- handover_margin = 30 dbm to 45 dbm

State cell_coverage_area & Location_enodeb using Algorithm 1.

Start {
1. Until Train Reaches Destination Do {
 1.1. Update train's velocity;
 1.2. Update position;
 1.3. Update NB-IoT base station coverage area;}
2. Estimation of Doppler Shift:
 For each time=time++ Do {
 2.1. Estimate Doppler shift (f_doppler)
 $f_{doppler} = \frac{v_{train}}{3.6} \times \frac{f_{tx}}{c} \times \cos(\theta)$;}
 If estimated_Doppler_shift ≥ f_doppler_threshold = $\frac{\pi}{4}$ Do {
 2.1.1. Trigger Doppler pre-compensation {
 Adjust carrier frequency; }
 }
3. Handover Management:
 3.1. Check RSSI_current & RSSI_neighbor{
 If RSSI_neighboring cell ≥handover margin Do {
 3.1.1. Initiate handover method;
 3.1.2. current_cell = neighboring_cell;
 3.1.3. base_station's parameters = new_base_station's parameters;}
 }
4. Channel Estimation and Compensation:
 For real-time channel estimation Do {
 4.1. COUNT NRS_base_station;
 4.2. If Estimate fast-fading channel =true, Do {
 Equalization & mitigate fading_effects; }
 4.3. Compensate for residual_Doppler_shift;
 }
5. Uplink and Downlink Transmission:
 5.1. Use NPUSCH & NPDSCH for data transmission;
 5.2. If velocity-induced impairments=true, Do{
 5.2.1. Adjust transmit power;
 5.2.2. Adjust modulation scheme;
 }
6. Do HARQ or repetition coding:
 Evaluate Network Performance:
 Calculate PER & throughput;
 If PER ≥ PER_threshold, Do {
 Modulation;
 Perform MCS;
 }
}
End

In high-speed train velocity matching in a 6G-enabled NB-IoT network, the Doppler frequency threshold ensures effective signal demodulation and system stability. NB-IoT and 6G systems rely on Orthogonal Frequency Division Multiplexing (OFDM) for efficient data transmission. The threshold π/4 corresponds to a phase shift of 45 degrees, which is small enough to avoid inter-symbol interference (ISI) and large enough to provide robustness against Doppler-induced errors. However, we choose fdoppler_threshold=π/4 for its practical implications in signal stability, demodulation accuracy, and computational efficiency, tailored to handle high-speed dynamics in a 6G-enabled NB-IoT environment. Message loss probability here depends laboriously on train velocity, handover efficiency, and SNR at the cell edge. Regular monitoring of message loss (Ploss) and optimization of parameters (e.g., increasing handover margins or using predictive algorithms) can significantly reduce message loss in high-speed scenarios. The Signal-to-Noise Ratio (SNR) at the edge of the cell is a critical factor in determining message loss probability. SNR depends on: a) Transmit power of the eNodeB, b) Distance between the train and the eNodeB and c) Path loss and environmental attenuation factors.

A. Message Arrival Probability

Let P denotes the arriving number of randomly generated messages through a single slot. Following the Poisson distribution, the possibility of arriving exactly m messages into a single time slot is: $P_m = \frac{(\lambda\Delta)^m}{m!} e^{-\lambda\Delta}$, m=0, 1, … (1)

If the process is compared with a one-dimensional Markov chain embedded for n numbers of arriving messages and represented as: {Q(n), n = 0,1, ...}, then the number of remaining messages holding at the consecutive Markov points can be represented by: $Q(n) = \max(\min(Q(n_1) + P(n)S(n), E), 0)$ (2)

S refers to the single slot served messages immediately after the departure from the requesting queue. Suppose M is the transition probability matrix with the elements (i, j) and the service is served into batches then the entries of the $M(i, j)$, where $i, j \in \{0, 1, \ldots E\}$ are as follows:

$$\left\{\begin{array}{c} 0 \to 0 \quad : \quad V_{0,0} = P_0, \\ 0 \to j \quad : \quad V_{0,j} = P_j, j = 1,2,\dots,E-1, \\ 0 \to E-M \quad : \quad V_{0,E-M} = \sum_{m=E}^{\infty} P_{m,} \\ i \to 0 \quad : \quad V_{i,0} = P_0, i \leq M, \\ i \to 0 \quad : \quad V_{i,0} = 0, i > M, \\ i \to E-M \quad : \quad V_{i,E-M} = \sum_{m=E-i}^{\infty} P_m, i > M, \\ i \to j \quad : \quad V_{i,j} = P_j, i \leq M, j = 1,\dots,E-i-1 \\ V_{i,j} = P_{j-i+M}, \quad i = M+1,\dots,E-1, \quad j = i-M,\dots,E-M-1 \\ V_{i,j} = 0, \quad i = M+1,\dots,M, \quad j = E-M+1,\dots,E \\ V_{i,j} = 0, \quad i = M+1,\dots,E, \quad j = 0,\dots,i-M-1. \end{array}\right\}$$

