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Towards Energy-Efficient Cooperative Spectrum Sensing for Cognitive Radio Networks – An Overview

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Abstract Cognitive radio has been proposed as a promising technology to resolve the spectrum scarcity problem by dynamically exploiting underutilized spectrum bands. Cognitive radio technology allows unlicensed users to exploit the spectrum vacancies at any time with no or limited extra interference at the licensed users. Usually, cognitive radios create networks in order to better identify spectrum vacancies, avoid resultant interference, and consequently, magnify their revenues. One of the main challenges in cognitive radio networks is the high energy consumption, which may limit their implementation especially in battery-powered terminals. The large consumption mainly occurs during the spectrum sensing stage, especially if a cooperative approach is employed, and has an impact on the data transmission stage. Many algorithms have been proposed in the literature in order to improve the energy efficiency of cooperative spectrum sensing methods in cognitive radio networks. In this article, we provide an overview of state-of-the-art research that addresses this problem. Furthermore, we suggest important design guidelines of an energy-efficient framework for cooperative spectrum sensing.

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1 Introduction

Due to worldwide growth of the number of mobile terminals and the request of higher data rates, a tremendous increase of the energy consumption of the telecommunications industry has been recently reported, which has a significant environmental impact. From the mobile terminals' perspective, given the limitation on energy resources, energy consumption poses a main concern. Thus, energy efficiency has recently triggered a significant amount of research [1]. Indeed, energy efficiency is receiving a higher priority for some wireless systems and becomes a pressing need for their operation. A notable example is Cognitive Radio (CR) [2].

CR technology was presented to be a tempting solution to the spectrum scarcity problem. The spectrum scarcity is a result of the exponentially-increase in the number of terminals, applications and data rates in view of the current static allocation of the limited frequency spectrum. CR technology allows unlicensed users to opportunistically exploit temporally and spatially unused portions of the licensed spectrum [3]. Several standardization organizations have developed CR standards or modified their standards with the objective of including this novel technology [4–7].

A key function of CR consists in the capability of acquiring the knowledge of the instantaneous spectrum status. Such capability can be accomplished by using geo-location techniques, by receiving control and management information or by performing spectrum sensing [8–10]. Geo-location methods require a central database, self-locating capability and frequently updates of the database by license-holders. Likewise, control and management information techniques require both infrastructure elements and a database. On the other hand, spectrum sensing is considered the most promising solution for spectrum awareness [11].

Spectrum sensing is a periodic monitoring process of the spectrum, which is aimed at detecting the presence of the licensed users [12,13]. Due to the high desired detection requirements [11], spectrum sensing performed by individual radios suffers from unreliable estimates in presence of multipath fading and shadowing [14–18]. Thus, spectrum sensing is usually performed in a cooperative fashion among several altruistic Cognitive Users (CU), which are willing to share their individual sensing results in order to provide a more reliable global estimate of the spectrum occupancy. This approach is referred to as Cooperative Spectrum Sensing (CSS) [19,20]. The application of CSS in CR systems induces new design and optimization challenges, such as transmission delay [21,22], security risks [23, 24] and energy consumption [25,26]. Much effort has been devoted to overcome these implementation challenges, which may offset the potential benefits of CSS [27].

In the literature, there are several surveys, tutorials and overview papers in topics related to CR. For example, Surveys in CR networking, spectrum management, architectures, routing, standardization activities, economic aspects and recent advances are found in [4,27–35]. Other surveys on MAC protocols and strategies can be found in [36–38]. The applications of game theory and artificial intelligence in Cognitive Radio Networks (CRNs) have been reviewed in [39] and [40], respectively. As for spectrum sensing, [41–46] discuss the performance of different spectrum sensing techniques. In [47], wide-band spectrum sensing algorithms have been reviewed. However, the above mentioned works have not deeply discussed

CSS. The challenges associated to CSS have been surveyed in some other works. For example, a survey in the design of common control channel is presented in [48], while the security risks are reviewed in [49–52, 23]. Surveys in [13] and [53] are fully dedicated for CSS process, where its mechanisms, performance, and challenges have been discussed. However, a little attention has been paid to energy efficiency problem in CSS. This article provides an overview of current research activities that are aimed at reducing energy consumption of CSS applied to CRNs. To the best of our knowledge, this is the first work that handles this issue. The presented article classifies the available works on energy-efficient CSS into three approaches. The classification is based on the running stage of each work. All the works are discussed in detail, emphasizing on the performance in terms of energy efficiency.

The Energy Efficiency (EE) is defined as the ratio of the average transmitted bits to the average consumed energy [54]. Recently, it has gained an increasing importance, and it has received a lot of interest in different topics in wireless communications [55–60]. This attention is due to the limited energy resources at the CRs, which is often accompanied with a big demand for data rates. The EE is considered to be a comprehensive metric that is able to represent the overall performance of a CRN because it is capable of jointly taking into account the achievable throughput, the overall energy consumption and the detection accuracy. The combination of these indicators in a single metric has made the EE metric a relevant indicator of the quality of cognitive transmission.

2 Cooperative Spectrum Sensing

Cooperative spectrum sensing is the key factor of a successful cognitive transmission. The ultimate aim of CSS is to identify temporally and spatially unused portions of the spectrum. CSS usually starts by an individual spectrum sensing process, which is performed by each CU individually. This first stage is then followed by a sharing stage, where the sensing results are processed in order to make a final decision about the spectrum occupancy. CSS can be either centralized or distributed. In centralized CSS, local sensing results are reported at a common receiver that is in charge of making a global decision [61]. In distributed CSS, on the other hand, the CUs exchange their sensing results among themselves without the need of an infrastructure [62, 63]. This article focuses on the centralized CSS that is shown in Fig. 1. In this section, we review in detail the stages that constitute CSS and the available metrics to evaluate the achievable performance.

