Energy Management Strategy Based on Battery Capacity Degradation in EH-CRSN (Workshop)

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Abstract. Energy Harvesting Cognitive Wireless Sensor Network (EH-CRSN) is a novel network which introduces cognitive radio (CR) technology and energy harvesting (EH) technology into traditional WSN. Most of the existing works do not consider that battery capacity of the sensor is limited and will decay over time. Battery capacity degradation will reduce the lifetime of the sensor and affect the performance of the network. In this paper, in order to maximize the network utility of the energy harvesting sensor node in its life cycle, we are concerned with how to determine the optimal sampling rate of sensor node under the condition of battery capacity degradation. Therefore, we propose an optimal adaptive sampling rate control algorithm (ASRC), which can adaptively adjust the sampling rate according to the battery level and effectively manage energy use. In addition, the impact of link capacity on network utility is further investigated. The simulation results verify the effectiveness of the algorithm, which shows that the algorithm is more realistic than the existing algorithm. It can maximize the network utility and improve the overall performance of the network.

Keywords: Energy management · Cognitive radio · Battery degradation · Sampling rate control

1 Introduction

In order to alleviate the spectrum shortage of unlicensed frequency bands and prolong the network lifetime, energy harvesting cognitive wireless sensor network (EH-CRSN) has been proposed and developed. In EH-CRSN, sensor nodes can opportunistically access the vacant licensed channels which can provide a spectrum-efficient, energy-efficient, and long-lived wireless networking solution in the coming era of the Internet of Things (IoTs) [1]. In RF-powered CRSNs, sensor nodes can harvest energy from dedicated RF power sources and ambient RF signals (e.g., WiFi signals, TV, and microwave radio)

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[2], and store them in batteries for later use. However, the lifetime of battery is closely related to the charging and discharging cycles. Frequent battery charging and discharging operations can cause irreversible battery capacity degradation and endanger the lifetime of sensor nodes.

Existing works hardly consider the degradation of battery capacity and link constraint, which is not practical. Reference [3] studies the network utility maximization problem in static route rechargeable sensor networks. however, the impact of battery capacity degradation is neglected. Reference [4] proposes a fast sampling rate control algorithm based on RF energy harvesting wireless sensor networks. However, it considers that the energy consumption rate does not exceed the energy harvesting rate. Reference [5] proposes a distributed solution called QuickFix, to compute the optimal sampling rate and routing path. However, insufficient battery capacity would result in the loss of recharging opportunities. Reference [6] does not consider the link capacity constraint for congestion control. Reference [7] proposes a double-threshold policy under channel fading conditions. Reference [8] studies random Markov chain framework to capture the degradation status of battery capacity. However, it does not consider the issue of maximizing network utility.

In this paper, we propose an adaptive sampling rate control algorithm (ASRC) which can adaptively determine the sampling rate of each RF-powered cognitive wireless sensor node under the condition of battery capacity degradation. Our algorithm achieves the goal of maximizing the overall utility of the network.

The rest of the paper is organized as follows: Sect. 2 establishes the system model and the mathematical model of optimization problem; Sect. 3 proposes the optimization strategy and algorithm to solve the problem; Sect. 4 gives the simulation results; Sect. 5 summarizes the relevant conclusions.

2 System Model and Problem Formulation

2.1 Network Model

We consider a static-routing RF-powered CRSN with N sensor nodes (excluding the sink node), each sensor node only has a unique link to the next hop. Figure 1 is illustration of an RF-powered CRSN. All sensor nodes are equipped with CR module and EH module. They can opportunistically access the licensed spectrum of the PU and transmit the data collected from the environment to the sink node.

