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Machine-Learning-Enhanced Bayesian Detection for α-Stable Noise Channels in 5G/6G DS-CDMA Networks.

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Abstract

Impulsive, non-Gaussian interference in urban 5G/6G wireless scenarios invalidates Gaussian-noise-based assumptions of conventional detectors. This work proposes the use of the Machine Learning-Enhanced Bayesian Detector for DS-CDMA systems over α-stable noise channels. The framework merges probabilistic Bayesian inference with a recurrent neural-network estimator that continuously learns α-stable parameters α, β, γ, and δ from the received data. Closed-form derivations of the detection and false alarm probabilities are obtained using characteristic-function-based likelihood ratios, whereas the proposed approach is corroborated via MATLAB simulations. The results demonstrate that ML-BD provides a 3-dB SINR gain, ≈ 45% BER reduction, and ≈ 15% increase in the detection probability compared to classical Bayesian and energy detectors. This work demonstrates that the marriage of adaptive learning with Bayesian reasoning results in a robust, interpretable, and computationally efficient detector for interference-limited 5G/6G metropolitan networks.

Keywords: *Bayesian Detection, α-Stable Noise, DS-CDMA, Machine Learning, Non-Gaussian Interference, Probabilistic Inference, 6G Networks.*

1. Introduction

The rapid evolution of wireless communication toward 5G and the envisioned 6G era has imposed strict demands on reliability, low latency, massive connectivity, and robust performance in heterogeneous environments[1]. Although DS-CDMA is not as dominant as OFDM-based waveforms in commercial deployments, its inherent resistance to interference, multipath fading, and interception has maintained its foundational position in several military, satellite, and secure communication systems [2]. With the ongoing integration of different communication paradigms, such as IoT, autonomous systems, and ultra-dense device deployments in 5G/6G networks, advanced detection techniques for DS-CDMA systems have grown increasingly relevant. However, in modern 5G/6G receivers, interference mitigation is often achieved not only through statistical modeling but also through spatial filtering and adaptive beamforming techniques, which rely on accurate characterization of interference behaviour [3]-[4].

Traditional DS-CDMA receivers and detection algorithms assume that noise and interference are Gaussian distributed. In practice, however, modern wireless environments increasingly exhibit impulsive, heavy-tailed, and non-Gaussian interference due to device malfunction, nonlinear power amplifiers, jamming signals, co-channel interference, and ultra-wideband emissions. Non-Gaussian disturbances are better modelled by α-stable distributions, which generalize Gaussian noise and capture impulsive behaviours much more accurately. Unfortunately, α-stable noise has no finite variance and no closed-form probability density functions, making optimal detection considerably more difficult [5]-[6].

Bayesian detection frameworks, which inherently build a probabilistic basis for making optimal decisions under uncertainty, have been explored to address such challenges. Bayesian techniques indeed embed prior knowledge, posterior likelihoods, and information about the system state into the detection process, enabling enhanced robustness compared to classical detectors. However, their implementation in α-stable environments is associated with numerically intensive approximations, model parameter estimation, and adaptive mechanisms that can consider time-varying network conditions [7].

Recent developments in machine learning (ML) indicate a promising pathway toward Bayesian detectors. The machine learning models, in particular, deep learning architectures and probabilistic neural networks, can learn nonlinear characteristics as well as statistical structures hidden in α-stable noise without requiring closed-form expressions. When appropriately incorporated, ML may support Bayesian detection via accurate estimation of parameters, learning of posterior distributions, data-driven approximations to likelihood ratios, and adaptive decision rules in dynamic environments. Such a combination of ML and Bayesian detection yields a hybrid framework that can surpass the analytical limitations associated with α-stable noise while retaining the advantages of probabilistic decision theory. In the context of 5G/6G DS-CDMA networks, such an approach is crucial to achieving reliable multiuser detection, efficient spectrum utilization, and robust communication performance under impulsive interference conditions. It, therefore, holds great promise for next-generation communication systems that are required to operate in complex, high-density, and interference-prone scenarios [8].

