Evolution-Based Deployment Scheme for Green Internet of Things

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***Abstract*—In this generation of advance technologies, where communication between physical devices is vital, Internet of Things(IoT) play an important part in connecting the cyber and physical world. IoT is used in various applications such as agriculture, smart home and smart cities, through the deployment of Wireless Sensor Networks(WSNs). Although, in hostile environments, where human intervention is impossible, the life cycle of a deployed WSN becomes critical. Conserving the energy consumed by a wireless sensor network, is imperative, in prolonging the life cycle of the network. This paper addresses the challenging issue of minimizing the energy consumption of WSNs on a large scale. The contributions made by this paper are using the optimization model proposed in [25] to compare Genetic Algorithm(GA) and the Mixed Integer Linear Programming(MILP) algorithm, to solve the minimum energy consumption problem for an IoT. The MILP and GA approach in solving the minimum energy consumption problem, is flexible and efficient, and helps us to achieve our goal, i.e. minimum energy consumption and maximum network lifetime of a deployed WSN.**

I. Introduction

Internet of Things (IoT) is a vital part of the contemporary society, which helps us to communicate with technology in real-time, bridging the gap between internet applications and humans with tools like Artificial Intelligence (AI), actuators and cameras. The implementation of an IoT on a large-scale [1] is challenging and diverse for different deployment schemes. Since IoT consists of many objects that consume high power, power consumption of an IoT plays a vital role, in choosing the best deployment technique. Progress has been made in deploying energy-efficient WSNs, such as exact [2]-[4], ad hoc [5]-[7], hierarchy [8]-[10], and hybrid [9]-[11], but these schemes have failed to align themselves with the principles of *green networking*, thus resulting in a non-scalable and unsustainable IoT. Therefore, the research focus of this paper is to cost effectively deploy a green wireless sensor network, in a way that would prolong the network lifetime and consume minimum energy, with minimum pollution added to the environment.The contributions made by this paper are summarized as follows:

1) Based on the proposed framework in [25], we use the optimization model for deploying a green IoT by considering maximum number of sensors per relay S_{max}, maximum number of active relays R_{max} and minimum energy consumption E_{min} of the network.

2) We solve the minimum energy consumption problem through Mixed Integer Linear Programming(MILP).
3) We propose an evolution-based algorithm to solve the minimum energy consumption problem, and use MILP to set a benchmark result.
4) We compare our proposed algorithms of MILP and GA, and highlight the advantages of using an evolution-based algorithm to solve the minimum energy problem.

MILP is maximizing or minimizing a linear function subject to linear constraints on the variables, where one or more variables are restricted to a set of positive integers. We have transformed the model from [25] into linear equations and constraints to solve the energy problem, whereas an evolution-based algorithm is an algorithm based on natural-selection inspired by biology and genetics [28].

The remainder of this paper is organized as follows. Section II discuses the progress that has already been made on WSNs and explains how this model [25] is better. Section III describes the system framework for placing network elements in IoT. Section IV formulates the problem of green IoT deployment and formally presents the optimization model. Section V introduces the MILP algorithm to solve the minimum energy consumption problem. Section VI uses an evolution-based GA to solve the same energy problem, and gives quality results. Section VII discuses the experimental results of both, GA and MILP, introduced in sections V and VI. Section VIII concludes this paper.

II. Related Work

In this paper, we adopt the *hierarchical deployment scheme* with certain changes from [25], that would cater to prolong the network lifetime and facilitate our algorithm. Recently, a lot of work has been done on energy saving with the deployment of WSNs. WSNs can be classified into five categories on the basis of energy saving techniques, i.e. updating operating system [13]-[14], controlling transmitting power [15]-[17], managing duty cycle [18], [19], routing with minimized power [20]-[21], and clustering for data aggregation [10],[22]. In order to address the new challenges of energy saving in IoT, this paper presents a model that is better than previous studies in the following three ways. First, the model has considered energy saving of a node for transmitting and receiving data. Second, it has considered the data flow as link flow traffic, and addresses the energy consumption problem by limiting the link flow traffic between two nodes. Third, it optimizes energy consumption and prolongs network lifetime by considering maximum number of active relays R_{max} constraint, that can be used as a system budget constraint C for optimizing the overall cost of an IoT.