2.2 Energy Harvesting Model

We consider sensor nodes can harvest energy from dedicated RF sources to ensure a stable supply of energy. The amount of energy harvested by sensor node depends on the transmission power of RF energy source, the distance, and the propagation characteristics of the environment. In the terrestrial environment, the energy harvest rate of the node i from the uth energy source can be expressed as [9]:

$$E_{i,u} = \delta \frac{G_u G_i \lambda_u^{\alpha}}{4\pi d_{i,u}^{\alpha}} \cdot P_u \tag{1}$$

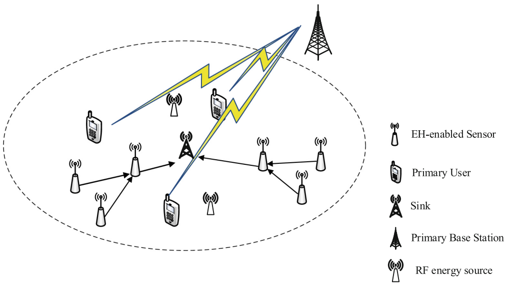

Fig. 1. Illustration of an RF-powered CRSN

Where δ is the energy conversion efficiency, G_u and G_i are the antenna gain of the uth energy source and the ith sensor node respectively; α is the path loss exponent; the RF signal wavelength, the energy collection efficiency; d is the distance between the node and the energy source; P_u is the transmission power of each energy source.

2.3 Energy Consumption Model

We consider the time cycle of energy harvesting is divided into a set $\mathrm{T} = \{1, \cdots, T\}$, and T represents the length of the cognitive wireless sensor life cycle. Let r_i^t represent the sampling rate of the node i at the time slot t. Each sensor node consumes additional energy due to the cognitive radio module, so the energy consumption rate of the whole node can be expressed as:

$$\omega(r^t) = e_\tau + (e_i^s + e_i^t)r_i^t + (e_i^r + e_i^t)\sum_{j \in A(i)} r_j^t \tag{2}$$

Where $r^t = [r_1^t, \cdots, r_N^t]^T$ is the sampling rate vector. Let e_i^s, e_i^r and e_i^t denote the energy consumption per bit of the sensor node data sensing, receiving and transmitting respectively; e_τ denote the energy consumed by spectrum sensing, and $A(i)$ denote a group of sensor nodes using the sensor node i as a relay node.

2.4 Battery Capacity Degradation Model

The number of charge and discharge cycles of the battery is related to the battery discharge depth (D). The discharge depth is denoted as the ratio of the amount of battery discharges to the battery capacity. Considering the exponential decay model of the battery energy level [8], the decay rate of battery capacity at the time slot t is:

$$q_i = \lambda e^{\theta\left(1 - \frac{B_i^t}{B_0}\right)} \tag{3}$$

Where q_i denote the amount of battery degradation of node i at the time slot t. B_i^t denote the battery energy level of node i at the time slot t; B_0 denote the initial capacity of the battery; the battery constant $\lambda > 0$, $\theta > 0$. Since the energy decay model is an exponential decay model which is only related to the current battery energy level, the node's current battery energy level can be expressed as:

$$B_i^t = \left[B_i^{t-1} + E_{i,u}\Delta t - \omega(r^t)\Delta t\right]_0^{B_i^c} \tag{4}$$

Where B_i^c denote the battery capacity of node i at the current time slot, Δt denote time interval of time slot t. Equation (4) can be recursively calculated by

$$B_i^t = B_i^0 + \sum_{k=1}^{t} E_{\mathrm{i},u}\Delta t - \sum_{k=1}^{t} \omega(r_i^t)\Delta t \tag{5}$$

The current battery capacity of the node can be expressed as:

$$B_i^c = B_0 - \sum_{k=1}^{t} \lambda e^{\theta(1-\frac{B_i^t}{B_0})} \tag{6}$$

When $B_i^c \leq D_{\min} B_0$ and $B_0 = 0$, the remaining storage space of the battery cannot maintain the continuously operation of sensor node, and the life cycle of the cognitive wireless sensors is over. $D_{\min}$ denote the ratio of the minimum discharge space for maintaining the operation of the wireless sensor to the initial battery capacity.

