Energy Efficient UAVs and Internet of Everything Networks Deployment via Genetic Algorithm

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Abstract

Internet of Everything (IoE) plays a significant role in integrating the cyber and physical worlds in this period of advanced technology, where communication between physical objects is critical. Through the deployment of smart sensor networks (SSN), IoE is employed in a variety of applications such as agriculture, smart homes, and smart cities. However, sometimes personal administration of the network becomes infeasible due to adverse circumstances, then the life cycle of installed IoE is crucial. Conserving the energy required by IoE is critical for extending the network's life cycle. The purpose of this work is to address the difficult problem of lowering IoE energy usage (EU) on a large scale. This paper provides mixed-integer linear programming (MILP) optimization problem for controlling the EU of IoE. We employ the Genetic Algorithm (GA) to tackle the NP-hard issue of minimizing EU with low complexity. The suggested technique for tackling the EU problem is adaptable and effective, and it assists the IoE network's aim of minimum EU and long system lifespan.

I. Introduction

The Internet of Everything (IoE) is an important component of modern society because it enables people to communicate dynamically with digitization, creating a link among web apps and individuals through the use of technologies such as Artificial Intelligence (AI), controllers, and sensors [1]. The installation of an IoE at a big level is difficult and varies depending on the deployment method [2], [3]. Because IoE is made up of numerous things that consume a lot of power, the power consumption of an IoE is very important when deciding on the optimum deployment approach. Although progress has been made in implementing energy-efficient smart sensor networks (SSN), they have failed to match the concepts of green networking, resulting in an IoE that is non-scalable and unsustainable [4]. Thus, this work aims to cost-effectively establish a green IoE which extends network lifetime while consuming the least amount of energy and emitting the least amount of pollutants into the environment.

We use the heterogeneous multi-layer technique from [5] and modified it to extend the IoE network's lifespan and make our approach easier to use. This work provides a three-fold approach to handling the power, clustering, and duty cycle concerns of energy conservation in the IoE network. Firstly, the model took into account the energy usage (EU) of an IoE (i.e., node) while communicating data. Secondly, by controlling link flow access to the network's IoE devices, data (link) flow is considered to address the EU issue. Thirdly, it minimizes the number of active deployed unmanned aerial vehicles (UAVs) (i.e., relay) that can be used as a network operator budget to reduce the overall cost of an IoE network, minimizing EU and maximizing the network longevity. The following is a summary of the major contributions:

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2020R1A4A1018607) and in part by the MSIT (Ministry of Science and ICT), Korea, under the Grand Information Technology Research Center support program (IITP-2021-2015-0-00742) supervised by the IITP (Institute for Information & communications Technology Planning & Evaluation) *Dr. CS Hong is the corresponding author.

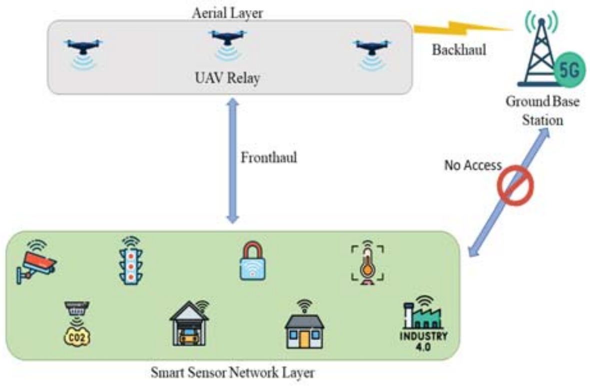

Fig. 1. Illustration of energy-efficient Internet of Everything network

- We proposed IoE network architecture and then develop optimization problem for their green deployment in view of maximum number of IoE per active UAVs, and while consuming least energy.
- The proposed problem is NP-hard, to overcome the time complexity, we employ genetic algorithm (GA) to efficiently solve the MILP [6].
- Simulations results demonstrate that, proposed GA can achieve sub-optimal results with low complexity.

II. System Model

We assume that the network provider provides service to the distant IoE devices when terrestrial service is unavailable. The system structure employs a static routing approach, which is advantageous for large-scale IoEs. Furthermore, IoE has poor power and antenna gain, making it difficult to connect to distant ground base stations (GBS). Furthermore, when the need for IoE coverage grows in remote events, network operators must meet the demand, which is challenging to manage with the present terrestrial-based network design [7], [8]. Hence, network operators utilize UAVs, which are dependable and efficient in deployment, to deliver on-demand services. Thus, we introduce UAV deployment and service allotment to each IoE device.

