

Performance Analysis of Blockage Detection in 6G Wireless Networks

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ABSTRACT- This paper presents a proactive blockage detection algorithm and performance for sub-terahertz (sub-THz) communication systems. It is a critical technology for next-generation wireless networks. Human body blockage is a significant challenge for millimeter wave and sub-THz systems. It often causes severe signal degradation and connectivity loss. Current solutions, such as time-domain approaches or machine learning models. These methods suffer from high computational complexity, limited accuracy and an inability to detect blockages before they occur. The proposed algorithm overcomes these limitations by applying spectral-domain analysis using the short-time Fourier transform (STFT). It provides precise detection of early blockage conditions. The blockage detection algorithm adopts a simple and threshold-based detection mechanism. The algorithm operates in three stages: initialization, active monitoring, and blockage recovery. The proposed algorithm demonstrates a detection probability of 81% and highlights its effectiveness in reliable detection. It detects blockages at least before their occurrence. Additionally, the algorithm achieves a higher mean time to blockage of up to 150ms under optimal parameter settings. These findings highlight the algorithm's effectiveness in mitigating connectivity issues in dense indoor deployments. It is adaptable to different network configurations and is suitable for various deployment scenarios. The proposed solution is well-suited for ultra-reliable low-latency communications, augmented reality, autonomous vehicles, and industrial IoT. These outcomes mark a key step toward seamless 6G communication.

Keywords: 6G, Blockage Detection, Detection Probability, STFT, Sub-terahertz.

ARTICLE INFORMATION

Author(s): Naziya Hussain, Vatsala Anand, Anuragh Vijjapu, G.A. Arun Kumar, R. Anil Kumar, and V. Preethi;

Received: 13/02/2025; **Accepted:** 05/07/2025; **Published:** 30/07/2025;

E- ISSN: 2347-470X;

Paper Id: IJEER 1302-12;

Citation: 10.37391/ijeer.130301

Webpage-link:

<https://ijeer.forexjournal.co.in/archive/volume-13/ijeer-130301.html>



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being human body blockage. Human body blockage occurs when people start move along the line of sight of communication links. It results in substantial attenuation of the received signal strength. This attenuation can lead to severe connectivity losses, reduce the reliability and quality of service. As the density of users and devices increases in indoor environments, the impact of blockage events becomes even more pronounced. Therefore, developing effective solutions to detect and mitigate the effects of blockage is crucial for the successful implementation of mmWave and sub-THz systems [2].

1. INTRODUCTION

The advent of 5G and upcoming 6G networks marks a new era in wireless communication. These are characterized by the utilization of mmWave and sub-THz frequency bands [1]. The bands range from 30GHz to 300 GHz and provide large gain in bandwidth and data rates. For example, they are facilitating improved user experiences and the growth of cutting-edge applications like augmented reality (AR), virtual reality (VR) and the Internet of Things (IoT). However, implementing these high-frequency systems presents challenges, the most critical

Researchers have traditionally used time-domain approaches for blockage detection. The machine learning algorithms require extensive training and often reactive in nature. These methods typically identify blockage events only after they have occurred. It is inadequate for maintaining seamless connectivity in real-time applications [3]. Consequently, there is a persistent need for proactive blockage detection techniques that can anticipate blockage events before they happen. This allows timely interventions to reroute communication or adjust system parameters [4]. In this context, work advocates for a novel approach that leverages spectral representation for proactive

blockage detection. By analyzing the spectral characteristics of the received signal, here, identify distinct signatures it precedes blockage events. This method capitalizes on the observed differences in signal power between non-blockage and pre-blockage states. These are significantly pronounced in the spectral domain often reaching two orders of magnitude. Such pronounced differences facilitate the development of simple. But effective threshold-based detection algorithms can operate in real-time [5].

To validate simulation results, performed a series of trials utilizing a terahertz source operating at 156 GHz. The findings revealed the presence of pre-blockage signatures characterized by oscillations in the received signal. This can be detected approximately 50ms before an actual blockage occurs. This lead time is critical and provides the necessary window for the system to react and implement strategies such as multi-connectivity. Further, enhancing user experience and maintaining service continuity.

