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PIPeR: Impact of Power-Awareness on Social-Based Opportunistic Advertising

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Abstract—Interest and social-awareness can be valuable determinants in decisions related to content delivery in mobile environments. Under certain conditions, we can deliver content with less cost and better delivery ratios, while only involving users that are interested in the type of content being delivered. However, the depletion of valuable power resources poses a deterrent to node participation in such interest-aware forwarding systems. No significant research contribution has been identified to collectively maximize the benefits of social, interest, and power awareness. In this work, we propose a new algorithm called PIPeR which integrates power awareness with an interest and socially aware forwarding algorithm called IPeR. Through simulations, we present and evaluate four modes of PIPeR. The results show that PIPeR is more fair and preserves at least 22% of the power IPeR consumes with less delay, while relying significantly on interested forwarders and with comparable cost to maintain similar delivery ratios.

I. INTRODUCTION

Content delivery in mobile environments is still by far a very unexploited market. Gartner forecasts an almost doubling of the global mobile ad revenue to reach around 24 billion dollars between 2013 to 2016 [1]. With this increase in mobile data traffic, the network infrastructure becomes overloaded and users experience occasional network service unavailability along with the rising service delivery cost [2]. Reliance on ad-hoc connections among mobile nodes to forward ads in a local area partially offers a relief from the network infrastructure overload. Several popular forwarding algorithms that are proposed for use in opportunistic networks offer effective ad delivery within small community places such as shopping malls or theme parks [3] [4]. These opportunistic forwarding algorithms exploit the temporal and spacial locality of the ad and the users in place. In practice, the success of many forwarding algorithms has typically been at the expense of power and bandwidth resources paid by participating nodes whose owners have no interest in being part of a forwarding process. Interest-aware forwarding algorithms however, are particularly sensitive to leveraging mobile users who have a vested interest in this process. The objective is to ultimately avoid unwelcomed resource utilization, while taking into account power resource levels of the involved mobile devices. The overall preservation and fairness of power consumption can motivate nodes to participate in such systems.

By surveying literature, we find a deficiency in research work that combines both social awareness and power awareness in opportunistic networks. There are many power-aware

routing protocols that mainly handle static sensor networks or wireless ad hoc networks [5], but such algorithms are not socially aware and do not capitalize on the advantages of opportunistic networking. On the flip side, there are many socially aware forwarding algorithms [3] [6] that rely on social awareness without paying attention to power awareness. Some forwarding algorithms even claim to be both context and power aware in decision making [7], but stop short of incorporating social awareness as a very important constituent of context.

We take steps in this work to leverage awareness of the power resources of nodes and integrate such knowledge with interest-aware social-based forwarding algorithms to enable soft real-time opportunistic ad delivery in mobile networks. We avoid engaging nodes whose owners would not be interested in a given ad and whose power resources are approaching exhaustion. More specifically, we build upon previous work that developed an interest-based socially-aware opportunistic forwarding algorithm, IPeR [6], and integrate into it awareness of the power level of mobile nodes. Our new algorithm, PIPeR, works by magnifying a node's interest-based social rank if its remaining power level is above a certain threshold, otherwise the node is penalized. Our algorithm not only considers interest and social popularity, but also power capability when making forwarding decisions. As such, it creates an incentive for node participation in the forwarding process. We propose four variations of PIPeR based on comparing the candidate nodes' power to a fixed/adaptive threshold value accompanied with an optional opportunistic selection of power-capable interested forwarders.

We evaluate the algorithm via simulation in mall environments with a realistic mobility model [8], and then validate our results using real social-based mobility traces from the SIGCOMM conference [9]. We also experiment with various power distributions. We compare PIPeR's performance to the benchmark Epidemic Routing algorithm and to IPeR [6] in terms of delivery ratio, cost, delay, effectiveness, power awareness and fairness. Our results show how integrating power awareness in interest-aware social-based opportunistic forwarding algorithms outperforms the benchmark algorithms according to the used metrics.