The transition probability matrix for the induced Markov chain

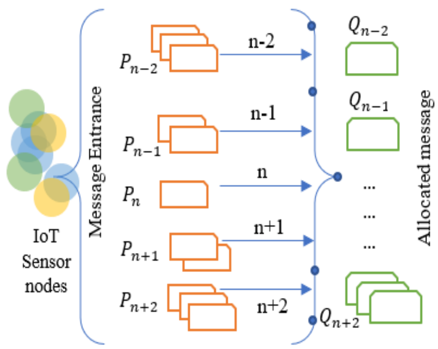

Fig. 3. Considered discrete-time queuing system: message arrival and departure time diagram.

There are various numeral ways to calculate the probability of remaining messages in the queue at the transition buffer time, precisely after the departure of the previous batch of messages (discussed in [2]).

B. Message Loss Probability

In case of the NB-IoT network, the possible message loss is rare; therefore, the assumed message loss probability is normally lesser than the message loss in the applied field. Let us consider that the succeeding circumstances are encountered simultaneously:

(i) Around m number of exact messages in the scheme on ${n_1}^{\text{th}}$ slot where $m = 0, 1, \dots E$;

(ii) The quantity of received messages in the n^{th} slot is accurately $E - m + 1$; then, during that slot, the number of lost messages is denoted by $Lost(n) \in \{0, 1, \dots\}$, and the probability mass function (pmf) over the condition of at least one message arrival is measured by:

$$f_{Lost(n)}(i) = \frac{\sum_{m=0}^{E} x_{D,m} P_{E-m+i}}{\sum_{m=1}^{\infty} \frac{(\lambda\Delta)^m}{m!} e^{-\lambda\Delta}}, i = 1, 2, \dots \quad (3)$$

$x_{D,m}$ is the probability of remaining exact $m = 0, 1, \dots E$ messages in the queue at the transition buffer time immediately after the departure of the previous batch of messages and the probability that in the slot there is at least one message is: $1 - e^{-\lambda\Delta}$.

Detecting that the Poisson parameter λ is unfolding the circumstance of an arbitrary slot as there is no message loss, i.e. $f_{Lost(m)}(0)$, attained by $1 - \sum_{i=1}^{\infty} f_{Lost(m)}(i)$ and message loss probability is: $P_E = \frac{\sum_{i=1}^{\infty} \sum_{m=0}^{E} x_{D,m} P_{E-m+i} \frac{i}{E-m+i}}{1 - e^{-\lambda\Delta}}$ (4)

Where, $\frac{i}{(E-m+i)}$ is the probability of losing an arbitrarily nominated message, receiving through n^{th} slot.

C. Waiting Time Measurement

Let a random message m_i has been selected from a service slot n. The probability of a particular message is being served by the gateway without any distributed waiting time, i.e. zero queuing delay implies two possible cases: (i) there are exactly M messages in that system; or (ii) the tagged message belongs to the slot of first Mmessages in case of more than Mmessages in an arriving slot. Calculated zero queuing delay is optimized to its nearest integer value with the help of the following form.

$$f_D(0) = \frac{\sum_{i=0}^{M} x_{D,i} (P_1 + \frac{2P_2}{2} + \dots + \frac{MP_M}{M} + \frac{MP_{M+1}}{M+1} + \dots)}{\xi_P} \quad (5)$$

ξ_P is the normalization constant and calculated by $\xi_P = \sum_{i=0}^{\lceil \frac{E}{M} \rceil - 1} f_D(i)$. Using induction method, calculated pmf for i numbers of message delay is:

$$f_D(i) = \frac{1}{\xi_P} \sum_{j=0}^{\min(M, E-(M(i-1)+1))} x_{D,j} \sum_{n=M(i-1)+1}^{\infty} \frac{\min(n+1-(M(i-1)+1), M, E-j)}{n} P_n + \sum_{j=M+1}^{\min(M_i, E-1)} x_{D,j} \sum_{n=M(i-j)+1}^{\infty} \frac{\min(n+1-(M_{i-j+1}), M, E-j)}{n} P_n + \sum_{j=M_{i+1}}^{\min(E_{(i+1)}-1, E-1)} x_{D,j} \sum_{n=1}^{\infty} \frac{\min(n, M(i+1)-j, E-j)}{n} P_n \quad (6)$$

