

PSO and FPO based Optimization of Energy Efficiency for RF Powered Wireless Sensor Networks

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ABSTRACT

In order to increase the longevity and energy constraints in a wireless powered sensor networks (WPSN), energy harvesting is the only effective means. In recent proposed WPSN, the sensors do transmit information once scavenge energy from environment through radio frequency (RF) signals. This paper presents concurrent wireless transfer of data and power to a clustered sensor network through non-orthogonal multiple access (NOMA) method so that the cluster head node harvests the energy wirelessly from RF signals transmit by its cluster members. Thus it utilizes the harvested energy to recoup the energy spent for data aggregating and forwarding. For such networks, attaining high energy efficiency on the trade-off between harvested energy and decode of information is a crucial challenge. Hence, bio-inspired algorithms are applied for determining optimal rate and power allotment for a clustered WSN as non-convex constrained energy efficiency (EE) maximization with respect to harvest period and transmission powers.

Exploring with algorithms, it is proposed a particle swarm optimization (PSO) and flower pollination optimization (FPO) to solve for Energy Efficiency maximization and to determine optimal rate control and power allotment. The simulated outputs showed that the utilization of two different algorithms, PSO convergence happens at a lesser amount of iterative than FPO, whereas FPO attains optimum energy efficiency on stabilizing energy efficiency, data transfer rate, transmission power and power partition ratio better than PSO.

1. Introduction

WSNs are normally constituted several low-power and inexpensive same or multitude kinds of sensors. They essentially do sensing and basic computing alike wireless communications of shorter distance. The longevity of WSNs is restricted because of limitations on energy reserves and availability of the real time sensors [1]. Harvesting of energy is appeared to be a significant technique in providing a green power source for self-supporting of wireless sensors, wherein the acquired energy from intended or environmental sources will be gathered to refill the sensor power unit with charges. Specifically, harvesting energy using RF [4] benefits more adaptability and endurance than non conventional way of harvesting energy using wind or solar, because the signals of RF emanated from surrounding transmitters are steadily obtainable. Several investigations have explored that the signals of RF are well suited for concurrent transmission of information (WIT) and transfer of energy (WET) by wireless [2]. The effort focuses here to find an essential negotiation between attainable yield and energy harvested [3].

Other design efforts choose the WET more in a traditional way alike wireless communication systems for wireless powered sensor networks (WPSNs) [5, 24]. The renowned protocol of “harvest then transmit” [6] wherein the allotment of time for WET of downlink and the time and transmitting power allotment for WIT of uplink are concurrently optimized in maximization of yield. Thereafter, associated researches were substantially carried out in WPSN framework with relays [7], radio of full duplex [8], cognitive WPSN [9], MIMO [10] and schemes of NOMA [11]. But, those efforts just aimed for WPSNs to have improved efficiency on spectrum as it causes huge energy dissipation while downlink WET. Hence, EE becomes widely a significant marker for WPSNs [12]. For original energy and requirement of quality of service (QoS), the suggested method [13] attempted to obtain EE of time slotted WPSNs maximum by utilizing linear programming problem for indexing sensors. The EE maximization problem for Time division WPSNs is investigated [14], and a Difference of Convex Functions (DC) dependent iteration technique was formulated to work out for maximum EE as it was intrinsically non-convex because of pairing power allotment between sensors. Unlike TDMA or TDMS methods, NOMA is intrinsically unusual because the basic functioning of its sensors will attain several simultaneous accesses by adopting the method of successive interference cancellation (SIC) in power spectral domain. Because of huge spectral efficiency of it, NOMA can be adjudged for 5G networks a hopeful multiple access method [15]. But, so far, an energy-efficient resource allotment for NOMA dependent WPSNs was not explored in any of earlier approaches.

This paper attempts to pay importance on three significant aspects.

