Learning Enhanced Environment Perception for Cooperative Power Control

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***Abstract*— The vast proliferation of wireless networking devices, coupled with the trend for short-range communications in dense residential environments, imposes new challenges for the efficient addressing of problems resulting from co-existence of heterogeneous devices (e.g., interference) under capacity and energy constraints. This paper proposes and evaluates a cooperative distributed algorithm for power control and interference mitigation based on ad-hoc communication of heterogeneous yet peer networking devices, driven by enhanced situation awareness and learning capabilities; the learning capabilities evolve the way a network element perceives its environment. The gains of this approach are highlighted through its application in WiFi APs. The results reveal that the introduction of learning capabilities in cooperative power control leads to interference mitigation while introducing minimum overhead in the network nodes.**

Keywords– co-existence; interference mitigation; cooperative power control; learning; data mining.

I. INTRODUCTION

The acute proliferation of wireless networking devices enables "anytime" and "anywhere" communications. This trend together with large scale deployment of heterogeneous radio access networks in short range context (APs, pico-cells, etc.) and in dense environments (i.e., residential areas) impose the need for developing mechanisms addressing issues related to co-existence in an efficient way; capacity and energy efficiency impose different constraints in the system whereas the mentioned co-existence results in high interference levels.

In such communication environments, power control mechanisms can be utilised to mitigate interference and enable reduced power consumption, extended battery lifetime, reduced cost, improved reliability and overall utility from the network perspective and, at the same time, improved QoS from the user perspective. Given the devices' heterogeneity and diversity, such mechanisms should be developed following a cooperative and distributed paradigm.

In this paper, a cooperative and distributed algorithm is presented and evaluated for addressing interference mitigation through power control among the networking devices which participate in the optimization procedure. In fact, the algorithm provides considerable enhancements and extensions to existing algorithms for cooperative power control [1][2], so as to further strengthen situation awareness, environmental perception, and knowledge-based decision making. Specifically, the proposed solution is applicable to short-range wireless networking environments, where heterogeneous devices belonging to different owners are able to exchange interference and power information thus exploiting inherent ad-hoc communication capabilities. Moreover, the algorithm deploys learning capabilities to the devices in order to facilitate the evaluation of the previous decisions and better interpret the environment conditions.

The rest of this paper is structured as follows: Section II presents proposed solutions available in the literature; Section III provides background information regarding fuzzy logic and k-Means; in Section IV, the baseline reference algorithm for cooperative power control is briefly described. Section V presents the learning-assisted algorithm by providing the case study which has been developed in the context of this paper whereas the proposed learning framework is described thoroughly afterwards followed by the presentation and analysis of the experimental results. Finally, Section VI concludes the paper.

II. RELATED WORK

The cooperative transmission power control adjustemnt has attracted the interest of researchers, given the benefits stemming from the introduction of power control schemes; thus several solutions have been proposed in the literature. In [3], Sun et al. propose to formulate the power control problem using a non-cooperative game; the solution converges once Nash equilibrium [1] is reached. The strategy for the transmission power identification is related to the Shannon capacity [10] on the one hand and the energy waste due to the caused interference on the other. In [4], an algorithm that allows for transmission power and transmission frequencies to be chosen simultaneously by cognitive radios competing to communicate over a frequency spectrum is being proposed; the solution is based on a cooperative game theoretic approach. The aim of this solution is to reduce the sensed interference by mainly considering the negative impact of every user to its neighborhood. In [5], a cooperative game-theoretic mechanism for optimizing power control is also proposed. In this solution, issues such as network efficiency and user fairness are seriously taken into account in order to optimize a SINR-based utility function. In [6], Bennis and Niyato propose a reinforcement learning framework (i.e., learning through trials and errors) for interference avoidance in 3G

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networks where a femto BS/AP gradually learns how, to adapt the channel selection strategy until reaching convergence by interacting with its local environment. Finally, Dirani and Altman in [7], propose a solution that addresses the problem of inter-cell interference coordination on OFDMA wireless networks by enhancing a fuzzy inference system with a reinforcement learning framework. This framework aims at dynamically adjusting power on parts of each base station's bandwidth, in order to control the interference it produces to its neighboring cells. In this paper an algorithm described in [1] and [2] is being further enhanced; the key idea is to strengthen the available solutions with learning capabilities so as to integrate in the cooperative power control scheme enhanced situation perception. The proposed solution is based on a hybrid model which exploits the merits of fuzzy logic and data clustering.

