This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LWC.2020.2978049, IEEE Wireless Communications Letters



# Energy Efficient Resource Allocation in Wireless Energy Harvesting Sensor Networks

Hosein Azarhava and Javad Musevi Niya

***Abstract*—Extending the sensor life time is one of the most important issues in widespread use of Wireless Sensor Networks (WSNs). The Energy Harvesting (EH) sensors have been proposed to overcome the mentioned problem in recent years. These sensors can harvest their required energy from environment in different methods, resulting in longer life time. We consider a TDMA based Wireless Energy Harvesting Sensor Network (WEHSN) in which the time slot consists of two time intervals; the first one is utilized to absorb energy whereas the second one is used to transmit the sensors' data. We investigate the energy efficient resource allocation in WEHSN with constraints on time scheduling parameters and transmission power consumption, where an EH sensor is allowed to transmit its data if the amount of its harvested energy is more than the consumption power. We derive the closed form expression for the optimization problem, corresponding to the energy efficiency and convert it to a parametric form, using Dinkelbach method. Then, we solve the new problem using Karush-Kuhn-Tucker (KKT) conditions. The numerical results shows the effectiveness of the proposed method.**

***Index Terms*—Energy Harvesting, Resource Allocation, Energy Efficiency, Wireless Sensor Networks.**

## I. Introduction

THE rushing development of Wireless Sensor Networks (WSN) and Internet of Things (IoT) applications such as smart home, smart factory and etc have attracted a lot of attentions in recent years. The efficient resource allocation like power and energy harvesting technology would extend sensors' life time and play a major role in maximizing system performance [1], [2] and [3].

Sultana et al. in [4], has considered a cognitive D2D communication system to improve the resource allocation efficiency as well as spectral efficiency. Nobar et al has studied a cognitive Wireless Powered Communication Networks (WPCN) with green power beacon [5], -in which the secondary network is wirelessly powered by an energy harvesting power beacon- to provide an efficient energy and spectrum performance, simultaneously. The authors of the paper have investigated two spectrum access schemes for the proposed model, i.e., a random spectrum access and a spectrum-sensing based spectrum access, which results in deriving the closed form expressions for service rate of the Secondary User (SU) and the Primary User (PU). Also, a modified model has been discussed by Nobar et al. in [6] to meet the required criteria of resource-limited cognitive WSNs and to maximize the performance of the secondary network under some QoS constraints. They have applied an infinite battery status for PU but limited battery life time in wireless sensor nodes.

Likewise, Ding et al. has studied an iterative joint resource management and time allocation in [7] to maximize the energy efficiency whereas Yang et al. in [8] has tried to maximize the energy efficiency via minimizing the total consumed energy in a cluster-based IoT network with energy harvesting property. Another approach by Pei et al. in [9], proposes a joint resource block and transmission power control scheme for the energy harvesting D2D communications which applies an underlaying Non-Orthogonal Multiple Access (NOMA) scheme to a cellular network under signal-to-interference-and-noise ratio constraint of the Cellular Users (CU). Furthermore, maximizing the netwok throughput in TDMA and NOMA for uplink wireless powered IoT networks, has studied in [10] by Wu et al, where the spectral and energy efficiency are limited to the circuit energy consumption.

In this letter, we consider an energy efficient resource allocation in a TDMA based WEHSN. Unlike [10], which only has optimized the network throughput, our target is to maximize the energy efficiency by decreasing the total energy consumption in the sensors. We derive the closed form expressions for the optimization problem defined for energy efficiency and then, we apply Dinkelbach algorithm to convert the optimization problem to parametric form and find the optimal resource allocation in the network. Using the mentioned algorithm, leads into much decrease in the energy consumption in the network, consequently, yielding better performance. The rest of this paper is organized as follows: Section II discusses the system model of WEHSN and problem formulation. In Section III resource allocation and optimal solutions are represented. The numerical results are presented in section IV, and finally, Section V concludes the paper.