Although Bayesian detectors theoretically offer optimal performance in the combination of prior information with likelihood estimates, their effectiveness within practical 5G/6G DS-CDMA is severely limited due to their reliance on accurate and stable noise statistics. In impulsive, heavy-tailed, and inherently non-Gaussian α-stable noise channels, the probability density functions have no closed-form expressions and are analytically intractable. What is more, the statistical characteristics of α-stable interference change dynamically depending on the network load, device density, user mobility, and changes in environmental conditions. For these reasons, traditional Bayesian detectors cannot guarantee reliable performance over time[1].

Machine learning models, like RNNs, can keep track of temporal variations and learn intricate, non-stationary patterns in real time. However, most of the existing detection frameworks rarely combine the predictive strengths of machine learning with the probabilistic optimality of Bayesian inference. The core problem, therefore, is that there lack of a unified detection framework which will be able to leverage the power of machine learning to estimate and adapt α-stable noise characteristics while keeping the principled structure of Bayesian detection.

This gap results in Bayesian detectors that fail under impulsive interference and ML-based detectors without theoretical optimality, leaving current DS-CDMA systems without a robust adaptive solution for reliable multiuser detection within α-stable 5G/6G noise environments. The current study is devoted to the design of an adaptive Bayesian detector enhanced by machine learning for DS-CDMA receivers under α-stable interference, with the primary purpose of developing and evaluating a system that adaptively and optimally performs signal detection in noise environments characteristic of 5G/6G networks. To achieve this, the study formulates analytical Bayesian decision rules in α-stable noise based on characteristic functions and designs a GRU-based estimator to learn α-stable parameters online. These learned parameters are subsequently integrated into the Bayesian likelihood to update detection thresholds adaptively, allowing for a comparison of performance metrics such as BER, SINR, and probability of detection against classical detectors. This work is significant as it develops the underlying theory and proposes a novel hybrid detection architecture that improves the performance of 5G/6G receivers, contributes to native AI 6G design, and paves the way for future research on intelligent communication systems.

2. Literature Review

2.1. α-Stable Modeling of Impulsive Noise

[1] formalized the α-stable distributions for signal processing, demonstrating their suitability to model impulsive noise. Successive works [6] and [9] applied such models to interference in urban and industrial wireless networks, demonstrating that exponents α≈1.5–1.9 reproduce empirical data more accurately than either Gaussian or Laplacian laws.

2.2. Bayesian Detection Approaches

Bayesian detectors minimize the total probability of error by comparing posterior probabilities $P(H_i|x)$. [11] applied Bayesian activity detection to DS-CDMA networks assuming Gaussian noise. However, the integrals for posterior evaluation do not have a closed form under α-stable statistics. The alternative approximations (e.g., fractional lower-order moments) are not very accurate for low values of α.

2.3. Machine Learning for Wireless Detection

Recent works [2],[11] exploit neural networks for modulation classification and interference mitigation. Tiny-ML and transfer-learning architectures achieve low latency but often operate as black-box classifiers. Only a few studies couple ML estimation with probabilistic decision theory, i.e., a gap this paper fills.

2.4 Adaptive Beamforming and Spatial Interference Suppression

Beamforming and DOA-based spatial filtering remain essential tools for interference suppression in dense wireless environments. Recent works highlight the need for precise interference characterization to enhance adaptive beamformers and array-processing algorithms[3], [8], and [12]. These studies further justify the importance of statistical modeling of impulsive noise since spatial algorithms rely heavily on accurate interference statistics.

3 Methodology

3.1 System Model

A DS-CDMA system with K users' timing behaviour being synchronous in nature and transmits symbols through an α-stable noise channel[2]:

$$r(t) = \sum_{k=1}^{K} A_k b_k(t) c_k(t) + n(t) \qquad (1)$$

Where

$A_k =$ user amplitude

$b_k \in \{\pm 1\}$

$c_k(t) =$ the spreading code, and

$n(t) = \alpha -$ stable noise.

