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Performance Analysis of Cooperative Spectrum Sensing Technique in Cognitive Radio with Different Fusion Rule and Technique

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***Abstract*— The spectrum sensing problem has gained new aspects with cognitive radio and opportunistic spectrum access concepts. It is one of the most challenging issues in cognitive radio systems. In cognitive radio mobile ad hoc networks (CR-MANETs), secondary users can cooperatively sense the spectrum to detect the presence of primary users. Spectrum sensing, that is, detecting the presence of the primary users in a licensed spectrum, is a fundamental problem for cognitive radio. As a result, spectrum sensing has reborn as a very active research area in recent years despite its long history. All the implementation and simulation were done in Matlab. Here we are proposing cooperative spectrum sensing with fading environment and trying to increasing detection probability and decrease false alarm. Also evaluate their performance in terms of probability of detection and false alarm.**

This paper is mainly divided into three parts: In first part, we are finding the probability of detection as well as probability of missed detection with respect to probability of false alarm with Rayleigh channel for cooperative spectrum sensing. Here, in this part energy detector sensing method is used because this method is having low complexity. We are also considering AWGN channel as a reference channel. In second part we are finding probability of detection with respect to probability of false alarm with different rules like AND, OR and K out of N in idle as well as in fading environment. Also I am comparing this all rules including individual detection and checking which rule give better detection probability. And finally I am comparing energy detector and match filter method with different SNR and finding that which methods give better result for detection.

***Index Terms*—Additive white Gaussian noise (AWGN), cognitive radio(CR), cooperative spectrum sensing, Matrix Laboratory (MATLAB), probability of false alarm(Pf), probability of missed detection(Pm), Region of Convergence(ROC), signal to noise ratio (SNR), spectrum sensing.**

I. INTRODUCTION

In recent years, there has been a rapid growth of different wireless technologies and standards. This trend may be spurred by the customer requirement of high-capacity and high rate wireless services in dissimilar environments, e.g., indoors and outdoors. The main precursors for CR research was the seminal work by Mitola and Maguire in 1999 and early spectrum measurement studies conducted as early as in 1995 to quantify the spectrum use, both in the licensed and unlicensed band. In the United States, CR research focused quickly on dynamic spectrum access (DSA) and secondary use of spectrum as the main objectives of the initial research. The most notable project in the spectrum management and policy research was the XG-project funded by DARPA. CR is being intensively investigated and debated by regulatory bodies as the enabling technology for opportunistic access to the so-called TV white spaces (TVWS): "We see significant scope for cognitive equipments using interleaved spectrum to emerge and to benefit from international economics of scale" [1]. More recently, on February 16, 2009, Ofcom published a new consultation providing further details of its proposed cognitive access to TVWS. With both the United States and United Kingdom adapting the cognitive access model, and the emerging 802.22 standard for cognitive access to TV bands being at the final stage, we can expect that CR may become mainstream technology worldwide in the near future. [2] In cognitive radio systems, the unlicensed (secondary) users can use the licensed spectrum as long as the licensed (primary) user is absent at some particular time slot and some specific geographic location. We can define cognitive radio as A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation. This is a very crucial feature of CR Networks which allow users to operate in licensed bands without a license. To achieve this goal, spectrum sensing is an indispensable part in cognitive radio. Cooperative spectrum sensing has recently been studied. There are several advantages offered by cooperative spectrum sensing over noncooperative spectrum sensing. Moreover, because of the hidden terminal problem, it is very challenging for single-CR sensitivity to outperform the primary user receiver by alarge margin to detect the presence of primary users. For this reason, if secondary users spread out in the spatial distance and any one of them detects the presence of primary users, then the whole group can gain benefit by collaboration The remaining part of this paper is organized as follows. Introduction is in first part. In second part we describe system model. In third part different fusion policy are there for detection in idle as well as in fading environment. Part four contain match filter detection. And part five and six contain simulation results and conclusion.

II SYSTEM MODEL

Describing the system model, we first list the main notations that are going to be used in this paper for additional clarity and to avoid any kind of confusion when going back to [3] and [4].

