Opportunistic Wireless Crowd Charging of IoT Devices from Smartphones

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***Abstract*—Current research that use wireless charging for the energy replenishment of nodes in a network mostly considers charging of sensors from special mobile charging vehicles (MCV) and focuses on optimal path planning of these MCVs. However, it may not be practical to use such vehicles due to its operational cost and other restrictions. To this end, in this paper, we consider to utilize smartphones owned by people and let the low cost Internet of Things (IoT) devices harvest energy from the smartphones that pass by. We study the wireless crowd charging of such IoT devices from these smartphones in an opportunistic manner, without changing their actual trajectories. As each smartphone user will limitedly support such a crowd charging process, the selection of IoT devices that will be charged from each smartphone has to be determined based on the trajectories of smartphone users. To address that, we model the problem using Mixed Integer Linear Programming (MILP) and decide the optimal charging relation between smartphones and IoT devices. Through simulations on both synthetic and real user traces, we show that MILP based solution offers a more successful crowd charging outcome with a better charging ratio than the greedy approach where the IoT devices can harvest maximum possible energy from all users encountered.**

***Index Terms*—Crowd charging, wireless energy harvesting, opportunistic network, wireless power transfer.**

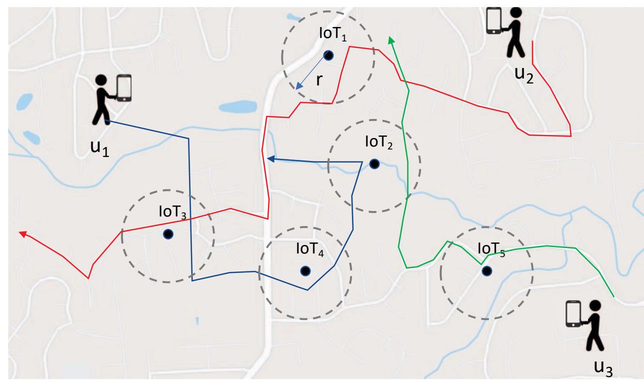

Fig. 1: Overview of the wireless crowd charging system. IoT devices on the routes of smartphone users receive wireless energy from smartphones opportunistically. Each IoT device needs to select the set of smartphones that they will harvest energy from considering the charging thresholds of smartphones and their spatio-temporal trajectory distributions.

I. Introduction

Internet of Things (IoT) technology has enabled many devices to be connected to collect and exchange data in various applications including smart cities [1], environmental monitoring [2], localization [3] and home automation. As the operation of IoT devices mostly depend on capacity limited batteries, their energy constraint has to be addressed for continuous operation. One common approach is to harvest energy from surrounding environment, such as solar, wind, or vibration [4], however its performance highly varies in practice and is intermittent and limited due to the uncontrollable environmental conditions such as cloudy skies [5].

Thanks to the recent breakthroughs in wireless power transfer (WPT) [6] and RF based energy harvesting techniques [7], wireless charging of low-power IoT devices and sensors have been considered as a practical remedy. Most of the current research, however, considers charging of sensors from mobile charging vehicles (MCV) such as robots, and UAVs and focuses on the optimal path planning of these MCVs in order to replenish the energy of sensors before they face energy shortage [8]–[10]. There are also studies that focus on designing novel beamforming based WPT systems [11]–[13] for IoT devices.

In this paper, our goal is to leverage the smartphones owned by people to wirelessly charge the IoT devices in their vicinity. The advantage of using smartphones as in the roles of mobile charging vehicles is that they are carried by people and most of the time they are charged at home during night by people thus there is no dedicated effort for their mobility and energy management. The idea of crowd charging has recently been considered in several different domains. For example, it has been considered for the charging of smartphones in a mobile social network environment [14]–[17], and for the charging of electric vehicles (EV) [18], [19] from other EVs with excessive energy. To the best of our knowledge, there is also only one very recent work [20] that considers charging of IoT devices from smartphones and studies a game theoretical incentive framework. However, authors assume that smartphone users will be provided incentives to change their regular routes and charge the IoT devices, which may not work in practice. Contrary to this study, in this paper, we study the charging of IoT devices from smartphones in an opportunistic manner, i.e., without having the smartphone users deviate from their original path or making them have a stop for charging the devices. An example scenario for the proposed system is illustrated in Fig. 1.

