Access Point Selection under Emerging Wireless Technologies

Ben-Alexander Cassell Timur Alperovich Michael P. Wellman
Brian Noble
Computer Science & Engineering
University of Michigan
Ann Arbor, MI 48109-2121 USA
{bcassell, timuralp, wellman, bnoble}@umich.edu

ABSTRACT

Users of wireless networks increasingly face a choice among multiple available access points. Clients generally make this decision with limited information about the access points or traffic trends in the system. We examine the strategic implications of an emerging wireless technology: utilizing multiple access points (APs) simultaneously. Clients using this technology require up-to-date information about the expected delays at available APs, which can be obtained through active probing. We model this scenario as a load balancing game, augmented to incorporate abstractions of these two technologies. Using techniques of empirical game-theoretic analysis, we evaluate a range of plausible strategies through simulation. We find that variants of the Hedge algorithms, previously shown effective at the single unit load balancing game under the bulletin board model, remain promising for scheduling multiple jobs per period; however, when delay information can only be obtained from using or probing an access point, all variants of the Hedge algorithm we examined were outperformed by simple decision-theoretic optimization policies.

1. INTRODUCTION

Mobile users typically encounter many accessible wireless networks throughout the day, each comprising of one or multiple access points (APs). Each user must make a decision on the specific set of APs to utilize, as emerging technologies support association with multiple APs [Chandra et al., 2004, Shakkottai et al., 2007] simultaneously. To make an informed decision, each user has to have a notion of the expected throughput for each AP. The most readily available metrics of throughput—signal strength and the network name—may be poor indicators of access point performance, as Nicholson et al. [2006] show. While a user can infer the performance of networks they are utilizing, to obtain such information about other networks they must resort to an active probe. These probes—being workloads themselves—impose additional load on the AP, reducing its performance for the incumbent users [Croce et al., 2009].

Thus, this problem presents a unique challenge: as there is currently no communication between the network clients, the individual users are not aware of any decisions the other users may make, and have no way to infer the network quality aside from using the network directly. To address these complexities, we perform empirical game-theoretic analyses of load balancing games that model AP selection under two technologies: simultaneous association with multiple APs, and active probing to measure an AP's performance. Whereas Shakkottai et al. [2007] address the problem of selecting the set of APs to utilize, our focus is on modeling AP information gathering, and understanding the impact of probing on the system. To the best of our knowledge, little attention has focused on the strategic and social welfare implications of probing on the network. To investigate these issues, we consider two models of information gathering: the bulletin board model [Kleinberg et al., 2009], and a model where delay information is distributed only through using or probing an AP.

In this paper, we explore several potential strategies for AP selection and probing. We employ simulation to evaluate outcomes of combinations of these strategies, and conduct empirical game-theoretic analysis to find strategic equilibria of the induced game. Our investigation is motivated by the question of policy selection; as such, we model the game as (ex ante) symmetric, and concern ourselves chiefly with equilibria where all players use the same (possibly mixed) strategy. We are then able to propose protocols that can be adopted by all clients without any incentive to unilaterally deviate to some other strategy. Although we focus on average delay as our measure of solution quality, the approach we present can easily be adapted to other utility attributes.

2. RELATED WORK

In the past decade, game-theoretic approaches to the AP selection problem have garnered increased attention. Much of the prior literature has focused on analytical results obtained from modeling AP selection as a load balancing game. Though not expressly addressing AP selection, Suri et al.

[2004] proved tight bounds for the *price of anarchy*—worst-case ratio between the outcomes of selfish play and socially optimal play—in a load balancing game with atomic jobs. Koutsoupias et al. [2007] present similar analysis for the variant where players have only partial knowledge about the delay at a particular AP. We do not expressly address price of anarchy in this work, since calculating the true expected delay from equilibrium play in our more complicated setting seems intractable, forcing us to work with approximations.