The system model of the IoE network is depicted in Fig. 1, which is composed of three levels, i.e, the SSN level, the UAVs level, and the GBS level. We assume the set of SSN devices $\mathcal{I} = \{1, 2, 3, .., I\}$, a set of UAVs $\mathcal{U} = \{1, 2, 3, .., U\}$ and a set of GBS $\mathcal{B} = \{1, 2, 3, .., B\}$. The communication radius for SSN, UAV, and GBS can be defined as $r \geq 0$. Let $G(N, E)$ denote the full IoE network, where N denotes the network nodes (e.g., SSN, UAV, GBS) and E denotes the communication links (edges). Moreover, we consider I^{UB}, U^{UB}, and B^{UB} as the upper bound of a smart sensor (SS) per UAV, maximum active UAVs, and maximum available GBS, respectively. Any two nodes in the IoE network can have the following communication policy:

- SS j and k cannot communicate data to each other whether $D(j, k) \leq r$ or not, where $\forall j, k \in \mathcal{I}$ $j \neq k$.
- SS j and UAV k can communicate data to each other when $D(j, k) \leq r$, where $\forall j \in \mathcal{I}$ and $\forall k \in \mathcal{U}$.
- There is just one channel for information flow between any two UAV j and k, where $\forall j, k \in \mathcal{U}$ $j \neq k$.
- SS j cannot transfer data straight to GBS k, where $\forall j \in \mathcal{I}$ and $\forall k \in \mathcal{B}$.
- UAV j can transmit data to any node (UAV or GBS) k if $D(j, k) \leq r$, where $\forall j \in \mathcal{U}$ and $\forall k \in \{\mathcal{U} \Cup \mathcal{B}\}$, $j \neq k$.

where $D(j, k)$ is the distance between node j and k.

III. Problem Formulation

For the sake of simplicity, we make the following assumptions before moving on with problem formulation:

- The IoE network nodes are considered static i.e., fixed SS, hovering UAVs, and GBS.
- Nodes in the same layer share the same features, i.e., energy values, maximum and minimum data rates.
- SSN and UAV layer nodes are energy-restricted, but GBS nodes are energy-enriched.
- $G(N, E)$ denotes a linked network; e.g., node j links to a node k with three levels, namely SSN, UAVs, and GBS.

Assume j and k are nodes in any of the proposed architecture's three tiers. We assume that to become two nodes neighbors, the distance should satisfy these conditions, i.e., $D(j, k) \geq r$, where r is the communication radius. For the network $G(N, E)$, we construct three matrix, i.e., an adjacency $A(j, k)$, a link flow $L(j, k)$, and an energy $E(j, k)$, $\forall j, k \in N$. Moreover, adjacency becomes true when two nodes are neighbour, i.e., $A(j, k) = 1$. The throughput gain and EU can be found in $L(j, k)$ and $E(j, k)$, respectively, when adjacency becomes true. We consider that energy for sensing and processing the data is much less than the data transfer. As a result, the EU's data transmission is characterized by the Friis free space model as follows:

$$E^{\text{TX}} = (E_e + \alpha_n \cdot D^2_{j,k}) \cdot \gamma, \tag{1a}$$

$$E^{\text{RX}} = E_e \cdot \gamma, \tag{1b}$$

where E_{TX} and E_{RX} is the data transmission and reception EU at a node, accordingly, α_n is the node's transmit amplifier, γ is the data size, E_e is radio electronics's EU. The data size γ in a unit time from node j to node k represents the data rate $R(j, k)$, which can compute energy for transmitter and receiver as given in the equations (1a) and (1b) respectively, in a unit time. Thus, the EU for each node can be given as:

$$\mu_j = \sum_{k \in \mathcal{U}} A(j, k) \cdot R(j, k) \cdot (E^I_e + \alpha_j \cdot D(j, k)^2), \ \forall j \in \mathcal{I}, \tag{2}$$

$$\begin{aligned} \mu_k = &\sum_{j \in \{\mathcal{I} \Cup \mathcal{U}\}} A(j, k) \cdot D(j, k) \cdot E^U_e \\ &+ \sum_{j \in \{\mathcal{U} \Cup \mathcal{B}\}} A(k, j) \cdot R(k, j) \cdot (E^U_e + \alpha_k \cdot D(k, j)^2), \ \forall k \in \mathcal{U}, \end{aligned} \tag{3}$$

$$\mu_o = \sum_{k \in \mathcal{U}} A(k, o) \cdot R(k, o) \cdot E^B_e, \ \forall o \in \mathcal{B}. \tag{4}$$