III. SYSTEM FRAMEWORK

The system framework [25] follows a static routing mechanism [23], which is favourable for large scale IoTs. Previous studies about deploying large-scale WSNs [23] shows that WSN architecture with a dynamic routing mechanism is barely operable in wide area outdoor environments due to electromagnetic interference, air humidity, and temperature [25]. More importantly, WSNs configured with dynamic routing require more power for data processing of a large number of nodes, and needs to exchange information among the nodes, frequently.

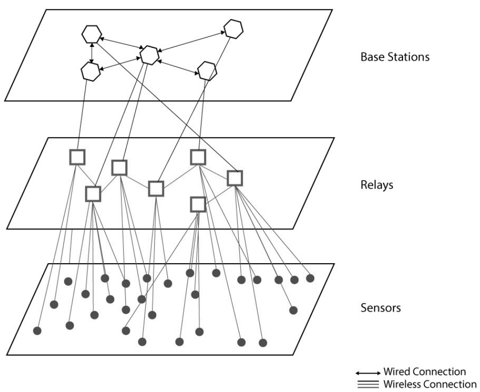

Fig. 1. A Hierarchical System Framework.

Figure 1 shows an example of the system framework [25], which consist of three layers. The first layer is the sensing layer which consists of objects and things, the second layer is the Relay layer which consist of relay nodes, and the third layer is the Base station layer, which consist of several base stations. We formulate the system framework as follows:
Let x and y be two points in the euclidean plane, where distance between x and y is given as $d(x, y)$. Consider S as a set of sensing nodes in the sensing layer having cardinality g, and R as a set of relay nodes having cardinality y. The set of base stations are denoted as B, having cardinality n. Let R be the communication radius of a sensing, relay and a base station layer object, where $R > 0$. We denote the entire network of IoT as $P(N.A)$ where N represents the node set, and A represents the wireless link set. The communication policy of any two nodes in the framework can be outlined as follows:

1) To any node $i \in S$ and $j \in S$, i and j cannot send data to one another, even if $d(i, j) \leq R$.
2) To any node $i \in S$ and $j \in R$, i can send data to j, if $d(i, j) \leq R$.
3) For any node $i \in R$ and $j \in R$, there exists only one path for information transfer between i and j.
4) To any node $i \in S$ and $j \in B$, i cannot send data directly to j, even if $d(i, j) \leq R$.
5) To any node $i \in R$ and $j \in R \Cup B$, i can send data to j, if $d(i, j) \leq R$.

We make the following assumptions for the system framework:

1) All nodes in the framework are at fixed locations.
2) Nodes present in a layer have same attributes, such as energy values, maximum data rate and minimum data rate.
3) Nodes in the sensing and relay layer are energy constrained, while base stations are not.
4) $P(N, A)$, represents a connected network; i.e, each node i in a layer has a path to a node j in any of the three layers, i.e sensing, relay and base station.

In the next section, i.e. Section IV, we formulate the *green IoT* and introduce the optimization model, based on this system framework.

IV. MODELLING THE GREEN IOT

In this section we introduce the variables that are going to be used in the equations ahead. After introducing the variable definitions we are going to introduce and formulate the system constraints.

A. Variable Definition

Following variables, and notations will be used in this paper.

E_{tx}, E_{rx}	energy consumption at a node for data transmission and receiving, respectively
$S_{max}, R_{max}, B_{max}$	maximum sensors per relay, maximum active relays, maximum base stations, respectively
E_e^S, E_e^R	energy consumption of radio electronics of a sensor and relay
$\varepsilon_n, \varepsilon_S, \varepsilon_R$	transmit amplifier of a node, sensing node, and a relay node, respectively
$d(i, j)$	the distance between node i and node j
L	data length
$D(i, j)$	data rate from node i to node j
$D(i, j)_{max}$	maximum data rate between node i and j
$\|D\|$	cardinality of a set D
g, y, n	cardinality of set S, R, and B
C	system budget constraint

