A Successive Refinement Approach to Wireless Infrastructure Network Deployment

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***Abstract*— There has been a recent proliferation in wireless infrastructure network deployments. In a typical deployment, an installer uses either a one-time site survey or rules of thumb to place wireless access points and allocate them channels and power levels. Because the access point location problem is inherently complex and one that requires tradeoffs among competing requirements, these approaches can result in either dead spots or significant unintended interference among wireless access points. This degrades network performance for end clients, with throughput reduction factors of 4x found in field measurements [1]. In this paper, we take a first step towards improving client performance by coordinating choices of channels and power levels at wireless access points using a *successive refinement* approach. Our contributions are two-fold: First, we develop a mathematical model that crisply defines the solution space and identifies the characteristics of an optimal channel and power-level configuration. Second, we present heuristics that, under some simplifying assumptions, yield near-optimal configurations. We use Monte Carlo simulations to evaluate the performance of our heuristics. We find that the choice of heuristics for transmit power control impacts performance more than the channel allocation strategy, especially at high densities. Also, surprisingly, randomly assigning channels to access points appears to be an effective strategy at higher deployment densities. Taken together, we believe that this study paves the way to designing rapidly deployable real-world infrastructure networks that also have good performance.**

I. Introduction

There has been a recent proliferation in the deployment of wireless infrastructure networks based on the IEEE 802.11 standard. These networks are created by placing a set of wireless access points (APs) within a geographical area, such as a floor of a building or a public space, so as to maximize coverage and prevent the creation of 'dead spots'. This placement problem is challenging because of competing pressures. On the one hand, the greater the number of APs, the better the coverage and the lower the likelihood of creating dead spots. Besides, mobile devices that are always likely to be close to an AP can use higher transmission rates and are less likely to suffer from connection drops due to dead spots. On the other hand, increasing the number of access points costs more money, both to purchase the APs and to install them. Moreover, in locations that are served by more than one AP, there is a problem of *interference*, that is, suppression of communication between a mobile device and a particular AP because of simultaneous communication between another mobile device and another AP. Therefore, blindly increasing the number of APs can not only be more expensive but in fact counter-productive.

The problem is further complicated by the following considerations:

- *Irregular AP coverage areas*: The Euclidean distance of a point from an AP does not uniquely determine whether that point is in the AP's coverage area.
- *Dynamic coverage areas*: Coverage areas may change over time due to shadowing and multi-path transmission, which can be induced simply by having people walk into a room, or shifting a metal cabinet by a few centimeters.
- *External Interference*: Interference can be caused not only by mobile devices and APs in the infrastructure (i.e. internal interference), but also by rogue APs in the coverage area, as well as cordless phones and microwave ovens that are essentially uncontrollable (i.e. external interference). Internal interference includes AP-AP interference, client-AP interference, and client-client interference.
- *Asymmetric channel conditions*: Channel state may differ in the client-to-AP and AP-to-client directions even on the same path. Moreover, the interference range of an AP may be much larger than its transmission range.

To cope with these problems, infrastructure designers have only four degrees of freedom. First, they can choose how many APs to install. Second, they can choose the location of each AP. Third, they can assign a power level to an AP; the greater the power level, the larger the coverage area[1]. Finally, they can assign any one of N non-overlapping channels to an AP because interference is caused only among APs assigned to the same channel.

A closer examination of the free variables, however, indicates a difficulty. Once the number of APs and the location of each AP is determined and the APs have been installed, it is difficult, if not impossible, to physically relocate them. Therefore, in practice, the only free variables that can be *dynamically* varied are the power level and the channel assigned to each AP. Given the inherently dynamic nature of wireless coverage, the problem, therefore, essentially reduces to an optimal (and dynamic) assignment of these two parameters to maximize coverage while simultaneously minimizing cost

[1] Although some modern cards [2] also allow modifying transmission rate separately from transmit power, we assume each AP uses the highest transmission rate supported for the transmit power used.

and interference.

In an ideal world, we envision that a wireless infrastructure installer can place a number of APs roughly equally spaced in a geographical area, without necessarily doing a site survey, and then simply walk away. The APs should manage their channel and power allocation to maximize coverage, taking into account the complications mentioned above. If there are persistent dead spots, then the system should automatically detect them and tell the installer where to add an AP. Conversely, if some AP's power level has been set to zero, the installer could be asked to remove that AP. Moreover, the system should dynamically adapt its parameters in response to changing workloads and environmental conditions. We term this approach *successive refinement*, as opposed to today's typical pre-planned deployments that use a one-time physical site survey followed by a static choice of operating parameters. We argue that our approach can not only improve the performance of currently deployed infrastructure networks but also make new deployments much easier. This approach is also well suited for dynamically changing environments.