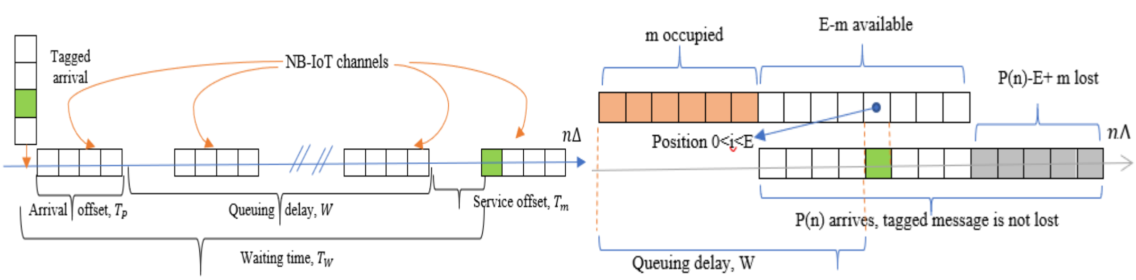

Fig. 4. Illustrated queuing delay and waiting time diagram in the discrete queuing message system.

D. Energy Consumption Measurement

Energy distribution per message transaction has been considered under the circumstances of three states of IoT data processing for IoT healthcare monitoring. The considering states/modes to measure consumed energy are as follows: (i) sleep mode, (ii) R_m-ready mode, and (iii) T_m-data transaction mode. The cumulative expanse of individually consumed energy of these three states with respect to time can be used further to predict the sensors' lifetime and edifice cost as illustrated in Fig. 3. A key reasons to consider the NB-IoT in the discussed field because of the delicacy to deal with the health-related data. Random speed of a train with random allocation of bandwidth makes the health-monitoring procedure more complex than the constant data distribution of IoT sensor nodes. NB-IoT is well-optimized to implement the random-access procedure of shared resources.

TABLE II
VARIABLES AND SYMBOLS

Symbol	Description	
$PowR_m$	consumed energy to exchange the data in between the AP and BS	Constant variable
T_R	Duration of random access	
T_M	Message transmission time	
$PowT_m$	Power consumed for random access	Random Variable
T_S	Search time for BS	
T_W	Waiting time	

It has been observed that the consumed energy due to message acceptance ($PowT_m$) is constant while the consumed energy to exchange the data in between the access point (AP) and base station (BS) ($PowR_m$) is exclusively dependent upon the distance among them. We assume that in case of continuous health data monitoring, some of the APs never go to the sleep state. Therefore, energy consumption (C_E) for each message transaction (in Joules) is:

$$C_E = PowR_m(T_S + T_W) + PowT_m(T_R + T_M) \qquad (7)$$

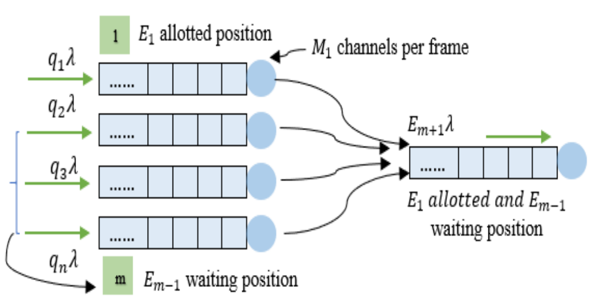

Fig. 5. Illustrated allotted and waiting positions with queuing delay in the enhanced discrete queuing message distribution system.

In Fig. 5, the illustration, allocation, waiting, and distribution of M number of messages in one slot are depicted. In each slot of the upcoming messages, the aggregated intensity is $q_i\lambda$ where E_1 is the priority field and must be allocated packets into L_i length entry queue from health devices, whereas the other packets coming from other mobile devices are also considered to be connected with the base station as per their requirement with some stipulated waiting time. The message waiting time is previously calculated in Equation 6.