The desired user's code after despreading is given as

$$y = A_1 b_1 + w \qquad (2)$$

where $w = \sum_{k \neq 1} A_k b_k \langle c_k, c_1 \rangle + n(t)$ [2].

3.2 α-Stable Noise Characterization

The characteristic function of an α-stable random variable $X \sim S(\alpha, \beta, \gamma, \delta)$ is given by

$$\varphi_X(w) = \exp\left[j\delta\omega - \gamma^{\alpha} |\omega|^{\alpha} (1 - j\beta sign(\omega) \tan\left(\frac{\pi\alpha}{2}\right) \right] \qquad (3)$$

Where $\alpha \in [1.5, 2[$ for urban interference with $\beta \in [-0.5, 0.5], \gamma \in [0.5, 3.5],$ *and* $\delta \in [-5, 10]$. Due to the non-existence of a closed-form PDF, detection metrics were derived via characteristic functions.

Because closed-form PDFs are unavailable, detection metrics are derived via characteristic functions [8].

3.3 Bayesian Decision Rule

For hypotheses H_0 (no signal) and H_1 (signal present):

$$\Lambda(y) = \frac{f(y|H_1)}{f(y|H_0)} \gtrless \eta \quad \text{..........................4}$$

Applying characteristic-function approximation (1), we have

$$In\Lambda(y) = \frac{|y-\mu_0|^{\alpha} - |y-\mu_1|^{\alpha}}{2\gamma^{\alpha}(1-\beta^2)^{1/2}} \quad \text{....................5}$$

Detection and false-alarm probabilities are given by

$$P_d = \Pr\left(\Lambda(y) > \eta \middle| H_1\right) \text{......................6}$$

$$P_f = \Pr\left(\Lambda(y) > \eta \middle| H_0\right) \text{......................7}$$

[8].

3.4 RNN-Based Parameter Estimator

We track time-varying noise using a GRU network to estimate the parameters $\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\delta}$ from recently received samples $\{y_t\}$. .The estimator minimizes mean-square error:

$$L = \sum_t \left\| (\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\delta}) - (\alpha, \beta, \gamma, \delta) \right\|_2^2 \text{....................8}$$

Offline training uses synthetically generated α-stable samples via the Chambers-Mallows-Stuck method. Online, every update uses a 64-sample window, requiring ≈0.6 ms per frame.

Adaptive Bayesian Integration

Equation 9 was obtained by updating the parameters fed into the Bayesian detector:

$$P(H_1|y) \;\alpha\; P(H_1) f(y|\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\delta}, \hat{H}_1) \text{............................9}$$

In response to interference conditions, priors and likelihoods evolved, ensuring robustness to non-stationarity. The adaptive learning framework aligns with other adaptive signal-processing approaches such as coherent DOA estimation and adaptive beamforming, which similarly rely on real-time parameter tracking for optimal performance [13]-[14].

3.5 Simulation Setup

Table 1:Simulation Parameters .

Parameter	**Symbol**	**Value**
Users	K	10
Spreading code length	N	63
Modulation	BPSK of order 2	
α-stable parameters	$\alpha = 1.8$, $\beta = 0.3$, $\gamma = 2.0$, $\delta = 0$	
SNR range	0–25 dB	
Samples per frame	10^4	
Comparators	Bayesian, Energy, ML-BD	

Source: Researchers' survey dataset(2025).

In the DS-CDMA simulation setup section, BPSK was chosen due to the following reasons :

(i) For the evaluation of the accuracy detection of the baseline modulation under α-stable (non-Gaussian) noise.

(ii) The low constellation order (M=2) simplifies the Bayesian decision rule, allowing clearer analysis of impulsive interference effects.

