SENSIC: Mobility-aware Cluster-based Cooperative Spectrum Sensing for Cognitive Radio Networks

G. Caso*, H. Soleimani*, L. De Nardis*, A. Tosti†, M.G. Di Benedetto*
* DIET Department, Sapienza University of Rome
Rome, Italy
Email: {caso, soleimani, lucadn, dibenedetto}@newyork.ing.uniroma1.it
† Telecom Italia SpA
Rome, Italy
Email: alessandro.tosti@telecomitalia.it

***Abstract*—This work proposes a novel framework for the organization and the management of a mobile cognitive radio network, focusing on the network performance in terms of cooperative spectrum sensing and data throughput. It relies on cooperation between secondary devices, that organize themselves in clusters defined according to both spectrum sensing reliability and mobility behavior of each secondary user. The proposed framework is compared by means of computer simulations with a simpler, non cluster-based scheme and with a cluster-based scheme in which the formation of the clusters and the election of the clusterheads are only related to the mobility behavior. Simulation results highlight that the adoption of a sensing plus mobility-aware clustering algorithm can lead to a sensing reliability comparable with the non-clustered solution (but involving on average a lower number of sensing nodes) and to a desirable improvement in data throughput of the secondary network, also leading to improved energy efficiency.**

I. Introduction

It was largely demonstrated that many portions of the RF spectrum are not used for significant periods of time and geographic areas [1]-[5], hinting that its scarcity is largely due to the ineffective fixed frequency assignments rather than actual spectrum shortage. This has stimulated various activities in the engineering, economics and regulation communities in order to define new spectrum management policies. Dynamic Spectrum Access with Cognitive Radio (CR) [6] is considered a possible solution [7]. Although regulators in US, Europe and UK introduced geolocation databases as a solution to check the presence of users on a given frequency band, FCC in US left open the possibility of using Spectrum Sensing (SS), that is a functionality allowing a CR (Secondary User (SU)) to detect the presence/absence of eventually incumbent users (Primary Users (PUs)), with the final goal to use that band if it is sensed to be idle. In the most challenging scenario, where the licensed transmitted signal to be detected is unknown, the most common choice for SS consists in using an Energy Detector, a solution referred to as Energy Detector Spectrum Sensing (ED-SS) [8]. Noting that reliability and availability of sensing information gathered from Local Spectrum Sensing (LSS) carried out by a single device is strongly affected by the propagation conditions, Cooperative Spectrum Sensing (CSS) was proposed a mean to in order to improve performance of LSS. In a typical CSS scenario, all nodes in a Cognitive Radio Network (CRN) share their sensing results with others, potentially increasing the probability of correct identification of spectrum usage. It was previously demonstrated that SS is affected by shadowing and fading characteristics of the physical channels between PUs and SUs [9]. The work in [10] analyzes the impact on cooperative sensing performance of spatio-temporal correlation between measurements and sensing decisions: results show that as the number of sensors increases, the correlation between the measurements increases as well, reducing the positive effect of cooperation. This suggests that efficient CSS may be achieved in most cases by using a properly chosen subset of SUs, and poses the question of how to select such a subset. Clustering has been proposed in order to address this issue, but most of the solutions proposed so far for CR, reviewed in Section II-A, neglect to address a second issue that can affect SS performance, that is SUs mobility. Indeed, although mobility is a topic extensively studied in various contexts of wireless communications, as, for example, ad-hoc and vehicular networking, the impact of mobility is a largely under-investigated topic in cognitive radio networking. With regards to this topic, results presented in [11][12] are interesting, as they show that mobile SUs are able to collect sensing samples at a wide range of locations, allowing an improvement in spectrum sensing performance by exploiting spatial diversity. In [10], moving from the observation that results in [11][12] were derived under several strong simplifying hypotheses, more realistic assumptions are made in measuring sensing performance, confirming a potential improvement by taking advantage of mobility, although to a more limited extent. No solution has been proposed so far, however, for integrating mobility in the CSS process. On the other hand, mobility has been widely investigated in the context of Mobile Ad-Hoc NETworks (MANETs) in both flat and clustered network organizations, and it seems logical to review the approaches proposed in this context, as briefly presented in Section II-B, in order to define a solution tailored for the case of a CRN.

