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RF Energy Harvesting Wireless Powered Sensor Networks for Smart Cities

JINGXIAN LIU[1], KE XIONG[1,2], (Member, IEEE), PINGYI FAN[3], (Senior Member, IEEE), AND ZHANGDUI ZHONG[4,5], (Senior Member, IEEE)

[1]School of Computer and Information Technology, Beijing Jiaotong University, Beijing 100044, China
[2]National Mobile Communications Research Laboratory, Southeast University, Nanjing 210018, China
[3]National Laboratory for Information Science and Technology and the Department of Electronic Engineering, Tsinghua University, Beijing 100084, China
[4]State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing 100044, China
[5]Beijing Engineering Research Center of High-Speed Railway, Broadband Mobile Communications, Beijing Jiaotong University, Beijing 100044, China

Corresponding author: Ke Xiong (kxiong@bjtu.edu.cn)

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ABSTRACT This paper investigates the optimal energy beamforming and time assignment in radio frequency (RF) energy harvesting (EH) wireless powered sensor networks for smart cities, where sensor nodes (SNs) first harvest energy from a sink node, and then transmit their collected data to the sink node via time-division-multiple-access (TDMA) manner by using the harvested energy. In order to achieve green system design, we formulate a problem to minimize the energy requirement of the sink node to support transmission between the sink node and the SNs under data amount constraint and EH constraint. For practical design, the energy consumed by circuit and information processing is also considered. Since the problem is non-convex, we use semidefinite relaxation (SDR) method to relax it into a convex optimization problem and then solve it efficiently. We theoretically prove that when the number of SNs are not greater than two, the relaxed problem guarantees rank-one constraint and when the number of SNs exceeds two, our obtained results are very close to the optimal ones. Simulation results show that when the data amount is relatively small, the energy consumed by circuit and information processing affects the system performance greatly, but for a relatively large data amount, the energy requirement of the sink node on its own signal processing is affected very limited and the system energy requirement is dominated by the transmit power consumption at the SNs. Furthermore, we also discuss the effects of the other parameters on the system performance, which provide some useful insights in future smart city planning.

INDEX TERMS RF energy harvesting, wireless powered networks, wireless sensor networks, resource allocation, energy beamforming, time assignment, smart city.

I. INTRODUCTION

Smart city is able to functionally and structurally improve the city's sustainability and efficiency, which ensures citizens' quality of life and health. To realize smart city, wireless sensor networks (WSNs) are required to be widely deployed to monitor our living environments, e.g., the water distributions, the structural health of buildings, or the traffic of urban road [1]–[4], as illustrated in Fig. 1. Besides, densely deployed small-battery sensor nodes in WSNs also can be used to monitor temperature, sound, localization, and so on [5], [6]. Information monitoring from ambient environments and those delivery to the sink node are the most important tasks of the sensor nodes (SNs) [7]. As is known, both data collection and transmission consume energy at the SNs. Since the capacity of the battery is limited, old batteries are required to be replaced by the new ones or to be recharged periodically. However, update or recharging of the batteries frequently may not feasible sometimes. For example, for body SNs, the SNs deployed under rivers and the SNs deployed in dangerous circumstances, it is impossible to update or recharge.

In order to sense and collect information sustainably and avoid batteries replacement, keeping the sufficient available energy supply for SNs with as less power consumption as possiable has been a significant issue in WSN [8], [9].

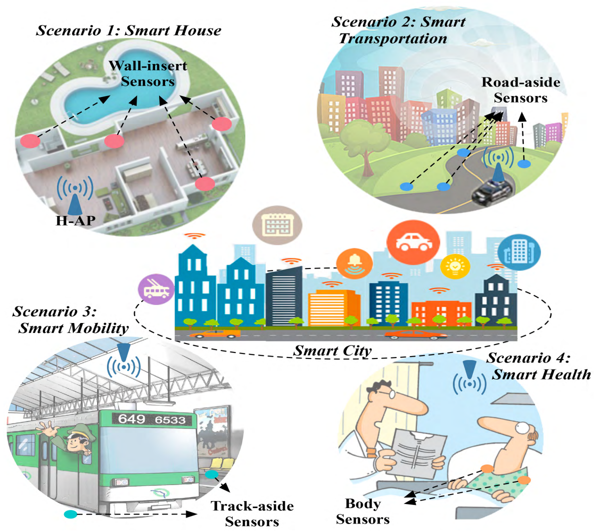

FIGURE 1. Illustration of smart cities (including smart house, smart transportation, smart mobility and smart health).

From the perspective of communication, there are two main ways to release this problem in wireless networks to meet the requirement of green communication. One is the energy efficient (EE) communication design, where the transmitting bits per Joule is maximized or the transmit power is minimized under the users quality-of-service (QoS) requirement [10]–[14]. Another way is employing energy harvesting (EH) technology to harvest energy from environmental energy sources (e.g. solar, wind, tide and radio frequency (RF) signals) [15]–[17]. EH from natural energy sources facilitates the realization of green communication. However, it closely depends on weather and external conditions resulting in instability of power supply. Besides, it also requires extra infrastructure such as wind turbines and solar panels. Comparatively, RF signals are ubiquitous, sustainable and controllable [18], [19]. Therefore, RF EH is widely regarded as an appealing solution to provide stable power supply for low-powered wireless devices. Since information and power can be carried by the same RF signals, simultaneous wireless information and power transfer (SWIPT) was proposed for RF EH, which has attracted much attention in various wireless communication systems [20]–[23]. Although SWIPT potentially alleviates the problem of energy scarcity and meantime decreases the delay of information transmission, it requires a relatively complex receiver architecture to seperate information and power receiving in practice. Thus, in 2014, the authors in [24] proposed a new network paradigm, wireless powered communication network (WPCN), in which hybrid access points (H-APs) or energy towers are deployed to transfer energy to power wireless terminals and the terminals harvest energy independent of information receiving, so WPCN avoids complex receiver design and control, which is more suitable for WSNs and internet of thing (IoT) [25]–[28].

So far, lots of related works on WPCN can be found in the literature, see e.g. [29]–[36]. In [29] and [30], they considered "harvest-and-store" protocol in multi-user WPCNs, where some users harvest energy and some users receive information from a common H-AP. Their goal was to maximize the sum of harvested energy at the EH users meanwhile guarantee the QoS of the information transmission. However, in their works, the harvested energy was only stored and not used for information transmission. In [31]–[36], the authors studied "harvest-then-transmit" protocol, where the users firstly harvest energy from the H-AP/energy tower and then use the energy to transfer the information to the H-AP/destination. Specifically, in [31] the minimum secrecy rate among the users was maximized, where however only single user was considered. In [32]–[36], multi-user WPCNs were considered. Particularly, in [32] the rate fairness among all users was investigated, in [33] the EE was maximized for the system, and in [34] the power consumption of the whole system was minimized. However, in these works, only single antenna was deployed at the H-AP/base station. Since by using beamforming technology, multiple antennas are able to focus energy onto a specific receiver, which greatly enhance the transmission quality. Thus, some works began to use multiple-antenna technology in WPCN. For multiple-antenna WPCNs, in [35] the minimum throughput among different users was maximized to achieve max-min fairness, and in [36], the closed-form expressions for the minimum power outage probability was presented and the spectral efficiency was enhanced by user selection schemes. In this paper, we consider a wireless powered sensor network system, where the single-antenna SNs harvest energy from a N-antenna sink node first, and then transmit their collecting data to the sink node. Our goal is to guarantee all SNs to complete their data transmission to the sink node with consuming as less energy as possible to meet the green requirement of future wireless system design. Compared with existing works, two main differences of our work are summarized as follows. *Firstly*, in all the works mentioned above, the circuit and information processing energy consumption were not considered in their system design. Comparatively, in our work, the circuit energy consumption and data amount dependent energy consumption were considered, which is more general and practical. *Secondly*, rather than system throughput maximization, max-min fairness design and power outage probability analysis, in our work, we investigate energy requirement minimization of the RF EH powered wireless sensor network to cater for the green requirement of future 5G communications [37], [38].

