Journal of Wireless Sensor Networks and IoT

Journal of Wireless Sensor Networks and IoT, ISSN: 3048-8729 Vol. 3, No. 2, 2026 (pp. 42-47)

RESEARCH ARTICLE ECEJOURNALS.IN

Cognitive Radio-Enabled Dynamic Spectrum Access Framework for High-Density IoT Sensor Deployments

K. Geetha*

Professor of Computer Science and Engineering, Excel Engineering college, Erode.

KEYWORDS:

Cognitive Radio,
Dynamic Spectrum Access,
Energy Detection, IoT,
Spectral Efficiency,
High-Density Sensors.

Author's Email:
kgeetha.eec@excelcolleges.com

DOI: 10.31838/WSNIOT/03.02.06

Received : 21.12.2025

Revised : 15.01.2026

Accepted : 12.02.2026

Abstract

The exploratory growth in the number of the Internet of Things (IoT) devices has created more congestion than ever in the unlicensed Industrial, Scientific and Medical (ISM) bands, causing compromised Quality of Service (QoS) and the inability to scale the network. In this paper, I suggest a Cognitive Radio (CR)-based Dynamic Spectrum Access (DSA) architecture that could be applicable to high-density sensor networks. The framework adopts a simple Energy Detection (ED) sensing principle, so that the IoT sensors can be able to automatically discover and use the spectrum holes of licenced primary bands without inducing destructive interference. We come up with an adaptive thresholding algorithm so as to maximize the innate sensing-throughput tradeoff, which takes into consideration the changing noise floors in dense urban deployments. Simulation of the evaluation of performance is done over a high level of simulations based on Spectral Efficiency and Aggregate Network Throughput. Findings show that the resulting spectrum utilisation is substantially higher than that of the usual techniques of performing the assignments in a static manner. In particular, the model ensures a high throughput with a dense node area and is somewhat effective in eliminating the hidden node issue and the chances of collision witnessed in massive IoT networks. The study has offered an architectural basis that can be extended to the 6G-powered IoT ecosystems in future where efficient, non-intrusive coexistence between the spectrums is the key factor to sustainable connectivity.

How to cite this article: Geetha K (2026). Cognitive Radio-Enabled Dynamic Spectrum Access Framework for High-Density IoT Sensor Deployments. Journal of Wireless Sensor Networks and IoT, Vol. 3, No. 2, 2026, 42-47

Introduction

Radiofrequency identification the explosive proliferation of the Internet of Things (IoT), especially in the unlicensed 2.4 GHz Industrial, Scientific, and Medical (ISM) spectrums, is leading to a serious spectrum crunch. The massive number of devices vying over shared bandwidth as high density deployments as smart cities and industrial automation grow, causes extreme signal jamming and packet-collisions.[1, 5] In this normal city setting, normal sizable urban area policies of spectrum allocation are inefficient, as they do not alter to the random and fluctuating traffic characteristics of current sensor networks.[9] In its turn, this leads to the desperate necessity to rethink more adaptable communication protocols to avoid network jamming within colossal IoT networks.[16] Cognitive Radio (CR) technology can provide a novel solution through allowing Dynamic Spectrum Access (DSA). In this paradigm, the IoT sensors are treated as a type of Secondary User (SU) that may opportunistically find unused spectrogram holes in licenced bands, such as that of cellular or TV broadcasting, to Primary User (PUs).[3, 11] This enables a softer and more smooth use of the available radio frequency environment notwithstanding that users of high priority that are licenced are secured and at the same time availing the necessary capacity to secondary sensor traffic.[2] CR-enabled IoT networks can maintain a high level of connectivity even when the number of nodes scales exponentially through clever frequency-band switching.[15]