2325-2944/20/$31.00 ©2020 IEEE
DOI 10.1109/DCOSS49796.2020.00066

The goal is to let the IoT devices harvest energy from the smartphones of users who are passing by them. While the mobility cannot be controlled per definition of the scenario, there are things that could be managed to increase the performance of the proposed wireless crowd charging scenario. For example, the power levels of the transmitters in the smartphones can be adjusted to maximize the wireless charging performance when they are in the vicinity of the IoT devices in need. Note that while it is technically possible to achieve long distance charging at higher charging rates (e.g., as high as to fully charge even a smartphone), due to the Federal Communications Commission (FCC) regulations which mandate a maximum of 1 watt power transmission, there is a limit on what is achievable. While the 1 watt power limit causes harvesting of very small energy (e.g., a few milliwatts in three feet) and will not help realize the charging of a smartphone, it will help power many low-power IoT devices in public and commercial places such as thermometers, window sensors, and motion sensors at reasonable distances.

In this crowd charging model, we assume that users will follow their regular trajectories which are known or could be predicted. The IoT devices on their paths will be eligible to harvest energy from smartphones, however each smartphone will have a certain threshold up to which it can share energy. Note that we do not allow the mobile users to stop or alter its paths in anyway in order to charge the IoT devices. We assume IoT devices are equipped with energy receiving capabilities and mobile users are equipped with energy transmitting capabilities. Such an energy harvesting can be achieved utilizing wireless energy sharing methods including far [21], [22] or near [23], [24] field technologies. The energy consumption due to mobility and other factors are not taken into consideration since this is beyond the focus of this paper. We propose an optimal user selection strategy for IoT devices (through communication and agreement between smartphones and IoT devices) with a goal of maximizing the total charging coverage (i.e., number of fully charged devices) and total energy harvested in the network. Through simulations, we evaluate the performance of proposed solution using traces generated from a real dataset as well as random walk based simulations. The results show the benefit of optimal selection strategy over a greedy approach where the IoT devices harvest maximum possible energy from all users encountered.

The rest of the paper is organized as follows. We provide our system model and assumptions in Section II. In Section III, we provide the details of the proposed Mixed Integer Linear Programming (MILP) based solution and the greedy approach. Then, in Section IV, we provide the details of the simulations made and show the simulation results that evaluate the performance of the proposed solution. Finally, we end up with conclusion in Section V.

II. System Model

We assume a set $S = \{s_1, s_2, \dots s_m\}$ of static IoT devices (e.g., sensors) that are rechargeable. Each sensor is equipped with wireless energy harvesting equipment and thus can harvest energy from the smartphones of mobile users passing by. We assume a set $U = \{u_1, u_2, \dots u_n\}$ of mobile users that participate to the crowd charging of IoT devices registered in the system. Both the IoT devices and mobile users are distributed in a two-dimensional region.

Notations	Description
S	Set of IoT devices in the crowd charging system.
U	Set of mobile users in the crowd charging system.
$P(s_i, u_j)$	Power rate of sensor s_i received from user u_j per min.
p_{min}	Minimum power dissipated upon contact with IoT devices.
$p_c(s_i)$	Power consumption rate per min for sensor s_i.
$E_n(s_i)$	Total energy need for a sensor s_i for a day.
$E_t(s_i)$	Total energy received by IoT device s_i by time t.
CR	Total Charging Ratio.
$\mathbf{T}$	Deadline for completing charging.
$\epsilon_{s_i,u_j}(t)$	Total energy provided by user u_j to IoT device s_i.
E^U	Total energy harvested by all IoT devices at the end of deadline ($\mathbf{T}$).
$\bar{u_j}$	Energy sharing threshold for mobile user j.

