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Using Neighbor's State Cross-correlation to Accelerate Adaptation in Docitive WSN

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***Abstract*: In WSN, sensor nodes have limited energy budget therefore this paper mainly focus on power saving by using the docition paradigm. Docition is a new teacher-student paradigm proposed to improve cognitive radio. Although it improves the infrastructure based networks it has a weakness in case of ad-hoc mobile networks. The energy constraints and the total mobility of the network complicate the selection of the appropriate teacher for a student. By selecting the wrong teacher, there is a high probability that the taught information may be faulty, and thus the student radio diverges from the best state. This causes a high amount of energy loss, though the most important concern in ad-hoc networks is energy limitation. In this paper, we propose a dynamic docition for teacher selection based on the auto-correlation degree of the teacher's candidate environment and the cross-correlation degree between the teacher candidate and the student environments. We validate our approach in the context of coexistence between WSN and WiFi. The WSN detects, models and exploits the unused time slots in the electromagnetic spectrum, left by WiFi, using dynamic docition. The simulation results show that the use of dynamic docition outperforms the existing docition in mobile networks. The improvements are shown through the low link overhead percentage (20% less overhead) and the low packet loss ratio (30% improvement).**

Keywords: **Docitive; Online Prediction Problem; WSN; pareto model; IEEE802.11 b/g;cognitive radio.**

I. INTRODUCTION

Now a days the radio spectrum congestion is the major problem that wireless sensor networks are facing [12][11]. Recently, in the domain of cooperative and distributed networks, to mitigate congestion and radio problems, a new paradigm has emerged called docitive networks [1]. Docitive network is a wireless network, where the docitive radio is an upgrade of cognitive radio [2]. Cognitive radio uses artificial intelligence and machine learning algorithms to process local channel observations. In addition to local observations, docitive radio includes information from the neighboring nodes to this process. The purpose of this information exchange is to accelerate and improve the decision process. *Docition* from the Latin *docere* is to teach, which relate to radios that teach other radios [1]. From this view docition is the teacher-student paradigm. It is generally known that intelligence is impacted by the degree of observation. Still as cognition and learning have received a significant attention from various communities in the past, the process of knowledge transfer, the teaching, over wireless medium has received fairly little attention to date. Similarly to distributed cognitive radio, docitive radio needs to cooperate with neighboring radios to have docition. The difference from regular distributed cognitive networks is that in docition the student teacher paradigm does not impose the use of the exchanged information: the teacher does not teach end results but proposes elements of the methods for getting there.

In the concept of docitive network, there was no indication about the circumstances to use docition, implying that it is always useful to use docition. Specifically when the authors in [1] defined the degree of docition they just cited the degrees as static choices, hence the node do not have dynamic behavior as to choose its own degree of docition. The degrees of docition ranged from no docition to perfect docition.

During docition, exchanging the Q-learning [3] table is essential as it contains the information of docition. As this table contains the information related to the observed state of the teacher it is crucial that a student node have the similar environment state as the teacher node. We claim that although docition provides fast convergence to the learning node, the assumptions taken by the paradigm impose coherence between the states of the teacher and the student. The reason is there are no measures taken in the docitive paradigm to insure that the teacher and student nodes have coherent states. In our study we are interested in mobile networks with no infrastructure such as MANET and WSN. We note that in such networks, nodes may not have coherent states, moreover the same weakness appear in the case of an unlicensed densely populated frequency band as the ISM band. For the rest of the paper we refer to the previously presented docition as classic docition (CD).

As a solution, in this paper, we present dynamic docition (DD) that enables the teacher and the student nodes, in case of mobility or incoherent channel state between them, to specify the level of docition dynamically based on the level of environment predictability. We add the *environment predictability probe* (EPP) as a new element to classic docition. This element estimates the level of coherence between the teacher and student nodes, and, based on the result, if the environment state is stable enough and there is a certain level of coherence, it is acceptable to apply docition otherwise no docition is applied.

To evaluate the DD performance, we apply it on the case of a coexistence situation between IEEE802.15.4 (wireless sensor) and IEEE802.11b/g (WiFi) technologies, where sensor nodes are mobile. To escape the WiFi interference, the sensors adopt the White Space (WS) modeling technique and the Pareto model proposed in [4]. The behavior of the nodes in this use case scenario is similar to the cognitive radio that adapt an unlicensed user (known as secondary user) to coexist with a licensed user (known as primary user) [5]. The use of such scenario in our case is to provide to weak technologies as the technologies using IEEE802.15.4 standard (limited power supply, low power, low processing and transmission rate) the adaptation means to coexist with dominant technologies like IEEE802.11 (unlimited power supply, high transmission power and rate, and high traffic generation). Applying DD in this scenario improves the efficiency of the power consumption and provides faster convergence time.