2.1 Stages of CSS

A typical frame structure of a cognitive transmission is shown in Fig. 2. CSS starts by a local sensing performed by each CU individually. Different methods to sense the spectrum are available in the literature, such as energy detection [64], matched filters based sensing [65], cyclostationarity-based sensing [66], wavelet-based sensing [67] and waveform-based sensing [68]. Energy detection is the most popular method due to its low computational and implementation complexity. Besides, it
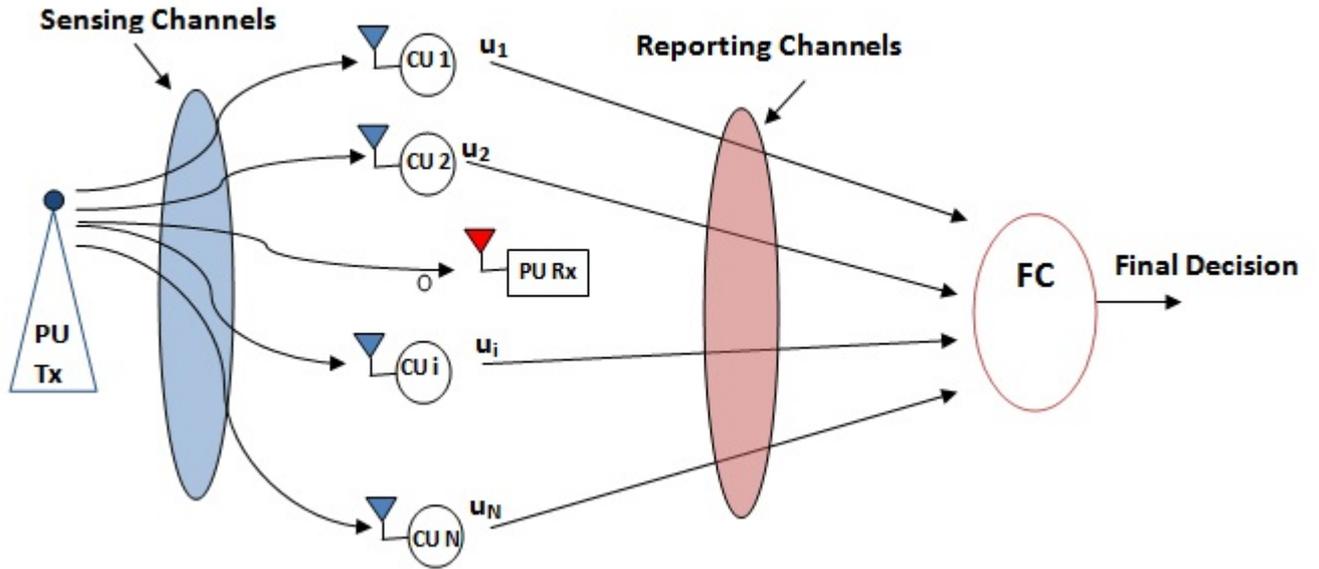
Fig. 1 *General description of centralized cooperative spectrum sensing process.*

does not require any prior knowledge about the signal to be detected, while the others depend mainly on the prior knowledge of the signals to be identified [69]. However, energy detection achieves the worst detection accuracy compared to the other available techniques [46, 44, 70].

Regardless the sensing method used, each CU, before sharing the local results with other CUs, has to find a way to represent the local result. There are two popular schemes to this end: soft-based and hard-based schemes. In soft-based scheme [71], the local result is reported as it is , usually by quantizing it with a large number of bits in order to minimize the impact of the resultant distortion. On the other hand, hard-based scheme are based on comparing the local result to a predefined threshold in order to make a local binary decision that can be transmitted via a single bit [14].

The next stage is to report the local results/decisions to a common receiver, called fusion center (FC), that is responsible for processing them and for making a global decision of the spectrum occupancy. The reporting of the results is usually accomplished through a common control channel based on either a centralized time-division multiple access (TDMA) [72] or a random access [73]. In a centralized TDM access, each CU has its own time slot for reporting its local result, while in a random access reporting scheme the CUs transmit their reports without any coordination.

At the FC, the results received from different CUs are processed by employing a specific fusion rule (FR) in order to make the global decision. In general, the

results received in soft-based CSS schemes are weighted and summed up, and then, the sum is compared to a threshold to make a global decision. FRs for soft-based scheme can be classified according the weights used, such as equal-gain combining (EGC), where the weights of the all CUs are identical, maximal ratio combining (MRC) [71], where each CU is weighted by its signal-to-noise-ratio (SNR) and likelihood-ratio (LR) [74], where the likelihood ratio statistical test is used to obtain the most likely decision of the spectrum availability. As for hard-based CSS schemes, the general rule is called K-*out-of-N* rule [75], where the number of CUs that detect a signal is compared to a threshold (K), where N is the total number of CUs. Depending on K, several rules can be derived for the K-*out-of-N* rule, such as the OR rule $(K = 1)$ [61], the AND rule $(K = N)$ [76] and majority-logic rule $(K = N/2)$, also called voting or counting rule [77]. Fig. 3 depicts the function of the K-*out-of-N* rule.
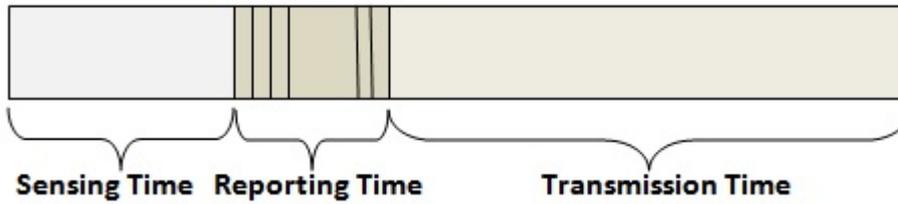

Fig. 2 *The frame structure of the cognitive transmission.*

2.2 Performance Metrics

In the literature, the performance of CSS has been evaluated by using different metrics, such as detection accuracy, energy consumption, and achievable throughput. Detection accuracy is measured by two probabilities: the detection probability and the false-alarm probability. The detection probability is defined as the probability that the CSS scheme identifies a used spectrum as used, while the false-alarm probability is the probability that the CSS scheme identifies an unused spectrum as used. The complementary probability of the detection probability is called missed-detection probability. It is apparent that a low false-alarm probability improves the efficient exploitation of the unused spectrum, as well as that a low missed-detection probability limits the resulting interference at the licensed users. Usually, the detection accuracy is evaluated through the error probability which represents the sum of false-alarm and missed detection probabilities.

