ENERGY-AWARE CONSTRAINED RELAY NODE DEPLOYMENT AND CAPACITY MAXIMIZATION FOR SUSTAINABLE DATA TRANSMISSION WIRELESS SENSOR NETWORKS

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ABSTRACT

In the recent past wireless sensor networks are finding significant area of research in various ranges of applications in data transmission environment. The sustainable data transmission plays vital role in wireless sensor network for energy aware relay node (RN) deployment to transmit and receive the message. However the major challenges faced by the researches in the existing algorithms are the generation of redundant nodes which reduces the network lifetime and energy consumption.By proposing the methodology, we want to reach the goals such as cost effectiveness, coverage, connectivity, and lifetime and data latency. In this paper, the proposed methodology has the constrained placement and varies from the existing methodologies. It provides two different methods of sensor nodes to be deployed, 1) Energy rich nodes (ERNs), and 2) Energy Limited Nodes (ELN). The problem constraint is eliminated by applying minimum weighted connected domination set (MWDCS) in a vertex weighted graph. The weight function of MWCDS is used to solve the problem constraint. This paper proposes a novel algorithm based on a Modified Particle Swarm Optimization (MPSO) approach for designing an energy-aware topology control protocol. The MPSO optimization algorithm is applied to improve the performance of wireless sensor network for energy-aware constrained relay node deployment and capacity maximization. The optimized solution is obtained by cooperatively applying MPSO and integer leaner programming (ILP) and the heuristic approach is given for the approximate solution. The effectiveness and stability of the algorithm is verified through experimental analysis and parameters such as network life time, accuracy, mean square error rate, coverage area and residual energy shows prominent results which outperforms existing counterparts.

Keywords: Relay Node, Energy Limited Nodes, Linear Programming, Energy Rich Nodes

