Proceedings of CONF-SPML 2027 Symposium: Intelligent Network Security and Machine Learning for Communication Systems
DOI: 10.54254/2755-2721/2027.MELB38461

Variable Step-Size LMS-Based Anti-Jamming Algorithm for Industrial IoT Communications over 2.4 GHz ISM Band

Haoxin Chen

School of Electronic and Information Engineering, South China University of Technology, Guangzhou, China
chenhaoxin2026@163.com

Abstract. Industrial Internet of Things (IIoT) systems deployed in factory environments face severe narrowband interference in the 2.4 GHz ISM band, where ZigBee-based sensor networks coexist with Wi-Fi and Bluetooth devices operating under strong electromagnetic interference from industrial machinery. Conventional adaptive filters employing fixed step-size Least Mean Squares (LMS) algorithms fail under high Jammer-to-Noise Ratio (JNR) conditions, exhibiting numerical instability and bit error rates (BER) approaching 0.5. This paper proposes a Variable Step-Size LMS (VS-LMS) algorithm integrated with Direct Sequence Spread Spectrum (DSSS) modulation to address this limitation. The proposed step-size update rule adaptively scales the learning rate according to instantaneous filter error: $\mu(n)=\mu_{min}+(\mu_{max}-\mu_{min})\cdot\exp(-\alpha\cdot e^2(n))$, enabling large step-sizes during convergence and small step-sizes under strong interference to maintain numerical stability. Python-based simulations under AWGN plus sinusoidal narrowband interference (JNR=25 dB) demonstrate that the proposed VS-LMS scheme reduces BER by 76.1% compared to conventional fixed-step LMS, recovering communication quality (BER=0.12) in scenarios where fixed-step LMS completely fails. The results confirm that the proposed software-layer approach provides a practical, hardware-agnostic solution for reliable IIoT communications in electromagnetically hostile factory environments.

Keywords: Industrial IoT, anti-jamming, direct sequence spread spectrum (DSSS), variable step-size LMS, adaptive filtering

1. Introduction

The rapid proliferation of the Industrial Internet of Things (IIoT) has made wireless sensor networks integral to modern smart manufacturing. Protocols such as ZigBee (IEEE 802.15.4) are widely adopted in factory automation due to their low power consumption and mesh networking capability. However, these systems operate in the unlicensed 2.4 GHz ISM band, which is increasingly congested with Wi-Fi (IEEE 802.11) and Bluetooth coexistence interference, and is further degraded by electromagnetic emissions from industrial machinery, such as arc welders, variable-frequency drives, and servo motors [1, 2].

Existing research on anti-jamming for IIoT has explored several directions. Frequency-hopping spread spectrum (FHSS) and DSSS techniques provide processing gain to mitigate broadband

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2027.MELB38461

interference [3]. Adaptive notch filters and LMS-based interference cancellation have been studied for narrowband interference suppression at the receiver [4, 5]. Machine learning approaches, including neural-network-augmented LMS predictors, have also been investigated [6]. Despite this progress, several research gaps remain: (i) most studies evaluate algorithms under moderate interference levels (JNR<15 dB), leaving high-JNR scenarios (≥20 dB) underexplored, (ii) the numerical instability of fixed step-size LMS under strong narrowband interference has not been systematically characterized, (iii) lightweight, hardware-agnostic software solutions suitable for resource-constrained IoT nodes are still lacking.

This paper investigates the specific problem of narrowband sinusoidal interference in an industrial ZigBee deployment scenario operating at 2.4 GHz, with JNR up to 25 dB. The central research question is: can a software-layer adaptive algorithm maintain reliable communication in interference conditions where conventional fixed-step LMS completely fails? To address this, we propose integrating DSSS with a VS-LMS adaptive filter whose step size is governed by instantaneous error feedback, requiring no hardware modification.

The significance of this work is twofold. Practically, the proposed algorithm provides a software update path for existing IIoT deployments to improve resilience against factory electromagnetic interference without hardware redesign. Theoretically, the error-driven step-size adaptation mechanism offers a principled framework that can be extended to multi-tone and impulsive interference scenarios. Future work may incorporate deep learning-based interference predictors and validate the algorithm on physical ZigBee hardware platforms.