The remainder of this paper is organized as follows. We discuss the related work in Section 2. Section 3 illustrates the concept of integrating power-awareness with interest-aware forwarding. Section 4 presents simulation-based evaluation of the new algorithm, followed by a conclusion in Section 5.

II. RELATED WORK

By surveying research work in the field of power awareness and social awareness, we cannot find similar work that considers combined social-based power-aware forwarding approaches. We can categorize the available work into social-aware forwarding algorithms, social-oblivious context and power-aware forwarding algorithms, and social-oblivious power-aware and energy-efficient routing algorithms for sensor networks and Wireless Ad hoc networks.

Many social aware forwarding algorithms such as HiBOP and BubbleRap [3] rely on social awareness and interest but do not pay attention to power awareness in forwarding. Few social aware forwarding protocols mention awareness of the node's remaining power as a sort of context awareness, such as SocialCast [10], yet they do not conduct proofs or experiments for such integration of power and context awareness.

Due to the energy constraints placed on nodes in ad hoc networks, designing power-aware ad hoc routing protocols is significant to maximize the lifetime of the nodes and the network itself. Some of these protocols target the least-power cost routes to minimize power consumption, yet they may deplete the battery of some forwarder nodes thus reducing network lifetime [11]. Other approaches, such as PILOT [12], use a higher power cost route to avoid using nodes whose batteries are depleting. Such approaches mainly maintain energy efficiency by combining awareness of the node's power with another cost function for the forwarder selection process [13].

To maximize the network lifetime, power-awareness and lifetime prediction routing protocols seek routes that minimize the variance among the nodes' remaining power. Such protocols improve the network lifetime, yet tend to create additional control traffic [14]. Seeking fairness via minimizing energy consumed per node, some protocols such as CMMBCR [15] choose the minimal total transmission power route whose nodes' remaining battery levels are above some threshold value, otherwise, route selection is based on another cost function. However, the performance of such algorithms varies based on the selected threshold value [14].

Finally, the majority of the proposed context and power aware routing protocols do not consider social information in decision making and mainly operate on static sensor networks or wireless ad hoc networks [5]. For instance, the context aware opportunistic routing protocol, SCAR [7], allows efficient routing of mobile sensor data to sink via best path selection. SCAR relies on nodes' history of colocation with sink nodes, their change degree of connectivity and their current power in path selection without considering social awareness. Furthermore, due to the limited power resources of the sensor nodes in wireless sensor networks, many power-aware and energy-efficient routing protocols propose solutions for WSN with rare paid attention to opportunistic networks.

III. INTEGRATING POWER AWARENESS WITH INTEREST-AWARE PEOPLERANK

In this section we illustrate the concept of introducing power awareness to interest-aware social-based forwarding algorithms that identify destination nodes by their interest profile. We briefly describe IPeR [6] as a representative

interest-based social-based forwarding algorithm in mobile opportunistic networks. We then introduce the PIPeR algorithm which integrates power awareness in IPeR.

A. IPeR: Interest-aware PeopleRank

IPeR is an interest-aware social forwarding algorithm [6] that introduces interest awareness in ranking the mobile nodes besides the typical social ranking and activeness used in the social-based ranking PeopleRank algorithm (CA-PeR) [4]. In specific, IPeR computes the similarity in interest between a candidate forwarder and the forwarded advertisement message, and uses this parameter in ad forwarder selection. IPeR also includes a damping factor (d) to determine the amount of reliance on opportunistic forwarding versus the interest-aware social ranking component. The interest-aware social ranking component rewards/penalizes the social ranking component of CA-PeR based on interest similarity.

