THE EFFECTS OF DIVERSITY SCHEMES ON ENHANCINGENERGY DETECTOR-BASED COOPERATIVE WIDEBAND SPECTRUM SENSING IN 5G NETWORKS

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ABSTRACT

The proliferation of 5G technologies and the vast deployment of Internet of Things (IoT) devices have heightened the demand for optimal spectrum utilization, necessitating robust spectrum management strategies. In this context, an efficient energy detector employing wideband spectrum sensing within a 5G environment is essential for identifying underutilized frequency bands suitable for cognitive radio applications across multiple sub-bands. While cooperative spectrum sensing (CSS) can enhance the detection capabilities of energy detectors amidst noise uncertainty, its performance often deteriorates under low signal-to-noise ratio (SNR) conditions. This study proposes an improved CSS framework that combines Maximal Ratio Combining (MRC) with the K-out-of-N fusion rule to address noise uncertainty in a complex Gaussian environment across multiple sub-bands in cooperative wideband spectrum sensing. Comparative performance analysis confirms that this integrated approach enhances detection probability and maintains a low false alarm rate across various low SNR scenarios, significantly outperforming traditional cooperative and non-cooperative wideband spectrum sensing methods. These results highlight the potential for advancing cognitive radio technologies by optimizing detection algorithms to improve performance under challenging conditions.

KEYWORDS

Signal-Noise Ratio, Maximal Ratio Combining, Wideband Spectrum Sensing, Energy Detection, K-out-of-N fusion rule

1. INTRODUCTION

The rise in wireless technologies and Internet of Things (IoT) devices has greatly increased the need for radio frequency spectrum. However, spectrum is a finite resource, and most of it has already been allocated. Despite this, the Federal Communications Commission (FCC) has reported that many allocated spectrum bands remain underutilized [1]. Cognitive radio has arisen as a key enabler for next-generation wireless communication networks, addressing challenges related to spectrum scarcity and inefficient utilization [2].

To ensure that primary users' operations remain unaffected, secondary users must reliably detect active primary users, a process known as spectrum sensing. However, noise uncertainty can undermine secondary users' ability to detect primary users, particularly in challenging

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environments accurately. Cooperative spectrum sensing, where multiple secondary users collaborate, has been introduced to enhance detection performance and mitigate these limitations [3]. Nevertheless, cognitive radios operating in low signal-to-noise ratio (SNR) conditions experience degraded detection performance in cooperative wideband spectrum sensing, leading to unreliable sensing outcomes at the fusion center [4,5,6]. Furthermore, a hard fusion rule, such as the K-out-of-N fusion rule, is expected to enhance decision accuracy at the fusion center.

However, poor SNR conditions during the pre-detection stage inhibit their effectiveness [4,5]. This highlights the necessity of an optimal system that improves the SNR of each sensed channel before transmitting the results to the fusion center.

Maximal Ratio Combining (MRC), a signal processing technique, has been widely implemented in power line communication to mitigate noise effects [7]. Additionally, MRC has been utilized in Decode-and-Forward Relaying Systems to analyze error probabilities [8]. Moreover, L-selection combining and MRC have been implemented as advanced diversity reception techniques to mitigate interference in received signals [9].

This paper analyzes the performance of energy detection techniques for wideband spectrum sensing under Additive White Gaussian Noise (AWGN) which is independently and identically distributed (i.i.d.). We developed an architecture that integrates Maximal Ratio Combining (MRC) with the K-out-of-N fusion rule, employing six cognitive radios (CRs) and optimizing the value of k=2 to enable more accurate signal detection and decision-making at the fusion center. Simulation results validate the efficacy of the proposed model, demonstrating significant improvements in detection accuracy and decision-making speed compared to non-cooperative methods. This research emphasizes the practical benefits of integrating MRC with the K-out-of-N rule in 5G spectrum sensing, advancing cognitive radio networks, and providing a robust framework for future enhancements in dynamic spectrum access.

The rest of the paper is organized as follows: Section II introduces the spectrum sensing methods. Section III discussed the proposed scheme architecture and model, detailing the implementation of Maximal Ratio Combining (MRC) and the K-out-of-N fusion rule to achieve reliable and accurate detection under very low SNR conditions. Section IV presents performance evaluation results, comparing non-cooperative and cooperative wideband spectrum sensing, and verifies that the proposed scheme improves detection performance across all poor SNR test cases. Finally, section V concludes the paper.