The proposed proactive blockage detection algorithm is designed to operate efficiently in indoor environments. Here, human movement is unpredictable. Algorithm works by applying a STFT to the incoming signal and separating it into non-blockage, pre-blockage and blockage states. The main contributions of the research are

- To detect pre-blockage signatures in the received signal, allowing early detection up to 50ms before blockage.
- To develop a proactive blockage detection algorithm that works efficiently in indoor environments, even with unpredictable human movement.
- To evaluate the performance of algorithm against detection probability, false alarm rate, and mean time to blockage.

2. LITERATURE REVIEW

Blockage detection is a critical area of research in 6G wireless networks due to its high reliance on terahertz frequency bands. Addressing these challenges is crucial for ensuring reliable communication in scenarios such as smart cities, autonomous vehicles, and industrial automation. The survey summarizes relevant studies on blockage detection and related technologies in THz communications.

Fazal-E-Asim et al. [6] focused on the use of reconfigurable IRS for mitigating blockages in THz communications. They proposed structured channel estimation techniques to improve signal quality in high-density environments. Their findings highlighted the importance of channel state information in adapting RIS configurations to bypass obstacles effectively. The paper also emphasized the need for scalable algorithms to address dynamic blockages. Zhinuk et al. [7] proposed a spectral-based approach for pre-emptive blockage identification in sub-THz communication systems.

The study demonstrated how one could detect and mitigate imminent blockages instantly by analysing spectral properties of the signal. That approach minimizes latency and enables robust connectivity. This makes it suitable for ultra-reliable low-latency communication applications. U. Sreenivasulu et al.

[8] proposed a deep-learning-based hybrid beamforming method for THz communications assisted by RIS. Their method optimized the configuration of large-scale antenna arrays to combat blockages while maintaining high energy efficiency. This study demonstrated the potential of integrating machine learning with RIS for adaptive and intelligent blockage management.

Liu et al. [9] proposed an improved spread orthogonal frequency-division multiplexing (S-OFDM) waveform based on the discrete Fourier transform (DFT-S-OFDM) to enhance the resilience of 6G systems. Such a design alleviates the negative impacts of channel impairments induced by blockage while favoring spectrum-efficient transmissions. They revealed challenges in THz bands that will need advanced innovations in waveform designs to deal with propagation effects. Anil et al. worked on improving hybrid precoding techniques by introducing a successive interference cancellation (SIC) and singular value decomposition (SVD)-based algorithm. This method effectively counteracts indoor blockages in sub-THz systems, ensuring better performance in high-density environments. Their approach balanced computational complexity and improved spectral efficiency.

Dheerajal et al. [11] proposed a multiband orthogonal frequency-division multiplexing (MB-OFDM) system with impairment-aware precoding. This system mitigates the squint effect in wideband THz communications and ensures resilience to blockages by dynamically adjusting beam directions. The study provided insights into efficient frequency management in wideband systems. Yuan et al. [12] characterized THz meta surface sensors with ultra-high frequency selectivity and polarization sensitivity. These sensors were shown to improve signal propagation and mitigate the effects of blockages in THz communication systems. Xie et al. [13] presented a multiplexed meta sensor design based on quasi-bound states in the continuum (quasi-BICs). Their device enabled efficient broadband sensing and signal traceability, making it suitable for environments prone to blockages.

Henri et al. [14] fabricated THz antenna arrays optimized for spatially resolved imaging and spectroscopy. These arrays improved the spatial resolution of THz systems and addressed blockages by enabling dynamic beam steering. This work underscored the importance of hardware innovations for overcoming communication barriers. Zarini et al. [15] explored resource allocation strategies for combining enhanced mobile broadband (eMBB) and URLLC services in RIS-assisted THz networks. Their framework balanced throughput and latency by dynamically allocating resources to bypass blockages. The study emphasized RIS's role in facilitating blockage-aware resource optimization. Wang et al. [16] proposed a novel simultaneous transmission and reflection surface (STARS) architecture for THz communications. This enables simultaneous transmission and reflection of signals. This dual capability reduced the impact of blockages by offering flexible path selection. The study demonstrated significant improvements in signal reliability in scenarios with high mobility. Fujii et al. [17] developed a two-block RNN model to predict trajectories with missing data. It handles cases where

detection fails due to occlusion or signal quality. The model uses two separate RNNs to update predictions based on whether the target was detected or missed, making it more reliable in real-world scenarios. Innovations in waveform design, beamforming and sensing are essential for ensuring reliable communication in dynamic, high-mobility 6G environments.