Moving from the above observations, in this work a novel framework for the organization and the management of a CRN of mobile devices is proposed, where the SUs use

978-1-4799-5396-7/14/$31.00

a CSS approach in order to take a decision on the PUs presence/absence in the considered frequency bands. In the considered scenario the SUs monitor a set of n channels, take independent decisions on the state of a channel by using ED-SS, and send them to a Fusion Center (FC) that applies a *n-out-of-N* fusion rule [13]. The proposed framework relies on a clustering algorithm adopting a novel metric that uses two parameters for the formation of the clusters and the election of the clusterheads: spectrum sensing reliability and mobility behavior, aiming at improving spectrum sensing performance and CRN data throughput.

The rest of the paper is organized as follows: Section II reviews and discusses previous work related to clustering for CRNs and for MANETs, focusing on mobility-aware solutions. Section III introduces the proposed solution for efficient and mobility-aware organization of a CRN, dubbed SENSIC. Section IV presents an extensive performance evaluation of the SENSIC solution based on computer simulations. The section first introduces the simulation setup and settings, and then presents simulation results. Finally, Section V concludes the paper, by discussing the results and identifying open issues and future work directions.

II. Related work on clustering

Clustering is the process of hierarchizing nodes in a network, by dividing them into different virtual groups called clusters and by assigning up to three different states: clusterhead (CH), clustergateway (CG), or clustermember (CM) [14][15]. A CH normally is the local coordinator of a cluster, performing intra-cluster transmission arrangement. A CG is a non-clusterhead node with inter-clusters links, so it can forward information between clusters. A CM is an ordinary node in a particular cluster. Clustering has been recently proposed for the organization of CRNs, but historically has been extensively analyzed for MANETs, showing that it can lead to performance improvements thanks to a more efficient resource utilization, higher system capacity and better routing performance. In the following, solutions proposed for CRNs are reviewed, before moving to the general case of MANETs, with particular focus on mobility-aware solutions.

A. Clustering-based solutions for Cognitive Radio Networks

Clustering is particularly relevant to the design of CSS solutions when the assumption of perfect physical channels between the SUs and the FC (called *reporting* channels) is no longer valid, as investigated recently by several authors. In [16], under the assumption that reporting channels experience Rayleigh fading, a cluster-based cooperative sensing scheme is proposed: the work assumes that clustering has been performed by upper layers, adopting a non-specified clustering algorithm for MANETs. The SU with the largest reporting channel gain within each cluster is selected as CH, in charge of collecting the sensing results from all the other users in the same cluster and forwarding them to the FC. The results presented in [16] show that the proposed technique leads to a reduction in the reporting error due to the fading channel, leading in turn to an improvement in sensing performance.

Moving from the observation that for a CRN the definition of clusters and the selection of the CHs should be related to the sensing capabilities of the SUs, in [17] a novel scheme for cluster-based CSS is proposed. The scheme, referred to as Clustered Hybrid Energy-aware cooperative Spectrum Sensing (CHESS), adopts a hybrid approach that combines sensing reliability and energy efficiency of the SUs for clusters formation and CHs selection. Once the network is clustered, only the CHs are in charge of performing the sensing operations and of forwarding data traffic generated by nodes in their own clusters to the FC.

Other clustering solutions for CRNs have been proposed: in [18] a clustering algorithm for CR users is proposed, especially designed to support network robustness. This is accomplished by forming clusters that are homogeneous in size and forcing nodes with a high connectivity degree to the border of a cluster. In [19] the authors propose a novel scheme, dubbed CogAd-hoc, with a rather peculiar approach when compared to classical cluster structures. The CogAd-hoc cluster has no restriction to the dimension and no gateway nodes. Moreover, there is no global common channel for the network, and every cluster has its own local control channel. Performance are measured with reference to the average number of clusters as a function of the total number of nodes, but no performance evaluation in terms of sensing is provided.

The solutions cited above show that clustering can be a viable approach for the organization of a CRN; however, they do not address explicitly the case of mobile SUs. It seems thus a natural evolution to include the issue (but also opportunity) of SUs mobility in the design of CSS schemes.