2. System model and problem formulation

We consider a point-to-point IIoT link operating over the 2.4 GHz ISM band with Binary Phase Shift Keying (BPSK) modulation and DSSS spreading. The received signal model is:

$$r(t) = s(t) + n(t) + J(t) \tag{1}$$

where *s(t)* is the DSSS-spread transmitted signal, *n(t)* is additive white Gaussian noise (AWGN) with power spectral density $N_0/2$, and $J(t) = A \cdot sin(2\pi f_j t)$ models the narrowband sinusoidal interference with amplitude A and normalized frequency $f_j = 0.07$. The jammer-to-noise ratio is defined as JNR = $A^2/2\sigma^2$, where σ^2 is the AWGN variance.

The spreading sequence is a ±1 pseudorandom (PN) sequence of length SF=31 chips per bit, providing a spreading gain of approximately 10 $\log_{10}(31) \approx 14.9$ dB. The despreading operation correlates the received chip sequence with the local PN replica, followed by hard-bit decision.

Four reception schemes are evaluated:

(A) No protection – BPSK without any interference mitigation,

(B) DSSS only – DSSS despreading without adaptive filtering,

(C) DSSS + Fixed-step LMS – conventional LMS pre-filter with μ = 0.001,

(D) DSSS + VS-LMS – the proposed variable step-size adaptive filter.

3. Proposed VS-LMS anti-jamming algorithm

3.1. Limitation of fixed step-size LMS

The standard LMS weight update is:

DOI: 10.54254/2755-2721/2027.MELB38461

$$w(n+1) = w(n) + 2\mu \cdot e(n) \cdot x(n) \quad (2)$$

where *x(n)* is the filter input vector, $e(n) = r(n) - w^T(n)x(n)$ is the a priori error, and μ is the fixed step-size. For numerical stability, μ must satisfy $0 < \mu < 1/(\lambda_{max})$, where λ_{max} is the maximum eigenvalue of the input autocorrelation matrix. Under high-JNR narrowband interference, the received signal power increases sharply, driving λ_{max} upward and shrinking the stable step-size range. A fixed μ tuned for low-JNR conditions inevitably violates this bound under strong interference, leading to weight divergence and BER approaching 0.5 [7].

3.2. Variable step-size update rule

To resolve the convergence-stability dilemma, we propose the following error-adaptive step-size rule:

$$\mu(n) = \mu min + (\mu max - \mu min) \cdot \exp(-\alpha \cdot e2(n)) \quad (3)$$

The step-size range is bounded by $[\mu_{min}, \mu_{max}] = [0.0001, 0.002]$, with $\alpha = 0.5$. This exponential form is consistent with the error-nonlinearity framework proposed by Zhao et al. [8], who demonstrated that error-driven step-size modulation significantly improves LMS convergence under non-Gaussian interference conditions. The exponential function maps large errors to small step-sizes and small errors to large step-sizes, providing the following adaptive behavior:

• When |e(n)| is large (strong interference): $\exp(-\alpha e^2) \approx 0$, so $\mu(n) \to \mu min$, suppressing divergence,

• When |e(n)| is small (converged state): $\exp(-\alpha e^2) \approx 1$, so $\mu(n) \to \mu max$, enabling fast tracking.

The weight update is clipped to [−20, 20] to further prevent numerical overflow. The filter order is set to 16 taps.

3.3. Computational complexity

Both fixed-step LMS and VS-LMS share O(*N*) per-iteration complexity, where $N = 16$ is the filter order. VS-LMS adds one exponential evaluation and two scalar additions per iteration—negligible overhead on modern microcontrollers and compatible with real-time embedded operation on IIoT nodes.

