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Optimal and Meta-Heuristic Algorithms for Object Tracking in Multi-Sink Wireless Sensor Networks

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Abstract: A Multi-sink Wireless Sensor Networks (WSNs) are being used in many applications due to its significant advantages over the single sink. One of the major applications in WSNs is object tracking due to its wide real-life applications such as wildlife animal monitoring and military area intrusion detection. Many of the prior researches on object tracking in WSNs have focused on tracking the location of objects accurately but few researches on data reporting. In this work, we propose an efficient data reporting method for object tracking in multi-sink WSNs. Since the energy resources are limited in the sensor nodes, full utilization of resources with minimum energy remains the main consideration when a WSN application is designed. Moreover, Network reliability has become an essential aspect that should be considered beside energy conservation to guarantee the quality of network. Consequentially, this paper aims to achieve both minimum energy consumption in reporting operation and balanced energy consumption among sensor nodes for WSN lifetime extension. Furthermore, data reliability is considered in our model where the sensed data can reach the sink node in a more reliable way. This work first formulates the problem as 0/1 Integer Linear Programming (ILP) problem, proposes a new scheme for selecting the optimal sink for data transmission and then proposes a swarm intelligence for solving the optimization problem. Through simulation, the performance of the proposed approach is evaluated and analyzed compared with the previous work which is related to our topic such as DTAR, NBPR, and MSDDGR protocols.

Keywords: object tracking; swarm intelligence; multi-sink, reliability; energy balance; traffic aware.

1. Introduction

WSNs are ad-hoc networks that have a wide variety of promising applications. A Wireless sensor network (WSN) is composed of large number of tiny, inexpensive, and battery operated sensor nodes which densely deployed over a geographical area. Such nodes are essential for monitoring physical or environmental conditions such as temperature, motion, and relative humidity, perform simple computation, and communicate via wireless multi-hop transmission technique to report the collected data to one or more sink nodes [1].

It is well known that the nodes in WSN have severe resource limitations such as energy, bandwidth, and storage resources. Energy is an extremely crucial resource because it not only determines the sensor nodes lifetime, but the network lifetime as well [2]. In WSNs, the major source of energy consumption is communication [3]. Consequently, most of the existing routing techniques in WSN attempt to find the shortest path to the sink to minimize energy consumption. As a result, highly unbalanced energy consumption which leads to energy holes around the sink and significantly minimize network lifetime [4-5]. Therefore, designing energy-balanced routing technique plays a crucial role in WSNs [4,5].

One of the major technical challenges for some critical applications of WSNs is to provide a reliable data transmission in dynamic and harsh environment [6-8]. In harsh environment, the dynamic nature of wireless channel conditions or unexpected node failure may cause a loss of important information [9]. This prevents the sensor network from achieving its primary purpose which is data transfer and the network resources will be wasted due to the retransmission of the lost packets. Therefore, routing techniques should give priority to reliable transmission. At the same time, it is critical to reduce packet loss in WSNs which will improve the network throughput and energy-efficiency.

Congestion control is one of the most essential issues in WSNs [10,11]. In event-driven WSNs such as those used in object tracking application, nodes normally operate under low or idle load states and suddenly become active and transmit data packet when event occur. As a result, a part of the network becomes overloaded and often leads to congestion. Due to limited storage memory on sensor nodes, congestion in WSNs can lead to buffer overflow. Therefore, such a buffer overflow problem may result in loss of important information and thus more energy consumption and delay due to the retransmission of the lost packets. Consequently, it is a highly needed to consider buffer space when designing routing protocols in WSNs to spread data traffic away from the congested areas [12,13].

Many researches focus on the design of routing protocols in WSN, single sink is often chosen. However, WSNs with single sink still suffer from many problems. The main problem is that the energy consumption rate of the sensor nodes close to the sink is much higher than the remote one. Therefore, this leads to unbalanced energy consumption which result in energy holes near the sink and significant network lifetime reduction. Moreover, the invalidation of the sink node will inevitably lead to the failure of the whole network [14]. Consequentially, it may be infeasible in practice to use WSN with single sink. So, the WSN with multiple sink nodes has been proposed [15,16].

Multi-sink topology has significant advantages over single sink. Firstly, multi-sink usage can balance the energy consumption and effectively solve the energy hole problem which will prolong the network lifetime. Secondly, it more reliable than single sink, in multi-sink if any sink node failures due to any reason the data will be transmitted through other sinks [17]. Thirdly, deploying more sink nodes in the network relieves the traffic congestion problem to a certain extent. Finally, multi-sink usage reduces the average distance from sensor nodes to sink nodes, resulting in more energy saving and thus extend the network lifetime [18,19].

In the last two decades, optimization techniques inspired by swarm intelligence have gained much popularity [20]. They mimic the swarms' behaviour of social insects like bees and ants, the behaviour of other animal societies such as fish schools, or birds flocks as well [20]. Swarm intelligent systems are robust, scalable, adaptable, and can efficiently solve complex problems through simple behaviour [21] such as the shortest path finding. Ant Colony System (ACS) is considered one of the most important swarm intelligence techniques that can provide approximate solutions to optimization problems in a reasonable amount of computation time [20]. ACS [22] has been inspired from the food searching behaviour of real ants which can be utilized to find the shortest path in WSNs. Unlike other routing approaches [23], the ant colony optimization meta-heuristic proposed in the literature for WSNs is based only on local information of sensor nodes [24].

In particular, object tracking has become one of the most interesting applications of WSNs due to its wide real-life applications such as wildlife animal monitoring [25,26] and military intrusion detection [27]. The object tracking process consists of two critical operations. The first operation is monitoring, where the movement states of the mobile object is detected and tracked by the sensor nodes. The second operation is reporting, where nodes detecting the object report their observations to the sink node [28]..

Many object tracking researches have been dedicated to localization of objects and do not consider many other parameters such as reliable data reporting [29-33], nodes energy consumption, nodes energy balancing, and congestion control. Therefore, in this paper, we take such parameters collectively into consideration. We believe that considering such parameters will enhance the overall performance of the WSNs as well as advance the object tracking operation. Furthermore, as the size of WSNs increases, it becomes inefficient to collect all information with single sink. So, WSN with multi-sink has been considered in our proposal. To do so, our contributions in this paper focus on: 1) formulating the object tracking problem in large scale multi-sink WSN into 0/1 integer programming with previously mentioned parameters, 2) reducing energy consumption in reporting operation for WSN lifetime extension, 3) balancing of energy consumption among sensor nodes to maintain and balance of residual energy on sensor nodes as well, 4) enhancing data reliability where the sensed data can reach any sink node in a more reliable way , 5) Reducing the probability of buffer overflow by taking into consideration the sensors buffer space to reduce the number of dropped messages, 6) Introducing the principle about selecting the optimal sink for data transmission, and 6) introducing a Swarm Intelligence as a heuristic solution based energy reduction and reliability as well as load balancing to forward packets to the chosen sink.

The rest of this paper is organized as follows: The related work is discussed in section 2. Following this, the problem description is introduced in section 3. Then, section 4 describes the problem formulation. In addition, the solution approach is described in section 5. The simulation results are depicted in section 6. Finally, the conclusions are presented in section 7.**1. Introduction**

The introduction should briefly place the study in a broad context and highlight why it is important. It should define the purpose of the work and its significance. The current state of the research field should be reviewed carefully and key publications cited. Please highlight controversial and diverging hypotheses when necessary. Finally, briefly mention the main aim of the work and highlight the principal conclusions. As far as possible, please keep the introduction comprehensible to scientists outside your particular field of research. References should be numbered in order of appearance and indicated by a numeral or numerals in square brackets, e.g., [1] or [2,3], or [4–6]. See the end of the document for further details on references.

2. Related Work

This section focuses only on the most related work to the proposal of this paper. It starts by explaining the work presented in [10, 34, 36] which are the more related work to our proposed approach followed by the differences from our proposal.

[10] Presented a Dynamic Traffic Aware routing algorithm (DTAR) for multi-sink WSNs. This algorithm can balance the network traffic by detecting congested areas along the route and distributing packets along multiple paths consist of idle or under-loaded nodes. Although this scheme [10] is presented for multi-sink WSNs, it doesn't consider the principle about selecting an optimal sink for data transmission which considered the first step for the selection of the optimal routing path. Furthermore, it is found out that some issues are not considered. First of all, the reliable data transmission which becomes one of the most essential issues in WSNs is not considered. Indeed, ignoring such issue might increase the packet loss as well as can cause more energy consumption due to packet retransmission as a result of unstable paths which inevitably affects the network efficiency. Secondly, the approach suffers from energy unbalancing. This might cause an energy hole problem, where the sensor nodes near the sink will deplete their energy faster than those further away. Therefore, this uneven use of energy leads to a significant network lifetime reduction.