B. Mobility-aware clustering in MANETs

As mobility is a prominently missing aspect in the design of clustering solutions for CRNs, in this section a brief review of mobility-aware clustering algorithms for MANETs is carried out, so to identify mobility-related metrics that might be ported to a mobile cognitive network scenario.

One of the first mobility-related clustering algorithm is the McDonald and Znati algorithm, known as $(\alpha; t)$-algorithm but also as Distributed Dynamic Clustering Algorithm (DDCA) [20]. The $(\alpha; t)$ criterion states that the probability of having an available path between each pair of nodes in a given cluster, over a time period t, is α, and this is evaluated as a function of a random walk mobility model. The purpose is to support robust and efficient routing, adaptively adjusting the scheme depending on the nodes mobility behavior.

In 2001 Basu, Khan and Little propose a novel clustering algorithm, dubbed MOBIC [21]. In order to elect CHs, it uses a mobility metric, defined as Aggregate Local Mobility (ALM) and denoted, for node Y, as M_Y. The node with lowest value of M is chosen as CH, assuming that a lower M value indicates that the node is relatively *less mobile* than its neighbors. A possible drawback of this algorithm is that it uses variations of signal strength as an indicator of mutual mobility between two SUs, since due to noise and possible obstacles in the environment, received signal strength may be lead to quite inaccurate estimate of mobility. Nevertheless, the mobility metric defined in MOBIC perfectly grasps the concept of relative mobility and its impact on topology, and it was thus the clustering algorithm selected for integration in the framework proposed in this work. Details on the MOBIC metric and procedures and how they have been integrated into the new framework are given in Section III.

III. The proposed framework: SENSIC

Moving from the previous observations regarding CSS, clustering and mobility, in this section a new framework for the organization of a mobile CRN is presented. The framework, dubbed *SENSIC* (SENSing + mobIC), integrates sensing reliability and mobility into a novel metric for CHs selection, enhancing the MOBIC metric by defining a novel sensing metric and by introducing revised re-clustering conditions. The ultimate goal of SENSIC is to elect as CHs the SUs showing *good* sensing performance and lower relative mobility with respect to their neighbors. The main features of SENSIC are presented in the following.