The contributions of our work are summarized as follows.

- We formulate an optimization problem to minimize the total required energy for information transmission by optimally jointly designing energy beam and allocating time and power under time constraint and the data delivery constraint of all SNs in the system.
- As the problem is non-convex and has no known solution, we first transform it into a convex optimization problem by using semidefinite relaxation (SDR) method and then solve it efficiently. Particularly, we theoretically prove that when the SNs are 1 or 2, the solution

of the relaxed problem guarantees rank-one constraint. It means that when the system has two active SNs, our proposed solution method guarantees the global optimal solution. For more than two SNs cases, although the rank-one constraint cannot be theoretically proved, our proposed method also tends to find the minimal consumed energy.

- We provide some simulation results to discuss the system performance. When we consider the energy consumption by circuit and information processing at the SNs, we find that the consumed energy of the sink node monotonically increases with the increment of the energy consumption by circuit and information processing at the SNs. Besides, with the increment of the number of the SNs, the energy requirement of the sink node increases with the time interval of the energy transmission (ET) phase. We also show that the number of SNs affects more than the transmission time constraint on the energy consumption of the whole system.

The rest of this paper is organized as follows. The system model is described in Section II. Section III presents the problem formulation and solutions, and Section IV shows the simulation results. Finally, Section V concludes the paper.

Notations: $\mathbb{R}$, $\mathbb{R}_+^n$, $\mathbb{S}_+^n$ and $\mathbb{C}^{N\times 1}$ denote the set of real munbers, n-dimensional non-negative real vectors, $n \times n$ positive semidefinite matrices and complex n-vectors, respectively. $\mathbb{E}\{\cdot\}$ represents the statistical expectation. For matrix $\mathbf{A}$, $\mathrm{Tr}(\mathbf{A})$ and $\mathrm{rank}(\mathbf{A})$ stand for the trace and rank of the matrix, respectively. $|\cdot|$ and $\|\cdot\|$ represent the Euclidean norm of complex numbers and vectors, respectively. The superscripts $(\cdot)^T$ and $(\cdot)^H$ denote the transpose and conjugate transpose (i.e., Hermitian) operations, respectively. Generalized inequality defined on the proper cone K is described as $\succeq_K$. $\mathbf{1}$ denotes a vector with all elements being 1. $\mathbf{I}_N$ stands for the $n \times n$ identity matrix.

II. SYSTEM MODEL

A. NETWORK MODEL

Consider a wireless powered sensor network, where a set of single-antenna SNs sense and collect data from their surrounding environment, as illustrated in Fig. 2. For a period of time, the SNs have to send their collected data to the sink node. Suppose that all the SNs are energy constrained. That is, they cannot always have sufficient energy to transmit their information and maintain their ordinary operations. Therefore, they have to harvest energy from the sink node at first and then use a part of energy to transmit their data and store the rest energy to maintain their ordinary operations. The sink node with huge battery/fixed energy source has stable and relatively sufficient energy supply, so their energy is enough for the SNs. In order to transfer information and energy efficiently, the sink node are deployed with multiple antennas (i.e., N antennas).

Suppose K SNs as a set are covered by the sink node, denoted as $\mathcal{K}$. For a given time period, it is divided into $K+1$ parts. For the first part, refer to ET phase, the sink node transfers energy to the K SNs. And for the rest K parts, refer to information transmission (IT) phase, K SNs transmit information to the sink node in a Time Division Multiple Access (TDMA) manner.

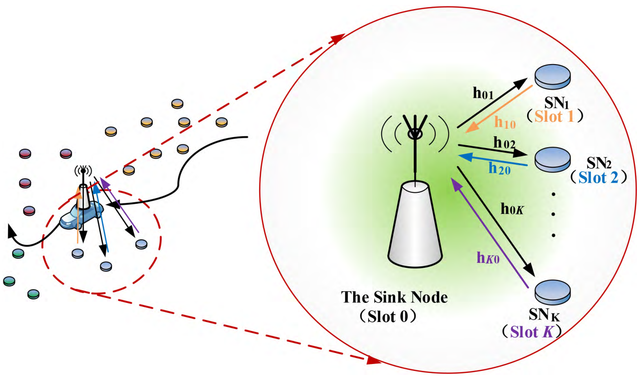

FIGURE 2. System model: network model.

B. CHANNEL MODEL

All channels are assumed to be block fading channels, so that the channel coefficients can be treated as constants within each fading block and they may change from block to block independently, following Rayleigh distribution.

Denote $\mathbf{h}_{0i} \in \mathbb{C}^{N\times 1}$ and $\mathbf{h}_{i0} \in \mathbb{C}^{N\times 1}$ as the channel coefficient of the small-scale channel fading between the transmitter and the receiver. In the ET phase, the transmitter is the sink node and the receiver is the i-th SN. And in the IT phase, the transmitter is the i-th SN and the receiver is the sink node. d_i describes the distance between the sink node and the i-th SN. m is the path-loss exponent. So d_i^{-m} represents the path loss.

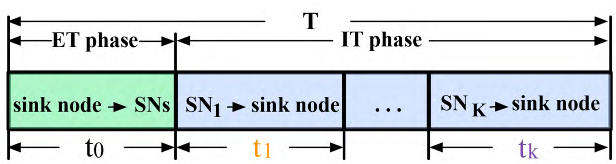

FIGURE 3. System model: transmission protocol.

C. TRANSMISSION PROTOCOL

Fig. 3 illustrates our proposed protocol. Assume each fading block is with the time period of T. It is divided into $K+1$ slots, i.e., $t_0, t_1, t_2, \ldots, t_K$. Therefore, it satisfies

$$t_0 + t_1 + \ldots + t_K \le T.$$

In order to achieve easy implementation in practical systems, we assume that t_0 is fixed, which means that for each given T, the system is preconfigured with the parameter t_0 for the sink node to transfer energy. For achieving better system performance, $t_1 \ldots t_K$ are allowed to be optimally designed to adapt to the channel quality between the sink node and the SNs.

Let $\mathbf{t} \triangleq [t_1, \ldots, t_K]^T$ as time allocation vector. It satisfies that

$$\mathbf{t}^T \mathbf{1} \leq T - t_0. \tag{1}$$

As aforementioned, in the ET phase with time interval t_0, the sink node transfers the RF signals to K SNs via its N antennas. The energy beamforming is employed to enhance the energy transfer efficiency. Let x_e be the energy symbol with unit energy, i.e., $\mathbb{E}\{|x_e|^2\} = 1$, and $\mathbf{w} \in \mathbb{C}^{N\times 1}$ is the beamforming vector. The received signal at the i-th SN can be given by

$$y_i^{(0)} = \frac{1}{\sqrt{d_i^m}} \mathbf{h}_{0i}^H \mathbf{w} x_e + n_i, \quad \forall i \in \mathcal{K}, \tag{2}$$

where $n_i \sim \mathcal{CN}(0, \sigma^2)$ is additive white Gaussian noise (AWGN) and $\mathbf{w}$ satisfies that

$$\|\mathbf{w}\|^2 = P_t. \tag{3}$$

P_t denotes the consumed power at the sink node. Thus, the harvested energy at the i-th SN can be calculated by

$$E_i^{(0)} = \rho \left| \frac{1}{\sqrt{d_i^m}} \mathbf{h}_{0i}^H \mathbf{w} \right|^2 t_0, \quad \forall i \in \mathcal{K}, \tag{4}$$

where $0 < \rho \leq 1$ denotes the energy conversion efficiency.