Similarity between the interest vectors of each candidate user and of the ad message $SInt(j, Ad)$ is computed by the Jaccard set similarity [16]; if it is above a certain threshold, the rank of candidate node for forwarding is rewarded (by adding a *reward* value), and penalized otherwise. A candidate mobile node is highly ranked if its owner is linked to popular friends and also if the user and their friends are interested in the ad. Then this node more likely becomes a candidate for forwarding the ad. The node's *IPeR* rank is computed as follows.

$$IPeR(i) = OpportunisticForward + (DampingFactor * SocialRank(i) * Activeness(i) * (SInt(i, Ad) \pm reward + \sum_{j \in F(i)} SInt(j, Ad) \pm reward)) \quad (1)$$

Thus, IPeR magnifies the mobile user's social rank if the user and his friends $F(i)$ are interested in the ad above a certain interest threshold, else it is penalized.

B. PIPeR: Power-aware IPeR

We explore the effect of integrating power-awareness with the interest-based social forwarding process of the IPeR algorithm. Accordingly, we introduce another parameter in ranking the nodes besides the interest-aware social ranking and activeness used in IPeR. In specific, to consider a mobile node for forwarding an ad, we elicit the candidate node's available battery level, and use this information as a means of indicating the node's willingness to forward.

We emphasize the power-awareness by rewarding the node whose battery level is above a certain battery threshold, and penalize it otherwise. Accordingly a candidate node is highly ranked if its battery is above a certain threshold, if its owner is linked to popular friends and also if she and her friends are interested in the advertisement. Thus the higher the rank of a mobile node and its contacts, the more likely a node becomes a candidate for forwarding the ad. The node's power-aware rank *PIPeR* is formalized by this equation.

$$PIPeR(i) = (Bat(i) \pm reward) * IPeR(i) \quad (2)$$

According to the logic of the PIPeR Algorithm, first, the advertiser node ranks the users in proximity using the PIPeR

function based on their candidacy to forward the ad. The advertiser then sends the ad to the "power-capable interested forwarders" whose Similarity Interest $SInt(j,Ad)$ is beyond a certain threshold and whose PIPeR value is rewarded by its current battery level for exceeding the battery threshold $batThr$. As these forwarders encounter other nodes, they check their interest, social rank, battery level, and whether they have already received this ad or not. In case of a match, they forward the ad to the new candidates. This process is repeated until the target time duration t expires or the target number of recipients is achieved. Any ad carrier node whose battery level goes below the preset battery threshold ceases to scan or forward ads in order not to exhaust the remaining battery level.

As shown in Algorithm 1, initially, all the nodes' PIPeR values favor opportunistic forwarder selection i.e. $PIPeR = (1-d)$. Whenever two nodes come in contact and if their owners are friends, the nodes exchange their PIPeR values, the count of each one's friends $|F(i)|$, their interest feature vectors $IntFV(i)$ and the nodes' current battery levels to update their PIPeR ranks as per equation 2 (lines 3-8). Whenever an ad holder i comes in contact with another node j , they exchange their current PIPeR ranks, and node i sends the ad interest vector $IntFV(Ad)$ to node j to receive the computed $SInt(j,Ad)$ (lines 9-11). If node j belongs to the destination set of this ad (line 12), node i delivers a copy of the ad to node j . If node j is not a destination node but its PIPeR rank and similarity interest exceed those of node i , then node i forwards a copy of the ad to node j (lines 12-13).

We present several variations of the PIPeR algorithm that meet various metrics. The variations are:

Adaptive Battery Threshold version (PAd): The logic behind this approach is to utilize the nodes whose 'wealth' is above the current average 'wealth' of the battery community. This PIPeR version continuously adapts the battery threshold used in selecting candidates based on the $obsAvgBat$ values noted from the battery levels of the encountered nodes. Accordingly, the candidates who maintain a battery level above the current observed average battery level are selected to be the next ad carriers. The $obsAvgBat$ is computed as follows:

Algorithm 1 Distributed PIPeR Algorithm

Require: $|F(i)| \geq 0$, $SInt(source,Ad) = 0.3$
 { i : node i , $F(i)$: Friend list, $IntFV(i)$: Interest Feature Vector,
 $bat(i)$: current battery level, $batThr$: battery level threshold, $PIPeR(i)$: PIPeR value,
 $SInt(i,Ad)$: Similarity Interest between $IntFV(i)$ and $IntFV(Ad)$, $buffer(i)$: buffer of
 the to-be-forwarded ads}

- 1: $PIPeR(i) \leftarrow 1 - d$
- 2: \forall time t every n seconds
- 3: **while** i is in contact with j **do**
- 4: **if** $j \in F(i)$ {if j is a friend of i } **then**
- 5: send($PIPeR(i)$, $|F(i)|$, $IntFV(i)$, $bat(i)$, $batThr$)
- 6: receive($PIPeR(j)$, $|F(j)|$, $IntFV(j)$, $bat(j)$, $batThr$)
- 7: update($PIPeR(i)$) (Eq. 2)
- 8: **end if**
- 9: {for all encountered nodes whether they are friends or not}
- 10: **while** $\exists Ad \in buffer(i)$ **and** **Scanning-Condition** = true **do**
- 11: send($IntFV(Ad)$, $batThr$)
- 12: receive($SInt(j, Ad)$, $batThr$)
- 13: **if** **Opportunistic-Interest-Condition** or $SInt(j,Ad) \geq$ Destination-Interest-Threshold **or** ($SInt(j,Ad) \geq SInt(i,Ad)$ **and** $PIPeR(j) \geq PIPeR(i)$) **then**
- 14: Forward(Ad , j)
- 15: **end if**
- 16: **end while**

$$obsAvgBat(i) = \frac{Bat(i) + \sum_{j \in contact(i)} obsAvgBat(j)}{1 + |j|} \quad (3)$$

Then *Scanning-Condition* in code line 9 is set to $bat(j) \geq obsAvgBat(i)$ to pick the next forwarders. Also, the nodes exchange their observations of $obsAvgBat$ instead of a fixed battery threshold $batThr$ in code lines 5, 6, 10 and 11.

Fixed Battery Threshold version(Px): This PIPeR version compares the candidate's battery level to a fixed battery threshold $batThr$ instead of an adaptive battery threshold. The application fixes a battery threshold above which the 'wealthy' members of the community become suitable candidates to forward the ad. The fixed battery threshold version sets *Scanning-Condition* to $bat(j) \geq batThr$ in code line 9.

Interest-aware Opportunistic version (Opp): This approach of PIPeR adds an extra opportunistic portion to the candidate selection process. This is achieved by forwarding the ad to any interested forwarder whose battery level is above the fixed threshold $batThr$. These favored forwarders need not be socially popular users, but rather be power-capable interested forwarders. Thus, *Opportunistic-Interest-Condition* is set to the condition $bat(j) \geq batThr$ and $SInt(j,Ad) \geq Interested-Forwarder-Threshold$ in code line 12.

These variations can be combined together to achieve collective benefits. We present four combinations in the evaluation section; namely Px for a fixed threshold $x\%$, PxOpp for Opportunistic fixed threshold $x\%$, PAd for adaptive threshold and PAdOpp for adaptive Opportunistic combination, and depict their achieved benefits.

C. System Realization Assumptions

For our algorithm to operate effectively, it has to attain interest-related assumptions such that direct interest is extracted from the social profile of the candidates which is cached on the mobile nodes. To maintain soft real-time opportunistic ad delivery in mobile networks, PIPeR forwards short-duration ads to target users located in a place within a short period of time. Also, the algorithm does not assume the existence of a fully connected social graph among the users in place. Finally, to achieve power-awareness, each node is assumed to provide its current power level when requested.

IV. EVALUATION

In this section, we evaluate our proposed algorithm via simulation, and validate our results using real social-based mobility traces and a real power-consumption dataset. We briefly describe our setup, and present a subset of our results.