Unfortunately, we are far from this ideal world. We do not really know how to deal with irregular coverage, asymmetric and dynamic channel conditions, external interference, and changing coverage areas. In this paper, we take a first step towards our ultimate goal of building a self-managing successive refinement framework for wireless infrastructure networks. We make some assumptions that allow us to solve a far simpler problem. Our goal in making these simplifications is to develop intuition for the problem that can serve as the basis for eventually constructing a more realistic solution. As discussed in Section VII, our simplified model does indeed point a way toward solving the general problem in real-world deployments, a topic we plan to explore in future work.

Our contributions are two-fold. First, we develop a mathematical model that describes the solution space and identifies the characteristics of an optimal channel and power-level configuration. Second, we present heuristics that, under some simplifying assumptions, yield near-optimal configurations. We use Monte Carlo simulations to evaluate the performance of our heuristics. We find that the choice of heuristics for transmit power control significantly impacts performance, and, that, surprisingly, randomly assigning channels to access points appears to be an effective strategy at higher deployment densities.

The rest of the paper is organized as follows: Section II discusses related work, Sections III and IV describe the mathematical model for our problem, and Section V presents our proposed heuristics. Section VI presents our evaluation of the proposed algorithms and Section VII presents a discussion of our findings and conclusions.

II. Related Work

There is a large body of literature that attempts to address the AP configuration and placement problem [3], [4]. This combination is typical of site survey based wireless deployments. We argue that wireless deployments need not only conduct one-time surveys, but also dynamically adjust in response to changes in environmental conditions, making successive refinement a better alternative.

Due to the cost of wireless site surveys, many companies are also recently trying to move toward dynamic reconfiguration of wireless infrastructure networks [1], [5], [6]. In particular, our successive refinement approach is similar to the vision shared by Autocell [1]. However, these management solutions are customized for proprietary hardware and use proprietary algorithms to achieve their ends, which makes them both hard to validate and hard to compare with other algorithms. In contrast, our algorithms are meant for commodity hardware and are published openly.

Power control is a well-studied problem for wireless networks in general. For wireless infrastructure networks, proposed solutions include methods that compute optimal power levels off-line and then select appropriate power levels based on such values [7]. Akella et al [8] use a state machine approach for combined power and rate control. However, none of these solutions take into account the degree of interference actually experienced in the environment to decide on the appropriate transmit power to use at each of the APs. We later show that this is crucial in determining the performance of any power control technique.

Channel assignment for infrastructure networks has also been studied in the literature and has been shown to be NP-hard [9]. Mishra et al [10] use a client-based channel assignment that assigns channels to APs based on the interference experienced by clients. However, they are not able to accurately capture the degree of interference at individual APs and also require a feedback mechanism from agents running on the clients. Most other techniques [11] support channel assignments by solving complex optimization problems that are not well suited for a dynamically changing environment. We advocate that any approach be efficient and adopt a refinement strategy to adapt to changes in the environment.

Self-management of *chaotic* networks was first proposed by Akella et al [8]. This work studied autonomous mechanisms that use local information for making decisions. They focused mainly on transmission rate and power control whereas our work also addresses channel assignment. In parallel, Wetherall et al [12] are also exploring coordination mechanisms to make better self-management decisions.

Finally, a new class of *Spectrum Etiquette* protocols [13] have also been proposed for coordination between wireless devices that share the medium. These protocols, although well-grounded, are hard to realize on existing wireless infrastructure networks. In contrast, we propose techniques that can run on existing infrastructure without requiring any protocol modifications to APs.

III. Model

We now state the general problem more formally. This allows us to state our assumptions crisply and delineate the scope of our solution.

We assume that the wireless network infrastructure is meant to cover a given geographical area, A. At a point with coordinates (x, y) in A, we define a utility function $U(x, y)$. This utility function is proportional to the transmission rate that can be obtained by a client at that point, and is zero at points where there is no coverage. The transmission rate at a given point, in turn, depends on the load from other clients at the closest AP, and the signal strengths and the degree of interference among multiple APs that cover that point. For instance, if there is a single AP serving that location, with a high signal strength, and that has no other clients, then the transmission rate is high. On the other hand, a point that is far away from all the APs, or is too near multiple APs would have a low transmission rate.

We model the degree of interference, for locations in overlapping AP coverage areas, as being proportional to the sum of the traffic loads in each such AP. We can summarize this discussion as follows. Let $AP(x, y)$ be the AP with the highest signal strength at (x, y), where $AP(x, y) = \phi$ if no AP has a signal strength higher than the signal floor at that point. Then, a mobile at (x, y) will associate with $AP(x, y)$. We define the set $Interfere(x, y)$ as the set of APs and clients that have a signal strength greater than the signal floor at (x, y) and are not $AP(x, y)$. Then:

$$U(x, y) \propto \frac{1}{load(AP(x, y))} \tag{1}$$

$$U(x, y) \propto signal\ strength(AP(x, y)) \tag{2}$$

$$U(x, y) \propto \frac{1}{\sum_{i \in Interfere(x,y)} load(i)} \tag{3}$$

We would like to choose channel assignments and power levels so as to maximize the overall utility, subject to constraints on the number of available channels, the number of available power levels, the traffic load at each AP, and the (x,y) placements of the access points[2].