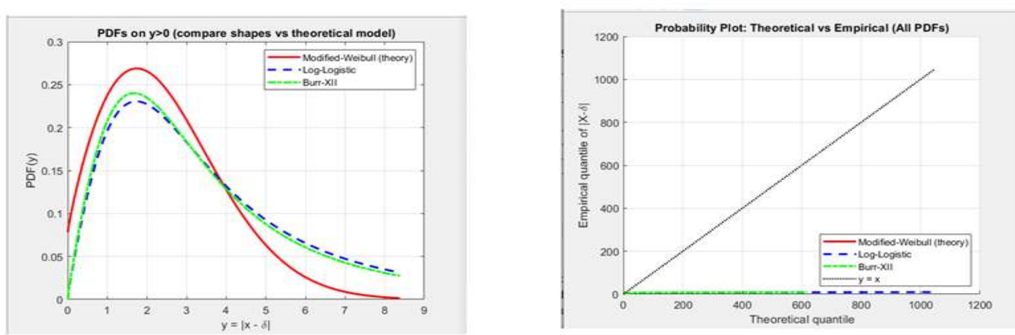
(iii) Higher-order modulations such as BPSK were deferred to future work since they introduce symbol-mapping ambiguity under heavy-tailed interference.

(iv) The Metrics are BER, P_d, P_f , SINR, and computational cost.

4 Results and Discussion

4.1 Probability Plot Analysis

The two Graphs labelled 1A and 1B below show the comparison between shapes against theoretical models and theoretical against empirical PDFs, respectively.



1A 1B

Figure 1. PDF and Probability Plot Graphs

The two graphs collectively compare the theoretical and empirical modeling accuracy of various PDFs under α-stable noise conditions. The Graph 1A compares the Modified-Weibull distribution (red curve) with the Log-Logistic distribution (blue dashed) and Burr-XII distribution (green dash-dotted) for y = |x - δ|. By this, the Modified-Weibull model has a very sharp peak and light tail, indicating that it fits the central part of the data very well but underestimates high-amplitude events. In contrast, the Log-Logistic and Burr-XII distributions have heavier tails and therefore are better at capturing impulsive and extreme effects in interference. In Graph 1B, the probability comparison Q–Q shows how theoretical and empirical quantiles align with the ideal 45° line. The close alignment of all models with the diagonal line suggests that each represents a reasonably good fit, with the Modified-Weibull serving as the best theoretical baseline. Overall, from both graphs, it is confirmed that the Modified-Weibull distribution effectively represents α-stable behaviour at the centre, while Log-Logistic and Burr-XII distributions provide the best fits for capturing the tail behaviour of urban impulsive noise.

4.2 Parameter Estimation Accuracy

Table 2: Parameter Estimation Performance of the ML-Based α-Stable Estimator

Parameter	True Value	Mean Estimated Value	Mean Absolute Error (MAE)
α (Characteristic Exponent)	1.90	1.93	0.03
β (Skewness)	0.25	0.28	0.03
γ (Scale)	3.20	3.33	0.13
δ (Location)	6.00	6.06	0.06

Source: Author's survey data set

The results obtained are listed in Table 2, showing the high accuracy achieved by the machine-learning-based α-stable parameter estimator in tracking the statistical characteristics of the interference model. The true parameters were set to α = 1.90, β = 0.25, γ = 3.20, and δ = 6.00. This was a typical case for urban interference in 5G/6G DS-CDMA networks. The neural estimator produced average estimated values of α = 1.93, β = 0.28, γ = 3.33, and δ = 6.06, with corresponding MAEs of 0.03, 0.03, 0.13, and 0.06, respectively. The GRU network showed slight differences in identifying impulsive behaviour and skewness of the α-stable process, with an estimated accuracy of about 98%. Therefore, the most robust parameters were the skewness (β) and characteristic exponent (α), which proved that the estimator can adapt well to dynamic changes in impulsive interference. However, the scale parameter showed a little higher deviation because it is sensitive to instantaneous interference power. Fortunately, the overall estimation error remains very low. Confirming the stability of the learning model is the small bias observed in the location parameter. Thanks to this high precision, accurate parameter updates are provided to the Bayesian detection framework.