III. BACKGROUND

A. Fuzzy logic

Fuzzy logic is an ideal tool for dealing with complex multi-variable problems; the nature of the decision making mechanism makes it very suitable for problems with often contradictive inputs. A fuzzy reasoner consists of three parts, namely:

- The fuzzifier, which undertakes to transform the input values (crisp values) to a degree that these inputs belong to a specific state (e.g. low, medium, high, etc) using the input membership functions.
- The inference part, which correlates the inputs and the outputs using simple "IF...THEN..." rules. Each rule results to a specific degree of certainty for each output; these degrees then are being aggregated.
- The defuzzifier, where the outcome of the abovementioned aggregation is being mapped to the degree of a specific state that the decision maker belongs to. Several defuzzification methods exist; the most popular is the centroid one, which returns the center of gravity of the degrees of the outputs, taking into account all the rules, and is calculated using the following mathematical formula:

$$u_{COG} = \frac{\int u_i \mu_F(u_i)du}{\int \mu_F(u_i)du} \tag{1}$$

B. k-Means

k-Means is a well known data-mining clustering technique. The core idea of data clustering is to partition a set of N, d-dimensional, observations into such groups that intra-group observations exhibit minimum distances from each other, while inter-group distances are maximized. k-Means [8] is based on the following objective function:

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\left(\sum_{k, x_k \in G_i} \left\| x_k - c_i \right\|\right) \tag{2}$$

where c is the number of clusters, G_i is the ith group, x_k is the kth vector in group J_i and represent the Euclidean distance between x_k and the cluster centre c_i. The partitioned groups are defined by using a membership matrix described by the variable U. Each element U_{ij} of this matrix equals to 1 if the specific j^{th} data point x_j belongs to cluster i, and 0 otherwise. The element U_{ij} is analyzed as follows:

$$U_{ij} = \begin{cases} 1, \text{ if } \left\| x_j - c_i \right\|^2 \le \left\| x_j - c_k \right\|^2, \text{ for each } k \ne i \\ 0, \text{ otherwise} \end{cases} \tag{3}$$

This means that x_j belongs to group i, if c_i is the closest of all centers.

IV. COOPERATIVE POWER CONTROL- BASELINE ALGORITHM

In this section we describe the baseline algorithm as proposed on [1] and [2]; both approaches propose a scheme for distributed interference compensation in Cognitive Radio that operates in license exempt spectrum bands. The solution concerns ad-hoc networks and is based on an information exchange scheme towards the identification of the appropriate transmission power levels. Each independent node of the topology sets its power by considering individual information as well as information related to the neighboring nodes. More specifically, a node sets its power level by considering its Signal to Interference plus Noise Ratio (SINR) and the interference caused to its neighbors. The main idea of this approach is to prevent users to operate in the maximum transmission power levels.

The authors assume a set of node pairs L that operate in the same frequency. The SINR for the ith pair is given below [1]:

$$\gamma_i(p_i^k) = \frac{p_i^k \cdot h_{ii}}{n_o + \sum_{j \ne i} p_j^k \cdot h_{ji}} \tag{4}$$

Where

- p^k_i: transmission power for user i on channel k
- h_{ii}: link gain between ith receiver and ith transmitter
- n_o : noise level (equals 10^{-2})
- p^k_j: transmission power for all other users on channel k, assuming that $j \in \{1,2,\dots,L\}$ and $j \ne i$
- h_{ji}: link gain between ith receiver and jth transmitter

It is also assumed that the channel is flat-faded without shadowing effects. Since the channel is static, the only identified attenuation is the path loss h (channel attenuation or channel gain). Given that indoor urban environments are considered, the channel gain is $h_{ji} = d_{ji}^{-3}$, where d is the distance between the jth transmitter and the ith receiver.

The decision for the transmission power levels takes into account the negative impact (i.e., interference) of a node to its neighboring nodes. This is formalized using Equation 5 which captures the notion of interference price; such price reflects the interference a user causes to other users within its transmission range and is given by:

$$\pi_i^k = \frac{\partial u_i(\gamma_i(p_i^k))}{\partial(\sum_{j \ne i} p_j^k \cdot h_{ji})} \tag{5}$$

where,

- $u_i(\gamma_i(p^k_i)=\theta_i \log(\gamma_i(p^k_i))$: logarithmic utility function,
- θ_i: user dependent parameter.

