IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 11 May 2024, accepted 31 May 2024, date of publication 5 June 2024, date of current version 13 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3410243

RESEARCH ARTICLE

Low-Complexity Design and Implementation of a Software-Defined 5G Energy Detector for Fast Initial Cell Selection

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This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) funded by Korean Government [Ministry of Science and ICT (MSIT)] through the Development of 5G+ Intelligent Base Station Software Modem under Grant 2021-0-00165.

ABSTRACT Energy detection is crucial during initial cell selection as it effectively assists the User Equipment (UE) in swiftly identifying a suitable Radio Frequency (RF) channel from numerous candidates. Implementing a Software-Defined Modem (SDM) presents a critical challenge of enabling energy detection, which traditionally requires high computational complexity in conventional hardware modems. This paper introduces a software-defined energy detector designed with low complexity, specifically tailored for an SDM. We design and implement an off-the-shelf energy detector that is fully software-based, with the goal of significantly reducing the time required for initial cell selection in an SDM. The software-defined energy detector is specialized for measuring 5G Synchronization Signal Blocks (SSBs). It emphasizes the key feature of the moving average filter which enables efficient computation of signal energy for an SSB. To enable real-time operation, the algorithm for the software-defined energy detector is designed to seamlessly utilize Single Instruction and Multiple Data (SIMD) functions. By implementing the software-defined energy detector, we optimize the detection parameters, thereby enhancing the practical performance of energy detection. The experimental results demonstrate that the software-defined energy detector can accurately evaluate the signal energy of the 5G SSBs with reasonable computational complexity.

INDEX TERMS Energy detector, softwarization, software-defined modem (SDM), 5G synchronization signal block (SSB).

I. INTRODUCTION

Innovative 5G technologies are being integrated with various industrial fields, such as railway, public safety, smart factories, autonomous driving, medical care, and Augmented Reality (AR)/ Virtual Reality (VR), to cultivate new vertical markets [1]. Each vertical market is diverse and requires specific requirements for 5G User Equipments (UEs). A railway locomotive requires a special emergency call feature that takes priority over emergency calls. A public safety operator needs to support massive group communication as well as direct communication between UEs for mission-critical purposes.

While specific features are tailored for vertical markets and are not essential for the commercial market, conventional System-on-Chip (SoC) modems require customization for vertical market needs. This customization is not ideal from a cost perspective, as developing a specific SoC modem requires a significant amount of resources, which is not generally affordable for vertical market sizes. Alternately, a Software-Defined-Modem (SDM) can be considered due to its flexible adaptation capabilities to meet the specific requirements of vertical markets. The SDM is an implementation technology that processes baseband signals using general-purpose hardware. The SDM can offer the benefits of flexible implementation at a low cost, making it more suitable for vertical markets than an SoC modem [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Abdel-Hamid Soliman.

Several Long Term Evolution (LTE) and 5G solutions based on SDM are readily accessible. The Open Air Interface (OAI) Project is a representative example of an SDM [3], [4]. This project offers open-source code for LTE and 5G entities, including base stations, core networks and mobile terminals. It enables straightforward realization by compiling the source code in a LINUX environment and connecting a suitable Radio Frequency (RF) device. Amarisoft has also launched LTE and 5G solutions for test and measurement purposes [5]. These solutions are in an one-box form, leveraging the concept of the SDM and enabling easy addition of new features through software updates.

Despite its benefits, an SDM has limitations in time-critical scenarios. SDM processes algorithms on general-purpose hardware, which typically results in longer processing times compared to dedicated hardware in an SoC modem. Hence, SDM faces the challenge of processing the initial cell selection which is one of time-consuming algorithms. During initial cell selection, a UE essentially selects a suitable RF channel from those it supports before cell synchronization [6]. Due to its wide bandwidth support, a 5G UE requires more time to select an appropriate RF channel in which a nearby cell can be detected. Performing this procedure faster is crucial for ensuring a fast and seamless user experience on the UE.

The difficulty mentioned earlier requires the UE to attempt network registration within a certain time limit during the initial cell selection procedure in many conformance test cases [7].