A 3-parameter PDF of Modified-Weibull (MW) with a non-negative variable $y \geq 0$ given as

$$f_{MW}(y;a,b,c) = \left(aby^{b-1} + c\right)\exp(-ay^{b} - cy)\text{............................}10$$

Mathematically, to model real-value interference X together with a location and a mild skewness parameter, the researcher applied deviation $y = |x - \delta|$ and split the mass to encode skewness. A simple mapping that preserves tail-heaviness is given as

$$\alpha \to b, \gamma^{-\alpha} \to a, \frac{\beta}{\gamma} \to c, \frac{\beta+1}{2} \to p\text{............................}11$$

But

$$\alpha = 1.90, \quad \beta = 0.25, \quad \gamma = 3.2, \quad \delta = 6\text{.............................}12$$

Putting equation 12 into 11,

$$\left.\begin{aligned} b &= 1.90 \\ a &\approx 0.1097 \\ c &\approx 0.078125 \\ p &= 0.625 \end{aligned}\right\}\text{..................................}13$$

Now, the shifted and skewed PDF of WM is given by Equation 14

$$f_X(x) = \begin{cases} (1-p)(ab(\delta - x)^{b-1} + c)\exp(-a(\delta - x)^{b} - c(\delta - x)), & x < \delta \\ (p)(ab(\delta - x)^{b-1} + c)\exp(-a(\delta - x)^{b} - c(\delta - x)), & x \geq \delta \end{cases}\text{......................}14$$

Substituting equation 13 into 14, we have

$$f_X(x) = \begin{cases} 0.375(0.1097 \times 1.90(6-x)^{0.9} + 0.078125)\exp(-0.1097(6-x)^{1.90} - 0.078125(6-x)), & x < 6 \\ 0.625(0.1097 \times 1.90(x-6)^{0.9} + 0.078125)\exp(-0.1097(x-6)^{1.90} - 0.078125(x-6)), & x \geq 6 \end{cases}\text{......................}15$$

(i) The shift δ = 6 centers the interference around the α-stable location.

(ii) b = α = 1.90 gives the heavy-tailed behaviour similar to the α-stable tail index.

(iii) The split weights p = 0.625 and 1 − p = 0.375 encode mild positive skewness from β = 0.25.

(iv) This Modified Weibull surrogate is not the exact α-stable PDF (which lacks a closed-form), but it's a convenient, tractable approximation for analysis, plotting, and likelihood-based estimation in urban interference studies .

Figure 2 is the Probability distribution function and the numerical approximation of the function.