In the IT phase, the i-th SN is scheduled to transfer its collected data to the sink node. Let x_i be the information symbol transmitted by SN_i, i.e., $\mathbb{E}\{|x_i|^2\} = 1$. In the slot of t_i, the received signal at the sink node can be given by

$$\mathbf{y}_0^{(i)} = \frac{\sqrt{p_i}}{\sqrt{d_i^m}} \mathbf{h}_{i0} x_i + \mathbf{n}_0, \quad \forall i \in \mathcal{K}, \tag{5}$$

where $\mathbf{n}_0 \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}_N)$ is noise vector, and p_i represents the transmit power at the i-th SN. As a result, the achievable information rate at the sink node in the i-th slot from the i-th SN is

$$R_i = W \log\left(1 + \frac{p_i \|\mathbf{h}_{i0}\|^2}{d_i^m \sigma^2 W}\right), \quad \forall i \in \mathcal{K},$$

where W represents the system bandwidth. For notation simplification, we note $\sigma^2 W$ to be N_0 in the sequel.

It is known that p_i depends on the harvested energy in (4). Besides, consider that the SNs also consume some energy to maintain their ordinary operations, such as to drive the basic actions of the circuit and information processing (data sensing, collecting and storage). This part of energy also comes from the harvested energy. That is, an energy constraint is given by

$$t_i p_i + Q_i \leq E_i^{(0)}, \quad \forall i \in \mathcal{K}, \tag{6}$$

where $t_i p_i$ is the consumed energy for information transmission and Q_i is the energy which needs to be stored to maintain circuit operations and information processing. Therefore, (6) means that all consumed energy associated with information transmission and processing can not exceed the harvested energy. Furthermore, as the energy consumed by information processing can be divided into two parts, one is used for the basic circuit consumption, which can be considered as constant. And the other is used for information processing, which is related to the data amount because more data is processed more energy is reqired. Therefore, Q_i can be expressed by

$$Q_i = Q_{\text{static}} + \alpha_i B_i,$$

where Q_{static} is the constant, describing the basic circuit energy consumption, and α_i denotes the energy consumed for information processing per bit. B_i is the data amount collected at the i-th SN, which also needs to be transmitted to the sink node.

Note that in existing works, Q_i was not considered for WPCN, which means they neglected the energy consumption of circuit and information processing at the SNs. Here, we consider Q_i to be composed of a static part and the data amount dependent dynamic part, which is more close to practice.

III. PROBLEM FORMULATION AND SOLUTIONS

It is assumed that in each T, all SNs have to transmit their collected data to the sink node, therefore, it must satisfy that

$$t_i R_i \geq B_i, \quad \forall i \in \mathcal{K}. \tag{7}$$

The goal is to minimize the energy requirement to complete the data gathering from all SNs to the sink node, under the constraints of time, energy harvesting and data transmission.

Defining $\mathbf{p} \triangleq [p_1, \ldots, p_K]^T$, which can be treated as power allocation vector, we can formulate the optimization problem as

$$\begin{aligned} \mathbf{P}_0 : \quad & \min_{\mathbf{w},\mathbf{t},\mathbf{p},P_t} \; t_0 \|\mathbf{w}\|^2 \\ & \text{s.t. } (1)\,, (3)\,, (6)\,, (7)\,, \\ & \qquad \mathbf{t} \succ_{\mathbb{R}_+^n} \mathbf{0}. \end{aligned} \tag{8}$$

One can observe that the problem is non-convex because of the constraint in (6). Therefore, it cannot be solved by using traditional convex methods. Instead, we solve it as follows.

Firstly, by introducing $\mathbf{W} \triangleq \mathbf{w}\mathbf{w}^H$, we can rewrite the constraints (3) as

$$\text{Tr}\,(\mathbf{W}) = P_t. \tag{9}$$

$E_i^{(0)}$ in (4) is rewritten as

$$\begin{aligned} E_i^{(0)} &= \rho t_0 d_i^{-m} \text{Tr}(\mathbf{h}_{0i}^H \mathbf{w} (\mathbf{h}_{0i}^H \mathbf{w})^H) \\ &= \rho t_0 d_i^{-m} \text{Tr}(\mathbf{h}_{0i}^H \mathbf{w}\mathbf{w}^H \mathbf{h}_{0i}) \\ &= \rho t_0 d_i^{-m} \text{Tr}(\mathbf{h}_{0i}^H \mathbf{W} \mathbf{h}_{0i}) \\ &= \rho t_0 d_i^{-m} \text{Tr}(\mathbf{h}_{0i} \mathbf{h}_{0i}^H \mathbf{W}) \end{aligned}$$

By substituting $E_i^{(0)}$ into (6), we can obtain

$$t_i p_i + Q_i \leq \rho t_0 d_i^{-m} \text{Tr}(\mathbf{h}_{0i} \mathbf{h}_{0i}^H \mathbf{W}), \quad \forall i \in \mathcal{K}. \tag{10}$$

Besides, the objective of problem $\mathbf{P}_0$ can be replaced by $t_0 \text{Tr}\,(\mathbf{W})$.

In order to achieve the equivalent problem transformation by replacing $\mathbf{w}$ with $\mathbf{W}$. It must satisfy that

$$\begin{cases}\mathbf{W}\succeq_{\mathbb{S}_+^n}\mathbf{0},\\ \text{rank}\left(\mathbf{W}\right)=1.\end{cases}\tag{11}$$

Then, we obtain an equivalent transformation from problem $\mathbf{P}_0$ as

$$\begin{aligned}\mathbf{P}_1:\quad &\min_{\mathbf{W},\mathbf{t},\mathbf{p},P_t}\ t_0\text{Tr}\left(\mathbf{W}\right)\\ &\text{s.t.}\ (1),(7),(9),(10),(11),\\ &\qquad \mathbf{t}\succ_{\mathbb{R}_+^n}\mathbf{0}.\end{aligned}\tag{12}$$

Observe that the constraint (10) has coupled variables, so problem $\mathbf{P}_1$ is still a non-convex optimization problem. Since t_0 is fixed, problem $\mathbf{P}_1$ has the same optimal solution with the following problem $\mathbf{P}_1'$, i.e.,

$$\begin{aligned}\mathbf{P}_1':\quad &\min_{\mathbf{W},\mathbf{t},\mathbf{p},P_t}\ \text{Tr}\left(\mathbf{W}\right)\\ &\text{s.t.}\ (1),(7),(9),(10),(11),\\ &\qquad \mathbf{t}\succ_{\mathbb{R}_+^n}\mathbf{0}.\end{aligned}$$

which is the power minimization problem. Therefore, by solving problem $\mathbf{P}_1$, the optimal solution to problem $\mathbf{P}_1'$ is also obtained. As a result, the system minimal power requirement (i.e., the optimal value of problem $\mathbf{P}_1'$) can be achieved.