The energy consumption is defined as the average energy consumed during local sensing, results' reporting and data transmission by all the CUs in the network. The energy consumption depends on the number of cooperating CUs, the sensing time and the detection accuracy. The achievable throughput is represented by the average successfully transmitted data by the scheduled CU. It is worthy mentioning that the achievable throughput is directly affected by the detection accuracy.
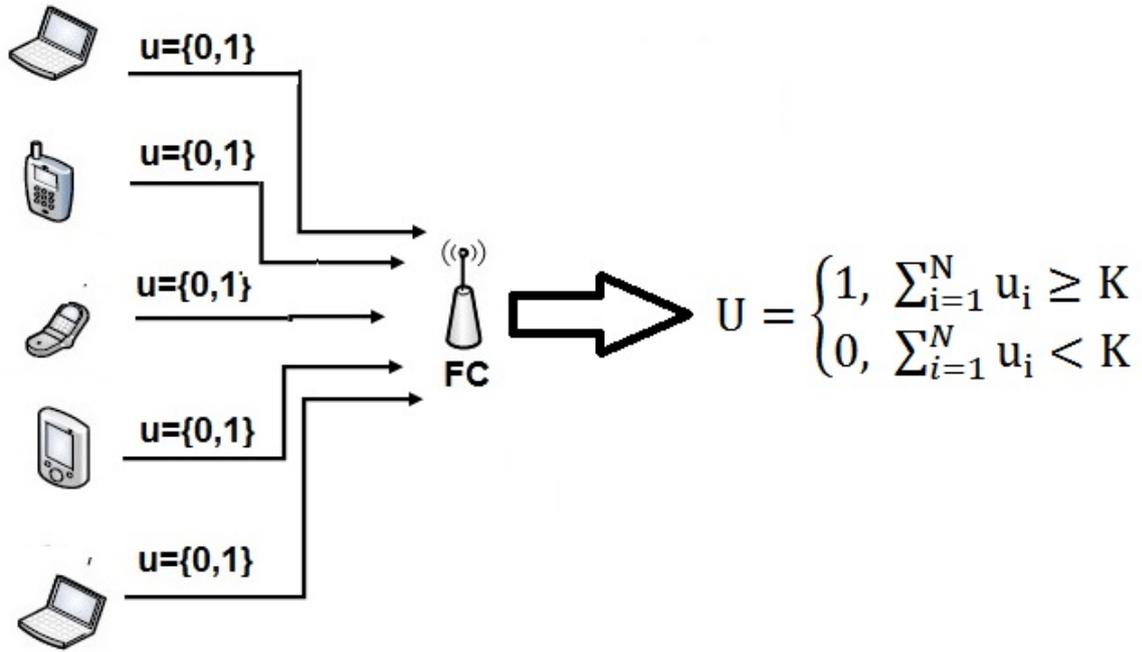
$$U = \begin{cases} 1, & \sum_{i=1}^{N} u_i \geq K \\ 0, & \sum_{i=1}^{N} u_i < K \end{cases}$$

Fig. 3 *The function of the K-out-of-N fusion rule.*

Energy efficiency is the most recent metric that has been used to assess the performance of CSS. The energy efficiency is defined as the average successfully transmitted data normalized by the energy consumption. Based on this definition, the energy efficiency combines all the other performance metrics presented above. Thus, the EE has been widely accepted as a comprehensive metric that can achieve the balance between the different aspects of CSS performance.

3 Energy-Efficient CSS Approaches

The energy consumption of CR system is related to: (*i*) the periodic nature of the process, (*ii*) its increase with the number of CUs, and (*iii*) the increase of the number of channels. Moreover, the energy loss in the case of missed-detection magnifies the problem. Thus, energy-efficient approaches for CSS are mandatory.

Many approaches aiming at improving the energy efficiency of CSS have been presented in the literature. In this section, we review these approaches. The presented approaches are classified, as shown in Fig. 4, according to the CSS stage that they are aimed at optimizing. As such, they can be split in three categories: (*i*) EE approaches for the local sensing stage, (*ii*) EE approaches for the reporting stage and (*iii*) EE approaches for the decision-making stage.
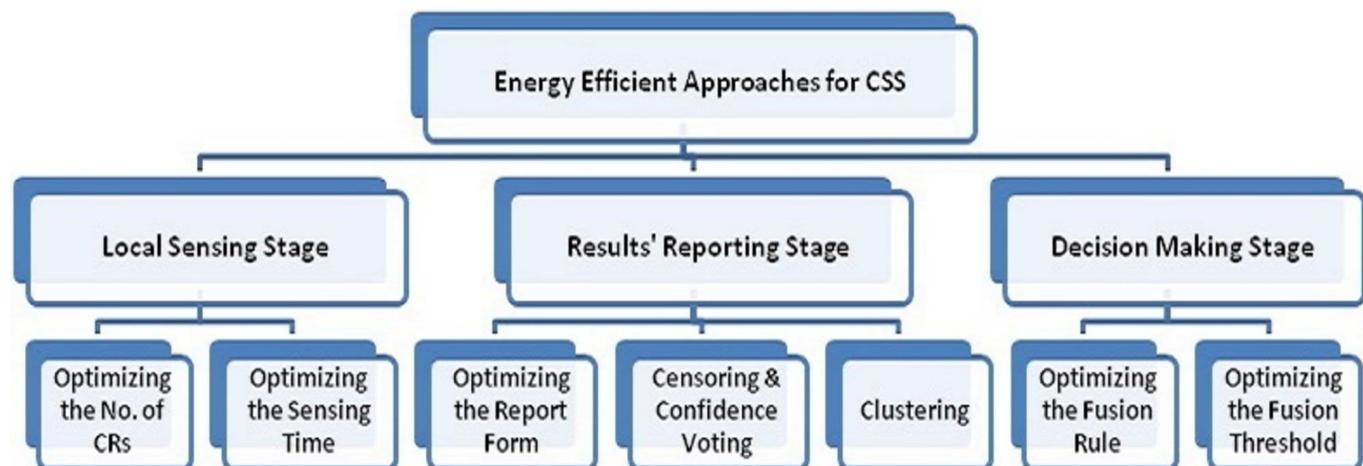
Fig. 4 *The classification of the several energy-efficient CSS approaches found in the literature.*

3.1 Energy-Efficient Approaches for The Local Sensing Stage

The energy consumed for local sensing is equal to the product of the number of sensing users, the sensing time and the sensing power. Thus, reducing energy consumption in the sensing stage can be accomplished in two different ways, either reducing the number of sensing users or by reducing the sensing time.