Intuitively, we expect that as the system becomes more uncorrelated and more dynamic, the use of CD becomes disadvantageous. In this paper, we quantify this claim by simulations, we propose *DD*, and we chose to apply it in the case of *startup docition* on WSN as it has the least energy cost relatively to other degrees of docition and validate its performance by the simulations.

II. DYNAMIC DOCITION

CD is composed of four elements: acquisition, intelligent decision, action, docition. The main contribution of DD on mobile networks is that it provides to the student an efficient manner to select a teacher and to know dynamically when to apply docition or not. In mobile networks, the teacher is the most important actor as it should give credible teachings. To determine the teacher existence DD is used. The DD adds a new element on CD which is the *EPP* to be applied before the *docition* element. Some models characterizing the spectrum activity can always be assumed (cf. [6], [7]). These models predict the spectrum occupation, and the duration of each recurring event, therefore based on these assumptions the *EPP* is used to construct a local channel model and estimate the level of similarity between teachers and students for present and future states.

The predictability of the environment is detected using correlation functions and stochastic modeling. Due to the mobility in ad-hoc networks there are some conditions related to the model integrity that are assured by the *EPP*. If the model validation test executed by a node is done before it changed its location then no teaching can be made by the node (GPS or the method in [10] can detect a location change). On the other hand if the node did not change its location after validating the model then the node is accepted as a teacher candidate. Although in [8] it was stated that if two nodes are able to communicate implies a minimum level of cross correlation between their environments, the EPP must assure the existence of such minimum level of cross correlation between the teacher and the student environments.

III. DYNAMIC DOCITION FOR WHITE SPACE DETECTION

To illustrate the application of dynamic docition, we use the white space detection in a coexistence environment between a wireless sensor network (WSN) and a WiFi network. In this case of coexistence, a white space is the inter-arrival time between two consecutive WiFi bursts. The problem in such coexistence scenarios is that the WiFi nodes do not detect the WSN nodes transmissions. Therefore the WiFi APs do not backoff when there are transmissions from the WSN. The aim is that each sensor node (SN) tries to model the white spaces that are not used by WiFi and based on the model the packet

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length or the number of packets to be sent is determined. The goal of applying DD is to optimize the convergence time which impacts the energy cost for a newly arriving SN to the WSN. Each of the existing nodes will send the white space model parameters to the new node along with the gain (the duration of applying the same model parameters) that was provoked by using the model. The new node chooses from all the neighboring teacher candidates the best suited model to use as its own startup model.

To construct the model, the teacher candidate will estimate the gain using the *online prediction problem*. In the evaluation of our proposal we use the modeling mechanism proposed in [4] as a use-case to illustrate the improvements made by DD.

As our aim is mobile network with no infrastructure, in this type of networks with limited energy supply, the mission of DD is to swap between startup docition and no docition. We adopt *startup docition* for white space detection. In startup docition, the initial concept, docitive radios teach their policies to any newcomers at the beginning when the nodes are going ON. We must emphasize that for the initial concept, the aim was static networks, and a newcomer is a base station that is going from OFF state to ON state. Based on this assumption Gains are expected due to the highly correlated environment and due to the fact that teaching nodes have an updated environment model where they have applied their cognitive actions. In the case of ad-hoc networks none of the above assumptions exists, therefore DD should be applied.

The Pareto model $P(\alpha,\beta)$ is declared by [4] as an acceptable model for WiFi white space modeling. Therefore each node will try to construct such model to be able to communicate with other nodes in the WSN.

A. Mecanism of the Teaching Node:

The teaching node must apply these steps:

1- Sampling the channel, and calculating white spaces durations (x_i) (inter-channel occupation time).

2- Modeling for future prediction by detecting $P(\alpha,\beta)$ using maximum likelihood estimation (MLE) [9]: $\beta = n/\sum_{i=1}^{n}\log(\frac{x_i}{\alpha})$; α is the minimum$[x_i]$; n is the number of WS samples.

3- Saving the time (duration) of the application of $P(\alpha,\beta)$.

4- Applying *online learning problem* (on the model) to estimate the model efficiency. A newly calculated Pareto exponent β' is adopted only if it does not belong to this interval$[\beta(1-k);\beta(1+k)]$. If β' is adopted then the time is reset (duration of the model application), go to step 2. If the level of resemblance between the old and the new model (gain) is high, the time (duration) is not reset. k is the acceptable percentage of deviation between β' & β.

5- Setting itself as teaching candidate if it did not change its location after validating the model and the gain is high.

6- Sending its teaching credentials (model parameter, application & testing duration) if it is a candidate teaching node and it detects a new node.

Remarks: 1- The Gain in (4) is the goodness of fit between the model and the new samples. This method for determining the efficiency of the chosen model is better than comparing the throughput level before and after a model change, because a sender does not need to cooperate with the receiver to know the throughput. 2- *EPP* covers from step 3 to 6 at the teaching node and all the steps at the learning node mechanism.