B. System Constraints

Let i and j be any node in one of the three layers of the framework proposed, if $d(i, j) \leq R$, then i and j are said to be neighbors. Given that, we introduce an adjacency matrix $N(i, j)$, a linkflow matrix $L(i, j)$ and an energy matrix $E(i, j)$ for the network $P(N, A)$, where i and $j \in N$, and $N(i, j) = 1$, if i and j are neighbors. The linkflow matrix $L(i, j)$ and energy matrix $E(i, j)$, gives the value of data transfer rate and energy consumption, if and only if

$N(i,j) = 1$

$$N(i,j) = \begin{bmatrix} N_{11} & . & . & N_{1(n-1)} & N_{1n} \\ . & . & . & . & . \\ . & . & . & . & . \\ N_{n1} & . & . & . & N_{nn} \end{bmatrix}$$

$$L(i,j) = \begin{bmatrix} L_{11} & . & . & L_{1(n-1)} & L_{1n} \\ . & . & . & . & . \\ . & . & . & . & . \\ L_{n1} & . & . & . & L_{nn} \end{bmatrix}$$

$$E(i,j) = \begin{bmatrix} E_{11} & . & . & E_{1(n-1)} & E_{1n} \\ . & . & . & . & . \\ . & . & . & . & . \\ E_{n1} & . & . & . & E_{nn} \end{bmatrix}$$

To address the green requirements we declare the following system constraints.

Maximum Data Transfer Constraint:
In WSNs, base stations are connected through wired links, that have more bandwidth, therefore the bandwidth is constrained at the sensing and the relay layer. By constraining the rate of data flow $D(i,j)$ between two nodes i and j, we can control the connection of each relay to a certain number of sensors, thus minimizing energy consumption, so that a single relay node, does not get exhausted.

$$D(i,j).N(i,j) + D(j,i).N(j,i) \leq D(i,j)_{max} \forall i,j \in R \quad (1)$$

$$D(i,j).N(i,j) \leq D(i,j)_{max} \forall i,j \in S \quad (2)$$

Maximum Relay Constraint:
The maximum relay constraint can be implemented in order to cost effectively implement the deployment scheme. The maximum number of relays R_{max} can be multiplied with the cost of each relay, to find the total cost, similarly, maximum sensors S_{max} per active relay, and base stations B_{max} can be used to find the cost of the network i.e. less than the total budget C.

$$0 \leq g.C_{S_{max}} + y.C_{R_{max}} + n.C_{B_{max}} \leq C_{total} \quad (3)$$

C. Optimization Model

The energy expenditure in data sensing and processing is much less as compared to data communication [24]. Therefore, energy consumption of data communication, is taken into account. According to the Friis free space model [12].

$$E_{tx} = (E_e + \varepsilon_n.d(i,j)^2).L \quad (4)$$

$$E_{rx} = E_e.L \quad (5)$$

Note that in (4) and (5), the data length L from node i to node j in a unit time is equal to its data rate $D(i,j)$, enabling us to calculate energy in a unit time. Note that in (6), we ignore the energy of a sensing node for receiving data [25], (7) excludes the energy consumption for receiving data from the base station and for transmitting data to the sensing node, and (8) omits the energy consumption when a base station sends data to a base station.

$$e_i = \sum_{j \in R} N(i,j).D(i,j).(E_e^S + \varepsilon_1.d(i.j)^2 \forall i \in S \quad (6)$$

$$\begin{aligned} e_j = &\sum_{i \in S \Cup R} N(i,j).D(i,j).E_e^R \\ + &\sum_{i \in B \Cup R} N(j,i).D(j,i).(E_e^R + \varepsilon_2.d(j.i)^2 \forall j \in R \end{aligned} \quad (7)$$

$$e_k = \sum_{j \in R} N(j,k).D(j,k).E_e^B \forall k \in B \quad (8)$$

Thus, our optimization model focuses on optimizing energy:

Min $(\sum_{i \in S} e_i + \sum_{j \in R} e_j + \sum_{k \in B} e_k)$
s.t.
$0 \leq g.C_{S_{max}} + y.C_{R_{max}} + n.C_{B_{max}} \leq C_{Total}$
$D(i,j).N(i,j) \leq D(i,j)_{max} \forall i,j \in S$
$D(i,j).N(i,j) + D(j,i).N(j,i) \leq D(i,j)_{max} \forall i,j \in R$

V. Mixed Integer Linear Programming

We use Mixed Integer Linear Programming(MILP) to achieve optimum energy levels for the system framework. We modelled the framework into a combination of integer linear equations, that were fed to the linear programming(LP) solver. The LP solver, solved these equations in a time proportional to the size of the problem, and gave us the the favorable condition for deploying sensors, relays and base stations, such that the energy consumed by them was minimum. The LP solver uses three matrices to generate solution, i.e neighbor matrix, $N(i,j)$, linkflow matrix $L(i,j)$, and energy matrix $E(i,j)$. Note that equations (6), (7) and (8) were used to calculate energy between neighbors i and j, and equations (1), (2) and (3) were used to calculate data transfer and network cost constraints.

Objective function:

$$\sum_{p=1}^{g \times y} E(i,j)_P \cdot N(i,j)_p = 0 \forall i \in S \wedge \forall j \in R \quad (9)$$

$$\sum_{p=1}^{y \times y} E(i,j)_P \cdot N(i,j)_p = 0 \forall i,j \in R \quad (10)$$

Constraints:

$$\sum_{p=1}^{g \times y} L(i,j)_p \cdot N(i,j)_p \leq D(i,j)_{max} \forall i \in S \wedge \forall j \in R \quad (11)$$

$$\sum_{p=1}^{y\times y} L(i,j)_p \cdot N(i,j)_p \leq D(i,j)_{max} \forall i,j \in R \tag{12}$$

$$\sum_{i=1}^{f} R_i \leq R_{max} \wedge f = |R_{max}| \tag{13}$$

$$\sum_{k=1}^{c} R(i,j)_k \leq |f-1| \wedge f = |R_{max}| \wedge R(i,j) \in A \tag{14}$$

(9) and (10) are the objective functions of this linear programming problem, that aim to minimize the energy consumed by the sensors and relays in the deployed network. (11) and (12) are the data transfer constraints between nodes on different layers of the network. These data rate constraints between two nodes were formulated into a linear equation such that, it constrained a certain number of sensors to connect to a single relay, given that a relay can connect to a maximum number of sensors, i.e. S_{max}, we reduced the energy load from a single relay, and divided it among all active relays, making sure that our network remains green, and consumes minimum energy. Furthermore, (13) makes our solution cost effective, in terms of the maximum relays R_{max} to be deployed, among all candidate locations. It ensures through integer linear programming that a certain number of relays are deployed which are less or equal to R_{max}, keeping the network cost under the system budget.

On top of that, (14) connects the active relays in a minimum spanning tree (MST) where $R(i,j)$ is the energy edge that belongs to A of network $P(N,A)$ and c is the number of possible connections that exist between the relays. (14) eliminates all trivial connections between the active relays, ensuring smooth and secure transfer of data with minimum power consumed in the network.

However, the results produced by MILP are optimized and gives us control over the system constraints, it cannot be ignored that this algorithm takes exponential time, and can get exhausting, if the set of equations is huge and the system to be solved is of very large-scale.

VI. A Genetic Algorithm

In order to make our minimum energy consumption algorithm efficient, i.e reducing its time complexity, we introduce an evolution-based algorithm. Let h be an individual in a population Q, where h is a matrix of size $g \times y$, and has all the characteristics of our proposed system framework. Here g^{th} row of a matrix h represents the sensor which is connected to y^{th} relay, selected randomly, among relays which are neighbors of g^{th} sensor. The evolution based algorithm primarily works on two principles, i.e. mutation and crossover. The mutation function changes or mutates the attributes assigned to each individual h of a population Q, randomly whereas, the crossover function produces two offsprings o and v, with the help of any two individuals $h1$ and $h2$, from the population Q. The following steps represent the main working of our evolution-based algorithm:

$Q \leftarrow [h_1, \ldots, h_{q-1}, h_q]$ {where h is an individual}
$S \leftarrow [S_1, \ldots, S_{q-1}, S_q]$ {where S_q is the fitness value of q^{th} individual}
for i = 0 to N_GEN **do**
  sort Q w.r.t fitness values stored in S
  if Probability of **Crossover** matches **then**
    for i = 0 to t **do**
      $Q[-i], Q[-(i+1)]$ = Crossover($Q[i], Q[i+1]$)
      $S[-i]$ = Fitness($Q[-i]$)
      $S[-(i+1)]$ = Fitness($Q[-(i+1)]$)
      {t is any constant}
    end for
  end if
  if Probability of **Mutation** matches **then**
    for i = t+1 to q-t **do**
      Mutation($Q[i]$)
      $S[i]$ = Fitness($Q[i]$)
    end for
  end if
end for
return $Q[0]$

The genetic algorithm proposed by this paper, enables us to deploy efficient, reliable and highly scalable IoT networks, and compute the favorable conditions for the deployment with minimum network cost, and optimized energy values, in polynomial time. Note that, GA operates on the principle of *Survival of the Fittest*, and can give extremely efficient results based on the randomness of the functions performed.

VII. Performance Evaluation

In this section we validate the effectiveness of our deployment scheme, and compare the results of our two algorithms. The values for the parameters were taken from [25], and were used in conducting extensive experiments.

The parameters were set as $E_e = 50nj/bit$ and $E_e^B = 2 \cdot E_e^R = 4 \cdot E_e^S = 4 \cdot E_e$, and $\varepsilon_1 = \varepsilon_2 = 100pj/bit/m^2$ and $D(i,j) = 100kbps$ for sensing nodes, and $D(i,j) = 200kbps$ for relay nodes, and $D(i,j)_{Max} = 400kbps.$

Figure 2 shows a topology of 100 sensors distributed randomly over a field of 100 by 100 meters. It also shows all possible candidate location of relays, i.e 121, each at the cross-section of a square of 10 by 10 meters. The following figures show the results of experiments conducted with the values, formulas and matrices introduced above.

Figures 3, 5 and 6 show various topologies, solved by MILP and GA. We can observe that, on a particular radius

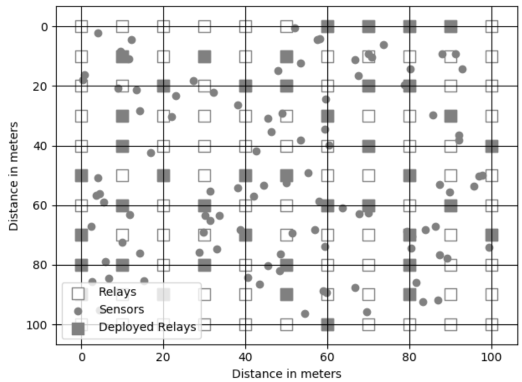

Fig. 2. A topology of a 100×100 meter field.

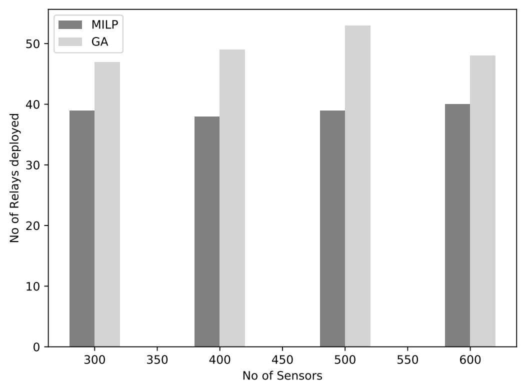

Fig. 3. Results of Topology with R = 15.

R, as the number of sensor increases, the relays R_{max} deployed to connect them do not increase significantly, i.e. because the distribution of sensors is uniform, which is evident in the topology of figure 1. The radius R of a relay, however is very crucial in determining the number of relays to be deployed. The number of active relays R_{max} reduces significantly, when the communication radius R of a relay increases, allowing a single relay to connect to more sensors S_{max} within it's range. Note that, GA is an evolution-based approach and gives approximate values to that of MILP.

