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Maximizing Energy Efficiencyin Mobile Energy Harvesting Wireless Sensor Networks using Particle Swarm Optimization

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Abstract: *Apromosing solution for enhancing the the lifetime of energy-constrained Mobile wireless sensor networks (MWSNs), is to harvest the energy from radio frequency (RF) signals. Simultaneous Wireless Information and Power Transfer (SWIPT) is such a technique which is applied to a MWSN where the energy harvested by relay nodes can be used for the purpose of forwarding data. The RF signal carries both information and energy at the same time. For enhancing the lifetime of the network, the transmittedRF energy can be recycled at the receiver side. In this case,a balance between harvestingenergy and forwardingdatais achieved in order to maximize the system energy efficiency. The received power is split into two continuous sets of power stream using arbitrary power splitting ratios. By considering the various power splitting abilities of receivers, a Resource Allocation (ResAll) algorithm is used to find the resource allocation policies. InResAll algorithm system energy efficiency is achieved by balancing data rate, energyefficiency, power splitting ratio and transmit power. Then Particle swarm optimization is employed to obtain the optimum resource allocation policies which further maximizes the system energy efficiency. A cost function is framed for this purpose and PSO attains maximum energy efficiency byimproving the solution of the cost function at each iteration with respect to given constraints.*

Keywords: *Energy Efficiency, Resource Allocation, Simultaneous Wireless Information and Power Transfer (SWIPT), Low Energy Adaptive Clustering Hierarchy (LEACH), Particle Swarm Optimization (PSO)*

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I. Introduction

The wireless sensors (nodes) which are powered by cells, with limited energy has restricted the lifetime of a wireless sensor network. This is an existing, basic issue being faced by the sensor networks which are used for long-haul tasks. Energy conservation techniques can only reduce the total energy consumption of the system but cannot compensate on the energy depletion. The deploying more number of nodes is not environment friendly because the deserted nodes will cause pollution to the environment. Replacing the cell or node is applicable only in cases in which the nodes can be located and physically accessed by humans or robots.

Wireless charging technology is a promising solution for addressing the energy limitations in sensor networks. The wireless charging technology, along with more cheap mobile robots, makes the power restoring process possible and controllable, and hence the power can be restored to satisfy energy requirements. Close alignment between the charger and nodes is not required when compared with the node or cell replacement techniques.

Wireless charging technology can be classified into two groups, which are Radio Frequency (RF) based wireless charging (radiative) and coupling-based wireless charging (non-radiative). RF waves are used as the medium for transferring energy in the case of radiative wireless charging. Here the transfer of energy is on the basis of the radiative electric field of the RF wave. Non-radiative wireless charging is commonly utilized in the appliances of daily use because of safety considerations.

As an RF signal consists of both information and energy, it is considered as a promising method of wireless energy transfer as it facilitates wireless information transfer along with energy harvesting simultaneously. To improve the lifetime of the sensor network the transmitted RF energy can be recycled at receiver side. This technique is referred to as simultaneous wireless information and power transfer (SWIPT) [8].

Here a data transmitting node transfers the energy together with the data to its cluster head. Based on Dynamic Power Splitting Scheme, the cluster head divides the received RF signals into two power streams with specific power splitting ratiosfordata forwarding and energy harvesting respectively. This method has two merits: (i) harvesting the RF energy from transmitters by the for compensating the data forwarding hence reducing the depletion of energy; (ii) in order to improve the Quality of Services (QoS), energy may be harvested from either interference signals or RF signals of transmitters, and even antenna noises.

This work focuses on implementing efficient resource allocation using particle swarm optimization with the aim of maximizing energy efficiency.