III. RESULT AND DISCUSSION

Existing Third Generation Partnership Project (3GPP) offers a Low-Power Wide-Area Network (LPWAN) technology called Narrowband IoT (NB-IoT). The extended Discontinuous Reception (eDRX) technique helps accomplish more power savings and gives the NB-IoT nodes a long life with low power consumption. A few characteristics of NB-IoT make it perfectly fit into implementing IoT-critical networks, such as moving smart healthcare establishments. This network supports up to ten million IoT devices per cell, which is ideal for massive connection-density IoT deployments in a 6G enabled network. NB-IoT also provides comprehensive area coverage deploying repetition techniques and increases the strength of the signal under challenging environments such as railway compartments and rural areas. Also, NB-IoT sustains a few kbps data rates, which are comparatively lower and suitable for crucial IoT networks. We developed an emulation setup to create key features of NB-IoT configurations to achieve a real-time implementation of our proposed mathematical model in a possible 6G environment. The novelty of our mathematical model has been accomplished during the procedure as shown in this result and discussion section. There are more than ten factors to focus on while designing real-time traffic management and control using 6G-enabled intelligent autonomous transport systems, already mentioned in Section III. Considering those factors as parameters, this section shows a different graphical representation captured during the implementation of Algorithm 1 and Algorithm 2 using the MATLAB interface [19]. We divided the entire simulation into three phases. The first and initial phase is to establish a comprehensive data exchange path connecting UEs (NBIoT medical devices) to gnodeB, 6G core, and monitoring center. Fig. 8 and 9 represent cell searching, MiB decoding, and successful channel response and bandwidth allocation receiving. In the next phase, we measured message loss probability over message intensity and sensor energy efficiency over sensor density for various base station distances and plotted Fig. 10- Fig. 13. All the parameter values for this particular phase execution are documented in Table III and put into the equations solved for cell structure architecture mentioned in Section III. The second phase of the experiment considers two co-related parameters at a time and is applicable for a probable stable connectivity establishment.

For more critical analysis, we designed a test bed with the MATLAB functions. We plotted imperative output graphical representation towards quality of service-aware 6G enabled NB-IoT for health monitoring in long-distance high-speed trains. Fig. 12- Fig. 17 depict the few most potential real-time variations among co-related parameters. Fig. 12 shows the Doppler Shift against train velocity during cell handovers. Fig. 13 shows 3D plotting of latencies against train velocity for multiple NB-IoT devices. Fig. 14 shows 3D plotting of throughput analysis against train speed for multiple NB-IoT device usage. Fig. 15 shows health data throughput against time (during Handover). Fig. 16 shows parallel changes of train velocity, Doppler shifting and bandwidth over time. Fig. 17 shows a comparison of QoS metrics at different train speeds.

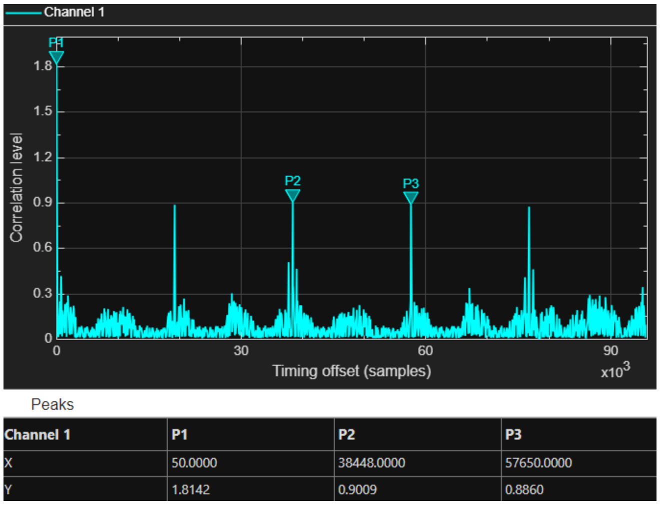

Fig. 6. Performing cell searching, OFDM demodulation and MIB decoding

Fig. 6 and Fig. 7 show the cell search procedure with 50 samples of timing offset to frame start. Fig. 6 shows three peaks for channel 1, which have been detected via 640 sub-frames. Mainly for this sample, we detected a -0.031Hz frequency offset through frequency offset estimation. After performing Orthogonal Frequency Division Multiplexing (OFDM) demodulation through an MIB decoding procedure, we detected a channel with a channel ID (NNCellID) 125, also called a cell identifier.