1) *CRN States* - Three different states are defined for the network: TRAINING, SENSING and DATA. The state is determined by the current condition of the network and by the result of the latest CSS decision on the data channels. As previously mentioned, a multi-channel scenario is considered where the PUs may choose, every time they need to transmit, one of n available channels. On their side, the SUs are able to sense the channels and transmit data using the one they are associated with, if it is sensed to be IDLE. The FC informs the SUs about the current state of the network by broadcasting appropriate control messages on a dedicated common control channel;
2) *Clustering Algorithm* - The algorithm combines a mobility metric derived from the one proposed in MOBIC [21], with a sensing metric. Following the approach in [21] the mobility metric is evaluated as follows. First, given a generic pair of neighboring nodes, a *relative* mobility metric is computed, as the ratio between the received power levels of two successive *Hello* messages transmissions. The relative mobility metric at the node Y, with respect to node X, denoted as $\mathsf{M}_Y^{\mathsf{rel}}(X)$, is given by
$$\mathsf{M}_Y^{\mathsf{rel}}(X) = 10\log_{10}\frac{R_\mathsf{x}P^{\mathsf{new}}_{\mathsf{r}X\to Y}}{R_\mathsf{x}P^{\mathsf{old}}_{\mathsf{r}X\to Y}}, \qquad (1)$$
where $R_\mathsf{x}P_\mathsf{r}$ is the power detected at the node receiving the *Hello* message and it is indicative of the distance between the transmitting and receiving node pairs. If $R_\mathsf{x}P^{\mathsf{new}}_{\mathsf{r}X\to Y} < R_\mathsf{x}P^{\mathsf{old}}_{\mathsf{r}X\to Y}$, then $\mathsf{M}_Y^{\mathsf{rel}}(X) < 0$ and this indicates that the two nodes are possibly moving away with respect to each other. On the contrary, the two nodes are possibly moving closer to each other. For a node with m neighbors, m such values of $\mathsf{M}_Y^{\mathsf{rel}}(.)$ exist and the node can calculate the ALM metric, denoted as $\mathsf{M}_{\mathsf{Mobic}}$, and defined as the variance (with respect to zero) of the entire set of relative mobility metrics of all its neighbors: $\mathsf{M}_Y^{\mathsf{rel}}(X_i)$,
$$\mathsf{M}_{\mathsf{Mobic}} = \mathsf{var}_0\{\mathsf{M}_Y^{\mathsf{rel}}(X_i)\} = \mathsf{E}[(\mathsf{M}_Y^{\mathsf{rel}})^2], \qquad (2)$$
with $1 \le i \le m$.
The sensing metric evaluation takes place when the network enters in TRAINING, following a control packet from the FC. Each SU in the network performs N_{Sensing} sensing operations and sends the results to the FC. After collecting the decisions from all SUs, the FC replies with the cooperative decision, obtained by applying the selected fusion rule. The SUs receive the FC decision and update a *wrong* decisions counter (N_{Errors}) if their local decision is different from the cooperative one, assuming a greater reliability of the cooperative decision with respect to the local one. N_{Sensing} can be adjusted according the desired training duration. When the FC announces the end of TRAINING, each SU evaluates the sensing metric ($\mathsf{M}_{\mathsf{Sensing}}$) as follows:
$$\mathsf{M}_{\mathsf{Sensing}} = \frac{N_{\mathsf{Errors}}}{N_{\mathsf{Sensing}}}. \qquad (3)$$
Next, the generic SU combines the mobility metric with the sensing one, as follows:
$$\mathsf{M}_{\mathsf{Sensic}} = \mathsf{M}_{\mathsf{Mobic}} * \mathsf{M}_{\mathsf{Sensing}}. \qquad (4)$$
$\mathsf{M}_{\mathsf{Sensic}}$ is defined so that the nodes with good sensing performance and low mobility will have a higher probability to be chosen as CH. In order to select the actual CHs, the SUs exchange packets containing the values of the SENSIC metric. The SUs with the best $\mathsf{M}_{\mathsf{Sensic}}$ values will automatically take the role of clusterheads: they will assume that each neighbor will enter in their cluster, and will inform them about the cluster formation. In the case of a SU contended between two CHs, the SU will choose as CH the node from which it has received packets at higher power and will inform the contending CHs of updating the list of common nodes within their clusters. Figure 1 shows an example of application of the algorithm, highlighting the three phases of the procedure.

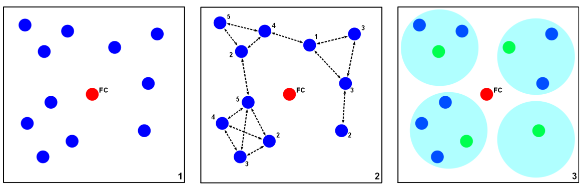

Fig. 1. SENSIC Clustering Algorithm Phases: 1) Non-Clustered SUs (blue); 2) Exchange of SENSIC Metric between neighboring SUs; 3) Election of clusterheads (green) and formation of clusters.

When the network leaves the TRAINING state each SU resets the N_{Errors} counter and starts switching between DATA and SENSING states. While in these states, *only* CHs will continue to sense the channels, to take local decisions and to transmit them to the FC. Note that the clustering procedure is not carried out in a particular network state but in a orthogonal way with respect to the DATA and the SENSING states, the only exception being the evaluation of $\mathsf{M}_{\mathsf{Sensing}}$ within the TRAINING. This is due to the fact the evaluation of the $\mathsf{M}_{\mathsf{Mobic}}$ metric has to be *continuosly* carried out using the exchange of *Hello* messages in order to promptly react to SUs mobility.

3) *Re-Clustering Conditions* - Re-clustering procedures are defined in order to modify the clusters and to elect new CHs, in case specific conditions occur. Two classes of re-clustering conditions are defined: sensing-related, triggered by a deterioration in sensing performance, and mobility-related, triggered by topology changes due to mobility. The procedure adopted to monitor the sensing-related re-clustering conditions is as follows. Every time a CH receives a decision from the FC, it compares it with its own decision and updates N_{Errors} as follows:

$$N_{\mathsf{Errors}} = \begin{cases} N_{\mathsf{Errors}} + \beta & \text{if } H_1 \\ \mathsf{max}(0, N_{\mathsf{Errors}} - \beta) & \text{if } H_2 \end{cases} \tag{5}$$

