Received March 14, 2017, accepted March 31, 2017, date of publication April 13, 2017, date of current version June 7, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2694046

Heterogeneous Statistical QoS Provisioning Over Wireless Powered Sensor Networks

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This paper was supported in part by the National Natural Science Foundation of China under Grant 61401330 and Grant 61671347, in part by the Natural Science Foundation of Shaanxi Province under Grant 2016JQ6027, and in part by the 111 Project of China under Grant B08038.

ABSTRACT The wireless energy transfer, which is a promising technology for the wireless sensor networks (WSNs), can efficiently solve the energy scarcity that results from the application boosting. However, not only the energy scarcity, but also the quality of service (QoS) guarantees need to be taken into account for the WSNs. Different types of applications in the WSNs impose the new challenge on heterogeneous QoS provisioning for the WSNs. To solve the above problem, in this paper, we develop the joint downlink energy assignment and uplink power control scheme with the heterogeneous statistical QoS provisioning (HeP) for wireless powered sensor networks (WPSNs). In particular, we build up the HeP model, where the aggregate effective capacity (AEC) is defined as the aggregate throughput under the statistical QoS constraints for the WPSNs. Based on the mode, we formulate the AEC maximization problems for uniformed time division and dynamic time allocation scenarios, respectively. For the uniformed time division scenario, we divide the AEC maximization problem into the hybrid access point determined downlink energy assignment problem and the sensor node determined uplink power control problem. Then, we solve these problems and obtain the corresponding closed-form solutions. For the dynamic time allocation scenario, we develop the joint time allocation, downlink energy assignment, and uplink power control scheme to maximize the AEC and iteratively derive the scheme. Extensive simulations are conducted to demonstrate the effect of heterogeneous statistical QoS on our developed resource allocation schemes for WPSNs. The results show that the HeP resource allocation schemes are superior to the schemes with homogeneous statistical QoS guarantees.

INDEX TERMS Wireless powered sensor networks, heterogeneous statistical QoS, effective capacity, power allocation, time allocation.

I. INTRODUCTION

Wireless Sensor Network (WSN) is very attractive for wireless communications due to its various applications, i.e., regional monitoring, medical observation, industrial process control, military surveillance, etc [1]. A WSN consists of a large number of spatially distributed sensor nodes (SNs) with low-power, computational and sensing capabilities. The distributed SNs can monitor the environment phenomena and cooperatively transmit their data to an access point (AP) or base station (BS) [2], [3]. Traditionally, the SNs are powered by non-rechargeable batteries with finite battery capacity. However, the finite battery capacity of SNs limits the applications boosting, which causes the energy scarcity, in WSNs [4]–[7]. The energy scarcity is a critical problem that holds back the further popularity and development of WSNs. Energy harvesting emerges as a promising solution to provide everlasting energy supply by enabling SNs to harvest energy from the ambient energy sources, i.e., solar, thermoelectric generator, vibration absorption device, etc [3]–[5]. However, the energy harvesting from the natural sources is an intermittent and uncontrollable process. In order to maintain reliable energy harvesting based communications for WSNs, dedicated radio frequency (RF) radiation is used as energy supply for SNs, which is known as wireless energy transfer (WET) [8]–[12]. The WSNs powered by wireless transferred energy from energy sources is referred to as the wireless powered sensor networks (WPSNs) [13], [14].

The application boosting in WSNs not only brings the problem of energy scarcity, but also imposes the new challenge on quality of service (QoS) provisioning. A great deal of existing works focused on the QoS guarantees for WPSNs [10], [15]–[17]. The authors of [10] proposed the energy efficiency maximization problem by jointly optimizing time allocation and power control subject to the minimum system throughput requirement. The authors of [15] jointly optimized the power allocation and time switching to minimize the average power consumption while satisfying the minimum signal to interference plus noise ratio (SINR) requirements. The authors of [16] maximized the throughput for wireless powered underground sensor networks while taking into account the communication reliability and data traffic demands. However, the delay-bounded QoS, which is urgently required by various WPSN applications, is not taken into account in these works. In [17], the authors proposed an optimal power control policy with the QoS constraints of delay and packet loss rate, where the delay requirement is supposed to be deterministic. For 5G wireless powered communications networks, statistical QoS guarantee is more practical than the deterministic QoS provisioning [18]–[20].

Combing statistical QoS provisioning principle with information theory, Wu and Negi [21] proposed the effective capacity (EC) concept, which refers to the maximum constant arrival rate that can be supported by the service rate under specified delay-bounded QoS requirement. Many efforts have been made on maximizing EC [19], [20], [22], [23]. However, to the best of our knowledge, no work has considered the statistical QoS guarantees for WPSNs. In practice, the boosting applications in WPSNs need various delay-sensitive services. The various QoS requirements for different types of service thus promote the diverse delay-bounded QoS guarantees among different uplinks, which correspond to the heterogeneous statistical QoS provisioning (HeP) for WPSNs. Some researchers have considered supporting HeP [18], [24], [25]. The magazine papers [18] proposed the concept of HeP for wireless communications networks. In [24], the authors optimized the power allocation scheme while guaranteeing the downlink HeP. In [25], the authors jointly optimized the uplink power and downlink bandwidth allocation scheme to maximize the EC for the uplink information transmission. However, for WPSNs, not only the power allocation, but also the wireless transferred energy assignment and uplink/downlink time allocation need to be taken into account while guaranteeing the HeP [9]–[12].

To remedy the aforementioned deficiencies, in this paper we propose the joint downlink energy assignment and uplink power control schemes with HeP for WPSNs. In particular, we consider a network model where downlink transferred energy are emitted by a hybrid access point (HAP) to replenish SNs and enable the uplink information transmission back to the HAP. First, we build up the downlink energy transfer and the uplink information transmission models, respectively. To support the HeP for uplink information transmission, we give the aggregate effective capacity (AEC), which is defined as the aggregate throughput under the delay-bounded QoS constraints. Then, based on our proposed system model, we address the uplink AEC maximization problems under the uniformed time division and dynamic time allocation scenarios, respectively. For uniformed time division scenario, the HAP makes the energy assignment for each downlink based on uplink QoS requirements while the SNs allocate the uplink transmit power based on the QoS requirements, the instantaneous channel state information (CSI), and the energy assigned by the HAP, which yields the optimal joint downlink energy assignment and uplink information transmission power control scheme. For dynamic time allocation scenario, we develop the joint time allocation, downlink energy assignment, and uplink power control scheme. To derive this scheme, we propose the iterative algorithm based on Lagrange-Dual method and subgradient algorithm. Finally, we conduct extensive numerical simulations to demonstrate the effect of heterogeneous statistical QoS requirements on our proposed resource allocation schemes and compare the HeP resource allocation schemes with the schemes under homogeneous statistical QoS provisioning (HoP).

The remainder of this paper is organized as follows. Section II presents the system model for WPSNs, including the downlink wireless energy transfer and uplink information transmission models, and introduces some preliminaries about HeP and AEC. Section III optimizes the joint downlink energy assignment and uplink power control scheme to maximize the AEC under uniformed time division. Section IV formulates the AEC maximization problem with dynamic time allocation and iteratively derive the optimal joint time allocation, downlink energy assignment, and uplink power control scheme. Section V simulates and evaluates our developed heterogeneous QoS guaranteed resource allocation schemes for WPSNs. Section VI concludes the paper.

II. THE SYSTEM MODEL

We consider the WPSN model, as shown in Fig. 1, where there is one hybrid access point (HAP) and N wireless sensor nodes (SNs), denoted by SN_i $(1 \leq i \leq N)$, respectively. As shown in Fig. 1, each SN senses the environment and sends the collected data information on the orthogonal frequency division multiple access (OFDMA) subchannels to the HAP while the HAP plays the role of downlink energy transferring and uplink information receiving. The SNs need to harvest energy from the received signals radiated by the HAP in the downlink and store the harvested energy in a rechargeable battery for uplink information transmission. This kind of ''harvest-then-transmit'' protocol is popular used in existing works [10], [26], [27].