More recently, computer scientists have extended load balancing games to more accurately model unique attributes of the AP selection problem. Mittal et al. [2008] consider the ability of wireless users to move physically closer to a less crowded AP to improve signal strength. Cesana et al. [2008] model network selection as a non-cooperative game between users and network service providers. Shakkottai et al. [2007] have explored modeling the problem of multiple simultaneous AP selection as a population game, and examine the costs of running a network under their model. There have even been attempts [Xu et al., 2010] to empirically evaluate strategic AP selection protocols in deployed systems. In this work, we characterize the impact of probing on the delay incurred by all users and explore the strategy space to suggest an AP selection protocol that could be widely adapted.

3. EMPIRICAL GAME-THEORETIC ANALYSIS

Empirical game-theoretic analysis (EGTA) is based on the idea of using simulation of strategy profiles to induce a game model for games that are too complex to specify and solve analytically [Vorobeychik and Wellman, 2009, Wellman, 2006]. To perform EGTA we first propose some pool of strategies that are available to players in our game. We then estimate a payoff matrix by repeated observation of the outcome of play for each profile of strategies in our game simulator. This empirical payoff matrix then forms the basis for applying traditional game-theoretic analysis, such as finding a *Nash equilibrium*: a profile of strategy assignments for each player such that no single player has incentive to deviate from its prescribed strategy.

For all the games we examine in this paper, players have identical incentives. This enables us to take advantage of specialized algorithms for symmetric games. To find symmetric equilibria of our games we use *replicator dynamics* [Schuster and Sigmund, 1983], an iterative method that maintains a distribution over pure strategies. On each iteration, replicator dynamics updates the probability of each pure strategy according to its expected performance against the current distribution. Friedman [1991] demonstrated that fixed points of this iterative process correspond to symmetric mixed-strategy Nash equilibria with respect to the function used to evaluate strategy performance. Since finite symmetric games are guaranteed to have at least one such equilibrium [Cheng et al., 2004, Nash, 1951], replicator dynamics provides an applicable and straightforward search method.

4. GAME DESCRIPTION

We model AP selection as a dynamic load-balancing game with atomic work. The simplest variant considered has n players and n resources, with each player choosing one AP to process one job, a unit of work of size w, in each period. For consistency with prior literature, we use $w = \frac{1}{n}$ for all of our simulations.

Players choosing resource a are then charged a delay, d_a, equal to the total load on that resource in the current period. In our variants, load at an AP can arise from one of three sources: new jobs assigned to the AP in the current period, s_t, jobs assigned to the AP in prior periods that have not been processed by period t, u_t, or probes sent to the AP in the current period, q_t. The delay at AP a in period t, $d_{a,t}$, is then:

$$d_{a,t} = (s_t + u_t)\, w + pq_t,$$

where p is the size of a probe. We begin by examining a simulation version of the game described by Kleinberg et al. [2009]. Players are required to select one resource to send one job to in each period, with information revealed according to the bulletin board model (described in detail below). We then depart from prior work by explicitly modeling information gathering through probing. For both information settings, we also consider the problem of assigning multiple atomic jobs when APs can be used simultaneously.

4.1 Multiple AP Selection

In this variant, in each period, clients have j jobs, where $j > 1$, to assign to available APs. They may choose to use more than one AP, but, for each AP beyond the first, they are assessed a cost δ for the added complexity of managing connections to multiple APs. Define $\pi_{c,t}$ to be client c's assignment of its j jobs to available APs in period t, and $A_{c,t}$ the set of APs that are assigned work according to $\pi_{c,t}$. Let $\pi_{-c,t}$ be the assignments made by all other clients in the current period. Client c's objective is then to minimize its total delay, D_c, over all periods $t \in T$ in the dynamic game:

$$D_c = \sum_{t \in T} \left[(|A_{c,t}| - 1)\delta + \operatorname*{arg\,max}_{a \in A_{c,t}} d_a(\pi_{c,t}, \pi_{-c,t}) \right].$$

If c uses more than one AP in a period, it is charged the maximum of the delays over these APs. This cost structure defines the benefit of latency hiding provided by switching APs after a request has been sent in order to launch a new request. This capability also carries some risk, as increasing the set of APs that are used increases the likelihood of using an AP with extreme delay.