In NBPR (multi-sink probabilistic routing algorithm based on Naive Bayesian Classification model) [34], a multi-sink routing algorithm is presented. It takes the advantage of the Naive Bayesian Classification model to select the optimal routing in multi-sink sensor networks by means of probabilistic routing method. When the source node needs to transmit data to the sink, first of all, it select the optimal sink by means of Naive Bayesian Classification model mainly taking the transmission energy consumption and residual energy into account. Once the optimal sink is selected, the source node selects the relay node by probability which depends on the residual energy in the forwarding nodes. Furthermore, the forwarding node must choose the node whose hop count is smaller than it in order to avoid forming a loop.

Meanwhile, the analysis of NBPR algorithm [34] shows that some issues are not considered which are reflected as drawbacks. Firstly, the network reliability, as discussed above, this might increase the packet loss and packet retransmissions which affects the network efficiency. The second is the queue buffer size in which it has directly impact on network throughput and lifetime. Finally, node load which is an influential factor in the energy balance among sensor nodes from our point of view. That's to say, if more sensor nodes might choose the same node to relay their messages, more energy should be reserved for a node with heavier load. Therefore, taking residual energy and node load into consideration can balance residual energy among sensor nodes efficiently as proposed in [35]. Moreover, it selects the optimal sink by probability depends on the total residual energy of the nodes around each sink where, a part of energy resources at these nodes is used for sending this kind of information to each sink. This might affect the energy efficiency of the network.

Multiple Sink Dynamic Destination Geographic Routing (MSDDGR) algorithm has been given in [36]. When any node needs to send its data packet, it first selects the nearest sink as the current destination. Then, it selects a neighbor node closest to the chosen sink as the next hop. In addition, if any relay node sees that another sink is nearer to it, the current destination node will be changed to the new selected sink. However, MSDDGR algorithm doesn't consider some critical issues which regard as a drawback. The first is energy balancing, as described above; this might lead to unbalanced energy consumption in the network, which significantly minimize the network lifetime. The second issue is the network reliability which is one of the key issues in WSNs due to the high dynamics, limited resources, and unstable channel conditions. Thus, this might deteriorate the network performance as mentioned above. Finally, the packet buffer capacity of sensor nodes. As described above, this might increase the packet loss and packet retransmission which inevitably affects the network efficiency.

The proposed approach, develops, firstly, formulates the object tracking problem in multi-sink WSNs as into 0/1 integer programming for optimal solution. Then, a heuristic algorithm is developed to construct an efficient object tracking in multi-sink WSNs. It proposes a novel protocol based on energy reduction, reliability, and energy balance routing in multi-sink WSNs for object tracking. The proposed protocol consists of two steps which are the selection of the optimal sink and the selection of the relay nodes. The selection probability of the optimal sink depends on the transmission energy consumption and residual energy as the previous work in [34]. In our model, the energy consumption of data transmission is represented by hop count as in [34], where the less hop count implies the less energy consumption at a fixed transmission range. The difference from the previous work in [34] is that the minimum residual energy of sensor nodes on the paths used for a certain time interval to route data to each sink node reflects the residual energy on the routing paths to that sink where, the maximum minimum residual energy means the maximum residual energy on the routing paths to that sink. Moreover, in the selection of the relay nodes, unlike the previous work in [10,34,36], we consider the end-to-end reliability of a multi-hop route based on the Packet Reception Rate (PRR) which is one of the most commonly used reliability metrics [37]. In our model, the work analyzes the reliability of the whole path from the next hop node to the chosen sink, and then chooses the relay node with the best PRR which results in high reliability instead of dropping packets. Furthermore, the proposed approach considers the buffer size as in [10] and unlike the previous work in [34,36] to reduce the number of dropped packets and energy consumption due to retransmission the same packets but the proposed approach considers the information at one hop only. In addition, unlike the previous work in [10,34,36], the proposed protocol can balance energy consumption among sensor nodes evenly as much as possible through new effective function between nodes' residual energy and weight. In addition, it can effectively alleviate buffer overflow by integrating the normalized buffer space into routing choice.

3. Problem Description

Consider a multi-sink WSN deployed in a field for the purpose of object tracking. Our objective is to propose a data reporting model for this kind of service. To consider reliable object tracking taking into consideration nodes energy consumption, the energy balancing, and buffer size. The object tracking problem is modelled as a graph based on the nodes location in the monitored environment and their characteristics. The efficient object tracking in WSNs problem can be modelled as a simple undirected graph, G(V,L), where V is the set of sensor nodes in the network distributed in a two-dimensional plane and L is the set of all links (i, j) where, Link (i, j) exists if and only if , where NEBi is the set of neighbours of node i. Assuming that a multi-objects moving in the environment, they will be detected by some sensor nodes which denoted by source nodes. The frequency of object movement at each source node differs according to the number of objects that are within the sensing range of each source node. At each source node, the information about the presence of an object in its sensing range should be reported to one of the sink nodes. In order to select the optimal sink for each source node, it should satisfies two constraints, 1) the sensor nodes on the routing paths to that sink should have the maximum residual energy to achieve balanced energy consumption, 2) low transmission energy consumption. In our model, the minimum residual energy of sensor nodes on all paths that used to send messages from the source nodes to a certain sink during a certain time interval is used to evaluate the residual energy toward that sink. The maximum minimum residual energy of sensor nodes toward a certain sink means the maximum residual energy toward that sink. In addition, hop count is used to represent the energy consumption of data transmission in our model where, the less hop count implies the less energy consumption at a fixed transmission range. Once each of the source nodes select the optimal sink, its information should be sent to the chosen sink through intermediate sensor nodes which acts as a relay nodes. The chosen path from each source node to the chosen sink should be the best path which satisfies some constraints including 1) low communication cost, 2) its reliability greater than or equal target value, 3) at the same time, sensor nodes on that path should have the maximum energy weight cost compared with their neighbors to balance energy among sensor nodes, and 4) as well, sensor nodes should have the maximum buffer space to reduce number of lost packets and energy consumption due to retransmission of the same packets as a result of buffer overflow.

4. Problem Formulation for Optimal Solution

Based on the previous modelling to the object tracking problem, the problem can be solved optimally. In this section, the problem is mathematically formulated using Integer Linear Programming (ILP); then solved by any of the selected solver [24]. This solution is used to guarantee the optimal solution, if any, to the previously described problem. However, due to the complexity of the problem and its constraints, it is expected and it is well known from the previous experiences in similar problems that no optimal solution could be found in some cases of the problem representation. Therefore, the mathematical formulation is used to solve small-scale problems as well as it is designed to fully understand the problem with its major constraints. In addition, the optimal solution for small-scale problems could be used to measure the quality of any given heuristic that might be used to solve the same problem. In fact, in the next section, the paper explains a SWARM based optimization solution to the problem. This solution is used for large-scale problems.

To simplify the description of the problem and its formulation, the notations used to model the problem are given in Table 1.