H_1 is verified when the FC decision turns out to be different from CH decision, while H_2 is verified when the FC decision turns out to be equal to CH decision. β is the so-called Re-Clustering Coefficient (RCC), taking values between zero and one, and used to weigh the impact of a decision error by the CH. The RCC value will define in fact the number of consecutive sensing errors allowed to each CH before causing a sensing-related re-clustering. The sensing-related re-clustering condition is triggered when a CH experiences $N_{\mathsf{Errors}} = 1$. In this case the CH will send a re-clustering request packet to the FC, and the FC will in turn order all the SUs in the network to enter the TRAINING state and start a new evaluation of $\mathsf{M}_{\mathsf{Sensing}}$. As regards mobility-induced re-clustering, two mobility-related re-clustering conditions are defined:

a) *CH clash*: if two CHs move into each other's range, a timer is scheduled. If the CHs are in transmission range of each other when the timer expires, re-clustering is triggered, and the node with the lower mobility metric assumes the status of clusterhead. With respect to the original formulation of MOBIC, SENSIC introduces an important difference related to the presence of multiple channels: re-clustering only takes place only when the clashing CHs are transmitting data packets on the same channel.

b) *SU loss*: if SU in a cluster falls out of connectivity with its CH, it will be allowed either to choose a new CH, if it happens to be within range with a SU with a better $\mathsf{M}_{\mathsf{Sensic}}$, or to declare itself as an isolated CH.

It is worth observing that both conditions allow a local re-clustering of the network as it does not involve the FC.

4) *Spectrum Sensing* - The main difference between TRAINING and SENSING/DATA states consists in the fact that in the former state all the SUs are involved in the CSS, while in the latter ones the channels are sensed only by the CHs. In both cases, the FC will apply a fusion rule on the local decisions. The Majority rule is the rule chosen for SENSIC, as a data channel is supposed to be IDLE or BUSY if at least half of the collaborating nodes sensed the channel as IDLE or BUSY respectively. Moreover, in order to choose the threshold of the Energy Detector, the Constant False Alarm Rate (CFAR) operating mode is used: it is assumed that each involved node sets its sensing target on the local probability of false alarm (P_{fa}). In this way, by inverting the P_{fa} formula, each node is able to evaluate the ED threshold and the probability of detection (P_{d}) (assuming the knowledge of the average SNR between PU and SUs). The corresponding results in terms of cooperative probabilities (Q_{fa} and Q_{d}) can be then obtained by applying the majority rule formulas [13].

5) *Data Transmission* - While in TRAINING state, no data transmission is allowed throughout the network. While not in TRAINING, the data transmission on each channel depends on the CSS decision on the same channel. In case a channel is declared as BUSY by the FC, nodes belonging to clusters using that channel will enter the SENSING state, in which SUs are not allowed to transmit data and the CHs will only schedule periodic sensing. Oppositely, if a channel is declared as IDLE, the SUs in clusters using the channel will enter the DATA state, in which SUs are allowed to transmit data packets and the CHs will perform both sensing and data transmission. The association rule clusters-channels is provided by the FC, under the assumption of complete information on clusters, aiming at equally allocate clusters on channels, so to obtain a fair and efficient traffic channelization.

IV. Results and Discussions

SENSIC was compared by means of computer simulations with two other CSS schemes: a flat, non cluster-based cooperative sensing scheme and a cluster-based scheme in which the formation of the clusters and the election of the CHs are only related to the MOBIC algorithm.

A. Simulation Environment and Settings

The simulation environment foresees the presence of a PU and a set of 10 SUs. The PU is located in a fixed position ($[300, 300]$m) within a square area of 700×700 m^2 centered on the position of the FC. It alternates Activity and