- s(t) : signal waveform.
- n(t) : noise waveform which is modelled as a zero-mean white Gaussian random process.
- N_{01} : one-sided noise power spectral density, i.e., $N_{01} \equiv N_0$.
- $N02 = \frac{N01}{2}$: two sided noise power spectral density.
- fc : carrier frequency.
- Pd : probability of detection.
- Pf : probability of false alarm.
- Pm = 1− Pd : probability of missing.
- H0 : hypothesis 0 corresponding to no signal transmitted.
- H1 hypothesis 1 corresponding to signal transmitted.
- λ : energy threshold used by the energy detector.
- T : observation time interval, seconds.
- W : one-sided bandwidth (Hz), i.e. positive bandwidth of
- The low-pass (LP) signal.

The classical energy detection is under the test of the following two hypotheses:

$$H0: y(t) = n(t) \tag{1}$$

$$H1: y(t) = h(t) * x(t) + n(t) \tag{2}$$

y(t) is the signal received by secondary user, x(t) is the transmitted signal by primary user and n(t) indicates the additive white Gaussian noise, h(t) is the amplitude gain of the channel. Under H0, the input y(t) is noise alone. Under H1, the input y(t) is signal plus noise. The probability of detection and false alarm are generally expressed as:[11],[5]
Now received signal is in the form

$$r(t) = hs(t) + n(t), \tag{3}$$

where h=0 or 1 under hypotheses H0 or H1, respectively. As described in [7], the received signal is first pre-filtered by an ideal band pass filter with transfer function

$$H(f) = \begin{cases} \frac{2}{\sqrt{N_{01}}} \left| f - f_c \right| \le W \\ 0, \left| f - f_c \right| > W \end{cases} \tag{4}$$

To limit the average noise power and normalize the noise variance. The output of this filter is then squared and integrated over a time interval T to finally produce a measure of the energy of the received waveform. The output of the integrator denoted by Y will act as the test statistic to test the two hypotheses H0 and H1. [1234]

$$Y = \sum_{i=1}^{2u} ni'^2 \tag{5}$$

Y can be viewed as the sum of the squares of 2u standard Gaussian variates with zero mean and unit variance. Therefore, Y follows a central chi-square (χ^2) distribution with 2u degrees of freedom.

$$Y \sim \begin{cases} \chi_{2u}^2, H0 \\ \chi_{2u}^2(2\gamma), H1 \end{cases} \tag{6}$$

The probability density function (PDF) of Y can then be written as

$$f_Y(y) = \begin{cases} \frac{1}{2^u \Gamma(u)} y^{u-1} e^{-\frac{y}{2}}, H0 \\ \frac{1}{2}\left(\frac{Y}{2\gamma}\right)^{\frac{u-1}{2}} e^{\frac{-2\gamma+y}{2}} I_{u-1}\left(\sqrt{2\gamma y}\right), H1 \end{cases} \tag{7}$$

Where Γ (.) is the gamma function Iv(.) is the vth order modified bessal function.

NEYMAN-PEARSON CRITERIA

Spectrum sensing is a binary hypothesis testing problem, with the null and alternative Hypotheses

H0 : Primary user not active : $z = 0$, (8)

H1 : Primary user active : $z \neq 0$. (9)

There are two well-known strategies for solving a binary hypothesis testing problem; Baysian method and Neyman-Pearson (NP) method [9]. The Bayesian method is based on the minimization of a Bayesian risk function which, under equal costs of a false alarm and missed detection, reduces to the minimization of the probability of error. By introducing $\theta \in \{0,1\}$ as indices to the null and alternative hypotheses, the probability of error can be represented by $P\left(\hat{\theta} \neq \theta\right)$, where $\hat{\theta}$ is the decision on θ. The NP method is based on the maximization of the probability of detection $P\left(\hat{\theta} = 1 \mid \theta = 1\right)$, while maintaining a given probability of false alarm $P\left(\hat{\theta} = 1 \mid \theta = 0\right)$.

