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# RATE-MAXIMIZED COOPERATIVE SU SELECTION BASED ON EIGENVALUES FOR COGNITIVE RADIO NETWORKS

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**Abstract:** It is clear that the future of wireless communication systems will face the problem of spectrum scarcity. Cognitive radio systems currently hold a significant position as a solution to this problem. Cognitive radios scan for spectrum gaps and make available for reuse of empty spectrum bands. In this study, we proposed a novel threshold for this method using a different cooperative spectrum sensing method with Standard Condition Number (SCN) for cognitive radios. Detailed simulation studies were included to evaluate the performance of the method. In the simulation studies, different eigenvalue-based sensing methods and energy-based sensing methods were compared using MIMO-OFDM based communication systems. The simulation studies proved the efficiency of the proposed cooperative method.

**Keywords:** Cognitive radio, Radar systems, Spectrum sensing, Standart condition number, Noise uncertainty

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## 1. Introduction

In recent years, as a result of the rapid development of wireless communication technologies, spectrum shortage problem has been emerged. The biggest factor that leads to spectrum shortage is the fixed spectrum assignment policies. According to the fixed spectrum assignment policy, a spectrum region assigned to the licensed user with a fixed spectrum assignment is not allocated to other users even if the licensed user does not use this band (Wang & Liu, 2011). Thus, the radio frequency spectrum cannot be used efficiently. The report prepared by Federal Communications Commission (FCC) reveals the spectrum utilization rates. As seen in the report, the rate of use in some spectrum regions is very low (Zhang et al., 2010; Akan et al., 2009). Therefore, to use the spectrum more efficiently, some methods have been developed (Li et al., 2012). In order to increase the efficiency of the spectrum, the most important of the developed technologies is Cognitive Radio. Cognitive Radio (CR) is an adaptive, intelligent radio technology that can automatically detect vacant spectrum bands in a wireless radio spectrum. The initial step in CR systems is to evaluate the current spectrum and determine the spectrum gaps. Because, when spectrum detection is done incorrectly, legal responsibilities arise as licensed users will restrict their access to the spectrum. Different detection methods have been proposed to make the most accurate sensing for different channel environments and detection scenarios. The detection method to be used should be determined according to whether the noise level is known, the antenna number/secondary user in the system or the modulation scheme. For example, if the noise level is known, the energy detection method is the most successful method. Besides when the energy level is known, energy detection is a simple method that can be applied to any signal type without requiring priori knowledge about the primary user (PU) signal (Li & Lu, 2016; Zhang et al., 2008). However, when the noise level is not known, it should be determined by some estimation methods (Guo et al., 2005). Therefore, the estimation errors that may occur constitute an unsuccessful spectrum detection value. But the most fragile method against the noise uncertainty factor is the energy sensing method. Cyclostationary-based detection is only applicable to OFDM-based systems and may not be available in some systems (Gibson & Zafar, 2008; Qi et al., 2009). Although eigenvalue based detection methods are not very favorable in terms of calculation cost, they are highly resistant to noise uncertainty (Zeng & Liang, 2009; Kortun et al., 2014). Eigenvalue based detection methods can be examined in two groups as semi-blind (requiring knowledge of noise level) and blind (Zeng & Liang, 2009; Edelman, 2005). These methods of detection have been applied for both non-cooperative and cooperative detection scenarios (Souid et al., 2017; Matthaiou et al., 2010). As it is known, cooperative detection is more successful than non-cooperative methods despite the negative effects of wireless communication channel (Taherpour et al., 2010).

Although the eigenvalue based spectrum detection methods are not very advantageous in terms of calculation cost, they are frequently used because they do not require any prior knowledge about the signal and noise power to be detected. There are different eigenvalue statistics used for eigenvalue based detection in the literature.

Although the most common ones are Standart Condition Number (SCN) and Demmel Condition Number (DCN ) statistics (Kortun et al., 2011; Kortun et al., 2012), different eigenvalue ratios are used. Some of these studies have been investigated both for finite sample length and asymptotically (Matthaiou et al., 2010; Pillay & Xu, 2012). In some studies, double threshold methods have been proposed to increase the probability of detection(Li et al., 2012; Verma & Singh, 2016). Different threshold values for different eigenvalue-based detection methods have also been proposed, since the determined threshold value directly affects the detection performance (Çiflikli & Ilgin, 2018).