Both of the algorithms presented in [1] and [2] are based on a tradeoff between the capacity of a user and the interference caused to the corresponding neighborhood. This balance is being captured by the following objective function:

$$u_i(\gamma_i(p_i^k)) - \alpha \cdot p_i^k \sum_{j \neq i} \pi_j^k \cdot h_{ji} \tag{6}$$

The first part indicates a relation to the Shannon capacity for the corresponding user, while the second part captures the negative impact in terms of interference prices that a user causes to its neighborhood. The *a* factor is introduced so as to capture uncertainties in the network; these uncertainties are related to how correctly each network node has received and compiled information regarding the interference price which should have been available by the node's neighbors. This is related to the fact that once a network element adjusts its transmission power it informs its neighbors in an ad-hoc manner. This implies that even though a network element has collected information from all of its neighbors in order to adjust its transmission, the gathered data could be obsolete and, as a consequence they will not capture the current neighborhood's state. The obsolescence of the interference prices is related to the update interval (i.e., the periodic update) of each network element. In [1], α is set in a static manner as 25%. In [2] a fuzzy reasoner is introduced in order to identify, in a more dynamic way, uncertainties in the network based on the network's status; the inputs (number of users, mobility, update interval) of the fuzzy reasoner capture the volatile nature of the ad-hoc network, whereas the output of the fuzzy reasoner is the *Interference Weight*. The *a* factor is defined as 1/β Interference Weight + 1 (β has the maximum value of the Interference Weight).

The algorithm consists of three steps, namely, the initialization, the power update and the interference price update. The former is related to the introduction of initial valid transmission power and interference price values. The second concerns the transmission power update based on the interference prices each node receives from its neighbors. Finally, the latter captures the communication of its interference prices to the neighborhood, by every network node. The second and the third steps are asynchronously repeated until the algorithm reaches a steady state (i.e., a state where every network element has the same transmission power for two consecutive time iterations).

The main deficiency of the afore-described scheme is related to the static definition of the environment (i.e., *a* factor that captures the network's dynamics). Even in the case where the fuzzy reasoner is used for capturing the uncertainties in the network, the environment interpretation model (i.e., membership functions of the fuzzy reasoner) is static. More specifically, in the latter case, the environment interpretation is based on expert's knowledge and is induced to the network elements by its input membership functions. This implies that all network elements that have the same configuration have the same situation perception as well. Moreover, it would be a major benefit for the network administrators to enable network elements to evolve the way they interpret their environment; this could be achieved by changing the shape of the input membership functions. In order to tackle the static definition of the situation perception, we propose a feedback based learning scheme that evaluates how the network performed after a transmission power adjustment, in terms of the interference prices.

V. LEARNING ENHANCED COOPERATIVE POWER CONTROL FRAMEWORK

A. Case Study

In this paper, we apply the previously described solution in WiFi networks for the interference mitigation. More specifically, we suggest that the WiFi APs should cooperate in order to minimize the caused interference by adjusting their transmission power. In the envisaged topology we assume the presence of several WiFi APs located in the considered area. These APs communicate via wireless links in order to exchange their interference values. Based on these values each network element adjusts its transmission power (Figure 1).

Given the assumption that the APs communicate asynchronously and each one might have its locally-set update interval, it is possible that the APs are unaware of the current network's status (from the messages exchange). This implies that the use of the fuzzy reasoner is imperative in order to capture the uncertainties [2]; the new application area though, poses the need for modification of the inputs and the inference engine of the fuzzy logic controller. Thus, the number of the WiFi APs in the vicinity, the number of users in the vicinity (associated to WiFi APs) and the update interval are used as inputs of the fuzzy reasoner. The way a network element perceives its environment is based on the input and output membership functions. As in [2], the inputs' membership functions initially are set to have triangular shape.

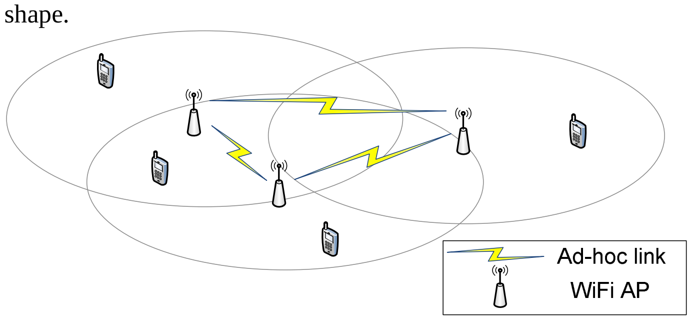

Figure 1 Envisaged network topology

Table I provides the rules of the inference of the fuzzy reasoner. The most crucial input for the decision making process is the update interval. The latter depicts the frequency of the information updates about the interference price of a network element to its neighbors.

