Energy Efficiency Under Double Deck Relay Assistance on Cluster Cooperative Spectrum Sensing in Hybrid Spectrum Sharing

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ABSTRACT Rapid growth in demand for spectrum resources and technology expansion in wireless communication systems such as satellite communication networks and upcoming 5G networks has led us to investigate the best cognitive radio network scheme towards achievements of energy efficiency in wireless communication networks for cooperative spectrum sensing. In this paper, we introduce a double-deck cluster cooperative relay assistance model in hybrid spectrum sharing for cognitive radio networks. This proposed model enables the attainment of energy efficiency by optimizing cooperative secondary users in their respective cluster groups. According to the design of this model, we apply the power allocation scheme under mathematical analysis based on its power constraints. Normalized energy consumptions and amplifying gains are achieved and assessed for both network scenarios when cognitive relays are used and not used in the network. Simulation results show that there is a good performance on the energy efficiency of our proposed scheme compared to a traditional scheme.

INDEX TERMS Cognitive radio, cognitive relay assistance, cooperative spectrum sensing, energy efficiency, hybrid spectrum sharing.

I. INTRODUCTION

The rapid development and timely technological advancement in wireless communication services have led to a fast increase in demand for spectrum resources by both secondary users (SUs) and primary users (PUs) [1]. However, a task force of the Federal Communication Commission (FCC) was formed to conduct a study that showed a scarcity of spectrum resources, and even the available ones were already under license to be used by other communication operators [2]. Therefore, to solve these challenges several surveys were made on cognitive radio (CR) technology whereby cognitive cycles, features, and spectrum sensing models were studied to meet the fast-growing demand for wireless communication services [3]. The introduction of CR technology has enabled spectrum resources to be utilized in opportunistic sensing access (OSA) without causing interferences to PUs in the

spectrum [4], [5]. Despite good performance in detection made under OSA, however, tremendous energy consumption (EC) is rising as another problem to be researched [6], [7]. However, there are several studies have been made on energy efficiency (EE) in cognitive radio networks (CRNs); In [8], authors have proposed an energy-based sensor selection scheme in cooperative spectrum sensing (CSS) to enhance the lifespan and energy efficiency of sensors by avoiding unequal battery drainage among them. In [9], the authors proposed a three double threshold method in spectrum scarce vehicular communications to limit sensing overheads and the number of secondary users (SUs) involved in spectrum sensing (SS) to reduce EC. In [10], a cluster CSS with four fusion rules scheme was proposed to maximize EE by optimizing the fusion rule, whereby the transmission power and sensing time were presented by the joint optimization problem. Authors in [11] proposed a heterogeneous node based on an adaptation of a low energy clustering hierarchy scheme whereby the global information is updated by involving the

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average cluster radius and optimal numbers before it is broadcasted. In [12], the authors proposed an energy awareness optimal relay selection scheme to reduce transmission errors by determining optimal relays underweighted objective functioning. In [13], the authors proposed a scheme on optimal hybrid spectrum sharing (HSS) under bandwidth constraints of control channels and multiple hard decisions to maximize the throughput of the CRN. In [14], authors have proposed a spectrum mapping scheme in SS under kennels function based on vector machine adoption to enhance performance accuracy by using filtration and accuracy threshold. However, in all these works, the basic aim is not based on cooperating cluster groups (CCG) of CRs under double decking relay assistance (DDRA) with a target to reduce EC in CRNs at the same time maintaining the detection accuracy of the spectrum status. Therefore, these disadvantages led us to come with novel contributions of our paper which rely on the design of a DDRA model on cluster CSS in HSS strategy under the power allocation scheme, optimal energy consumption (OEC), and reliable throughput. The energy optimization problem involves several power constraints, as can be shown in (1).

$$E_{opt} = min_{N,w} KMw\beta \tag{1}$$

where E_{opt} is the OEC reliable for accurate detection of PU signals, K is the number of CRs, M is the number of CCG formed, whereas N is the number of samples used, and β is the mean product transmission power under-sampling interval. The main advantages of our work include; 1. Determination of OEC proportional to reliable throughput required for detection. 2. It can be used in the large scale CRN and wide geographical area such as 5G terrestrial-satellite fusion networks due to its ability to propagate signals in CCG. 3. It enables the determination of maximum throughput reliable for PD to be achieved. 4. Enables determination of amplifying gains (AG) through cooperative relay assistance (CRA) and minimal channel distances. The organization of this paper is structured as follows, in section II, the system model and preliminaries are presented, followed by section III, where the EE of the proposed scheme is analyzed. In section IV, the simulation results are shown and explained, whereas, in section V, statements and conclusion of the proposed scheme are summarized.

II. SYSTEM MODEL AND PRELIMINARIES

A. SYSTEM MODEL

Descriptions of the CRN proposed in combatting EC problems are as shown in Fig.1, which involves PUs and SUs grouped into clusters sending information to their respective cluster heads (CHs), then from CHs to the central cluster head (CCH) where the overall signal collected is then propagated to the FC through a single relay assisted channel. The main function of the FC is to receive the overall sensed information from a CCH then determine the global decision under fusion rule on whether there is an existence of PUs or not in the spectrum, after a decision is made then the FC broadcasts
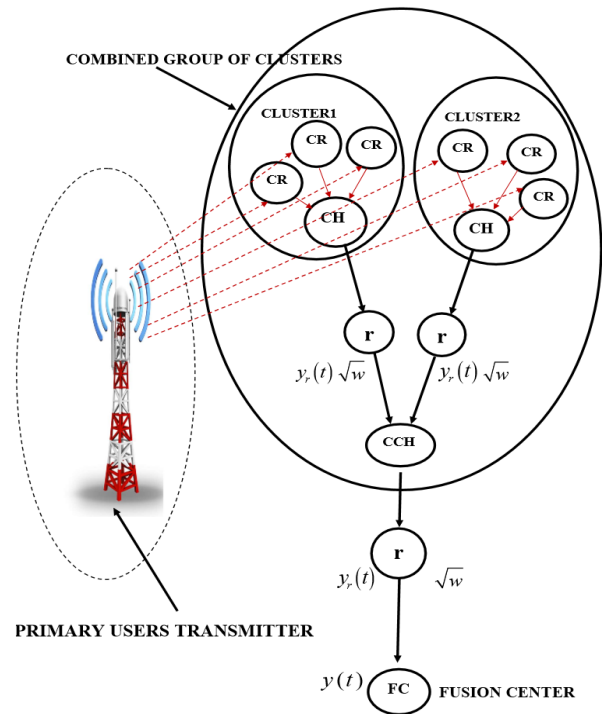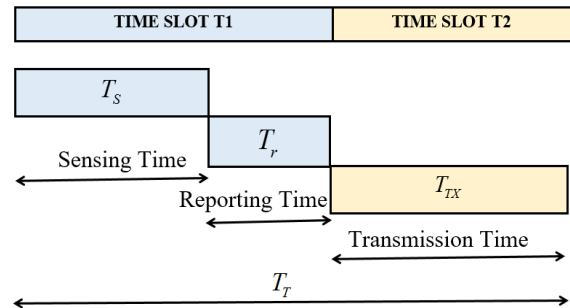