2. METHODOLOGY

2.1. Non-Cooperative Spectrum Sensing

Non-cooperative spectrum sensing allows each cognitive radio to independently scan and analyze the spectrum, making decisions based on its observations. The scheme faces challenges like noise uncertainty and hidden node problems, where a cognitive radio might not detect a primary user due to obstructions or distance [4]. This can lead to incorrect assumptions about free channels, potentially causing interference and missed detection.

The primary user AWGN corrupted signal is received by the receiving antenna and processed through the energy detector [4,5]. If the received signal y is sampled, the nth sample, y(n) is given as:

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

y(n) represents the signal received at the SU, where n =1,2,3…, w(t) signifies the additive white Gaussian noise (AWGN), and s(t) denotes the primary user's (PU) transmitted signal as observed by the secondary user (SU). The hypotheses, H_0 and H_1, conform to the absence or presence of the PU, respectively. The test statistic for energy detection is:

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

This computed energy is compared to a predetermined threshold to ascertain the occupancy of specific PU channels. The threshold, represented by λ, is obtained in Equation 3, and is applied in energy detection (ED) assuming complex Additive White Gaussian Noise (AWGN).

$$\lambda = Q^{-1}(Pf).\sqrt{2(Ps + \sigma^2 N)} \tag{3}$$

The inverse Q-function, denoted as Q^{-1}, defines the threshold λ that maintains a specified false alarm probability (PFA). The number of samples is represented as N, and Ps denotes the signal power used for detection. The threshold λ is rightly set based on these parameters to achieve the desired PFA.

2.2. Cooperative Spectrum Sensing

Cooperative sensing involves multiple sensors cooperating to detect primary users' presence across frequency bands. This method minimizes interference with incumbent users and maximizes vacant spectrum usage. However, increasing the number of nodes complicates data management and decision-making. Low SNR significantly challenges cooperative sensing by increasing missed detection rates and false alarms, especially in AWGN and fading scenarios [5]. Assume that K cognitive radios (CRs) are sensing the primary user channel in 5G environment under additive white Gaussian noise (AWGN) conditions. The signal received at the i-th CR is:

$$y_k(i) = \begin{cases} w_i(n), & H_0 \\ s_i(n) + w_i(n), & H_1 \end{cases} \tag{4}$$

Each CR employs energy detection to compute its test statistics, E_k .

$$E_k = \sum_{i=1}^{N} |y_k(i)|^2 \tag{5}$$

The models and architectures of cooperative and non-cooperative wideband spectrum sensing and their sub-band frameworks in energy detection design are illustrated and discussed in [4,5].

2.3. Maximal Ratio Combining

In spectrum sensing, the MRC combines the measured signal strengths from multiple sensors or cognitive radios (CRs), weighted according to the SNR of each CR [7,8,9,]. This approach allows CRs with higher reliability to influence the final decision more substantially.

MRC weights each received signal before summing:

$$E_{mrc} = \sum_{k=1}^{k} w_k E_k \quad (6)$$

Where E_{mrc} is the combined energy statistic used for decision-making in MRC schemes, the weighting factor w_k is:

$$w_k = \frac{SNR_k}{\sum_{k=1}^{k} SNR_k} \quad (7)$$

The weight w_k is directly proportional to the channel's SNR.

The instantaneous signal-to-noise ratio (SNR) is:

$$SNR_k = \frac{(|h_k|^2 P_s)}{\sigma_n^2} \quad (8)$$

The post combined SNR is:

$$SNR_{mrc} = \sum_{k=1}^{k} SNR_k \quad (9)$$

Equation 9 shows that the MRC adds the individual SNRs, leading to the optimal diversity gain. The probability of false alarm (PFA) and the probability of detection under MRC in energy detection (ED) are:

$$PFA_{MRC} = Q\left(\frac{\lambda - \mathrm{N}\,\sigma_n^2}{\sqrt{2N}\,\sigma_n^2}\right) \quad (10)$$

