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Maximizing energy efficiency using Dinklebach's and particle swarm optimization methods for energy harvesting wireless sensor networks

K MOHAIDEEN PITCHAI

Department of Computer Science and Engineering, National Engineering College, Kovilpatti, Tamilnadu 628503, India
e-mail: kmpcse@nec.edu.in

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Abstract. Recently, new ideas for harvesting energy of the sensor nodes from the surroundings are proposed. As compared to these renewable energy sources, radio frequency (RF) signals are widely considered as a promising solution to provide power to low-powered sensor nodes in a continuous manner. Here the energy efficiency of the Wireless Powered Sensor Network (WPSN) is viewed as the maximization problem, and it is derived as a nonlinear fractional programming problem. Also, it is non-convex and hence, it is challenging to solve. Dinklebach's method is used to transform the concave-convex fractional problem into a convex optimization problem with the usage of methods in convex optimization theory. Also, an intelligent algorithm based on Particle Swarm Optimization (PSO) is provided to solve the energy efficiency maximization problem systematically and distributively. The simulation results show that the proposed algorithms based on Dinkelbach's method and the PSO method achieve maximum energy efficiency.

Keywords. Dinklebach's method; particle swarm optimization; energy efficiency; wireless sensor network; maximization problem; energy harvesting.

1. Introduction

Wireless Sensor Networks (WSNs) support continuous monitoring from ambient environments, where the sensor nodes collect and transfer data to the sink node. However, the sensor nodes consume more energy for data gathering and transmission, and, quickly the level of energy of those nodes is drained if it operates over long periods. The recharging of the nodes may not be feasible since these are deployed in critical circumstances [1]. Therefore, new ideas for harvesting the energy of the nodes from the surroundings are proposed. The nodes will collect energy from various energy sources like solar, wind, and radio frequency (RF) signals. These sources directly depend on weather conditions, which results in the generation of power in an unstable manner [2]. Also, those sources will require massive infrastructures like wind turbines and solar panels. As compared to these renewable energy sources, RF is widely considered as a better solution to provide power to low-powered sensor nodes in a continuous manner [3].

In [4], a new paradigm named Wireless Powered Sensor Network (WPSN) has been proposed where the sink nodes provide power to the low power sensor nodes wirelessly, and those nodes harvest energy for them. There is a lot of related literature on WPSN [5–8]. A protocol "harvest and energy" was proposed in [9] and [10] where the sensor nodes harvest energy from hybrid access points (H-APs) in multi-user WPSN environments. Thus the nodes maximize their harvested energy from the H-APs and are also guaranteed for quality information dissemination. The secrecy rate among the nodes was maximized in [11] in a single–user consideration. However, in [12] and [13], the multi-user WPSN was considered.

2. Related works

Hieu and Kim [14] developed a geographic routing method named Stability Aware Geographical Routing in Energy Harvesting (SAGREH) to improve the energy harvesting ability of sensor networks based on the selection of routes' link quality. It is measured by considering location information and the residual energy. This protocol improves the average energy consumption, hop count, and delivery ratio. Li and Shi [15] proposed an Intelligent Solar Energy-Harvesting system for sensor nodes deployed in remote which uses solar power. Also, the nodes use the lithium battery as an additional power source. Here the trigger-based circuits are used when the life of the lithium battery is drawn out. These circuits have two sub-circuits namely the charging sub-circuit and control sub-circuit.

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Yin Wu and Wenbo Liu [16] maximized the working performance of the sensor network under energy harvesting constraints. They proposed a genetic-based unequal clustering algorithm for energy harvesting sensor networks. Initially, the base station forms clusters of different sizes and then the cluster heads are selected in which the size of the cluster heads near to the base station is of small size. Then the base station constructs an optimal route among the cluster heads. Their simulation results show that there is a significant improvement in the balance of network energy consumption and packet delivery ratio. Zhi Ang Eu *et al* [17] designed an opportunistic routing protocol for multi-hop energy harvesting sensor networks. This protocol accounts for the energy constraints to recharge the nodes once they get depleted. It chooses an optimal forwarder using the regioning approach for identification of the awaken nodes which cannot be determined well in advance. This protocol increases the throughput efficiency as compared with other non-opportunistic routing protocols. Yao Yukun *et al* [18] proposed a clustering algorithm based on energy harvesting using solar power. This algorithm executes a restoration mechanism when the nodes' harvesting energy reaches the energy threshold. It re-elects the cluster head in the next round based on the current energy harvesting level of the nodes. This algorithm outperforms energy-balanced routing in terms of the number of alive nodes and data delivery ratio.