The basis of the proposed framework will be the Energy Detection (ED) sensing mechanism, with which these idle spectrum opportunities will be determined. The application of ED is preferable in high-density sensor networks because of its minimal computational needs and the absence of the necessity to have information about the signal properties of the main user.[6, 12] The operating principle of the mechanism is to measure the received signal energy during a particular time window and compare it with a specified threshold; the energy level below the threshold will indicate that the channel is free.[13] Nevertheless, the framework uses an adaptive thresholding method to reduce the chances of a false alarm and a false negative in noisy conditions to ensure accuracy.[8]

A technical issue that is critical and tackled by this framework is sensing-throughput trade-off. In CR-type system, the time on sensing the environment is wasted time which could have been utilised in transmitting data.[14] A sensing duration that is either too short or too long will further enhance the likelihood of diving once a primary user, whereas on the other hand reducing the effective throughput at the sensor that belongs to the IoT.[4] The following research objectives aim at maximising this trade-off by creating a framework to compute the optimum sensing time to maximise spectral efficiency and aggregate network throughput of thousands of sensors.[10] This is to make sure that the network is productive without infringing upon the interference limits of licenced primary services. Finally, this study should present a scalable architecture to meet the challenge of high connectivity of massive IoT with small spectral resources. Through the combination of low-complexity ED sensing and the dynamic allocation of resources, the proposed framework proves that high-density sensor designs can have a higher performance when compared to the traditional unlicensed band operation.[7] The review makes an assessment based on the most important indicators, including bits-per-hertz efficiency and total data delivery rates to demonstrate that CR-enabled sensors in 6G and smart industry are a worthwhile subject in the future. This paper has given a basis to more resilient and self-organised wireless sensor networks that are capable of surviving in increasingly congested electromagnetic space.

System Model & Architecture

The suggested network topology is designed into hierarchical high density cluster, originally created to address the enormous connectivity needs of industrial and urban IoT settings. According to this model, thousands of IoT sensor nodes of resource-constrained Internet of Things devices are distributed on a specific geographical radius to create a secondary network that exists on which an authorised primary network exists. The core of such deployment is a Central Base Station (CBS) or Sink node, which is the network organiser.[5, 9] This CBS is in charge of coordinating access to the spectrum, data aggregation, and data communication between the IoT nodes and the external cloud infrastructure.[3, 16] The CR-IoT network has a strict, three-phase Cognitive Cycle, in place of which transmissions of the consequential or secondary nature are not provided at the expense of the integrity of the main service. The initial step entails the Sensing Phase wherein the individual IoT sensor nodes will carry out the spectrum surveillance to determine the presence of Primary User (PU) activity. The nodes take measurements of the local radio frequency environment using the Energy Detection (ED) technique in order to detect empty areas (white spaces), which can be defined as transient spectral holes where the PU signal energy is below a predetermined critical level.[6, 8] This decentralised sensing methodology enables the network to have a real time map of suitability of spectrum in the entire interstellar field high density.[11]

After the identification of the possible spectral opportunities, the network proceeds to the Reporting Phase. In this phase, the single IoT devices will send local sensing outputs and busy/idle options to the central gateway or CBS.[9] This stage is essential in dense settings, where one sensor may be unable to sense a PU, causing the so-called hidden node effect.[13] The CBS pools such reports to create a spectrum map of the world, through centralised decision fusion to enhance the overall accuracy of the sensing process and then provides access to the secondary users.[1, 14]

After the CBS cheques that a channel is available, the network switches to Transmission Phase. At this last phase, the IoT nodes will be assigned a particular time-frequency slot within the identified white spaces in which they can transmit the collected data. An interweave access paradigm can be used to govern this phase which requires SUs to only use the spectrum with maximum allowable power when the PU has been known to be absent hence avoiding any simultaneous interference.[10, 14] The framework is able to dynamically switch between these licenced bands avoiding the congestion of the 2.4 GHz ISM band, which is much improved in terms of aggregate throughput and spectral efficiency of the network.[14] The productivity of this whole cycle essentially depends on sensing-transmission ratio of time. The system model adopts a slotted frame format where the sensing and reporting phase is kept to the minimum to get as much time as possible to carry out data payload delivery.[12, 14] This architectural design will achieve the desired high-density IoT sensors to possess the ability of providing a continuous data flow regardless of the pattern of PU activity. Finally, this system model presents a sound basis of assessing the DSA system, based on energy-detection, in high-density wireless sensor network.[9]