TABLE I: Notations and their description

For the energy harvesting model, we assume a simplified commonly used [20], [25] empirical wireless energy harvesting model which is defined as follows:

$$\mathcal{P}(s_i, u_j) = \begin{cases} \frac{\alpha}{(d+\beta)^2} l_j p_{min}, & \text{if } d \leq r, \\ 0, & d > r. \end{cases} \quad (1)$$

where $\mathcal{P}(s_i, u_j)$ is the power rate of a sensor s_i received from a user u_j per min. α and β are the environmental constraints and r is the maximum charging range for sensors. Similarly, p_{min} is the minimum power dissipated when the IoT device harvests energy from a nearby mobile user. l_j is the charging level of a mobile device which we set to 6 for the rest of the paper. Also, let $p_c(s_i)$ be the consumption rate of sensor s_i per min. We calculate the energy need of sensor s_i for a day as:

$$E_n(s_i) = p_c(s_i) \times 24 \times 60$$

We assume that sensors can harvest energy up to its need and no more. The model assumes that mobile users crowd charges the devices as an energy backup for the next day, hence we do not take into account the energy loss due to consumption by the devices. Also, since the main goal is to see the benefit of crowd charging for IoT devices, we do not take into the energy consumption by the mobile devices. However, we assume that there is a threshold to identify the maximum amount of energy that can be shared by a given mobile user to prevent excessive utilization of a single user device. We denote this threshold for u_j as $\bar{u_j}$. Let $E_t(s_i)$ be the total energy received by the IoT device s_i by time t and let CR be the ratio of totally charged IoT devices at the end of deadline $\mathbf{T}$. CR can be expressed formally as:

$$CR = \frac{|\{s_i \mid s_i \in S,\ E_{\mathbf{T}}(s_i) = E_n(s_i)|\}}{|S|} \quad (2)$$

where $|S|$ is the total number of available IoT devices in the network.

Similarly, since we do not consider losses due to mobility and other factors, the total energy harvested can be calculated based on the total energy provided by all users. Let E^U be the total energy harvested from a set U of mobile users at the end of deadline $\mathbf{T}$. Then, E^U can be expressed as:

$$E^U = \sum_{t=0}^{\mathbf{T}} \sum_{s_i \in S} \sum_{u_j \in U} \epsilon_{s_i,u_j}(t) \tag{3}$$

where ϵ_{s_i,u_j}(t) is the total actual energy provided by the user u_j to the sensor s_i at time t. Note that ϵ_{s_i,u_j}(t) will be less than or equal to $\mathcal{P}(s_i, u_j)$ at any time t. The notations used throughout the paper and their descriptions are summarized in Table I.

III. Proposed Solution

In this section, we first provide a greedy approach for energy harvesting scheduling of IoT devices from smartphones and then provide the details of a Mixed Integer Linear Programming (MILP) based optimal user selection strategy.

1) Greedy Charging (GC): In this simple approach, we allow the IoT devices to greedily harvest energy from the mobile devices they encounter. That is, as the smartphone users move following their own trajectories and when they come to the transmission range of IoT devices, the devices harvest energy following (1) until their needed energy amount E_n is satisfied. Note that as there is a limit on the amount of energy that can be shared by each smartphone, once the charging of earlier IoT devices on the trajectory of a smartphone user make the smartphone reach that limit, it stops charging thus the IoT devices in the rest of the trajectory will not benefit from this smartphone. Moreover, if this smartphone is their only option to be charged, then they will not be charged as the drawback of this greedy approach.

2) Optimal Charger (OC) selection: The objective of opportunistic crowd charging is to maximize the amount of energy harvested in the network with a goal of fully charging the IoT devices that fall on the trajectory of the mobile users without any deviation from their original trajectories. However, due to the overlap between the sets of IoT devices that are on the trajectories of each smartphone user, the selection of IoT devices which will harvest energy from each smartphone is critical. To this end, we utilize a Mixed Integer Linear Programming (MILP) based optimal charger selection strategy to maximize the amount of energy harvested and number of IoT devices charged.