3.1.1 Optimizing the number of sensing users

The number of sensing users plays a significant role in the energy consumed in CSS. This is related to the fact that any reduction in the number of sensing users leads to a reduction in all the preceding stages. In [78–80], the energy consumption is reduced based on different scenarios by using the minimum number of CUs that satisfies predefined thresholds on the detection accuracy. In [78], an energy efficiency optimization problem is formulated by minimizing the number of sensing CUs while satisfying predefined constraints on the detection and false-alarm probabilities. However, considering a limited frame length, minimizing the number of sensing CUs does not necessarily maximize energy efficiency. In limited frame length, modifying the time given for a stage will affect the time distribution for other stages in CSS. Hence, minimizing the the number of sensing CUs may decrease the reporting time but it gives more time for data transmission which consumes more energy. In [80], the minimum number of sensing CUs that satisfies two constraints on detection and false-alarm probabilities is mathematically formulated. Unlike [78], in [80] only the energy consumed in sensing stage is considered, while energy consumed in results' reporting and data transmission have

not been taken into consideration. A similar approach is presented in [79], where a dynamic algorithm is presented to let only the minimum number of CUs participate in the sensing process. The proposed algorithm continuously checks a binary indicator which represents the satisfaction of the desired detection accuracy in terms of detection and false alarm probabilities. A new joining CU is ordered to sense if the desired detection accuracy is not attained. Otherwise, it can join the network without sensing. The energy consumed in data transmission has not been considered in [79]. It is worth mentioning that the attention in [78–80] has been focused to energy consumption not to energy efficiency, representing a drawback in all of them. Moreover, they assume identical sensing performance for all CUs, which is unrealistic assumption in light of different channel conditions including the multi-path fading and shadowing.

In [81], the CUs are divided into non-disjoint subsets such that only one subset senses the spectrum while the other subsets enter a low power mode. The energy minimization problem is formulated as a network lifetime maximization problem with constraints on the detection accuracy. However, the mapping between network life time and energy consumption is not investigated. Similarly, the authors of [82] propose an algorithm that divides the CUs into subsets. Only the subset that has the lowest cost function and guarantees the desired detection accuracy is selected. The desired detection accuracy is defined by two thresholds on detection and false-alarm probabilities, while the cost function is represented by the total energy consumption. The proposed algorithm is built based only on the OR rule. Although OR rule can limit the interference at the licensed users, but it causes a high false-alarm rates. Moreover, the achievable throughput of the proposed algorithm is not discussed in the paper. In both works [81,82], the proposed algorithms assume that the local sensing performance of each CU is available at the FC in advance, which requires extra resource expenditure in terms of time and energy due to the accompanied overhead.

A distributed approach for selecting the participating CUs is proposed in [83], where the expected energy consumption is calculated by each CU prior to the beginning of the CSS process: if it is lower than a given threshold, the corresponding CU will participate. Otherwise, it will not participate. However, the optimization of the participation threshold is not investigated, especially in terms of the achievable detection accuracy.

Another distributed approach for selecting the sensing CUs is presented in [84]. The proposed algorithm is based on excluding CUs that have high correlated spectrum sensing results. In detail, it is assumed that each CU has the ability to overhear the sensing results of other CUs. Thus, each CU calculates its correlation is within an acceptable range, it will participate in the sensing stage. Otherwise, the corresponding CU will not participate. Besides its additional complexity, the ability to overhear the sensing result of other CUs is not always possible.

In [85], the instantaneous battery level is considered as a base for selecting the participating CUs in CSS. Particularly, the FC classifies the CUs into two groups based on their battery level which is assumed to be known at the FC. The minimum number of sensing CUs is determined such that a predefined threshold on detection probability is satisfied. The minimum number of the sensing users is selected from the second group (which has th battery highest level). If the number of CUs in the second group is less than the minimum required number of CUs, the

rest is selected form the first group (which has the lowest battery level) with equal probabilities. Although the algorithm shows a good performance in extending the lifetime of the CRN by considering the battery level, it does not guarantee the achievable energy efficiency.

In [86], a two-stage CSS is proposed, where CUs are divided into two groups. In the first stage, the first group senses the spectrum and reports the local decisions to the FC. If the FC decides that the spectrum is occupied, the CSS will be terminated. Otherwise, a second stage will be commenced, where the second group of CUs senses and reports the results to the FC. At the FC, the sensing results of both stages are processed in order to issue a global final decision. The energy efficiency is maximized by optimizing the number of CUs in each group and the fusion thresholds. A suboptimal solution for the maximization problem is found using the well-known particle swarm optimization algorithm. A practical drawback is in combining sensing results obtained at different time instants. This might degrade the reliability of the global decision as it is based on results gathered from two different stages.

Three different energy-efficient CSS algorithms for multi-channel systems are proposed in [87]. The three approaches select the sensing users based on their SNRs. In the first algorithm, the minimum number of CUs that satisfies the desired false-alarm probability and minimizes the the energy consumption is assigned to sense a specific channel. The energy consumption includes the energy consumed in sensing and reporting. The second algorithm assigns the CUs with the highest SNRs over a specific channel to sense it, while, in the third algorithm, it is assumed that CUs already sensed the channel, and only the CUs with the highest SNRs will report their sensing results. However, the three proposed algorithms assume the availability of the SNRs at the FC which is unrealistic assumption. Moreover, the energy consumed in data transmission is not taken into account.