FIGURE 1. System model.

FIGURE 2. Time frame.

the information results to other cognitive radio users so that they can utilize the spectrum gap in an opportunistic manner [15]. However, during sensing time, an adaptation of the dual transmission power levels is made by the SUs according to the results obtained.

A double-deck scenario is based on relay assistance CR with the CCH as a core part of the network to receive a signal from CCG. Each CH has digital filters (DF) which restore distorted signal and separate it when contaminated by noise signal or interferences during its transmission time. However, under HSS, the spectrum resources are well utilized by both OSA and SS, whereby, SUs begin by detecting the spectrum environment then followed by the initiation of two levels of powers due to the coexistence of both PUs and SUs in the spectrum, given that there must be an interference tolerable environment among them. The time frame (TF) structure is described in Fig.2, where the total frame distance is assumed

to be static and is given by T_t causing the total distance of the TF to be short, and hence more energy can be gained in the transmission phase. Other TFs include reporting time T_r, transmission time T_{RX}, and sensing time T_s which is extended due to the inclusion of OSA and SS enabling the detection accuracy to increase. The information sensed can be given in binary hypothesis test H_1 when the PU is present and H_0 when absent [16], as shown in (2).

$$y(t) = \begin{cases} n(t), & H_0 \\ hy_i(t) + n(t), & H_1 \end{cases} \quad (2)$$

where $n(t)$ is zero-mean additive white Gaussian noise (AWGN), $y(t)$ is the sample signal sensed by SUs during the SS period, $y_i(t)$ is the primary user signal, whereas, H_0 and H_1 are the hypotheses test for PUs absent and present.

B. COOPERATIVE SPECTRUM SENSING

In this paper, SUs cooperate into cluster groups having uniform transmission distances from sensing nodes to the CH of the same cluster group, whereas each cluster group is assumed to be far or close from CHs to the CCH with a respective periodic time, hence cognitive relays are used to AF the weak signal to the CCH, where local decisions of all CCG are collected to be propagated to the FC through a single CRA relay channel. Hence, the overall signal received at each CH can be given as shown in (3).

$$y_{cli}(t) = \sum_{i=1}^{K} h_{chi} x_i(t) + \sigma y_i(t) + n_i(t) \quad (3)$$

where σ is the binary symbol representing PUs present for $\sigma = 1$ and PUs absent for $\sigma = 0$, K is the number of CRs, h_{chi} is the fading channel from CRs to CHs, $y_{cli}(t)$ is the summation of signal received at each CH, and $n_i(t)$ is the noise signal. Therefore, we assume that the signal gain contribution of relays between CHs and CCH are negligible due to the short transmission channel distance between CHs and CCH. Hence the relay output signal from the CH is approximately to be equal to the output signal at the CH, whereas, the cognitive relay contribution between CCH and FC is assumed to be large to the global output signal at the FC due to long transmission channel distance involved. In that regard, the cognitive relay output signal between CHs and CCH can be presented as shown in the cognitive relay equation below,

$$y_{ai}(t) = h_{ai} y_{cli}(t) + n_i(t) = y_{cli}(t) \quad (4)$$

where h_{ai} are the fading channels from CHs to cognitive relays of each cluster group channel, $y = a_{ai}(t)$ is the output relay signal between CH and CCH propagating the signal to CCH, and $y_{cli}(t)$ is the output signal at CHs. Therefore, the overall signal received at the CCH can be presented as given in (5).

$$y_{cch}(t) = \sum_{j=1}^{M} h_{hhj} y_{clij}(t) + n_j(t) \quad (5)$$

where h_{hhj} is a fading channels from CHs to the CCH, $y_{clij}(t)$ is a summations of signals received at each CH, $y_{cch}(t)$ is the summation of signal received at CCH, M is the total number of clusters in the network, $n_j(t)$ is noise signals, whereas j and i are iteration times of the signal. The cognitive relay equation of the network at the CCH can be given as shown in (6), whereas the amplified signal by the cognitive relay received at the FC can be given as shown in (7).

$$y_r(t) = h_{hr} y_{cch}(t) + n(t) \quad (6)$$
$$y(t) = \sqrt{w} h_{rf} y_r(t) + n(t) \quad (7)$$

where, $y_r(t)$ is the signal received at the cognitive relay, $y(t)$ is the overall sampled signal of the CRN received at the FC, and $\sqrt{w}$ is the amplification factor of the global network signal. However, by substituting (5) into (6), the overall sampled signal can be as given in (8).

$$y(t) = \sqrt{w} h_{rf} (h_{hr} y_{cch}(t) + n(t)) + n(t) \quad (8)$$

Likewise, by substituting (5) into (8) the equation representing the signal carrying both hypothesis (H_0) and (H_1) is obtained as shown in (9) below.

$$y(t) = \sqrt{w} h_{rf} (h_{hr}(\sum_{j=1}^{M} h_{hhj} y_{cli}(t) + n_j(t)) + n(t)) + n(t) \quad (9)$$

Therefore, to achieve the sensed signal for PUs present $\sigma = 1$ in the spectrum, we substitute (3) into (9) and when absent $\sigma = 0$ we substitute (3) into (10). However, whenever PUs are present, then the signal is detected by cognitive sensors and transmitted in the CRN [17]. Hence, overall signal equations after substitution can be given, as shown in (10) and (11).