## II. System Model and Problem Formulation

We consider a WEHSN, which consists of one Hybrid Access Point (HAP) plugged to an infinite power supply and $M$ sensors capable of energy harvesting (see Fig. 1). We use "harvest-and-then-transmit" protocol proposed in [11]. At first, sensors harvest energy in downlink (DL) from a Wireless Energy Transferring (WET), then, they transmit information in uplink (UL) towards a Wireless Information Transmission (WIT). The total time interval for energy harvesting and information transmission is denoted by $T_{max}$. We consider a TDMA-based WEHSN in which whole sensors harvest energy

The authors are with the WiLab, Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, East Azerbaijan, Iran (e-mail: azarhava@tabrizu.ac.ir; niya@tabrizu.ac.ir).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LWC.2020.2978049, IEEE Wireless Communications Letters



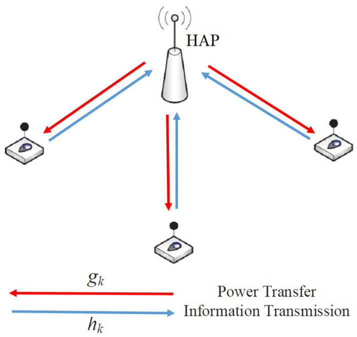


Fig. 1. System Model of Wireless Energy Harvesting Sensor Networks

during DL WET and transmit information in duration of UL WIT. The second interval is divided into $M$ slots belonging to each sensor. The perfect Channel State Information (CSI) is assumed to be available in each sensor for resource allocation. The DL channel gain between the HAP and sensor $i$, and the UL channel gain between sensor $i$ and HAP are denoted by $g_i$ and $h_i$, respectively.

During the downlink period, HAP broadcasts the energy signal with a constant power $P_0$, during $\tau_0$ omnidirectionally to all sensor. Thus, the amount of harvested energy at sensor $i$ can be expressed as

$$E_i^h = (\eta_i P_0 g_i - P_{c_r i})\tau_0 = f_i \tau_0 \qquad \forall i \in \{1, 2, ..., M\}, \quad (1)$$

where $\eta_i \in (0, 1]$ is the constant energy conversion coefficient of sensor $i$ and $P_{c_r i}$ is consumed power in the circuit in energy harvesting period. We assume the amount of harvested energy in each sensor is positive ($f_i > 0$). if $f_i < 0$ the corresponding sensor is prohibited to participate in transmission due to lack of enough energy.

During the uplink period, due to TDMA-based WEHSN, each sensor transmits information in allocated time slot $\tau_i$. Therefore, the consumed energy in each sensor during the information transmission will be equal to $(p_i + P_{c_t i})\tau_i$, where $p_i$ denotes the power allocated for sensor $i$ in WIT and $P_{c_t i}$ is the circuit power consumption in information transmission period. Then, the achievable throughput (normalized by bandwidth) for sensor $i$ can be expressed as

$$r_i = \tau_i log_2(1 + \frac{p_i h_i}{\sigma^2}) \quad (2)$$

where $\sigma^2$ is the additive white Gaussian noise power at the HAP. Therefore, the system throughput would be obtained as

$$R = \sum_{i=1}^{M} r_i = \sum_{i=1}^{M} \tau_i log_2(1 + \frac{p_i h_i}{\sigma^2}) \quad (3)$$

Then, the consumed energy of each sensor and total energy consumption in the network will be as follows

$$E_i^T = (p_i + P_{c_t i})\tau_i \quad (4)$$

$$E_T = \sum_{i=1}^{M} E_i^T = \sum_{i=1}^{M} (p_i + P_{c_t i})\tau_i \quad (5)$$

Also, the Energy Efficiency (EE) is defined as

$$EE = \frac{R}{E_T} \quad (6)$$

We can formulate the EE maximization as

$$\begin{aligned} &\max_{(\tau_0, \{\tau_i\}, \{p_i\})} \quad EE \\ &s.t\ C_1 \ : \ E_i^T \leq E_i^h \\ &\quad C_2 \ : \ \tau_0 + \sum_{i=1}^{M} \tau_i \leq T_{max} \\ &\quad C_3 \ : \ 0 \leq \tau_0, \quad 0 \leq \tau_i, \quad 0 \leq p_i \end{aligned} \quad (7)$$

where $C_1$ constraint assures that the consumed energy in WIT duration is less than the harvested energy in each sensors. No information will be transmitted, if the first constraint, $C_1$, does not hold for sensor $i$. The problem defined in (7) is known as fractional programming (FP) [12]. Thus, we could convert the optimization problem given in (7) to parametric form [12] as

$$\begin{aligned} &\max_{(\tau_0, \{\tau_i\}, \{p_i\})} \quad \{R - \lambda E_T\} \\ &s.t\ C_1,\ C_2,\ C_3 \end{aligned} \quad (8)$$