Introduction

To improve WSN's nodes utilization rate, we defines a minimization problem of distances between two relay nodes, which are used in a multi-hop WSN for tunnel monitoring. We find a relationship between self-organized neighbor clusters which are composed of a multi-hop route to collect monitoring data. The relationship leads to a multi-objective optimization problem. Therefore, we make use of particle swarm algorithm (PSO), which is appropriate to a multi-objective optimization problem, to search for an optimized results [1]. A new strategy is used to assist in the placement of Relay Nodes (RNs) for a WSN monitoring underground tunnel infrastructure. By applying for the first time an accurate empirical mean path loss propagation model along with a well fitted fading distribution model specifically defined for the tunnel environment, we address the RN placement problem with guaranteed levels of radio link performance. A two-tier clustering multi-hop framework in which the first tier of theRN placement is modeled as the minimum set cover problem, and the second tier placement is solved using the search-and find algorithm [2].We consider the problem of constrained relay node (RN) placement where sensor nodes must be connected to base stations by using a minimum number of RNs. The latter can only be deployed at a set of predefined locations, and the two-tiered topology is considered where only RNs are responsible for traffic forwarding. We propose a one-step constrained RN placement (OSRP) algorithm which yields a network tree. The performance of OSRP in terms of the number of added RNs is investigated in a simulation study by varying the network density, the number of sensor nodes, and the number of candidate RN positions [3].Wireless sensor networks (WSNs) provide an effective approach for underground pipeline inspection. Such WSNs comprise sensor nodes (SNs) and relay nodes (RNs) for information sensing and communication.WSNs can perform accurate and real-time inspection, especially in adverse environments. However, transmitting information between underground and aboveground nodes is very challenging. First, in-pipe SNs conducting controlled maneuvers underground are mobile. Second, SNs need to transmit the information wirelessly to aboveground base stations (BSs). In addition, radio propagation is complex because radio waves travel in a multi-medium environment. Finally, the SNs have limited energy supply. Therefore, proper deployment of a WSN is critical to providing reliable communications and efficient inspection. The methodology presents a channel-aware methodology for deploying aboveground RNs in WSNs for underground pipeline inspection. Specifically, first, the work provides a path loss model for radio propagation over multiple transmission media. Then, based on the path loss model a method is developed for optimum placement of the RNs so as to minimize the energy use of SNs and allow reliable communications. This method takes into account characteristics of the wireless channels, power consumption constraint, pipeline coverage requirement, and the limit of the number of the RNs [4].The constrained relay node placement problem in a wireless sensor network seeks the deployment of a minimum number of relay nodes (RNs) in a set of candidate locations in the network to satisfy specific requirements, such as connectivity or survivability. In the proposed methodology, the constrained relay node placement problem in an energy-harvesting network in which the energy harvesting potential of the candidate locations are known a priori. Our aim is to place a minimum number of relay nodes, to achieve connectivity or survivability, while ensuring that the relay nodes harvest large amounts of ambient energy. We present the connectivity and survivability problems, discuss their NP-hardness, and propose polynomial time O(1)-approximation algorithms with low approximation ratios to solve them. We validate the effectiveness of our algorithms through numerical results to show that the RNs placed by our algorithms harvest 50% more energy on average than those placed by the algorithms unaware of energy harvesting. We also develop a unified-mixed integer linear program (MILP)-based formulation to compute a lower bound of the optimal solution for minimum relay node placement and demonstrate that the results of our proposed algorithms were on average within 1.5 times of the optimal [5]. The use of solar harvesting technologies is used rechargeable sensor nodes are evolving. Moreover, in a tree based rechargeable wireless sensor network, the nodes that belong to different routes will have different energy dissipation due to unequal harvested-energy and utilized-energy. Network sustainability and energy efficiency are important issues in a tree based rechargeable sensor network. AMarkov Decision Process based switching algorithm has been designed for a sustainable data collection tree while reducing energy consumption in the network. Further, analysis of energy consumption has been performed using a real-time sensor traffic pattern. A prediction model has been adopted to estimate the harvesting energy (based on solar power) for the rechargeable sensor nodes. In this work, the state of each node is defined based on different independent energy levels. The state of each node may change with time depending on harvested-energy and utilized-energy. The proposed Markov Decision Process approach finds the optimal switching policy for sensor nodes which switch from one parent to another based on energy levels to preserve sustainability [6]. An open source wireless sensor network (WSN) for data analytics, is implemented for monitoring infrastructure and environment. The wireless sensing unit is optimized to be low power for extremely long-term deployments. Several features, such as data compression and online reconfiguration, are introduced to further reduce power consumption. A low-power WSN over optimized time division multiple access scheme is designed to be scalable and reliable for a network with hundreds of sensors. Real-time data visualization and analytical tools are provided with a representational state transfer (RESTful) application programming interface. We utilize SnowFort to develop a real-time damage detection application in structural health monitoring [7]. The binary integer linear programming(BILP) model of the problem of Energy Minimizationunder the constraint of Data Precision in the context of correlateddata collection in wireless sensor networks, called EMDP was implemented. Theexact solution of our BILP model determines, in each round ofdata collection, the role of each node in terms of sensing, datarelaying, and processing. It gives the baseline for optimal networkoperations and helps characterizing the complexity of EMDPproblem. Moreover, a heuristic solution is used, namely,CORAD, which is an energy-aware correlation-based adaptivedynamic clustering algorithm for data collection [8].In particular, two problems are studied: relocation of sensors with minimum number of mobile sensors and formation of k-barrier coverage with minimum energy cost. These two problems wereformulated as 0–1 integer linear programming (ILP). The formulation is computationally intractable because ofintegrality and complicated constraints. Therefore, we relax the integrality and complicated constraints ofthe formulation and construct a special modelknown as RELAX-RSMN with a totally uni-modularconstraint coefficient matrix to solvethe relaxed 0–1 ILP rapidly through linear programming [9].A sensor node in SDSN is able to conduct multiple tasks with different sensing targets simultaneously. A given sensing task usually involves multiple sensors to achieve a certain quality-of-sensing, e.g., coverage ratio. It is significant to design an energy-efficient sensor scheduling and management strategy with guaranteed quality-of-sensing for all tasks. 1) the subset of sensor nodes that shall be activated, i.e., sensor activation, 2) the task that each sensor node shall be assigned, i.e., task mapping, and 3) the sampling rate on a sensor for a target, i.e., sensing scheduling. They are jointly considered and formulated as a mixed-integer with quadratic constraints programming (MIQP) problem, which is then reformulated into a mixed-integer linear programming (MILP) formulation with low computation complexity via linearization. To deal with dynamic events such as sensor node participation and departure, during SDSN operations, an efficient online algorithm using local optimization is developed [10].