2.5 Problem Formulation

We establish a mathematical model and propose an optimal adaptive sampling rate control algorithm (ASRC) to manage battery energy. Assuming that adjacent nodes operate on orthogonal channels, the utility function is assumed to be increasing and strictly concave. For example, let $U(r_i^t) = \log(1 + r_i^t)$, which is known to guarantee the fairness of each sensor nodes [10]. The network utility maximization problem in RF-powered CRSN with link and battery capacity constraints can be expressed as:

$$\max_{r_i^t} \sum_{t\in T}\sum_{i\in N} U(r_i^t)$$

$$s.t \begin{cases} r_i^t + \sum\limits_{j\in A_i} r_j^t \leq c_i^t \\ B_i^t \leq B_i^c \\ B_i^t \geq B_i^c - B_0 D \\ B_i^t \geq 0 \end{cases} \tag{7}$$

Constraint 1 indicates that the flow over one link should not exceed the link capacity to avoid link congestion. Constraint 2 indicates that the battery energy level should be within the current battery capacity range. Constraint 3 indicates that the battery energy level must be within the discharge space to avoid excessive battery discharge. Constraint 4 indicates that the battery level must be greater than zero. We can decouple the original optimization problem into separable subproblems and then solve it locally by dual decomposition [6].

3 Optimal Adaptive Sampling Rate Control Algorithm

3.1 Introducing Lagrange

We introduce the Lagrangian multipliers $\lambda_i^t, u_i^t, \alpha_i^t \geq 0$ for each sensor node at each time slot, and $\lambda = [\lambda_i^t]_{i \in N, t \in T}$, $u = [u_i^t]_{i \in N, t \in T}$, $\alpha = [\alpha_i^t]_{i \in N, t \in T}$ are the Lagrangian multiplier matrixes. The Lagrangian function for our optimization problem is:

$$
\begin{aligned}
L(R, \lambda, u, \alpha, \beta) = \sum_{t \in T} \sum_{i \in N} U(r_i^t) + \sum_{t \in T} \sum_{i \in N} [\lambda_i^t (c_i^t - (r_i^t + \sum_{j \in A_i} r_j^t)) \\
+ u_i^t (B_i^c - B_i^t) + \beta_i^t (B_i^t - (B_i^c - B_0 D)) + \alpha_i^t B_i^t]
\end{aligned} \tag{8}
$$

We define the intermediate variables as follows, these equations can be proved through expansion of both sides and mathematical induction.

$$
\begin{cases}
\zeta_i^t = \sum\limits_{k=t}^{T} (u_i^t - \alpha_i^t - \beta_i^t) \\
\sigma_i^t = [\zeta_i^t (e_i^s + e_i^t) + \sum\limits_{j \in R(i)} \zeta_j^t (e_j^r + e_j^t)] \Delta t \\
\eta_i^t = \lambda_i^t + \sum\limits_{j \in R(i)} \lambda_j^t
\end{cases} \tag{9}
$$

Thus, the Lagrangian is:

$$
\begin{aligned}
L(R, \lambda, u, \alpha, \beta) = \sum_{t \in T} \sum_{i \in N} [U(r_i^t) - r_i^t \eta_i^t + r_i^t \sigma_i^t + (\beta_i^t - u_i^t) \sum_{k=1}^{t} q_i] \\
+ \sum_{t \in T} \sum_{i \in N} [\lambda_i^t c_i^t + (u_i^t - \beta_i^t) B_0 + \beta_i^t B_0 D - \zeta_i^t (B_i^0 + \sum_{k=1}^{T} E_{i.u} \Delta t)]
\end{aligned} \tag{10}
$$

Through the Lagrangian function, the original optimization problem can be decomposed, and the subproblem is:

$$
P(\lambda, u, \alpha, \beta) = \max_{r_i^t \geq 0} \sum_{t \in T} \sum_{i \in N} [U(r_i^t) - r_i^t \eta_i^t + r_i^t \sigma_i^t + (\beta_i^t - u_i^t) \sum_{k=1}^{t} q_i] \tag{11}
$$

It is not difficult to judge that the subproblem is also a convex optimization problem, and the optimal solution satisfy the KKT optimization condition:

$$
\frac{1}{r_i^t} + (\sigma_i^t - \eta_i^t) + (\beta_i^t - u_i^t) \frac{\theta}{C_0} (e_i^s + e_i^t) \Delta t \sum_{k=1}^{t} q_i = 0 \tag{12}
$$

The slackness conditions are as follows:

$$
\begin{cases}
u_i^t (B_i^c - B_i^t) = 0 \\
\beta_i^t (B_i^t - (B_i^c - B_0 D)) = 0 \\
\alpha_i^t B_i^t = 0
\end{cases} \tag{13}
$$