A. Simulation Setup and Parameters

We build our own simulator for a mall environment with 20 shops randomly distributed over an area of 1000m x 1000m. For accurate mobility patterns, we import user traces from the Self-similar Least Action Walk (SLAW) mobility model [8] which implements social contexts present among people sharing common interests in small scale communities such as malls, or theme parks. To experiment with various conditions, we vary user density and ad hoc wireless range as shown

TABLE I: Simulation Environment Parameters

Parameter	Nominal Value	Range
No. of users	100	20 - 300
No. of shops	5	1 - 20
Set of Interests	10	5, 10
Similarity interest distribution	discrete uniform	discrete normal, discrete uniform
Destination set	18% of the users	10% - 50%
damping factor	0.87	$d = 1 - \text{div} [4]$
$SInt(\text{source}, \text{Ad})$	0.3	0 - 1
Initial Battery Distribution	Full Battery	Discrete Normal, Full Battery, Real dataset [17]
Fixed Battery Threshold	50% for full 20% for normal	20% - 80%
Power Consumption (in mW) [18]	Samsung i900 Omnia phone, idle=2, forward message=1600, receive message=1496, Wifi(TCP mode) Scan=664, Bluetooth(RFCOMM mode) Scan=173, discovered node=29	

in Table I. Since our focus is on relatively short-time ads that target users during a single visit, we are interested in the system's performance during the first hour of simulations. We assume all ads have the same size for simplicity of cost calculations. Our results are based on ads generated by 5 shops and are shown as an average of 20 runs changing the random distribution of the users' mobility, profiles, friends list and initial battery levels. Our simulator generates random social profiles including interest for each user. Furthermore, the constructed friendship graph includes up to 20% of the available users in the friend list per user. Table I lists the most prominent parameters of our simulation environment.

In reality, not all users are interested in the same ads. To simulate this, we set the similarity interest of a certain percentage of the users with $SInt(InterestedNode, Ad) \geq 0.5$ for interested forwarders and $SInt(DestinationNode, Ad) \geq 0.9$ for destination nodes. While we test various user interest distributions, we only show results for the discrete uniform distribution; users are equally distributed between 11 categories with varying interest rates ranging from 0 to 1. Accordingly, the destination set constitutes 18% of the mobile users population while the interested forwarders cover 36%.

The $SInt(\text{source}, \text{Ad})$ acts as a knob controlling the acceptable set of contacted uninterested users since it acts as a starting cutoff point for forwarder selection. As per the experiments we conducted in previous work [6], we set $SInt(\text{source}, \text{Ad})$ to 0.3 in this paper's simulation runs.

The simulation runs are based on realistic power consumption values and various battery level distributions. We imported the power consumption values of a popular phone brand as studied by [18] - listed in Table I - which are comparable to other popular mobile brands. Also, we experiment with various battery distributions for different purposes. For instance, one set of simulation runs starts with full battery levels for all nodes to extract the pure effect of each algorithm on consuming the nodes' power. Another simulation set uses discrete normal battery distribution to resemble the battery communities in real life. A third used distribution is based on a real dataset of the remaining battery capacity recorded by [17] for 10 mobile nodes in 24 hours. By examining various battery thresholds, we found that for each battery distribution there is a suitable threshold towards an optimum power-aware performance; the results presented in this paper rely on threshold value 50% for the full battery distribution.

B. Validation with Real Traces

We validate the performance of our algorithm using real datasets as we import the mobility traces, interests and friendship graphs gathered during the SIGCOMM 2009 conference [9]. In this conference, 76 participants were given smartphones with the MobiClique application installed for mobile social networking use during the conference. This dataset provides real friendship and interest graphs from the participants' Facebook social profile. We pick any of the users to be the source of the ads and show the results within a 1-hour time frame.

C. Simulation Metrics

The metrics we choose aim to assess two goals in our work. First, evaluating the effectiveness and efficiency with which we can opportunistically reach users interested in the ads. Second, determining the fairness in the amount of power consumed by different nodes in the network. We particularly use the following metrics:

Cost: Cost is measured by forwarded ad replicas and time spent to accomplish this process. We measure the total number of ad replicas that have been generated at any given time, and also measure the cost per unit delivery ratio.