First, this paper studies λ resource allocation of energy efficiency for NOMA- WPSNs by developing a maximization of EE with respect to harvest period and transmission powers. Second, it studies two significant characteristics in optimizing λ for EE maximization. Third, using the global variables, it explores for λ a comparative study between particle swarm optimization (PSO) [17] and flower pollination optimization (FPO) based solutions algorithm for maximizing EE. The convergence speed and the stability of the PSO and FPO algorithms are depicted by performing simulations

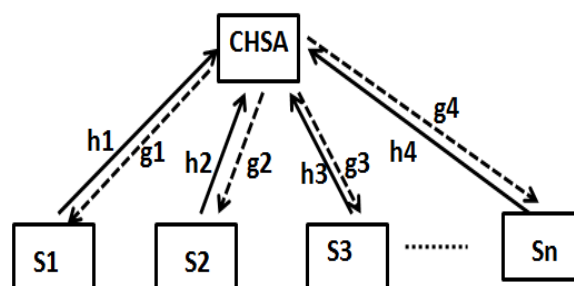


Figure 1 Network System

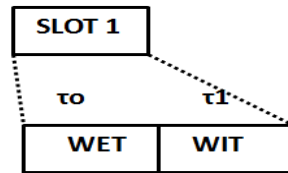


Figure 2 Slot System

This paper treats a partitioned WPSN that comprises of a cluster head with an antenna (CHSA) and M sensors each with an antenna. Figure 1 shows that the CHSA transfers power to all of the sensors like WET while down linking and acquire data signals from all of the sensors like WIT while up linking. WET and WIT will operate over the same spectral band which has bandwidth W . CHSA synchronize to all of the sensors and behave in the mode of half duplex. Figure 2 depicts the slot method of WPSN, it comprises two stages, WET and WIT, and both will be operated in a time period τ_0 and τ_1 . Assumed here the slot time $T=1$. So

$$\tau_0 + \tau_1 \leq 1 \quad (1)$$

2. WET Module

Every sensor does have a power storage device of energy infinite. Let e_i , where $i=1, 2, \dots, M$, describe i^{th} sensor's original energy. $e_i=0$ is set when zero energies remain due to earlier transmission. So, the accessible energy at i^{th} sensor after finishing WET can be described as

$$E_i = \xi_i h_i P_0 \tau_1 + e_i, \forall i, \quad (2)$$

Where the parameter ξ_i ($0 < \xi_i < 1$) describes the conversion efficiency of energy that largely relies on type of i^{th} sensor hardware. P_0 describes CHAS transmission power and h_i as gain of the downlink channel between the CHAS and i^{th} sensor.

3. WIT Module

NOMA scheme differs by “harvest and transmit” [6]. Its sensors send data to the CHAS by concurrently devouring their scavenged energies. The total utilized power of i^{th} sensor is limited with its accessible maximum power during WIT period

$$\eta_i P_i + P_{ic} \leq E_i \tau_1, \forall i, \quad (3)$$

where P_i describes the transmission power of i^{th} sensor, η_i , P_{ic} describe parameters related to power amplifier and circuit of sensor i , respectively.

Because of restricted transmission power and interference through multiple accesses; WPSN yield drastically deteriorates. To avoid it, the SIC receiver at the CHAS can be utilized. The sensors information is sequentially decoded of uplink channel gains g_i in increasing order to improve the rate. It is denoted that sensor i is the i^{th} sensor in the decrypting chain. Particularly, when i^{th} sensor is decrypted, CHAS removes the reconstruction of signal out of composite signal

for i^{th} sensor. This procedure lasts till entire sensors are decrypted. CHAS typically contains constant power source and potentially capable for computing and communication. Hence, absolute removal is possible at SIC receiver.

It is defined that $\tau = (\tau_0, \tau_1)$ and $\mathbf{P} = (P_1, P_2, \dots, P_M)$. Then, attainable throughput for sensor i can be evaluated

$$R_i^{NO}(\tau, \mathbf{P}) = \tau_1 W \log_2 \left(1 + \frac{g_i P_i}{\sum_{k=i+1}^M g_k P_k + \sigma^2} \right), \quad (4)$$

where σ^2 is the noise variance of CHAS.