Formally, the objective function we wish to maximize is:

$$Maximize \int_{(x,y) \in A} U(x, y) dx dy \tag{4}$$

Given that we need to assign channels and transmit power levels to each of the APs, the problem is therefore a joint channel assignment and power control (CAPC) optimization problem. Our long-term goal is to solve the general CAPC problem in realistic settings. As mentioned earlier, in this paper we solve a simpler version of the CAPC problem by choosing a simpler form of the utility function. Harder versions of the CAPC problem correspond to more complex utility functions.

IV. Solution Model

Our model attempts to maximize the objective function indicated in Section III. We make the following simplifying assumptions:

[2]Though the discussion so far has assumed static coverage areas and traffic loads, it can be trivially extended with a time parameter to allow us to compute the overall utility at each point in time.

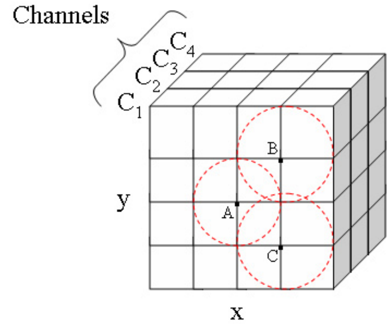

Fig. 1. Model Lattice that represents (x,y) location coordinates in the vertical plane and channels in the horizontal plane.

- *APs in 2-D plane*: We assume APs are located in a two-dimensional plane.
- *Omni-directional Antennas*: We assume all APs are equipped with omni-directional antennas.
- *Physical Interference Model*: We use the interference model used in [14] for modeling signal path loss in our model. Using this model and the assumptions listed above, our coverage areas can be represented as circular disks in a 2-dimensional plane.
- *Centralized solution*: We assume that a single central coordinator determines the optimal solution. Given that most real deployments have a centralized controller for authentication, authorization, and accounting (AAA), this assumption is not particularly strong.
- *Cooperation*: We assume that the APs are cooperative.
- *Access Point Interference*: We only consider AP-AP interference for our model.
- *Symmetric channels*: We assume channels are symmetric.
- *Identical APs*: We assume all APs have identical discrete power levels and choice of channels.

Based on these assumptions, we can geometrically represent our model as shown in Fig. 1. The vertical plane on the lattice embeds the locations of each of the access points, which are fixed. The channels are represented by the third dimension as the horizontal plane on the lattice. The transmit power and corresponding coverage areas of each of the APs are represented by dashed circles around the origins A, B, and C. Larger transmit powers correspond to larger circles on the 2-D plane. Therefore, using this model, overlapping circles indicate interference between neighbouring APs.

With this model and the stated assumptions, we translate the CAPC optimization problem to two simple geometric problems:

1) *Packing variable-size disks on a rectangle (PACK-RECT)*: Here, we model the utility function as follows:
    - $U(x, y) = 0$ if there is no coverage at (x, y) i.e. $AP(x, y) = \phi$
    - $U(x, y) = 1$ if $Interfere(x, y) = \phi$
    - $U(x, y) = -\infty$ if $Interfere(x, y) \neq \phi$

Here, we study power-control only (i.e. a single channel), ignoring the effects of client load and assuming uniform signal strength in a coverage area. Given the utility function above, it is easy to see that no coverage overlap between adjacent APs is allowed. The problem thus reduces to a packing problem for *fixed-location* variable-sized disks on a 2-dimensional plane where the objective is to maximize the coverage of the plane. This problem is computationally hard because there are p^n possible solutions where n is the number of access points and p is the number of discrete power levels for each AP. For even small deployments with 10 APs and considering only 5 possible power levels, there are more than 9 million possible solutions.

2) *Packing variable-size disks on a stack of rectangles (PACK-ST)*: This problem extends the previous one for multiple channels, keeping the utility function the same. In this case, each rectangle represents a separate channel. Due to the additional degree of freedom, we now need to solve the channel assignment problem as well. It has been shown in [9] that the channel assignment problem for Wireless LANs is NP-hard[3].

Optimal solutions to even these simplified problems are computationally hard. Therefore, in an effort to build practical solutions, we devise heuristics to approximate the optimal solution. We then compare their performance relative to the optimal solution, computed using exhaustive search.

V. Heuristics

We now present three heuristic power-control algorithms for the PACK-RECT problem and two algorithms for joint channel assignment and power control (PACK-ST). All APs are initialized to the lowest power level (i.e. transmit power of zero) when the algorithms begin execution.

