OPTIMIZATION WITH PSO AND FPO BASED CONTROL FOR ENERGY EFFICIENT OF SENSORS IN WSN

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***Abstract*:-** *A wireless network consisting of a large number of small sensors with low-power transceivers can be an effective tool for gathering data in a variety of environments. The data collected by each sensor is communicated through the network to a single processing center that uses all reported data to determine characteristics of the environment or detect an event. The communication or message passing process must be designed to conserve the limited energy resources of the sensors. Clustering sensors into groups, so that sensors communicate information only to cluster heads and then the cluster heads communicate the aggregated information to the processing center, may save energy. In this paper, we propose a distributed, randomized clustering algorithm to organize the sensors in a wireless sensor network into clusters. We then extend this algorithm to generate a hierarchy of cluster heads and observe that the energy savings increase with the number of levels in the hierarchy. Results in stochastic geometry are used to derive solutions for the values of parameters of our algorithm that minimize the total energy spent in the network when all sensors report data through the cluster heads to the processing center.*

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.

Keywords- *Wireless Sensor Networks; PSO;FPO;*

I. 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].

Sensors in these multi-hop networks detect events and then communicate the collected information to a central location where parameters characterizing these events are estimated. The cost of transmitting a bit is higher than a computation [1] and hence it may be advantageous to organize the sensors into clusters. In the clustered environment, the data gathered by the sensors is communicated to the data processing center through a hierarchy of cluster heads. The processing center determines the final estimates of the parameters in question using the information communicated by the cluster heads. The data processing center can be a specialized device or just one of these sensors itself. Since the sensors are now communicating data over smaller distances in the clustered environment, the energy spent in the network will be much lower than the energy spent when every sensor communicates directly to the information processing center.

For wireless sensor networks with a large number of energy-constrained sensors, it is very important to design a fast algorithm to organize sensors in clusters to minimize the energy used to communicate information from all nodes to the processing center. In this paper, we propose a fast, randomized, distributed algorithm for organizing the sensors in a wireless sensor network in a hierarchy of clusters with an objective of minimizing the energy spent in communicating the information to the information processing center [5]. We have used results in stochastic geometry to derive values of parameters for the algorithm that minimize the energy spent in the network of sensors.

1.1 WET Module

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

$$Ei=\xi ihiP0\tau 1+ ei, \forall i, (1)$$

Where the parameter ξi ($0<\xi i<1$) describes the conversion efficiency of energy that largely relies on type of ith sensor hardware. $P0$ describes CHAS transmission power and hi as gain of the downlink channel between the CHAS and ith sensor.

1.2 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 ith sensor is limited with its accessible maximum power during WIT period

$$\eta iPi+ Pic \le Ei\tau 1, \forall i, (2)$$

where Pi describes the transmission power of ith sensor, ηi, Pic 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 gi in increasing order to improve the rate. It is denoted that sensor i is the ith sensor in the decrypting chain. Particularly, when ith sensor is decrypted, CHAS removes the reconstruction of signal out of composite signal for ith 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 $\boldsymbol{\tau}$ = ($\tau 0$, $\tau 1$) and $\mathbf{P}$= ($P1$,$P2$,…,PM). Then, attainable throughput for sensor i can be evaluated

$$R_i^{NO}(\tau,\mathbf{P}) = \tau_1 W \log_2\left(1+\frac{g_i P_i}{\sum_{k=i+1}^{M} g_k P_k + \sigma^2}\right), \quad (3)$$

where σ2 is the noise variance of CHAS. So to assure the QoS of ith sensors, fix the constraints of QoS as minimal requirement with the rate Ri >0 ,

$$R_i^{NO}(\tau,\mathbf{P}) \ge R_i, \forall i. \quad (4)$$

2. Power consumption sources and conservation mechanisms

This section first presents the chief sources of power consumption with respect to the protocol stack. Then, it presents an overview of the main mechanisms and principles that may be used to develop energy efficient network protocols.

2.1. Sources of power consumption

The sources of power consumption, with regard to network operations, can be classified into two types: communication related and computation related. Communication involves usage of the transceiver at the source, intermediate (in the case of ad hoc networks), and destination nodes. The transmitter is used for sending control, route request and response, as well as data packets originating at or routed through the transmitting node. The receiver is used to receive data and control packets – some of which are destined for the receiving node and some of which are forwarded [8]. Understanding the power characteristics of the mobile radio used in wireless devices is important for the efficient design of communication protocols. A typical mobile radio may exist in three modes: transmit, receive and standby. Maximum power is consumed in the transmit mode, and the least in the standby mode. For example, the Proximal RangeLAN2 2.4 GHz 1.6 Mbps PCMCIA card requires 1.5 W in transmit, 0.75 W in receive, and 0.01 W in standby mode. In addition, turnaround between transmit and receive modes (and vice-versa) typically takes between 6 and 30 microseconds. Power consumption for Lucent's 15 dBm 2.4 GHz 2 Mbps Waveland PCMCIA card is 1.82 W in transmit mode, 1.80 W in receive mode, and 0.18 W in standby mode. Thus, the goal of protocol development for environments with limited power resources is to optimize the transceiver usage for a given communication task [7].