The optimal decision that minimizes the probability of error is the maximum a posterior (MAP) decision [9]

$$\hat{\theta} = \arg \max_{\theta \in \{0,1\}} P\left(H_0 \mid y_1^K\right) \tag{10}$$

If no prior information on H0 is available, the MAP decision is equivalent to the maximum likelihood (ML) decision which is equivalent to choosing H1 if and only if

$$\frac{p(y_1^K \mid \underline{z \neq 0})}{p\left(y_1^K \mid \underline{z = 0}\right)} > \frac{1}{2} \tag{11}$$

The optimal NP method similarly employs a likelihood ratio test (LRT) [9] by choosing H1 if and only if

$$L(y_1^K) = \frac{p(y_1^K \mid \underline{z \neq 0})}{p\left(y_1^K \mid \underline{z = 0}\right)} > \lambda \tag{12}$$

where the threshold λ is found by solving (numerically or analytically)

$$P_f = \int_{y_1^K : L(y_1^K) > \lambda} p\left(y_1^K \mid \underline{z = 0}\right) dy_1^K \tag{13}$$

for a given desired probability of false alarm Pf .

In both (11) and (12), we need to evaluate the likelihood function $p(y_1^K \mid \underline{z})$ for z = 0 and otherwise. From Bayes' rule, we have

$$p(y_1^K \mid \underline{z}) \alpha \frac{p(\underline{z} \mid y_1^K)}{p(\underline{z})} \tag{14}$$

or in other words, the likelihood can be found from the a posteriori probability (APP) distribution of $\underline{z}$. The detection problem can therefore be decomposed into a Bayesian inference problem, namely finding $P\left(\underline{z}=0 \mid y_1{}^K\right)$ and $P\left(\underline{z}\neq 0 \mid y_1{}^K\right)$.

III FUSION POLICY

After the secondary users individual results are send to the band manager, then depending upon which method is used for decision combining, the band manager can use diverse fusion rule along with any of the above mention decision combining method for effective decision making. There are number of rule for fusion that the base station or band manager can use

.AND Regulation for Fusion

$$Q_d = \coprod_{i=1}^{n} Pd$$

$$Q_{fa} = \coprod_{i=1}^{n} Pfa \tag{15}$$

OR REGULATION FOR FUSION

$$Q_d = 1-\left(1-P_d\right)^n$$

$$Q_{fa} = 1-\left(1-P_{fa}\right)^n \tag{16}$$

K OUT OF N REGULATION

$$Q_d = \sum_{i}^{k}\left[C_n{}^i\left(P_d\right)^i\left(1-P_d\right)^{n-i}\right]$$

$$Q_{fa} = \sum_{i}^{k}\left[C_n{}^i\left(P_f\right)^i\left(1-P_{fa}\right)^{n-i}\right] \tag{17}$$

IV MATCH FILTER DETECTION

The matched filter provides an alternative to the signal correlator for demodulating the received signal r (t). A filter that is matched to the signal waveform s(t), where $0 \le t \le T_b$, has an impulse response

$$h(t) = s(T_b - t),\ 0 \le t \le T_b \tag{18}$$

Consequently, the signal waveform-say, y(t) at the output of the matched filter when the input waveform is s(t), given by the convolution integral

$$y(t) = \int_0^t s(\tau)h(t-\tau)dt \tag{19}$$

If we substitute in (19) for $h(t-\tau)$ from (18), we obtain

$$y(t) = \int_0^t s(\tau)h(T_b - t + \tau)dt \tag{20}$$

And if we sample y(t) at $t = T_b$, we obtain

$$y(T_b) = \int_0^{T_b} s^2(t)dt = E \tag{21}$$

Where E is the energy of the signal s(t). therefore, the matched filter output at the sampling instant $t = T_b$ is identical to the output of the signal correlator.

The impulse responses of the two matchfilter are

$$h_0(t) = s_0(T_b - t),$$

$$h_1(t) = s_1(T_b - t), \tag{22}$$

Now suppose the signal waveform $s_0(t)$ is transmitted. Then the received signal $r(t) = s_0(t) + n(t)$ is passed through the two match filters. The response of the filter with impulse response $h_0(t)$ to the signal component $s_0(t)$. Also the response of the filter with impulse response $h_1(t)$ to the signal component $s_0(t)$. Hence, at the sampling instant $t = T_b$, the outputs of the two matched filters with response $r_0(t)$ and $h_1(t)$ are respectively.

$$r_0 = E + n_0$$

$$r_1 = n_1$$

Note that these outputs are identical to the outputs obtained from sampling the signal correlator outputs at $t = T_b$.