where $\lambda$ is a non-negative parameter. We define $F(\lambda) = \max\{R - \lambda P_T\}$. Since $F(\lambda)$ is continuous and strictly decreasing, the equation $F(\lambda) = 0$ will yield a unique answer. Therefore, the optimal point of problem (7) and converted problem (8) will be the same [12]. To maximize EE, we have to find the proper $\lambda$, which is calculated according to Dinkelbach Algorithm [12] as follow

| Dinkelbach Algorithm |
| --- |
| 1. Set tolerance $\delta$, step $k = 0$ , $\lambda_k = 0$ |
| 2. Solve (8) to obtain $(\tau_{0,k}, \{\tau_{i,k}\}, \{p_{i,k}\})$ |
| 3. While $\delta \leq F(\lambda_k)$ |
| 4. $k = k + 1$ |
| 5. $\lambda_k = \frac{R_{k-1}}{E_{T,k-1}}$ |
| 6. Solve (8) to obtain $(\tau_{0,k}, \{\tau_{i,k}\}, \{p_{i,k}\})$ |
| 7. End while. |

In the following section, we use Dinkelbach Algorithm and solve the problem (8) to allocate optimal resources to each sensor.

## III. Resource Allocation

First, we assume that $\tau_0$ and $\{\tau_i\}$ are fixed. In this case, problem (8) is a convex optimization problem related to $\{p_i\}$ and also satisfies the Slater's condition [13]. Thus, the optimal solution can be obtained efficiently by applying the Lagrange dual method [13]. To this end, we need the Lagrangian function of problem (8) which can be written as

$$\begin{aligned} \mathcal{L}(\{p_i\}, \{\gamma_i\}) = &\sum_{i=1}^{M} [\tau_i log_2(1 + \frac{p_i h_i}{\sigma^2}) - \lambda(p_i + P_{c_t i})\tau_i] \\ &- \sum_{i=1}^{M} \gamma_i[(p_i + P_{c_t i})\tau_i - f_i \tau_0] \end{aligned} \quad (9)$$

where $\{\gamma_i\}$ is Lagrangian coefficient. Due to complementary slackness, the optimal lagrange multipliers are zero in constraints $C_3$, so the corresponding lagrangian multipliers in constraints $C_3$ are omitted in equation (9). To satisfy Karush-Kuhn-Tucker (KKT) [13] conditions we have

$$\frac{\partial \mathcal{L}}{\partial p_i} = \tau_i \frac{h_i log_2(e)}{\sigma^2 + p_i h_i} - \lambda \tau_i - \gamma_i \tau_i = 0 \;\forall i \in \{1, ..., M\} \quad (10)$$

$$\gamma_i[(p_i + P_{c_t i})\tau_i - f_i \tau_0] = 0 \;\; \forall i \in \{1, 2, ..., M\} \quad (11)$$

To solve (10) and (11), we consider three cases.

Case 1) $\gamma_i \neq 0 \;\forall i \in \{1, 2, ..., M\}$, in this case we have

$$p_i = \frac{f_i \tau_0}{\tau_i} - P_{c_t i} \quad (12)$$

$$\gamma_i = \frac{h_i}{\sigma^2 + p_i h_i} - \lambda \quad (13)$$

To satisfy KKT, both $\{p_i\}$ and $\{\gamma_i\}$ should be greater than zero ($0 < \{p_i\}$ & $0 < \{\gamma_i\}$).

Case 2) where $\gamma_i = 0 \;\forall i \in \{1, 2, ..., M\}$, in this case we have

$$p_i = \frac{log_2(e)}{\lambda} - \frac{\sigma^2}{h_i} \quad (14)$$

Case 3) In this case, first, we separate zero and nonzero $\gamma_i$s so that $\gamma_i \neq 0 \;\forall i \in \{1, 2, ..., K\}$ and $\gamma_i = 0 \;\forall i \in \{K+1, ..., M\}$. Then, according to equations (12) and (14), we could obtain the $p_i$ corresponding to each $\gamma_i$.

Case 1) To obtain the pair $(\tau_0, \{\tau_i\})$, we substitute (12) in maximization problem (8). Thus, the problem is converted to

$$\begin{aligned} \max_{(\tau_0, \{\tau_i\})} & \sum_{i=1}^{M} [\tau_i log_2(1 + \frac{f_i h_i \tau_0}{\sigma^2 \tau_i} - P_{c_t i}\frac{h_i}{\sigma^2}) - \lambda \tau_0 (f_i + P_{c_r i})] \\ s.t \; & C_4 : \;\; 0 < \tau_i(A_i) - \lambda f_i \tau_0 \;\; \forall i \in \{1, 2, ..., M\} \\ & C_2, \; C_3 \end{aligned} \quad (15)$$