So, the sampling rate can be obtained from Eq. (12):

$$r_i^t = [U'^{-1}(\eta_i^t - \sigma_i^t + (u_i^t - \beta_i^t)g_i)]^+ \tag{14}$$

Where

$$g_i = \frac{\theta}{C_0}(e_i^s + e_i^t)\Delta t \sum_{k=1}^{t} q_i \tag{15}$$

3.2 Dual Problem

From the sampling rate formula (14), the Lagrangian multipliers in the equation can be solved by the dual problem of the optimization problem. The dual problem can be expressed as:

$$\begin{aligned} &\min_{\lambda,u,\alpha,\beta} P(\lambda, u, \alpha, \beta) \\ &s.t \quad \lambda_i^t, u_i^t, \alpha_i^t, \beta_i^t \geq 0 \end{aligned} \tag{16}$$

The optimal solution to the dual problem can be solved iteratively by the subgradient method. The Lagrangian multipliers is updated in the opposite direction of the subgradient of the dual function:

$$\begin{cases} \lambda_i^{t,k+1} = [\lambda_i^{t,k} - \nu_\lambda(c_i^t - (r_i^t + \sum_{j\in A(i)} r_j^t))]^+ \\ u_i^{t,k+1} = [u_i^{t,k} - \nu_u(B_i^c - B_i^t)]^+ \\ \beta_i^{t,k+1} = [\beta_i^{t,k} - \nu_\beta(B_i^t - (B_i^c - B_0 D)]^+ \\ \alpha_i^{t,k+1} = [\alpha_i^{t,k} - \nu_\alpha B_i^t]^+ \end{cases} \tag{17}$$

3.3 Battery Management Strategy

It can be seen from the sampling rate formula (14) that the sampling rate is related to the battery level under the condition of battery degradation and limited discharge space. We demonstrate the following lemma, which optimizes the sampling rate of nodes at different battery energy levels to maintain a reasonable energy level. Theoretical estimation of the life cycle of cognitive wireless sensors is also solved.

Lemma 1: When $B_i^c - B_0 D > 0$, if the battery energy level meet $B_i^c - B_0 D \leq B_i^t \leq B_i^c$, $r_i^t = 1/\eta_i^t$.If the battery energy level is equal to $B_i^c - B_0 D$, then $r_i^t = [U'^{-1}(\eta_i^t - \sigma_i^t - \beta_i^t)g_i)]^+$, if the battery energy level is equal to B_i^c, then $r_i^t = [U'^{-1}(\eta_i^t - \sigma_i^t + u_i^t)g_i)]^+$.

When $B_i^c - B_0 D \leq 0$, if the battery energy level meet $0 \leq B_i^t \leq B_i^c$, then $r_i^t = 1/\eta_i^t$. If the battery energy level is equal to 0, then $r_i^t = [1/(\eta_i^t - \sigma_i^t)]^+$, if the battery energy level is equal to B_i^c, then $r_i^t = [U'^{-1}(\eta_i^t - \sigma_i^t + u_i^t)g_i)]^+$.

Proof: When $B_i^c - B_0 D > 0$, if the battery energy level meet $B_i^c - B_0 D \le B_i^t \le B_i^c$, it is easy to know by the slackness conditions (13): $u_i^t = 0, \alpha_i^t = 0, \beta_i^t = 0$, from sampling rate formula (14): $r_i^t = 1/\eta_i^t$. Also, if the battery energy level is equal to $B_i^c - B_0 D$, $\beta_i^t > 0, u_i^t = 0, \alpha_i^t = 0$, via calculation, $r_i^t = [U'^{-1}(\eta_i^t - \sigma_i^t - \beta_i^t)g_i)]^+$, if the battery energy level is equal to B_i^c, $u_i^t > 0, \beta_i^t = 0, \alpha_i^t = 0$, via calculation, $r_i^t = [U'^{-1}(\eta_i^t - \sigma_i^t + u_i^t)g_i)]^+$.