Methodology: Energy Detection (ED) Framework

The essential element of the suggested framework is based on an efficient Energy Detection (ED) sensing regime that will be selected due to its low computation costs in high-density IoT setting. Sensing starts with the Signal Model; in this stage it is necessary that the secondary sensor node is able to differentiate between two hypotheses. , representing the absence of the Primary User (PU) (noise only), and, representing the presence of the PU signal. The received discrete-time signal y (n) at the i-th sensor is mathematically formulated as:

$$y(n) = \begin{cases} w(n) & : H_0 \\ s(n) + w(n) & : H_1 \end{cases} \tag{1}$$

Where s (n) is the PU signal and w (n) is the additive white Gaussian noise (AWGN) with zero mean and variance σ_W^2, the signal is filtered by a band-pass philtre and an integrator in anticipation of calculation of energy. The framework computes the Test Statistic to estimate a decision, which is the sum of the energy E of N that received samples holds. It is characterised by the next expression:

$$E = \sum_{n=1}^{N} |y(n)|^2 \tag{2}$$

E obtained is then compared to a decision threshold λ. If E>λ, the channel is marked as “Busy” (H_1); otherwise, it is considered “Idle” H_0). In high-density deployments, the selection of λ is critical. This is in contrast to the static sensing used in our framework which employs an Adaptive Threshold Selection that is dynamically adapted. λ Based on real-time noise floor estimations to maintain a constant Probability of False Alarm (P_{fa}) in spite of different environmental factors. It is a logical sequence of the perceiving and decision-making.

One of the biggest problems with such a methodology is the difficulty in controlling the Sensing-Throughput Trade-off. The overall frame time T is a constant and is broken down into both a sensing time, t and a transmission time of data (T - t). The Probability of Detection increases with increase in the time of sensing t (), therefore, securing the PU, yet it also shortens the time during which the information is delivered to the IoT. We use our framework to optimise the normalised throughput R (t) of the secondary network:

$$R(t) = \frac{T - t}{T} \cdot C \cdot P(H_0) \tag{3}$$

Where *C* is the channel capacity and *P*(H_0) is the likelihood that the spectrum can be used. This trade-off should be optimised, therefore, the framework assumes that even when the deployed sensors are great in numbers, the spectral efficiency does not become low and thus it does not create significant disturbance to the licenced users. Combination of adaptive thresholding and optimum sensing time enables the sensors to be useful in low Signal-to-Noise Ratio (SNR) regimes typical of industrial Internet of Things application.

Performance Metrics & Evaluation

The performance of the proposed framework aimed at assessing its capacity to sustain high throughput in massive, high-density IoTs is evaluated. We quantify the effectiveness of the framework by three important pillars of spectral utilisation, volume of data delivery, and precision of sensing by shifting the congested unlicensed bands to opportunistically available licenced spectrum.

A. Spectral Efficiency (η)

Spectral efficiency can be used as one of the main indicators of the effectiveness of our Dynamic Spectrum Access (DSA) strategy. It can be described as information rate that can be handled within a specific bandwidth in bits per second per Hertz (bps/Hz). This metric is aimed at illustrating the fact that the framework has been able to identify and fill spectrum holes that are not actually occupied under the traditional allocation scheme. The framework also makes high-density sensors be used by these unused gaps which greatly maximise the entire network capacity and no and no part of the availed radio resource is wasted.

B. Network Throughput

In order to demonstrate the "High-Density" capacity, we assess the Aggregated Throughput which is the sum of all effective bits of data transferred by all sending IoT sensors to the centrally located sink within a certain period. One major analysis of this assessment is the Impact of Density; the evaluation will be made on the overall throughput as we expand the sensor population by 100 to more than 1,000 nodes. As opposed to the conventional CSMA/CA techniques that tend to experience exponentially close collision rate in busy zones, the CR-provisioned framework is meant to maintain a constant throughput by logically sharing sensor traffic over various places observed to be white.