B. Mecanism of the Learning Node:

1- If the node detects a location change, it sends a beacon.

2- The node receives the credentials of the candidate teaching neighbors.

3- A minimum level of consensus between the teaching candidates should exist. If the correlation among them is low no docition is applied, else the node goes to step 4; the Average of the β_i received $E(\beta)$ is calculated and the deviation percentage from this average is analyzed. If the deviation is higher than K (ex: K=10%) then there is no correlation. The acceptable teacher candidates are the nodes that have the β_i existing in the interval $[E(\beta)-y;E(\beta)+y]$ where $y=\frac{K*E(\beta)}{2}$; N is the number of teacher candidates, β_i is the received Pareto shape, K is the ratio that restricts the accepted correlation level between the neighboring teacher candidates. Moreover, it is used to filter the teacher candidate nodes.

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4- The node selects as teacher the one with the highest gain and that has a β that falls in the accepted deviation. If there is no acceptable candidate, no docition is applied.

5- After a time of stability, the node changes its state from learning node to teacher node.

Step 3 explanation: the main idea is to prove that CD is unsuitable for Ad-hoc networks. If the neighborhood has diverse states or has high deviation from an average β there is no docition. Otherwise, if there is a quasi-total agreement to one choice of β then apply docition. In case of DD the deviation percentage determines the restriction on applying docition. If there is a loose interval for β deviation the docition may be applied most of the time with a consequence on the Packet Loss Rate (PLR) (cf. Fig 2, Fig 3).

IV. SIMULATION

We used Matlab simulator to compare our proposed DD protocol against CD performance. On a surface we set a grid of overlapping WiFi access points (APs) and wireless sensors nodes. Each AP has a coverage area (πR^2) and a permissive overlap area π (R^2-$R1^2$). The permissive area usually exists to allow an overlap between multiple APs and a certain level of interference. This is to enable the hand over between mobile nodes and APs. The sensor nodes are distributed using the Poisson point process (PPP) distribution and submitted to the interference of the WiFi APs.

Each AP is assigned a WiFi traffic generator. The sensor nodes sample the durations of the channel vacancies between WiFi transmissions (the White spaces "WS") and use the MLE to reconstruct their model. From [4], the sensors adopt the Pareto model construction methods and steps. The Pareto model used has two parameters; α and β. α is determined as the minimum acceptable WS length "1ms" and β is found using the MLE and the WS samples. To sample the WS samples we adopted the same parameter values used in [4] as they were optimized using empirical results: 100ms windows are used for sampling the channel state. As a consequence the maximum white space length can reach 100ms. The sampling rate used is 200Hz.

For the teaching node, we fixed at 10% the acceptable deviation from the old beta. Henceforth, by the acceptable deviation we refer to the K value at the learning node mechanism.

The simulation is divided into two parts. The first part deals with the energy cost of the signaling stage of docition. The second part compares the performance of implementing DD and CD on a WSN.

Energy Cost of The Signaling Stage Of Docition:

The sensors can construct the WS Pareto model using two methods: the direct one based on the clear channel assessment (CCA) samples and the indirect one based on docition information received in the packets header. A comparison between the energy cost of both is done in fig 1. First we calculate the energy cost for a CCA sample and the energy cost for adding the docition information in the header, then for the case of the CCA sampling we multiply this cost with a number of samples and for the case of docition information we multiply it by the number of teacher candidates. The energy cost in the case of docition information exchange is related to the transmission and reception duration of the number of bits. Therefore for docition the added cost is equal to the cost of the extra bits sent, we have in total 16 bits sent:

-2 bits are used to indicate the duration of the model usage (the gain) (cf. Table 1):

Table 1: duration mapping

00	01	10	11
t(ms)< 100	t>=100 & t<200	t>=200 & t<500	t>= 500

-14 bits are used as the float value of beta:

* 4 bits are used for the integer part (max value =15)

* 10 bits are used for the decimal part (max value =1024)

Due to the addition of the docition information to the beacons and to insure that the cost will not exist during all the beacon exchange but just when there are docition, the packet length indicates if the 16bits are added or not so the nodes do not always execute the additional 16 bit listening.

The energy cost is E=U*I*t.

T:duration(Seconds)	U: voltage(Volt)	I: current(Amp)

The CCA is performed by sampling 8 symbols the duration is128microseconds.

The duration for transmitting or receiving one bit is 64 microseconds and it needs 0.0174Amp for transmission and 0,0197Amp for reception, the voltage used is 3V.