To accelerate the initial cell selection, the UE can initially filter out unsuitable RF channels whose signal energy is negligible. The UE can estimate the activity of an RF channel by detecting its signal energy, and selectively search for the energy-detected RF channels [8], [9]. This allows the UE to avoid searching inactive RF channels and significantly reduce the time required for initial cell selection. Hence, energy detection prior to cell search helps the SDM perform initial cell selection faster.

Conventional research has addressed the issue of energy detection from a theoretical perspective [10]. Comprehensive analysis of the performance is considered in multi-path channels [11], [12], [13], and enhanced schemes suitable for these channels are proposed [14], [15], [16]. Energy detection is also considered for recognizing discontinuous transmission in mobile communications [17], [18], as well as for jointly conducting energy detection with resource allocation [19]. Some research works consider distributed situations and propose cooperative methods to improve energy detection [20], [21].

The aforementioned conventional research works aim at general signals and do not specifically design energy detection for 5G signals. These approaches generally involve significant computational complexity, which is not desirable for SDMs. Furthermore, some research works consider the waveform of the target signal for energy detection. Energy detection is further enhanced to consider the correlation of the target signal [22], and specialized to WiFi and Low Power Wide Area Network (LPWAN) which co-exist in an unlicensed band [23], [24]. Energy detection is also combined with machine learning algorithms for effectively learning the behavior of energy-observed signals [25], [26]. However, none of them specifically addresses 5G signals or offer solutions that could alleviate the computational complexity burden on SDMs.

There are several difficulties associated with implementing energy detection on an SDM. Unlike the SoC modem where signal levels are determined by hardware in the analog domain, the SDM must derive signal energy digitally from the baseband signal sampled from an RF device. While hardware in the SoC modem can provide measured energy as the signal is received in real-time, the SDM fundamentally has limitations in terms of time consumption and requires careful consideration to enable energy detection along with real-time operations. The energy detection in 5G is more challenging due to the burst characteristics of the signal waveform over time. This means that signal energy cannot be observed for most of the time, making accurate energy detection challenging. Moreover, it is questionable whether the signal energy derived from digital signal processing is sufficiently accurate for selecting the RF channels in an initial cell selection procedure.

There are conventional research works that can be useful as references in terms of computational complexity. A low-complexity energy detection algorithm is proposed for addressing timing misalignment issues in femtocell environments [27], but this is not applicable to 5G initial cell selection. A low-power spectrum sensor is also investigated, utilizing a high-order band-pass filter function and spectral cooperative sensing with fast spectrum sensing time [28], which are not directly applicable to a software environment. Furthermore, a spectrum sensing algorithm achieves low computational complexity by leveraging Fast Fourier Transform (FFT) and is successfully implemented on a software-defined radio platform [29]. However, this algorithm is not optimal for detecting the energy of 5G burst signals.

The novelty of this paper lies in the implementation of a software-defined 5G energy detector that can operate with low computational complexity. This paper proposes an efficient algorithm of 5G energy detection that can operate in a software environment. The proposed algorithm aims to derive the signal energy of Synchronization Signal Blocks (SSBs) that can be detected at specific time intervals. This algorithm is specifically designed for a software-defined environment to minimize computational complexity. These characteristics differentiate the algorithm from conventional ones, which typically detect the energy of general signals using dedicated hardware.

This paper also demonstrates the performance of 5G energy detection in practical scenarios. For practical assessment, the proposed energy detector is implemented with software and a testbed which operates in real-time. The proposed algorithm is implemented as real-time software running on a LINUX machine, which handles received signals from a Universal Software Radio Peripheral (USRP) device. The experiment results from the implementation provide insight into how initial cell selection is practically conducted in real-world environments.

The further contents in this paper provide the software design of the proposed energy detection and the experimental results of the software-defined energy detection. Section II explains the assumptions and requirements of the system model for a software-defined energy detector. Section III presents the algorithmic design of the software-defined energy detector and outlines the steps required to implement the energy detection algorithm in software. Section IV shows experimental results that demonstrate how the proposed energy detection can accurately work in practical signal environments.