In this paper, we investigate the spectrum detection problem in the presence of complex Gaussian noise with eigenvalue based spectrum detection model. Unlike eigenvalue based detection methods, we propose two innovations in this study. First of them, we propose a new threshold value to improve the detection performance. Second, we propose a new cooperative detection method. It has been seen from the simulation studies that this method provides a significant increase in performance compared to traditional non-cooperative methods. In order to measure the success of the obtained threshold value, the results were compared with different eigenvalue based spectrum detection methods such as classical MME and MET.

The remaining of the paper is organized as follows. In Section II, we describe the system model and the basic assumptions about the PU signal, noise and eigenvalue based spectrum sensing. The proposed threshold derivation and the presence of some statistical values for cooperative detection are described in section III. The performance analysis of the proposed method is given in section IV. In this section, detection scenarios are examined both cooperatively and non-cooperatively. In addition, energy-based spectrum sensing is included in the results. Finally, Section V concludes the paper. Throughout this paper, we use boldface letters for matrices and normal letters for column vector.

## 2. Material and Methods

### 2.1. Basic Assumptions and Cooperative Sensing Model

Consider a spectrum detection scenario as shown in Figure 1. A primary base station (PBS) services a population of randomly distributed secondary user (SU)'s within its coverage. In the proposed detection model, we assume that there are $L$ secondary users, and each secondary user has $m$ detection antennas. Assume that the signal that each secondary user detects is stored in the $x$ matrix. This assumption applies to an OFDM signal in which each PU is contained. We indicate the hypothesis of the PBS signal being passive and active (within the coverage of the CR) by $H_0$ and $H_1$, respectively. We assume that noise samples at different antennas have independent zero-mean Gaussian random variables. Under $H_1$, we assume that the noise and PBS signal are independent variables. Let the observed signals at the PUs $\boldsymbol{x} = [\mathrm{x}_1, \ldots \ldots, \mathrm{x}_\mathrm{k}] \in \mathbb{C}^{\mathrm{mxn}}$ be a complex matrix comprising the sensing signals at $m$ antennas.

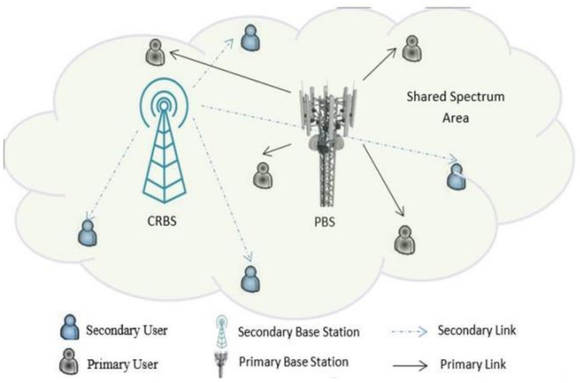


**Figure 1**. Typical detection scenario.

The multiple PU sensing problem can be expressed as the following binary hypothesis test (Patil & Patil, 2016) (equation 1):

$$\begin{cases} H_0: \boldsymbol{x} \sim \mathcal{N}\left(0, \sigma_\eta^2\, \boldsymbol{I}_m\right) \; \textit{if the PBS is passive}, \\ H_1: \boldsymbol{x} \sim \mathcal{N}\left(0, \sigma_s^2\, \boldsymbol{I}_m + \sigma_\eta^2\, \boldsymbol{h}\boldsymbol{h}^H\right) \; \textit{if the PBS is active}. \end{cases} \tag{1}$$

Besides $\boldsymbol{h} \in \mathbb{C}^{\mathrm{px1}}$ is the channel coefficient vector between PBS and SU. The active or passive state of the primary transmitter for conventional MME is determined by comparing a test statistic with a threshold value. conventional eigenvalue based spectrum detection (with SCN statistic) is expressed mathematically as follows (equation 2).

$$\frac{cov(\boldsymbol{x})l_{max}(\boldsymbol{R_\eta})}{cov(\boldsymbol{x})l_{min}(\boldsymbol{R_\eta})} \tag{2}$$