Delivery Ratio: We measure the portion of successfully reached destination nodes over time to reflect efficiency.

Delay: Each ad sent to one of the destination nodes reflects a degree of user satisfaction. User satisfaction may be measured by the average delay consumed until an ad is delivered to any destination node.

Effectiveness: An algorithm is effective if it contacts a high portion of the interested users while simultaneously avoiding the uninterested ones. We measure it by the ratio of contacted users classified by their interest; users are either interested forwarders, destination nodes, or uninterested forwarders.

Power Consumption: Algorithm power-efficiency is reflected by its ability to conserve the overall power consumption. We measure this metric by computing the total consumed power from all the nodes' batteries over time as well as the total consumed power per unit delivery ratio.

Fairness: A fair algorithm would not exhaust some nodes' batteries in ad forwarding while preserving other nodes' power. That is, it seeks reducing variance among the nodes' battery levels. We measure fairness via 3 measures:

The *final mean and standard deviation* of the nodes' power community as they present the effect of each algorithm in shaping the final battery distribution.

The *variance* among the nodes' battery levels over time. The ability of an algorithm to reduce/increase the variations among the nodes' battery levels along the forwarding process is a measure of fairness; fairness indicates community closeness which is inversely proportional to variance.

Monitoring the *battery distribution over time* clustered in four categories ranging from category 1 for battery levels less than 25% till category 4 for 75% and above. Figures 3a and 3b are samples of battery clustering over time as per IPeR and P50Opp respectively. It is an auxiliary mean to the above two measures towards measuring an algorithm's fairness.

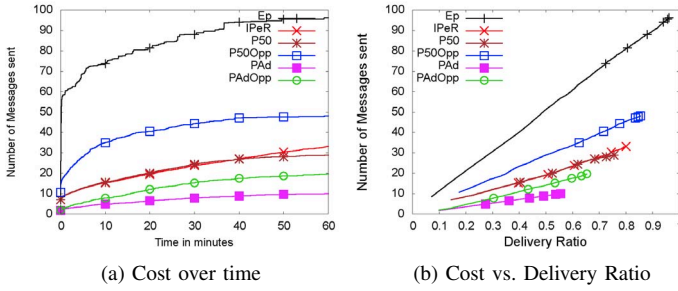


Fig. 1: Cost

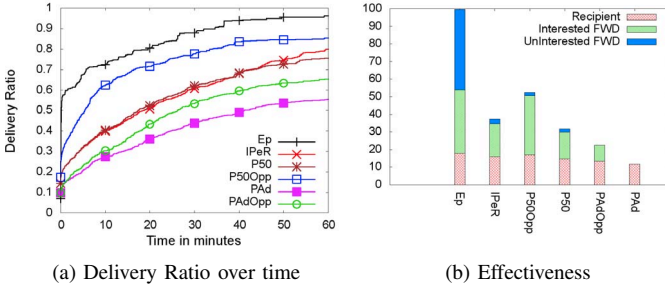


Fig. 2

D. Results

We examine the effectiveness of our PIPeR algorithm, by comparing the performance of its 4 variations to IPeR and the benchmark power-oblivious Epidemic algorithm. We only share the SLAW-based full battery distribution experiment results as a representative set for space limitation and for similarity to the results of the other battery distribution experiments and the SIGCOMM experiments.

Cost, Delay and Delivery Ratio: From the cost time analysis illustrated in Figure 1a, we observe that all PIPeR versions - except P50Opp - reduce cost, in comparison to IPeR, to percents ranging from 87% to 30% to reach 94% of the destination nodes IPeR contacted. The cost to delivery ratio shown in Figure 1b proves that PIPeR costs less ad messages per unit delivery ratio than IPeR, mainly because PIPeR avoids forwarding ads to forwarders with low power. We also highlight the PIPeR achievement in reducing delivery delay in Figure 2a and in Figure 6; all PIPeR versions gain savings in delay over IPeR ranging from 54.4% to 0.3%. For instance, P50Opp costs more to reach more destination nodes with a reduction in delay to the half.