The detector observes the correlator or matched filter outputs r_0 and r_1 and decides whether the transmitted signal waveform is $s_0(t)$ or $s_1(t)$, which correspond to the transmission of either a 0 or a 1, respectively. The optimum detector is defined as the detector that minimizes the probability of error or increase the detection probability.

The physical phenomenon is the reflection of radio waves (that are transmitted from an antenna) off structures like buildings, mountains, trees, what not..Thus the received signal is a sum of several reflections with different delays, different phase changes and different amplitude attenuations.

V. SIMULATION RESULTS

Figure 1 and 2 shows the plot of detection probability of AND rule under AWGN channel and Rayleigh channel respectively. From figure 2 we can see that as we increase the probability of false alarm the probability of detection exponentially increased.

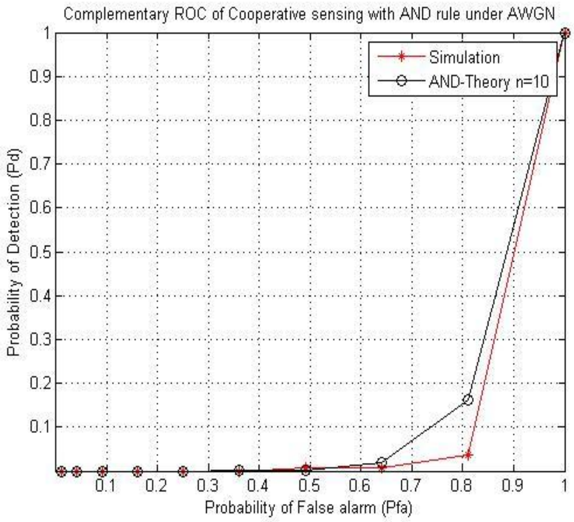

Figure.1 Pd with AND rule under AWGN channel.

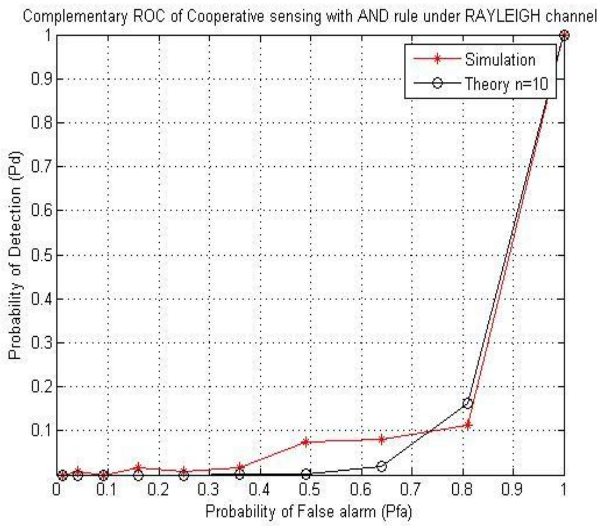

Figure 2 Pd with AND rule under Rayleigh channel.

II Simulation with OR rule

Up to now we show simulation with AND rule in ideal and fading environment. Now we are going to see it with OR rule. Figure 3 and 4 shows probability of detection vs. probability of false alarm using OR rule.

Figure 5 and 6 shows the plot of cooperative spectrum sensing with K out N rule under AWGN and Rayleigh channel respectively. We plot the graph of probability of detection vs. probability of false alarm. Here we can see that red line shows simulation value and black line shows theoretical value. Also we can see that both simulations as well as theoretical graph are very similar. We can see that detection probability is increase as the false alarm probability is increase

Figure 7 shows the plot of cooperative spectrum sensing with all the different rule. We plot the graph of probability of detection vs. probability of false alarm. Here we see that black line shows plot for AND rule, green line shows plot for OR rule, red line hows plot for K out of N rule and blue line shows individual detection. We can see that the OR rule give better performance than other rule and the plot of K out of N is in between the OR and AND rule. Individual detection line is go linearly