$$y(t) = \sqrt{w} h_{rf} (h_{hr}(\sum_{j=1}^{M} h_{hhj}(\sum_{i=1}^{K} h_{chi} x_i(t) + \sigma y_i(t) + n_i(t)) + n_j(t)) + n(t)) + n(t) \quad (10)$$
$$y(t) = \sqrt{w} h_{rf} (h_{hr}(\sum_{j=1}^{M} h_{hhj}(\sum_{i=1}^{K} h_{chi} x_i(t) + n_i(t)) + n_j(t)) + n(t)) + n(t) \quad (11)$$

By applying test statistic formula in (11) under N number of samples, the total signal $y(t)$ of the CRN at the FC can be given as shown in (12) below,

$$Y = \sum_{t=1}^{N} |y(t)|^2 \quad (12)$$

where t is the number of the hypothesis tested and $y(t)$ is the overall output signal of CRNs. At this stage of transmission, the FC makes a global decision by identifying PUs presence or absence in the spectrum to enable SUs to utilize spectrum holes opportunistically [18], [19].

In our paper, we use the K-means algorithm to formulate cognitive radios into cluster groups with their CHs and the CCH, as shown in Algorithm 1.

Algorithm 1 K-Means Clustering Algorithm for CSS in Hybrid Spectrum Sharing

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Input: M: Number of clusters
Initialize: $N_1, K = 1 : M$
Train data: $X = [X_1, X_2 \ldots . X_N]^X$
Output: $N_m : K = 1 : M$
Repeat:
1. Assign data closest to centroid by using euclidean distance between trained data X_N^X and cluster mean
2. Calculate $\sum_{K=1}^{M} \sum_{X_N^X \in C_K} |X^X - M|^2$
3. Calculate $M_K = 1/n(C_K) \sum_{X_N^X \in C_K} X_N^X$
4. Compute new centroid of each trained data cluster to achieve CHs
5. Determine the CCH of CHs achieved in 4
6. **Until** convergence

III. SOFT AND HARD DECISION COOPERATION

In our paper, we use both the soft decision combination at the CH of each cluster group under the Log-Likelihood Ratio (LLR) and hard decision combination at CCHs and FC deciding the global network status by applying weighted decision fusion rule.

A. SOFT DECISION COMBINATION

In the soft decision combination, the energy values from PUs are detected at SUs as local detected signals and then propagated to the CH of each cluster group for the local decision to be made under the Log-Likelihood ratio. Therefore, the test statistics of the detected signals received and combined at CHs can be expressed as,

$$Y_c = \sum_{j=1}^{M} \sum_{t=1}^{N} |y(t)|^2 \tag{13}$$

where the detected signal $y(t)$ received at CH of each cluster is used to determine the PUs presence or absence under hypotheses test H_1 and H_0. However, the test statistic Y_c under hypothesis H_1 with the non-central variables and degree of freedom is an independent random variable with a non-central Chi-square distribution random variable. Whereas under hypothesis H_0 with the degree of freedom is an independent Chi-square distribution random variable.

The average signal to noise ratio (SNR) of the PUs signal detected at SUs and then propagated to the CH can be expressed as,

$$SNR_p = \frac{1}{N} \sum_{t=1}^{N} \frac{|h_{chi}|^2 |y_i(t)|^2}{n_i(t)} \tag{14}$$

Therefore, by assuming that the SNR of all SUs are similar to all cluster groups and Gaussian noise with unit variance, hence under central limit theorem (CLT) the test statistic distribution under hypothesis H1 or H0 can be expressed as,

$$Y_c = \begin{cases} N(df, 2df), & H_0 \\ N(df(1 + SNR_p), 2df(1 + SNR_p)^2), & H_1 \end{cases} \tag{15}$$

where df is the degree of freedom under Chi-square distribution, SNR_p is a non-central independent Chi-square random variable. Since the decision at CHs is made under the Likelihood Ratio Test (LRT), therefore, for the binary hypothesis test, the Log-likelihood ratio can be expressed as,

$$D_c = \sum_{t=1}^{N} \log \frac{f_Y(Y_c/H_1)}{f_Y(Y_c/H_0)} \underset{<H_0}{\overset{>H_1}{}} C_{Thresh} \tag{16}$$

where D_c is the decision metric, log is the natural logarithm, Y_c is the average signal to noise ratio of primary users at CH of each cluster group, C_{Thresh} is the cluster threshold value for the CH local decision, $f_Y(Y_c/H_1)$ and $f_Y(Y_c/H_0)$ are the probability density function for the cluster head decision under hypothesis test H_1 and H_0.

B. HARD DECISION COMBINATION

In the hard decision combination, the local cluster decision at CHs achieved during soft decision is converted to single-bit decision 1 or 0, then propagated to the CCH and the FC whereby we use the weighted fusion rule to determine the global network decision. Therefore, considering the number of clusters M with local single-bit decisions from CHs received and combined at the CCH and the FC. We let C_{W1} be the weighted factor for the PUs presence, C_{W0} be the weighted factor for the PUs absence, and $dc = [dc_1, dc_2, \ldots . dc_M]$ be the summed single-bit decision received at the CCH. Therefore, the Likelihood Ratio Test for the local decision received at the CCH can be expressed as,

$$\frac{P(dc_1, dc_2, \ldots . dc_M/H_1)}{P(dc_1, dc_2, \ldots . dc_M/H_0)} = \frac{P(dc/H_1)}{P(dc/H_0)} \underset{<H_0}{\overset{>H_1}{}} \frac{P_0}{P_1} \tag{17}$$

where $P_1 = P(H_1)$ and $P_0 = P(H_0)$ are the probabilities of PUs presence and absence. Therefore, the Log-likelihood Rate Test can be expressed as,

$$\sum_{j=1}^{M} [(1 - D_c) \log(\frac{1 - P_{det}}{1 - P_{fa}}) + D_c \log(\frac{P_{det}}{P_{fa}})] \underset{<H_0}{\overset{>H_1}{}} \log \frac{P_0}{P_1} \tag{18}$$

Therefore, let the weighted factor for the PUs absence $C_{W0} = \log(\frac{1 - P_{det}}{1 - P_{fa}})$ and for PUs presence $C_{W1} = \log(\frac{P_{det}}{P_{fa}})$, hence the weighted decision fusion rule can be expressed as,

$$\sum_{j=1}^{M} [(1 - D_c)C_{W0} + D_c C_{W1}] \underset{<H_0}{\overset{>H_1}{}} \log \frac{P_0}{P_1} \tag{19}$$

Therefore, the decision metric for hard decision combination at CCH and FC can be expressed as,

$$C_W = \begin{cases} C_{W0} & if \ D_c = 0 \\ C_{W1} & if \ D_c = 1 \end{cases} \tag{20}$$

Hence, as shown in (20), the global network decision is determined by selecting the weighted factor of either PUs presence or absence by weighted fusion rule.