4.2 Information Models

We examine AP selection under two models of information revelation. We begin with the bulletin board model, an information model for load balancing first described by Mitzenmacher [1997]. In this model, agents are informed of the delay of each resource at the end of each round. In contrast to the complete information setting, agents are not given the means to perfectly predict how different choices on their part would have affected these delays. This degradation in available information is justified by the difficulties experienced in the real world by clients that attempt to model AP performance. Without knowledge of the number of users of a given AP, distributions of user workloads, and the time it takes for the client's message to be processed at the destination, among other causes of delay, discerning the base capabilities of an AP may be impossible. If the base capabilities are unknown, the client will not be able to predict with any certainty how long its work would have been delayed had they made different choices.

The other information model we consider is one in which a client receives delay information for a particular AP only if the client either sent work to that AP, or sent a probe to the AP to gather this information. Probes have a fixed cost, p, that is incurred by both the probing client and the users of the AP that was probed. Clients are not required to wait for their probes to return, and can still learn some information from ignoring a long-delayed probe. Even without receiving the probe result, the client confirms that the delay at the AP is at least as great as the longest delayed AP that they used in the current period. This probing cost structure exhibits an externality, in that probers are partially insulated from the costs of their probes. If a probed AP has a longer delay than the client's current work assignment, it learns this information at the cost p. The imposed cost to social welfare, however, may be as large as np. That is, when client c probes a, it adds delay p at a to every user (at most n) of that AP. The additional cost realized by another user i of a may be less than p, if a was not already the most heavily loaded AP in use by i.

4.3 Rate-Limited Resources

In contrast to one-shot models of network congestion, we consider a dynamic game in which work assigned to an AP in one stage can persist to later stages. Since the link from client to AP is generally of much higher bandwidth than the link from AP to network, the client can send additional requests to the AP before receiving responses to earlier requests. For simplicity, we describe the work processed by an AP per period, k, in units of jobs, and examine seven such settings: $k \in \{0, 1, 2, 3, 4, 5, 6\}$.

5. STRATEGIES

Clients in our simulations adopt strategies that combine a policy for determining an assignment of jobs to APs, and a policy for determining which APs to probe to gather information. To construct our initial strategy pool, we take the cartesian product of the sets of policies for each component of a strategy. The following sections detail the base policies for association and probing that we tested in our simulations, and any variations to them that were necessary to adjust to the different games we examined.

5.1 Association Policies

5.1.1 *Random.*

Perhaps the most obvious strategy for AP selection is to select an AP randomly. If we consider the set of possible actions to be selecting a single AP, then for n clients and n identical APs, having all clients randomizing over this set of actions is a Nash equilibrium. This equilibrium is referred to as the worst case by Koutsoupias and Papadimitriou [2009], as the expected average delay from playing this equilibrium is the furthest from social optimal for the stated action set. When clients have more than one job to schedule per stage, there are two natural extensions of this strategy: choosing one AP at random and sending all jobs to that AP (R1), or choosing an AP at random for each job (RJ).

5.1.2 *Hedge Algorithm.*

The Hedge Algorithm is a no-regret online learning algorithm for congestion games. Our initial Hedge variant is the bulletin board variant proposed by Kleinberg et al. [2009]. The probability of Hedge selecting AP a in some period t is given by:

$$\Pr(a, t) \propto \exp\left(-\varepsilon \sum_{\ell=1}^{t-1} d_{a,\ell}\right),$$

where ε is some small number that governs exploration versus exploitation. For our simulations, $\varepsilon = \frac{1}{v^3\sqrt{t}}$, where v is analogous to the client's belief about the number of users in the system. Though Kleinberg et al.'s analysis requires $v \geq n$, where n is the true number of players, we found that simulation outcomes were not strongly affected by agents over- or underestimating the number of other agents in the system, and present results for the case where $v = n$.