In all these works, a single antenna was used at the base station. Recently multiple-antenna technology is focused on the sink node, which will improve the quality of the transmission. In this paper, a WPSN system is considered, where a single antenna node harvest energy initially from a multiple-antenna base station node and then transmit the collected data to the base station. Thus all sensor nodes will send their data to the base station node with less energy consumption.

3. System model

The proposed network model considers the multiple antennas based Wireless Powered Sensor Network (WPSN) as shown in figure 1. The single-antenna sensor nodes sense the information from their surrounding environment. The sink node supplies the electrical energy to all the sensor nodes in Wireless Energy Transfer (WET) phase.

The sensor nodes send their sensed data to the sink node in Wireless Data Transmission (WDT) phase. The sink node has a vast energy source, and it supplies energy sufficiently to the sensor nodes [19]. The sensor nodes cannot have sufficient energy to transmit their sensed information and perform their operations. Hence it is essential, the sensor nodes should harvest energy received from the sink node and utilize a part of the energy for their operations, and the remaining energy will be stored to perform their

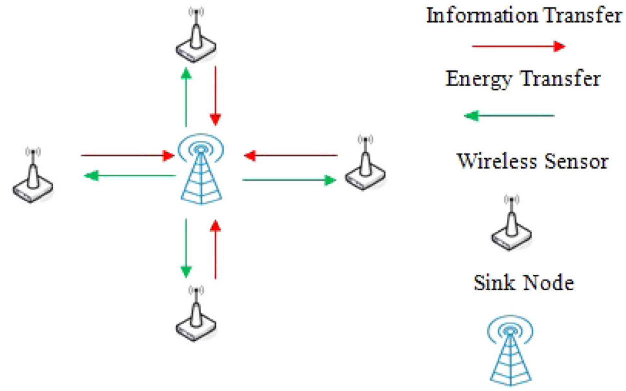

Figure 1. Multi-antenna wireless powered sensor network.

normal operations [20]. Figure 2 shows the architecture model of the proposed system where the time duration of transmission (T) is divided into two different intervals, namely WET and WDT. Consider the number of sensor nodes that are covered by a sink node is denoted as 'k'. The duration of the WET interval is $T_E = \sigma T$ and the duration of the WDT interval is $T_D = (1-\sigma)T$ where $0 \leq \sigma \leq 1$ and it satisfies $T_E + T_D \leq T$.

3.1 *Wireless energy transfer (WET)*

The sink node transfers energy to the 'k' sensor nodes in this phase. The energy harvested by each sensor node in this phase is stored in rechargeable batteries of the sensor node. In this phase, the RF energy is transferred from the sink node to 'k' sensor nodes through its multiple antennas (n). Let w denote the beam weight of the antenna of the sink node and $w = [w_1, w_2, \ldots\ldots, w_k]$ denotes the beam weight vector. Thus the transmission power of the antenna of the sink node is

$$P_t = \|w\|^2 \text{ such that } \|w\|^2 \leq P_{at} \tag{1}$$

P_at is the maximum per-antenna transmission power of the sink node. The channel gain between the sink node and sensor node 'i' is given by h_i. The RF energy of the received signal by the i^{th} sensor node is given by

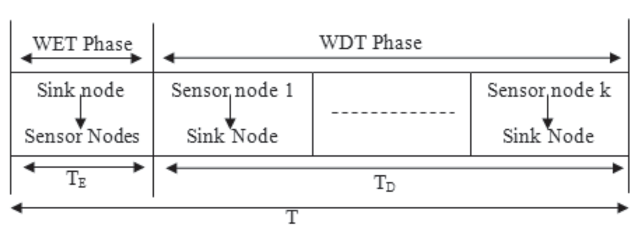

Figure 2. Illustration of WET and WDT intervals.

$$y_i = h_i w + g_i \quad \forall i \in (1, 2, \ldots k) \tag{2}$$

Here g_i is the Gaussian noise power. Also, w satisfies the constraint that $\|w\|^2 = P_{at}$. From equation 2, the received power of node i is calculated as

$$\begin{aligned} P_r(i) &= \|y_i\|^2 - PL(d) = \|h_i w\|^2 - PL(d) \\ &= \|h_i\|^2 P_{at} - PL(d) \quad \forall i \in (1, 2, \ldots k) \end{aligned} \tag{3}$$

The path loss at distance d, PL(d) (expressed in dB) can be calculated using the equation 4 when the sensor nodes are in the line-of-sight (LOS) and using the equation 5 when sensors are non-line-of-sight (NLOS).