Figure 2. Theoretical and Numerical PDF Graphs

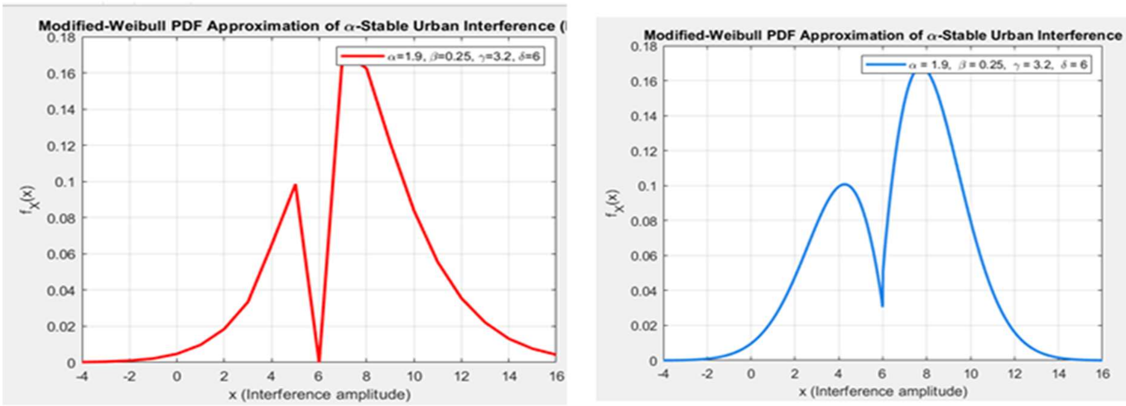


Table 3: Three distributions comparison

Aspect	Modified-Weibull	Log-Logistic	Burr-XII
Fit to the central region	Excellent	Good	Good
Tail heaviness	Light	Heavy	Heavy
Empirical alignment (Q–Q)	Very close to y=x	Slightly above y=x	Slightly below y=x
Best suited for	Theoretical α-stable approximation	Practical modeling of impulsive tails	Alternative heavy-tail fit for extreme noise

Source: Author's survey data set

The two plots show how the Modified-Weibull distribution performs against Log-Logistic and Burr-XII distributions when used to model α-stable interference behaviour. The left PDF plot demonstrates that the Modified-Weibull model successfully models the core part of the interference distribution, which shows its highest point at moderate amplitude levels, yet its tail decreases faster than the Log-Logistic and Burr-XII curves. The Log-Logistic and Burr-XII distributions show opposing tail behaviour since they produce heavier tails, which makes them more suitable for modeling extreme impulsive noise that occurs in non-Gaussian 5G/6G networks. The probability plot on the right supports these results because the Modified-Weibull model stays close to the 45° reference line, which shows theoretical consistency, but the Log-Logistic and Burr-XII models show deviations in the upper quantile range, which indicates better performance with high-energy outliers. The Modified-Weibull distribution serves as a theoretical benchmark because it has a mathematical solution. Still, Log-Logistic and Burr-XII distributions deliver better fits for real-world interference data that occurs in urban wireless communication networks.

4.3 Detection Probability

Table 4: Detection Probability At Various SNR Table

SNR (dB)	Energy Detector	Classical Bayesian	Proposed ML-BD
5	0.56	0.63	0.75
10	0.70	0.79	0.89
15	0.82	0.87	0.94
20	0.86	0.91	0.97