3. COMMUNICATION SYSTEM MODEL WITH BLOCKAGE

Figure 1 shows the components of 6G wireless networks, including machine-critical and broadband communications. A central base station connects to various systems like satellites, autonomous vehicles, drones, hospitals and schools using OFC, Free Space Links and RF Links. Machine-critical communications involve technologies such as surveillance cameras, sensors, Wi-Fi and visible light communication (VLC). These are essential for real-time tasks. Enhanced broadband services like video streaming and AR/VR are highlighted in urban environments like apartments and hospitals.

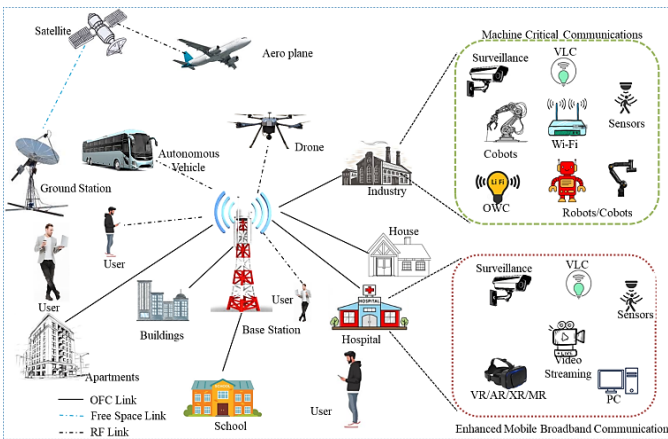


Figure 1. Integration of Machine-Critical and Broadband Communications in 6G

This section presents the system model for simulating blockage scenarios in a 6G wireless network operating at sub-terahertz (sub-THz) frequencies. The model includes a high-frequency transmitter, propagation channel, and receiver. We model blockage effects as resulting from human movement in indoor environments.

3.1. Transmitted Signal Model

The transmitted signal $s(t)$ is modelled as a cosine waveform modulated at the carrier frequency:

$$s(t) = A \cos(2\pi f_c t) \quad (1)$$

Here, A is the signal amplitude and $f_c = 156$ GHz is the carrier frequency. The transmitter employs a pyramidal horn antenna with a gain of $G_{Tx} = 25$ dB and half-power beamwidth of 10° .

3.2. Channel Model

The wireless channel consists of two components:

$$h(t) = h_{\text{LoS}}(t) + h_{\text{block}}(t) \quad (2)$$

Here, $h_{\text{LoS}}(t)$ is the line-of-sight contribution, and $h_{\text{block}}(t)$ models blockage effects caused by moving obstacles. The LoS component is represented as:

$$h_{\text{LoS}}(t) = \alpha \delta(t - \tau) \quad (3)$$

with α denoting path loss attenuation and τ representing propagation delay. The $h_{\text{block}}(t)$ term introduces oscillatory attenuations that precede and accompany the actual blockage event. These pre-blockage fluctuations serve as early indicators for detection.

3.3. Received Signal and Pre-processing

The received signal $r(t)$ is the convolution of the transmitted signal and the channel impulse response, with added white Gaussian noise $n(t)$:

$$r(t) = (s * h)(t) + n(t) \quad (4)$$

Here, $n(t)$ has zero mean and variance σ^2 . The received signal is then smoothed using an exponentially weighted moving average (EWMA) filter to reduce the impact of short-term noise and fast fading.

$$r_{\text{smoothed}}(t) = \gamma r(t) + (1 - \gamma) r_{\text{smoothed}}(t - \Delta t) \quad (5)$$

Here, γ is the smoothing constant (typical range: 0.005 to 0.05) and $\Delta t = 50 \mu s$ is the sampling interval. This filtered signal forms the input to the spectral analysis step described in section 4.