In the case of clear line-of-sight, the omnidirectional antennas transmit the power to the receiver node. With a LOS propagation channel, there is no object on the signal path causing penetration, refraction, diffraction, and reflection loss. As a result, the overall path loss is smaller than in a non-line-of-sight (NLOS) channel when compared at the same distance. The free-space model is a theoretical model, where the path loss is only determined by distance and frequency. The fundamental assumption behind the free-space model is that there are no obstacles between or beside the transmitter and receiver. The free space path loss can be defined as

$$PL(d) = \frac{P_t}{P_r(i)} G_t G_r(i) = \left(\frac{4\pi d}{\chi}\right)^2 \tag{4}$$

Here, d is the distance between the transmitter and the receiver, λ is the wavelength and G_t and G_r are the transmitter and receiver antenna gains, respectively.

The two-ray path model is used in the case of non-line-of-sight. The two-ray model considers both the direct path and the ground reflected waves. Assuming the antenna heights are small compared with the total path length; the path loss in the two-ray model can be expressed in decibels as

$$PL(d) = 40\log_{10}(d) - 20\log_{10}(H_r) - 20\log_{10}(H_t) \tag{5}$$

Here, d is the distance between the transmitter and the receiver; H_t and H_r are defined as the height of the transmitting and receiving antenna, respectively.

The position of sensor nodes is assumed to be unknown or uncontrollable due to the dynamic nature of the network. The high energy transmission is achievable over long distances (in kilometers) by unidirectional antennas when there is a clear line-of-sight path exists between the sink node and the sensor node. But this requirement (kilometer range) is not desirable for wireless sensor networks; hence omnidirectional antennas are used in this proposed work due to their tiny receiver size and are appropriate for low-power sensor nodes with low sensing activities. Also, the Omni-directional antennas are suitable for the nodes whose location is unknown [21].

Here the sensor nodes are uniformly scattered around the sink node and they are having mobility. Due to this scenario, omnidirectional antennas are used. These types of antennas are most suitable for applications when the locations of sensor nodes are either unknown or uncontrollable. Also, these types of antennas are tiny in size. But their power transfer efficiency will rapidly drop due to an increase in the distance [22]. An omnidirectional antenna with transmission radius $r1$ (area of a circle with radius $r1$) will consume transmission power P is defined in equation 6, while a uni-directional antenna with beam width α and the uni-directional range in the direction of peak gain $r2$ will consume transmission power P is defined in equation 7 [23].

$$P = c1\pi(r1)^2 \tag{6}$$

$$P = c2\frac{\alpha}{2}(r2)^2 \tag{7}$$

Unidirectional radiation is not suitable for a WSN due to several undesirable requirements, such as LOS, complicated tracking mechanisms, and the inherent large scale of devices. But unidirectional antennas provide effective power transmission over long distances (in kilometers) [24]. Hence a combination of techniques used i.e directive antennas are used for sink nodes and omnidirectional antennas for sensor nodes or vice-versa. Omni-directional radiation is only appropriate for ultra-low-power sensor nodes with very low sensing activities.

The power of energy harvesting is a function of received power. Thus the power of energy harvesting of the i^{th} sensor node is given by

$$P_h(i) = \eta_i \sigma T \|h_i\|^2 P_{at} - PL(d) \quad \forall i \in (1, 2, \ldots.k) \tag{8}$$

Where η_i denote energy harvesting efficiency which depends on the design of sensor i.

3.2 *Wireless data transfer (WDT)*

Figure 3 shows the antenna in the sink node is configured with separate receiver architecture. The energy transmitter and information receiver in the sink node are equipped with separated antennas. The antenna in the sensor node is configured with co-located receiver

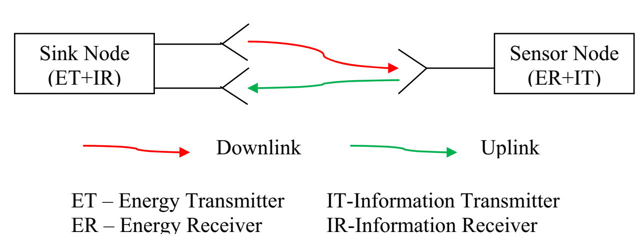

Figure 3. Antenna configuration.

architecture. The energy receiver and information transmitter are separate circuits but they share the same antenna. The energy is transferred through downlink and the information is transferred through the uplink. Due to co-located receiver architecture, the sensor node uses a power splitting scheme to divide the radio frequency signal into two portions namely the energy harvesting portion and information processing portion.