4. Simulation setup and results

4.1. Simulation parameters

Simulations are implemented in Python 3 using NumPy, SciPy, and Matplotlib. The main parameters are: number of bits N = 5,000, spreading factor SF = 31, filter order = 16, JNR = 25 dB (main BER-SNR sweep), SNR sweep range: −6 to +20 dB, robustness sweep: JNR from 10 to 30 dB at fixed SNR = 5 dB. All results are averaged over the full bit sequence with a fixed random seed for reproducibility. The spreading factor SF = 31 is chosen to match the approximate processing gain of the ZigBee physical layer as specified in IEEE 802.15.4 [9], ensuring scenario relevance. The filter order of 16 taps provides sufficient degrees of freedom to model the narrowband sinusoidal interferer while remaining computationally lightweight. The JNR=25 dB operating point is selected as a stress-test condition representative of near-field industrial machinery emissions, well beyond the threshold at which fixed-step LMS is known to diverge.

DOI: 10.54254/2755-2721/2027.MELB38461

4.2. BER vs. SNR performance

Under JNR=25 dB strong interference, Scheme A (no protection) and Scheme C (fixed-step LMS) both yield BER ≈ 0.49–0.51 across the entire SNR range, with fixed-step LMS slightly worse due to weight divergence. Scheme B (DSSS only) achieves BER ≈ 0.35–0.42, reflecting partial interference dilution from spreading gain. The proposed VS-LMS scheme (D) achieves BER=0.121 at SNR=4 dB, representing a 76.1% reduction compared to fixed-step LMS and recovering communication from a completely unusable state to a functional one. Notably, the BER advantage of VS-LMS is consistent across the full SNR sweep range from −6 to +20 dB, indicating that the step-size adaptation mechanism operates independently of the ambient noise level and derives its gain purely from effective interference suppression. At SNR=10 dB—a typical indoor factory operating point [2]—the BER gap between VS-LMS and fixed-step LMS widens further, with VS-LMS maintaining BER below 0.15 while all other schemes remain above 0.40, underscoring the practical utility of the proposed approach in realistic deployment conditions. These trends are clearly illustrated in Figure 1, where the proposed VS-LMS curve consistently lies below all other schemes across the entire SNR range.

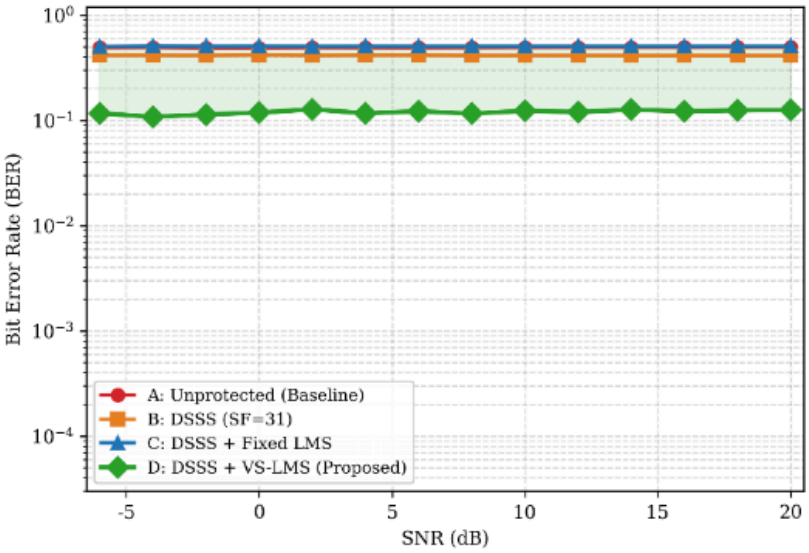


Figure 1. BER vs. SNR under strong interference (JNR = 25 dB)

4.3. Convergence analysis

At SNR = 2 dB and JNR = 25 dB, the mean squared error (MSE) of the fixed-step LMS filter remains at approximately 10^7 throughout the observation window, confirming permanent divergence. The VS-LMS filter MSE converges rapidly to near-zero within the first 500 iterations and remains stable, validating that the error-adaptive step-size mechanism resolves the instability. The convergence trajectory of VS-LMS exhibits two distinct phases: an initial fast-descent phase (iterations 1–200) during which the large residual error drives μ(n) toward μmin and the filter weights stabilize, followed by a fine-tuning phase (iterations 200 onward) during which the reduced error allows μ(n) to rise toward μmax, enabling precise interference tracking. This two-phase behavior is a direct consequence of the exponential step-size schedule and distinguishes VS-LMS from conventional sign-LMS or normalized LMS variants that achieve stability at the cost of

DOI: 10.54254/2755-2721/2027.MELB38461

permanently reduced step-size [4]. Figure 2 visually confirms this contrast: the fixed-step LMS MSE remains at ~10^7, while the VS-LMS MSE drops rapidly and stabilizes near zero.