Where Q(.) is the complementary cumulative distribution fuction (CCDF) of a standard normal distribution and λ is the detection threshold [4,5].

$$\mathrm{PD}_{\mathrm{MRC}} = Q\left(\frac{\lambda - \mathrm{N}(\sigma_n^2 + \sum_{k=1}^{k} SNR_k)}{\sqrt{2N}(\sigma_n^2 + \sum_{k=1}^{k} SNR_k)}\right) \quad (11)$$

2.4. K-Out-of-N Fusion Rule

The k-out-of-N rule is a decision fusion strategy the fusion center uses to declare the presence of a primary user if at least k out of N cognitive radios report detection. The K-out-of-N fusion rule is ideal for limited resources or when reducing the system's complexity and power consumption is a priority, as not all N cognitive users participate in the decision process [4,10,11].

Each CR makes a local binary decision:

$$u_k = \begin{cases} 1, & if\ E_k > \lambda\,(detection) \\ 0, & otherwise \end{cases} \quad (12)$$

Where λ is the detection threshold. The fusion center makes a global decision D based on the rule:

$$D = \begin{cases} 1, & if\ \sum_{k=1}^{N} u_k \geq \mathrm{k}\,(declare\ H1) \\ 0, & otherwise \end{cases} \quad (13)$$

The global probability of false alarm (PFA) under independent decision is:

$$P_{FA}^{K-out-of-N} = \sum_{j=K}^{N} \binom{N}{j} (P_{FA})^j (1 - P_{FA})^{N-j} \quad (14)$$

Where $P_{FA} = Q\left(\frac{\lambda - \mathrm{N}\sigma^2}{\sqrt{2N}\,\sigma^2}\right)$

Similarly, The global probability of detection (PD) under independent decision is:

$$P_D^{K-out-of-N} = \sum_{j=K}^{N} \binom{N}{j} {P_D}^j (1 - P_D)^{N-j} \quad (15)$$

Where $\mathrm{P_D} = Q\left(\frac{\lambda - \mathrm{N}(\sigma\ + \mathrm{SNR})}{\sqrt{2N}(\sigma^2 + \mathrm{SNR})}\right)$

Equations (14) and (15) model the probability that at least k CRs report detection

3. PROPOSED SCHEME

3.1. System Architecture

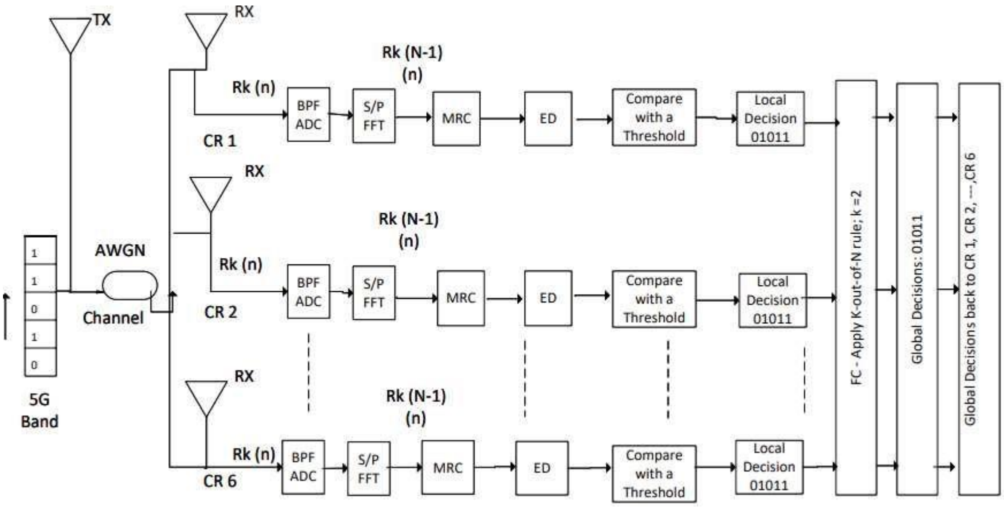

Figure 1: Architecture for Cooperative Wideband Spectrum Sensing with MRC

The system architecture for wideband cooperative spectrum sensing is designed to enhance efficient spectrum utilization, a necessity in 5G and beyond, by managing vast spectral signals across multiple sub-bands in cognitive radio (CR) networks. The architecture implements Maximal Ratio Combining (MRC) at the pre-detection stage alongside an optimized K-out-of-N fusion rule at the fusion center, facilitating precise detection of spectral opportunities even under low SNR and AWGN conditions.