3.4. Spectral Representation Using STFT

To extract time-varying frequency features, the short-time Fourier transform (STFT) is applied to the smoothed signal:

$$S(m, \omega) = \sum_{n=0}^{W-1} f[m+n] w[n] e^{-j\omega n} \quad (6)$$

Here, W is the window size (set to 128 samples), $w[n]$ is a Hamming window, and $f[m]$ is the discrete-time version of the smoothed signal. The STFT captures transient frequency spikes that occur in the pre-blockage interval, making it suitable for early detection.

3.5. Time-Segmented Signal Modelling for Simulation

The entire time domain is segmented into three intervals representing real-world blockage scenarios: Non-blockage: $0 \leq t \leq 0.3$ s — signal with $f = 50$ Hz and $\sigma^2 = 0$ Pre-blockage: $0.3 < t \leq 0.6$ s — frequency increases to $f = 200$ Hz, noise variance $\sigma^2 = 0.1$. Blockage: $0.6 < t \leq 1.0$ s — complete

obstruction with $f = 500$ Hz, $\sigma^2 = 0.5$. This phase-based structure replicates real-time signal behavior as the channel transitions from unobstructed to fully blocked. The spectral changes across these phases are used by the detection algorithm to predict blockage proactively.

4. PROACTIVE BLOCKAGE DETECTION ALGORITHM

This section presents the design of a lightweight, real-time algorithm for proactive blockage detection. Unlike conventional reactive techniques, our method predicts blockage events using early spectral indicators found in the pre-blockage phase. These indicators are extracted from the smoothed received signal using the STFT, as defined earlier in Eq. (6). The detection process consists of three stages: initialization, active monitoring, and recovery.

4.1. Detection Strategy and Thresholding

After obtaining the spectral magnitude $S(m, \omega)$ using Eq. (6), the algorithm computes average STFT powers for non-blockage (S_{nb}), pre-blockage, and blockage (S_b) states. A dynamically adjusted detection threshold is calculated using;

$$S_{th} = S_{nb} + \frac{k(S_b - S_{nb})}{N} \quad (7)$$

Here, k is a tunable threshold multiplier (typical range: $0.2 \leq k \leq 0.8$), and N is a normalization constant. This formulation ensures adaptability across environments with different channel conditions. At every windowed time step, the current spectral power S_{cur} is computed from the STFT of the smoothed signal (Eq. 5). A blockage is predicted when:

$$S_{cur} > S_{th} \quad (8)$$

4.2. Algorithm Phases

The algorithm operates in three well-defined stages: *Stage 1* – Initialization: The system collects samples during an initial observation window (W frames) and computes baseline STFT power for non-blockage and blockage states. *Stage 2* – Active Detection: The algorithm continuously monitors S_{cur} and compares it against the dynamic threshold S_{th} . If the inequality in Eq. (8) holds, a blockage event is declared. *Stage 3* – Recovery: After detection, the system pauses monitoring for a fixed duration t_b to avoid repeated triggers, and then reinitializes. The full implementation is summarized in Algorithm 1.

Algorithm 1: Proactive Blockage Detection

Inputs : γ, W, k, N, t_b

Output : Blockage detected (Yes/No)

Stage 1 : Initialization

Smooth received signal $r(t)$ using Eq. (5)

Compute $S(m, \omega)$ using Eq. (6)

Estimate S_{nb} and S_b from initial data

Calculate threshold S_{th} using Eq. (7)