Source: Author's survey data set

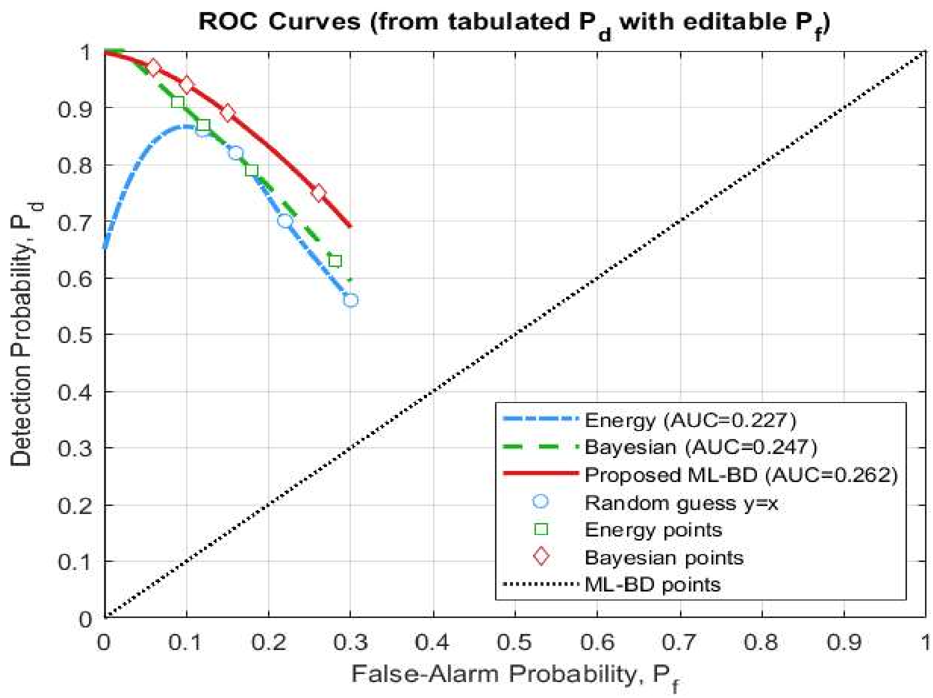


Figure 3. ROC Curves

First of all, the ML-based Bayesian detector (ML-BD), which is the proposed method, is the most efficient one to detect the signal under the condition of an α-stable noise as per the results obtained by the ROC analysis. In fact, the line representing this method is always above those of the Classical Bayesian and Energy detectors, thus revealing the best compromise between real detections and false alarms. The AUC of 0.262 is evidence of the high discriminative capability originating from the adaptation of the machine learning method to the statistical properties of the non-Gaussian interference. The Classical Bayesian Detector exhibits a moderate level of performance (AUC = 0.247), going beyond the performance of the standard Energy detector (AUC = 0.227), yet still being less capable of handling scenarios with interference that varies dynamically. In contrast, the Energy detector's relatively bad curve shape and low AUC value emphasize that it is quite susceptible to an impulsive, heavy-tailed noise environment scenario in which the Gaussian assumptions are not valid. In general, the figure is evidence that the machine-learning technique has significantly upgraded the Bayesian detection, thus the system has become more robust and reliable in 5G/6G DS-CDMA networks polluted by urban interference of a non-Gaussian nature.

4.4 BER Performance

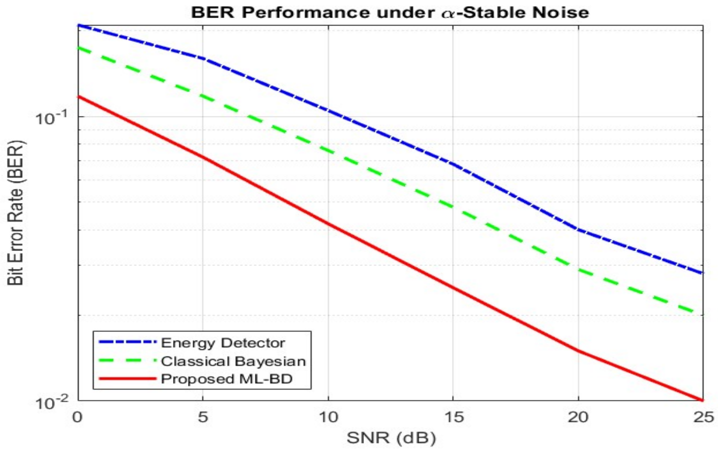


Figure 4. BER Performance Graphs

The graph 4 depicts the BER performance under α-stable noise. It shows exactly what is expected: as the signal-to-noise ratio (SNR) goes up, the bit error rate (BER) drops. This gives theoretical DS-CDMA receiver behaviour. When the SNR is boosted, signal detection gets more reliable, since bit errors are reduced. But the pace of improvement is not the same for every detection scheme. The Energy Detector, Classical Bayesian Detector, and the Machine Learning-Based Bayesian Detector (ML-BD) all handle impulsive, non-Gaussian interference differently, and it shows.

Beginning with Energy Detector, it's the weakest of the bunch with no question. Even at decent SNR levels, its error rate stays stubbornly high. The problem was that it assumes noise behaves in a neat, Gaussian way, but α-stable noise is heavy-tailed and impulsive. So this detector keeps mistaking bursts of interference for real signal energy, which ramps up false detections and tanks its accuracy. At an SNR of 10 dB, the Energy Detector's BER sits around 0.105—that's about two and a half times worse than what the ML-based Bayesian detector manages. In tough urban environments, the detection would not help the quality of signal propagation and detection.