Let $P_t(i)$ is the transmission power of the i^{th} sensor node to transmit its collected information to the sink node. The received RF energy signal by the sink node is given by

$$y = \sqrt{P_t(i)}h_i w + g \quad \forall i \in (1, 2, \ldots..k) \tag{9}$$

Here g is the Gaussian noise power. Also, w satisfies the constraint that $\|w\|^2 = P_{at}$. From equation 9, the received power of sink node is calculated as

$$\begin{aligned} P_r &= \|y\|^2 - PL(d) = P_t(i)\|h_i w\|^2 - PL(d) \\ &= P_t(i)\|h_i\|^2 P_{at} - PL(d) \quad \forall i \in (1, 2, \ldots .k) \end{aligned} \tag{10}$$

The path loss at distance d, PL(d) (expressed in dB) can be calculated using the equation 4 when the sensor nodes are in line of sight (LOS) and using the equation 5 when sensors are not line of sight (NLOS). The consumption power of the i^{th} sensor node is given by

$$P_c(i) = (1 - \sigma)TP_t(i) + \rho_i B_i \tag{11}$$

Here ρ_i is the energy consumption per bit for information processing and B_i is the amount of data collected at the i^{th} sensor node. The energy storage of sensor node i (E_i) depends on the harvested and consumed power. Also it changes over time to time. It can be calculated as

$$\frac{dE_i}{dt} = P_s(i) = P_h(i) - P_c(i) \tag{12}$$

The energy storage of the sensor node is limited and hence, the value of the stored energy cannot exceed the maximum value of the stored energy E_{max}. If the value of the stored energy goes below the value of the minimum stored energy E_{min}, the sensor node goes to sleep state. Hence the sensor nodes should have minimum stored energy for continuous operation ($E_i \geq E_{min}$). Hence, the throughput (R_i) achieved at the sink node from the sensor node i can be calculated as

$$R_i = BW \log_2\left(1 + \frac{P_t(i)\|h_i\|^2 - PL(d)}{\sum_{j=1\&j\neq i}^{k} P_t(j)\|h_j\|^2 \psi^2}\right)(1 - \sigma)T \tag{13}$$

Here ψ is the noise variance at the sink node and 'BW' is the bandwidth of the channel.

3.3 *Problem formulation*

The energy efficiency of the WPSN is considered as the maximization problem and here it is derived as a nonlinear fractional programming problem [12]. Also, it is not strongly convex optimized and hence, it is not easy to solve. The throughput of the whole network (R_N) is calculated by

$$\begin{aligned} R_N &= \sum_{i=1}^{k} R_i \\ &= BW \log_2\left(1 + \frac{\sum_{j=1\&j\neq i}^{k}\left(P_t(j)\|h_j\| - PL(d)\right)}{\psi^2}\right) \\ &\quad \times (1 - \sigma)T \end{aligned} \tag{14}$$

There are two parts in the total energy consumption of WPSN. The first one is the energy wastage during the RF energy transmission in the WET interval (E_{WET}). The next part is the energy loss due to the data transmission in the WDT interval (E_{WDT}). The total energy consumption of the whole network is given as

$$\begin{aligned} E_{TOTAL} = E_{WET} + E_{WDT} &= \sum_{i=1}^{k} \eta_i \|h_i\|^2 P_{at}\sigma T - PL(d) \\ &+ \sum_{i=1}^{k} P_t(i)(1 - \sigma)T + \rho_i B_i \end{aligned} \tag{15}$$

The energy efficiency of the WPSN is calculated as the ratio of throughput to total network energy consumption. Hence the energy efficiency maximization problem is defined as

$$\max_{P_t, \sigma, P_{at}} \left(\frac{BW \log_2\left(1 + \frac{\sum_{i=1}^{k}(P_t(i)\|h_i\| - PL(d))}{\psi^2}\right)(1 - \sigma)T}{\sum_{i=1}^{k} \eta_i \|h_i\|^2 P_{at}\sigma T - PL(d) + \sum_{i=1}^{k} P_t(i)(1 - \sigma)T + \rho_i B_i} \right) \tag{16}$$

Subject to equations 8, 11 and 13.