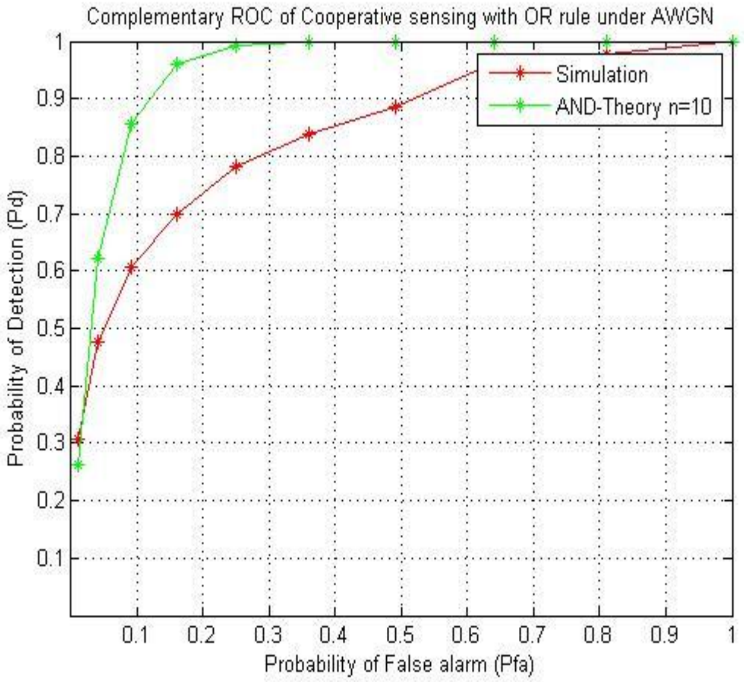

Figure. 3 Pd vs Pfa with OR rule under AWGN channel

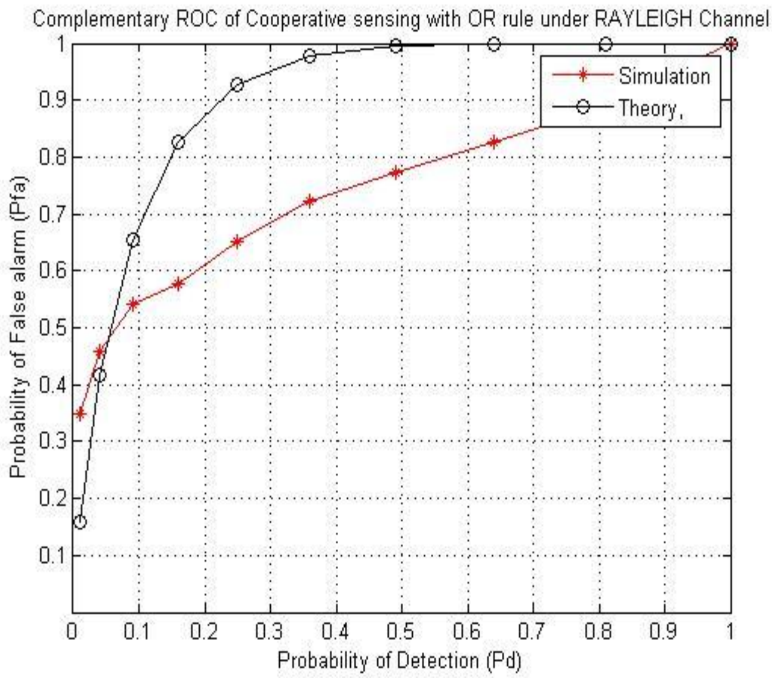

Figure.4 Pd vs. Pfa with OR rule under Rayleigh fading

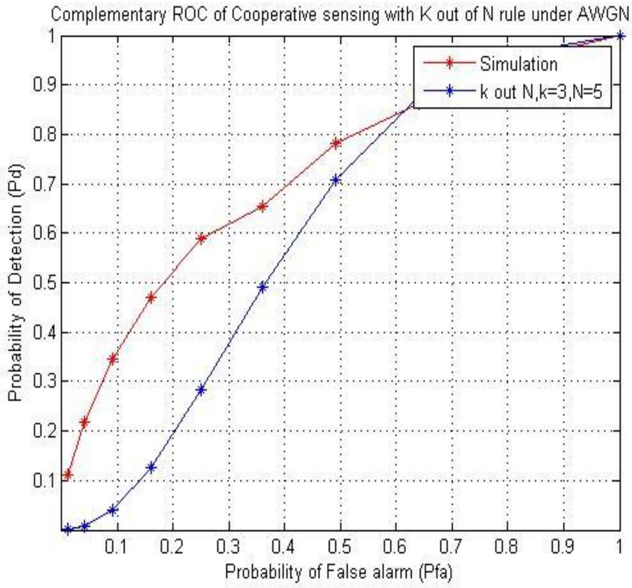

Figure 5 Pd vs Pa with k out of N under AWGN

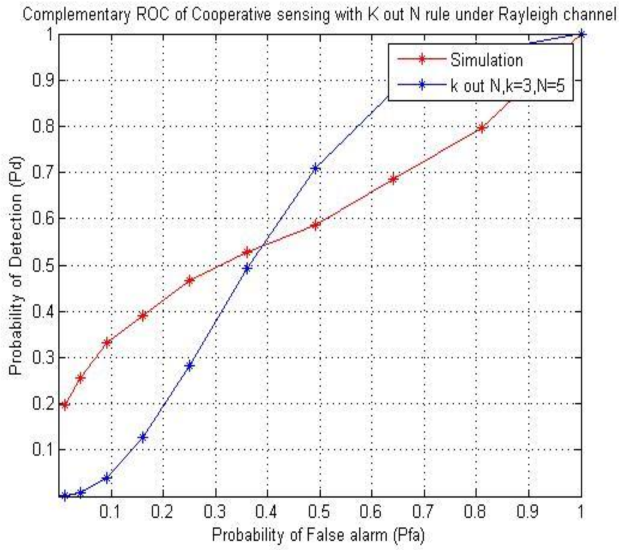

Figure 6 Pd vs Pa with k out of N under Rayleigh

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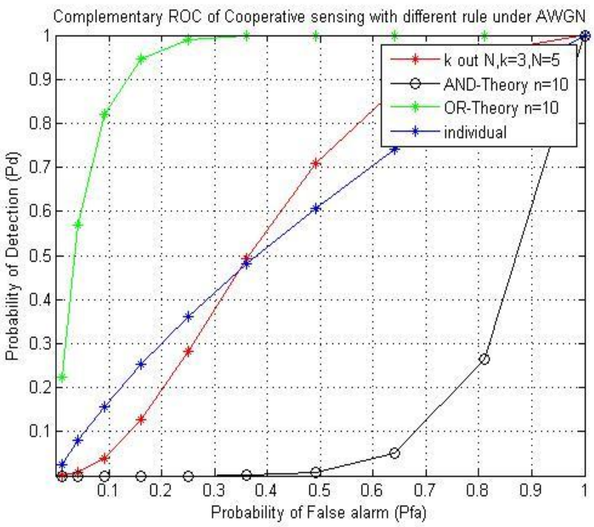

Figure .7 cooperative Sensing with Different Rules

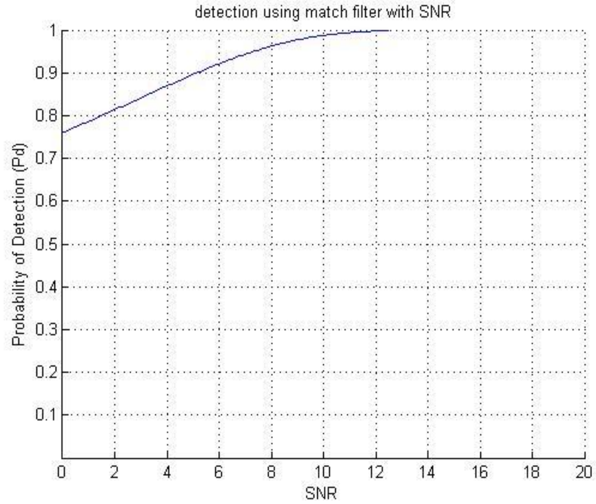

Figure .8 Detection Using Match Filter

VI CONCLUSION

From this paper we conclude that, as we increased the probability of false alarm, the probability of detection is increased in a exponential manner. Here, we used the Rayleigh fading channel and also it compared to AWGN reference channel taking different rules. We conclude that in a fading environment the results are not as good as compared to AWGN channel. But the results are better as we increased the number of users. Here, we also compared the theoretical results with the simulated results. Also we see that as the comparison of all the rules and can identify that which rule is better and we see the detection using match filter is much better then energy detector with different SNR.

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