The downlink and uplink channels are quasi-static channels, where the channel gains are unchanged during a frame but vary independently from frame to frame [28]. For a frame duration, denoted by T, the wireless energy transfer (WET) phase occupies the first $\tau_i T$ $(0 < \tau_i < 1)$ of a frame, during which the HAP transfers energy to SN_i, and the remaining $(1 - \tau_i)T$ of a frame is used to transmit information for SN_i, which corresponds the wireless information transfer (WIT) phase [10], [26], [27]. We assume that the CSI of both downlink and uplink can be efficiently estimated and reliably

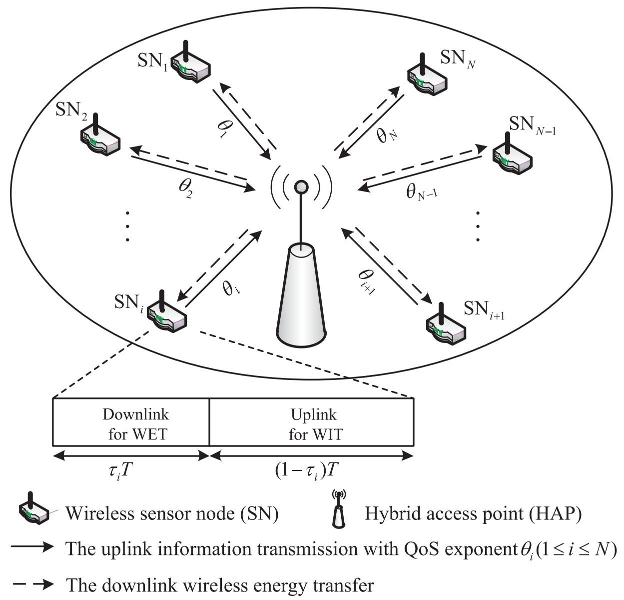

FIGURE 1. The wireless powered sensor network model with heterogenous QoS provisioning.

transmitted to the HAP and SNs [29], respectively. Each uplink corresponds to a delay-bounded QoS exponent required by the service. Based on the QoS exponents required by the uplink service and the instantaneous CSI fed back from the HAP, the SNs optimize the information transmission power allocation to maximize the uplink throughput. Meanwhile, according to the uplink QoS exponents, the HAP allocates the energy and transfers it to each SN to coordinate the uplink throughput. The entire uplink throughput of WPSNs can thus be maximized by joint downlink energy assignment and uplink power allocation. The Nakagami-m fading channel model is employed for the uplinks [23]. We denote by γ the instantaneous channel signal-to-noise ratio (SNR). The probability density function (PDF) of γ, denoted by $p_\Gamma(\gamma)$, is given as follows:

$$p_\Gamma(\gamma) = \frac{\gamma^{m-1}}{\Gamma(m)} \left(\frac{m}{\overline{\gamma}}\right)^m \exp\left(-\frac{m}{\overline{\gamma}}\gamma\right), \gamma \ge 0, \tag{1}$$

where $\Gamma(\cdot)$ represents the Gamma function, m is the Nakagami-m distribution parameter, and $\overline{\gamma}$ denotes the average SNR.

A. THE DOWNLINK WIRELESS ENERGY TRANSFER

In the downlink, the HAP transfers energy for SNs to prolong the lifetime of WSNs. Let us denote by E_i $(1 \le i \le N)$ and E_{tot} the energy transferred to SN$_i$ and the total energy at HAP available to be transferred to SNs, respectively. Then, we have

$$\sum_{i=1}^{N} E_i \le E_{\text{tot}}. \tag{2}$$

The energy harvested from received noise is assumed to be negligible since the power of noise is much smaller than the received signal power [10], [26]. The received power for SN$_i$, denoted by $P_{r,i}$, can be formulated as follows [11], [27]:

$$P_{r,i} = E_i \tau_i T K \|d_i\|^{-\ell}, \tag{3}$$

where K represents the average channel loss coefficient, $\|d_i\|$ is the SN$_i$-to-HAP distance, and ℓ denotes the path-loss exponent. We denote by P_i the uplink transmission power for SN$_i$. Then, the average power of P_i needs to satisfy

$$\mathbb{E}_{\gamma_i}\left[(1-\tau_i)P_i\right] \le \eta E_i \tau_i K \|d_i\|^{-\ell}, \forall i, \tag{4}$$

where γ_i is the instantaneous channel SNR for ith uplink, $\mathbb{E}_{\gamma_i}[\cdot]$ is the expectation over γ_i, and $\eta \in [0, 1]$ is the power splitting factor.

B. THE UPLINK INFORMATION TRANSMISSION WITH HeP

In WPSNs, each SN senses the environment and transmits the collected information to the HAP, forming the uplink data transmission. Different SNs bring different services with various delay-bounded QoS requirements, which promote the needs of HeP for WPSNs. Based on the large derivation principle (LDP), Chang [30] showed that for a stationary and ergodic queuing system, the queue length $Q(t)$ $(t \ge 0)$ converges in distribution to a finite random variable $Q(\infty)$ satisfying that

$$-\lim_{x\to\infty} \frac{\log \Pr(Q(\infty) \ge x)}{x} = \theta, \tag{5}$$

which indicates that the probability of the queue length exceeding the queue length bound x decays exponentially as the bound x increases. The parameter θ $(\theta > 0)$, which is called QoS exponent [21], [22], represents the exponential decay rate dominated by the queue length bound. A large θ indicates that a stringent QoS demand is supported. In contrast, a small θ means that the system can provide a loose QoS requirement [31].

In this paper, we aim to maximize the entire uplink data transmission throughput under the heterogenous QoS constraints for WPSNs. Let us denote by $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_N]$ the heterogeneous QoS exponents for WPSNs, where θ_i $(1 \le i \le N)$ is the QoS exponent corresponds to the ith uplink. We define $\{R_i[t], t = 1, 2, \ldots\}$ as the instantaneous data rate, where t is the time index. Consider a stationary and ergodic service process $S_i[u] \triangleq \sum_{t=1}^{u} R_i[t]$, which is the partial sum of instantaneous data rate. We assume that

$$\Lambda_C(\theta_i) = \lim_{u\to\infty} (1/u) \log(\mathbb{E}\{e^{-\theta_i S_i[u]}\}), \tag{6}$$

exists for all $\theta_i \ge 0$. Then, we can define effective capacity (EC) for SN$_i$, denoted by $E_C(\theta_i)$, as follows [21]:

$$E_C(\theta_i) \triangleq -\frac{\Lambda_C(-\theta_i)}{\theta_i} = -\frac{1}{\theta_i} \log\left(\mathbb{E}\left\{e^{-\theta_i R_i[t]}\right\}\right), \tag{7}$$

where $\mathbb{E}[\cdot]$ is the expectation operation. We denote by B the bandwidth for each uplink. Then, $R_i[t]$ can be derived as follows:

$$R_i[t] = (1-\tau_i) T B \log_2(1 + P_i[t]\gamma_i[t]). \tag{8}$$

To simplify the expression, we omit the index t in the following. Substituting Eq. (8) into Eq. (7), the EC for the ith uplink can be rewritten as follows:

$$E_C(\theta_i) = -\frac{1}{\theta_i}\log\left(\mathbb{E}_{\gamma_i}\left\{e^{-\theta_i(1-\tau_i)TB\log_2(1+P_i\gamma_i)}\right\}\right). \quad (9)$$

For the uplinks in WPSNs, the aggregate effective capacity (AEC), denoted by $\widetilde{E}_C$, is defined as the sum of effective capacities for all uplinks. Based on Eq. (9), the AEC can be derived as follows:

$$\widetilde{E}_C(\boldsymbol{\theta}) = \sum_{i=1}^{N} -\frac{1}{\theta_i}\log\left(\mathbb{E}_{\gamma_i}\left\{(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}\right\}\right), \quad (10)$$

where $\beta_i \triangleq (\theta_i T_f B/\log 2)$ is the normalized QoS exponent for SN_i.