IV. ENERGY EFFICIENT

A. STRATEGICAL POWER ALLOCATION

Since the overall signal collected at the FC is achieved under energy detection, therefore, the test statistic formula can be used to achieve the mean $E(Y)$ and variance $Var(y)$ of the signal which can be used to allocate the power by multiplying expectation E on both sides in (12). The resultant equation of the mean $E(Y)$ can be given as shown in (21), whereby the total transmission channel distance is assumed to be small and cognitive relays are assumed to have an equivalent allocation of power under independent AWGN signal $n(t)$.

$$E(Y) = E(\sum_{t=1}^{N} |y(t)|^2) \tag{21}$$

Therefore, by substituting (11) and (12) into (21), the mean for both hypothesis H_0 and hypothesis H_1 can be determined as shown in (22) and (23). For Hypothesis H_0 the mean $E(Y)_0$ is given as,

$$E(Y)_0 = E(\sum_{t=1}^{N} |\sqrt{w}h_{rf}(h_{hr}(\sum_{j=1}^{M} h_{hhj}(\sum_{i=1}^{K} h_{chi}x_i(t)$$
$$+ n_i(t)) + n_j(t)) + n(t)) + n(t)|^2) \tag{22}$$

For Hypothesis H_1 the mean $E(y)_1$ is given as,

$$E(Y)_1 = E(\sum_{t=1}^{N} |\sqrt{w}h_{rf}(h_{hr}(\sum_{j=1}^{M} h_{hhj}(\sum_{i=1}^{K} h_{chi}x_i(t)$$
$$+ \sigma y_i(t) + n_i(t)) + n_j(t)) + n(t)) + n(t)|^2) \tag{23}$$

Therefore, from both (22) and (23) we let, $E(|h_{rf}|^2) = E(|h_{hr}|^2) = E(|h_{chi}|^2) = E(|h_{hhj}|^2) = 1$, then we allocate transmission power constraint to expectations of PUs signal, SUs signal, and noise signal by letting, $E(|x_i(t)|^2) = P_s$, $E(|n_i(t)|^2) = P_n$, $E(|n(t)|^2) = P_n$, and $E(|y_i(t)|^2) = P_p$. Whereby transmission power allocation can be given as P_p for PU signals, P_s for SU signals and P_n for the noise signal. Therefore, the transmission power allocation for the overall signal can be given as shown in (24) and (25). For the absence of PUs in the spectrum, it can be given as,

$$E(Y)_0 = N(w(MKP_s + MP_n + 2P_n) + P_n) \tag{24}$$

whereas, for PUs present in the spectrum, the equation can be given as,

$$E(Y)_1 = N(w(MKP_s + MP_p + MP_n + 2P_n) + P_n) \tag{25}$$

Therefore, from (24) and (25) we can determine the mean and variance for hypothesis H_0 and H_1 by letting $\mu_0 = w(MKP_s + MP_n + 2P_n) + P_n$ and $\mu_1 = w(MKP_s + MP_p + MP_n + 2P_n) + P_n$, whereby the mean and variance for hypothesis H_1 can be given as $E(Y) = N\mu_1$ and $Var(y) = 2N\mu_1^2$, whereas for hypothesis H_0 can be given as, $E(Y) = N\mu_0$ and $Var(y) = 2N\mu_0^2$. Therefore, the achievement of the mean and variance can be used to determine the probability of detection (PD) and the probability of false alarm (PFA) in the spectrum under both hypothesis H_1 and H_0, as can be shown in (26) and (27).

$$P_{det} = Q(\frac{\lambda - N\mu_1}{\sqrt{2N\mu_1^2}}) \tag{26}$$

Algorithm 2 Water Filling Algorithm for Power Allocation

Input: P: Input power allocated.
1. **Initialize**: P_n: Noise power, P_t: Transmission power, C_M: Transmission sub-channels, P, I_j: Channel interference.
2. Running the water-filling for set P_n with P, achieve the water level as noise level N_L.
3. Move the cluster channels set C_M if $P_t \geq I_j$.
4. Perform power decrement on set C_M.
5. Perform power increment on set P_n with $\Delta = P_t - I_j$.
6. Update the common water level as power level P_L, for P_t.
7. if $P_t \geq I_j$ **return to** 3.

$$P_{fa} = Q(\frac{\lambda - N\mu_0}{\sqrt{2N\mu_0^2}}) \tag{27}$$

where $Q = \frac{1}{\sqrt{2\pi}} \int \exp(-\frac{t^2}{2})dt$ is the complementary cumulative distribution function (CCDF) of the standard Gaussian random variable respectively.

However, for the power allocation to be successfully achieved, we consider the channel capacity (CC) under Rayleigh fading channels with independent channel coefficients h, zero mean, and variance which is equal to 1. Therefore, the CC of our proposed scheme can be expressed as,

$$C = \log(1 + \frac{1}{P_n} \sum_{j=1} P_j|h_j|) \tag{28}$$

where P_n is the noise power, $P_j(j = 1, \ldots n)$ is the channel power and $h_j(j = 1, \ldots n)$ is the fading channel coefficient. Therefore, the above power allocation strategies can be solved by using the water filling algorithm, as summarized in algorithm 2.