Pause periods, with durations of the periods randomly chosen following an exponential distribution with mean equal to 20 seconds. At the beginning of each Activity period, the PU chooses one of four possible 20 MHz Wi-Fi channels for its own data transmissions, using a fixed power of 110 mW. The SUs communicate among them and with the FC using the same power of the PU, both on data channels (when transmission is allowed) and on the control channel (modeled as well as a 20 MHz 802.11 channel). Both static and mobile SUs were considered; when mobility is present, SUs move within the playground according to a Gauss-Markov mobility model with an average speed $v = 5$ m/s. Finally, regarding the physical propagation channels, the following model for power attenuation is adopted, for both PU-SUs and SUs-SUs channels:

$$\alpha_{\mathsf{channel,dB}} = \alpha_{\mathsf{PL,dB}} + \alpha_{\mathsf{f,dB}} \tag{6}$$

where $\alpha_{\mathsf{PL,dB}}$ is the attenuation factor for the path loss model, depending on carrier frequency of the working frequency band and distance between devices, and $\alpha_{\mathsf{f,dB}}$ is the fast fading coefficient, modelled using the Jakes approximation of the Rayleigh fading model.
The implementation of the environment was carried out within the OMNeT++ simulation environment, taking advantage of the MiXiM framework [22]. Each run covered 3 hours of simulated time, during which each collaborating SU took local decisions with a CFAR sensing target $P_{\mathsf{fa}} = 0.05$, exploiting a sensing phase of $T = 50\mu$s and then transmitting its decision to the FC during the subsequent exchange phase of 1 second. Finally, a global decision was taken by the FC each 5 seconds.

B. Simulation Results

Figures 2 and 3 present the cooperative sensing performance in both static and mobile cases for a network clustered with the SENSIC framework, compared with a non-clustered network (all the SUs are involved in CSS) and with a network clustered using the MOBIC algorithm. Note that in the static case, the mobility metric (2) for each SU show non-zero values thanks to the hypothesis of fading channels, that guarantees different received power levels between two consecutive exchanges of *Hello* packets. Figures 4 and 5 present the throughput performance in both cases for the same network scenarios.

In the static case results show that SENSIC matches the sensing performance of the non-clustered algorithm while involving a lower number of cooperating SUs. This is a very interesting outcome in terms of power efficiency: the use of a lower number of SUs to sense the channels could lead to significant energy savings, and might prove crucial in applying the cognitive paradigm to energy-limited scenarios, such as in sensors networks. Figures 4 and 5 show a significant increase in the offered data traffic for the clustered models that can be explained as follows. In the case of non-clustered model it may happen that although the last decision by the FC was of channel IDLE, in the next sensing time some of the SUs sense the channel as BUSY. In this case, in order to protect

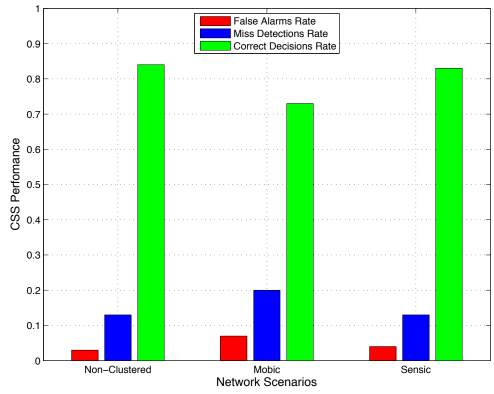

Fig. 2. CSS performance in a Static Scenario for Non-Clustered, MOBIC-Clustered and SENSIC-Clustered Networks

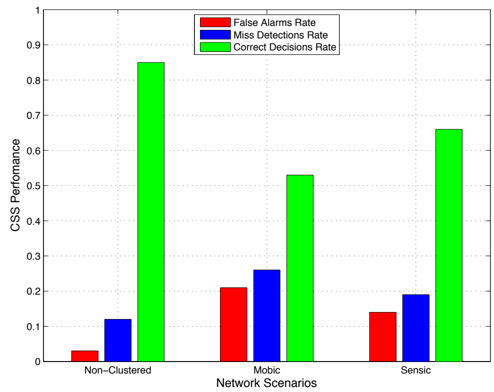

Fig. 3. CSS performance in a Mobile Scenario for Non-Clustered, MOBIC-Clustered and SENSIC-Clustered Networks