Since, we do not allow mobile users to change their trajectory to charge the IoT devices and we only allow a certain percentage of user energy to be harvested, the greedy selection of users to harvest energy from can cause some IoT devices not charged in the amount of their need from the users passing by them. Thus, an optimal selection of chargers is important for IoT devices to gain the optimal benefit. The MILP program for optimal charger selection is formulated as below:

$$\max \quad (E^U + CR) \tag{4}$$

$$\text{s.t.} \quad 0 \leq \epsilon_{s_i,u_j}(t) \leq \ min(E_n(s_i) - E_t(s_i), \mathcal{P}(s_i, u_j))) \tag{5}$$

$$\sum_{t=0}^{\mathbf{T}} \sum_{s_i \in S} \epsilon_{s_i,u_j}(t) \leq \bar{u_j} \times 100, \ \forall u_j \in U \tag{6}$$

$$E_t(s_i) = \sum_{u_j \in U, d \in 1..t} \epsilon_{s_i,u_j}(d), \ \forall s_i \in S \tag{7}$$

$$E^U \leq \sum_{s_i \in S} E_n(s_i) \tag{8}$$

The objective function (4) first aims to maximize the total energy harvested in the network from users U and also aims to increase the total charging ratio (CR), which is defined as the number of IoT devices fully charged for the same total energy harvested. Note that the objective function is indeed $M \times E^U + CR$, where M is the largest possible value for CR, so it gives priority to E^U over CR. Since $CR \leq M = 1$, we simply write it as in (4) without presence of $M = 1$. Constraint (5) denotes how much energy can be harvested from mobile user u given the user node and IoT devices are within the transmission range (r). Similarly, constraint (6) restricts each mobile user to share more energy than the predefined upper threshold ($\bar{u_j}$). We use 100 as the current mobile user's energy since we assume that each node will always have sufficient energy for the IoT device to harvest from. Constraint (8) limits the total energy harvested by the total energy demand in the network. Overall, with all these constraints, we want to utilize the energy from smartphones as efficient as possible within their limitations (e.g., mobility, threshold on the energy amount that can be shared). The ideal goal is to fully supply the demand from all IoT devices and fully charge each of them separately.

IV. Evaluations

In this section, we provide the evaluation of the proposed crowd charging based solutions for IoT devices. We first provide the details of the simulation setting used, then list the performance metrics and provide the results.

Simulation setting. We develop a custom Java based simulator to simulate the crowd charging scenario studied. We use two different user traces to evaluate our proposed methods:

- Synthetic traces: We generate trajectories for multiple users that move on a 1km by 1km torus using random walk mobility model whose parameters are shown in Table II. We set $\bar{u_j}$ to 0.2 and the number of users to 30 when generating different results. We also deploy 20 IoT devices on the same area and set the charging range to 30 m.
- KAIST traces [26]: These traces contain trajectories for 92 mobile users. We set number of IoT devices to 12 and generate results for different number of users. Similarly, we set $\bar{u_j}$ to 0.2 to generate results for different number of

Parameters	Values
Constant α in wireless energy harvesting model	0.64
Constant β in wireless energy harvesting model	10
Number of IoT devices $\|S\|$	[20, 12]
Charging range (r)	[30, 50] m
Energy sharing threshold for mobile users ($\bar{u_j}$)	0.2
Minimum energy dissipated upon contact p_{min} in unit/min	600
Consumption power rate for sensor $p_c(s_i)$ of s_i in unit/min	[0.02 - 0.06]
Charging level l_j	6
Deadline **T**	300 min
Torus area	1 km $\times$ 1 km
Speed (min, max) of users in random walk	(4, 10)
Epoch period (min, max) in random walk	(8, 15) min

TABLE II: Simulation parameters and their values

users. In addition, we also show results based on varying $\bar{u_j}$. The charging range is set to 50 m.

The simulation parameters and their values are summarized in Table II.