where $A_i = (1 - \lambda\frac{\sigma^2}{h_i} + \lambda P_{c_t i})$ and constraint $C_4$ comes from substituting (12) in (13) to satisfy $0 < \{\gamma_i\}$. constraint $C_2$, $C_3$, $C_4$ are linear, then the object function in (8) could be rewritten as

$$\begin{aligned} -\{R - \lambda E_T\} &= \sum_{i=1}^{M} [L_i + K_i] \\ L_i &= -\tau_i log_2(1 + \frac{f_i h_i \tau_0}{\sigma^2 \tau_i} - P_{c_t i}\frac{h_i}{\sigma^2}) \quad (16) \\ K_i &= \lambda \tau_0 (f_i + P_{c_r i}) \quad (17) \end{aligned}$$

where $\nabla^2(L_i) > 0$ proves the convexity of $L_i$ and $K_i$ appears to be linear function from equation (17). Thus, the maximization problem (15) is a concave optimization problem and also satisfies the Slater's condition. To obtain optimal solution, the Lagrangian function of problem (15) takes a form as

$$\begin{aligned} \mathcal{L}(\tau_0, \{\tau_i\}, \{\alpha_i\}, \beta) &= \sum_{i=1}^{M} [\tau_i log_2(t_i) - \lambda \tau_0 (f_i + P_{c_r i})] \\ + \sum_{i=1}^{M} \alpha_i[\tau_i(A_i) - \lambda f_i \tau_0] &+ \beta(T_{max} - \tau_0 - \sum_{i=1}^{M} \tau_i) \end{aligned} \quad (18)$$

where $t_i = (1 + \frac{f_i h_i \tau_0}{\sigma^2 \tau_i} - P_{c_t i}\frac{h_i}{\sigma^2})$ and $\{\alpha_i\}$ and $\beta$ are Lagrangian coefficients. Since the amount of $P_{c_t i}$ is assumed to be negligible, $t_i$ will be positive. Then, the KKT condition are as following

$$\frac{\partial \mathcal{L}}{\partial \tau_0} = \sum_{i=1}^{M} [\frac{f_i h_i}{t_i \sigma^2} log_2(e) - \lambda(f_i + P_{c_r i})] - \sum_{i=1}^{M} \alpha_i \lambda f_i - \beta = 0 \quad (19)$$

$$\frac{\partial \mathcal{L}}{\partial \tau_i} = log_2(t_i) - \frac{f_i h_i \tau_0}{t_i \sigma^2 \tau_i} log_2(e) + \alpha_i(A_i) - \beta = 0 \quad (20)$$

$$\alpha_i[\tau_i(A_i) - \lambda f_i \tau_0] = 0 \quad (21)$$

$$\beta(T_{max} - \tau_0 - \sum_{i=1}^{M} \tau_i) = 0 \quad (22)$$

Since $\gamma_i \neq 0$ for $i \in \{1, 2, ..., M\}$ and constraint $C_4$, the parameter $\alpha_i$ is equal to zero from (21). Substituting (20) in (19), we obtain the following equation

$$\begin{aligned} &\sum_{i=1}^{M} [\frac{f_i h_i}{t_i \sigma^2} log_2(e) - \lambda(f_i + P_{c_r i})] \\ &- log_2(t_i) + \frac{f_i h_i \tau_0}{t_i \sigma^2 \tau_i} log_2(e) = 0 \;\; \forall i \in \{1, 2, ..., M\} \end{aligned} \quad (23)$$

Defining $\theta_i = \frac{\tau_0}{\tau_i}$, all $\theta_i s \;\forall i \in \{1, 2, ..., M\}$ can be found from (23). Also, to satisfy (22), we should have $(\tau_0 + \sum_{i=1}^{M} \tau_i = T_{max})$, therefore, we can derive $\tau_0$ and $\tau_i \;\forall i \in \{1, 2, ..., M\}$ as follow

$$\tau_0 = \frac{T_{max}}{1 + \sum_{i=1}^{M} \frac{1}{\theta_i}} \;\; \& \;\; \tau_i = \frac{\tau_0}{\theta_i} \quad \forall i \in \{1, 2, ..., M\} \quad (24)$$