B. NUMBER OF SAMPLE CONSTRAINT

Since thresholds PD and PFA are equivalent to PD of both detection and false alarm of sensed information, hence N can be determined by substituting (26) into (27) for both hypothesis H_0 and H_1 as shown below,

$$\lambda = \sqrt{2N}\mu_1 Q^{-1}(P_{det}^{th} + N\mu_1) \tag{29}$$
$$\lambda = \sqrt{2N}\mu_0 Q^{-1}(P_{fa}^{th} + N\mu_0) \tag{30}$$

Hence, we substitute (29) into (30) to achieve N as shown below,

$$N(\mu_0 - \mu_1) = \sqrt{2N}(\mu_1 Q^{-1} P_{det}^{th} - \mu_0 Q^{-1} P_{fa}^{th}) \tag{31}$$

$$N = 2(\frac{\mu_1 Q^{-1} P_{det}^{th} - \mu_0 Q^{-1} P_{fa}^{th}}{\mu_0 - \mu_1})^2 \tag{32}$$

C. THROUGHPUT CONSTRAINT

Power gains and reliable throughput play an important role in the determination of EE without causing signal interference to PUs. Therefore, channel gains from one node to another

can be denoted by $G_{rf} = |h_{rf}|^2$, $G_{hr} = |h_{hr}|^2$, $G_{chi} = |h_{chi}|^2$, and $G_{hhj} = |h_{hhj}|^2$. In that regard, we let the throughput constraint Z_{CRN} for both hypothesis to be given as,

$$Z_{CRN} = P(H_0)(1 - P_{fa})Z_0 + P(H_1)(1 - P_{det})Z_1 \quad (33)$$

However, it is logical to express (33) as given below,

$$Z_{CRN} = P(H_0)(1 - P_{fa})Z_0 \geq P(H_1)(1 - P_{det})Z_1 \quad (34)$$
$$Z_{CRN} \simeq P(H_0)(1 - P_{fa})Z_0 \quad (35)$$

Therefore, whenever the PU signal is inactive in the spectrum, the throughput of the network can be given as,

$$Z_0 = \log_2(1 + \frac{w \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_s}{w \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_n + P_n}) \quad (36)$$

where Z_0 is the throughput of the network when PU signals are inactive in the spectrum. G_{chi}, G_{hhj}, G_{hr}, and G_{rf} are power gains of the signal.

D. OPTIMAL ENERGY CONSUMPTION
The average transmission power (ATP) of the network in this paper is used to determine the average EC reliable for the signal to be detected and transmitted without causing interferences to PUs in the spectrum. This can be given as shown in (37) below,

$$P_{avg} = P(H_1)(1 - P_{det})w(d_{ch}^{-\alpha} d_{hh}^{-\alpha} d_{hr}^{-\alpha} d_{rf}^{-\alpha}(P_s + P_p + P_n))$$
$$+ P(H_0)(1 - P_{fa})w(d_{ch}^{-\alpha} d_{hh}^{-\alpha} d_{hr}^{-\alpha} d_{rf}^{-\alpha}(P_s + P_n)) \quad (37)$$

where $d_{ch}^{-\alpha}$, $d_{hh}^{-\alpha}$, $d_{hr}^{-\alpha}$ and $d_{rf}^{-\alpha}$ are distances from one node to another. Hence we can use the ATP equation in (37) to calculate the average energy required for the network signal to be sensed and transmitted from SUs to the FC as shown in (38) below,

$$E_{avg} = \sum_{i=1}^{K} \sum_{j=1}^{M} NwP_{avg}T \quad (38)$$

From (38), T is the frame transmission time, w is the power AG, and N is the number of samples. Let $P_{avg}T = \beta$, hence the average transmission energy of the signal can be written as shown in (39) below,

$$E_{avg} = KMNw\beta \quad (39)$$

where β is the ATP per transmission TF of the CRN. Therefore, the minimum EC of the network under throughput reliable for accurate detection without causing interference can be as given below,

$$E_{opt} = min_{N,w}KMNw\beta \quad (40)$$

where K is the number of SUs in each cluster group, whereas M is the number of CCG which must be greater than 1 and kept constant against the AG w. Therefore, conditions required to achieve the optimal EC are such that, the PD is let to be greater than or equal to its relative threshold $P_{det} \geq P_d^{th}$

and PFA be greater than or equal to its relative threshold $P_{fa} \leq P_{fa}^{th}$. Hence, we can achieve the relationship of the threshold throughput by substituting (35) to (36), as shown in (41) being equal or greater than the detection threshold.

$$P(H_0)(1 - P_{fa})$$
$$\times \log_2(1 + \frac{w \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_s}{w \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_n + P_n})$$
$$\geq Z_{th} \quad (41)$$

Hence, the minimum AG of the network can be achieved by expanding (41) as shown in (42) and (43) below,

$$\frac{w \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{G_{hhj}}G_{hr}G_{rf}P_s}{w \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_n + P_n}$$
$$\geq 2^{\frac{Z_{th}}{P(H_0)(1-P_{fa})}} - 1 = \gamma \quad (42)$$
$$w$$
$$\geq \frac{\gamma P_n}{\sum_{i=1}^{K} G_{chi}(\sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_s - \gamma \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_n)}$$
$$= w_{min} \quad (43)$$

The network threshold interference of the network channel can be expressed as,

$$P(H_1)(1 - P_{det})w \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_s + P_n \leq I_{thresh} \quad (44)$$

Hence the maximum AG of the network channel can be expressed as,

$$w \leq \frac{I_{thresh}}{P(H_1)(1-P_{det}) \sum_{i=1}^{K} G_{chi} \sum_{j=1}^{M} G_{hhj}G_{hr}G_{rf}P_s + P_n}$$
$$= w_{max} \quad (45)$$

Finally, the OEC problem can be obtained by substituting (32)-(39), as shown below,

$$E_{opt} = KMw(\frac{\mu_1 Q^{-1}P_d^{th} - \mu_0 Q^{-1}P_{fa}^{th}}{\mu_0 - \mu_1})^2 \quad (46)$$

The optimal amplifying gain within the feasible region between the w_{max} and the w_{min} calculated in (46), can be achieved by using the bisectional algorithm, as shown in Fig.3. However, the determination procedure of the optimal channel gain involves usage of the estimation error tolerance expressed as,

$$E_{rt} = |\frac{10 \log_{10} \check{w} - 10 \log_{10} w}{10 \log_{10} w}| \quad (47)$$

where E_{rt} is the estimation error tolerance of the channel gain, w is the actual amplifying gain, and $\check{w}$ is the estimated amplifying gain.