Performance metrics. In order to evaluate the performance of the proposed charger selection strategies, we utilize two performance metrics:

- Charging Ratio (CR): This is the total number of sensors fully charged (e.g., sensor s_i is fully charged if it harvests all of its demanded energy $E_n(s_i)$ at the end of deadline (**T**)) to the total number of sensors in the network. It is calculated using (2).
- Supply Demand Ratio: This metric is the indication of how much energy is harvested in the network given a certain amount of energy demand. A higher supply demand ratio means a higher energy harvested in the network. This metric can be expressed as:

$$\frac{E^U}{\sum_{i \in S} E_n(s_i)}$$

.

Results. We first look at the performance comparison of MILP based solution to greedy solution in the KAIST traces shown in Fig. 2. Fig. 2a shows the charging ratio achievable from both strategies. We can clearly see that optimal charging strategy outperforms greedy approach. With increasing number of users, the available energy in the network increases, thus IoT devices are able to harvest more energy and consequently receive sufficient energy to be fully charged. Similarly, Fig. 2b shows the total supply demand ratio achievable using greedy and optimal (i.e., MILP based) charging strategies. The optimal charging strategy is able to harvest more energy even with fewer users due to its smart selection of charging users. However, when the number of users are increased, even greedy method is able to obtain total supply demand ratio of 1. Fig. 2c shows the charging ratio obtained for different energy sharing threshold. To this end, we use 50 users and 12 IoT devices to generate these results. We can see that when we increase the sharing threshold, the IoT devices can harvest more energy during the limited contact duration of nodes and IoT devices

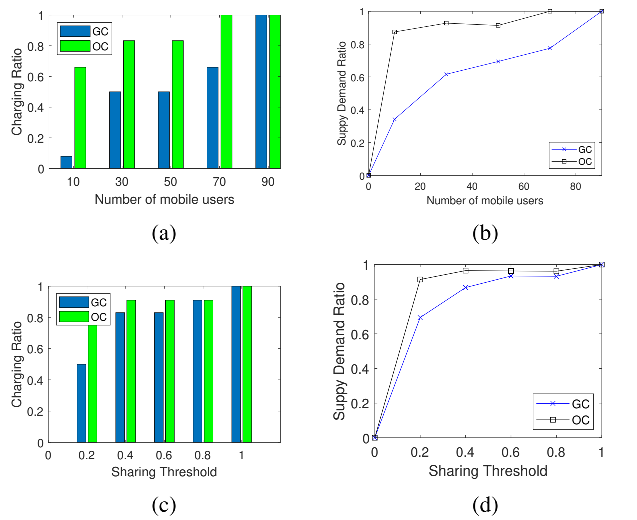

Fig. 2: Comparison of Greedy Charging (OC) against Optimal Charging (OC) in terms of (a) charging ratio given different number of mobile users, (b) supply demand ratio for different number of mobile users (when $\bar{u_j}$ = 0.2), (c) charging ratio for varying $\bar{u_j}$, (d) supply demand ratio for varying $\bar{u_j}$ (when $|U|$ = 50) using KAIST traces.

and thus the number of fully charged IoT devices increases. Similarly, Fig. 2d shows achievable supply demand ratio for increasing sharing threshold. In all the cases, we can see the optimal charging strategy outperforms the greedy approach for charger selection.

Also, in Fig.3, we show the charging ratio and supply demand ratio for different number of users and different sharing thresholds using synthetic traces. We consider 30 mobile users and 20 IoT devices to generate these results. From Fig. 3a, we can see that optimal charging is able to charge more IoT devices with a given number of users than greedy approach. However, when the number of users is increased to 70, both methods can charge all the IoT devices. This clearly shows the benefit of optimal charging strategy over greedy charging especially when there are limited number of users in the network. Similarly, Fig. 3b shows the total achievable supply demand ratio for different number of mobile users. As expected, the optimal strategy is able to harvest more energy from users due to its careful selection of charging users thus provides a higher supply demand ratio. Fig. 3c and Fig. 3d show the impact of sharing threshold on achievable charging ratio and supply demand ratio, respectively. The results show that optimal charging strategy outperforms greedy approach again in this setting, by providing higher charging ratio and supply demand ratio especially when the amount of energy shared by smartphones is limited (i.e., sharing threshold is small).