To reduce design complexity, the received signal was segmented into five sub-bands within a 100 MHz channel bandwidth, resulting in a total bandwidth of 500 MHz from 3.3 GHz to 3.5 GHz.

We adopted the energy detection (ED) method owing to its simplicity and non-coherent characteristics and tackled the challenges of noise uncertainty by employing cooperative sensing. Each cognitive radio (CR1-CR6) receives a continuous signal via its antenna, encompassing a wide range of frequency components from multiple primary user (PUs) sub-bands. A bandpass filter (BPF) is applied to the signal to eliminate frequencies outside the target bandwidth, mitigating aliasing in later processing stages. The signal is subjected to a Fast Fourier Transform (FFT), after which the energy of each frequency element or sub-band is determined by adding the squared amplitudes of the FFT results, reflecting the power distribution across the frequency spectrum.

Energy detection plays a vital role in spectrum sensing by assessing whether a signal is present in a frequency band based on the energy levels in that sub-band. Each CR generates a local binary decision transmitted to the fusion center. The fusion center aggregates these decisions using the K-out-of-N fusion rule to reach a global decision.

3.2. Integration of MRC and k-out-of-N Rule

- Each CR will use the MRC-combined statistic E_{mrc} instead of each CR's own received energy E_k .
- The detection rule at each CR now depends on the MRC-weighted decision statistic:

$$E_{mrc} = \sum_{k=1}^{k} w_k E_k \tag{16}$$

Each CR applies energy detection using :

$$u_{MRC} = \begin{cases} 1, \ if \ E_{MRC} > \lambda \ (detection) \\ \ \ 0, \ otherwise \end{cases} \tag{17}$$

The fusion center applies the k-out-of-N rule using these MRC-based decisions:

$$P_{FA}^{(K-out-of-N,MRC)} = \sum_{j=K}^{N} \binom{N}{j} ({P_{FA}}^{MRC})^{j} (1 - {P_{FA}}^{MRC})^{N-j} \tag{18}$$

$$P_{D}^{(K-out-of-N,MRC)} = \sum_{j=K}^{N} \binom{N}{j} {P_D}^{MRC^{j}} (1 - {P_D}^{MRC})^{N-j} \tag{19}$$

Where ${P_{FA}}^{MRC}$ and ${P_D}^{MRC}$ are computed using the MRC-based detection probabilities.

By integrating MRC and k-out-of-N rule, the system gains improved SNR, adaptive decision making and reduced noise uncertainty.

3.3. The Algorithm

The algorithm outlines the procedure for comparing detection probabilities between noncooperative and cooperative spectrum sensing in wideband cognitive radio networks. As more cognitive radio users engage in the sensing process, integrating Maximal Ratio Combining (MRC) the K-out-of-N fusion rule's optimal k value significantly enhances detection performance, particularly in challenging low-SNR environments and low false alarm rates. The algorithm effectively validates the proposed scheme's ability to enhance cooperative wideband spectrum sensing, showing its robustness across a channel environment with varying SNR conditions ranging from -20 dB to 1 dB.

Algorithm Wideband Sensing with MRC and K-out-0f-N Fusion Rule

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Input: numCRs, SNR_range, Pd_i, Pfa_i, Weights_MRC, MaxPfa, Noise Power
Output: NonCoopPd, Optimal-K, Best Num. of CRs needed to declare detection
1: Initialize: Set optimal K to 1, maxPd to 0
2; Initialize NonCoopPd to 0
3: Compute detection threshold = Noise Power* qfuncinv(pfa_i)
4: Calculate NonCoopPd using the computed threshold
5: Perform MRC using Weights_MRC
6: Compute the combined Pd and Pfa from the MRC output for the current SNR 7: for K =1 to numCRs do:
8: Use MRC outputs to calculate Pd and Pfa by applying K-out-of-N at the fusion center 9: If Pfa <= MaxPfa and Pd > maxPd then:
10: update optimalK = K
11: update maxPd = Pd
12 End if
13 If K < numCRs, repeat k+1, otherwise, go to end
14 End for
14 Return NonCoopDet
15: Return an array of optimal_K corresponding to each SNR in the SNR_range
16: End Algorithm