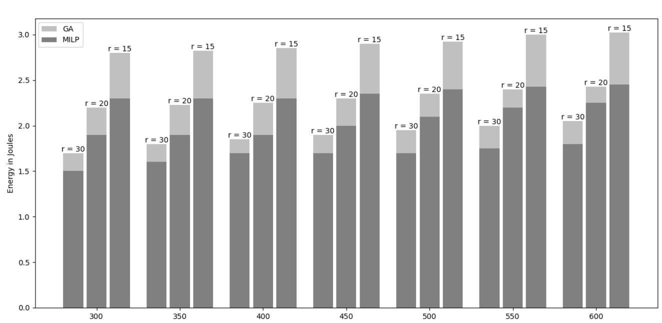

Fig. 4. Comparison of Energy consumtion between MILP and GA

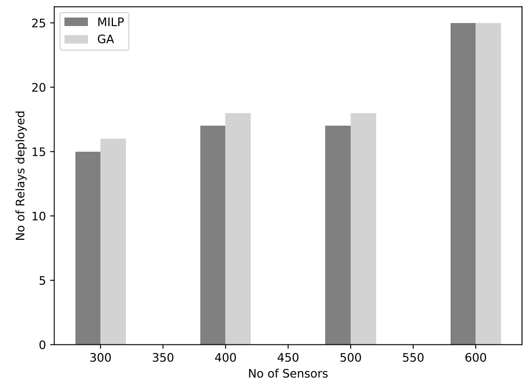

Fig. 5. Results of Topology with R = 30.

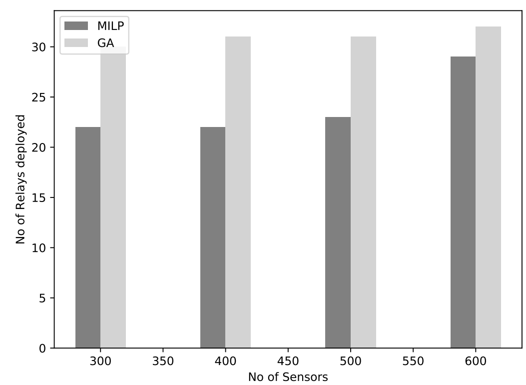

Fig. 6. Results of Topology with R = 20.

The energy values in figure 4 shows that the MILP consumes less energy as compared to GA. It shows that as the radius R of a relay in a network decreases, the number of active relays R_{max} for that network increases, thus increasing the energy consumption of the deployed network. A trend of increasing energy consumption E_{min} of an IoT with the increase in the total number of sensors, can also be observed. According to this figure, GA generates less optimized results than MILP but it is more reliable and efficient as it takes a very small amount of time on huge data sets unlike MILP. We have shown that an evolution based algorithm, is more reliable in terms of it's working ability, and yields highly optimized solution for a sustainable green IoT.

Note that, the results of each topology were generated by running the simulations hundred times, each for our algorithms of GA and MILP. A median value of the simulation, for each topology was plotted, and a desired trend was noticed. The analysis on the above statistical values, was done in accordance to the assumptions made, in the start of the paper.

VIII. Conclusion

This paper has addressed the problem of energy consumption of a WSN, making possible the implementation of an IoT on a large-scale. Our paper has modelled the proposed framework [25] and addressed the energy problem, data-rate and cost constraints in deployment of an IoT, through MILP and GA. In our algorithms of MILP, we optimized the system framework into a green network, by conserving cost, energy and pollution. Following, we ran an evolution-based algorithm, performing functions of crossover and mutation in different generations to get the best individual as our final answer, which was done in polynomial time complexity, as compared to the MILP algorithm that took exponential time. At last, we highlight the advantages of using an evolution-based algorithm to solve the minimum energy problem.

Moving on, the compressed sensing technique [8], [22] might be efficient for minimum energy consumption of an IoT, based on our optimization model, whereas other models [26] of energy consumption may achieve a more energy efficient deployment scheme. Coverage and connectivity [27] in IoT is also an area of interest we might want to work in the future.

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