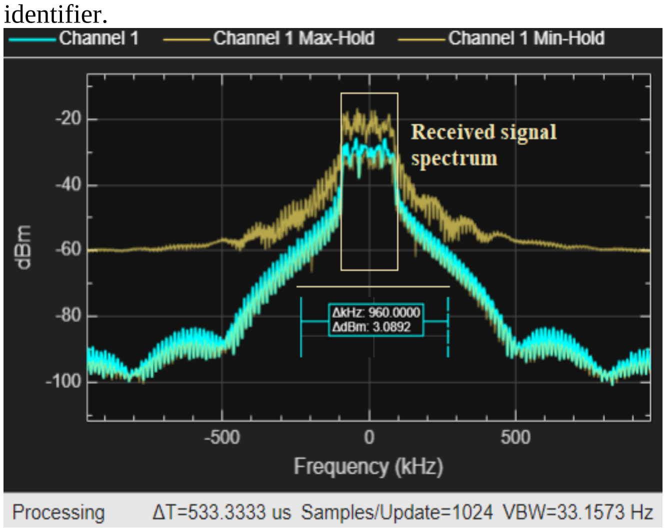

Fig. 7. Plotted received signal spectrum for channel id 125.

MIB typically stores other parameter values like Antennas or Narrowband Reference Signals (NRS) ports=1, which means our narrowband cell uses one reference signal port. The current system frame number or SFN is also there; in his case, the value of SFN is 640. Other values are HyperSFN or extended SFN, common in extended 5G/6G networks to support any illustrative time possibilities. This variable helps to store queuing delay (as shown in Fig. 3).

TABLE III

PARAMETERS WITH EFFECTIVE VALUES FOR FIG. 8-FIG.11

Parameter	Sign	Value
Coverage area	A	-
Radius of coverage-area in urban zone	R_1	10 km
Radius of coverage-area in rural zone	R_2	30 km
Relay (Number)	R_n	0, …, 1000
Intensity of message generation (per minute)	λ_i	40,50,100
Mean sensor density in A	σ	10, …, 1000/km^2
NB-IoT channels	N	70
Base station waiting queue	B	3× N
Allocated channels/ compartment	γ_N	0, … 0.95
Duration of frame	Δ	10 ms
Velocity of train	v	0,100,…,350

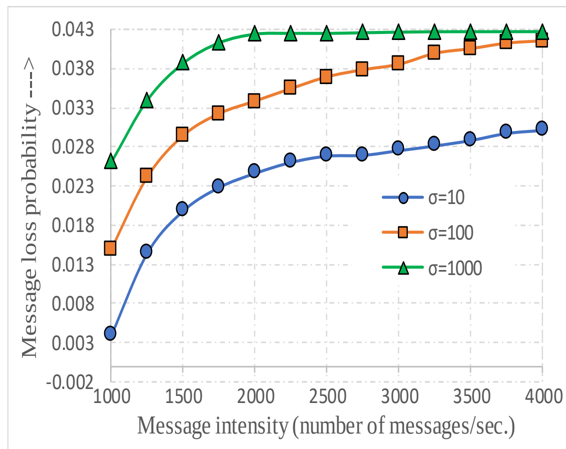

Fig. 8. Message loss probability over message intensity when R_1=10 km.

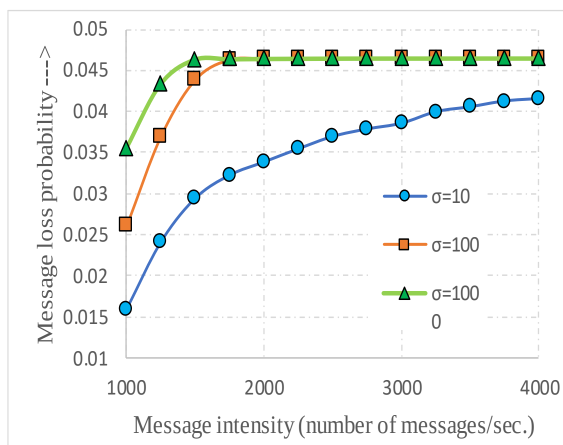

Fig. 9. Message loss probability over message intensity when R_2=30 km.

The results plotted in Fig. 8 and Fig. 9 conclude how the different constant values of σ influence the possibility of message loss, which is higher up to some extent, while the NB-IoT is proving significant support in the circumstances in both the cases of urban and rural areas in spite of dynamic velocity of IoT devices. We consider the message generation intensity up to 4000 which can only be accumulated by NB-IoT network apart from other supportive railway offered connectivity.