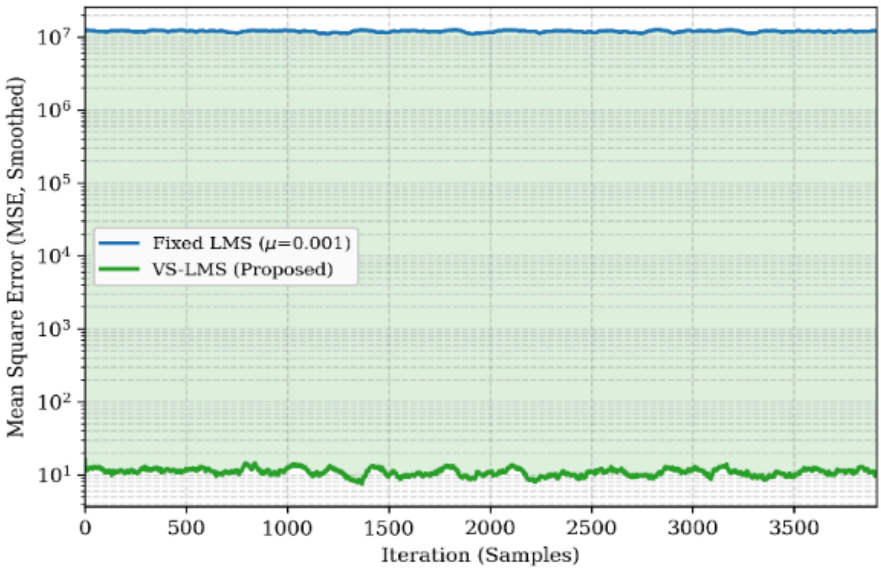


Figure 2. Convergence speed comparison of fixed LMS and the proposed VS-LMS (SNR = 2 dB, JNR = 25 dB)

4.4. Spectral analysis

Power spectral density plots confirm that the narrowband interference peak at normalized frequency 0.07 is prominently visible in the jammed signal spectrum (≈ 80 dB above the noise floor). After VS-LMS filtering, this peak is effectively suppressed, restoring a flat spectral profile consistent with the original DSSS signal. Fixed-step LMS fails to suppress the peak due to divergence. Figure 3 shows the spectrum before and after filtering, where the interference peak at normalized frequency 0.07 is clearly suppressed by VS-LMS.