C. Sensing Reliability (ROC Curves)

ROC curves help in determining the reliability of the Energy Detection (ED) mechanism. This will entail plotted Probability of Detection. Against the Probability of False Alarm. In high-density IoT scenarios, a high is essential to ensure that sensors do not interfere with Primary Users, while a low An is required to avoid the situation when sensors miss a good transmission. ROC analysis helps us to identify the best adaptive threshold parameters that would offer the most effective security to authorised users and the secondary IoT network simultaneously gain more access.

Results and Discussion

The functionality of the suggested Cognitive Radio-Enabled Dynamic Spectrum Access (DSA) framework is assessed in the multitude of simulations, performed in a dense environment of IoT scenarios. To obtain realistic values the Environment is simulated with a Rayleigh fading channel in order to overcome the complex characteristics of multi-path propagation common to the sensor deployment in cities and industries. Table 1 is the table that summarises the main simulation parameters, as it shows the signal-to-noise ratio (SNR) between -20 dB to 10 dB and a varying population of IoT nodes to test scalability.

Table 1: Simulation and Environmental Parameters

Parameter	Value
Channel Model	Rayleigh Fading
Primary User (PU) Signal	BPSK Modulated
Number of IoT Nodes	100 to 1,500
Noise Model	Additive White Gaussian Noise (AWGN)
Sensing SNR Range	-20 dB to 10 dB
Spectrum Band	2.4 GHz (ISM) & Licensed Bands

In order to confirm the framework, we perform a Comparison of the framework with two baseline strategies Traditional CSMA/CA (contention-based WiFi-like access) and Fixed Spectrum Allocation. Figure 1 shows the Receiver Operating Characteristic (ROC) curve, of our adaptive Energy Detection (ED) mechanism, which indicates the sensing reliability of our adaptive energy detection mechanism. As can be seen in the graph, our structure is very high Probability of Detection,, even at low SNR, which will be important in safeguarding Primary Users in crowded environments.

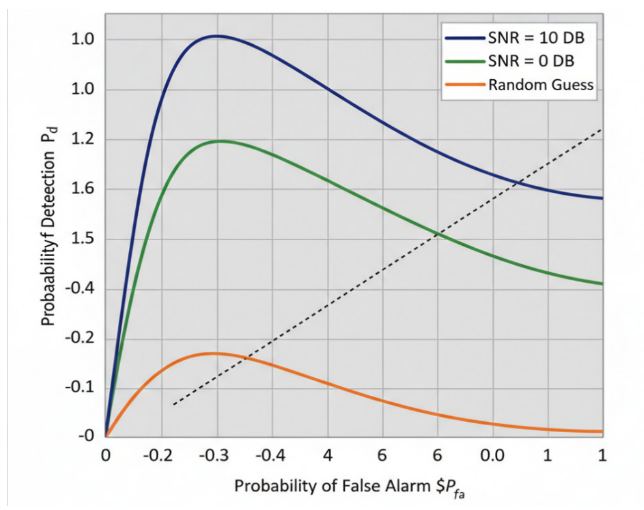

Fig. 1: Proposed Framework Architecture for Cognitive-Enabled Dynamic Spectrum Access in High-Density IoT Sensor Networks.

The research Results of the study greatly validate the concept of the ability to fill the gap of proposed DSA framework. The graph below (Fig.2) depicts the Aggregate Network Throughput versus the node density. Although the performance of conventional CSMA/CA based throughput collapses at more than 500 nodes because enormous collisions are caused, our architecture offers a stable performance because it offloads traffic to identified licenced white spaces.