Case 2) To obtain related $(\tau_0, \{\tau_i\})$ in case two, we substitute (14) in problem (8). Thus, the problem described in (8) is converted to

$$\begin{aligned} \max_{(\tau_0, \{\tau_i\})} & \sum_{i=1}^{M} [\tau_i B_i - \tau_0 \lambda P_{c_r i}] \\ s.t \; & C_5 : (\frac{log_2(e)}{\lambda} - \frac{\sigma^2}{h_i} + P_{c_t i})\tau_i \leq f_i \tau_0 \;\; \forall i \in \{1, 2, ..., M\} \\ & C_2, \; C_3 \end{aligned} \quad (25)$$

where $B_i = (log_2(\frac{log_2(e) h_i}{\sigma^2 \lambda}) - log_2(e) + \frac{\sigma^2 \lambda}{h_i} - \lambda P_{c_t i})$. The maximization problem in (25) is a linear optimization problem. Therefore, $(\tau_0, \{\tau_i\})$ can be easily calculated.

Case 3) By inserting the calculated $p_i$ from case three in problem (8), it is converted to (26), which is combination of problems (15) and (25)

$$\begin{aligned} \max_{(\tau_0, \{\tau_i\})} & \sum_{i=1}^{k} [\tau_i log_2(1 + \frac{f_i h_i \tau_0}{\sigma^2 \tau_i} - P_{c_t i}\frac{h_i}{\sigma^2}) - \lambda \tau_0 (f_i + P_{c_r i})] \\ & + \sum_{i=K+1}^{M} [\tau_i B_i - \tau_0 \lambda P_{c_r i}] \\ s.t \; & C_6 : 0 < \tau_i(A_i) - \lambda f_i \tau_0 \; \forall i \in \{1, 2, ..., k\} \\ & C_7 : (\frac{log_2(e)}{\lambda} - \frac{\sigma^2}{h_i} + P_{c_t i})\tau_i \leq f_i \tau_0 \; \forall i \in \{k+1, ..., M\} \\ & C_2, \; C_3 \end{aligned} \quad (26)$$

The solution for problem (26) to acquire $\tau_0$ and $\tau_i$, could be obtained similar to case (1) using the equation (24).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LWC.2020.2978049, IEEE Wireless Communications Letters



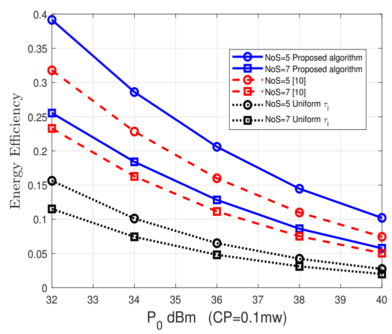


Fig. 2. Energy Efficiency vs. HAP transmit power

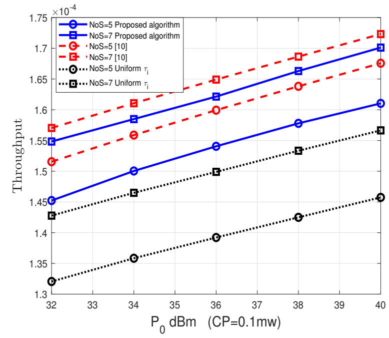


Fig. 3. Throughput vs. HAP transmit power

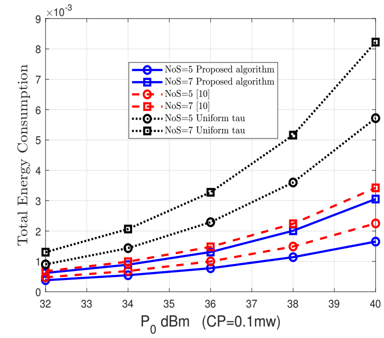


Fig. 4. Total Energy Consumption vs. HAP transmit power

## IV. Numerical Results

In this section, we present simulation results to evaluate the performance of proposed scheme. We use the following simulation parameters: identical channels for WET and WIT, the carrier frequency of 750 MHz and the bandwidth of 180 kHz as in typical NB-IoT systems [14]. We consider uniformly distributed sensors with a HAP in the center. The maximum distance between HAP and sensors are 50 meters. Both the DL and UL channel power gains are modeled as $10^{-3}\rho^2 d^{-\delta}$, where $\rho^2$ is an exponentially distributed random variable (Rayleigh fading assumption) with unit mean and $d$ is the link distance. The path loss exponent is $\delta = 2.2$. We assume that the circuit power consumption during the energy harvesting period for all sensors are equal and also, we have $P_{c_r i} = 0.1 P_{c_t i}\ \forall i$ .The other main parameters are assumed as $T_{max} = 1s$, $\sigma^2 = -120dBm$ and $\eta_i = 0.9\ \forall i$. Fig. 2 illustrates the energy efficiency of the proposed algorithm, compared to throughput maximization scheme in [10] and uniform allocation for $\tau_0$ and $\{\tau_i\}$ corresponding to different values of HAP transmission power. In Fig. 2 EE is evaluated vs. different Number of Sensors (NoS) 5 and 7. It can be observed that energy efficiency in each scheme decreases by increasing HAP transmission power, due to increasing of consumed energy in the sensors. Fig. 3 shows the throughput of the network for different number of the sensors vs. HAP transmission power. The proposed method in [10] exceeds the other schemes regardless of energy consumption in the network. But Fig. 4 demonstrates that the proposed method consumes less power compared to the other schemes. As a result, the proposed algorithm shows better performance from the aspect of energy efficiency which could be confirmed in Fig. 2.