Even though the function of effective capacity specified by Eq. (7) is convex [32], the aggregation of effective capacities with heterogenous statistical QoS requirements is nonconvex. However, there exists a unique real-valued number $\theta_0 \in [\theta_{\min}, \theta_{\max}]$, where $\theta_{\min} \triangleq \min\{\theta_1, \theta_2, \ldots, \theta_N\}$ and $\theta_{\max} \triangleq \max\{\theta_1, \theta_2, \ldots, \theta_N\}$, such that the following equation holds [24]:

$$\begin{aligned}\widetilde{E}_C(\boldsymbol{\theta}) &= \sum_{i=1}^{N} -\frac{1}{\theta_i}\log\left(\mathbb{E}_{\gamma_i}\left\{(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}\right\}\right)\\ &= -\frac{1}{\theta_0}\sum_{i=1}^{N}\log\left(\mathbb{E}_{\gamma_i}\left\{(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}\right\}\right). \quad (11)\end{aligned}$$

Equation (11) is a simple expression of AEC specified in Eq. (10) and it is clearly a convex function.

To optimize the resource allocation supporting statistical QoS requirements for WPSNs, in the following, we formulate and resolve the AEC maximization problems for uniformed time division and dynamic time allocation scenarios, respectively.

III. HETEROGENEOUS QoS GUARANTEED RESOURCE ALLOCATION FOR UNIFORMED TIME DIVISION

In this section, we jointly optimize the heterogeneous statistical QoS guaranteed downlink energy assignment and uplink power control scheme under uniformed time division for WPSNs. We set τ_i $(1 \le i \le N)$ are equal to τ_0, which is defined as the uniformed time division factor. To find the insights of the relationship among τ_0, the downlink energy assignment, and the uplink power control, we formulate the AEC maximization problem, denoted by $\boldsymbol{P1}$, as follows:

$$\boldsymbol{P1}\text{: }\arg\max_{\substack{(E_i,P_i):\\1\le i\le N}}\left\{-\frac{1}{\theta_0}\sum_{i=1}^{N}\log\left(\mathbb{E}_{\gamma_i}\left\{(1+P_i\gamma_i)^{-(1-\tau_0)\beta_i}\right\}\right)\right\}$$

$$\text{s.t.: } 1).\ \mathbb{E}_{\gamma_i}[(1-\tau_0)P_i] \le \eta\tau_0 E_i K\|d_i\|^{-\ell},\ \forall i; \quad (12)$$

$$2).\ \sum_{i=1}^{N} E_i \le E_{\mathrm{tot}}; \quad (13)$$

$$3).\ E_i \ge 0, P_i \ge 0, \forall i. \quad (14)$$

Observing problem $\boldsymbol{P1}$, we find that the objective function of problem $\boldsymbol{P1}$ is a sum of logarithmic functions and the constraints specified by Eqs. (12)-(14) are all linear. Thus, the optimization problem $\boldsymbol{P1}$ is convex. Due to the independence across all uplinks, problem $\boldsymbol{P1}$ can be equivalently rewritten as follows:

$$\boldsymbol{P1'}\text{:}\quad \arg\min_{\substack{(E_i,P_i):\\1\le i\le N}}\left\{\mathbb{E}_{\boldsymbol{\gamma}}\left[\prod_{i=1}^{N}(1+P_i\gamma_i)^{-(1-\tau_0)\beta_i}\right]\right\}$$

subject to Eqs. (12)-(14), where $\boldsymbol{\gamma} \triangleq (\gamma_1, \gamma_2, \ldots, \gamma_N)$ is the overall channel SNR in WPSNs.

Even though problem $\boldsymbol{P1}$ is simplified to problem $\boldsymbol{P1'}$, it is hard to obtain the closed-form solutions by solving problem $\boldsymbol{P1'}$ with Karush-Kuhn-Tucker (KKT) conditions. Alternatively, another efficient way is needed to solve problem $\boldsymbol{P1'}$. Notice that E_i and P_i are the decision variables of problem $\boldsymbol{P1'}$. Thus, the optimal solutions contain the SN-determined optimal uplink power control scheme and the HAP-determined downlink energy assignment scheme. This implies that SNs determine the uplink data transmission power control scheme while the HAP allocates the wireless energy to be transferred to each SN. Then, first, we derive the uplink power control scheme of a single SN. Based on the uplink power control scheme, the downlink energy assignment scheme can be obtained, which yields the joint downlink energy assignment and uplink power control scheme.

A. THE UPLINK POWER CONTROL SCHEME

In this subsection, we develop the uplink information transmission power control scheme for a single SN. First, we formulate the uplink EC maximization problem, denoted by $\boldsymbol{P2}$, as follows:

$$\boldsymbol{P2}\text{:}\quad \arg\max_{P_i:1\le i\le N}\left\{-\frac{1}{\theta_i}\log\left(\mathbb{E}_{\gamma_i}\left\{(1+P_i\gamma_i)^{-(1-\tau_0)\beta_i}\right\}\right)\right\}$$

$$\text{s.t.: } 1).\ \mathbb{E}_{\gamma_i}[(1-\tau_0)P_i] \le \eta\tau_0 E_i K\|d_i\|^{-\ell},\ \forall i; \quad (15)$$

$$2).\ P_i \ge 0, \forall i. \quad (16)$$

Problem $\boldsymbol{P2}$ is a convex optimization problem with respect to P_i for the given E_i. We denote by P_i^* and E_i^* the optimal values for P_i and E_i. Then, we can derive the optimal solution of problem $\boldsymbol{P2}$, which shows the relationship between P_i^* and E_i^* in the following Lemma 1.

Lemma 1: The optimal solution for problem $\boldsymbol{P2}$ is given by

$$P_i^* = \begin{cases} \dfrac{(\tau_0 E_i^*)^{\frac{1}{(1-\tau_0)\beta_i+1}}}{(\hat{\gamma}_i)^{\frac{1}{(1-\tau_0)\beta_i+1}}\gamma_i^{\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}} - \dfrac{1}{\gamma_i}, & \gamma_i \ge \hat{\gamma}_i;\\ 0, & \gamma_i < \hat{\gamma}_i,\end{cases} \quad (17)$$

where $\hat{\gamma}_i$ corresponds to the SNR threshold and can be obtained by plugging Eq. (17) into the equation $\mathbb{E}_{\gamma_i}[(1-\tau_0)P_i] = \eta\tau_0 E_i K\|d_i\|^{-\ell}$.

Proof: Please refer to Appendix A. ■

Lemma 1 gives the optimal uplink power control scheme under the given downlink assignment. The optimal downlink energy assignment is dominated by the HAP. Next, we study the downlink energy assignment based on the uplink power control scheme of a single SN.

B. THE JOINT DOWNLINK ENERGY ASSIGNMENT AND UPLINK POWER CONTROL SCHEME

For the assigned energy by the HAP, SNs can allocate uplink power based on Lemma 1. However, the total transferred energy at HAP is upper-bounded by E_{tot}. Thus, the HAP needs to coordinate the downlink transferred energy assignment for SNs to maximize the AEC with HeP. Plugging Eq. (17) into the objective function of problem $\boldsymbol{P1'}$, we can obtain

$$\begin{aligned} &\arg \min_{(E_i,P_i):1\leq i\leq N} \left\{ \mathbb{E}_{\boldsymbol{\gamma}} \left[\prod_{i=1}^{N} (1+P_i\gamma_i)^{-(1-\tau_0)\beta_i} \right] \right\} \\ &= \arg \min_{E_i:1\leq i\leq N} \left\{ \mathbb{E}_{\boldsymbol{\gamma}} \left[\prod_{i=1}^{N} \left(\frac{\tau_0 E_i \gamma_i}{\hat{\gamma}_i} \right)^{-\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}} \right] \right\}, \end{aligned} \tag{18}$$

where we have $\gamma_i \geq \hat{\gamma}_i$. Observing Eq. (18), we find that the objective function decreases as E_i increases. However, since the HAP coordinates the downlink energy assignment for each SN, the optimal energy assignment needs to satisfy the total available energy constraint which is shown as $\sum_{i=1}^{N} E_i \leq E_{\text{tot}}$. Accordingly, the problem $\boldsymbol{P1'}$ can be equivalently converted into the optimization problem $\boldsymbol{P3}$, which is given as follows:

$$\boldsymbol{P3}: \arg \min_{E_i:1\leq i\leq N} \left\{ \mathbb{E}_{\boldsymbol{\gamma}} \left[\prod_{i=1}^{N} \left(\frac{\tau_0 E_i \gamma_i}{\hat{\gamma}_i} \right)^{-\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}} \right] \right\}$$

$$\text{s.t.} \quad 1).\ \sum_{i=1}^{N} E_i \leq E_{\text{tot}}; \tag{19}$$

$$2).\ E_i \geq 0, \forall i. \tag{20}$$

To solve the convex optimization problem $\boldsymbol{P3}$, we give the following Lemma 2.