II. SYSTEM MODEL

The SDM UE is assumed to be in the standalone mode, exclusively using the 5G network, and performs initial cell selection for a 5G gNodeB (gNB).[1] The UE repeatedly configures an RF channel and performs cell search, which is equivalent to the process of detecting Synchronization Signals (SSs), until it chooses a suitable RF channel in which the UE succeeds in the cell search. The gNB periodically sends a Synchronization Signal Block (SSB), and its structure is illustrated in Fig. 1. The SSB occupies 4 consecutive Orthogonal Frequency Division Multiplexing (OFDM) symbols. The SSB consists of the Primary Synchronization Signal (PSS), the Secondary Synchronization Signal (SSS), and the Physical Broadcasting CHannel (PBCH). PSS and SSS allow the UE to synchronize with a nearby cell and identify the cell during initial cell selection. PBCH provides basic information about the cell so that the UE can access to it after the initial cell selection.

As in LTE, the gNB can configure its center frequency using one of the candidate channel rasters. Moreover, the gNB can configure the center frequency of the SSBs, denoted by Global Synchronization Channel Numbers (GSCNs), to enable faster initial cell selection procedures. The granularity of GSCNs is wide and it is advantageous for the UE to search for GSCNs in terms of reducing the overall search time. We assume that the frequency band of the gNB is above 3GHz, as commonly observed in commercial environments. In this case, the center frequency of an SSB is $3000\text{MHz} + (N_G - 7499) \cdot 1.44\text{MHz}$, where N_G represents the GSCN for the frequency of the subcarrier located at the center of the SSB.

During the initial cell selection procedure, the UE selects a candidate GSCN within the given frequency band and

[1] In non-standalone mode, a UE in initial cell selection should search for an LTE cell. Therefore, we assume standalone mode to focus on the problem of 5G initial cell selection.

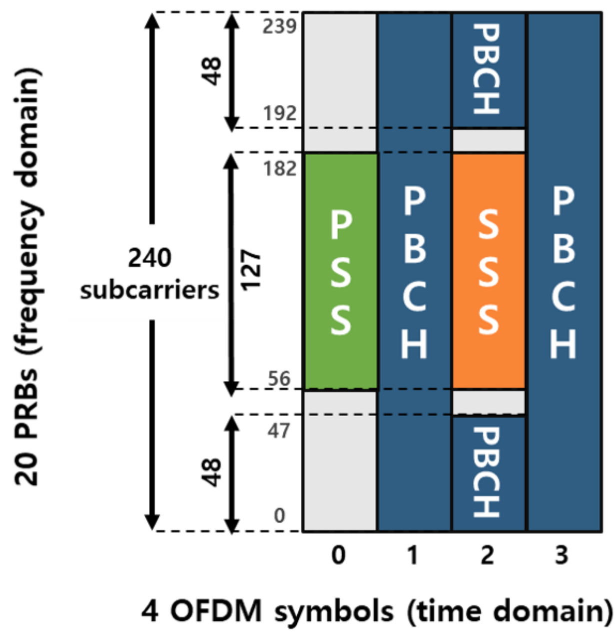

FIGURE 1. The structure of an SSB.

configures its center frequency to detect an SSB. The UE repeats the process until it successfully detects an SSB and identifies a suitable gNB. To minimize the number of attempts for SSB detection, the UE can group neighboring N_{GSCN} GSCNs as a GSCN group. This enables the UE to detect the signal energy of a GSCN group by measuring the received signal strength of the frequency band that includes the GSCNs. The UE then prioritizes cell search for the GSCNs whose signal energy is above a threshold.

Our design and implementation focus on efficiently detecting the signal energy of an SSB within a GSCN group in an SDM. The algorithm should efficiently measure the signal energy of SSBs for N_G neighboring GSCNs.

In the case of LTE, a base station transmits Cell specific Reference Signal (CRS) evenly over time, and a UE can easily detect its signal energy at any moment. On the other hand, the 5G gNB periodically transmits SSBs for several milliseconds and does not emit a signal for most of a frame if there is no downlink traffic. Therefore, a detection algorithm needs to focus on a specific time interval when SSBs are transmitted; otherwise, miss-detection occurs. The UE can prevent miss-detection by exhaustively detecting in time, but this requires significant computational complexity. However, the detection algorithm should also be suitable for the SDM in terms of complexity. The algorithm should be properly designed to handle received baseband samples in the digital domain with low computational complexity. Our algorithm design aims to minimize the computational complexity while keeping the miss-detection probability under 1%.