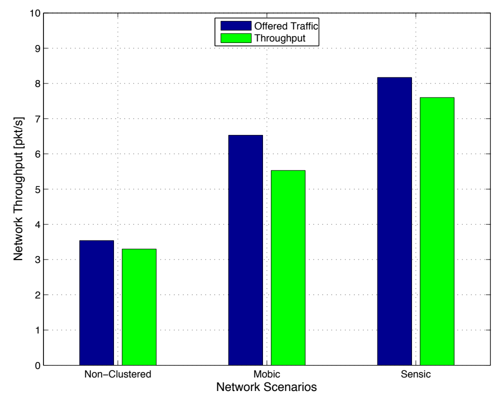

Fig. 4. Offered Traffic and Throughput performance [pkt/s] in a Static Scenario for Non-Clustered, MOBIC-Clustered and SENSIC-Clustered Networks

PUs in the area, those SUs decide to conservatively stop their own data generation and transmission, waiting for the next decision by the FC. This does not happen in the clustered models, where some of the SUs do not even sense: the SUs

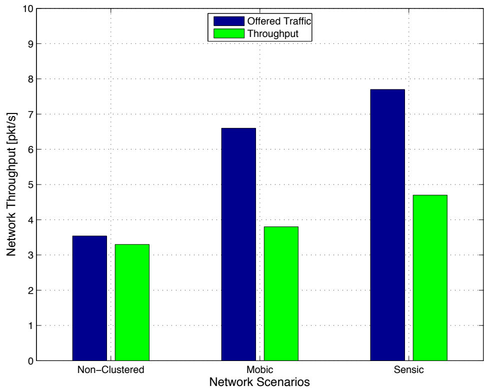

Fig. 5. Offered Traffic and Throughput performance [pkt/s] in a Mobile Scenario for Non-Clustered, MOBIC-Clustered and SENSIC-Clustered Networks

completely refer to the last cooperative decision, continuing in the data generation and assuming that, at least, they can trasmit data to the CHs (in a sort of underlay access with a reduced amount of *intra-cluster* power). SENSIC, compared with MOBIC, seems to better manage the traffic growth, with a significant throughput increase. On the other side, it looks clear from Figure 3 that the introduction of a mobility model degrades the sensing performance in the clustered models. In this case as well SENSIC behaves better than MOBIC; it can be expected that additional performance improvements can be obtained with the definition of a more specific mobility metric. In terms of throughput, SENSIC reaches good results, even if the difference between offered traffic and throughput starts to be more pronounced when compared to the static case.

V. Conclusions

This work proposed a cluster-based solution for the organization of mobile CRNs, measuring the performance of the solution in terms of CSS and data throughput. In particular, a novel framework for clustering is defined, based on metrics characterizing the SUs in terms of sensing reliability and mobility behavior. Simulation results confirm that clustering is an effective way to manage the entire network. Future work will focus on the accurate evaluation of the overhead introduced by the algorithm, as well as on the impact of different mobility models.

Acknowledgment

This work was carried out in the framework of the joint Telecom Italia - DIET Dept. Labs "AWESAM". Part of this work was supported by the "Ricerca Scientifica 2013" project by Sapienza University of Rome, ISCOM, COST Action IC0902, ICT ACROPOLIS NoE FP7 project n.257626, and funded by Telecom Italia in the contract 2014 with Sapienza University of Rome "Internet of Things".

References

[1] Federal Communications Commission (FCC); *Spectrum Policy Task Force* - Rep. ET Docket n. 02-135, Nov. 2002.

[2] McHenry, M.A.; *NSF spectrum occupancy measurements project summary* - Shared Spectrum Company, East Lansing, Michigan, Tech.Rep., Aug. 2005.

[3] McHenry, M.A.; McCloskey, D.; *Multi-band, multi-location spectrum occupancy measurements* - in Advanced Radio Technologies (ISART'06), International Symposium on, March 2006.

[4] OFCOM; *Mobile "Not-Spot" Measurement Campaign, 7 February 2011, OFCOM* - Feb. 2011.

[5] Harrold, T.; Cepeda, R.; Beach, M.; *Long-term measurements of spectrum occupancy characteristics* - in New Frontiers in Dynamic Spectrum Access Networks (DySPAN'11), 7th IEEE International Symposium on, pp. 83-89, May 2011.

[6] Mitola, J.; Maguire G. Q.; *Cognitive radio: Making Software Radios more personal* - in IEEE Personal Communications, Aug. 1999.