Table 1. **Our model notations Given Parameters**

Notation	Description
S	The set of all sensor nodes that in sensing or sensing-relaying state.
R	The set of all sensor nodes that in relaying state accept sink node.
Si	The set of all sink nodes.
L	The set of all links, $(i, j) \in L$ and $i \neq j$.
C	The set of transmission cost C(i,j)associated with link (i, j).
PRR	The set of packet reception ratio PRR(i,j)associated with link (i, j).
Q	The target end-to end success probability.
wq	Constant value less than or equal 1.
Ds	The set of all messages corresponding to the detected objects at each source node s, $\forall s \in S$.
Ts	Time interval
MRE_{s_i}	The minimum residual energy toward each sink node si during a given time interval, $\forall s_i \in S_i$
$mhc_{s_i}^{s}$	The minimum hop count from each source node s to each sink node si, $\forall s_i \in S_i, \forall s \in S$
$dis_i^{s_i}$	The Euclidean distance from node i to sink node si, $i \in S \cup R, s_i \in S_i$
hc_i^{s}	The number of hops from node i and sink si, $i \in S \cup R$
RE_j	The residual energy of each sensor node j, $j \in NEB_i, NEB_i \in S \cup R$
$se_{(i,j)}$	The energy required to do single hop transmission from i to j, $(i, j) \in L$.
Mes_i	The number of messages at node i, $i \in S \cup R$
w_j	The weight of a neighbor j, $j \in NEB_i, NEB_i \in S \cup R$
Ewr_j	The relation between the residual energy and weight for each neighbor node j, $j \in NEB_i, NEB_i \in S \cup R$
pz	The packet size.
Br_j	The ratio between buffer space and packet size.
bs_j	Buffer space at node j.
bm_j	The number of messages that can be received by node j without buffer overflow.
NRE_j	The ratio between REj and se(i,j) for each neighbor node j, $j \in NEB_i, NEB_i \in S \cup R$
ENC_j	The energy consumption for each neighbor node j, $j \in NEB_i, NEB_i \in S \cup R$
$P_{s_i}^{s}$	The set of all candidate paths between any pair (s, si), $\forall s \in S, \forall s_i \in S_i$.
PRR_{P_s}	The set of PRR for all candidate paths between any pair (s, si),$\forall s \in S, \forall s_i \in S_i$.
NEB_i	The set of neighbors of node j, $j \in S \cup R, NEB_j \in S \cup R$.
Indicator Parameter	
δ_j^{p}	The indicator function which is 1 if node j is on path p and 0 otherwise.
Decision Variables	
$t_{(i,j)}^{sd}$	1 if the source node s uses the link (i, j) to transmit message d through it to sink node and 0 otherwise, $\forall d \in D_s, \forall s \in S$, and $(i, j) \in L$.
$b_{s_i}^{sd}$	1 if the sink node si has the minimum load compared with the other sink nodes and 0 otherwise, $\forall s \in S, s_i \in S_i$, and $\forall d \in D_s$.
$h_{s_i}^{s}$	1 if the sink node si has the minimum hop count compared with the other sink nodes and 0 otherwise, $\forall s \in S, s_i \in S_i$.
$g_{s_i}^{sd}$	1 if the source node s uses the sink node si to report its message d to it and 0 otherwise, $\forall s \in S, s_i \in S_i$, and $\forall d \in D_s$.

z_K	1 if the difference between the load of sink node K and si is less than zero and 0 otherwise, $\forall s_i \in S_i, K \in S_i - \{s_i\}$.
$U_{(i,j)}^{sd}$	1 if the sensor node i uses node j to relay message d of the source node sand 0 otherwise, $\forall d \in D_s, \forall s \in S, i \in S \cup R, j \in NEB_i$, and $NEB_i \in S \cup R$
x_p^{sd}	1 if the source node s select the path p to send message d to sink node and 0 otherwise, $\forall s \in S, p \in P_s$, and $\forall d \in D_s$.
z_N	1 if the difference between Ewr_j of sensor node j and Ewr_N of sensor node N is less than zero and 0 otherwise, $\forall j \in NEB_i, N \in NEB_i - \{j\}$, and $NEB_i \in S \cup R$.
m_j	1 if the sensor node j has a maximum residual energy to weight ratio compared with other neighbors and 0 otherwise, $\forall j \in NEB_i$, and $NEB_i \in S \cup R$.
b_j	1 if the total number of messages that can be received by node j without buffer overflow greater than zero and 0 otherwise, $\forall j \in NEB_i$, and $NEB_i \in S \cup R$.
y_l	1 if the difference between the normalized buffer space of sensor node j and l is less than zero and 0 otherwise, $\forall j \in NEB_i, l \in NEB_i - \{j\}$, and $NEB_i \in S \cup R$.
k_p^{sd}	1 if the selected path p for each source node s and message d has PRR greater than or equal to the target end-to-end success probability and 0 otherwise, $\forall s \in S, \forall d \in D_s$, and $p \in P_s$.

Now, let's start with the selection of the optimal sink for each source node which depends on the minimum residual energy of sensor nodes located in the direction to that sink in our model. When the message sent from any source node s to a certain sink along the path p, the minimum residual energy of the sensor nodes on that path is recorded at the sink node if its value is less than the previous one. Therefore, every a certain time interval Ts each sink node broadcast a message contains the minimum residual energy toward that sink to all of the sensor nodes which defined as follows:

$$MRE_{s_i} = min\{E_{min\,p_n}^{s_i}\} \quad n = 1,2,\dots,N \tag{1}$$

Where, Pn and N are the set and the number of all paths used by the source nodes to send their messages to sink node si during a certain time interval Ts respectively. $E_{min\,p_n}^{s_i}$ the set of the minimum residual energy of the sensor nodes on all the paths Pn to sink node si during a certain time interval Ts.

Due to the use of multi-hop routing technique, the information about the detected objects at each source node should be transmitted as messages to the chosen sink through the relay nodes. Since the energy resource is limited on such nodes, it is highly needed to achieve energy balanced routing. The node with heavy weight and low residual energy should be prevented from being selected as a next hop. So, the proposed algorithm considers a model in which the selection of the relay nodes depends on the value of a new proposed function which enables the decision making according to the residual energy and weight of nodes. The computation of the weight for each node j is defined by equation (2) as follows:

$$w_j = \begin{cases} \sum_{i \in NEB_j} Mes_i & if \ \ dis_j < dis_i \\ 0 & otherwise \end{cases} \tag{2}$$

Since the objects detected in the monitored environment distribute non-uniformly, node's weight can be defined as the total number of messages at its neighbour nodes which may choose it to relay their messages. Equation (2) means that packets are prevented from being transmitted backward to the neighbours with higher hop count. This strategy ensures that the packets are forwarded closer toward the sink and prevents forming a loop.

In addition, the new function that combines residual energy and weight for each node j at time t namely node energy weight cost which defined as follows:

$$Ewr_j(t) = \begin{cases} exp\left(\left(NRE_j(t) - we_j(t)\right)\Big/_{IE_j}\right) * \left(\frac{NRE_j(t)}{1 + \left(IE_j - NRE_j(t)\right)}\right) & if \;\; we_j \neq 0 \\ 0 & otherwise \end{cases}$$

(3)

In event-driven WSNs such as those used in object tracking application, nodes normally operate under low or idle load states and suddenly become active in response to the detected or monitored event. As a result, a part of the network becomes overloaded and often leads to congestion. Since the sensor nodes have limited memory, it is impossible to buffer a large number of packets. Consequently, the buffer of the relay node may start overflowing, resulting in loss of important packets and more energy consumption due to the retransmission of the lost packets [38-40]. In order to avoid congestion or overloaded nodes, the normalized buffer space is integrated into routing choice. The normalized buffer space is defined as the ratio between the buffer space and packet size. It is used to express the number of packets that can be received by every sensor node without it starting buffer overflowing at a certain time. The normalized buffer space of node j at time t can be defined as follows:

$$bm_j(t) = \begin{cases} \frac{bs_j(t)}{pz} & if \;\; bs_j(t) \geq pz \\ 0 & otherwise \end{cases} \quad (4)$$

To compute the shortest path to the sink nodes from each source node s to get the solution set of $\{h^s_{s_i}\}$ and then the shortest path to the chosen sink si to get the solution set of $\{x^{sd}_p\}$ in order to minimize communication cost, the Dijkstra algorithm has been used. To fit the Dijkstra into our formulation, the algorithm is represented mathematically as follows [41]:

The sensor nodes are being processed according to their order. The sensor nodes that are yet to be processed denoted by U, initially$U \in S \cup R$. When a sensor node i is processed, the following task is performed:

$$F(j) = min\{F(j), D_{(i,j)} + F(j)\}, for \;\; all \;\; j \in NEB_i, NEB_i \in U \quad (5)$$

Where F(j) denotes the length of the shortest path from node i to node j which initially equal to zero for the first processed node. When the sensor node i is processed, the {F(j)} values of its neighbours that have not yet been processed are updated in accordance with equation (5).