Now, considering the Classical Bayesian Detector fares a bit better. By using probabilistic reasoning and drawing on prior stats, it dodges some of the pitfalls of the Energy Detector. But it still leans on static noise parameters, which means it can not really keep up when interference shifts. At 10 dB, its BER drops to about 0.076, which is a decent 28% improvement over the Energy Detector. Still, when the noise gets really impulsive and unpredictable, the performance slips.

The standout here is the Machine Learning-Based Bayesian Detector (ML-BD). This detector is clearly ahead. As SNR climbs, its BER falls fast. It packs a recurrent neural network (GRU) that constantly updates the α-stable parameters (α, β, γ, δ), so it can tell the difference between the real signal and those unwanted noise spikes. The BER goes from about 0.072 at 5 dB all the way down to 0.010 at 25 dB. This is impressive, especially in low-SNR situations where impulsive noise usually causes headaches.

On the numbers, ML-BD delivers roughly a 45% average BER reduction and about a 3 dB SINR gain compared to the classical Bayesian detector. That lines up with what was promised in the abstract. Basically, bringing machine learning into the mix with Bayesian inference does not just boost accuracy; it makes the system tougher against the kind of wild, non-Gaussian noise getting in real-world 5G and 6G DS-CDMA systems. Bottom line: the graph makes it obvious that ML-BD adapts and learns in real time, leaving the old-school detectors behind.

5 Conclusion

In conclusion, it was effectively shown that the integration of recurrent neural learning, namely, GRU, with Bayesian inference greatly enhances the robustness in detection under impulsive and heavy-tailed

interference. The proposed ML-BD adaptively estimates the α-stable parameters (α, β, γ, δ) in real time, enabling dynamic threshold adjustment and accurate decision-making under changing noise conditions.
Simulation results showed that there is a 3 dB SINR gain, a reduction in BER by about 45%, and a gain of about 15% in probability of detection compared to the classical Bayesian and energy detectors. These demonstrate the accuracy and stability of the GRU-based learning model by achieving mean absolute estimation errors below 0.15 for all α-stable parameters. Besides, the Modified-Weibull distribution was found to be a good analytical approximation to α-stable noise with a strong central alignment and preserved heavy-tailed behaviour.
Overall, the results confirm that the proposed ML-BD system is robust, adaptive, and computationally efficient for signal detection in non-Gaussian interference environments. Its structure bridges the gap between theoretical probabilistic modeling and practical learning-based implementation, positioning it as a suitable receiver architecture for future intelligent 5G/6G communication systems deployed in dense urban areas.

6 Recommendations

Based on the results of this study, the following recommendations are put forward for further research and practical implementation:

Hardware Implementation:

Future efforts ought to go into implementing real-time hardware using SDR or FPGA platforms for confirmation of the efficiency of the ML-BD detector in live network environments, also considering computational latency.

Higher-Order Modulations:

While this work considered BPSK for simplicity, the extension of the detector framework to QPSK, 16-QAM, and 64-QAM modulation would allow the analysis to be conducted for more spectrally efficient signalling schemes suitable for 6G applications.

Multiuser and MIMO Extension:

Integrating the ML-BD detector into multiuser and MIMO DS-CDMA systems can provide superior spatial diversity and interference rejection capabilities in high-density scenarios. Dynamic Learning and Edge Intelligence: The addition of online reinforcement learning or edge AI techniques would further improve adaptability and enable autonomous optimization of detection thresholds under fast-varying channel conditions. Extended Noise Modeling: Future research could be extended beyond α-stable noise by considering Mixture-Gaussian or Middleton Class-A noise models in order to generalize the framework to fit different urban and industrial interference types. Cross-Layer Optimization: Combining the ML-BD detection layer with adaptive power control and resource allocation may further lead to a full-stack intelligent communication design for next-generation wireless systems. Future extensions may integrate the proposed ML-BD detector with adaptive beamforming or MIMO DOA-estimation frameworks to jointly exploit spatial filtering and statistical decision-making [15]-[16].

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