In order to achieve the convexity of the proposed energy requirement optimization problem, we introduce a new variable $E_i = t_i p_i$. By doing so, (7) and (10) can be replaced by

$$t_iW\log\left(1+\frac{E_i\|\mathbf{h}_{i0}\|^2}{d_i^m t_i N_0}\right)\geq B_i,\quad \forall i\in\mathcal{K},\tag{13}$$

and

$$E_i+Q_i\leq \rho d_i^{-m}t_0\text{Tr}(\mathbf{h}_{0i}\mathbf{h}_{0i}^H\mathbf{W}),\quad \forall i\in\mathcal{K}.\tag{14}$$

For simplification, let $\mathbf{V} = t_0\mathbf{W}$ and $E_0 = P_t t_0$, so constraints (9) and (14) can be respectively rewritten as

$$\text{Tr}\left(\mathbf{V}\right)=E_0,\tag{15}$$

and

$$E_i+Q_i\leq \rho d_i^{-m}\text{Tr}(\mathbf{h}_{0i}\mathbf{h}_{0i}^H\mathbf{V}),\quad \forall i\in\mathcal{K}.\tag{16}$$

As for (11), it can be replaced by

$$\begin{cases}\mathbf{V}\succeq_{\mathbb{S}_+^n}\mathbf{0},\\ \text{rank}\left(\mathbf{V}\right)=1.\end{cases}\tag{17}$$

Let $\mathbf{E}\triangleq[E_1,E_2,\ldots,E_K]^T$. One can get an equivalent problem of $\mathbf{P}_1$ as

$$\begin{aligned}\mathbf{P}_2:\quad &\min_{\mathbf{V},\mathbf{t},\mathbf{E},E_0}\ \text{Tr}\left(\mathbf{V}\right)\\ &\text{s.t.}\ (1),(13),(15),(16),(17),\\ &\qquad \mathbf{t}\succ_{\mathbb{R}_+^n}\mathbf{0}.\end{aligned}\tag{18}$$

We observe that problem $\mathbf{P}_2$ in (17) becomes a convex optimization problem by dropping the constraint rank $(\mathbf{V}) = 1$. In this case, the SDR method [39] can be adopted. Therefore, problem $\mathbf{P}_2$ is relaxed into

$$\begin{aligned}\mathbf{P}_3:\quad &\min_{\mathbf{V},\mathbf{t},\mathbf{E},E_0}\ \text{Tr}\left(\mathbf{V}\right)\\ &\text{s.t.}\ (1),(13),(15),(16),\\ &\qquad \mathbf{t}\succ_{\mathbb{R}_+^n}\mathbf{0},\\ &\qquad \mathbf{V}\succeq_{\mathbb{S}_+^n}\mathbf{0}.\end{aligned}\tag{19}$$

Lemma 1: Problem $\mathbf{P}_3$ is a convex optimization problem.

Proof: The second order derivative of the objective function is shown in the following,

$$\frac{\partial^2\text{Tr}(\mathbf{V})}{\partial\mathbf{V}^2}=0,$$

which means the objective function is convex. Consider all constraints: rewrite (13), (16) into the form of convex function $f(\mathbf{X})\leq 0$, so (13) can be replaced by

$$B_i-t_iW\log\left(1+\frac{E_i\|\mathbf{h}_{i0}\|^2}{d_i^m t_iN_0}\right)\leq 0,\quad \forall i\in\mathcal{K},$$

and (16) can be replaced by

$$E_i+Q_i-\rho d_i^{-m}\text{Tr}(\mathbf{h}_{0i}\mathbf{h}_{0i}^H\mathbf{V})\leq 0,\quad \forall i\in\mathcal{K}.$$

Their Hessian matrices are described respectively as follows,

$$\mathbf{H_1}=\begin{bmatrix}h_{11} & h_{12}\\ h_{21} & h_{22}\end{bmatrix},$$

where

$$\begin{cases}h_{11}=\dfrac{\|\mathbf{h}_{i0}\|^4W}{d_i^{2m}{N_0}^2t_i\log\left(1+\frac{\|\mathbf{h}_{i0}\|^2E_i}{d_i^mN_0t_i}\right)^2},\\ h_{12}=\dfrac{-\|\mathbf{h}_{i0}\|^4E_iW}{d_i^{2m}{N_0}^2{t_i}^2\log\left(1+\frac{\|\mathbf{h}_{i0}\|^2E_i}{d_i^mN_0t_i}\right)^2},\\ h_{21}=\dfrac{-\|\mathbf{h}_{i0}\|^4E_iW}{d_i^{2m}{N_0}^2{t_i}^2\log\left(1+\frac{\|\mathbf{h}_{i0}\|^2E_i}{d_i^mN_0t_i}\right)^2},\\ h_{22}=\dfrac{\|\mathbf{h}_{i0}\|^4{E_i}^2W}{d_i^{2m}{N_0}^2{t_i}^3\log\left(1+\frac{\|\mathbf{h}_{i0}\|^2E_i}{d_i^mN_0t_i}\right)^2},\end{cases}$$

and $\mathbf{H_2}=0$, which means $\mathbf{H_2}$ is semidefinite matrix. Because $h_{11} > 0$ and $h_{11}h_{22}-h_{12}h_{21} = 0$, so $\mathbf{H_1}$ is semidefinite matrix. Both of them are semidefinite Hessian matrices, so constraints (13) and (16) are convex. (1), (15) and the other constraints are affine which are convex. As a result, problem $\mathbf{P}_3$ is a convex optimization problem. ■

Lemma 1 indicates that problem $\mathbf{P}_3$ is a convex optimization problem which can be solved by using some known methods (e.g. interior point method). In order to observe the optimal solution's characterizes of problem $\mathbf{P}_2$, the optimal solution is denoted as $(\mathbf{V}^*, \mathbf{t}^*, \mathbf{E}^*, {E_0}^*)$. Then, we obtain the following results.

Theorem 1: When $K\leq 2$, the optimal matrix $\mathbf{V}^*$ satisfies rank $\left(\mathbf{V}^*\right)=1$, *which means problem $\mathbf{P}_2$ has a global optimal solution.*

Proof: According to [40], in a convex optimization problem

$$\begin{aligned}\mathbf{Q}: \quad & \min_{\mathbf{X_1},\ldots,\mathbf{X_L}} \sum_{l=1}^{L} \mathrm{Tr}(\mathbf{C_l X_l}) \\ & \text{s.t. } \sum_{l=1}^{L} \mathrm{Tr}(\mathbf{A_{ml} X_l}) \trianglerighteq_m b_m, \quad m = 1, \ldots M, \\ & \mathbf{X_l} \succeq_{\mathbb{S}_+^n} \mathbf{0}, \quad l = 1, \ldots L,\end{aligned}$$

where $\mathbf{C_l}$, $\mathbf{A_{ml}}$ and $\mathbf{X_l}$ are Hermitian matrices, $b_m \in \mathbb{R}$, $\trianglerighteq_m \in \{>, <, =\}$, if problem $\mathbf{Q}$ is solvable, then problem $\mathbf{Q}$ will always have an optimal solution $(\mathbf{X_1^*}, \ldots, \mathbf{X_L^*})$ such that

$$\sum_{l=1}^{L} \mathrm{rank}(\mathbf{X}_l{}^*)(\mathrm{rank}(\mathbf{X}_l{}^*) + 1) \leq 2M.$$

In order to analyse our problem, we construct a problem as follows,

$$\begin{aligned}\mathbf{Q}': \quad & \min_{\mathbf{V}} \mathrm{Tr}(\mathbf{V}) \\ & \text{s.t. } E_i^* + Q_i \leq \rho d_i^{-m} \mathrm{Tr}(\mathbf{h}_{0i}\mathbf{h}_{0i}^H \mathbf{V}), \quad \forall i \in \mathcal{K}, \\ & \mathbf{V} \succeq_{\mathbb{S}_+^n} \mathbf{0}. \end{aligned} \tag{20}$$

If it is solvable, its optimal solution is $\mathbf{V}^\#$ and it satisfies $\mathrm{rank}(\mathbf{V}^\#)(\mathrm{rank}(\mathbf{V}^\#) + 1) \leq 2M$. In order to achieve $\mathrm{rank}(\mathbf{V}^\#) = 1$, M must be not more than 2.