II. System Model and Problem Formulation

1. System Model

A mobile WSN with N nodes and a mobile collector is considered here. These sensors which has a individual single antennas are randomly distributed over the field under consideration. Periodically, a deployed mobile collector conducts an information gathering tour beginning from the sink node. At each tour in the field it visits some previously determined anchor nodes, known as cluster heads for the purpose of collectinginformation from the neighbouring sensorsthrough multiple hop transmissions by staying near them for a specific time period. On the basis of a clustering protocol known as LEACH [11], the sensor nodes are grouped as clusters before starting the information gathering tour. In this case each cluster consists of a cluster head (CH) for collecting the information sensed by each sensor in its cluster through relays of other nodes. This collected information is then uploaded to the mobile collector, as illustrated in Fig.1. The CH also act as the anchors for the collector. The nodes transmit their sensed information to the CHs including the energy. The RF energy is also harvested from the data received by the CH and then the data is aggregated. A CH consists of a signal processing unit with rechargeable cell, an energy harvesting unit and a power splitting unitin order to continuously forwarding data and for harvesting the energy from the received RF signals, which is demonstrated in Fig. 2. The circuit in the receiver designed for data forwarding cannot be used for energy harvesting because of hardware restrictions [1]. As a result, energy harvesting unit must be always separated from the data processing unit.

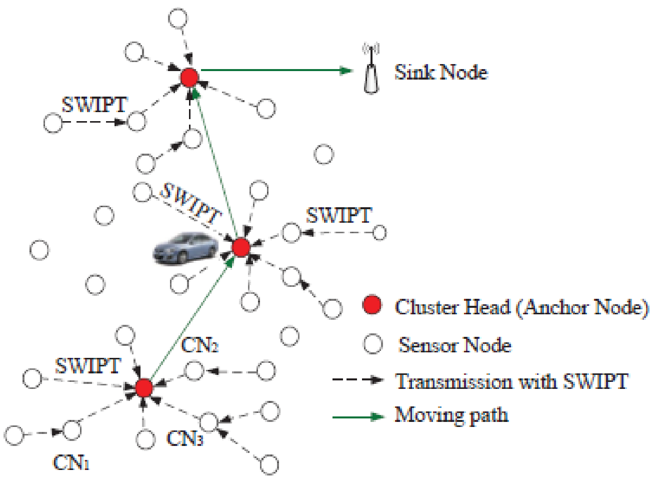

Fig 1: SWIPT in a 3 cluster WSN. [1]

Here, at the transmitter side, time-slotted transmission is employed and at the receiver side dynamic power splitting scheme is employed which enables the receiver for processing the data andenergy harvesting from the received signal at any instant. The basic principle behind this technique is illustrated in Fig. 2. The received signal from transmitter of the i^{th}node is splitted dynamically by the receiver at the j^{th}CH into two power streams for data processing and energy harvesting in ratios ρ_{ij}^{I} and ρ_{ij}^{E}respectively.

The effective coverage area of the RF antenna receives the incident electromagnetic waves. Then using an efficient power management circuit the received power is converted to DC using a rectifier and then this power is transferred to the storage cell in order to power a sensor. The energy harvested in the cell helps in lowering the minimum power transfer requirement $Qreq_{\min\ ij}$,, and hence further limits the power slitting ratio for harvesting energy thereby enhancing the network's rate of data delivery. The power splitting unit is assumed as perfect [1], and hence, it will not leads to any power loss or noise. The power consumed by each node is fixed as P_cWatts for processing a unit of data and does not depend on the amount of energy harvested. And hence, when the data processing rate of a sensor is R, the total power consumption of the circuit is P_c*R watts. Powering the CHs by more than one energy sources is worth in practical.