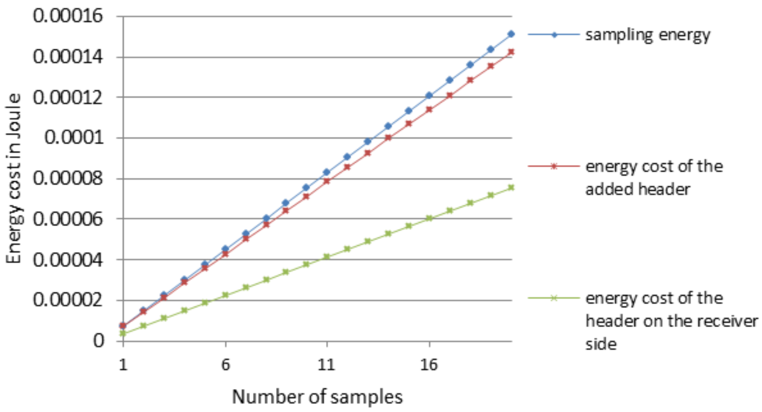

Figure 1: the energy cost in function of the number of the 16bits exchanged in case of docition and the number of CCA samples in case of sampling.

In fig 1 the docition signaling (middle curve) is less costly than the sampling (highest curve) and at the same time it distributes the energy between the sender and receiver. The cost on the receiver side is represented by the lowest curve.

System Simulation:

In what follows we simulate the total system of mobile sensors and fixed WiFi AP. A grid of 36 WiFi APs with a transmission radius of 100m is covering a surface of $10^6 m^2$. The sensor nodes coexist with these APs on the same surface and have a transmission radius of 50m.

The rate of selecting valid information from the neighbors is monitored at section a), since docition based methods main objective is to obtain information on the environment faster than self-acquiring of such information. We compare three methods of selecting the beta value: CD that is based on choosing the β value randomly from the neighbors, DD that is based on EPP and choosing the β value that occurs most often among the neighbors due to cross-correlated wireless spectrum state. The use of docition to obtain information is precisely to use them to improve the network performance. Therefore, in section b), we examine the PLR and the percentage of overhead introduced by docition.

Since we are interested in “startup docition”, the simulation consists of bringing outside nodes and placing them evenly in a plane which already contain distributed sensors based on PPP and WiFi APs. This simulation is repeated enough times to get good confidence intervals. As we study the “startup docition”, the worst case scenario is chosen for the mobile nodes where they are imported from an environment where there is very little WiFi traffic, therefore, they have big WiFi white spaces compared to the network nodes.

We performed four types of simulations. The first two observe the effect of the parameter K used by the student to filter the received values of β. During these two, 30 nodes are imported and the results are observed depending on the number of nodes in the network. In the third simulation, the nodes density is increased but the proportion of new neighbors for a node coming from outside (student) remain unchanged. Finally, in the fourth simulation, the total number of nodes in the network remains constant while the percentage of new neighbors increases.

While the first two scenarios correspond to the case where the existing sensor nodes are fixed and the only movement is the arrival of new nodes, the latter two allow observing the behavior of the sensor network in a mobile situation. In fact, the mobility has the effect that new nodes arriving from outside find in their new neighborhood, nodes that have a good estimate of beta as they have had time to get it, and other nodes newly arriving from elsewhere in the network without

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having consistent information about the environment. Therefore, by increasing the number of nodes arriving from outside, we can observe the mobility effect of sensors already in the network on the percentage of correct selection of information by docition. We call the first two scenarios "quasi-static scenario" and the last two "mobile scenario."

a) Testing the efficiency of the methods used in docition:

Quasi static scenario:

For each node is assigned the β of the traffic generated by the AP that covers it. The probability of choosing the right β from the neighbors is tested. In the static scenario all the neighbor nodes are supposed static. Therefore they are all teacher candidates because by construction of the scenario, they all have a good estimation of beta. The acceptable deviation percentage is set to 20% and R1=75% of R. In fig 2 the results show that for the CD, the probability of selecting the correct neighbor is relatively unchanging (~67%) in function of the number of nodes covering the region. In case the selection of β is based on the maximum number of neighbors that have adopted its value, the percentage of correct selection increments in function of the number of existing nodes. It presents a better estimation than the CD. Although, the latter performed better than the CD, the DD based on the deviation percentage from the average (middle column in Fig 2 and Fig 3) shows the best performance between the 3 methods.

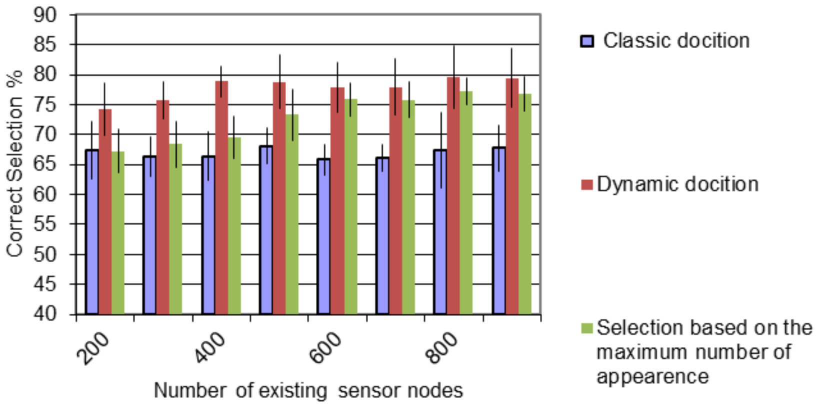

Figure 2: percentage of the correct selection of the true beta value in function of the number of nodes that existed before the arrival of the student nodes.