Where $lmax/lmin$ and $\xi$denote the test statistic and the threshold, respectively. $cov(\boldsymbol{x})l_{max}(\boldsymbol{R_\eta})$ and $cov(\boldsymbol{x})l_{min}(\boldsymbol{R_\eta})$ are defined as eigenvalues of the covariance matrix obtained from the same secondary user under $H_0$. Namely (equations 3 and 4),

$$l_{max} = \max_{l} \left[eig\left\{\frac{1}{n}\boldsymbol{x}\boldsymbol{x}'\right\}\right] \tag{3}$$

$$l_{min} = \min_{l} \left[eig\left\{\frac{1}{n}\boldsymbol{x}\boldsymbol{x}'\right\}\right] \tag{4}$$

However, in the proposed cooperative detection method, $l_{max}$ and $l_{min}$ are obtained from different users. This situation is expressed mathematically as follows. For more detailed information on the statistical behavior of eigenvalues of random matrices (Edelman, 2005) (equations 5 and 6).

$$\tilde{l}_{max}(\boldsymbol{R_\eta}) = max\{l_{max,1}, l_{max,2}, \cdots\cdots l_{max,L}\} \quad (5)$$

$$\tilde{l}_{min}(\boldsymbol{R_\eta}) = min\,\{l_{min,1}, l_{min,2}, \cdots\cdots l_{min,L}\} \quad (6)$$

In this study, $\hat{l}_{min}$ is taken from different SU and $\hat{l}_{max}$ is from a different SU. Thus, the test statistics can be calculated even greater at high noise levels (Section 4 contains a figure related to this equation). The probability of false alarm ($P_{fa}$) is defined as follows (equation 7).

$$P_{fa} = P\,(H_1|H_0) = P\,\left(\frac{\tilde{l}_{max}(\boldsymbol{R_\eta})}{\tilde{l}_{min}(\boldsymbol{R_\eta})} > \xi\right) \quad (7)$$

Under $H_0$, if the necessary arrangements are made, $\hat{l}_{max}$ converges to Tracy-Widom of order 1 (Deo, 2016) (equation 8).

$$P\left(\frac{\tilde{l}_{max}(\boldsymbol{R_\eta})\frac{n}{\sigma_\eta^2} - \mu_d}{\sigma_d}\right) \to TW_1 \quad (8)$$

Where $\mu_d$ and $\sigma_d$ are defined as scale and center parameters. The most accurate values for these parameters are defined as follows (equations 9-12).

$$\mu_d = \mu_m + (-1.2065)\sigma_m \quad (9)$$

$$\mu_m = n^{-1}\left(\sqrt{n-0.5} + \sqrt{p-0.5}\right)^2 \quad (10)$$

$$\sigma_m = \left(\frac{\mu_m}{n}\right)^{\frac{1}{2}}\left(\frac{1}{\sqrt{n-0.5}} + \frac{1}{\sqrt{p-0.5}}\right)^{\frac{1}{3}} \quad (11)$$

$$\sigma_d^2 = \frac{nm}{2+nm}\left(\sigma_m^2 - \frac{2}{nm}\mu_m^2\right) \quad (12)$$

According to detection theory, the threshold should be determined to maximize $P_d$ versus a specific $P_{fa}$ value. Since the probability distribution of the largest eigenvalue is known under the $H_0$ hypothesis, the threshold can be obtained as follows (equation 13).

$$P_{fa} = P\,(H_1|H_0) = P\,(\tilde{l}_{max}(\boldsymbol{R_\eta}) > \xi\,\tilde{l}_{min}(\boldsymbol{R_\eta})) \quad (13)$$

Where the center value of the smallest eigenvalue converges to $\sigma_\eta^2\left(1-\sqrt{m/n_s}\right)^2$ (equation 14).

$$P_{fa} = P\left(\tilde{l}_{max}(\boldsymbol{R_\eta}) > \xi\,\sigma_\eta^2\left(1-\sqrt{\frac{m}{n_s}}\right)^2\right) \quad (14)$$

Then, one side of equation 15 must be likened to the distribution TW1.

$$P_{fa} = P\left(\tilde{l}_{max}(\boldsymbol{R_\eta}) > \xi\sigma_\eta^2\left(1-\sqrt{\frac{m}{n_s}}\right)^2\right) \quad (15)$$