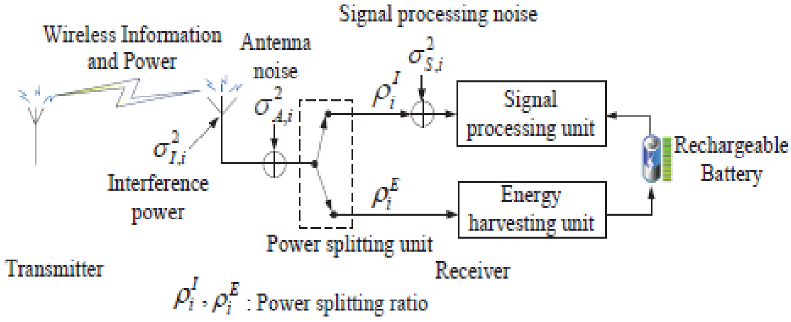

Fig: 2 Model of a receiver with SWIPT [1]

2. Communication Model

In the WSN one of the clusters is considered, in which there is a CH and N−1 sensors, represented as N $=\{N_1, N_2, . . . , N_{N-1}\}$, which are grouped into a cluster using LEACH algorithm. The directed graph of this sensor network is then modelled as a X = (M,C); M = N∪ CH is the group of all nodes, and C corresponds to the group of all the connected links between the sensors and the CH. The condition for a connected link (i, j) ∈ C to exist is that $d_{ij} \le r_{tx}$ where d_{ij} indicates the distance between i^{th} node and j^{th} node, r_{tx},denotes range of transmission sensors. The range of transmission of sensor nodes r_{tx}, is dependent upon the transmit power of sensors. The channel between transmitter and the receiver is assumed to be that of a quasi-static block fading model. The channel gains are calculated by obtaining the receiver feedback. As depicted in Fig. 2, corruption of received signal occurs due to an Additive White Gaussian Noise generated from theantenna at the receiver. Then the received RF signal is then given to a power splitting unit, at which it is split and thenseparately fed to the energy harvesting unit, andinformation processing unit.

The capacity of the channelacross thei^{th} transmitter and j^{th} receiver can be calculated as

$C = Wlog_2(1 + P_{ij}\gamma_{ij}\rho^I_{ij})$ (1)

Here W denotes the band width and P_{ij} denotes the transmitted power from i^{th} transmitter to j^{th} receiver, and γ_{ij} denotes the channel gain because of the attenuation shadowing and path loss.The maximum data rate R_{ij} that can be achieved in the case of reliable data forwarding from i^{th} transmitter to j^{th} receiver is always less than channel capacity C_{ij} between them, i.e.,

$R_{ij} < Wlog_2(1 + P_{ij}\gamma_{ij}\rho^I_{ij})$ (2)

In the case of transfer of energy, according to rule of energy conservation, the energy received by the receiving antenna, is always less than the harvested energy by denoted by Q_{Dij} Joules.

$Q_{Dij} \le P_{ij}$ ζij $\rho^E_{ij} n_{ij}$ (3)

where 0 <ζij< 1 represents the coefficient for harvesting energy from i^{th} transmitter by j^{th} receiver which implies that the entire energy radiated by i^{th}transmitter is not harvested by j^{th} receiver. 0 <n_{ij}< 1 shows the efficiency of energy conversion of j^{th}receiver in conversion of the received RF signal into electrical energy for storing in the cell, which is dependent upon the process of rectification used and the circuit used for harvesting energy [3]. Maximum values are assumed to R_{ij} and Q_{Dij} , i.e., the two sides of the inequality becomes equal.

3. Problem Formulation

Here, the Resource allocation problem is formulated as a problem that maximizes the system energy efficiency (Bit/J).

3.1 End-to-End Throughput

The sum of number of bits conveyed to receivers successfully per second is known as the end to end throughput.

$$F(P,p) = \sum_{i,j=1}^{N} \alpha_{ij} Wlog_2(1 + P_{ij}\gamma_{ij}\rho^I_{ij}) \qquad (4)$$

In which P = {P_{ij} ≥ 0, ∀i, j ∈ M } represents the policy for power allocation,ρ_{ij} is the policy for power splitting. For the purpose of ensuring a particular degree of fairness, the application layer fixes α_{ij} which is apositive weight accounting for the priorities of different receivers. To improve the system energy efficiency, the overall system energy consumption considered. The weighted energy consumed by the system U_{EC}(R,P, ρ), needed for reliable communication is modelled, as the total power dissipation, which is given by,

F_{EC}(R,P,p)= $\sum_{i,j=1}^{N} P_{ij}\ R_{ij}\ + \sum_{i,j=1}^{N} \varepsilon P_{ij}$ (5)

Where, ε>=1 is a constant accounting for the inefficiency of the transmitter.R_{ij} represents the data rate.