3.1.2 Optimizing the sensing time

Optimizing the sensing time/period constitutes another approach that can be adopted for enhancing the energy efficiency of CSS. In [88–90], the sensing time/period is investigated for individual sensing systems. An adaptive sensing period based on the past spectrum occupancy pattern is presented in [88]. Also, they propose a sequential sensing policy that enforces the CUs to extend the sensing time when its sensing result lies in a specific range. In [89], the CU switches to a non-sensing mode (sleep mode) when a licensed user is detected. The non-sensing time is optimized for maximizing a utility function that combines energy saving and throughput loss. The sensing and transmission durations are optimized in [90] with the aim of maximizing the energy efficiency while satisfying constraints on detection accuracy and maximum available power. However, the proposals in [88–90] consider only a single CU and do not investigate their proposal based on CSS scenario.

As for CSS, [91,92] and [80] consider the sensing time as a possible approach in order to reduce the energy consumption. In [91], the CUs perform an initial short sensing stage called coarse sensing. If the sensing result of a CU lies outside a specific predefined range, a binary local decision will be reported from the corresponding CU to the FC. In the case that the sensing result lies in the predefined

range, no local decision will be reported from the corresponding CU. At the FC, a global decision (either used or unused) can be made only if the majority decide it. The global decision cannot be made if no majority exists, and therefore, a another sensing stage is commenced by all CUs, called fine sensing. The fine sensing stage is two times longer that the coarse stage. Regardless of the fine sensing results, all CU will report their binary decision to the FC where the global decision should follow the majority decision. Although this two-stage sensing scheme can affectively reduce sensing time, it causes extra energy consumption in reporting stage since it is repeated twice, which is not taken into account. Moreover, the influence of waiting the first global decision on the achievable throughput is not investigated in [91], which might degrade energy efficiency.

In [92], a utility function that consists of the difference between the achievable throughput (revenue) and the consumed energy (cost) is maximized by optimizing the sensing time. A constraint is kept on the detection probability. However, the utility function does not consider the energy/time spent during reporting the results to the FC. Also, only the AND rule is adopted at the FC, which causes a high missed detection rate. The optimal sensing time that minimizes energy consumption is obtained in [80]. Two constraints on the false alarm and detection probabilities are set, while only the sensing energy is considered in the formulated problem.

In [93], energy efficiency is maximized by optimizing the number of sensing users, the sensing time, the transmit power and the local detection threshold jointly and individually. An iterative algorithm is presented to solve the joint optimization. An interesting property of [93] is considering the energy efficiency as a performance metric to be maximized with a constraint on the detection probability. However, the energy consumed in reporting is not considered in energy consumption calculations.

A utility function that includes the difference between the achievable throughput and the consumed energy is maximized in [94] by a joint optimizing of the sensing time and the number of sensing users. The optimal solution is found using an iterative algorithm. However, the energy and time consumed in reporting the results to the FC are not taken into consideration.

In [95] the sensing time is optimized in order to maximize the energy efficiency. The energy consumption function includes all the energy consumed in sensing, reporting and data transmission. However, no closed form expression of the optimal sensing time is given. Instead, the golden section search algorithm is used to find the optimal value.

A related work is in [96], where the sampling rate of the sequential sensing is optimized in order to reduce the energy consumption. The optimization problem is subject to constraints on detection and false alarm probabilities. However, the work only considers a single CU, and energy expenditure during CSS has not been considered while formulating the optimization problem.

3.2 Energy-Efficient Approaches for The Reporting Stage

The second stage of CSS is the reporting stage, where CUs transmit their local sensing results to the FC. Compared to the sensing power, the power consumed

in the reporting could be higher. On the other hand, the time spent in sensing is much longer than the time spent in reporting. Therefore, the energy consumed in the reporting stage may be comparable to the energy consumed during the sensing stage. Several works have studied techniques for reducing the energy consumption during the reporting stage, as summarized as follows

3.2.1 Optimizing the report form

In order to report the local result to the FC, each CU has to represent its own result by using a finite a number of bits. The reporting load has a contrasting impact on the overall performance of the CSS. On the one hand, increasing the number of bits enhances the amount of knowledge that is available at the FC, which improves the detection accuracy. On the other hand, a larger number of bits requires more bandwidth and increases the energy consumption. A single-bit reporting scheme is called hard-based scheme, while multiple-bit reporting schemes are called soft-based reporting schemes. Although many works have compared them under different setups and assumptions [97–101], none of them has investigated the resulting energy consumption nor energy efficiency.

In [102], a novel reporting scheme is proposed, which requires a single bit as in the hard-based scheme, but, at the same time, it is capable of achieving a similar detection accuracy as in soft-decision scheme. The idea is that each CU reports one bit in a time slot that is related to its sensing result, so that at the FC the sensing result can be inferred from the arriving time slot. Considering the collision probability between CUs, the proposed scheme is shown to be more energy-efficient than both soft-based and hard-based schemes. A main drawback is that the scheme requires a high accuracy in the synchronization between the FC and CUs.

3.2.2 Censoring and Confidence Voting

Censoring is a promising approach that can significantly reduce the reporting CUs. In censoring, a CU does not report its sensing result unless it lies outside a specific range [61, 103, 104]. The censoring thresholds are optimized for minimizing the energy consumption with constraints on the detection accuracy in [72]. Two setups for the availability of the prior information about the probability of spectrum occupancy are considered, namely, blind setup and knowledge-aided setup. However, the considered problem would show more effectiveness if the energy efficiency maximization was considered rather than energy consumption minimization as a problem objective. Besides, energy consumed in data transmission is not considered while computing the total energy consumption.

Recently, in [105], censoring and truncated sequential sensing are combined in order to reduce the energy consumption in CSS. Specifically, the spectrum is sequentially sensed, and once the accumulated energy of the sensed samples lies outside a certain region, the sensing is stopped and a binary decision is sent to the FC. If the sequential sensing process continues until a timeout, censoring is applied and no decision is sent. The thresholds of the censoring region are optimized in order to minimize the maximum energy consumption per CU subject

to a constraint on the detection accuracy. Similar to [72], transmit energy is not considered. Moreover, only two FRs are investigated instead of considering the general *K-out-of-N* FR.