By rearranging the terms (equations 16-19),

$$P_{fa} = P\left(\tilde{l}_{max}(\boldsymbol{R_\eta})\frac{n}{\sigma_\eta^2} > \xi\,\sigma_\eta^2\left(1-\sqrt{\frac{m}{n_s}}\right)^2\frac{n}{\sigma_\eta^2}\right) \quad (16)$$

$$P_{fa} = P\left(\tilde{l}_{max}(\boldsymbol{R_\eta})\frac{n}{\sigma_\eta^2} > \xi\left(1-\sqrt{\frac{m}{n_s}}\right)^2 n\right) \quad (17)$$

$$P_{fa} = P\left(\left(\frac{\tilde{l}_{max}(\boldsymbol{R_\eta})\frac{n}{\sigma_\eta^2} - \mu_d}{\sigma_d}\right) > \frac{\left(\xi\left(1-\sqrt{\frac{m}{n_s}}\right)^2 n\right) - \mu_d}{\sigma_d}\right) \quad (18)$$

$$P_{fa} = 1 - TW_1\left(\frac{\left(\xi\,\left(1-\sqrt{\frac{m}{n_s}}\right)^2 n_s\right) - \mu_d}{\sigma_d}\right) \quad (19)$$

It follows that (equation 20);

$$TW_1^{-1}(1-P_{fa}) = \left(\frac{\left(\xi\,\left(1-\sqrt{\frac{m}{n_s}}\right)^2 n_s\right) - \mu_d}{\sigma_d}\right). \quad (20)$$

Where $P_{fa}$ is the limit determined by the FCC ($P_{fa}$ = 0.1). When this parameter is substituted, $TW_1^{-1}(0.9)$ has a predetermined value (equations 21 and 22).

$$0.45 = \left(\frac{\left(\xi\,\left(1-\sqrt{\frac{m}{n_s}}\right)^2 n_s\right) - \mu_d}{\sigma_c}\right) \quad (21)$$

Thus;

$$0.45\,\sigma_d = \left(\left(\xi\left(1-\sqrt{\frac{m}{n_s}}\right)^2 n_s\right) - \mu_d\right) \quad (22)$$

Where $n_s$ is defined as the smoothing factor. Specifies the number of samples to be taken consecutively. The goal is to reduce the process cost by minimizing the number of samples (equation 23).

$$0.45\,\sigma_d + \mu_d = \left(\xi\left(1-\sqrt{\frac{m}{n_s}}\right)^2 n_s\right) \quad (23)$$

Therefore (equation 24),

$$\frac{0.45\,\sigma_d + \mu_d}{n_s} = \left(\xi\left(1-\sqrt{\frac{m}{n_s}}\right)^2\right) \quad (24)$$

Finally, the proposed threshold can be obtained as follows (equation 25).

$$\xi = \frac{0.45\,\sigma_d + \mu_d}{n_s}\left(1-\sqrt{\frac{m}{n_s}}\right)^2 \quad (25)$$

If the proposed threshold is observed, the parameters $n_s$ and $p$ are sufficient for the calculation. The noise power does not need to be determined. Thus the method is completely blind. Theoretically, $Pd$ is given in the Appendix.

## 3. Result and Discussion

In this section, we present some numerical results to evaluate the performance of the proposed cooperative eigenvalue based detectors. In this study, the detection model given in Figure 1 was used. Figure 2 shows $P_d$ for different SNRs with $P_{fa}$ = *0.1*, $n_s$ = *100*, *L = 4* and $=$ 2 . In order to evaluate the performance of the proposed method more accurately, performance analysis has been made according to $L$ and $m$ numbers at different values.

The most important reason for this is that while selecting values $\tilde{I}_{max}$ and $\tilde{I}_{max}$these values are selected from different users in such a way that they are proportionally greatest. Analysis has been made according to $L$ and $m$ numbers at different values. The graph of the variation of these values is given in Figure 3. In the graph, the variation of the test statistics with the threshold value for n = 1000, m = 4 and L = 4 is given for different noise levels. Where the threshold value is about 2,1. As can be seen, the point at which the proposed test statistic value is greater than the threshold value (blue circle) is at the level of -11 dB. But the same value is -4.7 dB for the classical method (black circle). Mathematically, it can be written as $P_d = P\ (H_1|H_1) = P\ (\tilde{I}_{max}/\tilde{I}_{min} > \xi)$. As can be seen, the point at which the proposed test statistic value is greater than the threshold value (blue circle) is at the level of -11 dB. But the same value is -4.7 dB for the classical method (black circle). Therefore, it makes a higher probability of detection at the higher noise levels recommended.