Lemma 2: For WPSNs under uniformed time division scenario, the maximum aggregate effective capacity needs to satisfy $\sum_{i=1}^{N} E_i^* = E_{tot}$.

Proof: Please refer to Appendix B ■

Based on Lemma 2, we can derive the optimal joint downlink energy assignment and uplink data transmission power control scheme, which is shown in Theorem 1, for WPSNs under uniformed time division scenario.

Theorem 1: For WPSNs under uniformed time division scenario, the optimal joint downlink energy assignment and uplink data transmission power control scheme supporting HeP is given as follows:

$$\begin{cases} E_i^* = \dfrac{\beta_i \prod\limits_{j=1,j\neq i}^{N} [(1-\tau_0)\beta_j+1] E_{\text{tot}}}{\sum\limits_{k=1}^{N} \left\{ \beta_k \prod\limits_{j=1,j\neq k}^{N} [(1-\tau_0)\beta_j+1] \right\}}; \\ P_i^* = \begin{cases} \dfrac{\left[\tau_0 \beta_i \prod\limits_{j=1,j\neq i}^{N} [(1-\tau_0)\beta_j+1] E_{\text{tot}} \right]^{\frac{1}{(1-\tau_0)\beta_i+1}}}{\left(\hat{\gamma}_i \sum\limits_{k=1}^{N} \left\{ \beta_k \prod\limits_{j=1,j\neq k}^{N} [(1-\tau_0)\beta_j+1] \right\} \right)^{\frac{1}{(1-\tau_0)\beta_i+1}} \gamma_i^{\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}} - \dfrac{1}{\gamma_i}, & \text{if } \gamma_i \geq \hat{\gamma}_i; \\ 0, & \text{if } \gamma_i < \hat{\gamma}_i. \end{cases} \end{cases} \tag{21}$$

Proof: Please refer to Appendix C. ■

Observing Eq. (21), we find that E_i^* is a function of θ_i $(1 \leq i \leq N)$ and τ_0 while P_i^* is a function of θ_i, γ_i $(1 \leq i \leq N)$ and τ_0. This implies that for uniformed time division scenario, the HAP makes the transferred energy assignment based on the uplink QoS requirements and the uniformed time division factor. Then, each SN dynamically allocates its uplink data transmission power control scheme based on the corresponding QoS requirement, the instantaneous SNR fed back from the HAP and the uniformed time division factor.

To further analyze the insights of Theorem 1, we discuss the specific cases of Theorem 1 in the following Remarks 1 and 2 for single-channel and multi-channel homogeneous QoS provisioning (HoP), respectively.

Remark 1 (Single-Channel HoP): When $N = 1$, the optimal joint downlink energy assignment and uplink power control scheme is reduced to

$$\begin{cases} E_i^* = E_{\text{tot}}; \\ P_i^* = \begin{cases} \dfrac{(\tau_0 E_{\text{tot}})^{\frac{1}{(1-\tau_0)\beta_i+1}}}{(\hat{\gamma}_i)^{\frac{1}{(1-\tau_0)\beta_i+1}} \gamma_i^{\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}} - \dfrac{1}{\gamma_i}, & \gamma_i \geq \hat{\gamma}_i; \\ 0, & \gamma_i < \hat{\gamma}_i, \end{cases} \end{cases} \tag{22}$$

which is the statistical QoS-driven power allocation for energy harvesting based wireless networks.

Remark 2 (Multi-Channel HoP): When $\theta_i = \theta$ $(1 \leq i \leq N)$, the optimal joint downlink energy assignment and uplink power control scheme can be derived as follows:

$$\begin{cases} E_i^* = \dfrac{E_{\text{tot}}}{N}; \\ P_i^* = \begin{cases} \dfrac{(\tau_0 E_{\text{tot}})^{\frac{1}{(1-\tau_0)\beta+1}}}{(N\hat{\gamma}_i)^{\frac{1}{(1-\tau_0)\beta+1}} \gamma_i^{\frac{(1-\tau_0)\beta}{(1-\tau_0)\beta+1}}} - \dfrac{1}{\gamma_i}, & \gamma_i \geq \hat{\gamma}_i; \\ 0, & \gamma_i < \hat{\gamma}_i, \end{cases} \end{cases} \tag{23}$$

where $\beta = (\theta T B)/\log 2$. Eq. (23) indicates that the HAP allocates its entire energy equally to each SN for WPSNs with HoP.

Based on the analyses for Theorem 1, both the optimal downlink energy assignment and uplink power control scheme are functions of the uniformed time division factor, which indicates that there is a trade-off between the maximized AEC and the time allocation. In the following, we develop a joint time allocation, downlink energy assignment, and uplink power control scheme for WPSNs with HeP.

IV. HETEROGENEOUS QOS PROVISIONING RESOURCE ALLOCATION FOR DYNAMIC TIME ALLOCATION

In this section, we jointly optimize the time allocation, downlink energy assignment, and uplink power control scheme to maximize the AEC for WPSNs. The corresponding AEC maximization for dynamic time allocation scenario, denoted by $\boldsymbol{P4}$, is expressed as follows:

$$\begin{aligned}\boldsymbol{P4}:&\arg\max_{\substack{(E_i,P_i,\tau_i):\\1\le i\le N}}\left\{-\frac{1}{\theta_0}\sum_{i=1}^{N}\log\left(\mathbb{E}_{\gamma_i}\left\{(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}\right\}\right)\right\}\\
\overset{(a)}{=}&\arg\min_{\substack{(E_i,P_i,\tau_i):\\1\le i\le N}}\left\{\mathbb{E}_{\boldsymbol{\gamma}}\left[\prod_{i=1}^{N}(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}\right]\right\}\\
&\text{s.t.}\quad 1).\ \mathbb{E}_{\gamma_i}[(1-\tau_i)P_i]\le\eta\tau_iE_iK\|d_i\|^{-\ell},\ \forall i; \qquad (24)\\
&\qquad\ \ 2).\ \sum_{i=1}^{N}E_i\le E_{\text{tot}}; \qquad (25)\\
&\qquad\ \ 3).\ E_i\ge0, P_i\ge0, \forall i, \qquad (26)\end{aligned}$$

where equality (a) holds due to the monotonically increasing nature of $\log(\cdot)$ and mutual independence of each uplink. Similar to problem $\boldsymbol{P1}$, the optimization problem $\boldsymbol{P4}$ is also convex. However, due to the complex relationship among E_i, P_i, and τ_i $(1\le i\le N)$, the method used in Section III cannot be employed to derive problem $\boldsymbol{P4}$. In the following, Lagrange-Dual method and subgradient algorithm are used to iteratively solve problem $\boldsymbol{P4}$.

A. LAGRANGE-DUAL METHOD BASED ANALYSES

We derive the Lagrange function of problem $\boldsymbol{P4}$ as follows:

$$\begin{aligned}J_3=&\ \mathbb{E}_{\boldsymbol{\gamma}}\left[\prod_{i=1}^{N}(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}\right]\\
&+\lambda_i\left(\frac{\mathbb{E}_{\gamma_i}[(1-\tau_i)P_i]}{\tau_iP_{oi}}-\eta K\|d_i\|^{-\ell}\right)\\
&+\vartheta\left[\sum_{i=1}^{N}E_i-E_{\text{tot}}\right],\end{aligned} \tag{27}$$

where λ_i and ϑ are the non-negative Lagrangian multipliers associated with constraints in Eqs. (24) and (25). Due to the convexity of problem $\boldsymbol{P4}$, the duality gap between problem $\boldsymbol{P4}$ and its dual problem is zero. The dual function can be formulated as a pointwise infimum of the Lagrangian function, which is shown as follows:

$$\mathcal{D}(\boldsymbol{\lambda},\vartheta)=\inf_{\substack{(E_i,P_i,\tau_i):\\1\le i\le N}}J_3, \tag{28}$$

where $\boldsymbol{\lambda}=[\lambda_1,\lambda_2,\ldots,\lambda_N]$ is the Lagrangian multiplier. The dual problem, which defines the maximum value of the Lagrangian over the non-negative dual variables [34], is relatively easier to solve. The dual problem can thus be formulated as follows:

$$\begin{aligned}\boldsymbol{P5}:\ &\arg\max_{\boldsymbol{\lambda},\vartheta}\ \mathcal{D}(\boldsymbol{\lambda},\vartheta)\\
&\text{s.t. } \boldsymbol{\lambda}\ge0,\ \vartheta\ge0.\end{aligned} \tag{29}$$