In [106], a confidence voting scheme is presented. It works as follows: if the sensing result of a specific CU agrees with the global decision, it gains its confidence; otherwise, it loses its confidence. When a user's confidence level drops below a threshold, it considers itself as unreliable and stops sending its results. But it keeps sensing the spectrum and tracking the global decision. As long as the result matches, it gains its confidence. Once its confidence level passes beyond the threshold, it rejoins the voting. The energy saving and the detection accuracy of this approach are investigated in [106]. However, confidence level is based on the global decision which is in some cases not reliable enough, especially in case of malfunction or malicious CUs. Moreover, detection accuracy cannot be guaranteed since the number of reported CUs is varying in each sensing round.

Another simple approach for reducing the number of reporting CUs without affecting the detection accuracy can be found in [107]. The idea is based on an instantaneous processing of the received results at the FC. Whenever a global decision can be made, the reporting process is terminated and the rest of the CUs do not report their local sensing results. Despite its simplicity, this approach does not impact the detection accuracy and it offers more energy efficiency than other approaches. On the other hand, in case of non-identical sensing performance among CUs, the reporting order of CUs brings extra complexity and overhead at the FC . A similar approach to [107] is presented in [108], where the reported sensing statistics from CUs will processed sequentially at the FC. The FC performs a hypothesis test each time after receiving a statistic from a CU. The FC stops the reporting process when statistics gathered is sufficient for making a decision at a specified reliability level. Otherwise, it will acquire an additional statistic from another CU and repeat the above procedures until it terminates. Unlike [107], the FC employs Neyman-Pearson decision strategy instead of *K-out-of-N* FR. The analytical and simulation results in [108] do not show the performance of the proposed algorithm in terms of energy efficiency.

3.2.3 Clustering

Clustering is a popular approach to reduce the overhead load between the CUs and the FC. In clustering, CUs are separated into clusters and one from each cluster is nominated as cluster-head, which is in charge of collecting sensing results from cluster-members and reporting a cluster-decision to the FC on behalf of the cluster-members [109]. The cluster-head can be dynamically changed in each CSS round. Fig. 5 shows an example of cluster-based CSS. The energy saving and the accuracy loss are investigated in [106]. In addition to energy consumption analysis, time delay is conducted in [110]. In [111] and [112] clustering and censoring approaches are combined in one energy-efficient algorithm considering the noisy reporting channels. In [113], a multi-level cluster-based CRN is proposed, where the cluster-head that are far away from the FC can forward their cluster decisions to the near cluster-head rather than the FC. Such a technique aims at reducing en-

ergy consumption in reporting process, however, it may generate synchronization challenges.

Although clustering reduces reported information to the FC, it induces extra energy consumption during results exchange inside the cluster itself. Besides, creating clustering is a complicated process that adds a significant amount of complexity to the CRNs, especially in mobile CUs scenario.
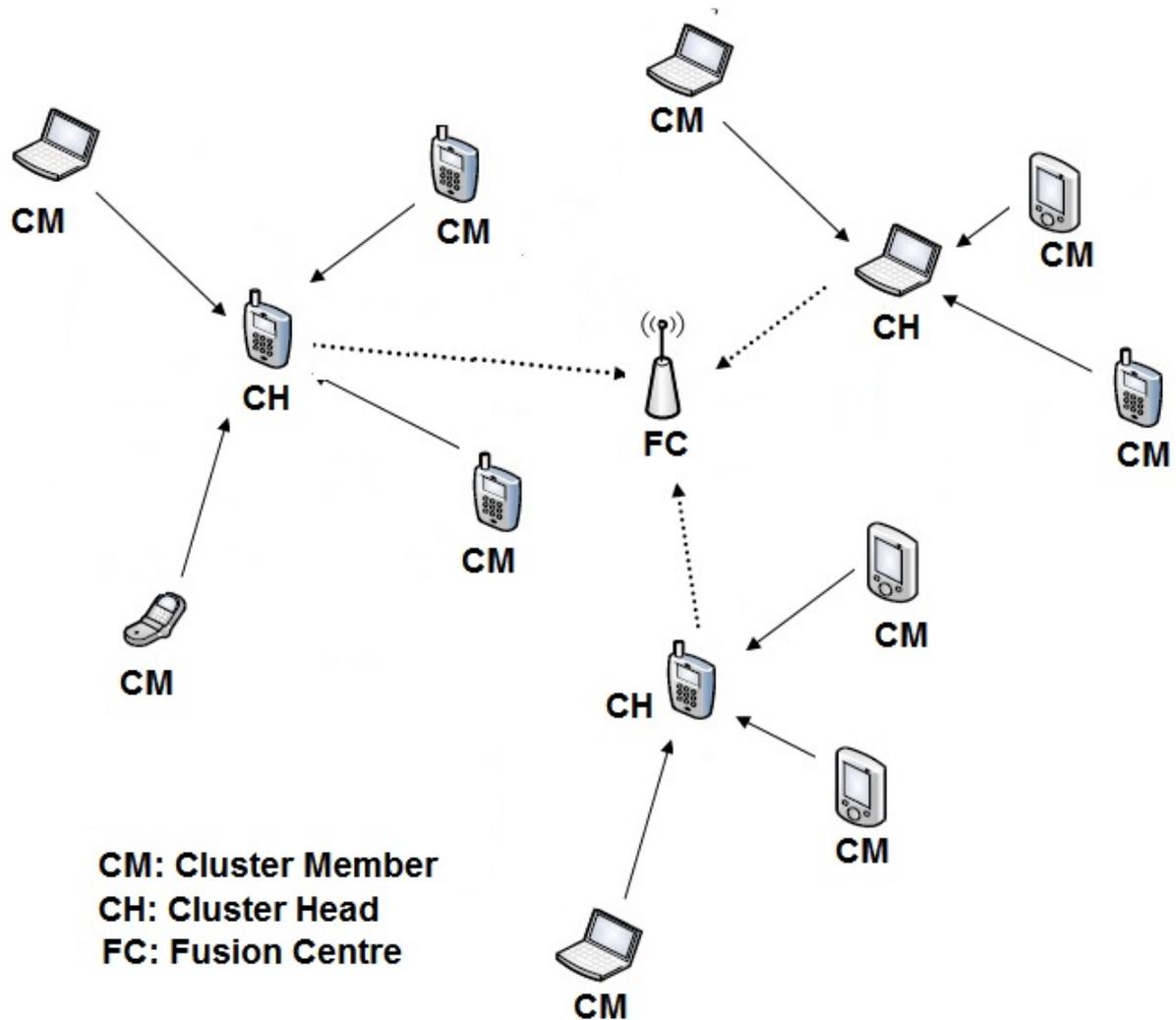