Related works

YashuangGuoet al. [11] has presented dynamic resource management is investigated for serving on-demand video streaming users in wireless sensor networks with time varying channel conditions. The WSN is equipped with multi-homing capability, simultaneously connecting to different wireless interfaces. In order to take advantage of the time varying nature of wireless channels, we utilize the joint quality selection associated with quality adjustment at application layer and resource allocation associated with power allocation, subcarrier assignment, and time fraction determination at physical layer to perform the dynamic resource management. By using Lyapunov optimization technique, we develop a quality-aware streaming (QAS) algorithm to maximize the network utility, which is the difference of time-averaged users' perceived video quality and time-averaged WSN transmit power.Andres Gomez et al. [12] have presented a self-sustainable wireless sensor node for low power, high precision radiation dosage rate monitoring. We propose an energy-efficient data acquisition algorithm that can reduce the energy per measurement, while guaranteeing minimal loss of precision. The proposed node is designed to work in collaboration with an unmanned aerial vehicle used for two essential mission steps: air-deployment of the wireless sensor nodes at suitable locations, and acquiring data logs via low-power, short-range radio communication in fly-by mode after a wake-up command. The system uses off-the-shelf components for defining the mission, drop-zone and trajectory, for compressing data and managing communication. The node is equipped with a novel low-power nuclear radiation sensor, and has been designed and implemented with self-sustainability in mind as it will be deployed in hazardous, inaccessible areas. To this end, the proposed node uses a combination of complementary techniques: a low-power microcontroller with non-volatile memory, energy harvesting, adaptive power management and a nano-watt wake-up radio. The node consumes only 31 mW in sleep mode and 1.7mW in active mode, and has the capability to achieve perpetual monitoring once deployed.AshutoshTripathi et al. [13] has presented the scenario and node distribution across the Battle field in India. It uses clustering algorithms to send the data overdifferent geographic region. During the Battle, data gatheringand data aggregation to base station is important and criticaltask. Based on event, clustering algorithm is used. It assumes that sensor node uniformly distributed and coordinatesof the base station and nodes are known. It is essentialto enable the cluster head based selection scheme used in battlefield and the performance of proposed protocol computeintensive and can significantly benefit over the others scheme. The proposed scheme works better data gathering in terms of stability periodand lifetime than the LECH scheme. The proposed scheme isimplemented and simulated with LEACH. Jau-Yang Chang et al. [14] have presentedsuitable deployment for the RSs is one of the most important features of the demand nodes (DNs) to obtain a high data transmission rate in such systems. Considering a tradeoff among the network throughput, the deployment budget, and the overall coverage of the systems, efficient RS deployment schemes and corresponding algorithms must be developed and designed. A novel cluster-based RS deployment scheme is proposed to select the appropriate deployment locations for the relay stations from the candidate positions. To make an ideal cluster distribution, the distances between the DNs are calculated when deploying the RSs. We take into account the traffic demands and adopt a uniform cluster concept to reduce the data transmission distances of the DNs. On the basis of the different candidate positions, the proposed scheme makes an adaptive decision for selecting the deployment sites of the RSs. A better network throughput and coverage ratio can be obtained by balancing the network load among the clusters. Simulation results show that the proposed scheme outperforms the previously known schemes in terms of the network throughput and the coverage ratio. Additionally, a suitable deployment budget can be implemented in multi-hop relay networks.GanXiong et al. [15] have presented the relay nodes (RNs) deployment optimization to improve the energy efficiency in wireless sensor networks (WSNs). First, the energy dissipation model of multi-hop relay transmission scheme with random RNs deployment under a given BER requirement is established. Then, we present the optimal RNs deployment to minimize the energy dissipation, which the position of RNs, the number of RNs and modulation sizes are optimized by two steps optimization. Numerical results show that, optimal RNs are deployed on the line between source node and destination node with the same hop distance. Meanwhile, RNs deployment with joint optimization can further reduce the energy dissipation in comparison with single parameter optimization.A vector RNs placement algorithm is proposed, which can obtain the energy-efficient configuration of the whole network by calculating the location of the RNs when the source node location is fixed and the number of RNs is given. In order to solve the RNs deployment optimization under a given number of RNs, the authors remove the RNs from the initial optimal spanning tree to meet the requirement. The modulation size is a fixed value in the above works, without considering modulation size optimization.Changlin Yang et al. [16] have presented a new problem Minimum Energy Harvesting Node Placement for Energy Neutral Coverage and Connectivity (MEHNP-ENCC). We aim to determine the locations to place the minimal number of nodes used for sensing and relaying such that deployed nodes (i) cover all targets, (ii) have a path to the sink, and (iii) have energy neutral operation. We first model MEHNPENCC as a Mixed Integer Linear Program (MILP). After that a MILP-based approach called GMILP whereby a greedy heuristic is used to generate a collection of locations. We also propose two heuristics: (i) DirectSearch considers locations that cover one or more lines connecting targets to the sink whilst (ii) GreedySearch also considers locations farther afield from the said lines that have a high recharging rate.M. Arthi et al. [17] have presented to provide a better Quality of Service (QoS) with a minimum deployment cost. To dentify the candidate positions of RS that will achieve maximum system capacity. Based on the relay location, we propose two algorithms based on coverage and budget constraints. Using proper deployment of RS, an increased throughput and coverage can be achieved in a cost effective manner. Deployment cost of a RS is less compared to the BS deployment cost as it is small and easy to install and maintain. On the other hand, there is no dedicated backhaul required for RS since it receives its entire capacity from the centralized BS. RS deployment is more important in scenarios where coverage constraints are present. This includes areas having physical obstacles such as high buildings, valleys, villages that are in unreachable areas on rockier uplands etc. If the distance between the communicating nodes is less, it will select high modulation scheme leading to high data rates. For users nearer to the cell boundary, the distance from the BS can be reduced by proper positioning of RS thereby resulting in higher signal strength. Hong Zeng et al. [18] have presented a Connecting via Virtual Force and Compromise Strategy (CVFCS) for recovering from this damage using relay nodes placement. Different from most existing restoration, it considers the segments as collections of sensor nodes, and not as some representative node. Firstly, the approach uses virtual forces to adjust existing nodes of damaged deployment for increasing coverage degree. Then it finds the proper triangular Steiner points or minimum spanning tree edges to achieve the optimal connecting all segments by using relay nodes.A Connecting via Virtual Forceand Compromise Strategy (CVFCS) to restore connectivityby placing minimized RNs. Firstly, it uses virtual forces topull or push nodes towards their own optimizing placementrespectively, in order to achieve uniform distribution ofnodes in the same segment. These movements may reduce separation distance between different segments, and improvethe coverage degree by the existing nodes in the deployingarea. Then it adopts Steiner minimum tree or minimumspanning tree to place the optimal RNs for connectingsegments.Jobin George et al. [19] have presented modified genetic algorithm based relay node placement in wireless sensor networks. Our basic aim is to minimize the total number of relay nodes deployed and to provide maximum connectivity between sensor nodes and relay nodes such that fault tolerance is guaranteed.The energy consumption of sensor nodes in WSNsis a major problem because of its low battery life.Transmission of data is the main reason for the energy drainas power consumption is directly proportional to thetransmission distance. A solution to this problem is to deploy some costly but high powered relay nodes or clusterheads which can prolong the network lifetime and enhancethe capabilities of network in terms of connectivity, faulttolerance and also reduce the data transmission distance.The relay nodes act as cluster heads in the clusters of sensornodes where each sensor transmits data to its correspondingrelay node minimizing the transmission distance henceprolonging the network lifetime. Relay nodes are highpowered nodes as compared to the sensor nodes still theyhave small battery which may lead to its failure. The canmake the network dis-functional also relay nodes can bedamaged or become idle due to several conditions likeenvironmental problem, external damage and hardwaremalfunctioning. Therefore the data sensed by the sensornodes connected to the relay node cannot reach the basestation. Hence it is necessary to place sufficient number ofrelay nodes connected to a sensor such that in case of failureof a relay node it is still connected to another relay node. Asthe relay nodes are expensive it is also necessary tominimize the number of relay nodes talking into account theconnectivity problem.