To complete the informal description of the algorithm, it is only necessary to specify the order in which the nodes are processed. The next node to be processed is one whose F(j) value is the smallest over all the unprocessed nodes as follows:

$$i = argmin\{F(j)\}, j \in U \quad (6)$$

Recalling that U denotes the set of unprocessed nodes, Thus after node i is processed it is immediately deleted from U. where, U=U - {i}

The total communication cost for a graph G and object tracking tree T is defined as the sum of the individual contributions of all source and relay nodes in G:

$$Total \;\; communication \;\; cos\,t\,(G,T) = \sum_{s\in S} \sum_{d\in D_s} \sum_{(i,j)\in L} t^{ds}_{(i,j)}\, C_{(i,j)} \quad (7)$$

Based on these computations the problem is formulated as follows:

The objective function:

$$Z_{IP} = min \sum_{s\in S} \sum_{d\in D_s} \sum_{(i,j)\in L} t^{ds}_{(i,j)}\, C_{(i,j)} \quad (IP)$$

Subject to:

$$\sum_{s_i \in S_i} h_{s_i}^{s} = 1 \qquad \forall s \in S \tag{8}$$
$$\sum_{K \in S_i - \{s_i\}} z_K \left(MRE_{s_i} - MRE_K\right) < 0 \qquad \forall s_i \in S_i \tag{9}$$
$$2 - \sum_{K \in S_i - \{s_i\}} z_K = b_{s_i}^{sd} + 1 \qquad \forall s_i \in S_i, \forall s \in S, \forall d \in D_s \tag{10}$$
$$\sum_{K \in S_i - \{s_i\}} z_K \leq 1 \qquad \forall s_i \in S_i \tag{11}$$
$$\sum_{s_i \in S_i} b_{s_i}^{sd} = 1 \qquad \forall s \in S, \forall d \in D_s \tag{12}$$
$$\sum_{s_i \in S_i} h_{s_i}^{s} b_{s_i}^{sd} \leq g_{s_i}^{sd} \qquad \forall s \in S, \forall d \in D_s \tag{13}$$
$$\sum_{p \in P_{s_i}^{s}} x_p^{sd} = 1 \qquad \forall s \in S, \forall d \in D_s, s_i \in S_i \tag{14}$$
$$\sum_{i \in S \cup R} U_{(i,j)}^{sd} = 1 \qquad \forall s \in S, \forall d \in D_s, j \in NEB_i, NEB_i \in S \cup R \tag{15}$$
$$\sum_{N \in NEB_i - \{j\}} z_N \left(Ewr_j - Ewr_N\right) < 0 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{16}$$
$$2 - \sum_{N \in NEB_i - \{j\}} z_N = m_j + 1 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{17}$$
$$\sum_{N \in NEB_i - \{j\}} z_N \leq 1 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{18}$$
$$\sum_{p \in p_{s_i}^{s}} k_p^{sd} PRR_p \geq Q \quad \forall s \in S, \forall d \in D_s, PRR_p \in PRR_{p_{s_i}^{s}}, s_i \in S_i \tag{19}$$
$$k_p^{sd} + 1 \leq x_p^{sd} + 1 \qquad \forall p \in P_s, s \in S, d \in D_s \tag{20}$$
$$\sum_{l \in NEB_i - \{j\}} y_l \left(bm_j(t) - bm_l(t)\right) < 0 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{21}$$
$$2 - \sum_{l \in NEB_i - \{j\}} y_l = b_j + 1 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{22}$$
$$\sum_{l \in NEB_i - \{j\}} y_l \leq 1 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{23}$$
$$\sum_{p \in P_s} \sum_{j \in NEB_i} \delta_j^{p} x_p^{sd} m_j b_j k_p^{sd} \leq U_{(i,j)}^{sd} \quad \forall s \in S, \forall d \in D_s, i \in S \cup R, NEB_i \in S \cup R \tag{24}$$
$$\sum_{j \in NEB_i} m_j \leq 1 \qquad NEB_i \in S \cup R \tag{25}$$
$$\sum_{j \in NEB_i} b_j \leq 1 \qquad NEB_i \in S \cup R \tag{26}$$
$$\sum_{(i,j) \in L} t_{(i,j)}^{sd} \geq 1 \qquad \forall s \in S, \forall d \in D_s \tag{27}$$
$$z_K = 0 \ \ or \ \ 1 \qquad K \in S_i - \{s_i\} \tag{28}$$
$$b_{s_i}^{sd} = 0 \ \ or \ \ 1 \qquad \forall s \in S, \forall d \in D_s, s_i \in S_i \tag{29}$$
$$h_{s_i}^{s} = 0 \ \ or \ \ 1 \qquad \forall s \in S,, s_i \in S_i \tag{30}$$
$$g_{s_i}^{sd} = 0 \ \ or \ \ 1 \qquad \forall s \in S, \forall d \in D_s, s_i \in S_i \tag{31}$$
$$z_N = 0 \ \ or \ \ 1 \qquad N \in NEB_i - \{j\} \tag{32}$$
$$x_p^{sd} = 0 \ \ or \ \ 1 \qquad \forall s \in S, \forall d \in D_s, p \in P_s \tag{33}$$
$$U_{(i,j)}^{sd} = 0 \ \ or \ \ 1 \qquad \forall s \in S, j \in NEB_i,, NEB_i \in S \cup R, \forall d \in D_s \tag{34}$$
$$m_j = 0 \ \ or\ 1 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{35}$$
$$k_p^{sd} = 0 \ \ or\ 1 \qquad \forall p \in P_s, \forall s \in S, \forall d \in D_s \tag{36}$$
$$t_{(i,j)}^{sd} = 0 \ \ or\ 1 \qquad \forall s \in S, \forall d \in D_s, (i,j) \in L \tag{37}$$
$$b_j = 0 \ \ or\ 1 \qquad \forall j \in NEB_i, NEB_i \in S \cup R \tag{38}$$
$$y_l = 0 \ \ or \ \ 1 \qquad l \in NEB_i - \{j\} \tag{39}$$

To simplify the description of the formulation the constraints are divided into sets and each set is recognized by its functionalities as follows:

Routing Constraints:

The routing constraints involve constraints 8, 13, 14,15,24, 25 and 26.

Constraint (8): It is used to guarantee that any source node s must choose only one sink node.

Constraint (13): Once the sink node siis selected, and it has the maximum minimum residual energy compared with the other sink nodes. Then the decision variable $\boldsymbol{g_{s_i}^{sd}}$must be enforced to 1.

Constraint (14): It is used to guarantee that any source node s must choose only one path to the chosen sink.

Constraint (15): To avoid cycle, the use of any node j as a relay node for the same source node sand message d is equal 1, except the sink node.

Constraint (24): Once the path p is selected, and the PRR of that path is greater than or equal the target end-to-end success probability. As well as, the node j is on the path and has the highest residual energy to weight ratio compared with other neighbour nodes. In addition, the node j can receive the message without buffer overflow. Then the decision variable $\boldsymbol{U_{(i,j)}^{sd}}$ must be enforced to equal 1.

Constraint (25-26): They are used to guarantee that any node i must choose only one node j from its neighbours.

Energy Constraint:

The energy constraints contain constraints 9, 10, 11, 12,16, 17, and 18.

Constraint (9-12): They are used to balance energy consumption of the whole network. Any source node s must choose only one sink node si to report its message d to it. The chosen sink should have the lowest load compared with the other sink nodes.

Constraint (16-18): They are used to maintain higher and balance residual energy on nodes. Any node i must choose only one node j from its neighbours which have the highest residual energy to weight ratio compared with other neighbour nodes.

Reliability Constraint:

The reliability constraints contain constraints 19and 20.

Constraint (19-20): It used to guarantee that the selected path p for the source node s and message d has a PRR greater than or equal the target end-to-end success probability.

Buffer Constraint:

The buffer constraint contains constrains 21, 22, and 23.

Constraint (21-23): It is used to prevent buffer overflow. Any node i must choose only one node j from its neighbours which has maximum buffer space as described from equation (21) to equation (23).

Decision variables Constraint:

The decision variable constraints are composed of constraints 28 through 39.

Constraint (28-39):

$\boldsymbol{t_{(i,j)}^{sd}}, \boldsymbol{z_K}, \boldsymbol{g_{s_i}^{sd}}, \boldsymbol{b_{s_i}^{sd}}, \square_{s_i}^{s}, \boldsymbol{z_N}, \boldsymbol{x_p^{sd}}, \boldsymbol{U_{(i,j)}^{sd}}, \boldsymbol{m_j}, \boldsymbol{b_j}, \boldsymbol{y_l}$, and $\boldsymbol{k_p^{sd}}$equal 0 or 1.

Redundancy Constraint:

The redundancy constraints include only constraint number 27.

Constraint (27): For all $\sum_{(i,j)\in L} \boldsymbol{t_{(i,j)}^{sd}}$must be greater than or equal to 1.

5. The Proposed Solution

This section describes the second solution approach for the reliable object tracking problem which is divided into two steps as described below.

1- The selection of the optimal sink by a probability which depends on the residual energy and the energy consumption of data transmission.

2- The selection of the relay nodes using swarm intelligence taking residual energy, weight, and buffer space of the relay nodes into account. As well as, the energy consumption and reliability of data transmission.