CM: Cluster Member
CH: Cluster Head
FC: Fusion Centre

Fig. 5 *An example of cluster-based cooperative spectrum sensing.*

3.3 Energy-Efficient Approaches for The Decision-Making Stage

Every CSS round ends by making a global decision about the spectrum occupancy. The global decision is made by processing the received local results/decisions, where a specific FR is applied. Regardless of the form of the received results, a predefined fusion threshold is needed to make a decision. In [114], the fusion threshold of the *K-out-of-N* FR is optimized for maximizing energy efficiency without constraints, while a constraint on resulting interference represented by the missed detection probability is set in [115]. In [116], the optimal fusion threshold that maximizes the throughput of CRN is obtained with constraints on the consumed energy per CU and the overall detection probability. However, these optimization problems require prior information bout the activity of the licensed users. Besides, an identical sensing performance among all CUs is assumed in [114–116], which is considered unrealistic assumption.

Three popular FRs for the noisy binary decisions are compared based on limited time assumption in [117]. The considered FRs are LR, MRC and EGC. It is assumed that the amount of prior information required for each FR is reported together with the sensing decision, which impacts the time and energy resources. Considering the limited time assumption, EGC has been proved to be the optimal FR in terms of detection accuracy and energy efficiency.

4 General Discussion and Concluding Considerations

In this section, we present a simple example to show the performance of some CSS approaches that have been reviewed in the previous sections. We consider a CRN of 20 CUs that experience the same signal-to-noise-ratio ($-20\,dB$). The cognitive transmission is divided into frames, where each frame lasts $50\,ms$. The sub-frame for data transmission is assumed $45\,ms$, while the reporting time for each CU is assumed $0.05\,ms$. The hard-based CSS is employed.

Fig. 6 plots the performance of six different EE approaches. First, the number of sensing users is optimized for energy efficiency maximization as proposed in [78]. Second, the sensing time is optimized for energy efficiency maximization , as presented in [95]. The third column shows the maximum energy efficiency if the fusion threshold is optimized, as proposed in [114] and [115]. The energy efficiency if clustering approach is applied, as proposed in [113]. The confidence voting approach, presented in [106] is shown in the fifth bar. Finally, the achieved energy efficiency by the optimal censoring threshold is represented by the last bar, as proposed in [72].

The results show that optimizing the number of sensing users is the most efficient approach in improving the energy efficiency. This is due to the reason that excluding some users from sensing will not only save sensing energy, but also will reduce energy consumption in reporting stage. Another observation that can be seen on Fig 6 is that the least significant approach is optimizing the sensing time as it directly affects the detection accuracy for all CUs. Although the clustering reduces energy consumed in reporting to the FC, it induces extra energy consumption during reporting the results to the cluster-heads.Therefore, clustering shows

a moderate energy efficiency value. As both censoring and confidence voting affect the detection accuracy, they do not outperform other techniques in energy efficiency. Optimizing the employed FR achieves a high energy efficiency since it does not require any other energy costs.
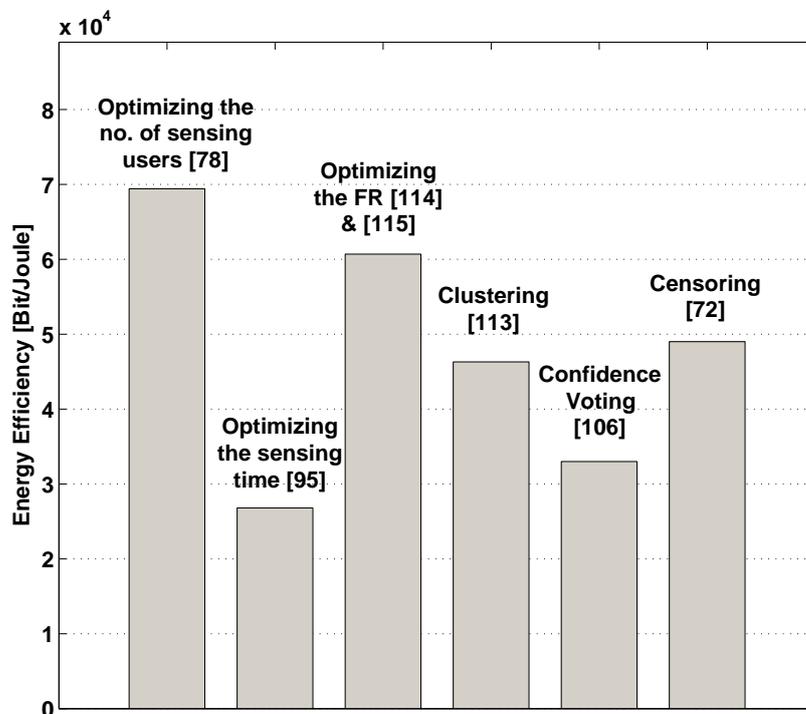

Fig. 6 *The energy efficiency for different energy efficient approaches.*

We conclude this article by providing some design guidelines that are useful for designing energy efficient CSS methods (summarized in Table 1):

- More practical conditions should be considered while proposing, designing and evaluating energy-efficient approaches. Table 2 summarizes the whole energy-efficient works discussed in this article. Apparently, faded sensing channels and noisy reporting channels have been rarely considered although channel characteristics might severely influence the performance. Therefore, we recommend that realistic channel conditions, for sensing and reporting, should be assumed in order to provide accepted practical evaluation.
- The overall performance of the CRN can be comprehensively described by the energy efficiency rather than using other metrics. In other metrics, additional constraints should be set in order to avoid negative effects on other performance

aspects. For instance, minimizing energy consumption is usually accompanied by additional constraint(s) on detection probability, false-alarm probability and/or throughput as shown in Table 2. However, employing energy efficiency as the evaluating metric will strike a balance between the different aspects of the performance from the CUs perspective since all the other metrics are inherently combined in it. The only constraint that might be required is an upper bound on the missed-detection probability, which limits the interference at the licensed users.