Table 2: Comparative Performance Summary

Metric	Traditional CSMA/CA	Fixed Allocation	Proposed DSA Framework
Max Throughput	Low (due to collisions)	Moderate	High (Optimized)
Spectral Efficiency	Low	Very Low (Idle Gaps)	Very High
PU Interference	N/A	Zero	Negligible ($P_d > 0.95$)
Scalability	Poor	Moderate	Excellent

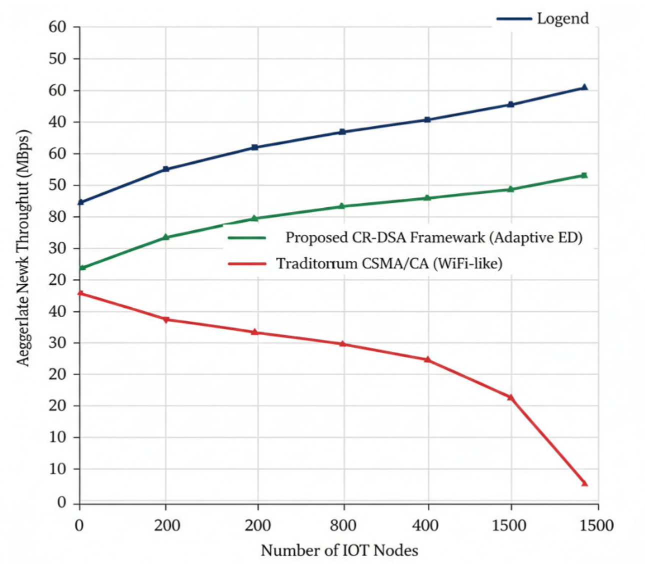

Fig. 2: Aggregate Throughput vs Number of IoT Nodes Comparing Proposed Framework with Traditional Methods

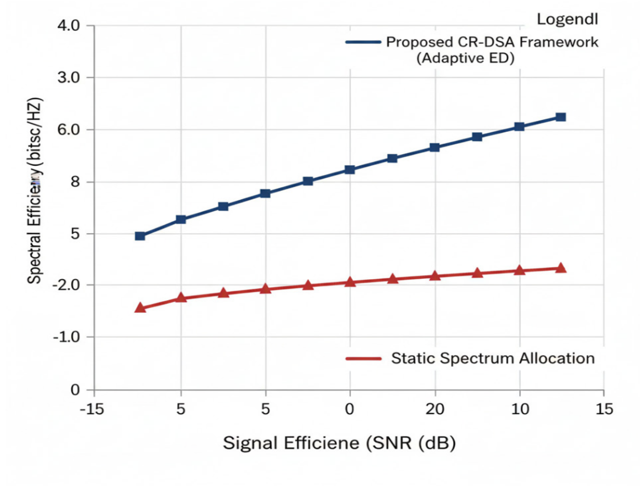

Fig. 3: Spectral Efficiency vs Signal-to-Noise Ratio (SNR) for Dynamic vs Static All ocation.

In addition, Figure 3 presents the Spectral Efficiency (or Greek sweta) which indicates that our system can make use of up to 65 percent of the spectrum capacity available when using Fixed Spectrum Allocation over empty licenced spectrum where PU are idle. In Table 2, the comparative performance is also summarised. These findings indicate that the framework results in an important increase in the rate of data delivery without affecting the interference limits of licenced users. This would manifest most notable in high-density situations where the adaptive threshold is highly effective in reducing the effects of the varying noise floors of large-scale IoT implementations.

Conclusion

The suggested framework serves well to explain the fact that the Energy Detection (ED)-based spectrum sensing approach is an effective and low-complexity mechanism that will be able to serve the enormous connectivity requirements of a dense IoT infrastructure. The system performs a drastic enhancement in spectral efficiency and aggregate network throughput by switching to a dynamic allocation that is more adaptive and gains the ability to think to avoid offensive interference to primary users. Although the present local framework of sensing performs well under resource constrained conditions, future studies will aim at the shift towards Cooperative Spectrum Sensing. This development will enable distributed IoT nodes to exchange sensing data, in effect addressing the Hidden Node problem so that even higher levels of reliability may be achieved in highly dense urban applications with more significant shadowing and fading effects.