5.1 Routing Scheme

Once the source node detects an object, the process of selecting the optimal sink node for data transmission is started. The selection of the sink node is related to the sink node cost. The sink having the maximum cost is to be considered as the optimal sink node. Our model takes the residual and hop count into account. When a message sent from any source node to a certain sink, the minimum residual energy of the sensor nodes on the routing path will be reported to that sink and then updates its residual energy information which represents the least received value at this sink. Such information is used to evaluate the residual energy of the sensor nodes located in the direction to a certain sink. That's to say, the higher residual energy means the greater sink cost. In this way, the energy balance factor is taken into consideration. Hop count is used to represent energy consumption of data transmission where, at a fixed transmission range the less hop count means the less energy consumption. The cost of a sink node si at the source node s is determined as follows:

$$P_{rs}(s, s_i) = \frac{MRE_{s_i}}{mhc_{s_i}^{s}} \quad (37)$$

After the source node selects which the sink the data will be sent to, it will send the data to a 1-hop neighbour according to the process of selecting the relay node using swarm intelligence. The proposed solution based swarm intelligence is composed of two phases. In the first phase, it starts with a set of forward ants placed in the source nodes and move through neighbour relay nodes until reach sink node. In this algorithm, for calculating the packet transfer probability to the next hop neighbour, residual energy, weight, normalized buffer space, hop count, and pheromone are considered. At each node i, a forward ant k selects the next hop node j, $j \in NEB_i$randomly with a probability $p_r^k(i, j)$which determined as follows:

$$p_r^k(i, j) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}[\psi_{ij}(t)]^{\gamma}[\varepsilon_{ij}(t)]^{\upsilon}[\delta_{ij}(t)]^{\varphi}}{\sum_{l \in NEB_i}[\tau_{il}(t)]^{\alpha}[\eta_{il}(t)]^{\beta}[\psi_{il}(t)]^{\gamma}[\varepsilon_{il}(t)]^{\lambda}[\delta_{il}(t)]^{\varphi}} \quad (38)$$

Where $\tau ij(t)$ is the pheromone value on the link (i,j) at the time t, $\eta ij(t)$, $\psi ij(t)$, $\varepsilon ij(t)$, and $\delta ij(t)$ are the heuristic information of link (i,j) for node j; α, β, γ, υ, and ϕ are the weight factors that control the pheromone value and the heuristic information parameters respectively.

When forward ant k reaches the chosen sink node, it is transformed into a backward ant and the second phase starts. The backward ant starts from the chosen sink node and moves towards its source node along the same path in opposite direction, depositing an increment of pheromone on that.

5.1.1 Calculation of The Heuristic Information

In order to maintain higher and balance residual energy on sensor nodes, the proposed function between residual energy and weight is used as a heuristic information when selecting the next hop neighbour node which denoted by η_{ij}.

$$\eta_{ij}(t) = \frac{Ewr_j(t)}{\sum_{l \in NEB_i} Ewr_l(t)} \quad (39)$$

According to this rule, the node with the greater value of η_{ij} will have a higher residual energy compared to its weight and a much better opportunity to be chosen as a next hop.

Since energy conservation is an essential issue in WSN, selecting the nodes with minimum hop count is required to minimize energy consumption and conserve much more energy as possible. Therefore, the between neighbour node j and the sink node si in terms of hop count is used as heuristic information which is denoted byψ_{ij}.

$$\psi_{ij}(t) = \frac{\left(hc_i^{s_i} - hc_j^{s_i}\right) + 1}{\sum_{l \in NEB_i}\left(hc_i^{s_i} - hc_j^{s_i}\right) + 1} \tag{40}$$

A neighbour node that has a greater value of $\psi_{ij}(t)$ is closer to the sink than the others and will be more likely to be chosen as next hop.

In order to avoid or reduce packet loss due to buffer overflow which in turn improve the overall network performance, it is critical to send packets to the sensor node with more buffer space or less traffic load. Therefore, $bm_j(t)$ can be used as heuristic information which denoted by $\varepsilon_{ij}(t)$

$$\varepsilon_{ij}(t) = \frac{bm_j(t)}{1 + \sum_{l \in NEB_i} bm_l(t)} \tag{41}$$

This rule enables decision making according to the buffer apace on the neighbour nodes, meaning that if a node has a greater value of ε_{ij} then it has a much better opportunity to be chosen as next hop.

Due to the dynamic behaviour of the wireless link quality over time and space, it is essential to use the current packet reception ratio of link (i,j), PRRij as heuristic information to improve the network throughput. It is denoted by $\delta_{ij}(t)$

$$\delta_{ij}(t) = \frac{PRR_{ij}}{\sum_{l \in NEB_i} PRR_{lj}} \tag{42}$$

Where, the greater value of δ_{ij} indicates that the link (i,j)more reliable than others. Thus, the neighbour node j will have more chance to be chosen as next hop.

5.1.2 Pheromone Calculation

In this algorithm, pheromone concentration is affected by the combination between energy, path length, and path quality in a new effective form. This may improve network reliability, reduce energy consumption, and achieve more balanced transmission among the nodes.

let's begin with the calculation of the path quality, qp, which related to the PRR as follows:

$$q_p = PRR_p \tag{43}$$

Where, PRRp, represents the packet reception ratio of the path p. Due to the use of multi-hop routing, the PRRp can be computed by the PRR of each hop on the path p as follow:

$$PRR_p = \prod_{(i,j) \in n_p} PRR_{ij} \tag{44}$$

Where, np is the set of edges on the path p (hop count). In this model, all nodes have the same fixed transmission range. So, the number of hops in the path p is considered as the path length, Lp as follow:

$$L_p = n_p \tag{45}$$

The increasing density of pheromone on the path p is defined as follows:

$$\Delta\tau = \left(\left({}^{1}/_{L_p}\right)^{w_1} \times \left(PRR_p\right)^{w_2}\right) \cdot \left(E_{min}()^{w_3}\right) \tag{46}$$

Where E_{min} is the minimum residual energy of nodes visited by ant k and the parameters w1, w2, and w3 determining the relative influence of the energy, path length, and path quality.

The sink node constructs the value of pheromone update operator, $\Delta\tau_{ij}$, and sent it back as a backward ant to its source node along the reverse path. Whenever a node i receives a backward ant k coming from neighboring node j, it updates its pheromone concentration according to the following rule:

$$\tau_{ij}(t) = (1-\rho)\tau_{ij}(t-1) + \rho\Delta\tau \tag{47}$$

Where, $\rho \in (0,1)$ is the evaporation constant that determines the evaporation rate of the pheromone [42].

6. Performance Evaluations

The performance of the proposed approach for multi-sink WSNs is evaluated through comparison with sophisticated algorithms designed for multi-sink WSNs such as DTAR [10], NBPR[34], and MSDDGR [36]. The section starts by describing the performance metrics followed by simulation environment and finally simulation results.

6.1. Performance Metric

For a comprehensive performance evaluation, several quantitative metrics considered are defined below.

Network Lifetime [43]. It is defined as the time duration from the begging of the network operation until the first node exhausts its battery.

Energy Imbalance Factor (EIF) [43]. It is defined to quantify the routing protocol energy balancecharacteristic which defined formally as the standard variance of the residual energy of all nodes.

$$EIF = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(RE_i - RE_{avg})^2}$$

Where n is the total number of sensor nodes, REi is the residual energy on node i, and REavg is the average residual energy of all nodes.

Throughput Ratio (TR) [44]. This metric is defined as:

$$TR = \frac{Number\ \ of\ \ packets\ \ received\ \ by\ \ the\ \ sin k}{Number\ \ of\ \ packets\ \ sent\ \ by\ \ source\ \ nodes}$$

Average End-to-End Delay (Seconds) [45]: It is defined as the average time a packet takes to travel from source node to the sink node. This includes propagation, transmission, queuing, and processing delay. The processing delay can be ignored as a result of fast processing speed [46].

6.1.1. Simulation Environment

In this work, the sink node, and sensor nodes are stationary after being deployed in the field. All the later experiments are done for both homogeneous and heterogeneous node energy distributions on a custom Matlab simulator. Poisson process of intensity λ packets per second is used to model the data traffic in the network. In addition, we choose a harsh wireless channel model, which includes shadowing and deep fading effects, as well as the noise [47]. The simulation parameters are listed in Table 4.2.