System Model

The Power Control & Distribution unit is responsible for voltage regulation and distribution for all functional components (memory, sensors, etc.) It also tracks the Maximum Power Point of the solar panel to maximize the power drawn. For instance, in time varying energy harvesting models (e.g., using solar energy), the heavy load may be performed when the energy source is available (during day light), and in the absence of energy the SNs activity may be reduced to a certain degree depending on their energy storage capacity. Dealing with issues such as SN scheduling and traffic control is out of the scope of the work. Nodes in H are then regarded as energy unconstrained nodes. With the previous assumption, it is trivially power efficient to useonly SNs from H for packet relaying to the BS(s). Therefore, the problem is to ensure data forwarding only through nodes from H, with addition of a limited number of RNs to ensure communication coverage (connectivity). Sensing is performed by all the SNs (both ERNs and ELNs), and its coverage is supposed to be assured a priori in the initial deployment. Dealing with sensing coverage is another problem and it is out of the scope of this work. Constrained RNs placement is considered, and potential positions of RNs are limited to areas near SNs position in the initial deployment. This is more realistic than unconstrained deployment in many situations, such as the existence of obstacles, inaccessible areas within the deployment regions, etc. It is also reasonable to assume feasibility of deploying RNs where SNs have been deployed. Accuracy of all the formulations and analysis presented hereafter relies on this model and its assumptions.The Q-LEACH energy aware protocol for wireless sensor networks, a system of routing the data is proposed with MPSO optimization. The energy dissipation during the transmission from cluster head to the base station can be minimized to improve the energy efficiency. The WSN consists of three networks named Wi-Max, Wi-Fi and LTE system for data communication. The WSN are deployed for long term monitoring of fields and are desired to process working without sudden changes in the transmission. It is also considered to estimate the data continuously better coverage of area should be estimated. The new Q-LEACH routing protocol achieves above mentioned requirement to improve the energy aware with various parameters.

Algorithm 1: General Solution Framework

Input: G = (V,H,E), Function F
2 Output: The set of positions, Sp, where to put the RNs.
3 Init: W = SP = ∅
4 Assign weights to vertices (construct *W*) using Eq. (1):
5 Run F(V,E,H,W) to get a MWCDS, say χ.
6 $\xi = \chi T(V \setminus H)$.
7 $\forall u \in \xi$ add the position of u to SP .
8 return SP

The proposed general framework is illustrated by Algorithm 1. This algorithm has as input (line 1), i) the communication graph, G = (V,H,E), which includes the set of vertices (V), the subset of vertices representing the ERNs ($H \subset V$), and the set of edges (E), ii) F, a function that calculates the MWCDS. The output of the algorithm (line 2) is the set of positions where the RNs should be placed to ensure connectivity. The algorithm starts by initiating the sets W, and Sp to empty set. The vertices' weights are then calculated by applying the formula given in Eq. (1) and inserted to the set W. The graph, G = (V, H, E), of P1 is transformed into a vertex weighted graph, Gw, using the following weight function:

$$W : V \rightarrow \{0, 1\}$$
$$\forall u \in H, W(u) = 0; \forall v \in \{V \setminus H\}, W(v) = 1$$

The resulted weighted graph, Gw= (V, E, W), is passed as input to the function, F, which produces the MWCDS χ. This MWCDS resolution will be developed later. The ELNs from χ are denoted ξ, whose positions represent the output of the algorithm. The RNs are then to be put in the positions col-located with these ones to replace the appropriate SNs in forwarding packets, while ELNs will be used only to collect and transmit their own data. With the addition of such RNs, the proposed solution ensures that the network can be connected only though ERNs plus the new RNs.