Because problem $\mathbf{Q}'$ has a larger feasible solution region than problem $\mathbf{P}_3$, so $\mathbf{V}^*$ is feasible for $\mathbf{Q}'$. As a result, in problem $\mathbf{Q}'$, $\mathrm{Tr}(\mathbf{V}^\#) \leq \mathrm{Tr}(\mathbf{V}^*) = E_0^*$. Due to $\mathrm{Tr}(\mathbf{V}^\#) \leq \mathrm{Tr}(\mathbf{V}^*) = E_0^*$, $\mathrm{Tr}(\mathbf{V}^\#)$ is feasible in problem $\mathbf{P}_3$. Then, we know that in problem $\mathbf{P}_3$, $\mathrm{Tr}(\mathbf{V}^*) \leq \mathrm{Tr}(\mathbf{V}^\#)$. This indicates that $\mathbf{V}^*$ is equal to $\mathbf{V}^\#$. Besides, $\mathbf{V}^*$ also satisfies $\mathrm{rank}(\mathbf{V}^*) = 1$ if $M \leq 2$. $M \leq 2$ means that there are at most 2 SNs (i.e., $K \leq 2$). ■

Once we obtain the optimal rank-one matrix $\mathbf{V}^*$, we can derive the optimal $\mathbf{W}^*$. The beamforming vector $\mathbf{w}^*$ then can be recovered from the eigenvalue decomposition (EVD) of $\mathbf{W}^*$. Otherwise, we could pick up the maximal eigenvalue and its relative eigenvector to approximately recover $\mathbf{w}^*$.

IV. SIMULATION RESULTS

This section provides some simulation results to discuss the system performance. We firstly discuss the energy requirement of the sink node versus the transmission data amount with the energy consumed by ordinary operations (the energy consumption of circuit and information processing). Secondly, we compare the solution difference between the original problem $\mathbf{P}_0$ and its relaxed problem $\mathbf{P}_3$. Lastly, we further discuss the effects of the parameters on the system performance.

In the simulations, we assume the system bandwidth W is 1MHz, $\sigma^2 = 10^{-8}$ and $m = 2$. The value of d_i is selected from 4m to 10m. We desire to show the effect trends of different values of parameters on system performance. Therefore, some commonly used values for wireless communication investigation are selected in our simulations [10]. For clarity, all the mentioned parameters are summarized in Table 1.

In order to evaluate the system performance for practical networks, two groups of practical parameters associated with ZigBee and WiFi networks, are also considered in some of our simulations. For ZigBee, we adopt the American standard at 915MHz with each channel bandwidth of 2MHz and the highest rate of 40Kbps [41]. For WiFi networks, we adopt IEEE 802.11a protocol at 5GHz with each channel bandwidth of 20MHz and the highest rate of 54Mbps [42].

TABLE 1. Simulation parameters.

Parameters	Values
Energy conversion efficiency	$\rho = 1$
Bandwidth	1MHz
Noise power spectral density	$\sigma^2 = 10^{-8}$
Path-loss exponent	$m = 2$
The distance from the sink node to the i-th SN	$d_i \in [4, 10]$

Without loss of generality, we also assume that B_i, α_i and Q_i at every SN are the same for all i, which are respectively represented as B, α and Q. In addition, we set $N = 12$, $K = 6$, $B = 10$Kbits, $T = 10$ms and $t_0 = 2$ms. All these parameters will not change unless otherwise specified.

Moreover, in the figures whose y-axis is energy requirement of the sink node or transmission energy consumption of the SN_1 of this section, the logarithmic coordinates are adopted for the y-axis. That is the consumed energy presented on the y-axis is with the unit of $\log_{10}$ Joule rather than Joule.

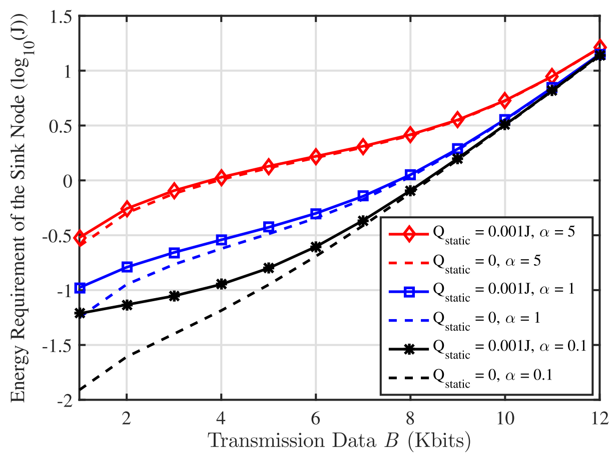

FIGURE 4. The energy requirement of the sink node versus the transmission data of the SNs B for different residual energy of the SNs ($\alpha \neq 0$).

A. ENERGY REQUIREMENT AT THE SINK NODE VERSUS B

Fig. 4 plots the energy requirement of the sink node versus the transmission data amount of SNs B. It is observed that all curves grow with the increment of B, since more data requires more transmit and more information processing energy consumption. It is also observed that for the curves associated with the same Q_{static}, for example, $Q_{\mathrm{static}} = 0$ or $Q_{\mathrm{static}} = 0.001J$, it shows that the larger α leads to the higher energy consumption at the sink node. Besides, for the curves associated with the same α, for example, $\alpha = 0.1$J/bit or $\alpha = 5$J/bit, it shows that the larger Q_{static} also leads to the higher energy consumption at the sink node. The reason is straightforward, as either of the increments of Q_{static} and α will increase the total power consumption at the SNs, which requires more energy transfer from the sink node. However, when B becomes relatively large, the differences among the curves decrease and all curves show similar behaviours on energy consumption. The reason can be explained as follows. For a relatively large B, the energy consumed at the SNs is dominated by their transmit power consumption.

Consider that in practical systems power is an important performance index for wireless energy harvesting circuit design, we also discuss the minimal power requirement in the simulations. Since t_0 is fixed in our considered system design, which is set as 2ms in our simulations as an example, the minimal energy requirement can be easily translated to minimal power requirement. In Fig. 5 and Fig. 6, the minimal power requirements for ZigBee [41] and WiFi [42] system are presented. It can be observed that the minimal power requirement in Fig. 5 and Fig. 6 have very similar trends versus B to that in Fig. 4, which means that the values of the system configurations just affect the minimal required energy or power but do not affect the varying trends of system performance.