3.2 Weighted Energy Efficiency

The sum of weighted number of bits deliveredsuccessfullytothe receivers per Joule of energy consumed is called as the weighted energy efficiency of the system and is expressed as

F_{eff} (R, P, ρ) =F(P, ρ)/F_{EC}(R, P, ρ) (6)

The resource allocation problem (ResAll) is then formulated into a nonlinear optimization problem:

$max_{R,\,P,\rho}$ [F_{eff} (R, P, ρ)] (7)

which is subjected to

C1:Q_{Dij} +Q_{Iij} >=Q_{min}^{req} (8)

C2: R_{minij} <=R_{ij} <=C_{ij} (9)

C3: $\sum_{i,j=1}^{N} \alpha_{ij}\, W\, log_2(1 + P_{ij}\, \gamma_{ij}\, \rho_{ij}^{I})$>=$R_{min}$ (10)

C4:$P_{i,j}^{min}$ <=$P_{i,j}$ <=$P_{i,j}^{max}$ (11)

C5: ρ_{min}^{E} <= $\rho_{i,j}^{E}$ <= ρ_{max}^{E} (12)

C6: ρ_{min}^{I} <= $\rho_{i,j}^{I}$ <= ρ_{max}^{I} (13)

C7: $\rho_{i,j}^{E}\ +\ \rho_{i,j}^{I}\ \leq 1$(14)

in which C1 is the minimum power transfer requirement$Q_{req\ \min\ ij}$ for power transfer fromj^{th}receivertoi^{th} transmitter. It shows that the energy harvested is invalid in the case when the energy harvested is lesser than the power consumed by the circuit for harvesting energy. C2 shows the minimum individual data transfer rate, $R_{\min\ ij}$, from i^{th} transmitter to j^{th} receiver and it is always less than the channel capacity. C3 indicates the Quality of Service constraint of the system which specifies thattotal end-to-end throughput must be greater than minimum value of the data rate of the system, R_{min}. C4 specifies the constraint for a power transmission which shows that the circuit for harvesting energy circuit is capable of operating even in the case where the RF incident power is greater than the threshold $P_{\min\ ij}$.The maximum transmit power is $P_{\max\ ij}$, whose value is dependent on the limitations in the hardware of the power amplifier. A threshold is required for triggering the charge pump in the circuit for harvesting energy and is specified in C4. C5−C7 represents the constraints for power splitting. C5 indicates that ratio of power splitting for energy harvesting is bounded by the lower limitρ_{min}^{E} and upper limit, ρ_{max}^{E}. C6 represents the lower limit and upper limits of the power splitting ratio for data processing., ie, ρ_{min}^{I} and ρ_{max}^{I} respectively, where ρ_{min}^{E} + ρ_{max}^{I} = 1 and ρ_{max}^{E} + ρ_{min}^{I} = 1. Power splitting constraint is specified in C7, which shows the passiveness of the power splitting unit, and hence no power gain can be attained by this process of power splitting**.**

The theoretical model (4.7) is practically, suitable for optimization for any node, including the CH node, in the case when 2 nodes which are inter connected and are able to transmit data. Additionally, on the basis of Quality of Service requirements of each nodes and the system, $R_{\min\ ij}$, and R_{min} are selected in such a way which helps in attaining a trade-off between system energy efficiency and the total system capacity. As the value of R_{min} increases, the transmit power has to be increased in order to satisfy the requirement of greater data rate there by reducing energy efficiency of the system. Then based on the ability of the receiver in dividing the received power, the values of ρ_{min}^{E} and ρ_{max}^{E} are selected.