Table 2 Simulation environment parameters

Parameters	values
Node distribution	Random
Number of sensor nodes	100
Network area	1000 m x 1000 m
Number of source nodes	10
Maximum number of retransmission	4

Packet size	64 byte
Buffer size	128 byte
Frequency	2400 MHz
Transmission power	0dBm
Maximum transmission range	200 m
Radio data rate	250 Kbps
Path loss exponent	4
Shadow fading variance	4
Noise power	-153dBm
Reference distance	1 m
Weights (α, β, γ, υ, and ϕ)	0.016/0.154/0.3/0.05/1.1
ϱ	0.65

6.3. Simulation Results

In this section, a variety of experiments are conducted to evaluate the performance of the proposed approach for multi-sink WSNs compared with DTAR [10], NBPR [34], and MSDDGR [36] in terms of network lifetime, network throughput, average end-to-end delay, and energy balance for homogeneous and heterogeneous networks. In all later experiments, each node is assumed to have an initial energy of 125mJ for homogenous network, while it is between 100 and 125mJ randomly for heterogeneous network. The same proposed scheme for selecting the optimal sink is used with the DTAR algorithm in all later experiments, since it doesn't consider the principle about selecting sink node.

6.3.1. Network Lifetime Evaluation for Homogenous and Heterogeneous Networks

In this set of experiments, the performance of the proposed approach is evaluated in terms of network lifetime for both homogenous and heterogeneous networks compared to DTAR [10], NBPR [34], and MSDDGR [36].

Network Lifetime Evaluation with Different Number of Sink Nodes

These experiments study the variation of the network lifetime with respect to the number of sink nodes for homogeneous and heterogeneous networks as shown in Figure 1 and 2 respectively. In these experiments, the average traffic rate λ is fixed to 5 packets per second respectively. As depicted in Figure 1 and 2, deploying more sink nodes prolong the network lifetime. This happens because, as the number of sink nodes increases, nodes have more choices among the sink nodes to route the data packets which reduce the number of nodes that participate in data transfer, and thus reduce the quick exhausting of sensor nodes energy which in turn prolong the network lifetime. Meanwhile, with more sink nodes in the network, the path length from a sensor node to a sink node is decreased and more energy can be saved. However, it is evident that the proposed algorithm achieves longer lifetime even while increasing the number of sink nodes as compared with the others. This can be justified as follow. The proposed approach can balance the energy consumption and traffic loads efficiently across the network. At the same time, they improve the packet delivery against unreliable links and buffer overflow, thus saving energy consumption due to the retransmission of the lost packets. In the case of MSDDGR algorithm, each sensor node depends on the location information of its neighbours and the location of sink nodes to forward data packets. However, it doesn’t consider both load balance among sink nodes and load balance among sensor nodes situated on the routing paths to reach sink nodes. Hence, data packets sent to an overloaded sink may keep using the same relay nodes and as a result depleting their energies, subsequently affect the network lifetime. As well as, it doesn't consider the reliable message delivery and congestion control mechanism for data transmission leading to a lot of lost packets and thus more energy consumption due to the retransmission of the lost packets. DTAR algorithm spreads traffic over underloaded paths to reduce congestion and buffer overflow unaware of energy consumption balance and the reliability of data transmission. This easily leads to energy unbalance and more energy consumption due to the retransmission of the lost packets as a result of unreliable wireless links. The NBPR relies on the residual energy to balance loads among sink nodes and to balance loads among sensor nodes situated on the routing paths to reach sink nodes. However, it is not sufficient to achieve effective energy consumption balance across the network. In addition, it doesn't consider how to alleviate congestion and how to avoid unreliable wireless links, which diminish the network throughput resulting in more energy consumption due to the retransmission of the lost packets.

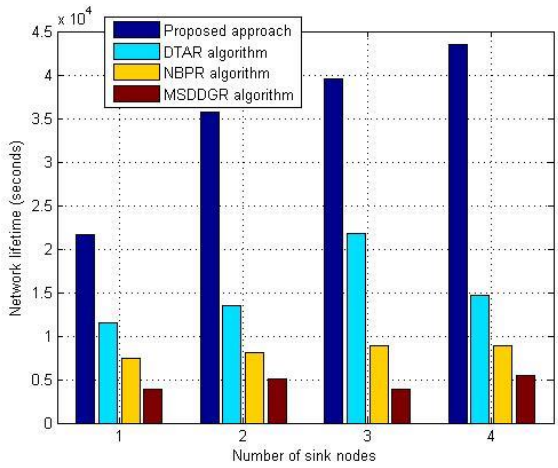

Figure 1. Network lifetime vs. number of sink nodes for homogeneous network

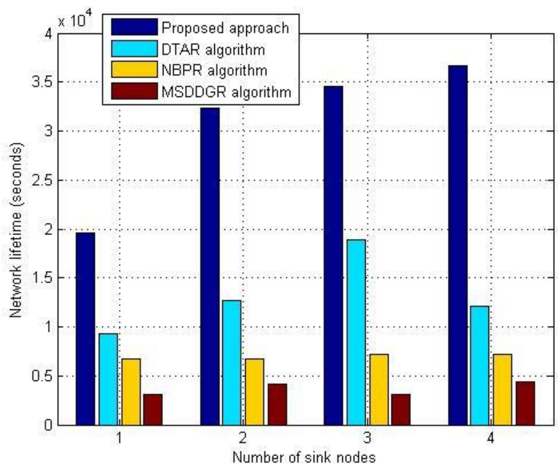

Figure 2. Network lifetime vs. number of sink nodes for heterogeneous network

Network Lifetime Evaluation with Different Average Traffic Rate

These simulation experiments evaluate the performance of the proposed approach with respect to traffic rate λ for homogeneous and heterogeneous networks as shown in Figure 3 and 4 respectively. In these experiments, the number of sink nodes is fixed to 2 sink nodes placed at (1000 m, 0 m) and (1000 m, 1000 m). It can be seen from the figures, the network lifetime decreases, as the traffic rate increase due to two reasons. First, as the network traffic increases, the probability of packet collision increases leading to more packet losses and retransmission and thus causes more energy waste. The second reason is that the relay load of nodes increases with increasing traffic rate. However, the proposed approach achieves the improvement on the network lifetime as compared with that proposed for single sink. The reason of this improvement can be explained by the fact that the multi-sink topology can balance energy consumption and effectively solve the energy hole problem more than single sink, which extends the network lifetime. In addition, the distance a data packet has to travel until reaching a sink node can be reduced by deploying multiple sink nodes in the network, resulting in more energy saving and longer lifetime. It can be seen also from the figures that the performance of the proposed scheme outperforms the DTAR, NBPR, and MSDDGR schemes designed for multi-sink WSNs, irrespective of the average traffic rate. This is because; the proposed schemes balance the energy consumption throughout the network and save energy consumption due to the retransmission of the lost packets effectively more than the others.

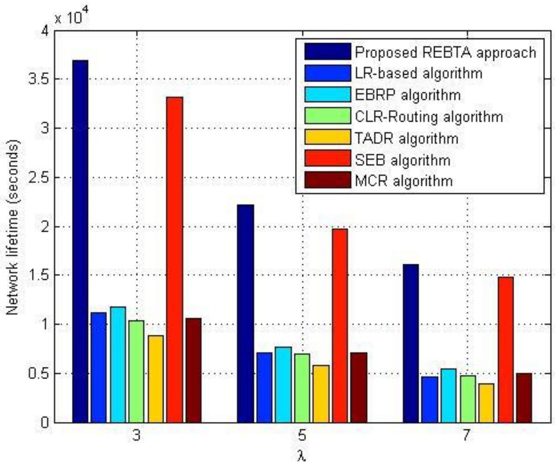

Figure 3. Network lifetime vs. traffic rate λ for homogeneous network

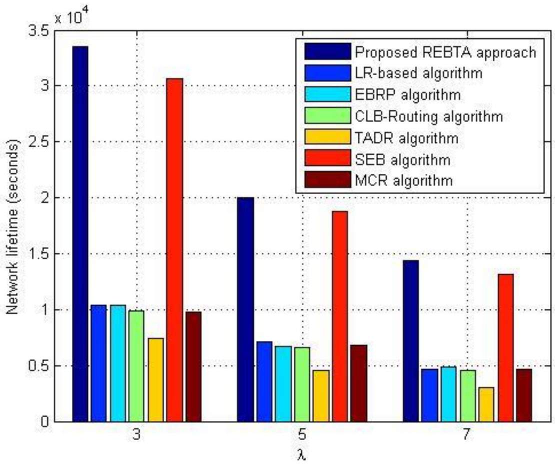

Figure 4. Network lifetime vs. traffic rate λ for heterogeneous network

6.1.1 Network Reliability Evaluation for Homogenous and Heterogeneous network

In this set of experiments, the performance of the proposed approach is evaluated in terms of TR for both homogenous and heterogeneous networks compared to the DTAR [10], NBPR [34], and MSDDGR [36] for homogeneous and heterogeneous networks.