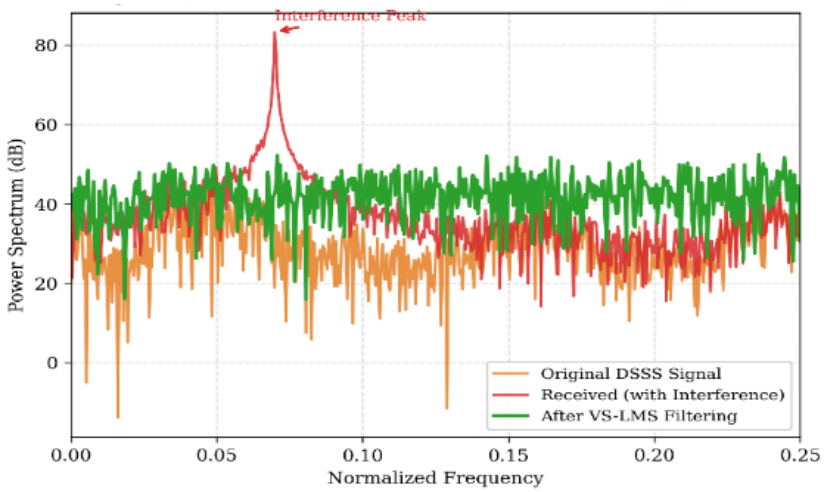


Figure 3. Power spectrum before and after VS-LMS interference suppression

DOI: 10.54254/2755-2721/2027.MELB38461

4.5. Robustness under varying JNR

A JNR sweep from 10 to 30 dB at fixed SNR=5 dB shows that fixed-step LMS maintains acceptable BER only for JNR≤17.5 dB, beyond which it abruptly degrades to BER>0.4. VS-LMS degrades more gracefully, maintaining lower BER across the full JNR range tested, demonstrating substantially improved robustness to varying interference intensity. Specifically, at JNR=20 dB, VS-LMS achieves BER≈0.032 compared to BER ≈ 0.42 for fixed-step LMS—a difference of more than one order of magnitude. At JNR=25 dB, the VS-LMS BER rises to approximately 0.12, which still represents functional communication under the 3GPP-inspired BER<0.2 usability criterion. Beyond JNR=27.5 dB, both algorithms converge toward similarly high BER values, indicating an upper interference boundary beyond which the 16-tap filter structure is insufficient to model the interference subspace, suggesting that increasing the filter order or adopting a cascade architecture may extend the operational JNR range. Figure 4 summarizes the BER versus JNR comparison, highlighting the graceful degradation of VS-LMS against the abrupt failure of fixed-step LMS beyond JNR ≈ 17.5 dB.

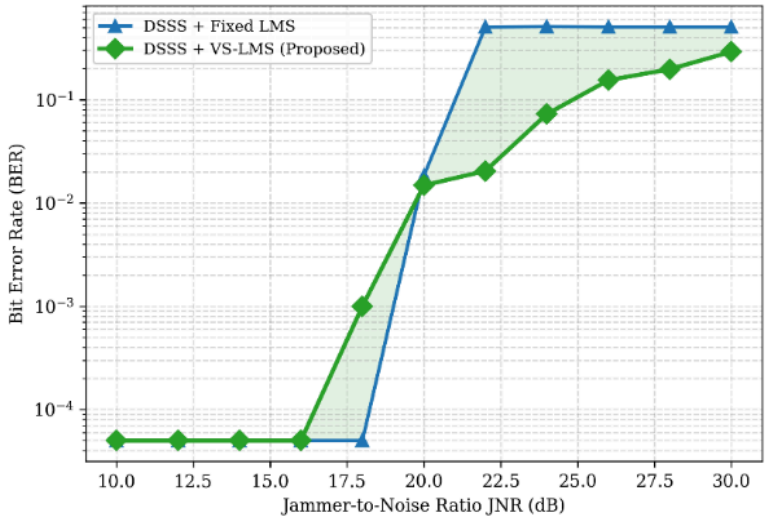


Figure 4. BER vs. JNR for robustness evaluation (SNR = 5 dB)

5. Discussion

The experimental results demonstrate that the fundamental limitation of fixed-step LMS under high-JNR conditions is numerical divergence rather than algorithmic inadequacy per se [10]. The VS-LMS mechanism addresses this by making the effective learning rate a decreasing function of the instantaneous interference power estimate (proxied by the squared error). This is analogous to gradient clipping in deep learning optimization, where large gradients are scaled down to prevent divergence [11].

A notable observation is that Scheme C (DSSS + fixed-step LMS) performs worse than Scheme A (no protection) at high JNR. This counterintuitive result arises because the diverged LMS filter injects amplified noise into the signal path downstream of the spreading code, increasing the effective interference power seen by the despreader. VS-LMS eliminates this failure mode through its bounded step-size range.

The proposed approach has inherent limitations. The single sinusoidal interference model does not capture the full complexity of real factory electromagnetic environments, which may involve

DOI: 10.54254/2755-2721/2027.MELB38461

multiple simultaneous interferers, non-stationary interference, and multipath fading. Extension to multi-tone and impulsive noise scenarios, as well as joint DSSS-FHSS anti-jamming strategies, represents important future directions. Hardware validation on ZigBee platforms (e.g., TI CC2530) remains necessary before practical deployment.