The equation 14 cannot be solved optimally due to the lack of convexity. The non-convex problems are not solved using any standard procedures. Here an equivalent transformation is produced through non-linear fractional programming to find an efficient solution for the problem (equation 16).

3.4 *Solution to optimization problem*

Dinklebach's method [14] is used to transform the concave-convex fractional problem into a convex problem with the usage of theory of convex optimization. Hence the maximization function (equation 16) is transformed into subtract form which is defined as follows.

$$q^* = \left(\frac{BW \log_2\left(1 + \frac{\sum_{i=1}^{k} (P_t(i)\|h_i\| - PL(d))}{\psi^2}\right)(1-\sigma)T}{\sum_{i=1}^{k} \eta_i \|h_i\|^2 P_{at}\sigma T - PL(d) + \sum_{i=1}^{k} P_t(i)(1-\sigma)T + \rho_i B_i} \right) \tag{17}$$

Here the maximal energy efficiency q^* is defined without loss of generality.

Theorem *The energy efficiency q* is maximal if and only if*

$$\max_{P_t,\sigma_t,P_{at}} \Bigg(BW\log_2\left(1 + \frac{\sum_{i=1}^{k}(P_t(i)\|h_i\| - PL(d))}{\psi^2}\right)(1-\sigma)T - q^*\left(\sum_{i=1}^{k} \eta_i \|h_i\|^2 P_{at}\sigma T - PL(d) + \sum_{i=1}^{k} P_t(i)(1-\sigma)T + \rho_i B_i\right)\Bigg) \tag{18}$$

Proof: From equation 8 and equation 11 that the value of numerator and denominator of equation 14 are positive and energy efficiency is well defined. Also, the numerator of equation 16 is in differentiable form and also non-negative. The denominator of equation 16 is in differentiable, and non-positive. Also, the constraints of convex set are compact.

3.5 *Algorithm for energy efficiency maximization*

Here Dinklebach's method based algorithm is proposed to solve the problem. This algorithm is an iterative process to find the suitable value of q^* by solving the equation 17. This process stops until the value of equation 17 is equal to a predetermined threshold value, which is described in the algorithm. Thus the proposed algorithm converges to optimal energy efficiency. Also, the transformed optimization problem (equation 17) is convex. In addition, an intelligent algorithm based on Particle Swarm Optimization (PSO) [6] is provided to solve the energy efficiency maximization problem (equation 16) systematically and distributively.

Algorithm: Dinkelbach's method for energy efficiency maximization

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Require:
n : maximum number of iterations
ϵ : threshold value
j : iteration index
q : energy efficiency
q^* : maximal energy efficiency
1. initialize: $\epsilon > 0$, $j = 1$, $q = 0$
2. while $j \leq n$ do
3. solve the maximization problem (equation 17) for the given value of q and assign it to a temporary variable x^*
4. if $x^* > \epsilon$ then
5. $q^* = \left(\frac{BW \log_2 \left(1 + \frac{\sum_{i=1}^{k} (P_t(i) \| h_i \| - PL(d))}{\psi^2} \right) (l - \sigma) T}{\sum_{i=1}^{k} \eta_i \| h_i \|^2 P_{at} \sigma T - PL(d) + \sum_{i=1}^{k} P_t(i)(l - \sigma) T + \rho_i B_i} \right)$
6. else
7. set $q = \left(\frac{BW \log_2 \left(1 + \frac{\sum_{i=1}^{k} (P_t(i) \| h_i \| - PL(d))}{\psi^2} \right) (l - \sigma) T}{\sum_{i=1}^{k} \eta_i \| h_i \|^2 P_{at} \sigma T - PL(d) + \sum_{i=1}^{k} P_t(i)(l - \sigma) T + \rho_i B_i} \right)$ and
$j = j + 1$
8. end if
9. end while