To establish the KKT conditions with complementary slackness, the Lagrange function J_3 is partially derived with respect to P_i, E_i, and τ_i. Setting the results to zero, we can obtain

$$\begin{cases}\dfrac{\partial J_3}{\partial P_i}=-(1-\tau_i)\beta_i\gamma_i(1+P_i\gamma_i)^{-1}\displaystyle\prod_{i=1}^{N}(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}p_\Gamma(\gamma)\\
\qquad\qquad+\left(\dfrac{1}{\tau_i}-1\right)\dfrac{\lambda_i}{E_i}p_\Gamma(\gamma)=0;\\
\dfrac{\partial J_3}{\partial E_i}=-\dfrac{\lambda_i\mathbb{E}_{\gamma_i}\left[\left(\frac{1}{\tau_i}-1\right)P_i\right]}{E_i}+\vartheta=0;\\
\dfrac{\partial J_3}{\partial \tau_i}=\beta_i\ln(1+P_i\gamma_i)\displaystyle\prod_{i=1}^{N}(1+P_i\gamma_i)^{-(1-\tau_i)\beta_i}p_\Gamma(\gamma)\\
\qquad\qquad-\dfrac{\lambda_i}{{\tau_i}^2E_i}p_\Gamma(\gamma)=0.\end{cases} \tag{30}$$

Based on Eq. (30), we can obtain the following Theorem 2 which shows the relationship among E_i^*, P_i^*, and τ_i^*.

Theorem 2: Given λ_i and ϑ, the relationship among the E_i^*, P_i^*, and τ_i^* is given as follows:

$$P_i^*=\left[\frac{\tau_i^*E_i^*\beta_i}{\lambda_i\displaystyle\prod_{i=1}^{N}\left(\frac{\tau_i^*E_i^*\beta_i\gamma_i}{\lambda_i}\right)^{\frac{(1-\tau_i^*)\beta_i}{1+(1-\tau_i^*)N\beta_i}}}-\frac{1}{\gamma_i}\right]^+, \tag{31}$$

where $[b]^+$ represents the maximum value between b and 0.

Proof: Please refer to Appendix D. ■

The complementary slackness conditions are given as follow:

$$\begin{cases}\lambda_i\left(\mathbb{E}_{\gamma_i}[(1-\tau_i)P_i]-\eta\tau_iE_iK\|d_i\|^{-\ell}\right)=0;\\
\vartheta\left(\displaystyle\sum_{i=1}^{N}E_i-E_{\text{tot}}\right)=0.\end{cases} \tag{32}$$

The slackness conditions in Eq. (32) indicate that either multipliers are zero or the equalities in constraints specified by Eq. (24) and (25) hold. In fact, if the total available power is not exhausted, the extra power for either downlink or uplink can improve the AEC. Under the circumstance, the optimal solutions can be achieved by setting $\mathbb{E}_{\gamma_i}[(1-\tau_i)P_i]=\eta\tau_iE_iK\|d_i\|^{-\ell}$ and $\sum_{i=1}^{N}E_i=E_{\text{tot}}$, which is similar to the proof of Lemma 2. We can thus obtain $\lambda_i>0$ and $\vartheta>0$. In the following, iterative numerical methods are employed to solve the dual problem $\boldsymbol{P5}$.

Algorithm 1 The Optimal Resource Allocation via Subgradient Algorithm

1: Input η, K, ℓ, d_i, and θ_i $(1 \le i \le N)$.
2: Initialize maximum tolerance ϵ and $\vartheta(0)$;
3: **for** each $i \in [1, N]$; **do**
4: Initialize $\lambda_i(0)$;
5: **end for**
6: Set $s = 0$;
7: Set $\partial J_3/\partial E_i = 0$, $\partial J_3/\partial P_i = 0$, and $\partial J_3/\partial \tau_i = 0$;
8: Obtain $E_i^*(0)$, $P_i^*(0)$, and $\tau_i^*(0)$;
9: Calculate $\widetilde{E}_C^*(0)$;
10: **repeat**
11: $s = s + 1$;
12: **for** each $i \in [1, N]$; **do**
13: Set $\partial J_3/\partial E_i = 0$, $\partial J_3/\partial P_i = 0$, and $\partial J_3/\partial \tau_i = 0$;
14: Obtain $E_i^*(s)$, $P_i^*(s)$, and $\tau_i^*(s)$;
15: Calculate $\widetilde{E}_C^*(s)$;
16: **end for**
17: Update λ_i and ϑ according to Eq. (33);
18: **until** $|\, \widetilde{E}_C^*(s) - \widetilde{E}_C^*(s-1) \,| < \epsilon$.

B. ITERATIVE SUBGRADIENT ALGORITHM

By employing the subgradient projection method [34], the Lagrangian multipliers are calculated iteratively as follows:

$$\begin{cases} \lambda_i(s+1) = \left[\lambda_i(s) + \upsilon(s)\frac{\partial J_3}{\partial \lambda_i}\right]^+, & \forall i; \\ \vartheta(s+1) = \left[\vartheta(s) + \upsilon(s)\frac{\partial J_3}{\partial \vartheta}\right]^+, \end{cases} \tag{33}$$

where $\partial J_3/\partial \lambda_i$ and $\partial J_3/\partial \vartheta$ are the gradients, $\upsilon(s)$ is the gradient step size, and s represents the gradient number. The dual problem can be iteratively updated via the subgradient algorithm given by Algorithm 1. In Algorithm 1, we initialize the Lagrangian multipliers $\lambda_i (1 \le i \le N)$ and ϑ. During each iteration, E_i^* , P_i^*, and τ_i^* are calculated by solving Eq. (30). The Lagrangian multipliers λ_i $(1 \le i \le N)$ and ϑ update until the condition for convergence is satisfied.

We also consider the computational complexity of Algorithm 1. The complexity from line 3 to 5 is N. From line 6 to 9, to solve $\partial J_3/\partial E_i = 0$ and $\partial J_3/\partial \tau_i = 0$ in Eq. (30), N times product is needed for each uplink and the complexity is thus N^2. Similarly, the complexity from line 12 to 16 is also N^2. Since there are N uplinks, the complexity of line 17 is N. Therefore, the complexity of Algorithm 1 is $\mathcal{O}(N+N^2)$.

V. PERFORMANCE EVALUATION

In this section, numerical simulations are conducted to evaluate the performance of our proposed QoS guaranteed resource allocation schemes for WPSNs under uniformed time division and dynamic time allocation scenarios, respectively. We use normalized AEC, which is defined as the AEC per Hz per second, to evaluate the performance of WPSNs. Throughout the simulations, we set the bandwidth, the time frame length, the available energy at the HAP and the parameters of Nakagami-m to be $B = 10$ MHz, $T = 0.2$ ms, $E_{\text{tot}} = 3$ J, $\bar{\gamma} = 5$, and $m = 2$. The power splitting factor and the downlink path loss parameters are set to be $\eta = 1$, $K = 1$, $d_i = 10$ m, and $\ell = 4$, respectively.