In order to maximize the aggregated energy efficiency of all the sensor nodes, the objective function (7) is used. By sing this function, the policy for data rate control R^*, policy for power splitting p^*, and policy for power allocation policy P^* is obtained.

III. Solution for the optimization problem

The resource allocation problem is solved using two methods,ie. Resource Allocation Algorithm (ResAll) [1] and Particle Swarm Optimization (PSO) [2].

1. ResAll Algorithm

The ResAll algorithm is based on theiterative Dinkelback method [13]. Usingthis algorithm, resource allocation policies are found out.

Input:

i - index of iteration;

I_{max} - maximum no: of iterations;

n –system energy efficiency;
e - an infinitesimal number;

Output:
n^{*}- maximum energy efficiency;
{ R^{*}, P^{*}, ρ^{*}} -resource allocation policies;

i = 1, n =0;
for (i ≤ I_{max})
{
if (F(P, ρ) − nF_{EC}(R,P, ρ)) < e
return {R^{*}, P^{*}, p^{*}}= {R,P, ρ}
n^{*}=F(P, ρ)/F_{EC}(R, P, ρ)
else
Set n = F(P, ρ)/F_{EC}(R, P, ρ)
i= i + 1
}
end

This algorithm provides resource allocation policies which maximizes energy efficiency This efficiency is further increased by solving the optimization problem using Particle swarm optimization (P.S.O) [2].Optimum resource allocationpolicies are obtained using PSO.

2. Particle Swarm Optimization

Particle swarm optimization (PSO) is a computational method in which optimization is done by trying to improve a candidate solution problem at each iteration with respect to a given quality measure of quality. It is a population based method. Here the population of candidate solutions, are known as particles. The objective of PSO is to find a solution for a constrained minimization problem based on a particularcost function.

Here the state of the algorithm is represented by a population, which varies in each iterationtill some criterion is met. Here, the population P={p_1,…,p_n} is the set of feasible solutions and is referred to as swarm. These feasible solutions p_1,…,p_n are referred to as particles, given by p_i = (P_i, R_i, ρ_i); i={1,2,..n}. A set of feasible solutions is considered as search space in which these particles move. The number of particles generally selected is between 10 and 50 in practical, for solving optimization problems.

The population is not changed from generation to generation in PSOs instead, the same population is maintained, by updation of the particle positions at each. In PSOs the particles "interact", or "influence" each other.

x_i(t) … the position (a vector which is d-dimensional)
p_i (t) …the 'historical' best position
l_i (t) …the neighbouring particles' historical best position; it represents the historical best known position of the entire swarm in case of fully connected topology
v_i (t) …the velocity; ie.,the step size acrossx_i (t) and x_i (t+1)
When the algorithm starts, initial velocities are set as 0, or some small values randomly and the initial particle positions are selected in a random manner.

PSO parameters:
w: it is the damping factor known as inertia weight whose value decreases from around 0.9 to around 0.4 during computation.
c_1,c_2 : Acceleration coefficients generally takes value between 0 and 4.
The velocity of the particle is updated as per the equation
v_i (t+1) =$c_2 u_2$ (l_i (t)-x_i(t)) + $c_1 u_1$ (p_i (t) -x_i(t)) + w(t)v_i (t) (15)
where, u_1 and u_2 represent random variables according to uniform distribution U(0,1). The first portion of the equation for velocity update is known as the personal component, the middle one represents the inertia term, third one represents the inertia term.
The i^{th} particle position is updated based on the equation :
x_i(t+1)= v_i(t+1)+v_i(t) (16)
The termination of this algorithm either occurs once the fitness values of the particles in the population becomes close enough or when a fixed number of iterations are reached, based on a given cost function. Here we formulate the cost function Z as
Z=1/F_{eff}(R, P, ρ) (17)

Subjected to constraints C1 to C7.
By using this cost function, we solve the optimization problem using PSO to find the optimum resource allocation policies (R^*, P^*, ρ^*) thereby maximizing the energy efficiency.