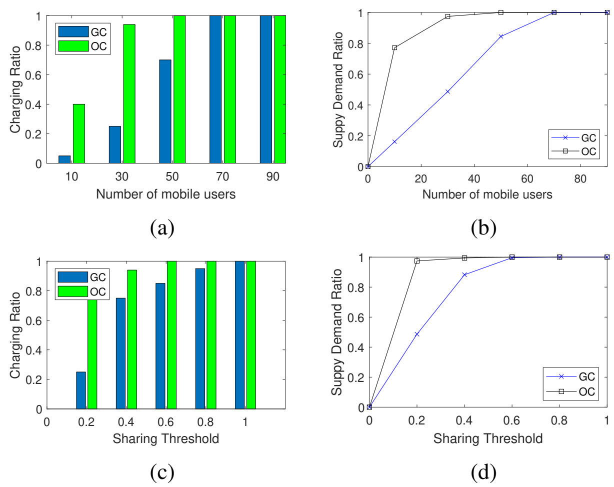

Fig. 3: Comparison of Greedy Charging against Optimal Charging in terms of (a) charging ratio given different number of mobile users, (b) supply demand ratio for different number of mobile users (when $\bar{u_j}$ = 0.2), (c) charging ratio for varying $\bar{u_j}$, (d) supply demand ratio for varying $\bar{u_j}$ (when $|U|$ = 30) using synthetic traces.

V. Conclusion

In this paper, we study the wireless crowd charging of IoT devices from the smartphones owned by people that are passing by. In contrast to prior work, we study a crowd charging scenario in an opportunistic manner and assume that the user devices charge the IoT devices through their originally scheduled paths. In other words, they do not change their trajectories for the purpose of charging the devices. We study two different charging strategies, namely, a greedy approach and optimal charging strategy that is determined by a MILP based model. Through simulations on both synthetic and real user traces, we show that MILP based strategy can achieve a better charging ratio than the greedy approach while providing more supply demand ratio. For future work, we plan to introduce limited deviations in user trajectories to improve the performance of crowd charging scenario for IoT devices.

References

[1] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of things for smart cities," *IEEE Internet of Things journal*, vol. 1, no. 1, pp. 22–32, 2014.

[2] F. Yucel and E. Bulut, "User satisfaction aware maximum utility task assignment in mobile crowdsensing," *Computer Networks*, vol. 172, p. 107156, 2020.

[3] F. Yucel and E. Bulut, "Clustered Crowd GPS for privacy valuing active localization," *IEEE Access*, vol. 6, pp. 23 213–23 221, 2018.

[4] T. Sanislav, S. Zeadally, G. D. Mois, and S. C. Folea, "Wireless energy harvesting: Empirical results and practical considerations for internet of things," *Journal of Network and Computer Applications*, vol. 121, pp. 149–158, 2018.

[5] B. Tong, G. G. Wang, W. Zhang, and C. Wang, "Node reclamation and replacement for long-lived sensor networks," *IEEE Transactions on Parallel & Distributed Systems*, no. 9, pp. 1550–1563, 2011.

[6] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "Wireless charging technologies: Fundamentals, standards, and network applications," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 2, pp. 1413–1452, 2015.

[7] F. K. Shaikh and S. Zeadally, "Energy harvesting in wireless sensor networks: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 55, pp. 1041–1054, 2016.

[8] L. Xie, Y. Shi, Y. T. Hou, and A. Lou, "Wireless power transfer and applications to sensor networks," *IEEE Wireless Communications*, vol. 20, no. 4, pp. 140–145, 2013.

[9] C. Lin, C. Guo, H. Dai, L. Wang, and G. Wu, "Near optimal charging scheduling for 3-d wireless rechargeable sensor networks with energy constraints," in *2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS)*. IEEE, 2019, pp. 624–633.