Network Throughput Evaluation with Different Number of Sink Nodes

These experiments study the variation of the network throughput with respect to the number of sink nodes for homogeneous and heterogeneous networks as shown in Figure 5 and 6 respectively. For testing this variation, the number of sink nodes is increased from 1 to 3 in the network. The average traffic rate λ is fixed to 5 packets per seconds. It can be observed that the network throughput increases when the number of sink nodes increases, because the average distance from sensor nodes to sink nodes is decreased. However, the proposed approach outperforms the other algorithms. This happens because the proposed approach improves the packet delivery ratio by selecting the more reliable paths and spreading data traffic over underloaded paths to reduce congestion and buffer overflow as much as possible. But, the DTAR reduces packet loss as a result of buffer overflow by preventing overloaded nodes from being selecting as next hop, while the packet losses due to the unreliable wireless links are not taken into account. The NBPR and MSDDGR protocols don't consider reliable message delivery and congestion control mechanism for data transmission.

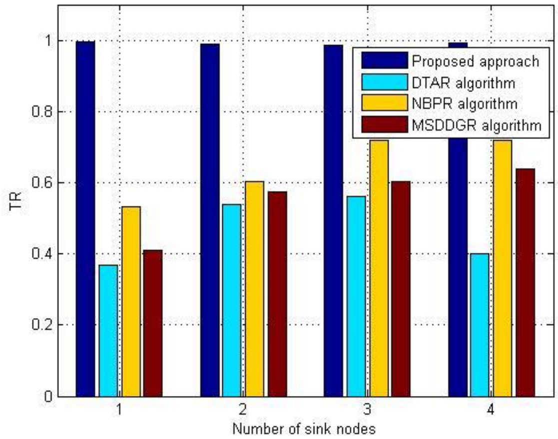

Figure 5. Network throughput vs. number of sink nodes for homogeneous network

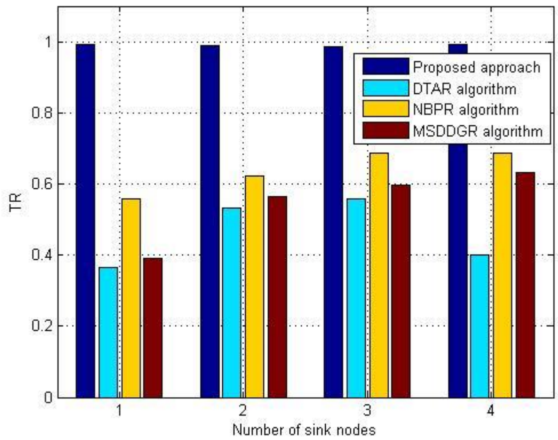

Figure 6. Network throughput vs. number of sink nodes for heterogeneous network

Network Throughput Evaluation with Different Average Traffic Rate

These simulation experiments study the variation of the network lifetime with respect to the average traffic rate λ for homogeneous and heterogeneous networks as shown in Figure 7 and 8 respectively. These experiments started with increasing the average traffic rate λ in a network from 3 to 7 packets per second. The number of sink nodes is fixed to 2 sink nodes placed at (1000 m, 0 m) and (1000 m, 1000 m). In general, as the average traffic rate increases, the traffic load in the network increases. As the traffic load increases, more packets reach buffer of sensor node, leading to more packet losses and therefore a decrease in the network throughput. However, it can be seen from the figures that when the traffic rate increases, the network throughput of the proposed approaches whether designed for multi-sink or single sink WSN is slightly decreased. Meanwhile, the proposed approach achieves further improvement in the network throughput compared with DTAR, NBPR, and MSDDGR algorithms even while increasing the average traffic rate in the network. The reason for such results is that the proposed approaches can effectively recover from congestion and buffer overflow as much as possible even in cases of high traffic by spreading traffic over underloaded paths, as well as avoid the unreliable paths as compared to DTAR, NBPR, and MSDDGR algorithms.

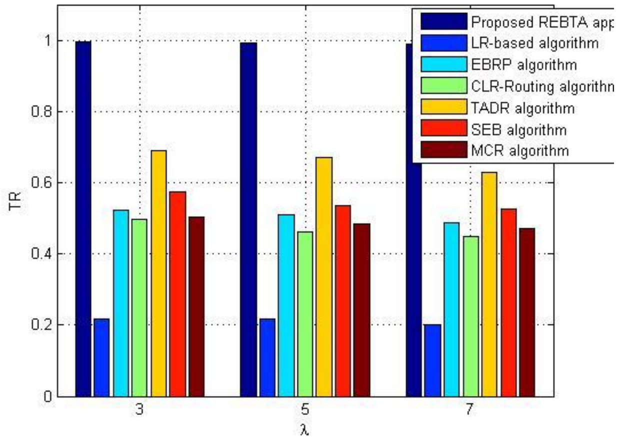

Figure 7. Network throughput vs. traffic rate λ for homogeneous network

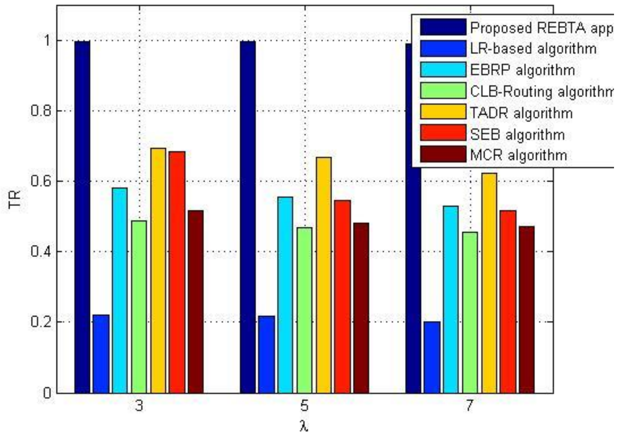

Figure 8. Network lifetime vs. traffic rate λ for heterogeneous network

6.3.3. Energy Balancing Evaluation for Homogenous and Heterogeneous Networks

This experiment is conducted to evaluate the performance of the proposed approach in terms of energy balance for both homogenous and heterogeneous networks compared to the DTAR [10], NBPR [34], and MSDDGR [36] for homogeneous and heterogeneous networks. The EIF was calculated during running time to find the network's balance efficiency. These simulation experiments are conducted in a network of 2 sink nodes placed at (1000 m, 0 m) and (100 m, 1000m). The average traffic rate λ is fixed to 5 packets per seconds. Figure 9and 10 present the variation of EIF over simulation time for homogeneous and heterogeneous networks respectively. It is clear from the figures that EIF increases with more running time. Indeed, in random topologies, some sink nodes are deployed in highly dense areas while the others are not. Since these areas are not necessarily overlapping, some sensor nodes are obliged to bind exclusively to certain sink nodes, subsequently enforcing an unbalance in the distribution of sensors among the sink nodes. Undoubtedly, it has a negative impact on the variance of residual energy across the network. It reveals the reason behind the augmentation of the EIF with more running time. However, it is obvious that the EIF of the proposed scheme can balance energy consumption efficiently more than that of the proposed scheme for single sink. This is due to the fact that multi-sink usage can balance energy consumption of the whole network and relieve the energy hole problem more than single sink. Also, it can be seen from the figures that the EIF of the proposed approach is less than that of the others. This is happens because, in the case of MSDDGR scheme, there is no notion of residual energy distribution leading to an unbalanced energy consumption in the network. NBPR scheme balance the load among sink nodes and balance the load among the sensor nodes situated on the routes to reach sink nodes based on the residual energy. The residual energy of sensor nodes is not sufficient to achieve effective energy balance across the network. DTAR scheme spreads the data traffic away from congested areas unaware of residual energy distribution, leading to unbalanced energy consumption in the network. But the proposed scheme balances the load among sink nodes depending on the least residual energy of sensor nodes that situated on the routes toward those sink nodes. As well as, it balances the load among sensor nodes depending of the energy weight cost presented in section 4, which provides more efficient energy balance than that depending on the residual energy only.