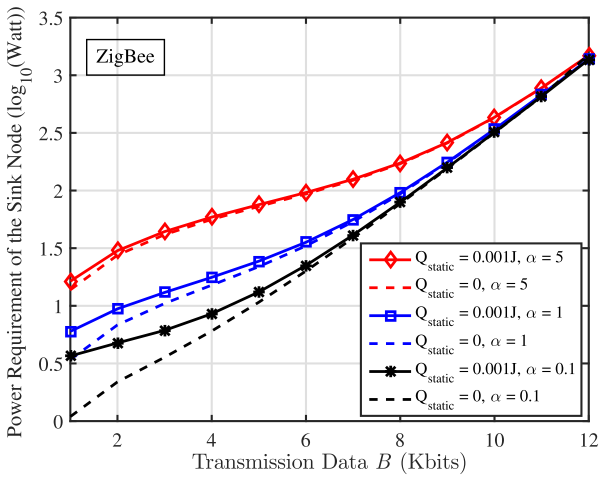

FIGURE 5. **The power requirement of the sink node versus the transmission data of the SNs B for different residual energy of the SNs with ZigBee standard ($\alpha \neq 0$).**

In order to clearly show the effect of the static circuit power consumption on the total energy consumed in the system, we plot the numerical results for different values of Q_{static} with $\alpha = 0$ versus B in Fig. 7. It shows that the energy requirement of the sink node monotonically increases with the increment of the transmission data B at the SNs. However, when B is relatively small, the the energy requirement of the sink node increase slowly and when B is relatively large, the energy requirement of the sink node increase more rapidly and the increasing rate seems to be linear. For comparison, the ideal case with $Q_{\text{static}} = 0$ is also plotted, which shows that the energy requirement of the sink node linearly increases with the increment of B. The reason is that, for $Q_{\text{static}} = 0$ case and for $Q_{\text{static}} \neq 0$ with relatively large B case, transmit power consumption at all SNs dominates the total energy requirement at the sink node.

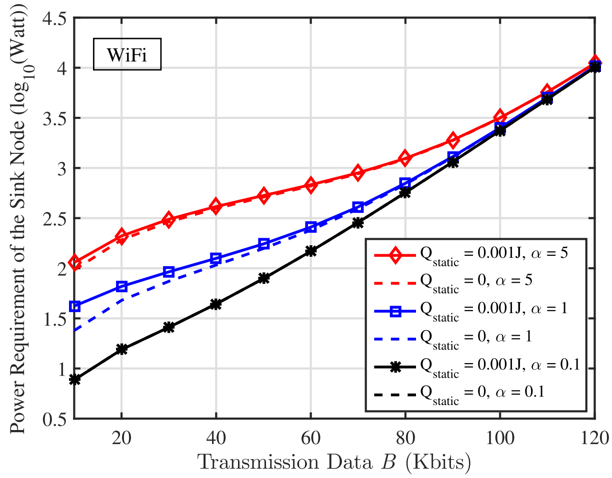

FIGURE 6. **The power requirement of the sink node versus the transmission data of the SNs B for different residual energy of the SNs with WiFi standard ($\alpha \neq 0$).**

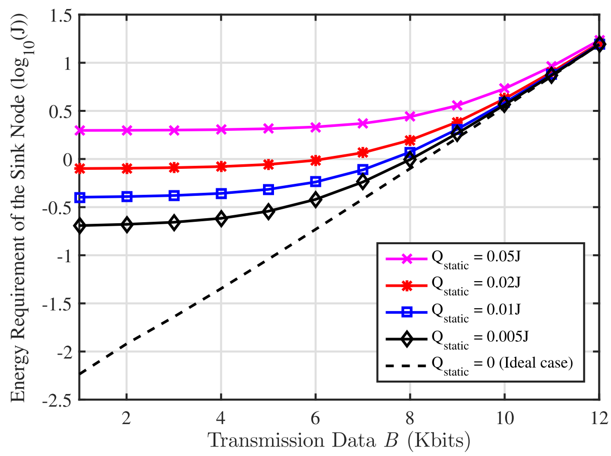

FIGURE 7. **The energy requirement of the sink node versus the transmission data of the SNs B for different residual energy of the SNs ($\alpha = 0$).**

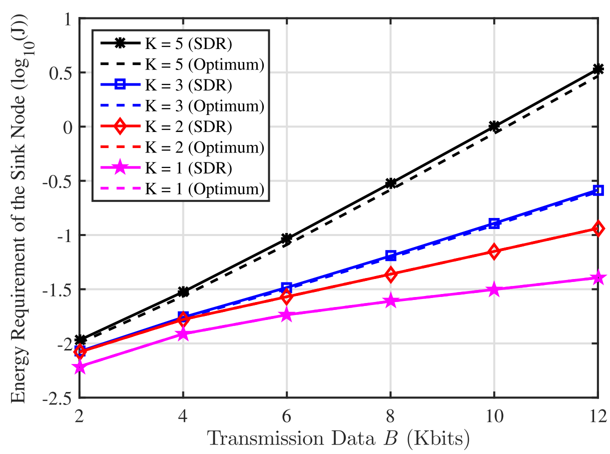

FIGURE 8. **The SDR results and the optimal results.**

B. OPTIMUM OF THE RELAXED PROBLEM

In this subsection, we discuss the solution difference between the original problem and its relaxed problem.

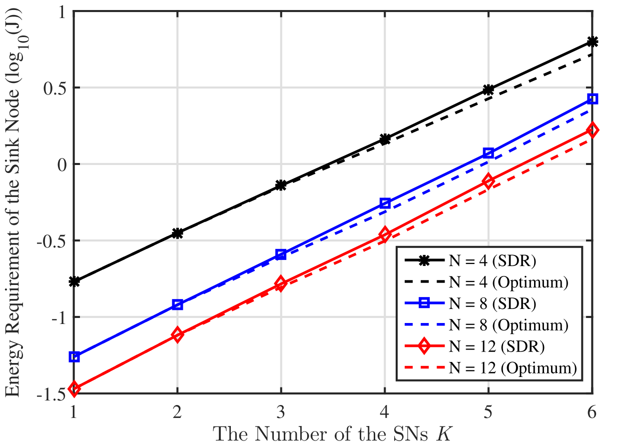

FIGURE 9. **The energy requirement of the sink node versus the number of the SNs K for different antenna number of the sink node N.**

Fig. 8 and Fig. 9 present the results of the minimal energy requirement at the sink node versus B and K, respectively. In the figures, the curves marked with "SDR" show the optimal value directly obtained by solving problem $\mathbf{P}_3$ and those marked with "Optimum" show the optimal value of problem $\mathbf{P}_0$ obtained by substituting the optimal $\mathbf{w}^*$, $\mathbf{t}^*$, $\mathbf{p}^*$ and $P_t{}^*$ derived from the optimal $\mathbf{V}^*$, $\mathbf{t}^*$, $\mathbf{E}^*$, $E_0{}^*$ associated with problem $\mathbf{P}_3$. In the two figures, one can observe that when K is 1 or 2, the optimal value of the original problem $\mathbf{P}_0$ is the same as that of the relaxed problem $\mathbf{P}_3$. This is consistent with the theoretical result in Theorem 1. When K exceeds 2, there is a gap between the SDR result associated with problem $\mathbf{P}_3$ and the optimal result of the original $\mathbf{P}_0$. However, the gap is not large. Moreover, Fig. 8 shows that the energy requirement of the sink node increases with the increment of K. The reason is that more SNs yield more data required to be delivered to the sink node, which consumes more energy. In Fig. 9, it also shows that for the same K, the energy requirement of the sink node decreases with the increment of N, since with more antennas equipped at the sink node, larger spacial degree of freedom (DoF) can be obtained, which improves the energy transfer efficiency in the ET phase, as well as the information transmission rates in the IT phase. Consequently, the total energy requirement at the sink node is reduced.

C. TRANSMIT ENERGY REQUIREMENT AT SNs VERSUS B

As shown in constraint (6), the energy consumed at the SNs is composed of two parts, one is for data transmission and the rest is for circuit consumption. In this section, we plot some results of the data transmit energy requirement versus B for different K and α. Without loss of generality, we present the data transmit energy requirement of the SN_1 for example. Fig. 10 shows three subfigures with different value of K. It illustrates that the transmit energy requirement of the SN_1 increases with the increment of B. Based on the result, one can see that larger K results in lower energy consumption of the SN_1. However, we observe that different values of α have almost no effect on the energy consumption of the SN_1 with the same K. That indicates the transmission energy of one SN is independent of its energy consumption of ordinary operations.