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TABLE I. RULES OF THE FUZZY REASONER

Rule Number	Num of WiFi APs	Num of Users	Update Interval	Interference price
1	Low	Low	Low	Low
2	Low	Low	Medium	Low
3	Low	Low	High	Medium
4	Low	Medium	Low	Low
5	Low	Medium	Medium	Medium
6	Low	Medium	High	Medium
7	Low	High	Low	Medium
8	Low	High	Medium	Medium
9	Low	High	High	High
10	Medium	Low	Low	Low
11	Medium	Low	Medium	Medium
12	Medium	Low	High	High
13	Medium	Medium	Low	Medium
14	Medium	Medium	Medium	Medium
15	Medium	Medium	High	High
16	Medium	High	Low	Medium
17	Medium	High	Medium	Medium
18	Medium	High	High	High
19	High	Low	Low	Medium
20	High	Low	Medium	Medium
21	High	Low	High	High
22	High	Medium	Low	Medium
23	High	Medium	Medium	Medium
24	High	Medium	High	High
25	High	High	Low	Medium
26	High	High	Medium	High
27	High	High	High	High

B. *Proposed Algorithm*

The proposed learning algorithm consists of three parts, namely, the monitoring/labeling, the classification and the adaptation of the fuzzy reasoner. Each network element that is part of the network monitors its own environment. Every time that the network elements collaboratively proceed in transmission power adjustment, their interference prices are being compared to the previous ones and the interference factor calculations are being labeled as:

- Beneficiaries: for the decisions that led to reduction of the interference value caused to the neighboring network elements,
- Neutral: for the decisions that led to similar interference values, thus the decision could not be characterized either as correct or wrong,
- Non Beneficiaries: the decision led to an increase of the interference value caused to the neighboring network elements.

More specifically, periodically, the network elements cooperatively identify the optimum transmission power using the methodology described in Section IV; the iterative procedure requires finite number of steps (i.e., maximum 30 iterations). Before every periodic transmission power adjustment, the interference value is being compared to the value before the last transmission power adjustment (Figure 2).

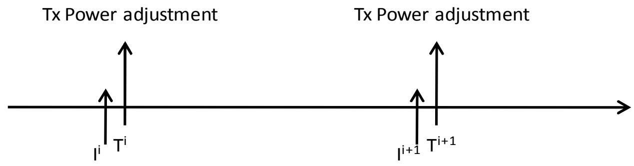


Figure 2 Timeline for Interference calculation and transmission poer adjustment

The input vector $\vec{Z}_i$ (i.e., num of WiFi APs, num of users, update interval) of each network element is being evaluated against a predefined fuzzy inference system and results to an *a* value which, in conjunction to the interference prices, is used for the calculation of the optimum transmission power. Comparing the interference prices just before the initiation of i^{th} the transmission power adjustment and the $(i+1)^{th}$ we label the decision accordingly(i.e., Y_i is beneficiary, neutral or non beneficiary). The comparison is done using the Euclidian distance metric. This procedure results to a set (*S*) of labeled decisions which have been correctly labeled (at a great level of certainty) through the afore-described phase. Table II presents the key points of monitoring/labeling part of the developed algorithm.

TABLE II. MONITORING/LABELING ALGORITHM

Input:	**Approximation Parameter ε, Sample Size N**
Output:	**Set of observations S**
1.	S ← O
2.	i=0
3.	while true
4.1	i++
4.2	Retrieve vector $\vec{Z}_i$ and $\vec{IP}_i$
4.3	α_i ← fuzzy logic ({# WiFi APs, # Users, Update Interval})
4.4	Calculate Tx power
4.5	Wait for $\vec{Z}_{i+1}$ and $\vec{IP}_{i+1}$
4.6	Calculate I^{factor}_{i+1}
4.7	If ($\lvert I^{factor}_i - I^{factor}_{i+1}\rvert < \varepsilon$) → Y_i=Neutral
	Else ($\lvert I^{factor}_i - I^{factor}_{i+1}\rvert > \varepsilon$) and ($I^{factor}_i - I^{factor}_{i+1} > 0$) → Y_i = Beneficiary
	Else ($\lvert I^{factor}_i - I^{factor}_{i+1}\rvert > \varepsilon$) and ($I^{factor}_i - I^{factor}_{i+1} < 0$) → Y_i = Non Beneficiary
4.8	S ← S U { $\vec{Z}_{i+1}$, $\vec{IP}_{i+1}$, Y_i}
5.	return S