Figures 2(a) and 2(b) depict the optimal energy assignments versus the QoS exponents for SN_1 and SN_2 (θ_1 and θ_2), respectively, under uniformed time division scenario. In this simulation, the uniformed time division factor is set to be $\tau_0 = 0.5$ and two cases ($N = 2$ and $N = 3$) are considered. As shown in Fig. 2(a), the assigned energy for SN_1 (E_1) increases as θ_1 increases and θ_2 decreases. The assigned energy for SN_2 (E_2) increases as θ_2 increases and θ_1 decreases. In Fig. 2(b), where the QoS exponent for SN_3 is fixed to be 0.006, the energy assigned to SN_3 (E_3) increases as both θ_1 and θ_2 decreases and E_3 decreases as both θ_1 and θ_2 increases. This implies that the HAP allocate more energy to the uplink with stringent QoS requirement and less energy to the uplink with loose QoS requirement so that the EC of each uplink data transmission can be coordinated, thus maximizing the AEC for WPSNs. Observing the curves in Figs. 2(a) and 2(b), we find that the HAP allocates the equal energy to SN_1 and SN_2 ($E_1 = E_2$) when the statistical QoS requirement for SN_1 is equal to the statistical QoS requirement for SN_2 ($\theta_1 = \theta_2$). This verifies that our proposed optimal downlink energy assignment scheme can not only be used for HeP WPSNs but also for HoP WPSNs.

Figure 3 depicts the curve of optimal uplink power control scheme of SN_1 corresponding to different QoS exponents and various instantaneous SNR, where the QoS exponent for SN_2 is fixed to 0.01. In Fig. 3, we set $N = 2$ and $\tau_0 = 0.5$. As illustrated in Fig. 3, when the QoS exponent of SN_1 is very large, more power is allocated to the channel with low SNR and less power is allocated to the channel with high SNR. When the QoS exponent is very small, the allocated power to SN_1 first increases and then decreases as the instantaneous SNR increases. This indicates that in the case of stringent QoS requirement, the optimal uplink power control scheme follows the channel inversion scheme, while in the case of loose QoS requirement, the optimal uplink power control scheme doesn't monotonously increase or decrease. Traditionally, the optimal power allocation scheme with HoP is water-filling scheme in the case of very loose QoS requirement and total channel inversion scheme in the case of stringent QoS requirement [32]. However, in our proposed joint downlink energy assignment and uplink power control scheme, the optimal uplink power control is dominated by the QoS exponents of both SNs. Based on the downlink energy assignment, the HAP allocates less energy for the uplink with loose QoS requirement. Thus, when the QoS exponent is very loose, the uplink power allocation cannot always increase as the instantaneous SNR increases.

In Fig. 4, we compare the HeP resource allocation scheme with HoP resource allocation scheme for uniformed time division scenario in WPSNs. As depicted in Fig. 4, the HoP resource allocation scheme achieves the same normalized AEC as the HeP resource allocation scheme when both two SNs have the same QoS requirements ($\theta_1 = \theta_2$). However, when the SNs have different QoS requirements, the HeP resource allocation scheme achieves larger normalized AEC than the HoP resource allocation scheme. Also, when the difference between θ_1 and θ_2 gets very large, the normalized AEC achieved by HeP resource allocation scheme gets very

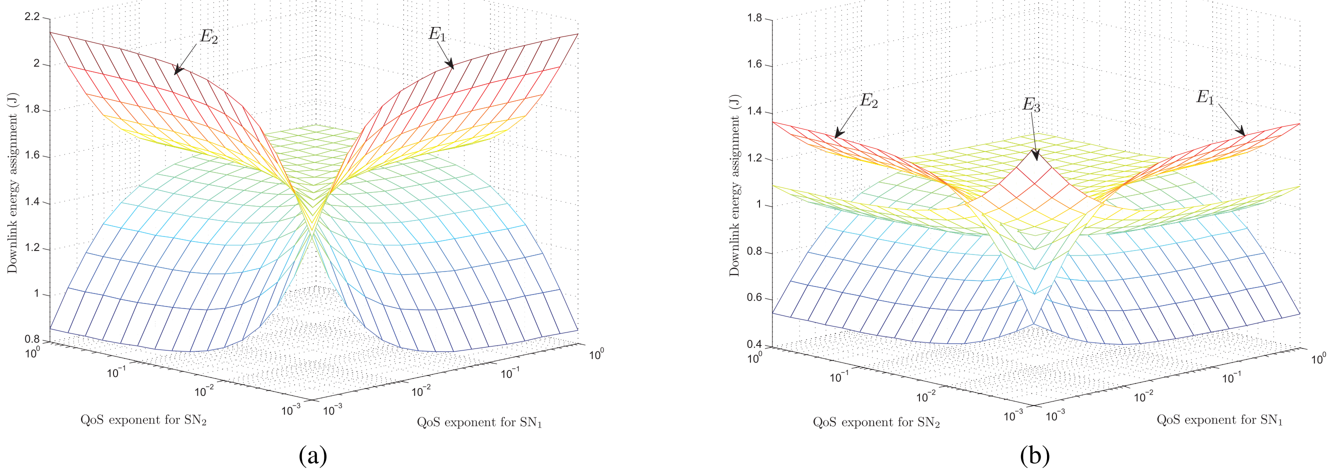

FIGURE 2. The downlink energy assignment with HeP under uniformed time division scenario for wireless powered sensor nodes: (a) when $N = 2$; (b) when $N = 3$ and $\theta_3 = 0.006$.

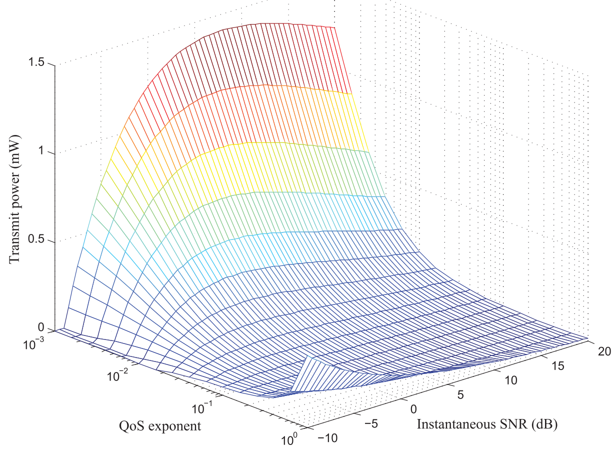

FIGURE 3. Optimal uplink power control scheme for SN_1 with statistical QoS provisioning for uniformed time division scenario.

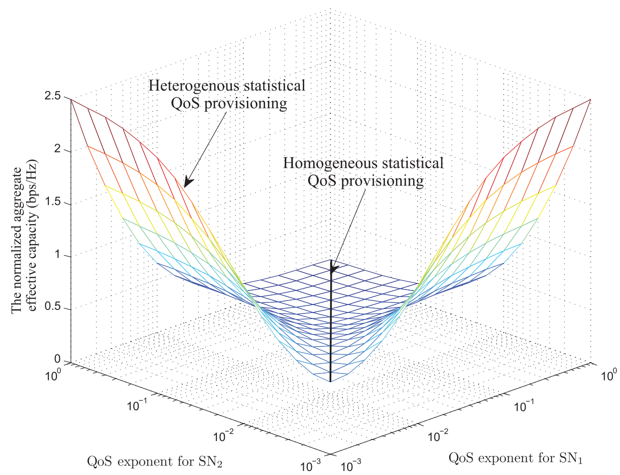

FIGURE 4. For uniformed time division scenario, the normalized AEC obtained by HeP and HoP resource allocation schemes, respectively.

large. For dynamic time allocation scenario, Fig. 5 compares the performance of HeP resource allocation scheme with HoP resource allocation scheme. In Fig. 5, we set $N = 2$ and show the performance of our proposed schemes versus the QoS exponent of SN_1 under two cases ($\theta_2 = 10^{-2}$ and $\theta_2 = 10^{-4}$). As shown in Fig. 5, the HeP resource allocation scheme can achieve lager normalized AEC than the HoP resource allocation scheme for both $\theta_2 = 10^{-2}$ and $\theta_2 = 10^{-4}$ cases. The traditional HoP resource allocation scheme can only achieve the maximum AEC when the required QoS exponents for SN_1 and SN_2 are homogeneous, i.e., $\theta_1 = \theta_2 = 10^{-2}$ and $\theta_1 = \theta_2 = 10^{-4}$, respectively. These analyses for the simulation results presented in Figs. 4 and 5 indicate that for both uniformed time division and dynamic time allocation scenarios, our proposed HeP resource allocation schemes can achieve better performance than the schemes with HoP.