A. Randomized Incremental Algorithm (RIA)

The idea behind this algorithm is to pick an AP at random and increase its power level, until either the maximum power is reached, or the AP begins to interfere with another AP. More formally, the algorithm first places all APs into an unordered *feasible* set. It then randomly picks an AP from the set and increases its power level by one step. If the transmit power of the AP cannot be increased any further or increasing its power causes interference, it is removed from the set, otherwise it is kept. The algorithm then selects another AP at random and repeats this process until eventually all APs have been removed from the set. This process is illustrated in Algorithm 1.

Due to randomization, a single run of this algorithm does not always yield a good solution. Therefore we run the algorithm many times and choose the run with the best performance. In the worst case, no APs interfere and the algorithm incrementally increases the power of each AP until all APs reach maximum transmit power. Therefore, the running time of RIA is bounded by $O(p * n)$, where p and n are the number of discrete power levels and access points respectively.

Algorithm 1 Randomized Incremental Algorithm (Tx = Transmit Power)

1: Place all APs into feasible set f.
2: Randomly select an access point AP_i from f.
3: **if** $AP_i's\ Tx \neq max.\ Tx$ **then**
4:   Increase AP_i's power by one.
5:   **if** ($\exists(x,y)$ s.t. $U(x,y) = -\infty$) **then**
6:     Decrease AP_i's power by one and allocate it this power level.
7:     Remove AP_i from f.
8:   **end if**
9: **else**
10:   Remove AP_i from f and allocate it its current power level.
11: **end if**
12: **if** $f = \emptyset$ **then**
13:   Terminate.
14: **else**
15:   Go to step 2.
16: **end if**

Algorithm 2 Generalized Greedy Power Allocation Algorithm (Tx = Transmit Power)

1: Place all APs in a set f
2: Order the set according to the power control algorithm being used.
3: Remove the first AP, AP_i from f.
4: Expand coverage of AP_i until ($\exists(x,y)$ s.t. $U(x,y) = -\infty$) or AP_i's $Tx = max.\ Tx$.
5: **if** ($\exists(x,y)$ s.t. $U(x,y) = -\infty$) **then**
6:   Decrease AP_i's power by one and allocate it this power level.
7: **end if**
8: **if** $f = \emptyset$ **then**
9:   Terminate.
10: **else**
11:   Go to step 3.
12: **end if**

B. Generalized Greedy Power Allocation Algorithm

Algorithm 2 illustrates the general steps followed by the other two power control algorithms. The generalized algorithm greedily increases the transmit power of an AP, chosen in turn from an ordered feasible set, to the maximum possible power, given AP interference and power constraints.

1) Distance-based Ordering Algorithm (DOA): The DOA algorithm orders the feasible set by decreasing distance of an AP from the center of mass (or centroid) defined by: ($\sum_i (x_i/n)$, $\sum_i (y_i/n)$), where (x_i, y_i) are the coordinates of AP_i and n is the number of APs. The DOA algorithm is based on the idea that APs farthest from the center of mass are likely to experience less interference and thus should

[3]The authors reduce the channel assignment problem to a maximum *k*-colorable graph problem on an unweighted graph, where *k* is the number of channels.

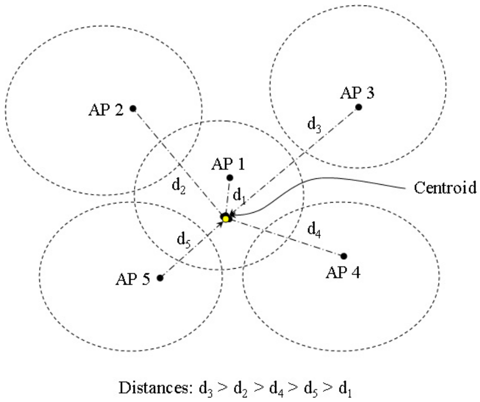

Fig. 2. The center point indicates the center of mass (or *centroid*) of the five APs.

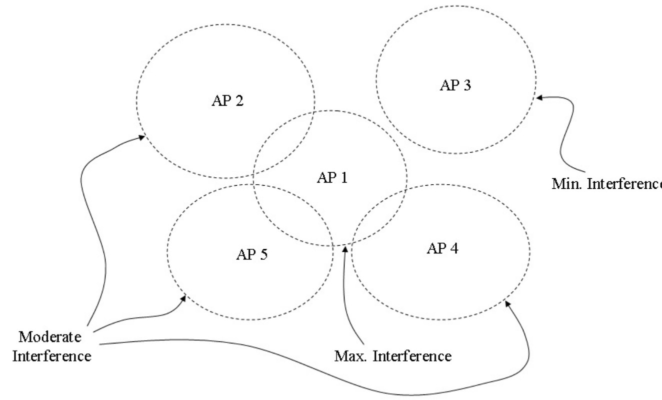

Fig. 3. The classification of APs based on interference performed by IOA. In this figure, all APs transmit at the maximum transmit power. Since $AP3$ does not interfere with other APs, it is the first AP whose transmit power is increased.

be the first to have their power level greedily increased. An illustration of the computed $centroid$ is shown in Fig 2. Using an efficient sorting algorithm such as quick-sort for set ordering, the worst case running time of DOA is bounded by $O(nlogn)$, where n is the number of access points.