Effectiveness: Figure 2b shows how PIPeR significantly reduces the percent of contacted uninterested forwarders by at least 26% compared to IPeR; P50Opp successfully contacts 90% of the interested forwarders and reduces its uninterested forwarders contact to 26% to deliver ads to an extra 6.7% destination nodes. Noteworthy, PAd does not contact any forwarders to reach 70% of the destination nodes contacted by IPeR. This is attributed to its adaptive selection based on interest and power capabilities which may lead to avoiding some of the interested forwarders for their low power resources.

Power Consumption: The main improvement of PIPeR over IPeR and Epidemic is conserving consumed power to

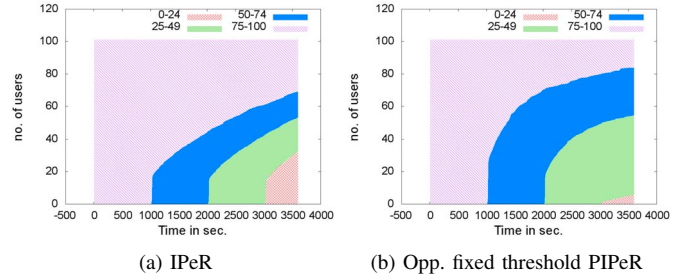


Fig. 3: 4-category Battery Consumption over time

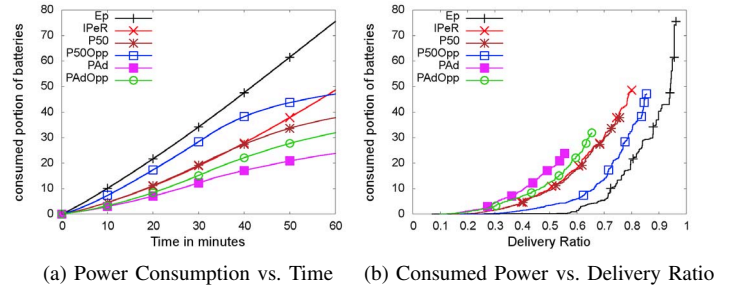


Fig. 4: Power Consumption

reach a comparable portion of the destination set. Figure 4a shows how PIPeR succeeds to conserve 22% of the power consumed by IPeR while the adaptive PIPeR versions conserve up to 48.8%. From another viewpoint, Figure 4b depicts how PIPeR consumes 0.5 power per unit delivery ratio in comparison to 0.6 by IPeR when the adaptive versions consume 0.4.

Fairness: As per mean and standard deviation measures in subfigure 5a, compared to IPeR, PIPeR preserves a higher mean battery level while preserving a smaller STD indicating a closer community. Moreover, PAd preserves the highest mean with 23% STD maintaining a battery community with moderate closeness and preserving significant overall power.

From the perspective of variance over time as a measure of progress in fairness, Figure 5b shows that as time passes, PIPeR versions tend to be more fair by decreasing variance while IPeR increases it. Figure 3 shows that over time, IPeR clusters the majority of the nodes in the border categories causing high level of variance, thus poor fairness, while PIPeR clusters the greater portion of the battery members in the middle categories thus encouraging less variance and maintaining a high degree of fairness. It is noteworthy that P50Opp maintains the highest level of fairness by seeking opportunistic selection and maintaining the 50% battery threshold. From Figures 5a and 5b, interestingly we notice how Epidemic satisfies the rule of "equality in injustice amended" by exhausting the majority of the community members' power to attain fairness.