Therefore, the initial values of the bisectional algorithm are w_{min} and w_{max}, whereby optimal amplifying channel gain can be achieved at a condition when the E_{rt} is greater than the channel gain as shown in algorithm 3 in Fig.3. The achievement of the optimal amplifying gain of the channel
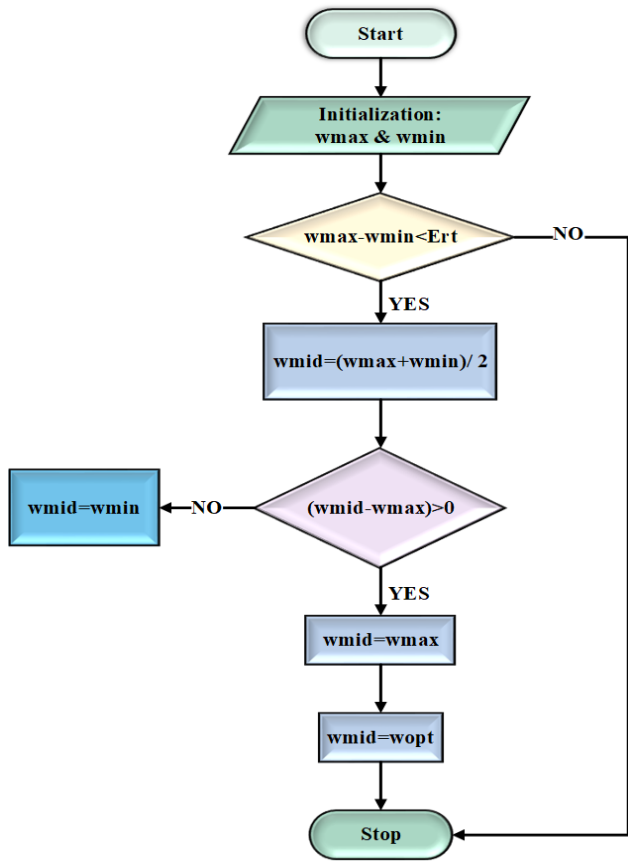
FIGURE 3. Bisectional Algorithm 3.

TABLE 1. List of parameter used.

Parameter	Value
Detection probability P_d^{th}	0.95
False alarm probability P_f^{th}	0.05
Noise variance Pn	0.001 w
Threshold Throughput Z^{th}	0.1 bps/Hz
Time interval T_s	1 ms
PU transmission power P_P	1 w
SU transmission power P_s	1 w
α	3
Probability of primary user absence $P(H_0)$	0.7
Probability of primary user presence $P(H_1)$	0.3
Number of clusters M	3 to 4
β	0.0876
SNR	-10 dB
G_{chi}	0.06
G_{hhj}	0.12
G_{hr}	0.06
G_{rf}	0.05

FIGURE 4. Clustering of secondary users.

enables us to determine the optimal energy consumption of our proposed network channel at its maximum throughput reliable for efficiency sensing of the PUs presence or absence in the spectrum.

V. SIMULATION RESULTS

In this section of the paper, simulation results describe the performance evaluation of the scheme proposed by considering parameters used as listed in Table 1. However, the simulation results of this paper are achieved and plotted by running Matlab software on PC with the processor 2.70 GHz, Intel (R) Core (TM) i5-7200U CPU. The EE of the proposed model is achieved due to determination of its minimum EC proportional to the throughput required for cognitive sensors to sense and perform accurate detection of the spectrum status under several power constraints as described in this paper. However, it should be noted that an optimal sensing time has to be well maintained proportional to the number of samples used to achieve high detection probability, less false alarm probability, maximum throughput, and minimum energy consumption of the CRN [20]. Therefore, less sensing time leads to low detection probability and high false alarm probability, whereas too much sensing time may lead to high levels of both interferences and energy consumption, which may affect the global energy efficiency of the proposed scheme.
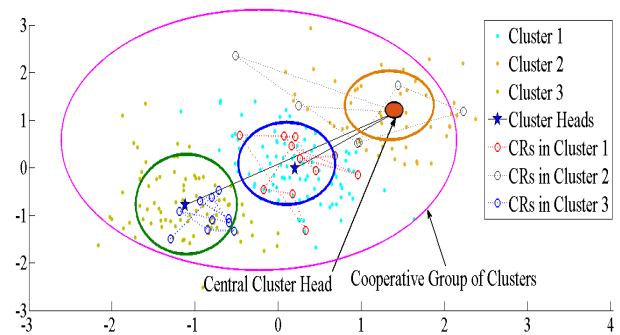
Clustering formation and SUs selection for the proposed scheme are made under the detection threshold, which enables cluster groups from different geographical areas to cooperate in both sensing and transmission phases, as shown in Fig. 4. In Fig. 5, shows the cooperative soft and hard decision combination, whereby the decoding BER 10^{-5} for the soft decision combination is achieved at 8dB SNR, whereas, for the hard decision combination is achieved at 10dB SNR. Therefore, the soft decision combination influences a good cooperative performance to clusters due to its contribution of adequate statistics for the CHs to perform a likelihood ratio test, whereas, the hard decision combination can reduce cost due to the reduction of sensing time and bandwidth. The power allocation solution is made by using the water filling algorithm for allocating transmission power and noise power. In Fig.6, the three cluster transmission channels to the CCH are allocated input power by water filling technique, whereby the noise set is filled first to achieve the noise level followed by transmission sub-channels to achieve the power level, as summarized in algorithm 2. In Fig.7, the signal characteristic of PD to SNR of both traditional and proposed schemes is equivalent to a non-fluctuating signal, while other factors are assumed to be constant. The fixed PD with SNR illustrates
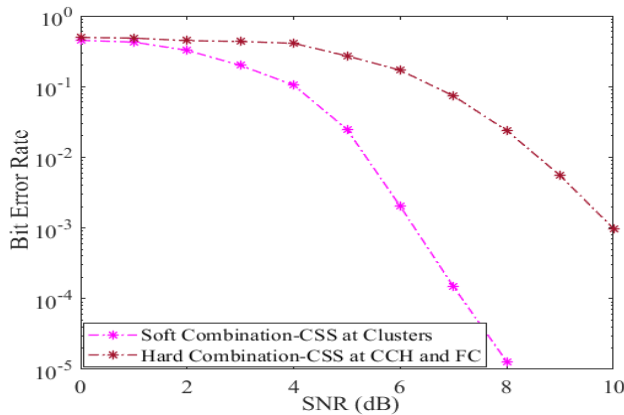
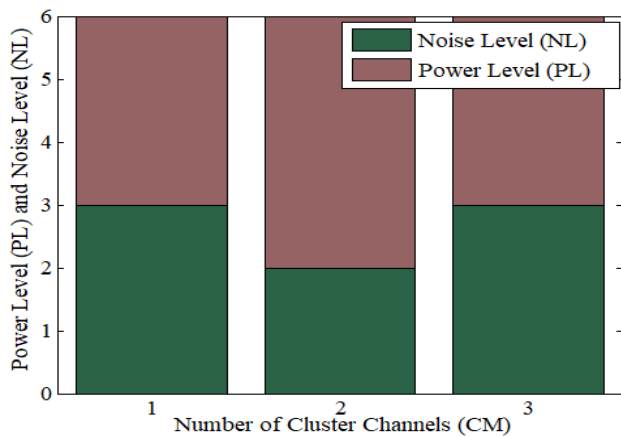**FIGURE 5.** Soft and hard combination decision.