So to assure the QoS of i^{th} sensors, fix the constraints of QoS as minimal requirement with the rate $R_i > 0$,

$$R_i^{NO}(\tau, \mathbf{P}) \geq R_i, \forall i. \quad (5)$$

4. Mathematical Representation of EE

The EE is described as a proportion of attainable yield to complete energy that consumed. The attainable yield of WPSN can be evaluated

$$f(\tau, \mathbf{P}) = \sum_{i=1}^M R_i^{NO}(\tau, \mathbf{P}) = \tau_1 W \log_2 \left(\sum_{i=1}^M \bar{g}_i P_i + 1 \right) \quad (6)$$

where $\bar{g}_i = \frac{g_i}{\sigma^2}$. The complete consumed energy E_{total} holds dual forms. The loss of energy is of one form because of the propagation in wireless channel during WET, E_{WET} . The energy utilization during WIT, E_{WIT} which is of another form is because of transmitting information in bundle. So, mathematically E_{total} is described

$$\begin{aligned} E_{total} &= E_{WET} + E_{WIT} \\ &= \left(P_0 + P_c - \sum_{i=1}^M \xi_i h_i P_0 \right) \tau_0 + \sum_{i=1}^M (\eta_i P_i + P_i^c) \tau_1 \end{aligned} \quad (7)$$

Eventually, maximization of EE for WPSN can be described

$$\max_{P_0, \tau, \mathbf{P}} \frac{\tau_1 W \log_2 \left(\sum_{i=1}^M \bar{g}_i P_i + 1 \right)}{\left(P_0 + P_c - \sum_{i=1}^M \xi_i h_i P_0 \right) \tau_0 + \sum_{i=1}^M (\eta_i P_i + P_i^c) \tau_1} \quad (8)$$

and $0 < P_0 < P_{\max}, \tau_0 \geq 0, \tau_1 \geq 0, 0 \leq P_i \leq \hat{P}_i, \forall i$

where $P_{\max}$ and P_i are the most permitted transmission powers for CHAS and i^{th} sensor, accordingly.

Focusing for EE upper limit, this paper considers that $\{g_i, h_i\}$ are exactly known by the WPSN. Particularly, h_i can be evaluated by the CHAS through transmitting flag signals to i^{th} sensor and gathering feedback from i^{th} sensor. h_i can be evaluated eventually. Hence, the consumed energy on evaluating h_i can be trivial. g_i can be evaluated by CHAS depending on the acquired signal of i^{th} sensor.

Because of convexity inadequacy, the equation (8) usually cannot be solved for optimal solutions. Forthcoming section, two basic properties are described for the optimal solution to equation (8) and then compare the performance of bio-inspired algorithms to determine efficient solutions.

Theorem 1 The maximization of EE described in equation (8) will be usually attained when $P_0 = P_{\max}$ and $\tau_0 + \tau_1 = 1$

Using above theorem, a reduced structure for equation (8) can be obtained by removing τ_0 and P_0

$$\begin{aligned} \max_{(\tau_1, \mathbf{P}) \in \mathbf{A} \times \mathbf{B}} EE(\tau_1, \mathbf{P}) &:= \frac{W \log_2 \left(\sum_{i=1}^M \bar{g}_i P_i + 1 \right)}{\Delta \left(\frac{1}{\tau_1} - 1 \right) + \sum_{i=1}^M (\eta_i P_i + P_i^c)} \\ \text{s.t., } \eta_i P_i + P_i^c &\leq \frac{\xi_i h_i P_{\max} (1 - \tau_1) + e_i}{\tau_1}, \forall i, \\ \tau_1 W \log_2 \left(1 + \frac{\bar{g}_i P_i}{\sum_{k=i+1}^M \bar{g}_k P_k + 1} \right) &\geq R_i, \forall i, \end{aligned} \quad (9)$$

Where $A = \{\tau_1 | 0 \leq \tau_1 \leq 1\}$ $B = \{(P_1, P_2, \dots, P_M) | 0 \leq P_i \leq P_i\}$ and $A \times B$ denotes the Cartesian product of A and B

Theorem 2 $(\tau_1, \mathbf{P})$ be the optimum for equation (9) satisfies

$$\tau_1 = \min \left\{ 1, \min_{\forall i} \frac{\xi_i h_i P_{\max} + e_i}{\xi_i h_i P_{\max} + \eta_i P_i + P_i^c} \right\} \quad (10)$$

When substituting (10) into (9), (9) becomes a minmax optimization and it is too hard to find solution because of poor differentiability of $\mathbf{P}$. To find a way, for Theorem 2, optimization

algorithms can be adopted. PSO and FPO are used to solve as depicted in Algorithms 1 and 2 respectively.