On sequence, we formalate three clusters using the labeled data in order to exclude the misclassfied data from the previous step; the clustering is performed using k-Means (Table III). Thus, each network element maintains a set of three clusters, one for classifying every decision type. By representing each cluster to a 3D grid we map each cluster to a geometrical object (i.e., sphere S_i). Each sphere is centered at $C_j=\Sigma_{i=1}^{|Ci|}S_i/|C_i|$ and has radius $R_j=\max_{i=1}^{|Ci|}\|CE_i-S_i\|$.

TABLE III. K-MEANS AND GEOMETRIC BOUNDS CALCULATOR PROCEDURES

Input:	**Set of observations S, Cluster Size k**
Output:	**Set of Bounds B**
1.	B←O
2.	$\{C_i, R_i\}$ = k-means(S, k)
3.	B = Geometric_Bounds(C_i, R_i)
4.	return B

For each couple of clusters i, j, the cluster centers C_i, define a line ε that interconnects the two points. This line can be described by the following set of equations:

$$p_m = x_m + u \cdot (y_m - x_m),\ m = 1 \ldots d \qquad (7)$$

Line ε intersects with spheres S_i and S_j in four points which can be retrieved by substituting the p_m values into the following hypersphere equations:

$$D_i \rightarrow \sum_{m=1}^{d} (p_m - x_m)^2 = R_i^2 \qquad (8)$$

$$D_j \rightarrow \sum_{m=1}^{d} (p_m - y_m)^2 = R_j^2 \qquad (9)$$

A simple way of identifying the bounds would be to extract the intersection points which belong to different hyperspheres and exhibit minimum distance from each other [11]**Error! Reference source not found.**. Then, as shown in Figure 3, we map the identified bounds to the input membership functions of the fuzzy reasoner; this results to the modification of the environment perception of each network element.

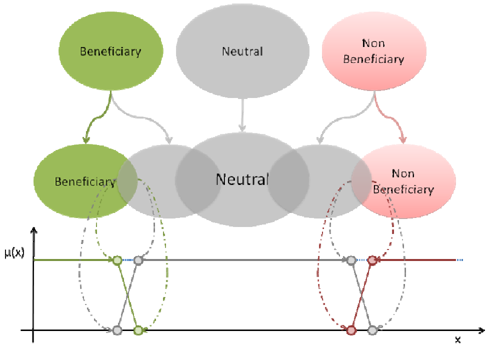


Figure 3 Clustering and bounds extraction mechanisms

C. *Experimentation Results*

In order to prove the validity of the proposed Learning Enhanced Cooperative Power Control Framework we have conducted a series of experiments that materialize the benefits from the introduction of the learning scheme. The modified version of [2], is used as the baseline for the comparisons. For the realization of the experiments we have artificially created a dataset consisting of 1000 pseudo-random tuples. The dataset reflects network topologies with a relatively small number of APs, as well as the collocated users. Figure 5 provides the Interference weight (i.e., outcome of the fuzzy reasoner) as a function of the APs' and the users' number, having as parameter the time interval before (Figure 5 (a)) and after (Figure 5 (b)) the learning procedure. It is apparent that the weight of the interference part of equation (3) is significantly affected, based on the feedback from the learning procedure; this implies that the transmission power extraction procedure is affected as well.

For the whole dataset we capture the values of the *a* factor; then we perform a fitting procedure in order to identify the polynomial functions that capture in the most suitable way the outputs. Figure 4 provides the 8th polynomial degree functions of the *a* factor before and after the learning procedure. After the learning procedure, the fuzzy reasoner has become more sensitive to the environment; this is being captured by the variation of the new a values (0.0458) instead of the old ones (0.0091).