Development of Energy Limited Nodes (ELN)

The proposed heuristic deploys the Energy Limited Nodes (ELN) based on the density of the targets. The deployment strategy ensures that the sensors will be deployed only if it covers target(s) that are not covered by other sensors. Each sensor is assumed to have uniform radius and the same central angle. The distance between the targets is calculated. We define *count* of a target to be the number of targets within a particular distance (same as the radius of sensors). Each target will have a corresponding *count*. The target with the highest *count* is identified. A sensor is deployed in that position. Since the sensor is directional, all the targets that are at the same distance from the sensor may not be covered. The orientation of the sensor is changed to check for maximum coverage. The change in orientation is in such a way that a 360 degreerotation is performed. At each orientation change, the number of targets that are covered, *c*, is calculated. The highest value of *c*for the sensor is memorized and the corresponding location is decided as its best position. All the targets that are covered by this sensor will then be removed from the list of uncovered targets. *count*is recomputed, ignoring all the covered targets. The next highest priority target would be identified as the one with the highest *count*. The position of the remaining sensors will be decided based on this procedure. The process will be repeated until all the targets are covered or the entire sensor is deployed. It might happen that all the sensors need not be deployed for complete coverage or that the given number of sensors may not be sufficient for full coverage.

Algorithm 2: Algorithm describing a Heuristic for F
1: **Input:** G = (V,H,E,W)
2: **Output:** A connected dominating set, χ, which is an approximation of theMWCDS.
3: **Init:** χ = χ1 = λ
Look up for a Dominating Set χ1
4: **while** V 6= **do**
5: **if** ∃u ∈ V, ˜ω(u) = 1 **then**
6: v = u
7: **else**
8: Chose arbitrary vertex v
9: **end if**
10: k = −1
11: **repeat**
12: k = k + 1
13: Dk = Nk(v) ∩ (H)
14: add progressively to Dk a minimum number of non-null weight vertices(u ∈ Nk(v) ∩ (V \ H)); until Dk dominates Nk(v)
15: Dk+2 = Nk+2(v) ∩ (H)
16: add progressively to Dk+2 a minimum number of non-null weightvertices (u ∈ Nk+2(v) ∩ (V \ H)); until Dk+2 dominates Nk+2(v)
17: **until** X
u2Dk+2
W(u) ≤ (1 + ǫ) X
u2Dk
W(u)
18: χ1 = χ1 ∪ Dk+2
19: V = V \ Nk+2(v)
20: **end while**
Connect the set χ1
21: Determine the connected components in χ1, cluster them and denote everycluster ci
22: Construct an auxiliary graph, ˆG = { ˆV , ˆE, ˆW } from G as follows:
23: ˆ V = {ci}
24: For every path, p ∈ G, of length 3 or less that connects a vertex from ci toanother one from cj , add an edge, e, to ˆE, and set ˆW (e) = W(p)
25: Compute a minimum spanning tree MST of ˆG

26: For every edge e ∈ MST, add the vertices that form e to λ
27: χ = χ1 ∪ λ
repeat
calculate distance matrix for targets;calculate *count*for every target based on sensingradius of the sensor, from distance matrix;
deploy sensor at the target position for which *count*is maximum;
while*start angle reaches maximum value* **do**calculate the number of covered target;
ifthe number of covered targets is better than the
previous number of covered targets **then**;
Set current value as the number of newly coveredtargets;
increase start angle by one unit;
end
remove covered targets
until*all m target covered or deployed n sensors*;

MPSO and integer linear programming (ILP)

The proposed system is evaluated by a radical simulation study wherever each the heuristic and therefore the ILP are evaluated. To demonstrate the advantage of the planned model over the one tiered and the two-tiered models, we have a tendency to compare the planned solutions with, i) the employment of ancient MCDS calculation and replacement of all the obtained set by RNs, that is equivalent to use a MCDS calculation based mostly resolution within the two-tiered model, and ii) the employment of constant technique then mistreatment the SNs in the set as relays while not replacement, that is equivalent to use associate MCDS calculation based mostly resolution within the one-tiered model. A trivial energy-aware resolution is additionally utilized in the comparison that minimizes the employment of ELNs by scheming the shortest ways on the node weighted graph with none RN addition. As stated earlier, our goal in formulating the integer linear program is not to solve it to optimality but to obtain good feasible solutions in the available time. The integer programs can be solved at one of the base stations. Apart from the topology information, we need to know which sensor node is one-hop away from the feasible sites. We propose to manually deploy one special sensor at each feasible site. The node ids of these special sensors are known a priori. These special sensors participate in the MAC protocol as ordinary sensors. Once the neighbor list of all the nodes is collected at the base stations sensor nodes one hop away from feasible sites can be determined. This offers a transparent read on the gain which may be obtained from the planned model and solutions, as well as the connected system. We have a tendency to do not claim direct comparison with any specific resolution from the literature given the distinction within the model. The planned heuristic for MWCDS calculation has additionally been evaluated and compared with a progressive algorithmic rule. MPSO is a computational method which could be defined within the heuristic methods categories. As a member of Swarm Intelligence methods (Ant Colony Optimization, Genetic Algorithm, etc.), this method tries to find best solutions from a set of candidate solutions (particles) based on predefined criteria. The differential feature of the PSO is that each particle memorizes both its position and velocity within the search area.