III. DESIGN AND IMPLEMENTATION OF THE SOFTWARE-DEFINED ENERGY DETECTOR

Fig. 2 illustrates the overall design of the proposed energy detector. The figure presents the role and functionality of

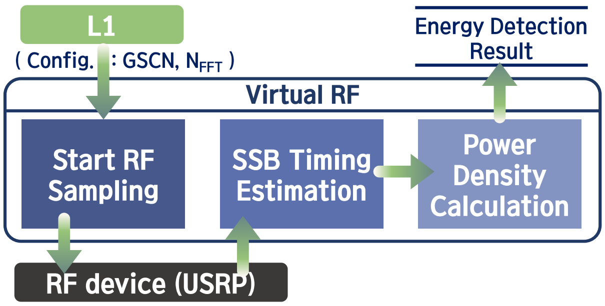

FIGURE 2. The overall procedure of the proposed energy detection.

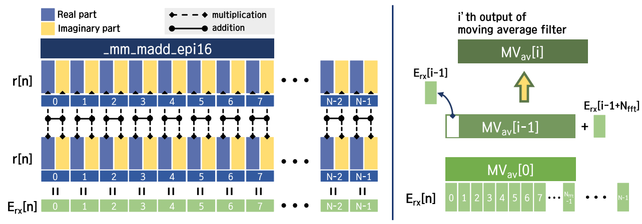

FIGURE 3. Signal energy estimation in a timing window.

Algorithm 1 Timing Window Estimation

for $i = 0$ to N_{SSB} **do**
  $MV_{av}[0] += E_{rx}[i]$
end for
$max_{MV} = MV_{av}[0]$, $\hat{n}_{SSB} = 0$
for $i = 1$ to N_s **do**
  $MV_{av}[i] = MV_{av}[i-1] + E_{rx}[i + N_{SSB} - 1] - E_{rx}[i-1]$
  if $MV_{av}[i] > max_{MV}$ **then**
    $max_{MV} = MV_{av}[i]$
    $\hat{n}_{SSB} = i$
  end if
end for
return $\hat{n}_{SSB}$

the virtual RF(vRF), which serves as hardware abstraction for an RF device. The vRF manages the configuration parameters of the RF device including center frequency, bandwidth, sampling rate and power gain. It also handles the transmission and reception procedures of the RF device by commanding through vRF-RF device interface. It commands for the sampling of received signals or the transmission of baseband signals at the beginning of a slot.

When energy detection begins, the vRF receives parameters of a GSCN and N_{fft} along with a configuration command, from the upper layer denoted by L1. Then, the vRF configures and commands the RF device to sample for the center frequency that corresponds to the configured GSCN. The sampling duration is set to the duration of an SSB period, ensuring that the received samples, denoted by $r[n]$, contain at least one SSB. The vRF stores $r[n]$ in a sampling buffer and initiates the signal energy detection process with respect to the SSB. Considering the time-domain characteristics of the SSB, the vRF roughly estimates the timing of the SSB transmission in the sampling buffer, and determines the timing window for energy calculation. The vRF then calculates the energy spectral density within the estimated timing window for N_{fft} and returns the energy detection results to the L1.

A. ESTIMATION OF THE SSB TIMING WINDOW

The UE in the initial cell selection assumes that an SSB is transmitted periodically at a certain interval, typically every 20ms. Hence, the transmission of one SSB only occupies a short period of time within the SSB period, which is only 0.7%. The UE will likely experience a miss-detection if it attempts to detect signal energy at a particular moment. Therefore, the UE needs to configure a suitable timing window that includes the SSB before performing the cell search.