5. Algorithms

a. Particle Swarm Optimization

Assume $EE(x)$ describe the objective function x which is of $(\mathbf{P}, \tau_1)$. Let $x_i = [x_{i1}, x_{i2}, \dots, x_{iM}]^T$ describe particle position of swarm i where i ranges from 1 to S , where S defines the particle size. Let $v_i = [v_{i1}, v_{i2}, \dots, v_{i,M+1}]^T$ describe particle velocity of swarm i . For comprehending better, certain used notations of PSO Algorithm can be defined as follows: V_{max} is a maximum value of particle velocity. $c1$ and $c2$ are acceleration PSO cognitive and social parameters. ξ and η are uniform distribution between 0 and 1 and ω describes an inertia. N defines maximum iterations number

PSO Algorithm

Input: V_{max} , ξ , η , $c1$, $c2$, ω , S and N .

1. Initialize swarm at $t = 0$
2. Randomly create a realizable population of $x_i(t)$ with velocity $v_i(t)$, in which $v_{id}(t) \in [-V_{max}, V_{max}]$ and d ranges from 1 to M . M is swarm size
3. Calculate value for i^{th} particle fitness, $EE(x_i(t))$ and fix the best result by i^{th} particle till the t^{th} iterative as $\hat{x}_i(t)$.
4. Choose highest fit particle b based on value and fix the best result by the swarm till the t^{th} iterative as $\hat{x}_b(t)$.
5. **redo**
6. Increase t by 1.
7. Compute every $vid(t)$ through

$$v_{id}(t) = \omega v_{id}(t-1) + c1\xi(x_{id}(t-1) - x_{id}(t-1)) + c2\eta(x_{bd}(t-1) - x_{id}(t-1)).$$
8. Find $\min\{V_{max}, \max\{vid(t), -V_{max}\}\}$ and set $vid(t)$.
9. Find $\min\{P_d, \max\{0, x_{id}(t-1) + v_{id}(t)\}\}$ and set $x_{id}(t)$.
- 10.

$$x_{i,M+1}(t) = \min\left\{1, \min_{1 \leq d \leq M} \frac{\xi_d h_d P_{\max} + e_d}{\xi_d h_d P_{\max} + \eta_d P_d + P_d^c}\right\}$$

11. **for every** particle i **perform**
12. **When** $x_i(t)$ is a realizable solution **then**
13. **When** $EE(x_i(t)) > EE(\hat{x}_i(t))$ **then**
14. Refresh $\hat{x}_i(t)$ with $x_i(t)$.
15. **end**
16. **When** $EE(x_i(t)) > EE(\hat{x}_b(t))$ **then**
17. Refresh $\hat{x}_b(t)$ with $x_i(t)$.
18. **end**
19. **end**
20. **end for**
21. **till** $t > N$.
22. **return** $\hat{x}_b(t)$.

b. Flower Pollination Algorithm

Assume $EE(x)$ describe the objective function x which is of $(\mathbf{P}, \tau_1)$. Let $x_i = [x_{i1}, x_{i2}, \dots, x_{iM}]$ be the pollen population. The two scale factors are α and β . p is switching probability. G is maximum generation and

$$p = 0.6 - 0.1 \times \left(\frac{MaxIter - t}{MaxIter} \right)$$

FPO Algorithm

Input: p, α, β and G .

1. Randomly create a realizable flowers/pollen gametes population of $x_i(t)$
2. Determine the best answer g_{best} in the original population
3. **While** t is less than maximum generation
4. **For all** n flowers in the population **do**
5. Obtain p from $0.6 - 0.1 \times \left(\frac{MaxIter - t}{MaxIter} \right)$
6. If $rand$ is less than p
7. Compute using the switching probability, the pollination type of global or local is chosen and the follower locations are modified in harmony using update equations given

$$P_k^{i+1} = P_k^i + \gamma L(G^* - P_k^i) \quad \text{for global pollination}$$

where L is a step vector drawn from a Levy distribution.