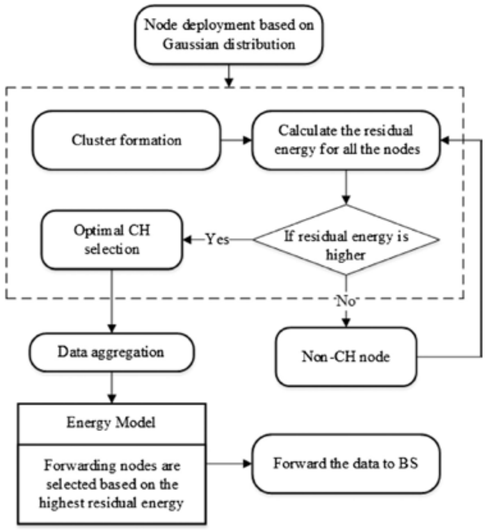

Figure 1: Q LEACH Protocol architecture

The figure 1 (a) shows the wireless sensor network protocol implementation. There are 2 main factors that impact the quantity of wireless nodes. The primary one is that the rate of entire wireless sensor network as a result of the wireless node is far a lot of fewer complexes than the normal node. A lot of sensor nodes lead far better performance and longer network time period.

Input.A set of sensor nodes $S=\{s1,s2,\ldots,sM\}$, where M is the number of nodes. Each sensor node si has a number of characteristics; $si=(\mathrm{pos}i,ei,ni)$, where pos$i$ represents the position of the node si within the deployment area, ei defines its residual energy, and ni is the number of neighbors existing within its communication radius.

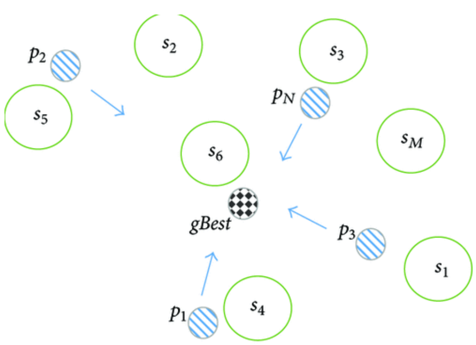

Figure 1: MPSO node setup

Another important input is a set of particles $P=\{p1,p2,\ldots,pN\}$, where N is the number of particles and $||P||\leq||S||$. Each $pi=(vi,\mathrm{pos}i,p\mathrm{Best}i,g\mathrm{Best})$, where vi is a vector that represents the particle pi velocity, pos$i$ is another vector that saves particle's position within the deployment area, and finally pBest$i$ and gBest refer to the current best solution the particle pihas achieved and the best solution within the search space, respectively.
Output. The fittest node $s\in S$, *that* will act as a sink node, where its location guarantees the network's performance in terms of connectivity, coverage, and operational lifetime.

Initialize vi for all particles to zero.

Adjust the initial fitness values of pBestpi and gBest to zero.

Each particle inherits the nearest node characteristics.

Use the following equation to compute the fitness value $f(pi)$ for each particle pi:

$f(pi)=\alpha 1||N(pi)||+\alpha 2\sum p\in N(pi)p.e+\alpha 3dp$, (1)

where$\alpha 1$, $\alpha 2$, and $\alpha 3$ are random numbers ranged in [0,1]. While $N(pi)$ refers to the sensors neighbors for the particle pi, $p.e$ refers to the residual energy within a neighbor node $p\in N(pi)$ and dp is the Euclidean distance between the position of the particle p and the center of the deployment area.

Update pBest$i$ using

$p\text{Best}i=\{pip\text{Best}if(pi)>f(p\text{Best}i)$,otherwise (2)

Select the optimized pBestpi value among all particles to update the value of gBest using

$g\text{Best}=\max\{p\text{Best}p \,||\, p\in P\}$(3)

Calculate the new velocity per each particle within the current iteration using

$vi(t+1)=\omega vi(t)+c1r1(p\text{Best}i-vi(t))+c2r2(g\text{Best}-vi(t))$ (4)

While t denotes the iteration counter and vi represents the particle velocity, ω parameter is a constant inertia-weight that controls velocity of the exploration within the search space. Also, $r1$ and $r2$ are random numbers in the range [0,1]. Whereas $c1$ represents the cognitive coefficient, $c2$ represents the social coefficient towards the best solution.

Each particle updates its position based on the new velocity by means of the following equation:

$\text{pos}i(t+1)=\text{pos}i(t)+vi(t+1)$(5)

The intended stopping criterion, within the MPSO part of the proposed algorithm, is when gBest value fixed into a certain threshold.Select the nearest node to the final obtained gBestparticle as the fittest position suiting enough to act as a sink node for the current scenario.Although the PSO proved that it is one of the best optimization techniques to solve many problems, it still suffers from the trapping within local optima specially in low dimensional search space. Therefore, the proposed algorithm uses the Gaussian jump to escape from the local minima. For limited iterations, when gBestvalue fixed into a certain threshold, each particle updates its position by a Gaussian jump (shift) using (6)

$\text{pos}'i=\text{pos}i+\text{gaussian}()$,(6) Herepos′*i* is the new position shift of particle *pi* and gaussian() is a random number based on the Gaussian distribution.