[7] Federal Communications Commission (FCC); Notice of proposed rule making and order: *In the Matter of Facilitating Opportunities for Flexible, Efficient, and Reliable Spectrum Use Employing Cognitive Radio Technologies* - ET Docket n. 03-108, Dec. 2003.

[8] Urkowitz, H.; *Energy Detection of unknown deterministic signals* - in Proc. IEEE, vol.LV pp. 523-531, Apr. 1967.

[9] Ghasemi, A.; Sousa, E. S.; *Collaborative Spectrum Sensing for Opportunistic Access in Fading Environments* - in New Frontiers in Dynamic Spectrum Access Networks (DySPAN'05), 1st IEEE International Symposium on, pp.131-136, Nov. 2005.

[10] Caso, G.; De Nardis, L.; Holland, O.; Di Benedetto, M.-G.; *Impact of Spatio-Temporal Correlation in Cooperative Spectrum Sensing for Mobile Cognitive Radio Networks* - in Wireless Communication Systems (ISWCS'13), Workshop CRAFT'13, 10th International Symposium on, Aug. 2013.

[11] Min, A. W.; Shin, K. G.; *Impact of mobility on spectrum sensing in cognitive radio networks* in Mobile Computing and Networking (MobiCom09), Workshop CoRoNet09, International Conference on, pp. 13-18, 2009.

[12] Arshad, K.; Moessner, K.; *Mobility driven energy detection based Spectrum Sensing framework of a Cognitive Radio* in Cognitive Wireless Systems (UKIWCWS10), 2nd UK-India-IDRC International Workshop on, Dec. 2010.

[13] Caso, G.; De Nardis, L.; Ferrante, G.C.; Di Benedetto, M.-G.; *Cooperative Spectrum Sensing based on Majority decision under CFAR and CDR constraints* in Personal Indoor and Mobile Radio Communications (PIMRC13), Workshop MACNET13, 25th IEEE International Symposium on, Sept. 2013.

[14] Yu, J.Y.; Chong, P.H.J.; *A Survey for Clustering Scheme for Mobile Ad-Hoc Networks* - in IEEE Communication Surveys, www.comsoc.org/pubs/surveys, 2005.

[15] Chawla, M.; Singhai, J.; Rana, J.L.; *Clustering in Mobile Ad-Hoc Networks: a Review* - in International Journal of Computer Science and Information Security (IJCSIS), Vol. VII, n.2, 2010.

[16] Sun, C.; Zhang, W.; Letaief, K. B.; *Cluster-Based Cooperative Spectrum Sensing in Cognitive Radio Systems* - in Communications (ICC'07), IEEE International Conference on, pp. 2511-2515, June 2007.

[17] De Nardis, L.; Domenicali, D.; Di Benedetto, M.-G.; *Clustered Hybrid Energy-aware cooperative Spectrum Sensing (CHESS)* - in Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM'09), 4th IEEE International Conference on, pp.1-6, June 2009.

[18] Li, D.; Gross, J.; *Robust Clustering of Ad-hoc Cognitive Radio Networks under Opportunistic Spectrum Access* - in Communications (ICC'11), IEEE International Conference on, June 2011.

[19] Lei, S.; Lei, L.; Cheng, Z.; *A novel Cluster-based architecture of Cognitive Wireless Ad-hoc Networks* - in American Journal of Engineering and Technology Research Vol. 11, No.9, 2011.

[20] McDonald, B.; Znati, T.E.; *A Mobility based framework for adaptive clustering in wireless ad-hoc networks* - in IEEE JSAC, Vol. XVII, n.8, Aug. 1999.

[21] Basu, P.; Khan, N.; Little, T.D.C.; *A mobility based metric for clustering in mobile ad-hoc networks* - in Distributed Computing Systems (DCS'01), 21st International Conference on, pp.413, 2001.

[22] Koepke, A.; Swigulski, M.; Wessel, K.; Willkomm, D.; Klein Haneveld, P.T.; Parker, T.E.V.; Visser, O.W.; Lichte, H.S.; Valentin, S.; *Simulating Wireless and Mobile Networks in OMNeT++: The MiXiM Vision* - in Simulation Tools and Techniques (SIMUTOOLS'08), 1st International Conference on, March 2008.