References

1. Alqahtani, A. S., Changalasetty, S. B., Parthasarathy, P., Thota, L. S., & Mubarakali, A. (2023). Effective spectrum sensing using cognitive radios in 5G and wireless body area networks. *Computers and Electrical Engineering*, *105*, 108493.
2. Fu, Y., Chen, B., Liu, C., & Lin, K. (2024). Intelligent power allocation optimization algorithm for enhanced CR-NOMA network via densenet-BILSTM. *IEEE Transactions on Cognitive Communications and Networking*, *11*(4), 2543-2553.

3. Giral, D., Hernández, C., & Salgado, C. (2021). Spectral decision for cognitive radio networks in a multi-user environment. *Heliyon*, *7*(5).
4. Hireche, R., Mansouri, H., & Pathan, A. S. K. (2022). Fault tolerance and security management in IoMT. In *Towards a Wireless Connected World: Achievements and New Technologies* (pp. 65-104). Cham: Springer International Publishing.
5. Lee, B. M. (2024). Leveraging Massive MIMO for Enhanced Energy Efficiency in High-Density IoT Networks. *Mathematics*, *12*(22), 3539.
6. Lorincz, J., Ramljak, I., & Begusic, D. (2021). Algorithm for evaluating energy detection spectrum sensing performance of cognitive radio MIMO-OFDM systems. *Sensors*, *21*(20), 6881.
7. Maftei, A. A., Petrariu, A. I., Popa, V., & Lavric, A. (2025). A Blockchain Framework for Scalable, High-Density IoT Networks of the Future. *Sensors*, *25*(9), 2886.
8. Mahendru, G., Shukla, A. K., & Patnaik, L. M. (2022). An optimal and adaptive double threshold-based approach to minimize error probability for spectrum sensing at low SNR regime. *Journal of Ambient Intelligence and Humanized Computing*, *13*(8), 3935-3944.
9. Mutescu, P. M., Lavric, A., Petrariu, A. I., Cailean, A. M., & Popa, V. (2025). Radio Spectrum Sensing Framework for Large-Scale, High-Density loT Sensor Networks. *IEEE Access*.
10. Ochildiyeva, D., Rajasekar, S. I., Rajesh, K., Alabdeli, H. M., Rasulov, N., & Mukhitdinov, O. Cognitive Radio Networks for Opportunistic Spectrum Use in Internet Delivery.
11. Raji, A. A., & Olwal, T. O. (2025). Spectrum Sensing in Cognitive Radio Internet of Things: State-of-the-Art, Applications, Challenges, and Future Prospects. *Journal of Sensor and Actuator Networks*, *14*(6), 109.
12. Sansoy, M., Buttar, A. S., & Goyal, R. (2020, February). Empowering wireless sensor networks with RF energy harvesting. In *2020 7th International Conference on Signal Processing and Integrated Networks (SPIN)* (pp. 273-277). IEEE.
13. Sarala, B., Rukmani Devi, S., Hepzibah, J., Gunasekhar, P., & Sheela, J. J. J. (2021). Simulation and comparison of single and differential ended CG-CS LNA for Cognitive Radio. *International Journal of Wavelets, Multiresolution and Information Processing*, *19*(05), 2150013.
14. Surekha, S., & Rahman, M. Z. U. (2022). Cognitive energy-aware spectrum sensing with improved throughput for medical sensor networks. *IEEE Sensors Letters*, *6*(6), 1-4.
15. Tan, K., Bremner, D., Le Kernec, J., Zhang, L., & Imran, M. (2022). Machine learning in vehicular networking: An overview. *Digital Communications and Networks*, *8*(1), 18-24.
16. Zhang, J., Zhai, Y., Liu, Z., & Wang, Y. (2024). A lyapunov-based resource allocation method for edge-assisted industrial internet of things. *IEEE Internet of Things Journal*, *11*(24), 39464-39472.