2) Interference-based Ordering Algorithm (IOA): The IOA algorithm uses the degree of interference at each AP to order the feasible set. IOA first instructs all APs to transmit at maximum power. Using this configuration, IOA assigns the degree of interference at each AP as the amount of overlap that an AP experiences in its coverage area with neighbouring APs. APs are then placed in the feasible set in increasing order of interference. The ordering thus gives priority to low interfering APs, ensuring that the aggregate interference is minimized while the coverage area is also maximized. An illustration of how IOA might classify APs based on the degree of interference is shown in Fig. 3. The worst case running time of IOA is also $O(nlogn)$.

C. Multi-Channel Algorithms

Thus far, we have assumed all APs share a single channel. We now study the multi-channel case. We assume *n* access points and *m* channels where *m* is typically much smaller than *n*. Therefore, the objective here is to devise algorithms that construct good channel re-use configurations. The following issues need to be addressed:

1) Which channel does each AP use?
2) What power-level should each AP use?

We assume separability and first allocate channels to APs and then allocate power levels. Power level assignment is done using the RIA, DOA and IOA algorithms presented earlier. Therefore, we concentrate on the first issue.

The general solution to channel assignment is known to be NP-hard [9], and therefore, we discuss a heuristic algorithm that approximates the optimal solution. We also describe a naive random channel allocation algorithm that is used as a straw man for comparison with our proposed algorithm.

1) Two-Phase Channel Assignment: This channel assignment algorithm operates in two phases. In the first phase, it generates a set of APs that are either ordered based on the metric used for power control (i.e. for DOA/IOA), or are in a random order (i.e. for RIA). In the second phase, the algorithm begins by removing the first AP from the set and assigning it to the first channel. Then, using this AP as a reference point, the algorithm removes $\frac{n}{m} - 1$ APs farthest in distance from this reference AP and also adds them to the first channel. Assuming that APs are uniformly distributed within an area, an assumption that is likely to be valid for most practical scenarios, this not only assigns the same channel to APs that minimally interfere with each other but is also likely to evenly divide the load across the channels. This process is repeated for each available channel in turn.

This algorithm has several variants. For example, instead of sequentially allocating $\frac{n}{m}$ APs to each channel, we can assign just two APs to each channel at each iteration of the algorithm and repeat this process in a round-robin fashion across all the channels until all APs have been assigned. We found that this variant performs almost exactly the same as the algorithm discussed above, thus we only present results for the first algorithm.

2) Random Channel Assignment: For random channel assignment, we begin with an unordered set of APs. We proceed sequentially through the set and uniformly at random assign a channel to each AP. Thus, although there is no limit to the number of APs that can be assigned to a channel, on average, we expect to assign approximately $\frac{n}{m}$ APs to each channel. Nevertheless, since this algorithm does not consider interference or distance between APs in its assignment process, we expect it to perform poorly in comparison with our two-phase channel assignment algorithm.

VI. EVALUATION

We now evaluate our algorithms for power-control and channel assignment. We first compare our power-control algorithms with each other and the optimal configuration. We then compare the two-phase channel assignment algorithm with random channel assignment.

A. Evaluation Methodology

We have written a compact simulator in Java to compare our algorithms. We emulate a random deployment scenario by randomly placing APs on a two-dimensional grid of fixed size (i.e. 500x500). APs are placed such that no two APs occupy the same location but however may be within interference range of one another (even if they transmit at minimum power). This may cause some APs to be effectively blocked out during the configuration generation process. We discuss the implications of this problem in later sections. The inputs to the simulation include:

- The number of deployed APs.
- The number of available channels.
- The number of transmit powers to choose from.
- The maximum transmit power of all APs.
- The power control algorithm being used.
- The channel assignment algorithm being used.

Coverage areas of APs are represented as uniform circular areas on the grid. As indicated in section IV, since we are solving the PACK-RECT and PACK-ST problems, the objective here is to maximize coverage of the grid while keeping the interference zero. The maximum transmit power of an AP is computed by taking the maximum coverage of the AP as a fraction of the total grid area (which is 30% for our simulations). This prevents any single AP from using up the entire grid, since, due to power limitations, this is unlikely to happen in practice. For most of our results, we have also fixed the number of transmit power levels to 15. The number of transmit power levels are quite diverse across different vendors [15][2] and we find that 15 power levels covers the space of most typical radios. For our multi-channel results, we also fixed the number of available channels to three. This represents the most widely-deployed 802.11b systems[4]. For transmission rate, we adopt a conservative approach where APs always transmit at 1 Mbps uniformly across their entire coverage area. We defer the study of dynamic rate-adaptation schemes based on *path loss* to future work.