RESULTS AND DISCUSSION

In this section, the implemented results regarding energy aware constrained relay node deployment and capacity maximization for sustainable data transmission wireless sensor networks.The proposed solution and model for minimum RN addition (MRA) are evaluated by simulation. Both the exact solution (ILP) and the heuristic algorithm are evaluated, denoted MRAILP and MRA-heuristic, respectively.The proposedsystem and model for minimum RN addition (MRA) arecalculated by MATLAB simulation. Each the precise answer(ILP) and therefore the heuristic formula are evaluated, denoted MRAILP and MRA-heuristic, severally. They are compared toi) the employment of MCDS-basedanswer within the one-tiered model (MCDS-1Tiered), that consists within the use of ancient MCDS calculation (without weights) then using the SNs within the set as relays while not replacement, ii) MCDS-based answer within the two-tiered model (MCDS-2Tiered), i.e., MCDS calculation thenreplacement of all the obtained nodes within the set by dedicated RNs, and eventually iii) a trivial energy-aware (TEA). TEA merely calculates the shortest methods on the node weighted graph, wherever weight zero is assigned to ERNs and weight one to ELNs, equally to the projected model however while not RNs addition.Before comparison, the parameter, E, of the planned heuristicis initial investigated. Note that this parameter presents atrade-off between the values (quality of the obtained solutions)and the runtime. High values tend to accelerate the search howeverfor a lower quality (higher cost), whereas lower values have theopposite impact. This trade-off is analyzed hereafter. Four variantsof the heuristic approach is compared with totally different values of E (0.1, 0.5, 1, 1.5),as well because the actual resolution (ILP), are compared in Fig. 1.

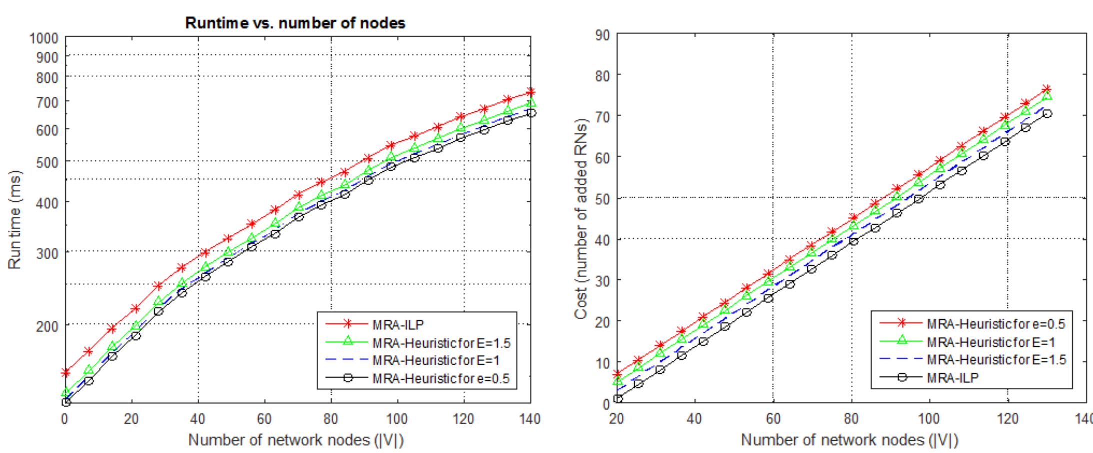

Figure 1: (a) Runtime vs. number of nodes, (b) Cost vs. number of nodes

The figure 2 (a) shows the high difference between solutions based on RNs addition (MRA and MCDS-2Tiered) and supported the one-tiered model (MCDS-1tiered, TEA). Within the former solutions, the energy consumption that affects the network lifetime is that for sending the nodes readings. This can be as solely ERNs and dedicated RNs– that are energy free nodes– are not to forward traffic.Therefore, the life time becomes solely proportional to the network traffic within the simulated situations that explains its exchangeability altogether the plots for MRA and MCDS-2Tiered. This conjointly explains constant performance of ILP and heuristic approach of MRA. Figure 2 (b) shows that the inevitable increase of the value vs. the quantity of nodes is swish and confirms quality. The value of the heuristic version of MRA does not exceed particular nodes for a network of 500 nodes. The ILP value is even a touch lower however it was unattainable to assess it for eventualities on the far side a hundred and fifty nodes. Additional significantly, MRA has extended lower value than MCDS-2Tiered.