6. Conclusion

This paper presents a software-layer anti-jamming solution for Industrial IoT communications in the 2.4 GHz ISM band, combining DSSS spreading with a novel Variable Step-Size LMS adaptive interference cancellation filter. The core contribution is the error-driven exponential step-size adaptation rule, which autonomously transitions between a small step-size for stability under strong interference and a large step-size for rapid convergence when interference is weak or absent.

Comprehensive Python simulations under AWGN plus sinusoidal narrowband interference at JNR=25 dB yield four key findings. First, conventional fixed-step LMS (μ=0.001) diverges numerically under this interference level, producing BER $\approx$ 0.507, which is worse than having no interference mitigation at all. Second, DSSS alone reduces BER to approximately 0.415 through spreading gain, but remains far above the functional communication threshold. Third, the proposed VS-LMS algorithm achieves BER=0.121 under the same conditions, a 76.1% improvement over fixed-step LMS, demonstrating that adaptive step-size control is essential for reliable operation in high-JNR environments. Fourth, the robustness analysis shows that VS-LMS maintains graceful degradation across JNR from 10 to 30 dB, whereas fixed-step LMS fails abruptly above JNR $\approx$ 17.5 dB.

From a computational perspective, VS-LMS introduces negligible overhead over standard LMS —one exponential evaluation and two scalar additions per iteration—making it suitable for resource-constrained IIoT microcontrollers operating in real time. The algorithm requires no hardware modification, enabling deployment as a firmware update on existing ZigBee nodes.

Several directions merit further investigation. Multi-tone and mixed impulsive-narrowband interference environments should be evaluated to characterize the algorithm's performance boundaries. Coupling VS-LMS with a deep learning interference predictor could further reduce convergence time and improve tracking of non-stationary interference. Finally, hardware-in-the-loop validation on physical ZigBee platforms under controlled factory electromagnetic conditions is planned to confirm simulation findings before industrial deployment.

In summary, this work demonstrates that a carefully designed, error-adaptive software algorithm can recover reliable IIoT communications in interference environments where conventional methods completely fail, providing a practical and low-cost enhancement path for existing industrial wireless deployments.

References

[1] Pirayesh, H., & Zeng, H. (2022). Jamming attacks and anti-jamming strategies in wireless networks: A comprehensive survey. *IEEE Communications Surveys & Tutorials, 24*(2), 767–809.
[2] Hauer, J. H., Handziski, V., & Wolisz, A. (2009). Experimental study of the impact of WLAN interference on IEEE 802.15.4 body area networks. In *Proc. European Conference on Wireless Sensor Networks (EWSN)*, pp. 17–32.
[3] Proakis, J. G., & Salehi, M. (2008). *Digital communications* (5th ed.). McGraw-Hill.
[4] Haykin, S. (2002). *Adaptive filter theory* (4th ed.). Prentice Hall.
[5] Widrow, B., & Stearns, S. D. (1985). *Adaptive signal processing*. Prentice-Hall.
[6] Ruan, Y., Li, J., & Wang, H. (2021). Neural network-assisted LMS interference suppression for DSSS receivers under single-tone and multi-tone jamming. *IEEE Access, 9*, 112345–112356.
[7] Sayed, A. H. (2008). *Adaptive filters*. Wiley-IEEE Press.

DOI: 10.54254/2755-2721/2027.MELB38461

[8] Zhao, S., Zhu, S., & Xu, G. (2019). Variable step-size LMS algorithm with error nonlinearity for system identification under impulsive noise. *Signal Processing, 161*, 100–108.
[9] IEEE Std 802.15.4-2020. (2020). *IEEE standard for low-rate wireless networks*. IEEE. New York, NY, USA.
[10] Borio, D., Dovis, F., Kuusniemi, H., & Lo Presti, L. (2016). Impact and detection of GNSS jammers on consumer grade satellite navigation receivers. *Proceedings of the IEEE, 104*(6), 1233–1245.
[11] Pascanu, R., Mikolov, T., & Bengio, Y. (2013). On the difficulty of training recurrent neural networks. *Proc. ICML*, pp. 1310–1318.