The computation considered in this paper is chiefly concerned with protocol processing aspects. It mainly involves usage of the CPU and main memory and, to a very small extent, the disk or other components. Also, data compression techniques, which reduce packet length (and hence energy usage), may result in increased power consumption due to increased computation. There exists a potential tradeoff between computation and communication costs. Techniques that strive to achieve lower communication costs may result in higher computation needs, and vice-versa [10]. Hence, protocols that are developed with energy efficiency goals should attempt to strike a balance between the two costs.

Theorem 1 The maximization of EE described in equation (4) will be usually attained when $P0 = P_{\max}$ and $\tau 0+\tau 1 = 1$ Using above theorem, a reduced structure for equation (4) can be obtained by removing $\tau 0$ and $P0$

$$\max_{(\tau_1,\mathbf{P})\in \mathbf{A}\times\mathbf{B}} EE(\tau_1,\mathbf{P}) := \frac{W\log_2\left(\sum_{i=1}^{M}\bar{g}_i P_i + 1\right)}{\Delta\left(\frac{1}{\tau_1}-1\right)+\sum_{i=1}^{M}\left(\eta_i P_i + P_i^c\right)}$$

$$s.t.,\ \eta_i P_i + P_i^c \le \frac{\xi_i h_i P_{\max}(1-\tau_1)+e_i}{\tau_1}, \forall i,$$

$$\tau_1 W\log_2\left(1+\frac{\bar{g}_i P_i}{\sum_{k=i+1}^{M}\bar{g}_k P_k + 1}\right) \ge R_i, \forall i, \quad (5)$$

Where $A = \{\tau 10 \le \tau 1 \leqslant 1\}$ $B = \{(P1P2.......PM) \vee 0 \le Pi \leqslant \}$and A × B denotes the Cartesian product of A and B.

Theorem 2 ($\tau 1$, **P**) be the optimum for equation (9) satisfies

$$\tau_1 = \min\left\{1, \min_{\forall i}\frac{\xi_i h_i P_{\max} + e_i}{\xi_i h_i P_{\max} + \eta_i P_i + P_i^c}\right\} \quad (6)$$

When substituting (6) into (5), (5) becomes a min max optimization and it is too hard to find solution because of poor differentiability of P [9]. 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.

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 $xi(t)$ with velocity $vi(t)$, in which $vid(t)\in[-V\max, V\max]$ and d ranges from 1 to M. M is swarm size
3. Calculate value for *ith* particle fitness, $EE\ (xi(t))$ and fix the best result by *ith* 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 *tth* iterative as $\hat{x}\ b(t)$.
5. **redo**
6. Increase t by1.
7. Compute every $vid(t)$ through $vid(t) = \omega vid(t\text{-}1) + c1\xi(xid(t\text{-}1)\text{-}\ xid\ (t\text{-}1))+c2\eta(xbd(t\text{-}1)\text{-}xid(t\text{-}1))$.
8. Find min{$V\max$, max{$vid(t)$, -$V\max$}} and set $vid(t)$.
9. Find min{Pd, max{0, $xid(t\text{-}1)+vid(t)$}} and set $xid(t)$.

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

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

FPO Algorithm

Input: p, α,β and G.
1. Randomly create a realizable flowers/pollen gametes population of $xi(t)$
2. Determine the best answer *gbest* 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×(
$MaxIter-t$
$MaxIter$
)
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 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 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.

3. 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 *ith* sensor distance and CHAS is fixed such a way di as 2.5i. Considering the reciprocity of the channel maintains for both downward link and upward link of *ith* sensor$i$, hi and gi are $0.1/di^2$. The values of the parameters are fixed to describe for standard WPSN contexts in performing simulation are given in Tables-1 and 2.

Table-1: Settings of WPSN

Parameter	Value	Parameter	Value
M	4	Pc	500mW
W	20KHz	Pi	1W
σ2	-110dB	Pic	10mW
Pmax	10W	ηi	1

Table-2: Settings of Algorithms

Algorithms	Parameter Settings
PSO	S=200, ω=1, $c1$=2, $c2$=2, $Vmax$ =10-3 and N_Iter=300
FPO	n=200 p=0.8 N_Iter=300,β=1.5, Lcoeff=0.01

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-1. 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.

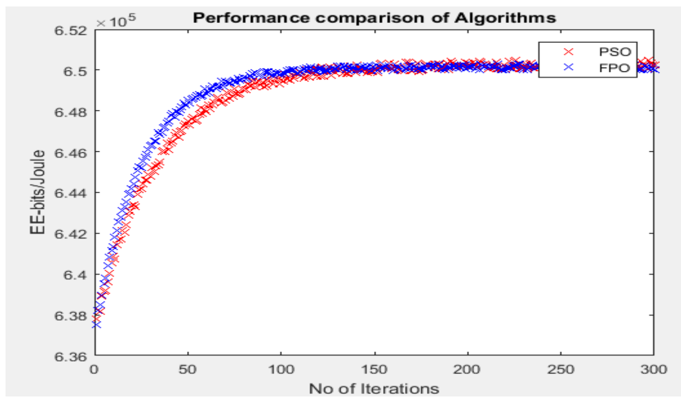

Figure-1: Performance comparisons of algorithms for EE Maximization

4. Conclusions

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 F 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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