The proposed energy detector takes into account the time-domain characteristics of a signal containing an SSB to estimate the appropriate timing window. Assuming that the signal energy of the received samples during the SSB transmission is relatively high, the proposed energy detector can identify the timing window by applying a Moving Average Filter (MAF). The tap size of the MAF is designed as the sample length of an SSB, denoted by N_{SSB}. N_{SSB} corresponds to 4 OFDM symbols and is calculated as follows:

$$N_{SSB} = 4(\frac{f_s}{f_{SCS}} + N_{CP}), \qquad (1)$$

where f_s, f_{SCS} and N_{CP} represent sampling rate, subcarrier spacing and the number of samples for a cyclic prefix, respectively. In this case, the MAF output will be maximized at the beginning of the time-domain signal, which includes the SSB. This MAF process reduces the computational burden of overall energy detection since the UE only needs to obtain energy at the timing that maximizes the MAF output.

Fig. 3 and Algorithm. 1 show how the timing window is estimated. Here, N_s represents the number of samples stored in the buffer for the energy detection, and $MV_{av}[i]$ denotes the output of the MAF. After initializing the variables, the algorithm iterates to calculate $MV_{av}[i]$ using $MV_{av}[i-1]$. During the iterations, the algorithm determines the maximal value of $MV_{av}[i]$. The values of $MV_{av}[i]$ for all i are calculated using simple summation operations, taking into account increments and decrements from the previous output denoted by $MV_{av}[n-1]$. It finally determines the boundary of the timing window as i which maximizes $MV_{av}[i]$.

The algorithm is well-designed for software implementation in terms of low complexity. The algorithm reduces the complexity of the MAF process from $N_{SSB} \times N_s$ to $N_{SSB} + 2N_s$ in terms of addition operations. The substantial reduction in complexity is particularly noteworthy given the large number of samples required for initial cell selection, especially considering the high value of N_s. This reduction translates to a significant decrease in computational resources or processing time, thereby enhancing the efficiency of the energy detection algorithm. Additionally, the algorithm allows for the utilization of Single Instruction Multiple Data (SIMD) functions to obtain energy levels for multiple samples simultaneously. A SIMD function conducts the multiplication of multiple data with one instruction, thereby requiring less computation time. The instantaneous energy level of the i-th received sample, denoted by $E_{rx}[i]$, can be efficiently calculated by invoking these SIMD functions repeatedly. The derived $E_{rx}[i]$ is used for calculating $MV_{av}[i]$. The above practical designs enable the SDM to estimate the timing window of the SSB with low computational complexity, and it is also advantageous in terms of real-time processing.

B. ENERGY LEVEL CALCULATION

Given the timing window of the SSB estimated from the MAF's output, the proposed energy detector calculates signal energy within the timing window. Denoting $\hat{n}_{SSB}$ as the offset where the timing window starts, the proposed energy detector calculates the energy level in an average sense as follows,

$$E_{av} = \frac{1}{N_{SSB}} \sum_{n=\hat{n}_{SSB}}^{\hat{n}_{SSB}+N_{SSB}-1} ||r[n]||^2. \quad (2)$$

(2) applies to the case that $N_{fft} = 1$ and when the L1 requests a representative level of the signal energy for the configured bandwidth. If the L1 configures N_{fft} as two or a higher value, then the proposed energy detector must calculate multiple energy levels for N_{fft} frequency bins in the signal's spectrum. This can be achieved by computing the average energy spectral density of the SSBas follows,

$$E_{av}[f] = \frac{N_{fft}}{N_{SSB}} \sum_{k=0}^{\frac{N_{SSB}}{N_{fft}}-1} \left|\left| FFT_{N_{fft}}\left(r[\hat{n}_{SSB}+N_{fft}*k], f\right)\right|\right|^2, \quad (3)$$

where $FFT_{N_{fft}}(r[n], f)$ denotes the f-th output of the N_{fft} point FFT process whose inputs are $r[n], r[n+1], \ldots, r[n+N_{fft}-1]$. The proposed approach allows for detecting the energy of multiple RF channels from a single sample buffer, thus reducing the time required to detect energy for different RF channels.

The proposed scheme leverages SIMD functions to minimize the computational complexity of the energy level calculation. The calculation of instantaneous energy levels of multiple received samples in (2) require repeated multiplication, which can be efficiently performed by a single instruction using SIMD functions. The proposed energy detector utilizes a specific storage scheme in the sample buffer, as illustrated in Fig. 3, where the real and imaginary parts of $r[n]$ are stored alternatively. Then, multiple energy levels are simultaneously calculated by executing a single instruction that combines multiplication and addition operations for multiple data, commonly referred to as a 'multiple and add' instruction. Based on actual measurement with the experimental parameters listed in Table. 1, the proposed energy detector requires 0.98ms to complete the energy detection process. On the other hand, it takes 1.25ms if SIMD functions are not used in the energy level calculation. Therefore, utilizing SIMD functions in the energy level calculation can reduce the overall detection time by 23%.