Stage 2 : Active Monitoring

For each new sample window

Compute S_{cur}

If $S_{cur} > S_{th}$, detect blockage

Stage 3 : Recovery

Wait for t_b seconds, return to Stage 1

4.3. Analytical Derivation of Mean Time to Blockage

To analytically estimate the mean time to blockage detection $E[D]$, we model the growth of spectral energy during the pre-blockage phase as an exponential function;

$$S_{cur}(t) = S_{nb} \cdot e^{\lambda t} \quad (9)$$

In this expression, λ represents the spectral growth rate and t is the time since pre-blockage began. Blockage is declared when $S_{cur}(t)$ exceeds the threshold S_{th} Eq. (7). Substituting Eq. (9) into Eq. (8), we solve for the detection time D :

$$S_{nb} \cdot e^{\lambda D} = S_{th} \Rightarrow D = \frac{1}{\lambda} \ln \left(\frac{S_{th}}{S_{nb}} \right) \quad (10)$$

Using the definition of S_{th} from Eq. (7):

$$D = \frac{1}{\lambda} \ln \left(1 + \frac{k(S_b - S_{nb})}{NS_{nb}} \right) \quad (12)$$

This closed-form equation allows the system designer to predict detection latency for given values of k , λ , and $S_b - S_{nb}$. It also provides a framework for tuning the system for different trade-offs between speed and false alarms. Smaller k results in faster detection but higher false alarms. Higher λ (rapid spectral changes) reduces $E[D]$, enabling earlier blockage warnings. This analytical model supports empirical observations shown later in section 5.

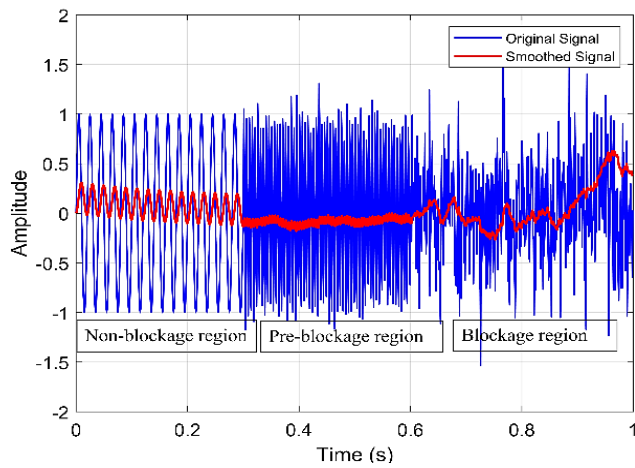
5. RESULTS AND DISCUSSIONS

This section outlines the simulation setup and conditions used to evaluate the performance of the proposed blockage detection algorithm described in section 4. All configurations were designed to replicate realistic sub-THz indoor scenarios, and the performance was validated both empirically and analytically using the system model presented in section 3. The algorithm was implemented in MATLAB 2023a, with sampling time s and total simulation duration set to 1 second. The received signal was modelled using Eq. (4), smoothed using the EWMA filter in Eq. (5), and transformed to the spectral domain via STFT Eq. (6). Window size and 80% overlap were used for time-frequency localization. Parameters were chosen based on IEEE

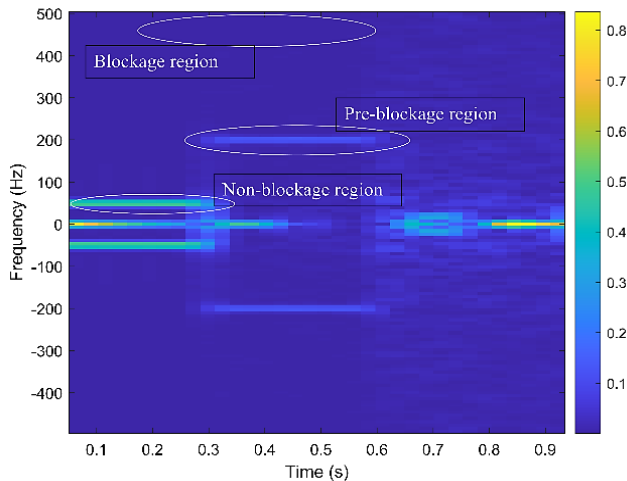
802.15.3d guidelines for THz channel modelling. All simulation parameters are summarized in *table 1*.