Figure 6 plots the curves of normalized AEC versus the SN_i-to-HAP distance corresponding to $\eta = 0.6$, 0.8, and 1.0 for uniformed time division and dynamic time allocation scenarios, respectively. In Fig. 6, we set $N = 2$ and $\theta_1 = \theta_2 = 10^{-3}$. Fig. 6 shows that the joint time allocation, downlink energy assignment and uplink power control scheme for dynamic time allocation scenario can achieve larger AEC than the joint energy assignment and uplink power control scheme for uniformed time division scenario. As depicted in Fig. 6, the normalized AEC decreases as the SN_i-to-HAP distance increases. This is due to the reason that the path loss increases as the communication distance increases, and thus, the received power decreases, which leads to a low normalized uplink effective capacity. As a result, the total WPSNs achieves a low normalized AEC. In Fig. 6, we can also find that for a given SN_i-to-HAP distance, the normalized AEC increases as η increases. This is because

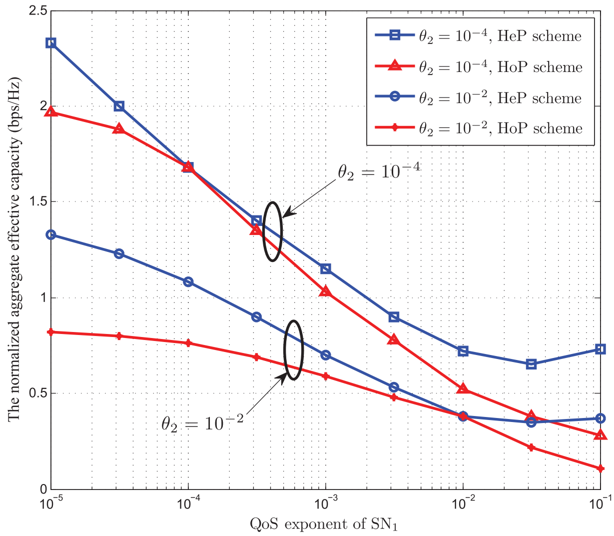

FIGURE 5. For dynamic time allocation scenario, the normalized AEC obtained by HeP and HoP resource allocation schemes, respectively.

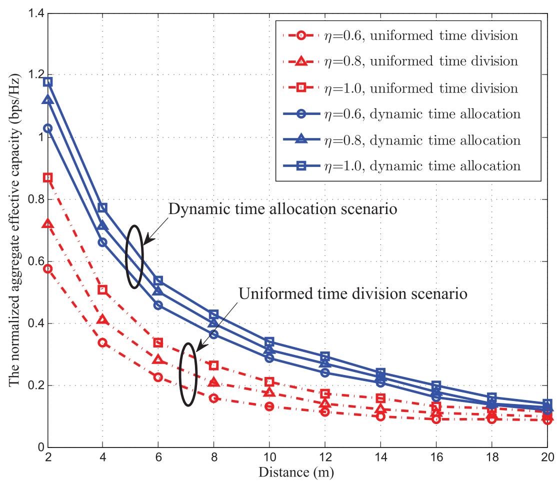

FIGURE 6. The normalized AEC of our proposed resource allocation schemes versus the SN_i-to-HAP distance.

a large η indicates that abundant supply of energy can be used for uplink data transmission, and thus high normalized uplink effective capacity can be obtained, which results in a high normalized AEC.

To further compare our proposed resource allocation scheme under uniformed time division with the scheme under dynamic time allocation, we plot the curves of normalized AEC versus the total energy at the HAP (E_{tot}) in Fig. 7, where we show the cases corresponding to $\theta_1 = 10^{-3}$, 10^{-2}, and 10^{-1}, respectively. In this simulation, we set $N = 2$ and $\theta_2 = 10^{-2}$. As depicted in Fig. 7, the normalized AEC increases as E_{tot} increases. This is because when E_{tot} increases, more energy can be allocated for the uplink information transmission, which leads to larger effective capacity. For a given E_{tot}, we can observe that when $\theta_1 \neq \theta_2$, i.e., $\theta_1 = 10^{-3}$ or $\theta_1 = 10^{-1}$, the achieved normalized AEC is larger than that when $\theta_1 = \theta_2$. This indicates that for both uniformed time division scenario and dynamic time allocation scenario,

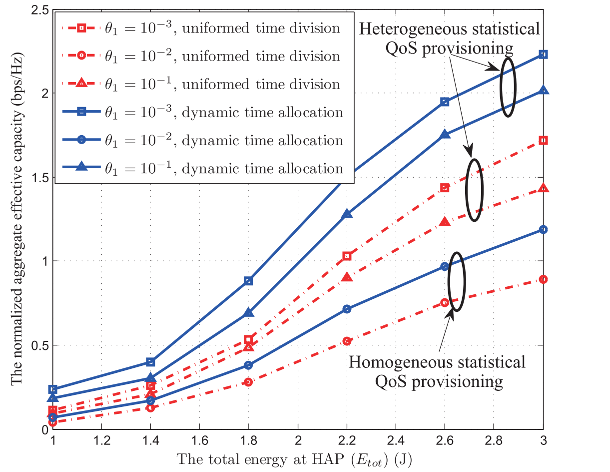

FIGURE 7. The normalized AEC of our proposed resource allocation schemes versus the total available energy at the HAP.

the HeP resource allocation schemes can achieve larger normalized effective capacity than the HoP resource allocation scheme. Another observation from Fig. 7 is that the joint time allocation, downlink energy assignment and uplink power control scheme can achieve larger AEC than the joint downlink energy assignment and uplink power control scheme for uniformed time division scenario. Thus, we can obtain the resource allocation scheme with dynamic time allocation is superior to the resource allocation scheme under unformed time division as the dynamic time allocation coordinates the uplink/downlink time to balance the downlink energy transfer and uplink information transmission for WPSNs.

VI. CONCLUSIONS

In this paper, we studied the heterogeneous QoS guaranteed resource allocation schemes for WPSNs. First, we build the downlink wireless energy transfer and uplink power control models for WPSNs. Based on the models, we formulated the AEC maximization problems with HeP for uniformed time division and dynamic time allocation scenarios, respectively. To efficiently solve the problem for uniformed time division scenario, we developed the joint downlink energy assignment and uplink power control scheme, where the HAP assigns energy for SNs based on the uplink QoS requirements and SNs allocate the data transmission power according to the uplink QoS requirements, the instantaneous CSI, and the energy assigned by the HAP. For dynamic time allocation scenario, we developed the joint time allocation, downlink energy assignment, and uplink power control scheme, where the time allocation are dynamically coordinated to balance the downlink energy transfer and uplink information transmission. The Lagrangian-Dual method and subgradient algorithm are employed to iteratively derive the scheme. Extensive simulations were conducted to evaluate the effect of heterogenous statistical QoS on the network performance for WPSNs and the simulation results demonstrated that our proposed HeP resource allocation schemes can significantly

$$\begin{cases} \dfrac{\partial J_2}{\partial E_j} = -\dfrac{(1-\tau_0)\beta_j}{(1-\tau_0)\beta_j+1}\mathbb{E}_{\gamma_j}\left[\left(\dfrac{\tau_0\gamma_j}{\hat{\gamma}_j}\right)^{-\frac{(1-\tau_0)\beta_j}{(1-\tau_0)\beta_j+1}} E_j^{-\frac{(1-\tau_0)\beta_j}{(1-\tau_0)\beta_j+1}-1}\right]\cdot \prod_{i=1,i\neq j}^{N}\mathbb{E}_{\gamma_i}\left[\left(\dfrac{\tau_0 E_i\gamma_i}{\hat{\gamma}_i}\right)^{-\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}\right]+\nu = 0; \\ \dfrac{\partial J_2}{\partial E_k} = -\dfrac{(1-\tau_0)\beta_k}{(1-\tau_0)\beta_k+1}\mathbb{E}_{\gamma_k}\left[\left(\dfrac{\tau_0\gamma_k}{\hat{\gamma}_k}\right)^{-\frac{(1-\tau_0)\beta_k}{(1-\tau_0)\beta_k+1}} E_k^{-\frac{(1-\tau_0)\beta_k}{(1-\tau_0)\beta_k+1}-1}\right]\cdot \prod_{i=1,i\neq k}^{N}\mathbb{E}_{\gamma_i}\left[\left(\dfrac{\tau_0 E_i\gamma_i}{\hat{\gamma}_i}\right)^{-\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}\right]+\nu = 0. \end{cases} \tag{38}$$

increase the AEC as compared with the HoP resource allocation schemes.