Figure 4 represents $P_d$ for different SNRs with $P_{fa}$ = 0.1, $n_s$ = 1000, $L$ = 4 and $m$ = 2 . Where again the performance of the proposed cooperative method is remarkable. Increasing the number of samples, improves detection performance in all methods. Increasing the number of samples increases the detection performance for all methods.

**Table 1.** OFDM parameters

| Parameter | Value |
|---|---|
| OFDM Bandwidth | 10 MHz |
| Number of Subcarriers (N) | 64 |
| FFT Size | 64 |
| Number of Used Subcarriers | 52 |
| Cyclic Prefix Length | 16 Samples |
| Modulation Scheme | QPSK |
| Number of OFDM Symbols | 1000 |
| Sampling Frequency | 10 MHz |
| Channel Model | AWGN |
| MIMO Configuration | 2×2 |
| Number of Received Samples | 1000 |
| False Alarm Probability ((P_{fa})) | 0.1 |

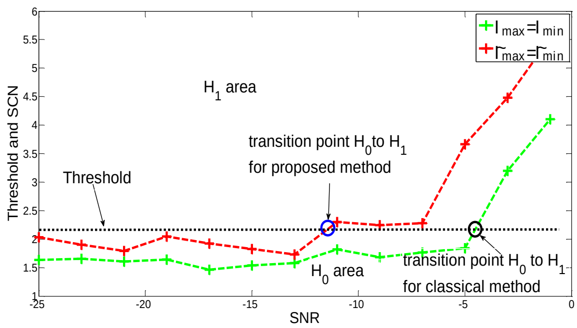


**Figure 2**. Threshold versus Test Statistics for $n$ = 1000, $m$ = 4 and $L$ = 4.

However, for the proposed method, it provided a significant increase in performance, particularly at high noise levels (between -25 dB and -15 dB). because when the number of samples increases, it converges the largest eigenvalue distribution further to TW1. This can be explained by equation 8. In addition, this graph shows that the classical MME and the cooperative MME (both AND and OR) perform very closely. Thus, the importance of the proposed cooperative detection emerges. Because cooperative detection can often improve performance when there are many secondary users. However, the proposed method offers successful performance even for relatively few users.

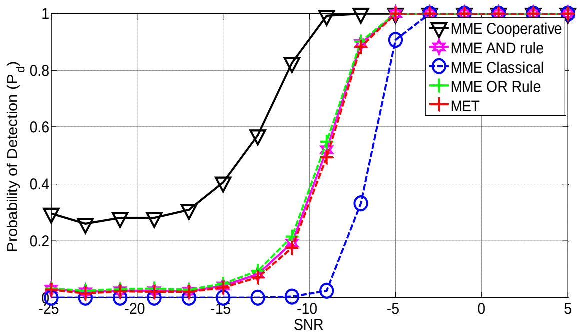


**Figure 3**. $P_d$ versus SNR, $P_{fa}$ = 0.1, $n_s$ = 1000, $L$ = 4 and $m$ = 2.

The $P_d$ versus SNR is shown in Figure 5, where the sample size is $n_s$ = 5000. Besides $L$ = 8 and $m$ = 4. The proposed cooperative MME sensed with a probability value of approximately 0.7 at -25 dB.

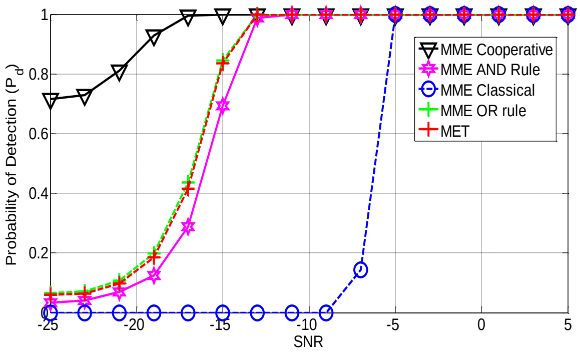


**Figure 4**. $P_d$ versus SNR, $P_{fa}$ = 0.1, $n_s$ = 5000, $L$ = 8 and $m$ = 4.

As seen, the increase of $L$ and $m$ has provided more successful perception for classical cooperative detection. However, the proposed method is noticeably more successful.

In addition, all of these methods are independent of the noise uncertainty factor. Such that the noise uncertainty factor generally ranges from 1-2 dB. Therefore, in methods such as energy detection (Kortun et al., 2012), the noise uncertainty factor may adversely affect detection performance. As mentioned in the introduction, this is one of the biggest advantages of eigenvalue-based perception.