8. Else consider ε as uniform distribution between 0 and 1 and compute

$$P_k^{i+1} = P_k^i + \varepsilon (P_l^i - P_k^i) \quad \text{for local pollination}$$

Where $\alpha = \beta = \varepsilon$

9. end
10. The fresh locations are then inspected to find whether the result is within the zone (basic boundaries).
11. The fitness value for new solutions is calculated. When observed better, the solutions are refreshed in the population.
12. The best outcomes finally after maximum iterations are the algorithm output.
13. The best estimate is calculated by utilizing the equation (10) and the sensors channel gains, CH and sensors transmit power.

6. Simulation

The simulations are performed for a WPSN with a CHAS and four sensors to verify and compare the effectiveness of Algorithm 1 and 2. The i^{th} sensor distance and CHAS is fixed such a way d_i as $2.5i$. Considering the reciprocity of the channel maintains for both downward link and upward link of i^{th} sensor, h_i and g_i are $0.1/d_i^2$. The values of the parameters are fixed to describe for standard WPSN contexts [22] in performing simulation:

Parameter	Value	Parameter	Value
M	4	Pc	500mW
W	20KHz	Pi	1W

σ^2	-110dB	P_{ic}	10mW
ξ_i	0.9	R_i	2Kbits
P_{max}	10W	η_i	1

Table 1 Settings of WPSN

Algorithms	Parameter Settings
PSO	$S=200$, $\omega =1$, $c1=2$, $c2=2$, $V_{max} =10^{-3}$ and $N_Iter=300$
FPO	$n=200$ $p=0.8$ $N_Iter=300$, $\beta=1.5$, $L_{coeff}=0.01$

Table 2 Settings of Algorithms

The respective EE for best solution $\hat{x}b(t)$ on every iterative is measured for both algorithms. PSO algorithm approaches stable value after 150 iterations whereas FPO after 80 iterations as shown in Figure 2. Being PSO and FPO algorithms operate on the CHAS which is normally with persistent potential for computing and storing, allotment of resource in real time for WPSNs is practicable. Additionally, the variance of EE achieved is just 0.01623 for FPO comparing 0.01956 for PSO from stability, which indicates the stability of FPO. Conclusively, solutions obtained through Algorithms were pretty nearer to global optimal values. The estimated proportion is around 99.8% for FPO and 99.6% for PSO, which again demonstrates the efficiency is superior in FPO.

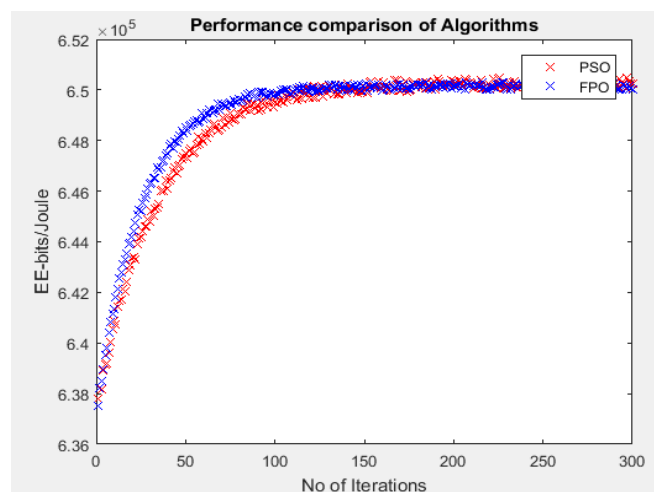


Figure 2 Performance comparisons of algorithms for EE Maximization

7. Conclusion

In this paper, the allotment of resource for concurrent transmission of wireless information and power in clustered wireless sensor networks are studied, focusing to find the optimum values of

bit rate, allotted transmit power in such a way WPSN energy efficiency in transmitting signals is maximized. Considering the circuit power utilization and the power scavenging capacity by the RF receivers into a goal function, the optimization on allotment of resource is deduced as a non-convex problem. In solving such convex problem, reputed bio inspired algorithms like PSO and FPO adopted by considering optimum data rates and transmitting powers during allocation. Simultaneously RF receiver adapts optimum power proportion in order to attain EE maximum. The outputs of the simulation depict that the algorithms converge with lesser amount of iterative and are efficient to refill the sensor node power and enhance EE.

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