PSO based algorithm for solving energy efficiency maximization problem

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Input:
1. $t = 0$, $lo_i = x_i$ and $v_i = 0$ $\forall i \in (1, 2, \ldots .p)$
2. repeat
3. $t = t + 1$
4. For all particle $\forall i \in (1, 2, \ldots .p)$ do
5. calculate the particle's updated velocity
6. $v_i(t) = \omega v_i(t-1) + c1|\mathrm{o_i}(\mathrm{t}-1) + \mathrm{c2gl_i}(\mathrm{t}-1)$
7. $v_i(t) = \min\{v_{\max}, \max\{v_i(t), -v_{\max}\}\}$
8. restrict each element in vector v_i in $[-v_{max}, v_{max}]$
9. Update particle's new position $x_i(t) = x_i(t-1) + v_i(t-1)$
10. $x_{i,k+1}(t) = \min\left\{1, \min_{1 \leqslant l \leqslant k} \frac{p_t(l) \| h_l \|^2 (l - \sigma) T}{\eta_l \| h_l \|^2 p_{at} \sigma T - PL(d) + p_t(l)(l - \sigma) T + \rho_l B_l}\right\}$
11. If $EE(x_i(t)) > EE(lo_i)$
12. Update $lo_i = x_i$
13. If $EE(x_i(t)) > EE(gl_i)$
14. Update $gl_i = x_i$
15. End for
16. Until $t > L$
17. return gl_i

Let $x_i = [x_{i1}, x_{i2}, \ldots\ldots, x_{ik}]$ denote the particle i's position $(1 \leq i \leq p)$ where p denotes the number of particles. Let $v_i = [v_{i1}, v_{i2}, \ldots\ldots, v_{ik}]$ denote the particle i's velocity. lo_n represents the n^{th} particle optimal local position and gl_n denote the global best position which is obtained by collecting information from all the particles. ω, $c1$ and $c2$ are constants. ω is the inertia weight. $c1$ and $c2$ are tuning parameters. η is distributed uniformly in the interval 0 and 1. $EE(x_i(t))$ denote the value of the solution at the position $x_{i,k+i}(t)$. L denotes the number of iterations.

The effect of the PSO algorithm depends on the fitness function evaluated using the equation (line number 9). This fitness function also depends on the distance between the sensor node and the sink node, the characteristics of the channel when the sensor nodes are in line-of-sight or not line-of-sight. The channel gain (h_i) in equation (line number 9) depends on the distance between the sensor node and the sink node. Path loss models capture the dependence of the channel gains on the distance between transmitter and receiver. In particular, in path loss models the channel gain between two nodes separated by a distance of d is deemed proportional to d^n, where n is known as the path loss exponent [25–28]. Table 1 contains the symbols and their descriptions used in the proposed methodology.

3.6 *Complexity analysis*

The time complexity of the proposed Dinkelbach method is $O(n)$. Since the maximum number of iterations of line 2 of the algorithm is '$n+1$' where 'n' is the number of sensor nodes. The time complexity of the proposed PSO algorithm is $O(n^2)$. Since the maximum number of iterations of line 2 and line 4 of the algorithm is 'n' where 'n' is the number of sensor nodes. Thus the time complexity of the proposed Dinkelbach's and PSO method is $O(n^2)$ where 'n' is the number of sensor nodes.

4. Simulation results

The performance of the proposed algorithms based on Dinkelbach's method and the PSO method for energy efficiency maximization is simulated using the MATLAB tool. The simulation on MATLAB is used to claim that the mathematical equations developed in the proposed algorithms are working fine to achieve maximum energy. But to check the performance of networks like network delay, energy efficiency and throughput, the network simulation tool NS2 is used. For the PSO method, initial values of $\omega = 0.7$ and $c1 = c2 = 1.494$ were used where the faster convergence can be obtained in the proposed algorithm [29, 30]. The channel gain h_i is defined as $h_i = 10^{-1} d_i^{-2}$ where d_i is the distance between the i^{th} sensor node and the sink node. $d_i = 0.5\,m$.

Figure 4 shows the average energy efficiency of the proposed PSO method, when the number of antennas, N, is 10. It is observed that the proposed method achieves convergence after 10 iterations. In this case, the convergence rate of the algorithm remains unchanged with the P_t value

Table 1. Variables and their descriptions.