4. PERFORMANCE EVALUATION

4.1. Simulation Setup

All simulations were conducted in a MATLAB environment to analyze the probability of detection (PD) performance when Maximal Ratio Combining (MRC) was integrated with the Kout-of-N fusion rule and when only the K-out-of-N fusion rule was applied. We evaluated PD as a function of the signal-to-noise ratio (SNR) and examined its relationship with the probability of false alarm (PFA). The detection performance was evaluated using six cognitive radios, with the optimal value of k selected as 2. The evaluation of energy detection under Additive White Gaussian Noise (AWGN) for cooperative and non-cooperative wideband spectrum sensing followed the methodology outlined in [4,5]. The K-out-of-N fusion rule was implemented solely for optimal decision-making at the fusion center.

Results demonstrated that cooperative sensing consistently outperformed noncooperative sensing across all sub-bands, mainly when an optimal k was chosen and high SNR. However, at very low SNRs, the probability of detection across varying PFA values was not significantly different from that of the non-cooperative approach, highlighting a key limitation. Although cooperative sensing remains a promising solution for mitigating noise uncertainty in energy detection, deplorable SNR conditions severely degrade the performance of cooperating nodes, particularly when the false alarm rate is reduced [4,5].

4.2. Detection Performance of Combined Maximal Ratio Combining and K-Out-ofN Fusion Rule

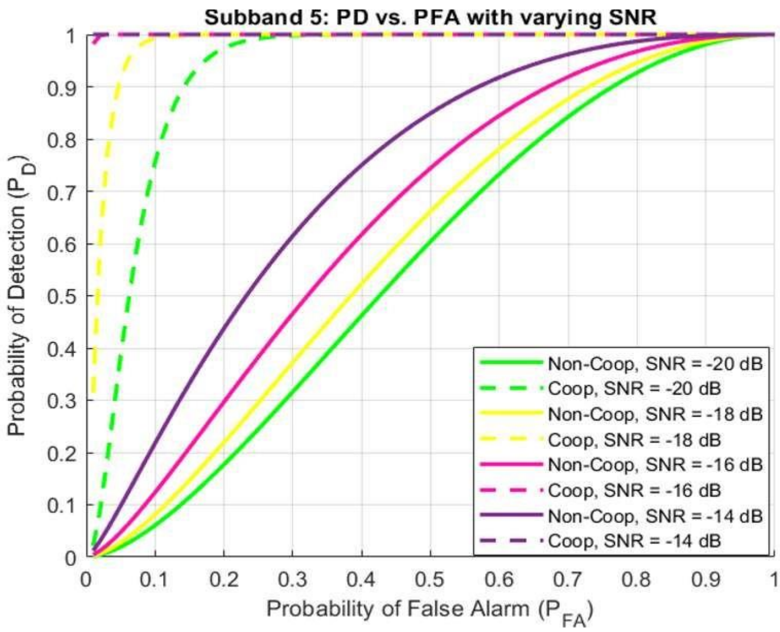

Figure 2: Plot of PD versus PFA across varying SNR with MRC and k-out-of-N Rule

Figure 2 shows the probability of detection (PD) versus the probability of false alarm (PFA) plots for six cognitive radios (CRs) in a cooperative setup. With the integration of Maximal Ratio Combining (MRC) and an optimal k value of 2 in the K-out-of-N fusion rule, cooperative wideband spectrum sensing consistently outperforms non-cooperative wideband spectrum sensing across various signal-to-noise ratio (SNR) conditions. This performance advantage is evident at low PFA and SNR levels, demonstrating improved detection reliability.

The findings demonstrate a notable improvement in detection accuracy relative to the results in (4,5), which were achieved under comparable methodological and environmental settings where the k-out-of-N rule was applied solely for the decision -making at the fusion center. The integration of MRC contributes to mitigating noise uncertainty, allowing cooperative sensing to achieve higher PD values, particularly at low SNRs, where traditional cooperative and non-cooperative sensing struggle.