To compute the utility, we have used Monte-Carlo sampling. That is, we randomly select some sample points within the coverage areas to estimate the cumulative coverage of all the APs. We could have used an exact method for computing coverage areas by first computing the coverage of each AP and then subtracting from it any overlapping zones. However, exactly computing overlaps is a mathematically daunting task. Monte-Carlo sampling provides a quick, simple, and fairly accurate approximation of the coverage of the grid. In our computations, we used different sample sizes and compared the relative error in the computed result. When comparing

[4]Our multi-channel results only present the benefits of using multiple channels and their effect on power control. We defer a study of the effect of varying the number of available channels on the performance of the algorithms to future work.

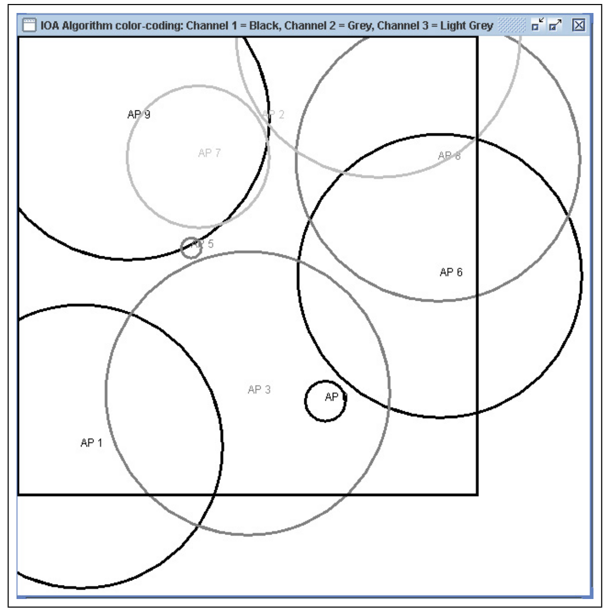

Fig. 4. The square represents the area on which the APs are placed. Each shade represents a separate channel.

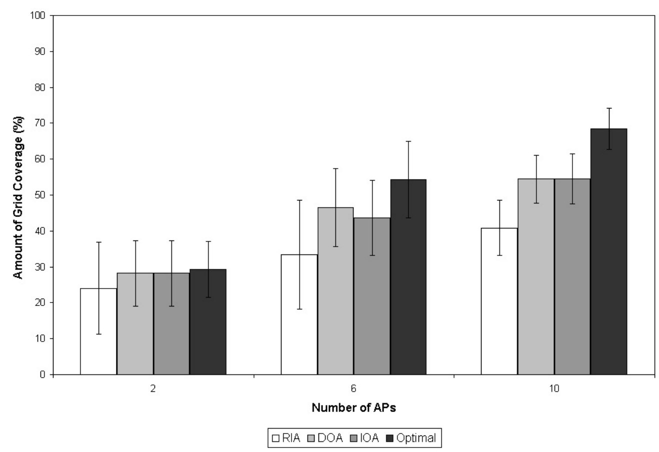

Fig. 5. Histogram of performance of power control algorithms against optimal configuration using single channel and five power levels.

sample sizes of 50,000 and 250,000 for example, we found that the error in the computed utility was less than $\pm 1.6\%$, which is acceptable. The area of the grid was 250,000.

B. Results

We repeated our simulation 30 times in order to minimize statistical variation in our results. For every run, we generate a set of randomized AP locations to prevent placement biases that could affect any of our algorithms. For RIA, in each run, we also ran the algorithm 10 times on the same set of AP locations and took the maximum of the computed utilities. An example output of our simulator is shown in Fig. 4. We now discuss our results further.

Fig. 5 presents the mean coverage area for each of our power-control algorithms and the optimal solution (using only

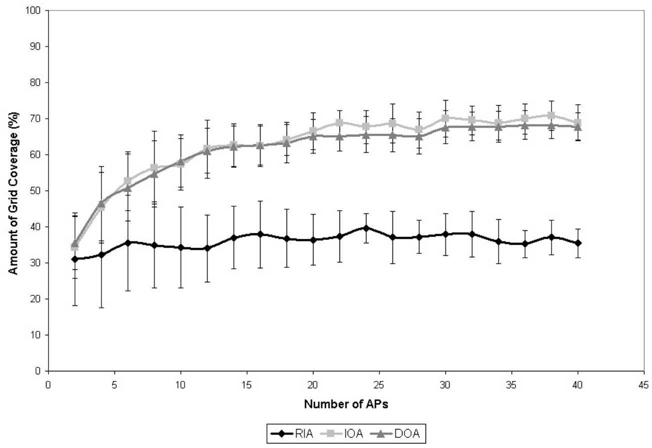

Fig. 6. Performance of power control algorithms using a single channel and 15 power-levels