We restrict to 10% the acceptable deviation percentage for DD. A better performance is shown in Fig 3. The drawback of additional restriction on the β selection results in more restrictions on the use of docition.

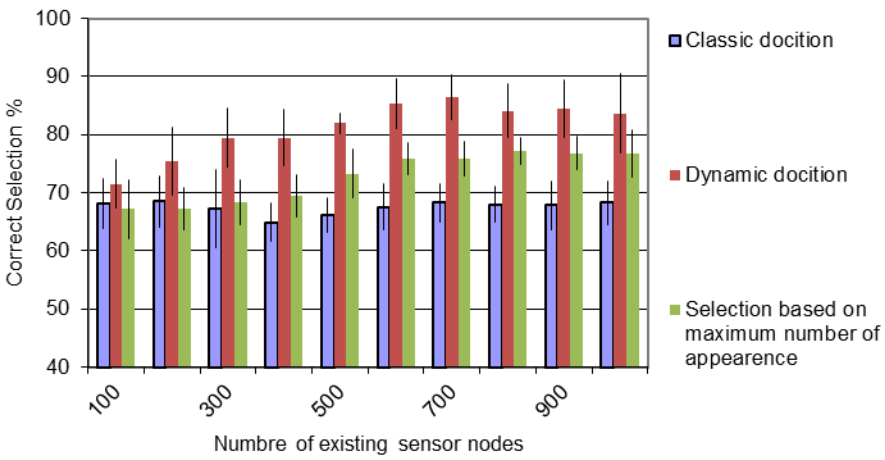

Figure 3: percentage of the correct selection of the true beta value in function of the number of nodes that existed before the arrival of the student nodes.

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Mobile scenario:

In the mobile scenario, the mobility of the neighbors eliminates their candidature to become teacher nodes in the case of DD. For the CD there is no distinction between selecting such nodes or selecting a teacher candidate node. Fig 4 shows the degradation of the classic docition. By contrast the results of DD are improving. Specifically, the mobile non teacher candidates cause a high diversity in the β values. Therefore, in the CD there is a high probability to select the wrong β value. The results shown in Fig 4 are influenced by forcing 70% of the new nodes neighbors to be imported from random locations.

For the experiment of Fig 5**,** 300 sensor nodes are set as existing nodes. The non expert neighbors' percentage is adjusted at the same time the percentage of the correct β selection is monitored. It is shown that the non expert nodes do not influence the nodes that are using DD, but they affect the CD because there are no distinction between the expert teachers and the non expert ones.

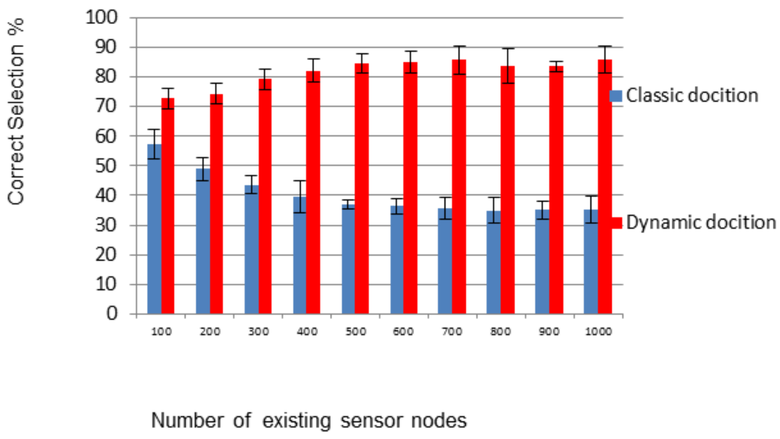

Figure 4: percentage of the correct selection of the true beta value in function of the number of nodes that existed before the arrival of the student nodes.