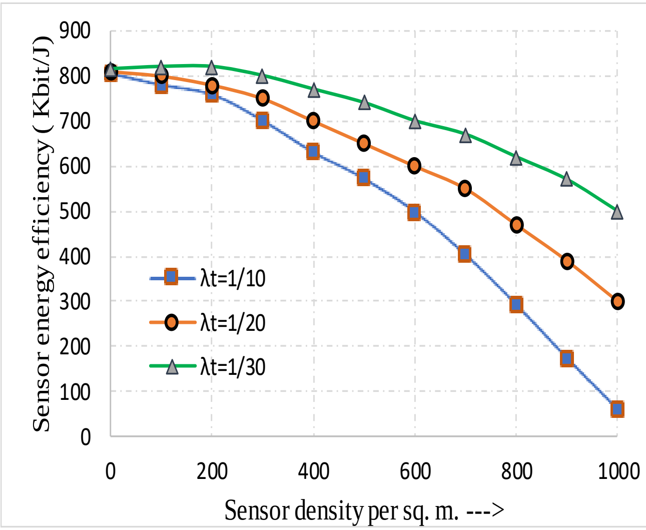

Fig. 10. Sensor energy efficiency over sensor density when R_1=10 km.

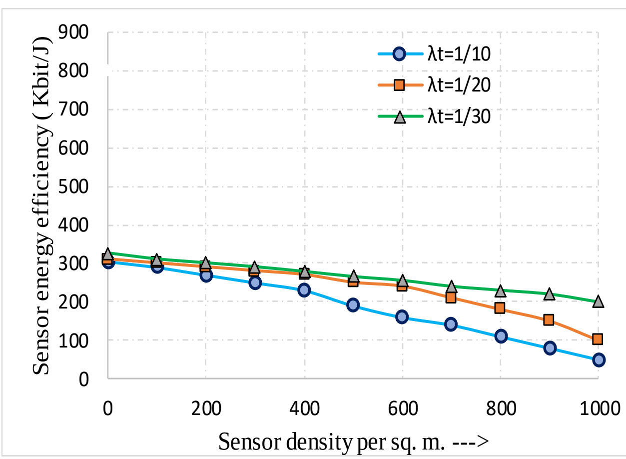

Fig. 11. Sensor energy efficiency over sensor density when R_2=30 km.

Fig. 10 and Fig. 11 are showing the performance utilization through the energy efficiency measurement of the used IoT healthcare monitoring devices. NB-IoT eventually decreases the message loss probability with a large coverage area throughout the railway coverage path and confirms a prioritized confidential data transmission within even a circumstance of lower bandwidth availability. Later it helps to enhance the battery capacity of IoT devices as well as energy consumption by the base stations.

We considered a situation where a train with 0-500 km/h velocity is changing its distance from the base station, and due to sudden changes in bandwidth crisis, the core network module is considered a handover. To get a smooth experience of these changes, we must consider three primary parameters: train velocity, base station distance, and possible handover situations. We assessed the known Doppler shift formula and manipulated it as per the scenario depicted in Algorithm 2.

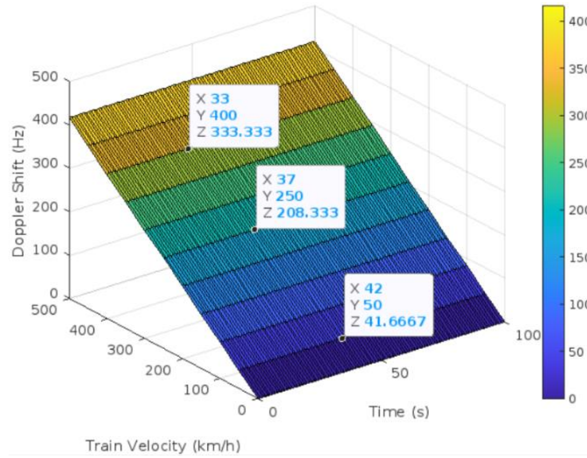

Fig. 12. Train velocity vs. Doppler shift with cell handovers.

We varied train velocities from 0 to 500 km/h and altered into m/s. We took a Doppler shift based on 900MHz carrier frequency, suitable for 5G/6G NB-IoT, and simulated handovers occurring every few seconds, with a base station ranging from 500 to 3000 meters. Finally, the calculated Doppler shift generates a 3D surface plot where the X-axis denotes time (in seconds), the Y-axis indicates the train velocity (in km/h), and the Z-axis represents the Doppler shift (in Hz). The color bar visually demonstrates the plot's magnitude of the Doppler shift.