Figure 6 shows the sensing performances for the proposed method and ED, based on specific noise uncertainty factor values. The ED method is known to be the most fragile method against noise uncertainty. Furthermore, the noise uncertainty factor is a parameter that always exists in the wireless communication environment. therefore, eigenvalue-based detection methods are more advantageous than ED-based methods with this feature. As can be seen, the increase in noise uncertainty factor from 0 to - 2dB leads to a significant decrease in performance in ED method.

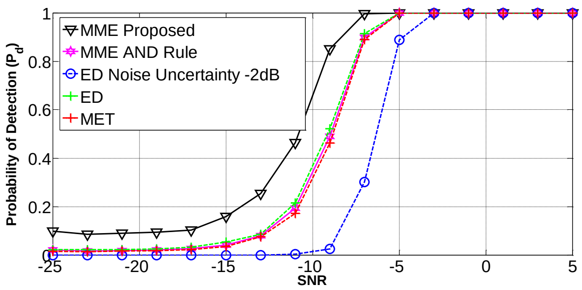


**Figure 5.** $P_d$ versus SNR, $P_{fa}$ = 0.1, $n_s$ = 1000, $L$ = 2 and *m* = 2.

## 4. Conclusion

In this study, spectrum detection problem in the presence of gaussian noise for eigenvalue MIMO-OFDM based communication systems is discussed. In this context, a new threshold was obtained for spectrum detection using SCN statistics. In addition to this, a new cooperative detection model has been proposed in contrast to traditional cooperative sensing. It is known that cooperative detection has a positive effect on detection performance, especially at high noise levels. The proposed new method has been supported by the simulation studies in which the performance increases considerably compared to the traditional methods. Future work will investigate the application of the proposed method in practical cognitive radio scenarios, including time-varying channels, heterogeneous user environments, and real-time implementation constraints. Moreover, the proposed method maintains low computational complexity due to its eigenvalue-based structure, making it suitable for practical cognitive radio implementations. Future work will investigate its performance under more realistic channel conditions and real-time communication scenarios.

## Appendix

$$P_{fa} = P\left(H_1|H_1\right) = P\left(\frac{\tilde{l}_{max}(\boldsymbol{R_x})}{\tilde{l}_{min}(\boldsymbol{R_x})} > \xi\right)$$

$l_{max}(\boldsymbol{R_x})$ are defined as eigenvalues of the covariance matrix obtained from the secondary user under $H_1$(include channel effect). Namely,

$$\tilde{l}_{max}(\boldsymbol{R_x}) = \rho_{max} + \tilde{l}_{max}(\boldsymbol{R_\eta})$$

$$\tilde{l}_{min}(\boldsymbol{R_x}) = \rho_{min} + \sigma_\eta^2$$

Where $\rho_{min}$ and $\rho_{max}$ are the largest and smallest eigenvalues of the channel effect.

$$P_d = P(\tilde{l}_{max}(\boldsymbol{R_x}) > \xi\, \tilde{l}_{min}(\boldsymbol{R_x}))$$

$$P_d = P\left(\tilde{l}_{max}(\boldsymbol{R_x}) + \rho_1 > \xi\, \sigma_\eta^2\left(1-\frac{m}{n_s}\right)^2\right)$$

$$P_d = P\left(\tilde{l}_{max}(\boldsymbol{R_x}) > \xi\left(\sigma_\eta^2\left(1-\frac{m}{n_s}\right)^2\right) - \rho_{min}\right)$$

$$P_d = 1 - TW_1\left(\frac{\left(\xi\left(\sigma_\eta^2\left(1-\frac{m}{n_s}\right)^2\right) - \rho_{min}\right) - \mu_d}{\sigma_d}\right)$$

### Author Contributions

The percentages of the author' contributions are presented below. The author reviewed and approved the final version of the manuscript.

| | F.Y.I. |
|---|---|
| C | 100 |
| D | 100 |
| S | 100 |
| DCP | 100 |
| DAI | 100 |
| L | 100 |
| W | 100 |
| CR | 100 |
| SR | 100 |
| PM | 100 |
| FA | 100 |

C= concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

### Conflict of Interest

The author declared that there is no conflict of interest.

### Ethical Consideration

Ethics committee approval was not required for this study because there was no study on animals or humans.

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