FIGURE 6. Power allocation by water filling algorithm.

FIGURE 7. Probability of detection Vs SNR of the proposed scheme.
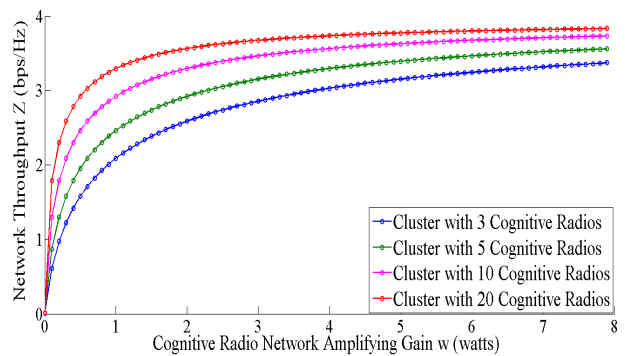
FIGURE 8. CRN throughput Z Vs AG w of clusters of the proposed scheme.

the signal characteristics of both the proposed and traditional schemes at a point where detection is made in a high noise uncertainty environment under the energy detection method. At this point, we assume that CRs sample and sensing time are maintained constant, since PD increases with the increase in CRs [10], hence, the large number of N in M the more targeted Z is achieved. However, since our proposed work involves a high noise uncertainty environment to detect PUs presence in the spectrum, therefore, to achieve high-efficiency detection, we decide to use the high SNR greater than 0 due to its better performance under the energy detection method rather than low SNR below 0 [21].

As shown in Fig.7, the decrease in SNR is proportional to the decrease in detection probability, since the higher the SNR used, the more noise is detected, and hence the high detection probability of the PUs present in the spectrum. However, it should be noted that the maximization of the detection threshold is also important for both detection and selection of the best CHs and CHH, which is proportional to the number of CRs samples since the detection threshold increases with the increase in detection probability [22].

Although the cluster cooperation scenario has a significant impact on energy efficiency improvement, throughput
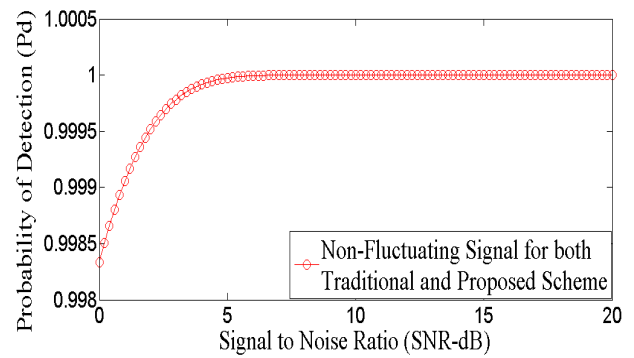
maximization, and minimization of errors, however, all these benefits depend on the number of CRs samples used in each cluster. In Fig. 8, numbers of CRs 3, 5, 10, and 20 of four CCG in ascending order increases proportionally with the increase in throughput required to transmit the network signal. However, an AG of the network may also be affected by the cluster content, whereby the cluster with more CRs spends more throughput with less AG at the beginning of transmissions, then slightly decreases the throughput level to the straight line while increasing AGs accordingly. Since the detection delay increase with the increase in false alarm rate and high-throughput, therefore, the proposed scheme has a great significance in reporting fewer detection delays in a high noise uncertainty spectrum environment under an energy detection method. The decrease in detection delays for the cooperative scheme proposed is due to all-time reporting of sensed information from individual CR sensors to CHs and from CHs to the CCH in a cooperative manner enabling real-time detection and high-throughput rather than when non-cooperation scenario is applied [11], [23].