For the multi-job variant of our game, we consider two forms of the Hedge algorithm. H1 selects a single AP in each period, and sends that AP all its jobs. HJ first selects an AP to send one job according to the Hedge probabilities. All remaining jobs are assigned sequentially according to the following probabilities:

$$\Pr(a, t) \propto \exp\left(-\varepsilon \left[\mathbb{1}_{-a}\delta + s_a w + \sum_{\ell=1}^{t-1} d_{a,\ell}\right]\right),$$

where the indicator $\mathbb{1}_{-a}$ is one if the client has not yet assigned a job to AP a in the current period, zero otherwise, and s_a is the number of jobs that the client has thus far assigned to AP a in the current period. In this way, HJ accounts for the added cost of utilizing more than one AP, as well as the potential benefits of spreading its work over multiple APs. For the probing variant of our game, both forms of Hedge fill in gaps in knowledge about AP delays by assuming an unobserved AP carried delay equal to that of the most recent observation of that AP. Since each client observes a different subset of the APs, differences in selection probabilities can arise in this information model, potentially disrupting convergence.

5.1.3 Decision-Theoretic Optimization.

Given beliefs about the distribution of traffic expected at each AP, clients can optimize their assignment of work while ignoring the choices of other agents. In the single-job setting, this strategy simply chooses the AP with lowest expected delay, that is, has been least trafficked prior to the current stage. When the client has to assign multiple jobs per round, there are again two variants: D1 and DJ. D1 sends all jobs to the AP that the client believes has been the least trafficked in the past. In the case of a tie for minimal predicted delay, D1 chooses randomly among the tied APs. DJ sequentially assigns jobs to the AP that has the lowest expected cost, where expected cost of using AP a, c_a, is calculated by:

$$c_a = \bar{d}_a + \mathbb{1}_{-a}\delta + s_a w,$$

where $\bar{d}_a$ is the average observed delay at AP a, and $\mathbb{1}_{-a}$ indicates whether or not the client has already assigned work to a in the current period. In cases where multiple APs have minimal expected cost, DJ chooses randomly among these APs. For the probing variant of the game, D1 and DJ fill gaps in their knowledge in the same manner as H1 and HJ.

5.2 Probing Policies

5.2.1 Naive Approaches.

We consider two naive approaches to probing: probe nothing (P0) and probe everything (PE). P0 never sends probes to any APs, and functions under the assumption that whatever information is needed for successful decision making can be obtained through trial and error. PE is the other extreme in naive probing; it sends a probe to every AP that the client is not currently using. PE thus replicates the information setting from the bulletin board model, though at significant added cost to the client and to other players.

5.2.2 Freshness-Based Approaches.

If a client's first observation of an AP carries a large delay, the client may never attempt to use that AP, since gaps in knowledge are filled by the most recent observation. To combat this phenomenon, freshness-based probing strategies track how stale are the observations of each AP. PS probes the AP that has been observed the least recently, and chooses randomly among ties. If the selected AP corresponds with an AP to which the client is assigning work in the current period, no probes are sent.

5.2.3 Variance-Based Approaches.

If a client's estimate of delay at a particular AP has significantly higher sample variance than other APs, use of that AP carries particular risk, given that client's cost is defined by the maximum among utilized APs. If an AP a carries lower delay than the client expected, the benefit in excess of expectations is bounded by $\arg\max_{a \in A_c} \bar{d}_a - \arg\max_{a \in A_c \setminus a} d_a$, where A_c is the set of APs that the client utilized. In other words, the client realizes this excess benefit from lower than expected delay only if a was expected to carry the highest delay, and this benefit is limited to the difference between the expected delay at a and the actual delay at the most trafficked AP in A_c. In contrast, if the actual delay at a is higher than expected, the added cost is only bounded by constraints of the system such as the number of jobs that have been assigned thus far, and the rate limitations of the APs. Thus clients are incentivized to take more observations of APs with high sample variance. PV probes the AP for which the client's estimate of delay at the AP has the highest sample variance, breaking ties randomly, and ignoring selections that coincide with an AP to which the client is sending traffic.