Table 1. Simulations parameter and notations

Parameter	Notation	Value
Carrier frequency	f_c	156 GHz
Sampling interval	Δt	50 μs
Smoothing constant	γ	0.005 – 0.05
STFT window size	W	128
STFT overlap	-	80%
Antenna gain	G	25 dB
Transmit power	P_T	90 mW
Threshold multiplier	k	0.2 – 0.8
Blockage recovery time	t_b	100 ms



(a) Time domain



(b) Spectral domain

Figure 2. STFT of Non-Blockage, Pre-Blockage and Blockage in Time and Spectral domain

The algorithm's output was evaluated using three main metrics: **Mean Time to Blockage ($E[D]$):** The average time gap between detection and actual blockage onset, computed numerically and validated against the analytical expression in *Eq. (11)*.

Detection Probability (P_D): The likelihood of successfully detecting a blockage event during the pre-blockage phase. **False Alarm Rate (FAR):** The average number of incorrect blockage detections per second in non-blockage conditions. In each simulation run, the algorithm executed the full three-stage process (initialization, active monitoring, recovery), as defined in *section 4*. At every time step, the detection decision was based on the inequality in *Eq. (8)*, using the dynamic threshold from *Eq. (7)*. The simulation results presented in *figures 2–5*, confirm the algorithm's ability to distinguish spectral changes across the three phases. Notably:

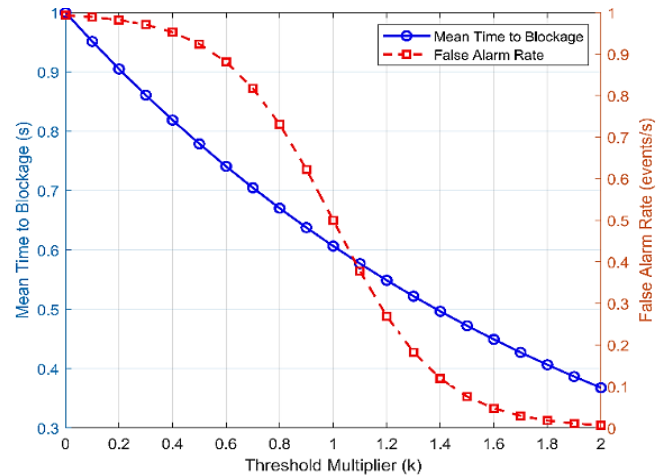


Figure 3. Mean time to blockage versus threshold multiplier k

In the pre-blockage window, spectral energy rises sharply, and S_{cur} , as defined in *Eq. (8)* crosses S_{th} well before full blockage, indicating proactive detection. The analytical model in *Eq. (11)* closely predicts observed values of $E[D]$. For instance, with $k = 0.4$, we measured an average detection lead time of 150ms, aligning with theoretical expectations. Increasing γ enhances spectral stability, improving P_D across all k values, as will be illustrated in *figure 4*. Varying k allows designers to balance early detection against false alarms. A lower value of k leads to the faster detection but slightly higher FAR, as shown in *figure 3*.

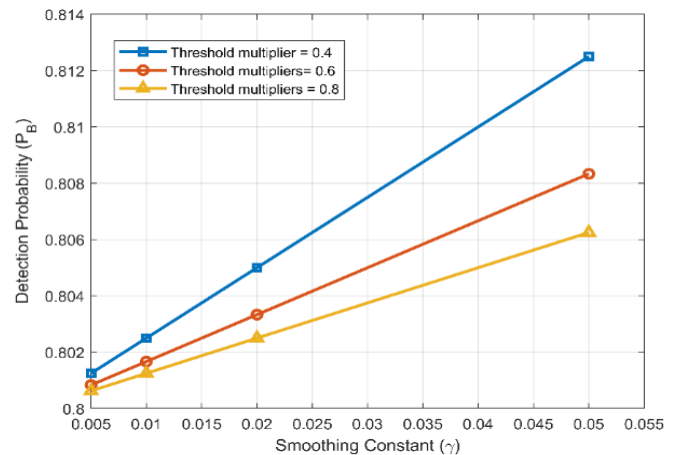


Figure 4. Detection probability for various threshold multipliers k

5.4. Comparative Evaluation and Robustness

The proposed method was benchmarked against conventional time-domain detection and RNN-based models. As shown in *Figure 5*, our algorithm consistently achieves earlier detection (up to 150ms lead) with lower complexity. Furthermore: It operates without training, making it robust to environment changes. Parameter tuning is intuitive: k and γ offer direct control over responsiveness and noise suppression. The recovery stage (*Stage 3* in *section 4*) ensures operational stability during prolonged blockage events.