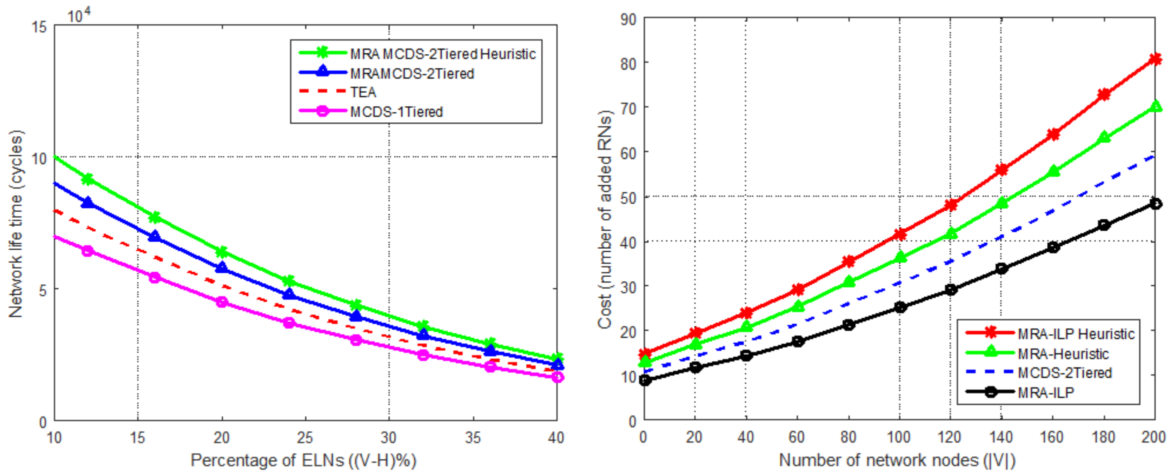

Figure 2: (a) Network lifetime vs. percentage of ELNs, (b) Cost vs. number of nodes

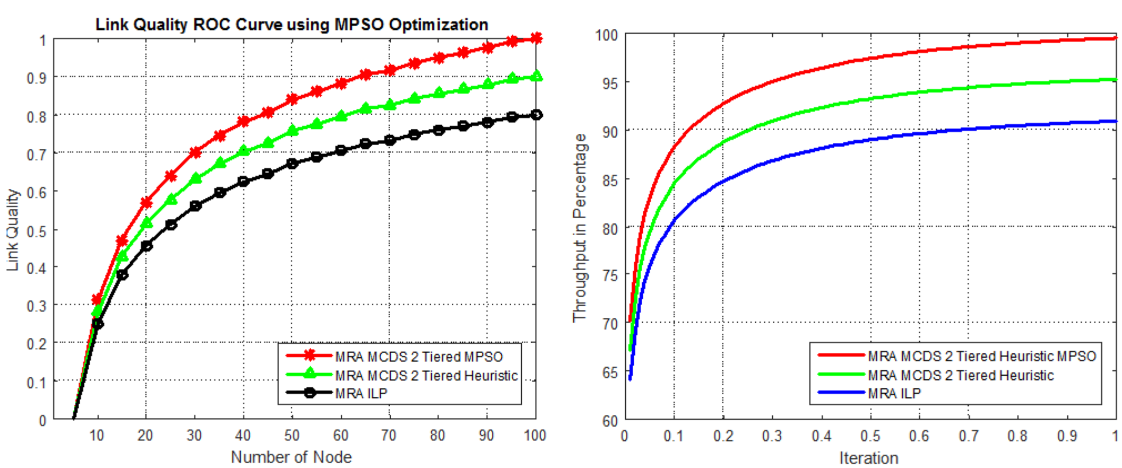

Figure 3 (a) Link quality optimization using MPSO algorithm, (b) Throughput maximization of WSN using MPSO

The figure 3 (a) shows the link quality improvement of WSN network using MPSO algorithm. The figure 3 (b) shows throughput maximization for Q-LEACH protocol with MPSO optimization. The throughput rate is high for WSN system based on its performance. Obtaining signal strength metrics for node connections is not easy. Within the past, once coping with wireless technologies, there has continuously been an unambiguous and easily out there metric - the Received Signal Strength Indicator (RSSI). This metric was helpful once neighbor cells could not share frequencies, and then it had been attainable to directly attribute the strength of a system contained inside one frequency to one cell. As digital modulation technologies have progressed, and network operators have developed a lot of complex and overlapping cell topologies, this restriction has been upraised in order that this metric is of immensely decreased relevancy.

Conclusion

Stainability in wireless sensor networks (WSN) has been considered during this paper from the attitude of energy-aware communication coverage. The General surroundings have been thought-about, wherever 2 kinds of sensor nodes (SNs), energy rich nodes (ERNs) vs. energy limited nodes (ELNs) are also deployed. Upon preparation, the planned resolution aims at limiting the employment of ELN to information reading, and making certain coverage through ERNs, with addition of a minimum range of relay nodes (RNs) for coverage. This can be fully totally different from the pure one-tiered and two-tiered models utilized in the paper. The problem has been reduced to finding the minimum weighted connected dominating set (MWCDS) in an exceedingly vertex weighted graph. The ILP has been derived as an optimum resolution for the problem in terms of the quantity of RNs to be added. Given the exponential computation quality of ILP solvers, a heuristic has been planned. Upper bounds for the approximation of the heuristic to the MPSO optimum, as well as for its runtime, are formally derived. The throughput of the WSN is highly improved by applying the MPSO optimization algorithm. The Q-LEACH protocol is proposed to obtain the high range of transmission to improve the performance of the WSN.

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