6. SIMULATIONS

For each experiment, we constructed empirical payoff matrices by taking the average total delay for each strategy in each profile, over 100 samples of the simulation. Each sample consisted of 50 periods of work assignment. To find equilibria of these games, we first performed iterative elimination of dominated strategies to reduce the size of our payoff matrix before solving. This step is of particular importance with the addition of a probing component to strategies, since games grow exponentially in the number of strategies. Once we obtained the reduced game, we calculated sample equilibria through replicator dynamics using several initial distributions, namely a uniform distribution over the nondominated strategies, and distributions that were weighted heavily towards one of the nondominated strategies. Through reexamining the payoff matrix, we can then calculate the expected delay to each player from playing each equilibrium strategy.

For all the experiments presented here, we use six identical APs and six identical players. In each period, each player is given some number of constant-size jobs for assignment. Here we consider two settings for j, the number of jobs each agent must assign per period: $j = 1$ and $j = 5$. After each stage, players received information about AP delays according to one of the information models described in Section 4.2. Under the bulletin board model, for $j = 1$, the set of strategies considered is $\{$D1, H1, R1$\}$, and for $j = 5$, this set is expanded to include DJ, HJ, and RJ. Since R1 was dominated for all values of k under the probing model with $j = 1$, for the probing model with $j = 5$ we removed R1 and RJ to reduce the number of profiles to sample from 475,020 to 54,264. For the game with $j = 5$, the switching cost, δ, was set to 0.01—an order of magnitude smaller than the delay of a single job on an empty AP. This difference in magnitude is consistent with state-of-the-art switching implementations [Giustiniano et al., 2009].

7. RESULTS

With our experiments we address two primary questions:

- What portion of the explored strategy space could form the basis of a widely adopted AP selection protocol?

- How do the new technologies that we modeled affect social welfare in equilibrium?

To answer the first question, we determine which strategies, if any, are dominated in each of the scenarios considered. We also find symmetric equilibria using replicator dynamics as described in Section 3.

(a) Bulletin board model

j	k	Eq^*	$S_{dominated}$
1	0	H1: 0.71, D1: 0.29	R1
1	1	H1: 0.73, D1: 0.23, R1: 0.04	
1	2	H1: 0.97, D1: 0.02, R1: 0.01	
1	3-6	H1: 1.00	D1, R1
5	0	H1: 0.66, DJ: 0.31, D1: 0.03	HJ, RJ
5	1-3	H1: ≈ 0.65, DJ: ≈ 0.35	HJ, RJ
5	4	H1: 0.67, DJ: 0.32, R1: 0.01	HJ, RJ
5	5	H1: 0.75, DJ: 0.24	
5	6	H1: 0.83, DJ: 0.12, D1: 0.03, R1: 0.02	

(b) Probing model

j	k	Eq^*	$S_{dominated}$
1	0	D1-P0: 0.99, H1-P0: 0.01	D1-PS, D1-PV, H1-PS, H1-PV
1	1	D1-PS: 0.88, H1-P0: 0.12	D1-P0, D1-PV, H1-PS, H1-PV
1	2-6	D1-P0: 1.0	D1-PS, D1-PV, H1-PS, H1-PV
5	0	D1-PS: 0.54, D1-P0: 0.46	D1-PV, H1-P0, H1-PS, H1-PV, DJ-P0, DJ-PV
5	1-2	DJ-PS: ≈ 0.99, D1-PS: ≈ 0.01	D1-PV, H1-P0, H1-PS, H1-PV, DJ-P0, DJ-PV
5	3-4	DJ-PS: 1.0	D1-P0, D1-PV, H1-P0, H1-PS, H1-PV, DJ-P0, DJ-PV
5	5	DJ-PS: 1.0	D1-P0, D1-PS, D1-PV, H1-P0, H1-PS, H1-PV, DJ-P0, DJ-PV
5	6	DJ-PS: 0.94, H1-P0: 0.06	H1-PS, H1-PV

Table 1: Summary of game-theoretic analysis under the two information models considered. The column "Eq^*" represents the lowest-delay symmetric Nash equilibrium found for the specified setting of model, j, and k.