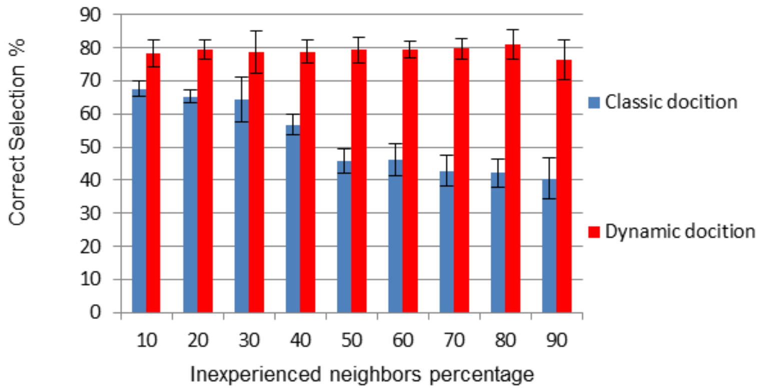

Figure 5: percentage of the correct selection of the true beta value in function of the percentage of inexperienced neighbors.

b) *Using channel sampling and MLE to determine the suitable WiFi WS model for traffic generation*

Previously, in subsection a) quasi static scenario, the student algorithm used in DD has proven to be highly efficient relatively to classic docition. For this part, a noise is indirectly introduced through the fact that the β values are not assigned directly to the nodes, but rather the nodes use channel sampling and the MLE to determine the APs WS model. In the subsection b) quasi static scenario, the DD and CD should have similar performance due to the correlated neighbors' environment, in contrast to what is going to happen in the mobile scenario where the performance of the teacher algorithm is highlighted. In this part, we compare the efficiency of 3 methods used to construct the Pareto distribution that models

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the WiFi WSs. The methods are: direct channel sampling with the use of MLE, CD and DD. The effect of the deviation from the WiFi WS model is determined. The deviation has an effect on the PLR and on the link overhead percentage.

Quasi static scenario:

Henceforth, the WSN nodes transmit packets with a length of 2ms. The WSN nodes predict WiFi WS lengths by finding the best β value as the appropriate Pareto shape. For the rest of the experiments we set the acceptable deviation percentage for DD to 10%.

The PLR and the link overhead ratio are monitored, in Fig 6 the traffic performance is shown. CD uses random β selection from the neighbors. The same performance tests are done for the DD. The traffic performance when using the β found by channel sampling and using the MLE represents the best performance that can be reached, because by executing the WS sampling the WSN nodes have the exact WiFi WS model that governs the wireless channel. R1 is set to 50% of R. In the case of static neighborhood, all the types of docitions along to the model construction using sampling and MLE have approximately the same performance level. The compared results show convergence to the best link characteristics. The overhead percentage reaches 38 % and the packet loss is 22% as shown in Fig 6. Although, we have similar performance outcome for the 3 methods, the DD showed a slightly better performance than CD.

In Fig 7 the same experiment as in Fig 6 is executed but more surface intersection is allowed between the WiFi APs (R1 equal 70% of R) to add more diversity for the neighboring β values. We suppose that by doing so, there will be a higher probability for a false β selection.

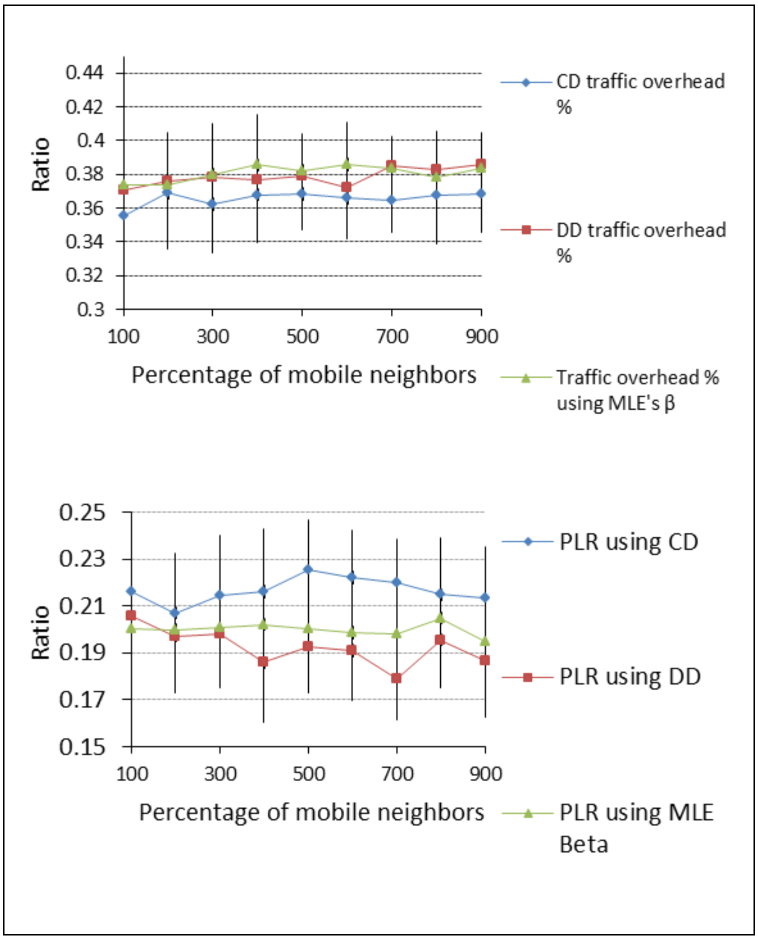

Figure 6: the upper graph represents the overhead % and the lower graph represents the PLR both graphs are in function of the number of nodes that existed before the arrival of the student nodes.