[10] C. Zhao, H. Zhang, F. Chen, S. Chen, C. Wu, and T. Wang, "Spatiotemporal charging scheduling in wireless rechargeable sensor networks," *Computer Communications*, vol. 152, pp. 155–170, 2020.

[11] X. Fan, H. Ding, S. Li, M. Sanzari, Y. Zhang, W. Trappe, Z. Han, and R. E. Howard, "Energy-ball: Wireless power transfer for batteryless internet of things through distributed beamforming," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 2, no. 2, p. 65, 2018.

[12] S. Mohanti, E. Bozkaya, M. Y. Naderi, B. Canberk, and K. Chowdhury, "WiFED: Wifi friendly energy delivery with distributed beamforming," in *IEEE INFOCOM*, 2018, pp. 926–934.

[13] P. S. Yedavalli, T. Riihonen, X. Wang, and J. M. Rabaey, "Far-field rf wireless power transfer with blind adaptive beamforming for internet of things devices," *IEEE Access*, vol. 5, pp. 1743–1752, 2017.

[14] T. P. Raptis, "When wireless crowd charging meets online social networks: A vision for socially motivated energy sharing," *Online Social Networks and Media*, vol. 16, p. 100069, 2020.

[15] E. Bulut, S. Hernandez, A. Dhungana, and B. K. Szymanski, "Is crowdcharging possible?" in *27th International Conference on Computer Communication and Networks (ICCCN)*. IEEE, 2018, pp. 1–9.

[16] A. Dhungana, T. Arodz, and E. Bulut, "Exploiting peer-to-peer wireless energy sharing for mobile charging relief," *Ad Hoc Networks*, vol. 91, 2019. [Online]. Available: https://doi.org/10.1016/j.adhoc.2019.101882

[17] A. Dhungana and E. Bulut, "Peer-to-peer energy sharing in mobile networks: Applications, challenges, and open problems," *Ad Hoc Networks*, vol. 97, p. 102029, 2020.

[18] R. Zhang, X. Cheng, and L. Yang, "Flexible energy management protocol for cooperative ev-to-ev charging," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 1, pp. 172–184, 2018.

[19] F. Yucel, K. Akkaya, and E. Bulut, "Efficient and privacy preserving supplier matching for electric vehicle charging," *Ad Hoc Networks*, vol. 90, 2019. [Online]. Available: https://doi.org/10.1016/j.adhoc.2018.07.029

[20] Q. Zhang, F. Li, and Y. Wang, "Mobile crowd wireless charging toward rechargeable sensors for internet of things," *IEEE Internet of Things Journal*, vol. 5, no. 6, pp. 5337–5347, 2018.

[21] M. Del Prete, F. Berra, A. Costanzo, and D. Masotti, "Exploitation of a dual-band cell phone antenna for near-field WPT," in *2015 IEEE Wireless Power Transfer Conference (WPTC)*. IEEE, 2015, pp. 1–4.

[22] T. Le, K. Mayaram, and T. Fiez, "Efficient far-field radio frequency energy harvesting for passively powered sensor networks," *IEEE Journal of solid-state circuits*, vol. 43, no. 5, pp. 1287–1302, 2008.

[23] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljačić, "Wireless power transfer via strongly coupled magnetic resonances," *science*, vol. 317, no. 5834, pp. 83–86, 2007.

[24] J. Jadidian and D. Katabi, "Magnetic MIMO: How to charge your phone in your pocket," in *Proceedings of the 20th annual international conference on Mobile computing and networking*, 2014, pp. 495–506.

[25] S. He, J. Chen, F. Jiang, D. K. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *IEEE transactions on mobile computing*, vol. 12, no. 10, pp. 1931–1942, 2012.

[26] I. Rhee, M. Shin, S. Hong, K. Lee, S. Kim, and S. Chong, "CRAWDAD dataset ncsu/mobilitymodels (v. 2009-07-23)," Downloaded from https://crawdad.org/ncsu/mobilitymodels/20090723, Jul. 2009.