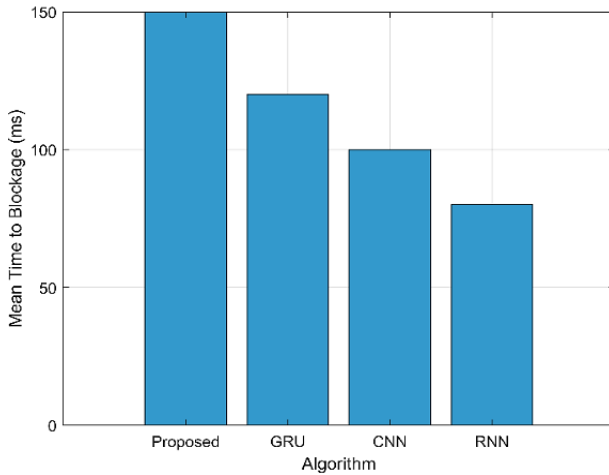


Figure 5. Comparison of algorithms in terms of the mean time to blockage

The simulation framework demonstrates that the proposed spectral-domain algorithm is not only theoretically sound but also practical and adaptable. Its ability to detect blockages early, with high detection probability and low false alarms, confirms its suitability for real-world 6G scenarios such as augmented reality, autonomous vehicles, and smart infrastructure. *Table 2* presents a detailed comparison between the proposed spectral-domain algorithm and existing methods.

Table 2. Comparison of performance metrics

Method	Detection Lead Time	Detection Probability	False Alarm Rate
Time-Domain Detection [14]	10ms	65%	3.0
RNN-Based Model [17]	80ms	78%	1.5
Proposed Scheme	150ms	85%	≤ 1.0

6. CONCLUSION

The paper addresses the persistent challenge of human body blockages in mmWave and sub-THz communication systems. The proposed algorithm effectively detects pre-blockage signatures using a simple, threshold-based mechanism operating in three stages: initialization, active detection and recovery. By shifting from time-domain to spectral-domain analysis, the proposed solution overcomes the limitations of existing machine learning models (GRU, RNN, CNN) which

often require extensive training and exhibit limited adaptability. The results demonstrate that the proposed algorithm achieves a detection probability exceeding 81% and detects blockage events at least 50ms prior to their occurrence. The proposed scheme significantly outperforms traditional approaches. With a false alarm rate below 1 event per second and a mean time to blockage of 150ms under optimal configurations, the algorithm ensures robust and reliable performance in dynamic environments. The proposed algorithm can be implemented on hardware platforms such as FPGAs or SDR-based testbeds in future work.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