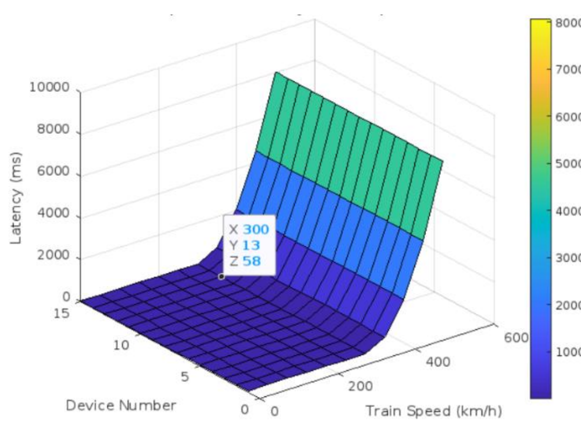

Fig. 13. 3D plotting of train speed vs. latency for multiple NB-IoT devices.

Next, we extended the previous logic and assumed an increasing latency value with increased train velocity, possibly at different UE-module data rates. We considered 15 active NB-IoT devices at a time with an initial latency between 10-50 ms. Primarily, the shifts in latency were linearly affected, but after the critical speed of the train (300 km/h), the latency increased more drastically. The Z-axis demonstrates a slight latency value difference for each of the 15 devices concerning the X-axis (representing train velocity) and Y-axis (holding the device indexes).

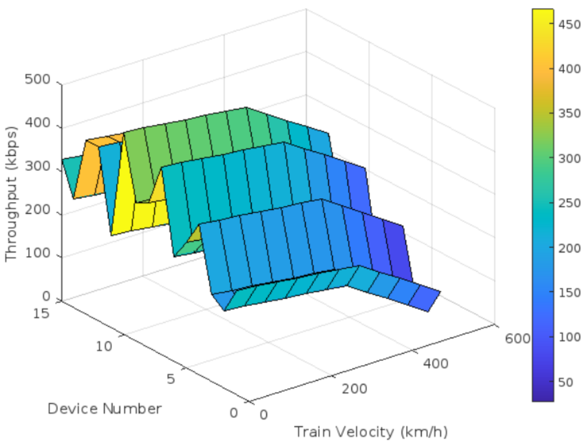

Fig. 14. 3D plotting of train velocity vs. throughput for Multiple NB-IoT devices.

Considering unstable train speed, we followed a similar case scenario to identify throughput variation against time slots. We assessed 15 NB-IoT devices having different initial throughputs. We considered Equations 2, 3, and 6, where we calculated how signal degradation, interference, and congestion have affected the message intensity and data exchange rate as the train moves at higher speeds. We observed that 15 UEs have random initial throughputs between 100 to 500 kbps, decreasing the data exchange rate primarily in linear patterns, which drastically decreases when the train speed crosses a critical velocity of 300 km/h. Fig. 14 shows how high-speed mobility (shown in X-axis) impacts the data rates or throughputs (shown in Z-axis) of the NB-IoT devices (shown in Y-axis).

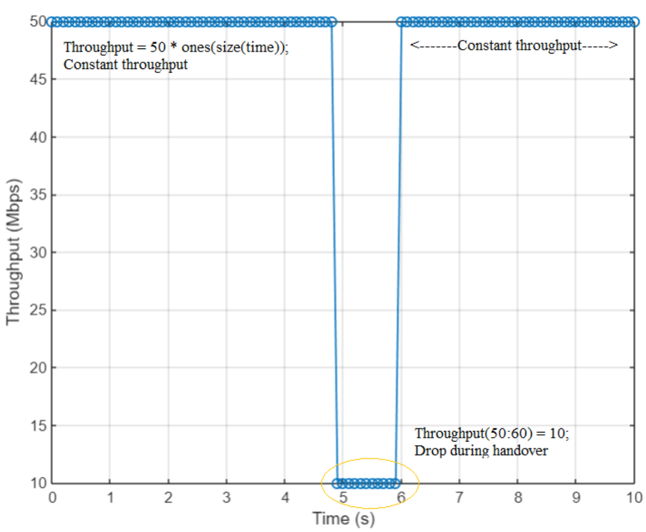

Fig. 15. Health data throughput vs. time (during handover).

Fig. 15 highlights a particular phase when a cell handover occurs, and a constant data exchange rate abruptly turns to a lower phase. We know that we need constant data throughput for continuous health monitoring. Therefore, we followed probable waiting time measurement using Equation 6 and successfully avoided data transmission during a sudden drop in bandwidth. So that the data waits in the virtual queue and the exchange takes place again, the network restores its stable position. This time (in the X-axis) vs. throughput (in the Y-axis), a time-series plot shows how much throughput can tear down during Handover or sudden bandwidth demand situations.