IV. Simulation Results

The simulation results using MATLAB v2018b are discussed here.

Nodes were clustered using LEACH (Low Energy Adaptive Clustering Hierarchy) algorithm. Hundred (100) nodes were deployed in an 100m* 100m area. Position of the sink node was fixed at (50,50). Each nodes has an initial energy E_0 of 0.5J. The node distribution is random.

1. Energy efficiency vs no: of iterations

Fig 3 shows the comparison of energy efficiency vs no: of iterations for ResAll algorithm and Particle Swarm Optimization. As seen in Fig. 3, on comparing with Resource Allocation algorithm, Particle Swarm Optimization is seen to be more effective, since optimal resource allocation policies are obtained with higher energy efficiency at the same number of iterations. This is achieved by by improving the solution of the cost function Z at each iteration with respect to thegiven constraints.
Maximum energy efficiency of 12Mb/J is obtained by using PSO while that obtained by using ResAll algorithm is 8M/J.

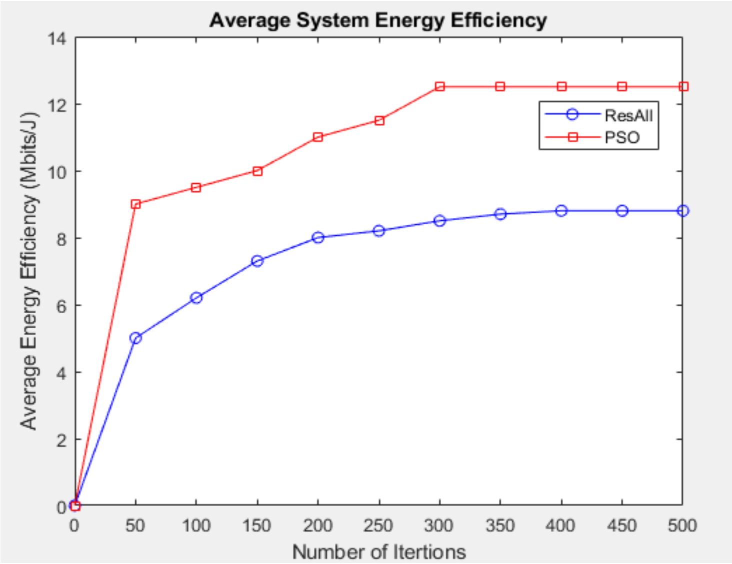

Fig 3: Energy efficiency vs no: of iterations

2. Simulation settings for ResAll

TABLE 1

Parameter	Values
W	200Mbps
e	0.02
P_{ij}^{min}	0.3dBm
R_{min}	50 Mbps

3. Simulation Settings for PSO

TABLE 2

Parameter	Values
w	1
c_1	1.5
c_2	2

V. Conclusion

The ever increasing ubiquitous applications of wireless sensor networks leads energy scarcity in the network, which is a serious threat to the lifetime of the network. In order to solve this issue, here, Simultaneous Wireless Information and Power Transfer (SWIPT) technique is applied to a MWSN. The nodes were clustered using LEACH algorithm. A resource allocation algorithm is designed by considering power splitting capabilities of relay nodes and cluster heads. Optimal Resource allocation policies are found out using Particle swarm optimization. Maximum system energy efficiency is achieved by balancingtransmit power, data rate, power splitting ratio and energy efficiency. This is achieved by framing a cost function and then improving the solution to the cost function at each iteration with respect to the constraints. Simulation results shows that the energy efficiency is further increased by solving the resource allocation problem using particle swarm optimization

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