Table 1 provides a summary of the game-theoretic analysis that we conducted. In this table, "Eq^*" refers to the equilibrium that has the lowest expected delay among the equilibria that we found through replicator dynamics, and "$S_{dominated}$" are the strategies that did not survive iterated elimination of dominated strategies. As mentioned above, k is the number of units of work of size w that are cleared by an AP each period. Under the bulletin board model, when players had only one job to schedule in each round, and $k \in \{0, 3, 4, 5, 6\}$, R1 is a dominated strategy. This is in stark contrast to previously examined load balancing games, where having all players choose uniformly at random is a Nash equilibrium. However, R1 is not dominated for $j = 5$, though RJ is dominated for most values of k, possibly because it incurs switching costs without explicitly exploiting latency hiding.

Consistent with the work of Kleinberg et al. [2009], we find the Hedge algorithm to be a reasonable strategy for games where players schedule one job each period, even when resources are rate-limited. For $k \in \{3, 4, 5, 6\}$, H1 is actually a pure strategy Nash equilibrium (PSNE). The improved performance of Hedge relative to selecting APs uniformly at random can be attributed to at least two factors. First, in the formulations of Koutsoupias and Papadimitriou [2009] and Kleinberg et al. [2009], the pure strategies comprise the basic actions of assigning work to a particular AP. In our setup, we take high-level strategies as basic actions, including the policy of choosing an AP randomly, as well as the Hedge algorithm and decision-theoretic optimization. Second, choosing an AP uniformly at random is suboptimal when other players are choosing according to a different distribution and the APs are rate-limited. Under this scenario, APs are no longer identical, and thus a strategy that accounts for these changing delays, such as Hedge, can outperform uniformly random selection.

Along with Hedge, we also found that decision-theoretic optimization can be a reasonable approach for games under this model, provided that it is not universally adopted. In the bulletin board model, all agents have the same information about delays at APs. Agents playing D1 or DJ eventually agree on which AP is expected to have lowest delay and proceed to send their work there. When all agents do so in tandem, the result is the maximum possible delay. Our results here are similar to the findings of Mitzenmacher [1997] for load balancing in a non-competitive setting when there are significant delays between information updates.

In the probing model, in contrast, most equilibria we found were comprised entirely of variants of decision-theoretic optimization. Table 1(b), shows a dramatic difference in equilibria of the two information models.[1] When $j = 1$, for all but one value of k D1-P0 is played greater than 99% of the time.[2] Surprisingly, for the value $k = 1$, D1-P0 is actually dominated, and its place in equilibrium is taken by D1-PS.

When $j = 5$, for all but one value of k, DJ-PS is played

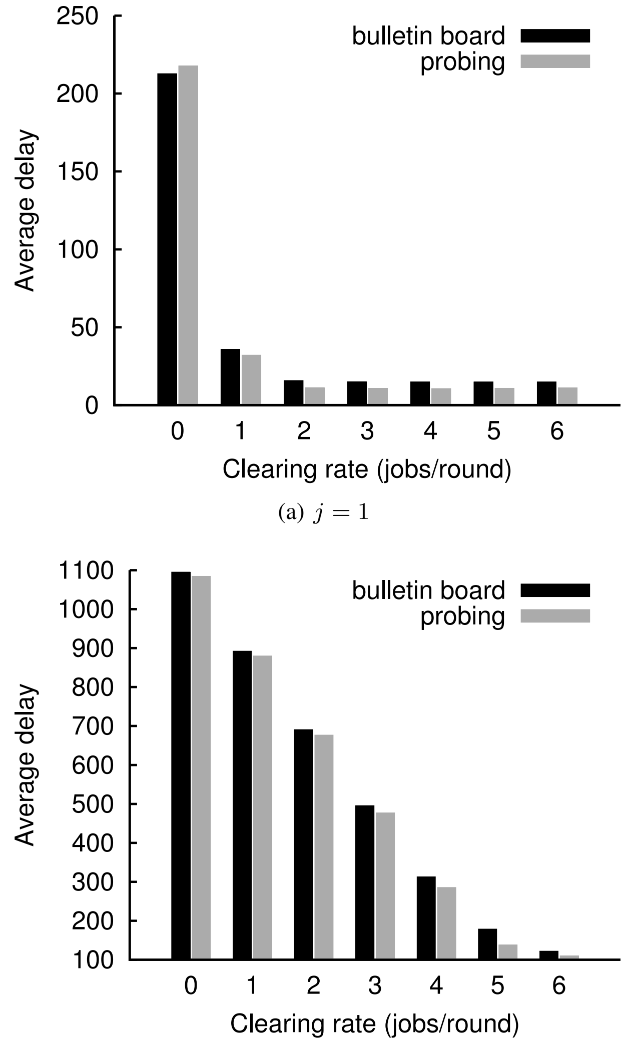
[1]Under the probing model, all strategies that employed either R1 for AP selection or PE for probing were dominated in all experiments, and so are excluded from the table for clarity. HJ is similarly excluded; though undominated in one setting ($j = 5, k = 6$), it is not present in any equilibria that we found.