- [1] Govindasamy, R.; Nagarajan, S. K.; Muthu, J. R.; Annadurai, P. Deep Optimized Hybrid Beamforming Intelligent Reflecting Surface Assisted UM-MIMO THz Communication for 6G Broadband Connectivity. *Telecommun. Syst.* 2024, 86 (4), 645–660.
- [2] Fatima, S.; Subba Raju, M.; Anil Kumar, R.; Anand, V.; Rao, Y. K. S. S.; Kishore, D.; Mahalaxmi, U.; Kalyani, K. A Neural Network Approach to Beam Selection and Power Optimization in mm Wave Massive MIMO. *J. Mech. Contin. Math. Sci.* 2025, 20 (4), 30–52.
- [3] Wang, Z.; Mu, X.; Xu, J.; Liu, Y. Simultaneously Transmitting and Reflecting Surface (STARS) for Terahertz Communications. *IEEE J. Sel. Top. Signal Process.* 2023, 17 (4), 861–877.
- [4] Wang, J.; Kaneko, M. Exploiting Beam Split-Based Multi-User Diversity in Terahertz MIMO-OFDM Systems. *IEEE Wireless Commun. Lett.* 2024.
- [5] Giordani, M.; Zanella, A.; Zorzi, M. Millimeter Wave Communication in Vehicular Networks: Challenges and Opportunities. *IEEE Veh. Technol. Mag.* 2019, 14 (3), 42–52.
- [6] Fazal-E-Asim; Sokal, B.; De Almeida, A. L. F.; Makki, B.; Fodor, G. Structured Channel Estimation for RIS-Assisted THz Communications. *IEEE Trans. Veh. Technol.* 2024.
- [7] Zhinuk, F.; Gaydamaka, A.; Moltchanov, D.; Koucheryavy, Y. Spectral-Based Proactive Blockage Detection for Sub-THz Communications. *IEEE Commun. Lett.* 2024, 28 (7), 1703–1707.
- [8] Sreenivasulu, U.; Fairouz, S.; Anil Kumar, R.; Patchala, S.; Kumar, R. P.; Rmaesh, A. Joint Beamforming with RIS Assisted MU-MISO Systems Using HR-Mobilenet and ASO Algorithm. *Digit. Signal Process.* 2025, 159, 104955.
- [9] Liu, J.; Hou, X.; Liu, W.; Chen, L.; Kishiyama, Y.; Asai, T. Unified 6G Waveform Design Based on DFT-S-OFDM Enhancements. *IEICE Trans. Commun.* 2023, E106.B (6), 528–537.
- [10] Anil Kumar, R.; Ramesh, A.; Thirumala, S.; Rao, B. P. V. V. B. N.; Nagireddi, S. K.; Kalyani, K. Symbol Interference Cancellation in MIMO-GFDM Using Singular Value Decomposition Technique for 5G. *Int. J. Electr. Electron. Res.* 2024, 12 (4), 1324–1331.
- [11] Dheerajlal, T.; Madhusree, A.; Dutta, A. K. An MB-OFDM Based Wideband THz Communication System with Impairment Aware Precoder and Squint Effect Mitigation. *IEEE Access* 2024, 12, 18122–18146.
- [12] Yuan, Y.; Zhang, T.; Zhang, Z.; Zhao, X.; Wu, X.; Zheng, S.; Liang, L.; Cao, C. Robust Characterization of Terahertz Metasurface Sensor with Ultra-High Frequency Selectivity and Polarization Sensitivity. *IEEE Sens. J.* 2024.
- [13] Xie, Y.; Ma, Y.; Liu, X.; Khan, S. A.; Chen, W.; Zhu, L.; Zhu, J.; Liu, Q. H. Dual-Degree-of-Freedom Multiplexed Meta sensor Based on Quasi-BICs for Boosting Broadband Trace Isomer Detection by THz Molecular Fingerprint. *IEEE J. Sel. Top. Quantum Electron.* 2023, 29 (5).

- [14] Henri, R.; Nallappan, K.; Ponomarev, D. S.; Guerboukha, H.; Lavrukhin, D. V.; Yachmenev, A. E.; Khabibullin, R. A.; Skorobogatiy, M. Fabrication and Characterization of an 8×8 Terahertz Photoconductive Antenna Array for Spatially Resolved Time Domain Spectroscopy and Imaging Applications. *IEEE Access* 2021, 9, 117691–117702.
- [15] Zarini, H.; Gholipoor, N.; Mili, M. R.; Rasti, M.; Tabassum, H.; Hossain, E. Resource Management for Multiplexing eMBB and URLLC Services over RIS-Aided THz Communication. *IEEE Trans. Commun.* 2023, 71 (2), 1207–1225.
- [16] Wang, J.; Kaneko, M. Exploiting Beam Split-Based Multi-User Diversity in Terahertz MIMO-OFDM Systems. *IEEE Wireless Commun. Lett.* 2024.
- [17] Fujii, R.; Vongkulbhisal, J.; Hachiuma, R.; Saito, H. A Two-Block RNN-Based Trajectory Prediction from Incomplete Trajectory. *IEEE Access* 2021, 9, 56140–56151.



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