When $B_i^c - B_0 D \le 0$, if the battery energy level meet $0 \le B_i^t \le B_i^c$, it is Easy to know by slackness conditions (13): $u_i^t = 0, \alpha_i^t = 0, \beta_i^t = 0$, from sampling rate formula (14): $r_i^t = 1/\eta_i^t$. Also, if the battery energy level is equal to 0, $\alpha_i^t > 0, u_i^t = 0, \beta_i^t = 0$, via calculation, $r_i^t = [1/(\eta_i^t - \sigma_i^t)]^+$, if the battery energy level is equal to B_i^c, $u_i^t > 0, \beta_i^t = 0, \alpha_i^t = 0$, via calculation, $r_i^t = [U'^{-1}(\eta_i^t - \sigma_i^t + u_i^t)g_i)]^+$.

According to the Eq. (3), the relationship between the battery discharge space and the sensor network life cycle can be approximated. We denote C_{T_n} as the battery capacity of the nth charge and discharge cycle, t_n is the length of the nth charge and discharge cycle, the amount of battery degradation in the nth time slot: $\Delta q = C_{T_n} - C_{T_{n-1}}$ and D_{min} is the minimum discharge space. It can be expressed as:

$$D_{\text{min}} B_0 = w(r_{\text{min}}^t) t_n \tag{18}$$

Where

$$\omega(r_{\text{min}}^t) = e_\tau + e_i^s r_{\text{min}}^t \tag{19}$$

The amount of battery capacity degradation during the nth charge and discharge cycle is:

$$\Delta q = \int_0^{t_n} \lambda e^{\theta(1 - \frac{B_i^t}{B_0})} dt \tag{20}$$

The number of charge and discharge cycles during the sensor life cycle $N_{cyc}(D)$ is:

$$N_{cyc}(D) = \int_{D_{\text{min}} B_0}^{B_0} \frac{1}{\Delta q} dB \tag{21}$$

So, the life cycle of the sensor approximately is:

$$T \cong \sum_{n=1}^{N_{cyc}(D)} t_n \tag{22}$$

The detailed steps of the proposed algorithm are as follows:

Adaptive sampling rate control algorithm (ASRC)

Input: network topology configuration, energy consumption rate, energy harvesting rate, link capacity, initial battery level, depth of discharge, life cycle T.
Output: Network utility $U(r_i^t)$.
Initialization: let the number of iteration k=1, each node starts with an arbitrary Lagrangian multiplier ;
Repeat
  for each node *i*=1,...,N do
  Each node sends $\lambda_i^t, u_i^t, \beta_i^t, \alpha_i^t$ to the sensor node $j, j \in A(i)$, collecting and forwarding information from neighboring nodes, and calculate $\eta_i^t, \sigma_i^t, \zeta_i^t$ according to the intermediate variable Eq. (9);
  for each time slot t=1,...,T do
  The node battery level state is updated, according to the battery level state, each node adaptively adjust sampling rate by the Lemma 1;
  Each node locally updates the Lagrangian multiplier according to Eq. (17);
End
k=k+1;
until λ, u, σ converge within a small range;

4 Simulation Results and Analysis

In this section, simulation results are provided to demonstrate the performance of the proposed ASRC algorithm and are compared with QuickFix in [5]. Figure 2 shows the simple network topology. All the results are obtained by MATLAB.

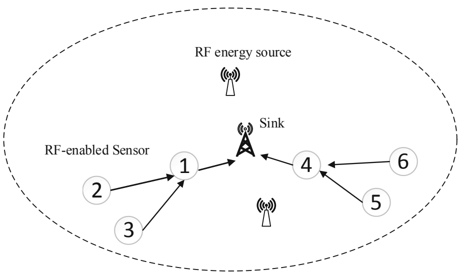

Fig. 2. Network topology

We consider the 20*20 m area, 6 sensor nodes are equipped with RF energy harvesting capability and cognitive function. For calculation conveniently, it is assumed that the sensor nodes are symmetrically distributed around the sink. Transmission power is 3 W. The energy consumption rate for sampling, transmitting and receiving are 100nJ/bit, 150nJ/bit, 158nJ/bit, respectively [4], and the energy consumed by spectrum sensing is 0.1 mJ/s. The link capacity is 2 kbps, Table 1 shows other detailed simulation parameters.