In Fig.9, the SNR of the proposed scheme is shown to be 0.811 dB greater than the traditional network, which is a non-clustered cooperative scheme. Initially, transmission signal curves of both traditional and proposed schemes indicate an approximately zero PD while increasing PFA to about 10^{-5}, a point where they slightly begin to increase the PD with a slight increase in PFA to 10^{0}. However, the system
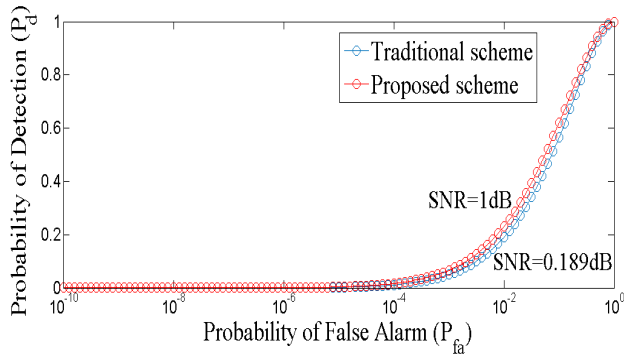
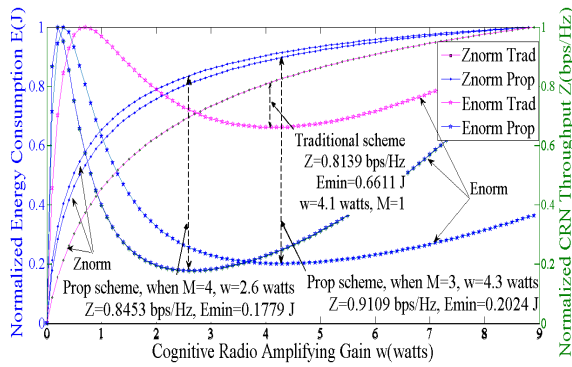**FIGURE 9.** Comparison of PD Vs PFA of traditional and proposed scheme.

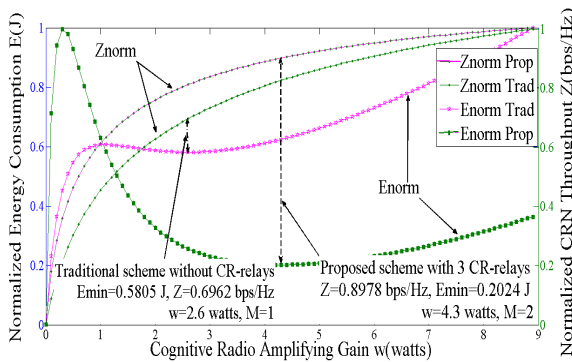**FIGURE 10.** Comparison of normalized EC Vs AG with cognitive relays.

FIGURE 11. Comparison of normalized EC Vs AG without cognitive relays.

TABLE 2. Comparison of minimum energy consumption between our proposed scheme and traditional schemes.

Parameter	Proposed Scheme	Traditional Scheme
Emin (J) when K=3	0.2024 J	0.6611 J
Emin (J) when K=4	0.1779 J	0.6611 J
Emin (J) for proposed scheme with CR-relays and traditional scheme without CR-relays	0.2024 J	0.5805 J

to have higher throughput and lower energy consumption compared to that of the non-cluster cooperation scheme, which propagates sensed information independently to the FC with low throughput and high energy consumption.

The effects of cognitive relays for both proposed and traditional schemes play an important role in signal amplification and forwarding, leading to fruitful results in high energy gains and throughput. However, the throughput of the proposed scheme is shown to increases with a decrease in the number of cluster groups when CRs are kept constant. As shown in Fig.10, when the number of clusters in the proposed scheme is 4, then the throughput used is shown to be 0.8453 bps/Hz and when the number of cluster groups decreases to 3, then the throughput used increases to 0.9109 bps/Hz. Whereas, for the non-cluster cooperative scheme, only one cluster is used with the throughput of 0.8139 bps/Hz. However, the number of cluster groups decreases with an increase in EC, such that, in Fig.10, the number of cluster groups decreases from 4 to 3 with an increase in EC from 0.1779 J to 0.2024 J. This proportionality can imply an increase in the network transmission channels, while other factors are assumed to be constant in the network. Therefore, an optimal requirement is important for the minimum EC and throughput required for a high detection probability to be achieved proportional to the number of samples used by the network.

To achieve an optimal amplifying gain and energy consumption, we use the bisectional algorithm in the determination of a feasible region between the minimum and maximum amplifying gain, as shown in Fig.10 and Fig.11 for different decision conditions, as summarized in Fig.3. However, the AG is shown to increase with the decrease in the number of clusters, while other factors such as cognitive relays and CRs samples are assumed to be constant. For instance, in Fig.10, it shows that, when 3 clusters are used, the AG is equal to 4.3 w, whereas, for 4 clusters, the AG is equal to 2.6 w. Therefore, the increase in the number of cluster groups and transmission channels can lead to an increase in transmission power consumption and a decrease in energy gains of the CRN.

In Fig.11, the AG is shown to be 2.6w for the traditional scheme without cognitive relays lower than the AG of 4.3w for the proposed scheme with cognitive relays. Despite the AG contributed by cognitive relays, other factors can also

complexity of the proposed scheme is well designed to avoid the global system delay due to its cooperative scenario in local detection, CHs reports to CCH, and single relayed transmission channel to the FC that enhance the reduction of packet traffic, reporting, and transmission delay compared to the traditional scheme [6], [23]. Since the cooperation scenario of our work is based on the collaboration of cluster groups by sending sensed information from CH of each cluster group to the CCH, therefore, the global information is sent to the FC through a single transmission channel for the final decision to be made regarding the PUs condition in the spectrum. Therefore, under the assumption of similar conditions, in Fig.10, the cluster cooperation scheme shows

affect the network gain. In Fig.10, the throughput level is shown to be 0.8453 bps/Hz for the proposed scheme higher than that of the traditional scheme without cognitive relays having the throughput of 0.6962 bps/Hz as shown in Fig.11. However, the EC of the proposed scheme with cognitive relays is 0.1779 J, as shown in Fig.10, lower than the EC of the traditional scheme without cognitive relays having 0.5805 J, as shown in Fig.11. The comparison of the energy consumption of our scheme with the traditional scheme is summarized as shown in Table 2.

VI. CONCLUSION

As we have proposed in this paper, the study aims to minimize the EC of CRNs in cluster CSS under relay assistance in the HSS scheme, whereby we have designed a CRN joining cluster groups of CRs into one CCG cooperating by sharing sensed information. As shown from simulation results, when the number of clusters is increased in the main CCG, then more EE is conserved. However, the application of cognitive relays in the proposed scheme is of great importance in assuring smooth signal transmission due to the increase in throughput constraints proportional to the increase in AG which is the result of using cognitive relays. Therefore, simulation results of the proposed scheme show good performance compared to the traditional schemes when cognitive relays are used or not by the traditional scheme.

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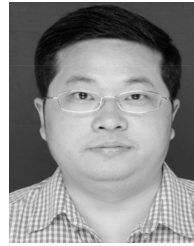
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