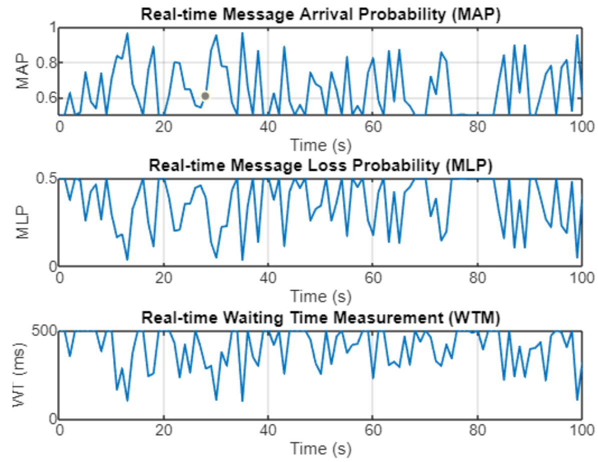

Fig. 16. Time vs. real-time message arrival probability, real-time message loss probability and real-time waiting time measurement.

Fig. 16 plots the measured waiting time of outgoing data concerning message arrival probability and message loss probability at a simultaneous time range. We considered train velocity, bandwidth availability, data throughput, and distance from the base station and measured probable channel deficiency to calculate message loss probability (Section III). Hence, the message loss probability complements the message arrival probability due to inadequate signal conditions. Therefore, the proposed adaptive transmission, multi-connectivity, and handover management offered in the 6G-enabled NB-IoT network are suitable for reducing data loss probability.

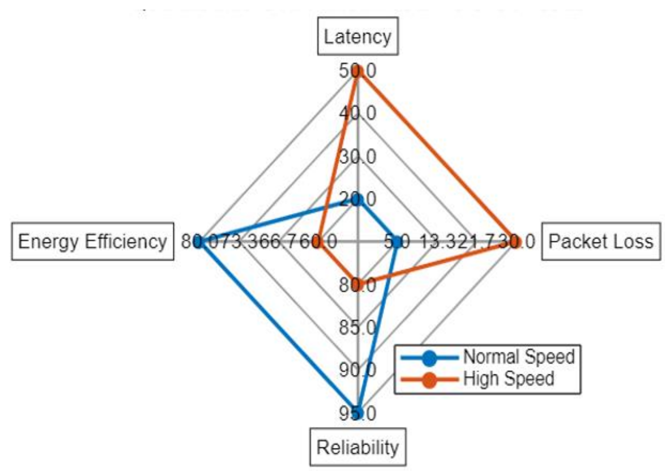

Fig. 17. QoS Metrics comparison at different Speeds

Fig. 17 is a radar plot graph that shows a comparative difference among various quality of service (QoS) metrics for the 6G-enabled NB-IoT network, considering our test bed. The depicted graph is focused on network QoS parameters:

reliability, energy efficiency, latency, and packet loss, denoting diverse conditions like high speed and average speed using distinct lines. Finally, we see a comparison of QoS metrics at diverse train velocities.

IV. CONCLUSIONS AND FUTURE WORKS

The opportunistic crowd-sensing scenario, discussed in this article, fundamentally enhances the work efficiency of IoT based healthcare monitoring modules while unchanging traffic network from a large number of congestions in the existing NB-IoT network in a high-speed train. We have evaluated a cognitive big data distribution aspect, where health-related data packets are competing to transform within a dynamically connected sensors toward a secure and assured destination. These data relatively help the healthcare industries as well as support better human living with supportive research developments [20]. To resolve the chances of message loss and higher energy consumption a quality-aware enhanced NB-IoT network architecture has been discussed for 6G standard, where moving IoT devices support with relaying network traffic to the NB-IoT base station. Simulation results support the achievement of NB-IoT connectivity to resolve this real-time problem. Future works can be enriched with the following footsteps:

- We expect a real-time achievement of 6G standard to make autonomous such IoT related applications using NB-IoT technology successfully in near future.
- Testing and validation will be our next contribution with the comparison test of NB-IoT health monitoring system in simulated and real-world train environments to validate its performance, reliability, and scalability. This includes conducting field trials and collecting feedback from users and stakeholders.

Acknowledgement: This research is supported by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2025R761), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. The authors extend their appreciation to the Deanship of Research and Graduate Studies at King Khalid University for funding this work through Large Group Project under grant number (RGP.2/556/45)

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