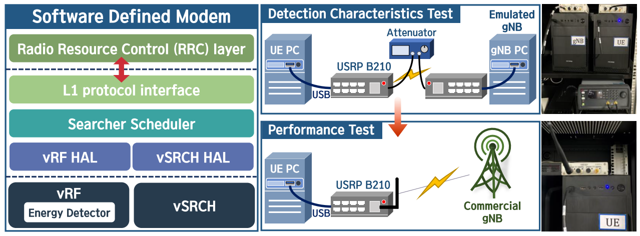

FIGURE 4. The software architecture and test environment.

TABLE 1. The test parameters.

parameters	value
CPU model	8G Intel CoreTM i7 Processors (3.7GHz)
Sampling rate	30.72 MHz
Center frequency	3459.36MHz
GSCN	7818
Bandwidth	20MHz
FFT size	1024
Subcarrier spacing	30kHz
SSB period	20ms

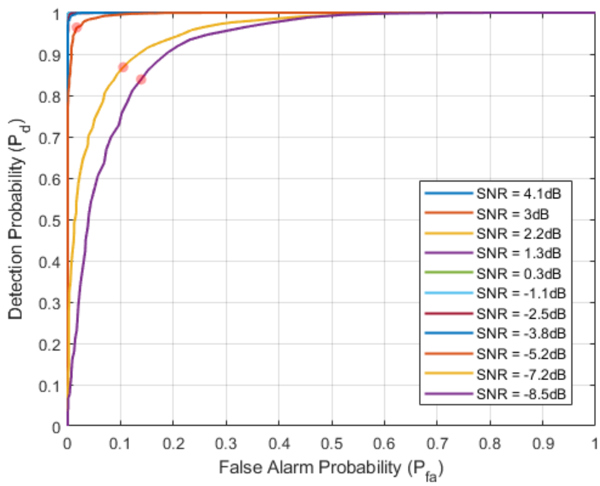

FIGURE 5. The ROC curves of the proposed scheme.

IV. ASSESSMENT OF THE DETECTION PERFORMANCE

To evaluate the performance of the proposed energy detector in practical environments, we analyze its detection characteristics. The initial step in evaluating the proposed energy detector involves determining a suitable threshold for identifying when energy is detected. This can be accomplished by constructing a Receiver Operating Characteristics (ROC) curve. The ROC curve is closely related to the characteristics of the RF device in the SDM system and can be obtained by conducting experiments with the specific RF device. Hence, we implement the proposed energy detector that can run on the SDM system in real-time. We also assess the ability of the proposed energy detector to accurately detect energy in a commercial environment.

TABLE 2. The false alarm and detection probabilities for various threshold levels.

SNR[dB]	Threshold[dBm]	P_{fa}	P_d	SNR[dB]	Threshold[dBm]	P_{fa}	P_d
-1.1	-86.2471	0	0.9995	-5.2	-86.3955	0.03	0.9788
-2.5	-86.2779	0.004	0.9980	-7.2	-86.4320	0.123	0.8915
-3.8	-86.3235	0.005	0.9918	-8.5	-86.4446	0.1580	0.8750

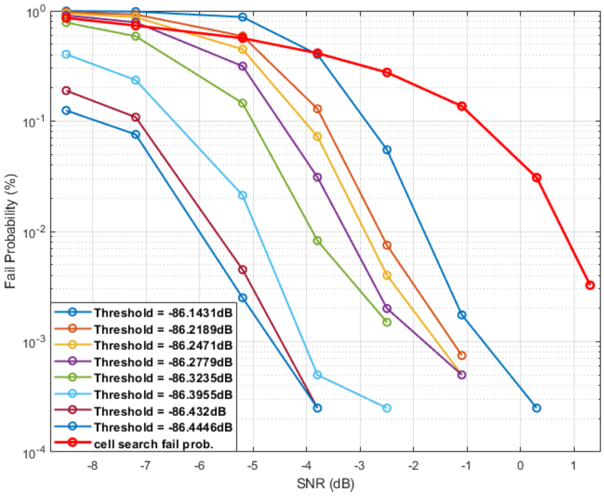

FIGURE 6. The failure probability for an emulated gNB.