The 7-metrics Analysis: Towards analyzing the performance of the compared algorithms in terms of the above mentioned 7 metrics, a radar graph of these metrics is presented in Figure 6. Epidemic achieves the highest delivery ratio in the least delay by consuming the highest cost and power to maintain a high level of fairness by exhausting the batteries of the majority of the members and by annoying a high portion of uninterested forwarders. IPeR is the least fair algorithm as it

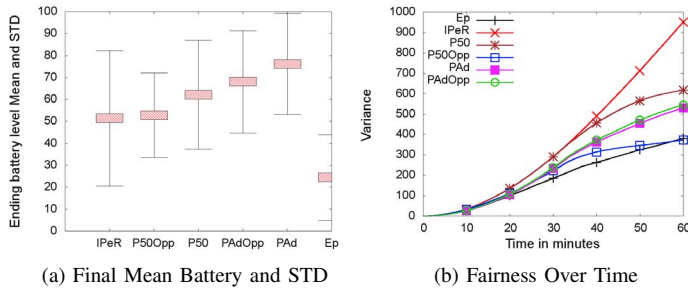


Fig. 5: Fairness Metric

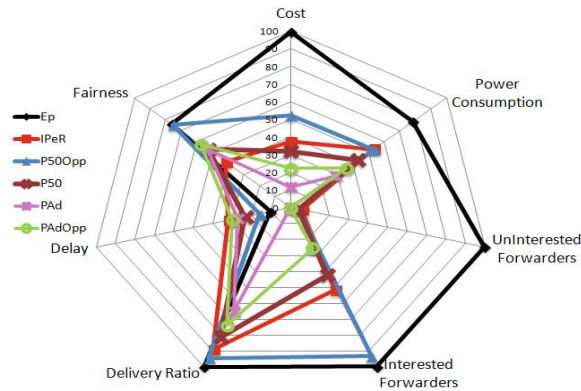


Fig. 6: The 7 Metrics Space

is not aware of utilizing the members' batteries with equal or close portions while P50Opp outperforms IPeR in all metrics except the extra cost required to reach more interested users.

On the other hand, the adaptive PIPeR versions are the most effective versions in cost, power consumption and uninterested forwarders contact despite the small delivery ratio they achieve. In addition, these versions avoid relying on any forwarders, so they succeed to avoid uninterested forwarders but they miss the chance to inform/utilize the interested forwarders. Notice that these versions are moderate in fairness as they do not exhaust the majority of the members' batteries leading to small difference in the community battery levels.

From another perspective, the opportunistic versions attain higher delivery ratio than non-opportunistic ones as they seek opportunities to contact more power-capable interested forwarders and avoid uninterested nodes. Actually they achieve higher delivery ratio in a comparable delay, power consumption and some extra cost to maintain a higher level of fairness.

To sum up, PIPeR offers several versions for advertisers to utilize in forwarding ads; P50Opp maintains high fairness to reach a higher delivery ratio and contacts a higher portion of interested forwarders than what IPeR contacts. On another front, adaptive PIPeR minimizes cost and overall consumed power with some delay by adapting to the average available power capabilities of the nodes in place.

V. CONCLUSION

In this paper, we have taken the first steps towards showing the impact of incorporating power awareness with

interest-based socially-aware opportunistic forwarding algorithms. We have demonstrated this impact by enabling soft real-time advertisement dissemination to disconnected mobile users while maintaining fair power consumption among nodes. We have introduced the PIPeR algorithm, which integrates power awareness into a representative interest-based socially-aware forwarding algorithm called IPeR. Our simulation-based evaluation demonstrates the promising gain in fairness and the reduction in power consumption, cost, as well as delay, while maintaining the benefit of creating an interest-aware social-based algorithm. Future investigations will include more parameters of power awareness such as battery depletion rate, device usage profiles and patterns, and the expected contact duration between the message holder and candidate forwarder nodes. From there we will formulate a framework for any interest and power-aware social forwarding algorithm that mainly capitalizes on opportunistic mobile networks.

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