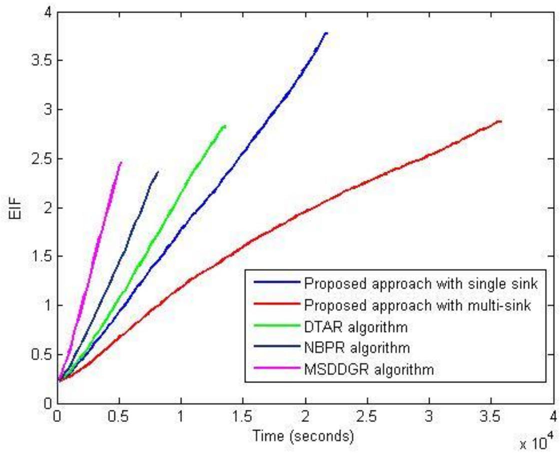

Figure 9. The EIF vs. simulation time for homogeneous network

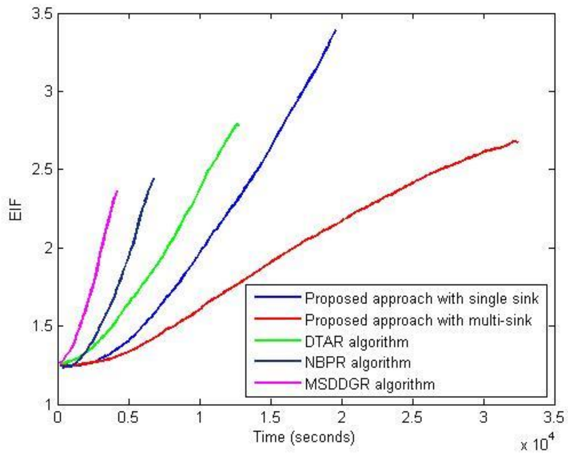

Figure 10. The EIF vs. simulation time for heterogeneous network

6.3.4. Average End-to-End Delay Evaluation for Homogenous and Heterogeneous Networks

In this set of experiments, the performance of the proposed approach is evaluated in terms of end-to-end delay for both homogenous and heterogeneous networks compared to the DTAR [10], NBPR [34], and MSDDGR [36] algorithms.

Average End-to-End Delay Evaluation with Different Number of Sink Nodes

These experiments study the impact of varying the number of sink nodes on the end-to-end delay for homogeneous and heterogeneous networks as shown in Figure 11 and 12 respectively. These experiments were conducted with varying the number of sink nodes from 1 to 3. As well as, the average traffic rate λ is fixed to 5 packets per second. As can be seen from the figures, the average end-to-end delay decreases with increasing the number of sink nodes, because the average distance from sensor nodes to sink nodes is decreased. However, it is clear from the figures that the proposed approach has the lowest end-to-end delay compared with the others, irrespective of the number of sink nodes. This can be justified as follow. The proposed scheme sends packets over the least congestion areas and avoids the unreliable wireless links, leading to a reduction in the network end-to-end delay. On the contrary, the NBPR and MSDDGR don't consider how to avoid congestion and unreliable data transmission, which result in an increase in the end-to-end delay due to the retransmission of a lot lost packets. The DTAR algorithm prevents data packets from going to possible congested areas, while the reliable data transmission is not taken into account, which increases the packet loss rate and the end-to-end delay.

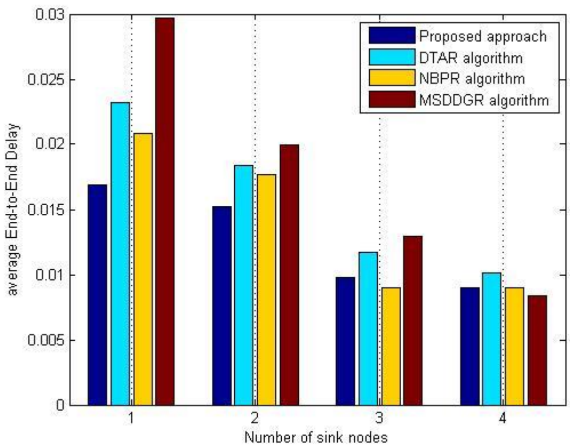

Figure 11. Average end-to-end delay vs. number of sink nodes for homogeneous network

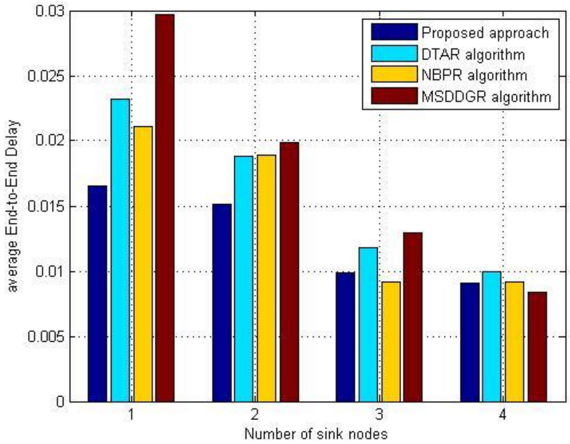

Figure 12. Average end-to-end delay vs. number of sink nodes for heterogeneous network

Average End-to-End Delay Evaluation with Different Average Traffic Rate

These simulation experiments study the variation of the end-to-end delay with respect to the average traffic rate λ for homogeneous and heterogeneous networks as shown in Figure 13 and 14 respectively. These experiments started with increasing the average traffic rate λ in a network from 3 to 7 packets per second with 2 sink nodes placed at (1000 m, 0 m) and (1000 m, 1000 m). The results show that the end-to-end delay increases with increasing the number of source nodes or the average traffic rate. The reason why the end-to-end delay is increased in this case is because the network traffic is increased with increasing the number of source nodes or the average traffic rate λ causes an increase in the queuing delay. It is evident that the end-to-end delays of the proposed approach lower than that of the proposed approach with single sink. This is due to the fact that in multi-sink topology, the average distance from sensor nodes to the sink nodes is decreased, which implies that the end-to-end delay decreases. However, the proposed approach performs a smaller end-to-end delay than the others. This can be justified as follow. Compared with NBPR and MSDDGR algorithms, the proposed approach reduces the number of dropped packets and packet retransmissions by avoiding the unreliable paths and the heavily congested areas or overloaded nodes. On the other hand, the DTAR algorithm can't avoid the packet loss and packet retransmissions due to unreliable wireless links, leading to increased end-to-end delay.

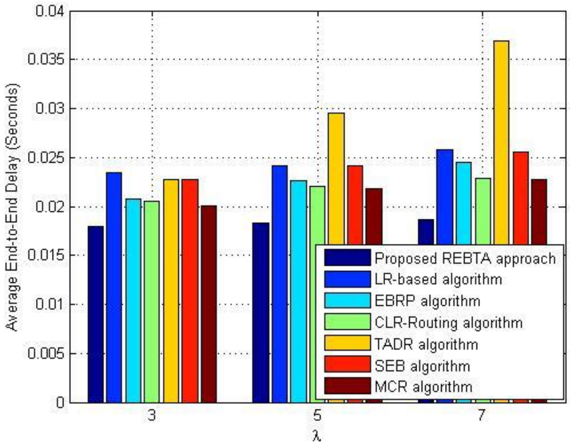

Figure 13. Average end-to-end delay vs. traffic rate λ for homogeneous network

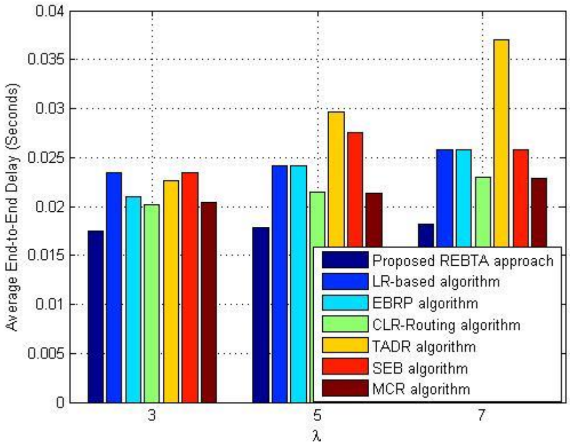

Figure 14. Average end-to-end delay vs. traffic rate λ for heterogeneous network

7. Conclusions

In this work, an efficient data reporting method for object tracking in multi-sink WSNs is proposed. In data reporting phase, the proposed approach not only reduces the energy consumption but also balanced the loads on the sink nodes and balanced the load among sensor nodes to extend the network lifetime. At the same time, the sensed data delivered to the sink with the highest possible reliability and minimum buffer overflow. A new scheme for selecting the optimal sink for data transmission is proposed. This work formulates the problem as 0/1 integer programming problem, and then proposes swarm intelligence for solving the optimization problem. Experiments have been carried out to evaluate and analyze the performance of the proposed approach compared to the previous work such as DTAR, NBPR, and MSDDGR protocols. Simulation results showed that the proposed approach is robust; achieve longer lifetime, and giving lower end-to-end delay compared to the previous works for both homogenous and heterogeneous networks.

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