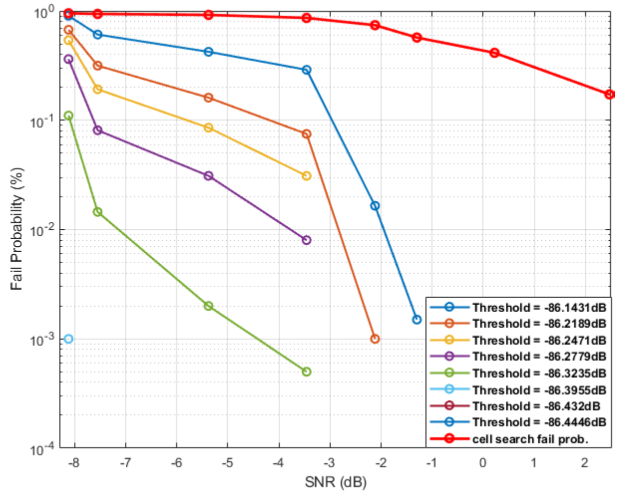

FIGURE 7. The failure probability for a commercial gNB.

Fig. 4 and Table. 1 illustrate the overall test environments, including emulated and commercial gNBs, and the software architecture of the 5G cell searcher. To obtain the ROC curves, an RF cable is used to connect the USRPs of the UE and the emulated gNB, and the UE repeatedly detects the signal energy of the emulated gNB. The parameters of the emulated gNB are configured similarly to those of the commercial LGU+ gNB. To detect the signal energy of a commercial gNB, the UE collects received samples using a 3.5 GHz antenna from the nearby LGU+ gNB.

The proposed energy detector is implemented as software in the testbed for experiments in real-world environments. To facilitate interoperability with cell search procedures, we implement off-the-shelf software, including the L1. The core algorithm is implemented as source code in the vRF, and the L1 triggers energy detection by passing the center frequency of the RF channels. This implementation enables the proposed energy detector to scale efficiently with bandwidth. The result of energy detection is passed to the L1, allowing it to determine which RF channel to search for cells and command the virtual SeaRCHer(vSRCH).

A. THRESHOLD LEVEL DECISION FROM THE ROC CURVES

The proposed energy detector requires a predefined threshold for measured signal energy to determine whether the SSB is present or not. An appropriate threshold can be configured by observing the ROC curve of the SDM system. The ROC curve reveals detection and false alarm probabilities, respectively denoted by P_d and P_{fa}. P_d represents the probability that the proposed energy detector detects an SSB that is actually transmitted. P_{fa} represents the probability that the proposed energy detector detects an SSB in a noisy signal when in fact there is no SSB present.

To obtain an ROC curve in a certain signal environment, the two probabilities with respect to Signal to Noise Ratio (SNR) are obtained through experiments. Therefore, we measured energy levels using the proposed energy detector in certain signal environments. The detection and false alarm probabilities are calculated based on various thresholds, which are used to generate an ROC curve. The above process is repeated with varying signal environments to obtain multiple ROC curves.

Fig. 5 shows the ROC curve of the proposed energy detector when the SNR ranges from -8.5dB to -1.1dB. The optimal threshold level of an ROC curve can be derived from the point on the ROC curve that is closest to (0,1). Table. 2 provides the exact values of the optimal threshold levels derived from the ROC curves. The decision of the threshold level can be made based on Table. 2, depending on the desired P_d and P_{fa} requirements for the proposed energy detector. The decision on the threshold level depends on our expectations regarding how the proposed energy detector will be operated. Any of the threshold levels in Table. 2 can be chosen based on the policy of energy detection. Assuming that the miss-detection probability aims to be 1%, the threshold should be higher than -86.3235 dBm. The miss-detection probability should be sufficiently small because the cell search time may be critically increased if the UE skips searching for the correct GSCN. However, the proposed energy detector also prefers to have a lower threshold level for detecting weaker signals, and the threshold level should be properly set according to the desired P_{fa}.