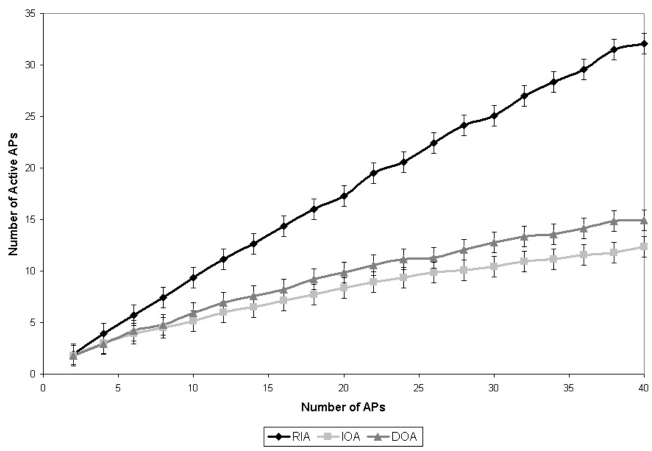

Fig. 7. Comparison of power control algorithms based on the number of APs used by the algorithms, using a single channel and 15 power-levels

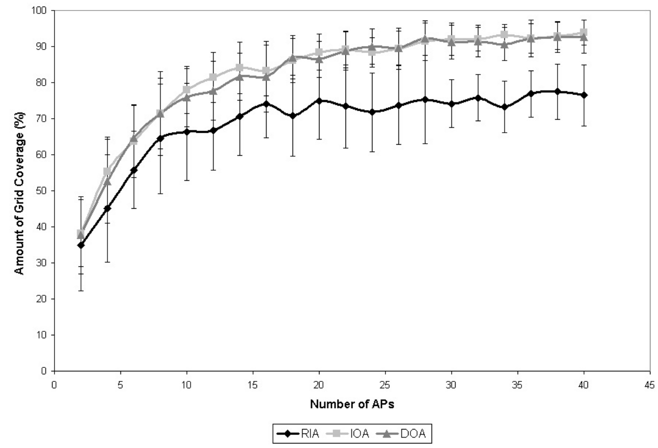

Fig. 8. Performance of power control algorithms using random channel assignment for 3 channels and 15 power-levels

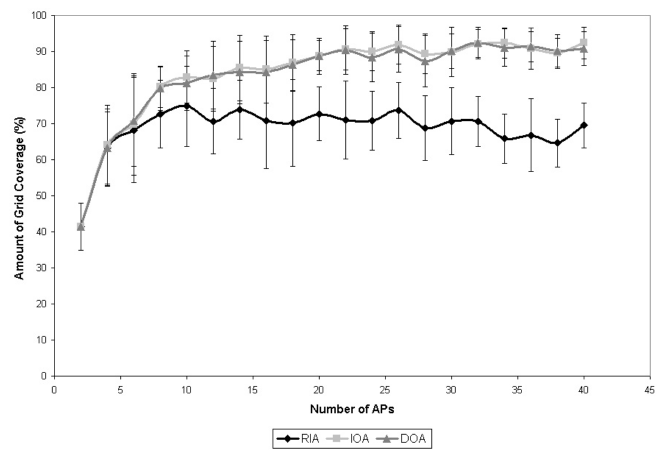

Fig. 9. Performance of power control algorithms using two-phase channel assignment for 3 channels and 15 power-levels

a single channel and five power levels). For these low density deployments, we see that the IOA and DOA algorithms perform quite close to the optimal solution, which was computed using exhaustive search of all possible configurations. For high density deployments, we are not able to provide a quantitative comparison since the search space for the optimal solution increases exponentially fast with increasing AP densities. In general, since we need to assign both power levels and channels to APs, the size of the search space effectively becomes $P^N * C^N$, where P = number of transmit powers, C = number of channels, and N is the number of APs. For P = 5, C = 3, and N = 10, we have ≈ 576 billion possible configurations! However, as we discuss later, we do obtain evidence of near-optimal behavior even for high density deployments from our multi-channel results. These results show that our algorithms cover almost 100% of the grid, clearly indicating that our algorithms are near optimal.

Fig. 6 presents a comparison of IOA, DOA, and RIA. We observe that RIA always performs worse than IOA and DOA, especially in high density environments. This is probably because RIA does not bias power-level increases towards APs that are in less congested areas, causing it to perform poorly in high-density environments where opportunities for interference increase. Another reason may be that RIA increments power levels at all APs. In contrast, DOA and IOA greedily maximize their coverage at each step of the algorithm. Consequently, with these algorithms, at high AP densities, APs that are close to an AP transmitting at high power may effectively be blocked from communicating at all. Although this may be thought of as negative behavior, it is actually beneficial since it serves to reduce the overall interference in the system. Figure 7 illustrates this by showing that the number of APs can be reduced by as much as 60% with the IOA algorithm while RIA uses almost all of the available APs. This result also gives us an intuition as to the optimal number of APs that would be required to cover a grid of given size.