Variable	Description
B_i	Amount of data collected at i^{th} sensor node
BW	Bandwidth of the channel
$c1$,$c2$	Constants
d_i	Distance between sensor node i and sink node
$EE(x_i(t))$	Fitness value of i^{th} particle at t^{th} time step
E_i	Energy stored in i^{th} sensor node
E_{max}	Maximum value of the stored energy
E_{min}	Minimum value of the stored energy
E_{TOTAL}	Total energy consumption of the whole network
E_{WDT}	Energy loss in WDT interval
E_{WET}	Energy loss in WET interval
g	Gaussian noise power of sink node
g_i	Gaussian noise power of i^{th} sensor node
gl_n	Optimal global position of n^{th} particle
G_r	Gain of receiver antenna
G_t	Gain of transmitter antenna
h_i	Channel gain for both uplink and downlink
H_r	Height of the receiver antenna
H_t	Height of the transmitter antenna
k	Number of sensor nodes covered by a sink node
L	Maximum number of iterations
lo_n	Optimal local position of n^{th} particle
n	Number of antennas in the sink node
p	Number of particles
P_{at}	Maximum per-antenna transmission power of the sink node
$P_c(i)$	Consumption power of i^{th} sensor node
$P_h(i)$	Energy harvesting power of i^{th} sensor node
$PL(d)$	Path loss at distance d
P_r	Received power of sink node
$P_r(i)$	Received power of i^{th} sensor node
P_t	Transmission power of the antenna of the sink node
$P_t(i)$	Transmission power of i^{th} sensor node
R_i	Throughput of sink node calculated from data received at i^{th} sensor node
R_N	Throughput of the whole network
T	Time duration of transmission
T_D	Time duration of WDT interval
T_E	Time duration of WET interval
v_i	Velocity of i^{th} particle
v_{max}	Upper bound of the velocity of each particle
w	Beam weight of antenna of sink node
x_i	Position of i^{th} particle
y	RF energy of received signal of sink node
y_i	RF energy of the received signal of the i^{th} sensor node
η_i	Energy harvesting efficiency of i^{th} sensor node
λ	Wavelength of the channel
ρ_i	Energy consumption per bit of i^{th} sensor node
ψ^2	Noise variance at the sink node
ω	Inertia weight

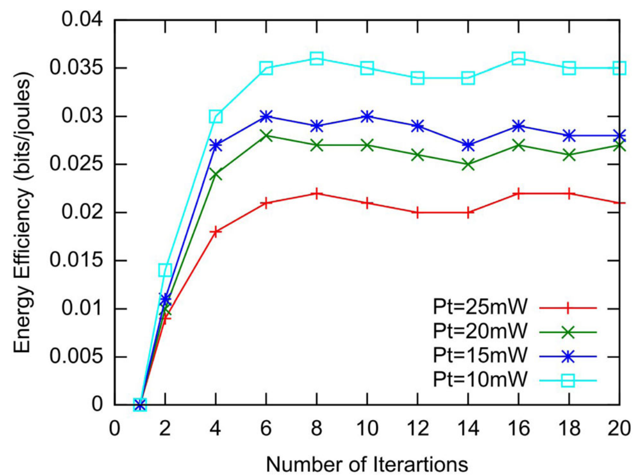

Figure 4. Energy efficiency by varying transmission power.

varies from 10mW to 25mW. Furthermore, it is observed that the increase of the P_t values corresponds to the decrease in the average energy efficiency. The reason behind such a trade-off is the channel interference at the receiver side reduces the total number of bits received by the receiver. Also, the average energy efficiency is directly proportional to the iterations for a given P_t value.

The total network delay is measured for each round of data collection in the energy harvesting network to evaluate the formulated optimization problem. Figure 5 shows the time interval of data collection is divided into five slots according to communication mode. Since the data collection time includes the transmission of sensing data from the sensor node to the sink node. The optimization problem is evaluated according to the parameter settings of table 2 under scheduled multi-channel (SMC), contention-based multi-channel (CMC) schemes with energy transfer and no energy transfer, respectively.

Figure 6 shows the throughput of the proposed algorithm and it increases with the number of sensor nodes as compared with the SAGREH protocol [14]. The throughput of the proposed Dinklebach's and PSO method is 750 kbps when the network of size 100 nodes whereas the SAGREH

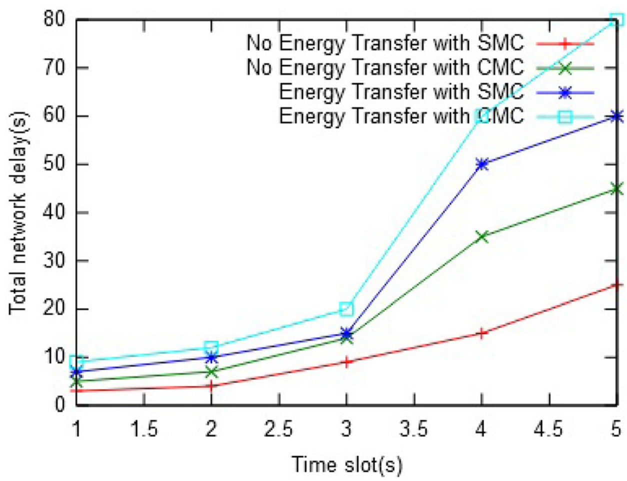

Figure 5. Total network delay by varying channel type.