D. EFFECTS OF VARIOUS PARAMETERS ON SYSTEM PERFORMANCE

1) TIME ASSIGNMENT VERSUS α

Similar to Fig. 10, without loss of generality, we take SN_1 as an example to show the effect of α on time assignment in Fig. 11. It plots the time assignment t_1 versus α according to the transmission time part in constraint (6). For a given K, the time assignment t_1 does not change with the increment of α. Since Q is a function of α at each SN, thus, the result in Fig. 11 indicates that the transmit energy requirement of one SN is independent of its related Q. Moreover, it is observed that the time assignment t_1 is larger when the K is smaller. That is because that for all SNs, the common fixed time is $T - t_0$, so the smaller K, the larger time can be assigned to each user.

2) ENERGY REQUIREMENT OF THE SINK NODE VERSUS t_0

In Fig. 12, the energy requirement of the sink node versus different values of t_0 is depicted. It is observed that the energy requirement of the sink node increases with the increment of t_0. Besides, the upward trend of the energy requirement of the sink node becomes rapidly when K becomes relatively large. For example, when $K = 1$, the energy requirement of the sink node almost does not change with the increment of t_0. But when $K = 3$, the energy requirement of the sink node

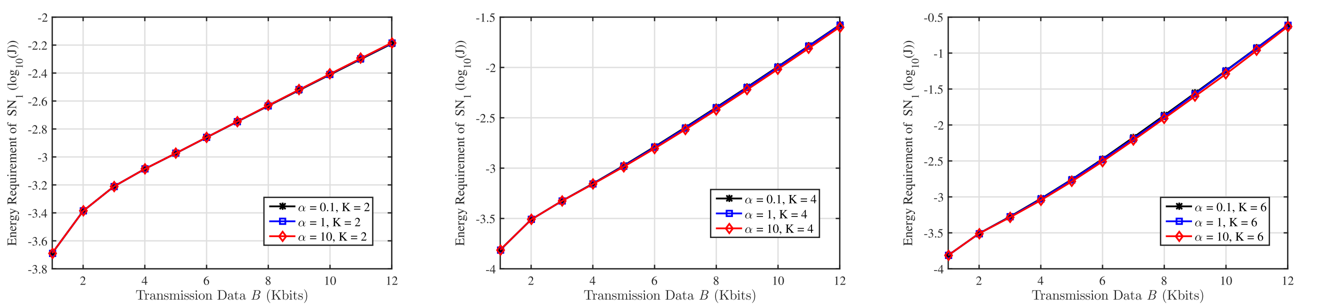

FIGURE 10. **The energy requirement of the SNs versus the transmission data of the SNs B for different residual energy of the SNs ($\alpha \neq 0$ and $Q_{\text{static}} = 0$).**

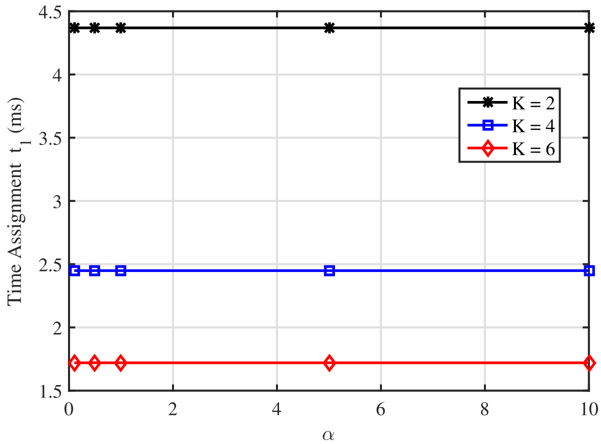

FIGURE 11. Time assignment t_1 with different K and α.

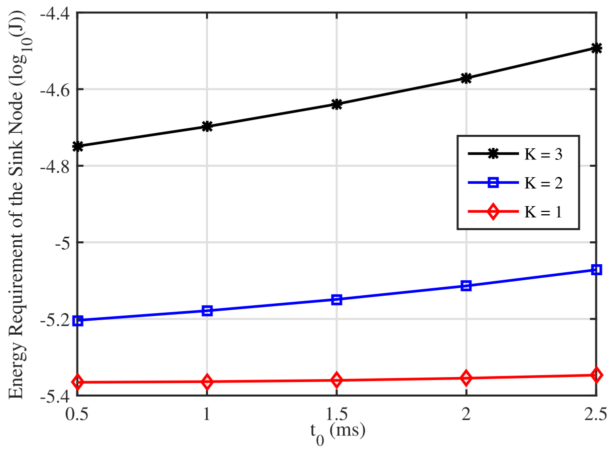

FIGURE 12. The energy requirement of the sink node versus t_0 for different K.

increases rapidly with the increment of t_0. The reason of this phenomenon is that when t_0 increases, the transmission time of all SNs will decrease, resulting in less transmission time for each SN and more energy requirement of the sink node.

3) TRANSMIT POWER OF THE SINK NODE VERSUS T

Fig. 13 plots the transmit power of the sink node w.r.t. the time constraint T, where the transmit power of the sink node decreases with the increment of the transmission time. That is because with the same energy requirement of the sink node, when the transmission time T increases, the transmit power will be decreased. Furthermore, it is observed that the transmit power decreases with the increment of N. The reason is that the more antennas equipped at the sink node leads to larger spatial DoF, which improves the power transfer efficiency.

4) ENERGY REQUIREMENT OF THE SINK NODE VERSUS N AND K

As aforementioned, with either the increment of K and or the decrement of N, the energy requirement of the sink node is increased. However, we expect to find the dominant factor between K and N, who affects greatly. In Fig. 14,

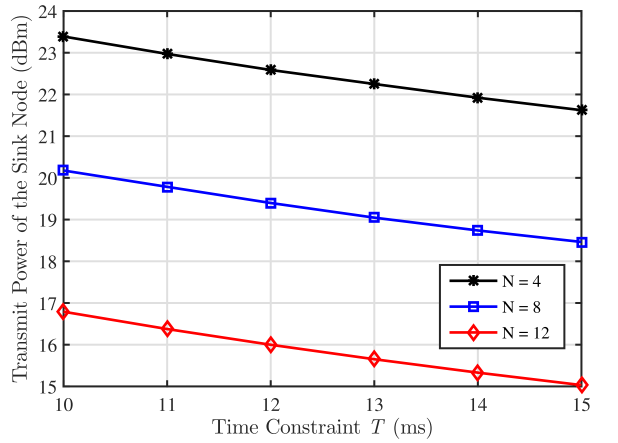

FIGURE 13. The transmit power of the sink node versus the transmission time T for different antenna number of the sink node N.

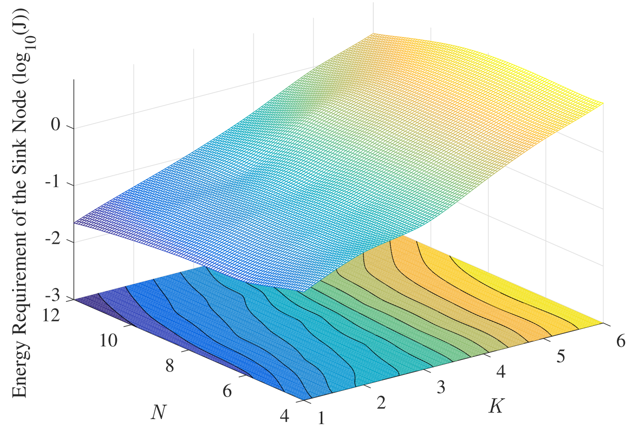

FIGURE 14. The energy requirement of the sink node versus K and T with decrement of the transmission distance.