We now turn our attention to the multi-channel case. Fig. 8 presents results for our power-control algorithms using random channel assignment and Fig. 9 shows the performance of the power control algorithms using our two-phase channel assignment algorithm. These figures demonstrate the benefits of using multiple channels over a single channel. For dense environments, we see an almost 37% increase in the cumulative coverage area as compared to a single channel. Moreover, the percentage grid coverage of the IOA/DOA algorithms increases to approximately 93%, from about 70% for the single channel case. Since the interference region is effectively partitioned among the three channels, the coverage area increases. In addition, we also observe that the gap between RIA and IOA/DOA has also decreased. Since the interference per channel has been reduced, RIAs blindness to interference does not hurt it as much.

When we compare the performance of the random channel assignment algorithm and our two-phase channel assignment algorithm, we see that both channel allocation algorithms perform roughly similarly across the board. At low AP densities, the two-phase algorithm does perform better because it places APs farthest away from each other (i.e. with least interference), onto a common channel. This gain is maximized for the first channel, but decreases for later channels, so that overall, the gain from this strategy is not too great, especially at higher AP densities. Intuitively, having multiple channels simply partitions the problem space into three. At high enough density, this reduction in problem size does not reduce the overall interference level, and a random channel assignment works just as well as a more complex channel allocation strategy. In such situations, performance depends more on the power-allocation algorithm than the channel allocation algorithm, as illustrated by the better performance of IOA and DOA over RIA for both channel allocation schemes. This leads us to advocate the (far simpler) random channel allocation strategy as a pragmatic solution in real-world deployments.

VII. Discussion and Conclusions

Deploying a wireless infrastructure network requires us to balance several conflicting requirements. In this paper, we have taken the first step towards an ideal world, where an installer can quickly set up a network and simply walk away. We propose a successive-refinement approach to deployment. We argue that this approach is better suited for real-world wireless deployments. We also present a mathematical and geometric model that crisply describes the solution space and identifies the characteristics of an optimal configuration. We design and evaluate heuristics that yield near-optimal configurations. We find that the choice of heuristics for transmit power control of access points is a crucial factor in determining the quality of the solution. We also find that a random channel assignment approach is effective for assigning channels as the deployment density increases.

We hasten to point out that our results are preliminary because they do not capture several aspects of the real-world problem. For example, our interference model is very simplistic and does not capture irregularity in the coverage of the APs. This affects IOA since it relies on the underlying geometric model. Also, our utility function assigns the same utility to each point on the covered grid. In reality, this utility is dependent upon many factors: uplink/downlink channel conditions, transmission rate, traffic load, etc. Finally, although our algorithms do perform well in simulation, we still need to test them on a real testbed.

Nevertheless, our results do allow us to develop some intuition about the form of the final solution:

- Although finding the optimal configuration even for our simple problem is hard, to our surprise, we find that simple heuristics closely approach this optimal configuration.
- In general, careful power control appears to be more important than careful channel allocation. This result should hold even in more general conditions.
- Surprisingly, both IOA and DOA perform almost identically even though IOA more accurately models the degree of interference and was thus expected to be superior to DOA. We can explain this phenomenon from a computational geometric perspective. Note that each AP's coverage area roughly corresponds to its Voronoi region [16], i.e. the region such that points in the region are closer to this AP than any other AP. Clearly, we need to first allocate power levels to APs in larger Voronoi regions, that are likely to be closer to the boundary area. The DOA metric does well because it sorts APs in order of their distance from the centroid, which, due its greedy nature, are assigned larger power levels and thus larger coverage areas. In this sense, DOA approximately allocates power levels in order of decreasing size of the Voronoi regions. Incidently, DOA is also insensitive to the underlying geometric model, making it suitable for non-circular coverage areas as well.
- We also observe that a naive random channel assignment is able to perform similarly to an interference-aware two phase channel assignment.

Based on these observations, we conjecture the following: For sufficiently dense deployments, an effective configuration strategy would be to first perform a random assignment of channels to APs, and then use a greedy power allocation algorithm that is the same as or similar in spirit to DOA. Since channel assignment is performed at random, coordination is only needed for power allocation.

Our future work lies in two directions. On the theoretical side, we intend to explore the use of computational geometry, in particular Voronoi diagrams, to study the general problem. We are also extending our model to allow overlapping coverage areas, which is necessary to support seamless mobility. For a start, this can be modeled simply by modifying the utility function as follows: $U(x,y) = -k*\alpha$ if $|Interfere(x,y)| = k$, where α is a tuning parameter. In this case, we essentially associate a disutility, corresponding to the number of overlapping APs k, at each point where overlap is possible (of course, this ignores the load at these APs). Our next step is to augment our model to incorporate other sources of interference such as Client-AP interference and Client-Client interference. Finally, we are considering algorithms that permit rapid reconfiguration in response to changes in the environment. On the practical side, we are constructing a real test bed on which to investigate the performance of our algorithms. We hope to use this experience both to refine our assumptions and to test our algorithms in a more realistic setting.

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