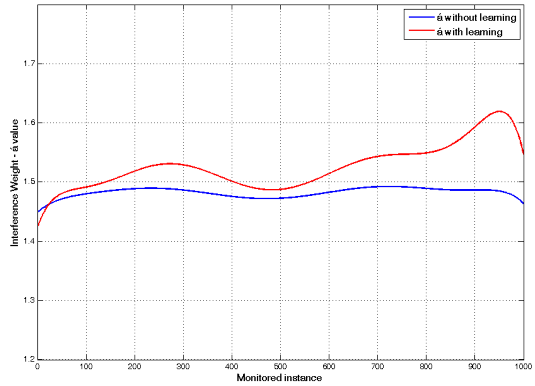
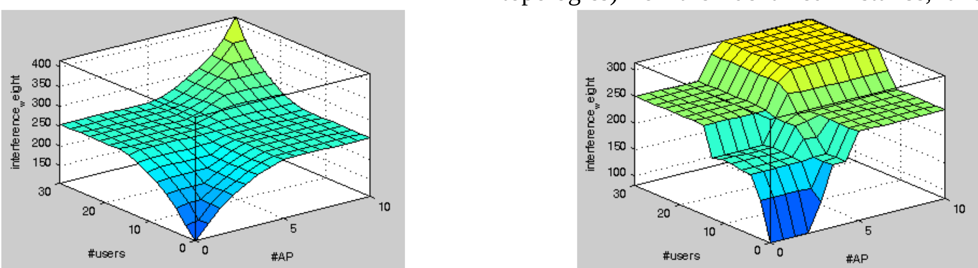


Figure 4 Interference weight *a* values before and after the learning procedure

For a given instance of the dataset, we identify the transmission power before and after the learning procedure. More specifically, following the approach presented in [2], we randomly create a set of experiments (10 different topologies) for the identified instance, and evaluate the



(a) (b)

Figure 5: Interference weight before (a) and after (b) the learning procedure

algorithm performance. As depicted in Figure 6, certain deviations to the final power values can be noticed when learning procedure is applied. In specific topologies (i.e., 2nd, 3rd and 8th) significant energy gains are achieved. In the rest of the topologies the learning framework achieves less significant gains but in no occasion energy waste occurs.

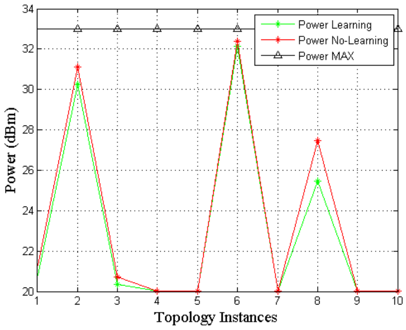


Figure 6 Transmission Power before and after the learning procedure

In Figure 7 the overall utility of the network for the ten (10) experiments is presented. The utility with the incorporation of the learning framework is significantly ameliorated compared to the one with the transmission power set to the maximum valid level. Moreover, after the deployment of the learning algorithm, the network elements achieve better results in the overall utility, in comparison to the ones with the cooperative power control without learning capabilities.

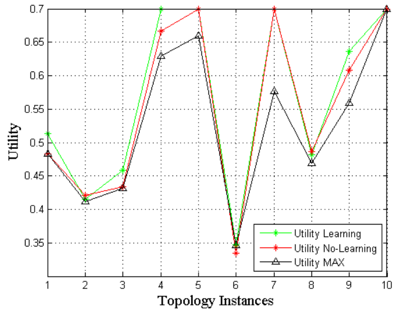


Figure 7: Overall utility before and after the learning procedure

VI. CONCLUSION AND FURTHER WORK

This paper proposes an algorithm for power control and interference mitigation. The solution leverages on the proposals of [1] and [2], by introducing learning capabilities in the network elements to optimize the environmental perception. The learning procedure captures the positive or the negative impact of an action (i.e., transmission power set value) in the interference that a network element causes to its neighbors.

The novelty of our contribution is the combination of the merits of fuzzy logic and data clustering for the optimal interpretation of the network uncertainties and its incorporation to the cooperative power control framework. The network uncertainties have been identified using the cluster overlaps; the latter are then being translated in the environment perception of the fuzzy reasoners (i.e., input membership functions).

In addition, this advanced mechanism for power control has been validated through its application in WiFi APs. The experimental analysis revealed that the learning framework leads to minimization of the interference. Furthermore, the results prove that the incorporation of the learning capabilities in the network elements lead to significant gains in terms of less transmission power and higher utility which results to reduced interference. Our future work includes the validation of the algorithm in additional topologies and the minimization of the communication overhead.

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