APPENDIX A
DERIVATION OF OPTIMAL UPLINK POWER CONTROL SCHEME (LEMMA 1)

Proof: Due to the monotonically increasing nature of $\log(\cdot)$, the problem $\boldsymbol{P2}$ can be rewritten as follows:

$$\boldsymbol{P2'}:\quad \arg\min_{P_i:1\leq i\leq N}\left\{\mathbb{E}_{\gamma_i}\left[(1+P_i\gamma_i)^{-(1-\tau_0)\beta_i}\right]\right\} \tag{34}$$

subject to Eqs. (15) and (16). The Lagrangian function of problem $\boldsymbol{P2'}$, denoted by J_1, is formulated as follows:

$$J_1 = \mathbb{E}_{\gamma_i}\left[(1+P_i\gamma_i)^{-(1-\tau_0)\beta_i}\right] + \kappa_i\left(\frac{\mathbb{E}_{\gamma_i}[(1-\tau_0)P_i]}{\tau_0 E_i} - \eta K\|d_i\|^{-\ell}\right), \tag{35}$$

where κ_i is the Lagrangian multiplier which corresponds to the ith uplink. Then, taking the derivation of J_1 with respect to P_i and setting the results to zero, we can obtain

$$\frac{\partial J_1}{\partial P_i} = -(1-\tau_0)\beta_i\gamma_i(1+P_i\gamma_i)^{-(1-\tau_0)\beta_i-1}p_\Gamma(\gamma_i) + \frac{\kappa_i(1-\tau_0)}{E_i\tau_0}p_\Gamma(\gamma_i) = 0. \tag{36}$$

Defining $\hat{\gamma}_i \triangleq \kappa_i/\beta_i$ and solving Eq. (36), we have the optimal uplink data transmission power control scheme under the given downlink wireless transferred energy assignment as shown in Eq. (17).

APPENDIX B
THE TOTAL AVAILABLE ENERGY CONSTRAINT (LEMMA 2)

Proof: We prove Lemma 2 by contradiction. Let us denote by E_i^* $(1 \leq i \leq N)$ and $\widetilde{E}_C^*$ the optimal downlink energy allocated for SN_i $(1 \leq i \leq N)$ and the maximum aggregate effective capacity, respectively. If $\sum_{i=1}^{N} E_i^* < E_{\mathrm{tot}}$ is satisfied, we have the residual energy, denoted by P_{re}, at the HAP. We denote by $\widetilde{E}_C'$ the maximum aggregate effective capacity when P_{re} is additionally allocated to the ith $(1 \leq i \leq N)$ downlink. Then, observing problem $\boldsymbol{P3}$, the additionally allocated power P_{re} leads to a smaller objective function of problem $\boldsymbol{P3}$ and thus $\widetilde{E}_C' > \widetilde{E}_C^*$, which contradicts the assumption that E_i^* $(1 \leq i \leq N)$ is the optimal downlink energy assignment and $\widetilde{E}_C^*$ is the maximum aggregate effective capacity. Lemma 2 is thus proved.

APPENDIX C
DERIVATION OF OPTIMAL DOWNLINK ENERGY ASSIGNMENT (THEOREM 1)

Proof: To derive the optimal downlink energy assignment, we write the Lagrangian function of problem $\boldsymbol{P3}$, denoted by J_2, as follows:

$$J_2 = \mathbb{E}_{\boldsymbol{\gamma}}\left[\prod_{i=1}^{N}\left(\frac{\tau_0 E_i\gamma_i}{\gamma_{1i}}\right)^{-\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}\right] + \nu\Big(\sum_{i=1}^{N}E_i - E_{\mathrm{tot}}\Big), \tag{37}$$

where ν is the Lagrangian multiplier. Let us take the derivation of J_2 with respect to E_j $(1 \leq j \leq N)$ and E_k $(1 \leq k \leq N)$, respectively, and set the results to zero. Then, we can obtain Eq. (38), as shown at the top of this page. Note that $\partial J_2/\partial E_j = \partial J_2/\partial E_k$. Then, combining equations in Eq. (38), we have

$$\begin{aligned} &-\frac{(1-\tau_0)\beta_j}{(1-\tau_0)\beta_j+1}E_j^{-1}\prod_{i=1}^{N}\left\{\mathbb{E}_{\gamma_i}\left[\left(\frac{\tau_0 E_i\gamma_i}{\hat{\gamma}_i}\right)^{-\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}\right]\right\} \\ &= -\frac{(1-\tau_0)\beta_k}{(1-\tau_0)\beta_k+1}E_k^{-1}\prod_{i=1}^{N}\left\{\mathbb{E}_{\gamma_i}\left[\left(\frac{\tau_0 E_i\gamma_i}{\hat{\gamma}_i}\right)^{-\frac{(1-\tau_0)\beta_i}{(1-\tau_0)\beta_i+1}}\right]\right\}, \end{aligned} \tag{39}$$

solving which, we can obtain

$$E_j = \frac{\beta_j[(1-\tau_0)\beta_k+1]}{\beta_k[(1-\tau_0)\beta_j+1]}E_k. \tag{40}$$

Based on Lemma 2 and Eq. (40), the optimal solution of problem $\boldsymbol{P3}$ can be derived for the special case, i.e., $N = 2$. When $N = 2$, the optimal downlink energy assignment is

$$\begin{cases} E_1 = \dfrac{\beta_1((1-\tau_0)\beta_2+1)E_{\mathrm{tot}}}{\beta_1((1-\tau_0)\beta_2+1)+\beta_2((1-\tau_0)\beta_1+1)}; \\ E_2 = \dfrac{\beta_2((1-\tau_0)\beta_1+1)E_{\mathrm{tot}}}{\beta_1((1-\tau_0)\beta_2+1)+\beta_2((1-\tau_0)\beta_1+1)}. \end{cases}$$

Based on the Mathematical Induction method, we can obtain the optimal downlink energy assignment as follows:

$$E_i^* = \frac{\beta_i\prod_{j=1,j\neq i}^{N}[(1-\tau_0)\beta_j+1]E_{\mathrm{tot}}}{\sum_{k=1}^{N}\left\{\beta_k\prod_{j=1,j\neq k}^{N}[(1-\tau_0)\beta_j+1]\right\}}. \tag{41}$$

Substituting Eq. (41) into Eq. (17), we have Eq. (21), where $\hat{\gamma}_i$ can be determined by plugging Eq. (21) into $\mathbb{E}_{\gamma_i}[(1-\tau_0)P_i] = \eta\tau_0 E_i K\|d_i\|^{-\ell}$.

APPENDIX D
DERIVATION OF THE RELATIONSHIP BETWEEN τ_i^*, E_i^*, AND P_i^* (THEOREM 2)

Proof: Solving $\partial J_3/\partial P_i = 0$, N equations can be derived as follows:

$$(1 + P_i)^{-1} = \frac{\lambda_i}{\tau_i E_i \beta_i \gamma_i \prod_{i=1}^{N} (1 + P_i \gamma_i)^{-(1-\tau_i)\beta_i}}. \tag{42}$$

Multiplying the N equations in Eq. (42), we can obtain

$$\prod_{i=1}^{N} (1 + P_i \gamma_i)^{-1} = \frac{\prod_{i=1}^{N} (\lambda_i)}{\prod_{i=1}^{N} (\tau_i E_i \beta_i \gamma_i) \left[\prod_{i=1}^{N} (1 + P_i \gamma_i)^{-(1-\tau_i)\beta_i} \right]^N}, \tag{43}$$

which leads to

$$\prod_{i=1}^{N} (1 + P_i \gamma_i)^{-(1-\tau_i)\beta_i} = \prod_{i=1}^{N} \left(\frac{\lambda_i}{\tau_i E_i \beta_i \gamma_i} \right)^{\frac{(1-\tau_i)\beta_i}{1+(1-\tau_i)N\beta_i}}. \tag{44}$$

Plugging Eq. (44) into Eq. (42) and making the equation transformation, we can derive Eq. (31) in Theorem 2.

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