– Following the energy efficiency definition, the transmit energy of the scheduled CU, if any, should be taken in consideration once the total energy consumption is calculated. Although transmit energy is spent after CSS, it is directly affected by the detection accuracy of CSS and the remaining time resources of the total cognitive frame. Similarly, energy and time that are spent in results reporting should be considered in the energy efficiency evaluation.

– According to limited time/ bandwidth resources assumption, decreasing (or increasing) the number of participating CUs in CSS does not necessarily entail reducing energy consumption (or increasing achievable throughput). Therefore, the available limited resources should be considered while optimizing the number of participating CUs for maximizing energy efficiency.

– Proposed approaches for a single stage should take into account the possible influence on the other stages. Specifically, a proposed algorithm may decrease energy expenditure in a specific stage, but it causes (or requires) additional energy consumption in preceding (or following) stages, leading to inferior overall performance of the proposed algorithm. For instance, some CU-selection algorithm requires additional information about each CU, which should be accounted while evaluating the performance. Also, in clustering approach, the induced overhead to form clusters and nominate heads causes extra time and energy resources. However, there are some other approaches with low complexity and have no side-effects. An example is censoring technique that can hugely reduces the reporting load, and consequently, energy consumption, without extra resources expenditure since censoring is performed distributively with a simple manner.

– The literature lacks a comprehensive solution that integrates several proposed algorithms among multiple stages of the CSS. However, the diversity of the scenarios and assumptions that delineate the cognitive transmission makes a unique universal solution not an easy task. For instance, algorithms designed for cognition in TV band should be different from those dedicated for cellular bands, where the different activity pattern of the licensed users should be considered. Similarly, other factors play a significant role in marking a specific solution among others, such as the amount of prior information, the number of CUs, the frame time length, the maximum allowable interference, the available limited power resources, channel characteristics and QoS requirements. Moreover, all cognitive transmission stages starting from the local sensing and ending by the data transmission should be included in the designed global energy-efficient framework.

Table 1: Summary of the proposed guidelines for designing EE CSS approaches

1	An EE algorithm that is designed for a specific stage should not induce extra energy consumption in the preceding/following CSS stages
2	An EE algorithm should not affect the detection accuracy, or should be able to keep it within an acceptable range
3	Realistic channel conditions including fading and shadowing should be considered while evaluating the performance of the proposed EE algorithm
4	Noisy reporting channels between the FC and The CUs should be considered.
5	Non-identical channel conditions should be taken into account while designing EE CSS algorithms.
6	Energy consumed during data transmission should be taken into consideration since it is directly affected by the CSS.
7	The performance of the designed EE CSS algorithms should be performed in terms of the energy efficiency with additional constraint on the detection probability.
8	The designer should take into account that the available resources including time and energy are limited.
9	Maximizing the energy efficiency of CSS is achieved by a comprehensive EE approach that addresses the energy efficiency in all CSS stages.

Table 2: Summary of the EE approaches for CSS

Work	Adopted Approach (Section No.)	Constraints	Channel fading considered?	Noisy reporting considered?	Employed energy metric	Transmit energy considered?
[78]	3.1.1	Detection and false-alarm probs.	No	No	No. of users	No
[79]	3.1.1	Detection and false-alarm probs.	No	No	Percentage	No
[80]	3.1.1 & 3.1.2	Detection and false-alarm probs.	No	No	Energy in *Joule*	No
[81]	3.1.1	Detection and false-alarm probs.	No	No	Network lifetime	No
[82]	3.1.1	Detection prob.	No	No	Energy in *Joule*	No
[83]	3.1.1	None	Yes	Yes	Energy efficiency in *bit/Joule*	Yes
[84]	3.1.1	False-alarm prob.	No	No	Energy in *Joule*	No

[85]	3.1.1	Detection prob.	Yes	Yes	Sensor's lifetime & no. of sensors	Yes
[86]	3.1.1	None	No	No	Energy efficiency in $bit/Hz/Joule$	Yes
[87]	3.1.1	Detection prob.	No	No	Energy in $Joule$	No
[88]	3.1.2	None	Yes	No	Energy efficiency ratio	No
[89]	3.1.2	None	ND	No	Energy saving ratio	No
[90]	3.1.2	Detection prob.	ND	No	energy efficiency in $bit/Joule$	Yes
[91]	3.1.2	None	No	No	Energy saving ratio	No
[92]	3.1.2	Detection prob.	No	No	Normalized utility function	Yes
[93]	3.1.1 & 3.1.2	Detection and false-alarm probs.	No	No	energy efficiency in $bit/Joule$	Yes
[94]	3.1.1 & 3.1.2	Detection prob.	Yes	No	Utility function	Yes
[95]	3.1.2	None	No	No	Energy efficiency in $Bit/Hz/Joule$	Yes
[96]	3.1.2	Detection and false-alarm probs.	No	No	energy consumption in $Joule$	No
[102]	3.2.1	false-alarm probability	No	No	Energy efficiency in $bit/Joule$	Yes
[105]	3.2.2	Detection and false-alarm probs.	No	No	Energy consumption in $Joule$	No
[106]	3.2.2 & 3.2.3	None	No	No	Energy consumption ratio	No
[107]	3.2.2	None	No	Yes	Energy efficiency in $bit/Joule$	Yes
[108]	3.2.2	None	No	No	No. of users	No
[110]	3.2.3	None	ND	No	Power consumption ratio	No

[111]	3.2.3 & 3.2.2	None	Yes	Yes	Energy saving percentage	No
[112]	3.2.3 & 3.2.2	None	No	No	Power consumption ratio	No
[113]	3.2.3	None	No	Yes	Energy in *Joule*	Yes
[114]	3.3	None	No	No	Energy efficiency in *bit/Joule*	Yes
[115]	3.3	Detection probability	ND	Yes	Energy efficiency in *bit/Joule*	Yes
[116]	3.3	detection probability and energy consumption	No	No	Normalized throughput	Yes
[117]	3.3	None	Yes	Yes	Energy efficiency in *Joule/bit*	Yes

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