[2]For $j = 1$ and $k = 2$ or 3, H1-P0 was a PSNE, though its expected delay was approximately 30% higher than that of the Eq^* PSNE, D1-P0.

with probability greater than or equal to 94%, including several settings for which DJ-PS is a PSNE. H1 on the other hand, is only found in Eq^* when 6 jobs are cleared from each AP in each period. We conclude that, whereas Hedge seems to be the most appropriate strategy to use as a protocol under the bulletin board model, decision-theoretic optimization holds that distinction under the probing model. D1 and DJ have dramatically improved performance relative to Hedge strategies under this model, since player beliefs are differentiated by which APs they have observed, and when the observations took place. Whereas this differentiation prevents all D1 and DJ agents from making the same assignments, it can also prevent Hedge from converging, due to the less predictable landscape. We also find that of the probing strategies considered, agents should either not probe, or probe to freshen up stale beliefs.

To answer our second question, the question of social welfare implications of the new technologies addressed here, we compare the lowest expected delays found in equilibrium for each setting considered. This metric is justified particularly in cases where we can designate a focal equilibrium to be implemented. Figure 1 compares the two information models under this metric.

One might expect a priori that reducing the amount of freely available information and incurring the externality of probing congestion would dramatically increase expected delay. We find, however, that generally the opposite is true. With exception of $j = 1, k = 0$, players are better off at equilibrium under the probing model than under the bulletin board model. Under the probing model, decision-theoretic optimization is able to converge to near-optimal assignments. Our results suggest that the benefits obtained from probing, in terms of enabling deterministic strategies to be successful, may outweigh the added social cost that probing imposes.



(a) $j = 1$

(b) $j = 5$

Figure 1: Lowest expected delay among found Nash equilibria for different rates of work clearing.

8. DISCUSSION

Using a recent analytical model as our starting point [Kleinberg et al., 2009], we have simulated and analyzed three extensions of the load balancing game, for the purpose of modeling the AP selection problem. First, we transformed the load balancing game from a repeated game to a dynamic game, in which work can persist at resources between periods, in order to more accurately capture the overlapping decision making that occurs in AP job assignment. This transformation, combined with the addition of a decision-theoretic policy to the strategy pool, lead to the domination of the uniformly random strategy in most settings we examined. This result contrasts with previous work on the load balancing games, where uniformly random resource selection has been shown to be a Nash equilibrium.

We pursued two further extensions to incorporate the emerging technologies of multiple simultaneous AP use and probing. We found continued support for the use of variants of the Hedge algorithm under the bulletin board model; however, under the probing model, Hedge was generally outperformed by decision-theoretic optimization. In the probing model, we observed that, surprisingly, the reduction in free information, and the significant social cost of gathering additional information through probing, did not result in longer expected delays. This result stems from easing the burden of concurrent decision making on deterministic approaches through breaking player symmetry within games, mirroring the findings of Mitzenmacher [1997] for non-competitive load balancing. Our results suggest that we should revisit, and possibly revise, established models when considering the impact of new technologies to strategic decision making.