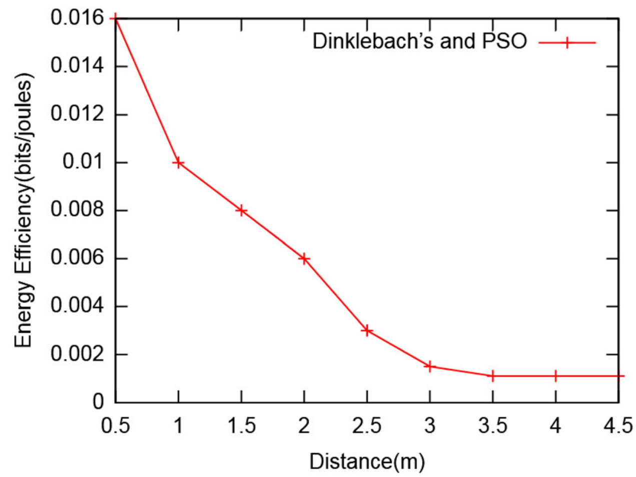

Figure 7. Energy efficiency by varying distance.

Table 2. Simulation parameters.

Parameter	Value/method
Area of deployment	$100 \times 100\,\mathrm{m}^2$
Location of sink node	(75,50)
Size of network	20–100
Initial power of nodes	4 W
Transmission power (P_t)	10–25 mW
Maximum per-antenna transmission power (P_{at})	1 W
Energy harvesting efficiency (η_i)	0.4
Noise variance (ψ)	– 70 dBm
Number of iterations (L)	20
Maximum velocity (V_{max})	10^{-3}
Bandwidth of the channel (BW)	100 MHz

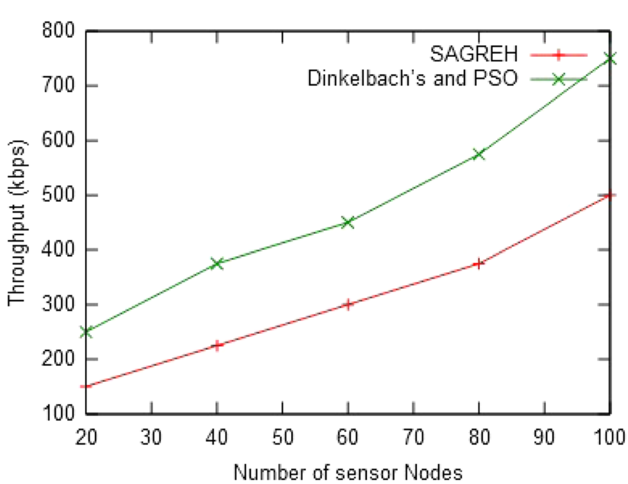

Figure 6. Throughput.

protocol achieves 500 kbps. During the design of the algorithm, the maximum per antenna transmission power is considered and hence the throughput is increased with the increasing of nodes.

Figure 7 shows the variations of energy efficiency as a function of the distance between the sensor nodes and the sink node for clear LOS. The energy efficiency corresponding to the best particle is recorded for different values of distances. The obtained energy efficiency values for different values of distances are plotted and it is observed that the proposed PSO-based algorithm converges to 0.0011 joules after a 3-meter distance. While increasing the distance, the energy efficiency value is decreased with minor variations because the proposed PSO-based algorithm runs on the sink node which is typically having sufficient power for communication and computation processes.

5. Conclusion

Here a WPSN is considered where the sensor nodes harvest energy from an N-antenna base station and then transmit the sensed information to the sink node. The sensor nodes store the harvested energy in their rechargeable batteries. Also, energy efficiency is considered a maximization problem, which is viewed as a non-linear fractional programming problem. An algorithm based on Dinklebach's method is proposed to solve this problem. An intelligent algorithm based on PSO is also used to solve this problem. The simulation results show that the average system energy efficiency of the proposed PSO method is increased when the transmission power of the nodes is decreased. In addition, the convergence speed of the proposed algorithm is unchanged for different values. Also, the throughput and end-to-end delay of the proposed Dinklebach's and PSO method achieves maximum throughput and minimum end-to-end delay as compared to the SAGREH protocol.

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