The higher PLR in Fig 7 relatively to the PLR in Fig 6 is caused by the small WS length that remains from the incremented percentage of superposed WiFi APs coverage area. All the docition methods have similar high performance, due to the stationary environment. The only cause to have a wrong β selection is by selecting a neighbor that exists in a different region of coverage. Although it has a low probability, its effect is shown by the weaker performance of classic docition.

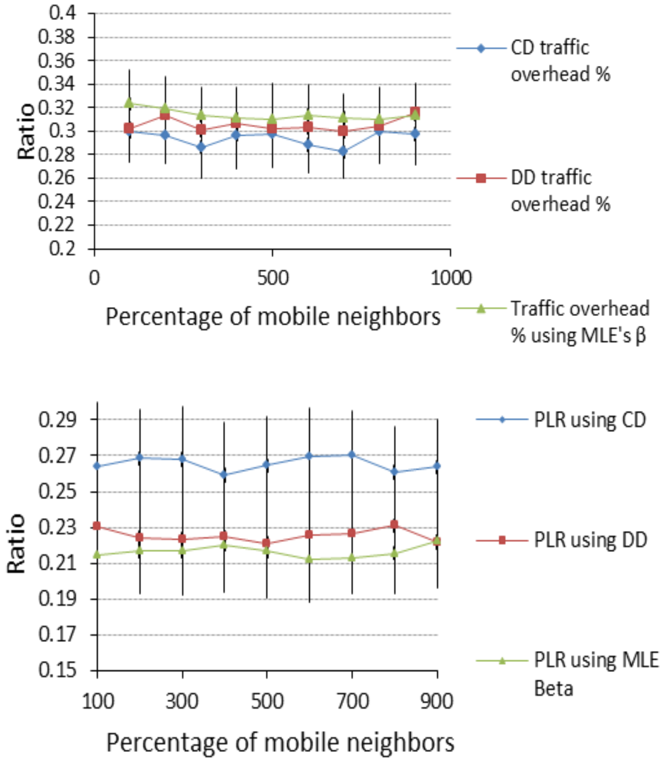

Figure 7: the upper graph represents the overhead % and the lower graph represents the PLR both graphs are in function of the number of nodes that existed before the arrival of the student nodes.

Mobile scenario:

In the following, R1 is set to 70% of R. By introducing the mobility aspect (50% of the neighbors are not teacher candidate), Fig 8 shows a high deterioration in the CD performance. In contrast, the resilience and stability of DD maintained a low PLR while keeping a minimum overhead percentage. Using the MLE as reference to estimate the performance of DD and CD, DD maintained a PLR of 20% the same as MLE. On the other hand, CD's PLR diverges and reaches 45%. During the simulation, the overhead percentage did not vary for CD and DD maintaining the value of 20% for CD and 30% for DD. Similar to fig 8, in Fig 9 the overhead percentage stabilizes on 17% for CD and 30% for DD. Due to space limitation we only show the overhead percentage for the case of fig 10 as it shows a deviations in the overhead percentage ranging between 14% and 28%.

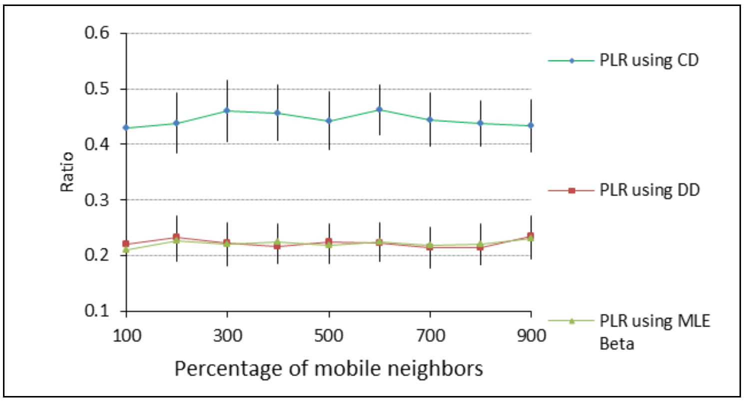

Figure 8: the PLR in function of the number of nodes that existed before the arrival of the student nodes.

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In Fig 9, the percentage of the neighbors that are none teacher candidate is raised to 70 %. More degradation of the CD performance is observed. The PLR increases in function of the number of existing nodes, till it reaches 50%. In contrast the DD performance is not influenced by the added inexperienced neighbors.