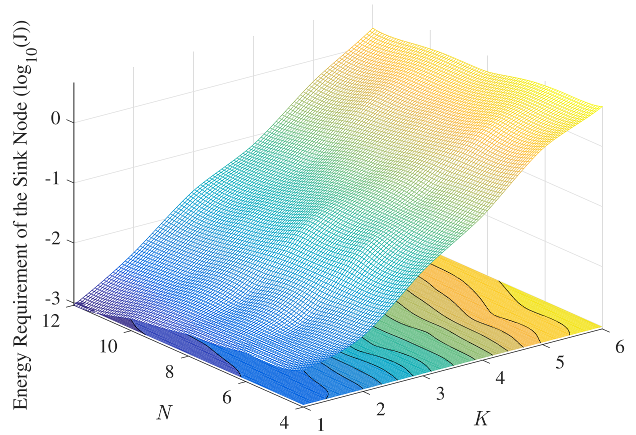

FIGURE 15. The energy requirement of the sink node versus K and T with increment of the transmission distance.

the distances between six SNs and the sink node are set to be [9 8 7 6 5 4]. We observe that by jointly consider K and N, the increasing trend of the energy requirement of the sink node is dominated by K. In Fig. 15, the distances between six SNs and the sink node are set to be [4 5 6 7 8 9]. It indicates that the effect of K is greater than N, which means that K is the dominant factor compared to N.

V. CONCLUSION

This paper studied the optimal energy beamforming and time assignment in RF EH wireless powered sensor networks for smart cities, where SNs firstly harvested energy from a sink node, and then transmitted their collected data to the sink node via TDMA manner by using the harvested energy. In order to achieve green system design, we formulated a problem to minimize the energy requirement of the sink node to support transmission between the sink node and the SNs under data amount constraint and EH constraint. For practical design, the energy consumed by circuit and information processing was also considered in the discussed system. Since the problem is non-convex, we used SDR method to solve it efficiently. We theoretically proved that when the number of SNs are not greater than 2, the relaxed problem guarantees rank-one constraint and when the number of SNs exceeds 2, our obtained results were very close to the optimal ones. Simulation results demonstrated that when the data amount is relatively small, the energy consumed by circuit and information processing affects the system performance greatly, but for a relatively large data amount, the energy requirement of the sink node is affected very limited, which is dominated by the transmit power consumption at the SNs. Furthermore, we also discussed the effects of the other parameters on the system performance. It is expected that such a solution can provide some useful insights on smart city planning.

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JINGXIAN LIU received the B.E. degree from the School of Computer and Information Technology, Beijing Jiaotong University, Beijing, China, in 2015, where she is currently pursuing the Ph.D. degree in computer science and technology with the School of Computer and Information Technology. Her current research interests are in the field of energy harvesting wireless communication and wireless sensor networks.

KE XIONG (M'14) received the B.S. and Ph.D. degrees from Beijing Jiaotong University (BJTU), Beijing, China, in 2004 and 2010, respectively. From 2010 to 2013, he was a Post-Doctoral Research Fellow with the Department of Electrical Engineering, Tsinghua University, Beijing. From 2015 to 2016, he was a Visiting Scholar with the University of Maryland, College Park. Since 2013, he has been a Lecturer with BJTU, where he is currently an Associate Professor with the School of Computer and Information Technology. He has authored over 60 academic papers in referred journals and conferences. His current research interests include wireless cooperative networks, wireless powered networks, and network information theory. He is a member of the China Computer Federation and a Senior Member of the Chinese Institute of Electronics. He also served as a Session Chair of the IEEE GLOBECOM'2012, the IET ICWMMN'2013, the IEEE ICC'2013, the ACM MOMM'2014, and the Publicity and Publication Chair of the IEEE HMWC'2014, and the TPC Co-Chair of the IET ICWMMN'2017. He serves as an Associate Editor-in Chief of the Chinese Journal *New Industrialization Strategy*, and the Editor of *Computer Engineering and Software*. Since 2017, he has been serving as the Leading Editor of the Special issue Recent Advances in Wireless Powered Communication Networks for EURASIP Journal on *Wireless Communications and Networking*. He also serves as a Reviewer of over 15 international journals, including the IEEE TRANSACTIONS ON SIGNAL PROCESSING, the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the IEEE TRANSACTIONS ON COMMUNICATIONS, the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE COMMUNICATION LETTERS, IEEE SIGNAL PROCESSING LETTERS, and the IEEE WIRELESS COMMUNICATION LETTERS.

PINGYI FAN (M'03–SM'09) received the B.S. degree from the Department of Mathematics, Hebei University, in 1985, the M.S. degree from the Department of Mathematics, Nankai University, in 1990, and the Ph.D. degree from the Department of Electronic Engineering, Tsinghua University, Beijing, China, in 1994. From 1997 to 1998, he was a visiting Research Associate with The Hong Kong University of Science and Technology. From 1998 to 1999, he was a visiting Research Fellow with the University of Delaware, USA. In 2005, he was Visiting Professor with the NICT of Japan. From 2005 to 2014, he visited The Hong Kong University of Science and Technology for many times. In 2011, he was a Visiting Professor with the Institute of Network Coding, The Chinese University of Hong Kong. He is currently a Professor of Department of EE with the Tsinghua University. His main research interests include B5G technology in wireless communications such as MIMO and OFDMA, network coding, network information theory, and big data analysis. He is an Oversea Member of the IEICE. He has received some academic awards, including the IEEE Globecom'14 Best Paper Award, the IEEE WCNC'08 Best Paper Award, the ACM IWCMC'10 Best Paper Award, and the IEEE ComSoc Excellent Editor Award for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS in 2009. He has attended to organize many international conferences including the General Co-Chair of the IEEE VTS HMWC2014, the TPC co-Chair of the IEEE International Conference on Wireless Communications, Networking and Information Security 2010, and a TPC Member of the IEEE ICC, Globecom, WCNC, VTC, and Inforcom. He has served as an Editor of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the *Inderscience International Journal of Ad Hoc and Ubiquitous Computing* and the Wiley Journal of *Wireless Communication and Mobile Computing*. He is also a Reviewer of over 30 international Journals including 20 IEEE Journals and eight EURASIP Journals.

ZHANGDUI ZHONG (SM'16) received the B.E. and M.S. degrees from Beijing Jiaotong University, Beijing, China, in 1983 and 1988, respectively. He is currently a Professor and an Advisor of Ph.D. candidates with Beijing Jiaotong University, where he is also a Chief Scientist with the State Key Laboratory of Rail Traffic Control and Safety. He is also a Director of the Innovative Research Team of the Ministry of Education, Beijing, and a Chief Scientist of the Ministry of Railways, Beijing. His research has been widely used in railway engineering, such as at the Qinghai-Xizang Railway, the Datong-Qinhuangdao Heavy Haul Railway, and many high-speed railway lines in China. He has authored or co-authored seven books, five invention patents, and over 200 scientific research papers in his research area. His interests include wireless communications for railways, control theory and techniques for railways, and GSM-R systems. He is an Executive Council Member of the Radio Association of China, Beijing, and a Deputy Director of the Radio Association, Beijing. He received the MaoYiSheng Scientific Award of China, the ZhanTianYou Railway Honorary Award of China, and the Top 10 Science/Technology Achievements Award of Chinese Universities.