## V. Conclusion

In this paper, we propose a new system model in which the wireless sensors use the harvest-then-transmit protocol to harvest the required energy for data transmission. Also, the sensors use TDMA in the remaining time interval to communicate with a Hybrid Access Point. We derive the optimization problem for energy efficiency as the system performance applying the constraints on the time schedule parameter and transmission power for each sensor. We use Dinkelbach algorithm to solve the problem and obtain the closed form expressions. The numerical results show that although the throughput could see a little decrease in comparision to the other methods, the energy consumption would decline much more to that of the other methods, resulting in the better energy efficiency as the performance of the network.

## References


[1] J. Huang, C. Xing, and C. Wang, "Simultaneous wireless information and power transfer: Technologies, applications, and research challenges," *IEEE Communications Magazine*, vol. 55, no. 11, pp. 26–32, Nov 2017.

[2] K. Kang, R. Ye, Z. Pan, J. Liu, and S. Shimamoto, "Full-duplex wireless powered iot networks," *IEEE Access*, vol. 6, pp. 53 546–53 556, 2018.

[3] Z. Chu, F. Zhou, Z. Zhu, R. Q. Hu, and P. Xiao, "Wireless powered sensor networks for internet of things: Maximum throughput and optimal power allocation," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 310–321, Feb 2018.

[4] A. Sultana, L. Zhao, and X. Fernando, "Efficient resource allocation in device-to-device communication using cognitive radio technology," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 11, pp. 10 024–10 034, Nov 2017.

[5] S. K. Nobar, K. A. Mehr, and J. M. Niya, "Rf-powered green cognitive radio networks: Architecture and performance analysis," *IEEE Communications Letters*, vol. 20, no. 2, pp. 296–299, Feb 2016.

[6] S. K. Nobar, K. A. Mehr, J. M. Niya, and B. M. Tazehkand, "Cognitive radio sensor network with green power beacon," *IEEE Sensors Journal*, vol. PP, no. 99, pp. 1–1, 2017.

[7] J. Ding, L. Jiang, and C. He, "User-centric energy-efficient resource management for time switching wireless powered communications," *IEEE Communications Letters*, vol. 22, no. 1, pp. 165–168, Jan 2018.

[8] Z. Yang, W. Xu, Y. Pan, C. Pan, and M. Chen, "Energy efficient resource allocation in machine-to-machine communications with multiple access and energy harvesting for iot," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 229–245, Feb 2018.

[9] L. Pei, Z. Yang, C. Pan, W. Huang, M. Chen, M. Elkashlan, and A. Nallanathan, "Energy-efficient d2d communications underlaying noma-based networks with energy harvesting," *IEEE Communications Letters*, vol. 22, no. 5, pp. 914–917, May 2018.

[10] Q. Wu, W. Chen, D. W. K. Ng, and R. Schober, "Spectral and energy-efficient wireless powered iot networks: Noma or tdma?" *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 6663–6667, July 2018.

[11] H. Ju and R. Zhang, "Throughput maximization in wireless powered communication networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 1, pp. 418–428, January 2014.

[12] W. Dinkelbach, "On nonlinear fractional programming," *Manage. Sci.*, vol. 13, no. 7, pp. 492–498, Mar. 1967. [Online]. Available: https://doi.org/10.1287/mnsc.13.7.492

[13] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

[14] Y. . E. Wang, X. Lin, A. Adhikary, A. Grovlen, Y. Sui, Y. Blankenship, J. Bergman, and H. S. Razaghi, "A primer on 3gpp narrowband internet of things," *IEEE Communications Magazine*, vol. 55, no. 3, pp. 117–123, March 2017.