Next, 500 existing nodes are used. Fig 10 is the result of varying the percentage of the inexperienced neighbors. The CD has an incrementing PLR with the percentage of inexperienced nodes. The DD proved to be the best suited for mobility, as it prevents the inexperienced nodes from poisoning the learning nodes.

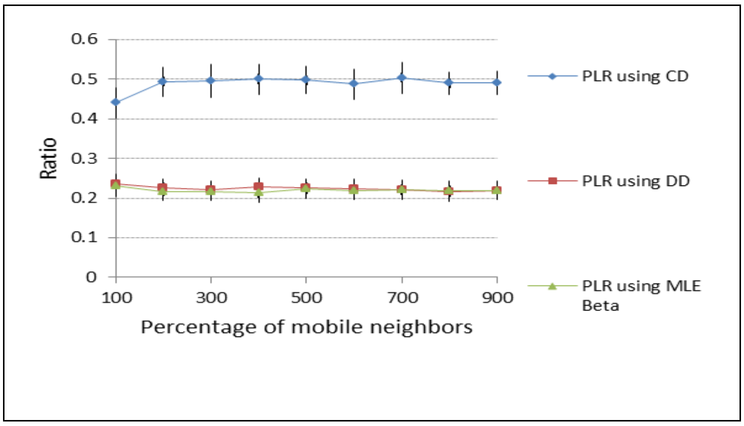

Figure 9: the PLR in function of the number of nodes that existed before the arrival of the student nodes.

What is presented is an added intelligence on when to apply docition. At the same time the selectivity when choosing a teacher provoke an improvement on the decision process even though a simple method for the teacher selection is used. More intelligent methods can be proposed, but the main idea in this approach is not to apply randomly the docition in case of a mobile network. The results show that the CD and DD achieve more or less the same performance in a static environment. In contrast, it is clearly seen the destructive effect of mobility on CD as the number of mobile inexperienced nodes increases. There is practically no effect on the DD as it filters the non expert mobile nodes.

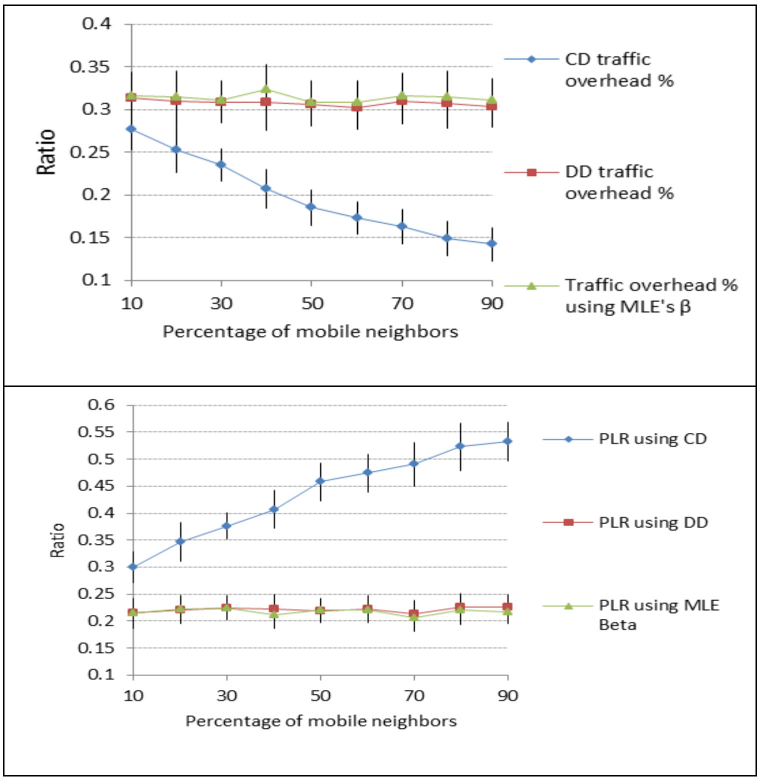

Figure 10: the upper graph represents the overhead % and the lower graph represents the PLR both graphs are in function of the number of nodes that existed before the arrival of the student nodes

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V. CONCLUSION

Based on cognitive radio, docition provides a mean to improve the methods of processing and reaction to link variations. In our work, we added the environment predictability aspects for docition, to improve the learning, optimize the energy consumption and to catalyze fast convergence of the wireless sensor nodes. By proving there is environment stability for the teaching node EPP proves that there is some state information that is worth teaching. Otherwise, if the environment state is chaotic, it is difficult to find useful information to teach. The EPP test the cross correlation between the student and the teacher to indicate the existence of useful information for the student among the taught data. Compared to CD, the simulation showed that DD provides an improvement of more than 50% of correct beta value's selection. An improvement is also shown on the PLR. Moreover the added energy cost on the signaling is estimated and it shows that exchanging the docition information has a lower energy cost than allowing a node to do its own channel sampling.

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