In summary, the ROC curves provide guidance for deciding the appropriate threshold level of the proposed energy detector. We can determine a threshold level from Table 2 that satisfies the requirements for miss-detection and false alarm. This will determine a SNR range within which the proposed scheme can accurately detect energy. The next sub-section presents the experimental results using the threshold level selected from Table. 2.

B. ENERGY DETECTION PROBABILITY

After configuring the threshold level based on the ROC curves, we repeatedly conduct experiments in both RF conduction and air environments to evaluate the overall detection performance. The proposed energy detector is configured with the threshold levels shown in Table 2. The threshold level is configured from −86.247 to −86.445 dBm to ensure that the proposed energy detector can detect energy with a certain level of false alarm. For considering the validity of energy detection results, we also let the SDM decode PBCH as well as detect energy.

Fig 6 shows the experimental results providing the failure probability of energy detection and PBCH decoding in a RF conduction environment. For any range of SNR, the detection probability clearly tends to vary with changes in the threshold level. For instance, the SNR at which the proposed energy detector achieves 10% failure probability is −3, −4 and −5dB when the threshold is set as −86.1431, −86.2471 and −86.3235dB, respectively. The results also indicate that as the threshold level decreases, the proposed energy detector becomes more successful in detecting signal energy. It reveals that the proposed energy detector operates appropriately based on the configuration of target threshold levels. Additionally, setting the threshold level needs to its maximum value is necessary to minimize the probability of false alarms. Conversely, a smaller threshold level can be chosen if the proposed energy detector needs to detect energy more aggressively, even at the cost of potential false alarms. This can be advantageous since in certain scenarios, a miss-detection can be more critical than a false alarm from the perspective of cell search time.

Based on the results regarding PBCH decoding, we can also observe that the proposed energy detector functions effectively even under sufficiently low SNR conditions. According to the criterion of 1% failure probability, the proposed energy detector, utilizing the specific threshold levels, is capable of detecting signal energy within an SNR range of −1dB – −8dB. The proposed energy detector demonstrates its ability to detect sufficiently weak signals for any threshold level, particularly evident in its performance in PBCH decoding. This is due to the fact that the PBCH decoder functions optimally when the SNR exceeds −1dB.

Fig. 7 illustrates the experimental results of the proposed energy detector in commercial environments. The failure probability of the energy detection appears to be similar to that depicted in Fig. 6. It indicates that the proposed energy detector performs similarly to its performance in lab environments, even when targeting commercial gNBs via the air interface. When the threshold level is appropriately set according to Table 2, the proposed energy detector can meet the requirements of commercial operators, as demonstrated by our lab experiments. In conclusion, the experimental results sufficiently demonstrate that the proposed energy detector can effectively enhance the efficiency of initial cell selection for UEs in commercial environments.

V. CONCLUSION

A 5G UE supporting wideband must conduct initial cell selection across numerous RF channels. Therefore, performing energy detection is essential to meet the time requirements for initial cell selection. This paper introduces a low-complexity energy detector specifically designed for searching 5G SSBs in SDMs. The key points of this paper are summarized as follows:

- The algorithm is effectively designed to ensure low computational complexity, enabling real-time operations. The algorithm utilizes the SSB timing window and conducts parallel computation using SIMD functions.
- Its implementation enables the evaluation of its characteristics in terms of the ROC curve. The performance evaluation with both emulated and commercial gNBs demonstrates that the software-defined energy detector can be effectively utilized in practical channel environments.

The proposed energy detector will contribute to making the initial cell selection procedure more efficient and reducing the latency experienced by users during power-on. Further enhancement in detection accuracy can be achieved by applying more advanced filtering techniques to determine the timing window. During this enhancement, it is essential to consider optimizing the computation flow while maintaining low complexity. To enhance scalability, future work could explore detecting larger bandwidth, which would require more sophisticated and lower-complexity signal processing in the frequency domain. Continuously enhancing energy detection will enable the next generation of mobile communications to utilize wider bandwidths while achieving shorter cell selection times.

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