References

Matteo Cesana, Ilaria Malanchini, and Antonio Capone. Modelling network selection and resource allocation in wireless access networks with non-cooperative games. In

5th IEEE International Conference on Mobile Ad Hoc and Sensor Systems, pages 404–409, Atlanta, 2008.

Ranveer Chandra, Paramvir Bahl, and Pradeep Bahl. Multi-Net: Connecting to multiple IEEE 802.11 networks using a single wireless card. In *23rd Joint Conference of the IEEE Computer and Communications Societies*, pages 882–893, Hong Kong, 2004.

Shih-Fen Cheng, Daniel M. Reeves, Yevgeniy Vorobeychik, and Michael P. Wellman. Notes on equilibria in symmetric games. In *6th International Workshop on Game Theoretic and Decision Theoretic Agents*, pages 71–78, New York, 2004.

Daniele Croce, Emilio Leonardi, and Marco Mellia. Large-scale available bandwidth measurements: Shortcomings of current techniques. In *6th International Conference on emerging Networking EXperiments and Technologies*, Rome, 2009.

Daniel Friedman. Evolutionary games in economics. *Econometrica*, 59(3):637–666, 1991.

Domenico Giustiniano, Eduard Goma, Alberto Lopez Toledo, and Pablo Rodriguez. WiSwitcher: An efficient client for managing multiple APs. In *Second ACM SIGCOMM Workshop on Programmable Routers for Extensible Services of TOmorrow*, pages 43–48, Barcelona, 2009.

Robert Kleinberg, Georgios Piliouras, and Eva Tardos. Load balancing without regret in the bulletin board model. In *28th ACM SIGACT-SIGOPS Symposium on Principles of Distributed Computing*, pages 56–62, Calgary, 2009.

Elias Koutsoupias and Christos Papadimitriou. Worst-case equilibria. *Computer Science Review*, 3(2):65–69, 2009.

Elias Koutsoupias, Panagiota N. Panagopoulou, and Paul G. Spirakis. Selfish load balancing under partial knowledge. In *32nd International Symposium on Mathematical Foundations of Computer Science*, pages 609–620, Český Krumlov, 2007.

Kimaya Mittal, Elizabeth M. Belding, and Subhash Suri. A game-theoretic analysis of wireless access point selection by mobile users. *Computer Communications*, 31:2049–2062, 2008.

Michael Mitzenmacher. How useful is old information? In *16th ACM SIGACT-SIGOPS Symposium on Principles of Distributed Computing*, pages 83–91, Santa Barbara, 1997.

John Nash. Non-cooperative games. *Annals of Mathematics*, 54:286–295, 1951.

A. J. Nicholson, Y. Chawathe, M. Y. Chen, B. D. Noble, and D. Wetherall. Improved access point selection. In *4th International Conference on Mobile Systems, Applications, and Services*, pages 233–245, Uppsala, 2006.

Peter Schuster and Karl Sigmund. Replicator dynamics. *Journal of Theoretical Biology*, 101:19–38, 1983.

Srinivas Shakkottai, Eitan Altman, and Anurag Kumar. Multihoming of users to access points in WLANs: A population game perspective. *IEEE Journal on Selected Areas in Communications*, 25:1207–1215, 2007.

Subhash Suri, Csaba D. Toth, and Yunhong Zhou. Selfish load balancing and atomic congestion games. In *Sixteenth ACM Symposium on Parallelism in Algorithms and Architectures*, pages 188–195, Barcelona, 2004.

Yevgeniy Vorobeychik and Michael P. Wellman. Strategic analysis with simulation-based games. In *Winter Simulation Conference*, pages 359–372, Austin, 2009.

Michael P. Wellman. Methods for empirical game-theoretic analysis (extended abstract). In *Twenty-First National Conference on Artificial Intelligence*, pages 1552–1555, Boston, 2006.

Fengyuan Xu, Chiu C. Tan, Qun Li, Guanhua Yan, and Jie Wu. Designing a practical access point association protocol. In *29th Joint Conference of the IEEE Computer and Communications Societies*, San Diego, 2010.