Table 1. Simulation parameters

Parameter	Value
RF harvesting band	900 MHz
Initial battery capacity	10 J
Initial battery level	0 J
Battery degradation parameter λ, θ	0.035, 2
Harvesting efficiency	0.9
Antenna gain G_s, G_r	8, 2
Path loss factor	2

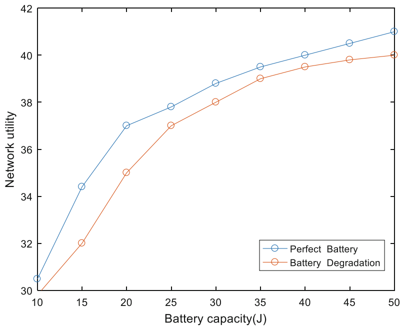

Fig. 3. Battery capacity impact on network utility

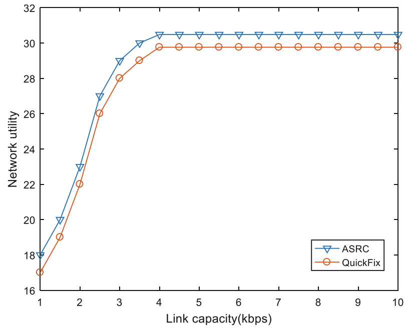

Fig. 4. Link capacity impact on network utility

In Fig. 3, we compare the impact of perfect battery and battery degradation on network utility. The ASRC algorithm considers the exponential decay model, so the perfect battery has better utility. But ASRC algorithm can adaptively adjust the sampling rate according to the battery level. It is more practical for those nodes in harsh environments.

In Fig. 4, we evaluate the impact of link capacity on network utility. Compared with QuickFix algorithm, ASRC effectively improves the network utility. Because the energy constraint of QuickFix algorithm only considers the node consumption rate not exceeding the energy harvesting rate. The excess energy collected cannot save the battery for later use, so it cannot be flexibly use in the time range.

Figure 5 shows that depth of discharge (D) impact on network utility. When D = 0.1 to D = 0.4, the network utility is improved which can also increase the accuracy of environmental monitoring. When D = 0.4 to D = 1, the network utility cannot be continuously improved due to the node link capacity is fixed. When D < 0.036, the battery discharge space does not guarantee the minimum communication requirements of the sensor node, so it is not considered.

Figure 6 shows that the curve of life cycle with depth of discharge. The two curves are very close. It can be seen that the life cycle of the theoretical calculation and the

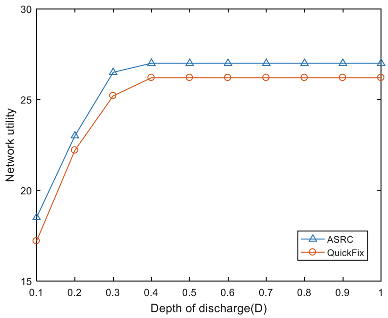

Fig. 5. Depth of discharge (D) impact on network utility

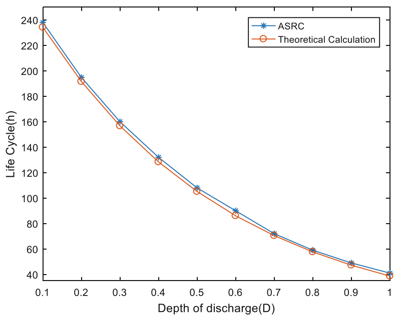

Fig. 6. Depth of discharge (D) impact on the life cycle

ASRC algorithm are almost same under the same discharge space, indicating that depth of discharge determines the life cycle of the wireless sensor.

5 Conclusion

In this paper, a novel cognitive wireless sensor network based on RF energy harvesting is considered. We have proposed a sampling rate control algorithm called ASRC for maximizing network utility under battery capacity degradation to manage battery energy. Also, we take the node link constraints into account. The results indicate that the proposed algorithm is more practical as compared to the existing algorithm for energy management in EH-CRSN. In future, we will jointly optimize sample rate and routing based on the characteristics of battery degradation to maximize network utility.

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