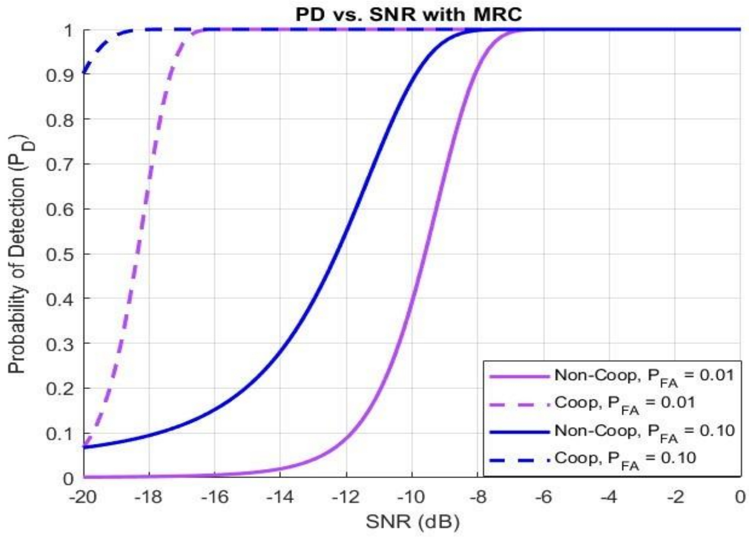

Figure 3: Plot of PD versus SNR across varying PFA with MRC and k-out-of-N Rule

Figure 3 depicts the probability of detection (PD) versus signal-to-noise (SNR) for six cognitive radios (CRs) within a cooperative sensing configuration. As noted in the preceding analysis, cooperative wideband spectrum sensing consistently surpasses non-cooperative wideband spectrum, especially at low false alarm probabilities (PFA) and low SNR values. The proposed framework substantially enhances detection capability by incorporating Maximal Ratio Combining (MRC) and selecting an optimal k value of 2 for the k-out-of-N fusion strategy. Specifically, at PFA = 0.10 and SNR of -20 dB, the proposed approach achieves an optimal PD of 0.9, an outcome that previous studies in [4,5] could not attain under the same conditions, with the K-out-of-N fusion rule implemented at the fusion center. This outcome underscores the advantage of integrating MRC into cooperative sensing, as it improves the SNR prior to detection, thereby boosting sensitivity to weak signals. These results further confirm the resilience of the proposed model in addressing noise uncertainty, promoting more dependable spectrum sensing, and improving the overall performance of cognitive radio networks in 5G scenarios

5. CONCLUSIONS

This study has successfully validated an improved cooperative spectrum sensing (CSS) framework that incorporates Maximal Ratio Combining (MRC) alongside the K-out-of-N fusion rule, designed to function effectively under low signal-to-noise ratio (SNR) conditions. By implementing this approach in a complex Gaussian noise environment, the findings demonstrate a significant enhancement in detection probability while preserving a low false alarm rate across various low SNR scenarios. This performance surpasses conventional cooperative and noncooperative wideband spectrum sensing methods, which tend to underperform in similarly challenging conditions.

The integration of MRC as a soft combining method effectively mitigates the harmful impact of noise uncertainty, a critical limitation in traditional CSS techniques. Additionally, the optimized selection of ‘K’ within the K-out-of-N decision rule improves detection accuracy, ensuring a more resilient and efficient sensing process even in suboptimal environments. These advances strengthen the reliability of spectrum sensing and contribute to the broader objective of optimizing spectrum utilization in increasingly crowded networks.

Future work will investigate incorporating artificial intelligence (AI) and machine learning (ML) methods to adaptively choose the optimal value of ‘k’ in the k-out-of-N fusion rule. AI-driven techniques could enable autonomous system adjustments to varying conditions, further optimizing detection performance without requiring manual recalibration.

We acknowledge, however, that real-world 5G and IoT deployments are affected by path loss, log normal shadowing, and multipath fading (e.g., Rayleigh or Rician). These effects significantly influence the reliability of spectrum sensing and cooperation decision making. We are considering the extension of our framework to integrate large-scale fading (path-loss and shadowing) and small-scale multi-path fading (e.g., Rayleigh Nakagami-m) to account for temporal variations in channel quality.

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