It is worth noting that in (2), the EU of an SSN for receiving data is ignored, while in (3), the data reception EU from the GBS and data transmission to the SSN is excluded, and the GBS's EU when transmitting data to another GBS is omitted (4). Thus we can define our optimization problem as:

$$\underset{\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}}{\text{Min}} \quad \sum_{j \in \mathcal{I}} \mu_j + \sum_{k \in \mathcal{U}} \mu_k + \sum_{o \in \mathcal{B}} \mu_o, \tag{5a}$$

$$\text{s.t.} \quad 0 \leq x \cdot M_{I^{\text{UB}}} + y \cdot M_{U^{\text{UB}}} + z \cdot M_{B^{\text{UB}}} \leq M^{\text{tot}} \tag{5b}$$

$$R(j, k) \cdot A(j, k) \leq R(j, k)^{\text{UB}}, \ \forall j \in \mathcal{I}, \ k \in \mathcal{U}, \tag{5c}$$

$$R(j, k) \cdot A(j, k) + R(k, j) \cdot A(k, j) \leq R(j, k)^{\text{UB}}, \ \forall j, k \in \mathcal{U}, \ j \neq k, \tag{5d}$$

where x, y, and z are the cardinality of SS set, UAV set and GBS set respectively, M^{tot} is the network budget constraint, and $R(j, k)^{\text{UB}}$ is the upper bound datarate from node j to k. To economically execute the deployment method, the upper bound UAV limitation can be enforced in (5b). The upper bound of UAVs U^{UB} product by the price of each UAV to get the overall price. Similarly, the upper bound of SS I^{UB} per active UAV and GBS B^{UB} can be used to calculate the network cost, which is less than the total budget M^{tot}. Because GBS in SSNs are connected through wired lines with higher capacity, bandwidth is limited at the IoE device and the UAV layer. We can manage the connection of each UAV to a set number of SSN devices by regulating the datarate $R(j, k)$ of two nodes j and k, thereby reducing EU and ensuring that a single UAV node does not get depleted as given in (5c) and (5d).

IV. Proposed Genetic Algorithm

We use a GA to make our lowest EU method more effective, e.g. reduce the complexity of computation time. We consider m to be a unique personality in an inhabitant P, where matrix m is an $a \times b$ dimensional with all of the properties of our suggested system model. Each row of the matrix m indicates the IoE device that is linked to the b^{th} UAV, which is chosen at random from among the UAVs that are neighbors of the mth IoE device. The GA is based on two fundamental principles: mutation and crossover [6].

The mutation function randomly modifies (i.e., mutates) the characteristics given to a unique personal m in an inhabitant P, while the crossover function generates two offspring f and g with the assistance of two unique personal m_1 and m_2 by the inhabitants P. The GA suggested in this research allows for the creation of effective, feasible, and hugely expandable IoE networks in polynomial time, as well as compute the beneficial circumstances for IoE network installation with minimal network price and minimum energy cost. It should be noted that a GA works on the *Survival of the Fittest* principle and could

Algorithm 1 Genetic algorithm for IoE network deployment

Initialize: Constant w, unique personal of an inhabitant $P \rightarrow [m_1, ..., m_p]$ and the fitness function value for each p^{th} individual $\Lambda \rightarrow [\lambda_1, ..., \lambda_p]$.
for $u = 0$ to N_{Gen} **do**
  Arrange P regarding fitness values saved in Λ
  if Mutation Probability equates **then**
    for $u = w + 1$ to $p - w$ **do**
      Mutation($P[u]$)
      $\Lambda[u] = \text{Fitness}(P[u])$
    end for
  end if
  if Crossover Probability equates **then**
    for $u = 0$ to w **do**
      $P[-u], P[-(u+1)] = \text{Crossover}(P(u), P(u+1))$
      $\Lambda[-u] = \text{Fitness}(P[-u])$
      $\Lambda[-(u+1)] = \text{Fitness}(P[-(u+1)])$
    end for
  end if
end for
Output: $P[0]$

produce effective outcomes dependent on the randomness of the functions executed. The intricacies of the genetic algorithm can be found in the pseudo-code presented in the Algorithm. 1.

V. Simulation Results and Discussion

In this part, we will go through the numerical findings that we used to illustrate the efficacy of our suggested GA method. We evaluate 300 and 600 IoE devices in two alternative configurations, randomly placed in a 100 m^2 area. During the study period, the IoE devices are assumed to be in a fixed location. As a result, we use a free-space pathloss model based on the distance to determine the throughput of each IoE device. All simulations are conducted several times, and the average results are provided.

In Fig. 2, we show the EU of an IoE network based on the objective function of an optimization problem (5a) when the communication radius is set to $r = 30$. It can be seen that as the number of generations rises, so does the complexity of the EU. Furthermore, we can see that EU is lower when SSN $=$ 300 compared to SSN $=$ 600. Similarly, in Fig. 3, we depict the EU in terms of generation number with a communication radius of $r = 40$. It can be noticed that the total EU decreases from the previous network setup due to a lower number of UAVs deployed with the increase in the area. As a result, there is a trade-off between EU and service area coverage.

VI. Conclusion

The EU analysis for hierarchical Green IoE network deployment was proposed in this study. We developed a MILP optimization problem and solved it using the GA method, which efficiently solves NP-hard problems. The results of the simulation show that the suggested approach achieves efficient EU for IoE deployment.

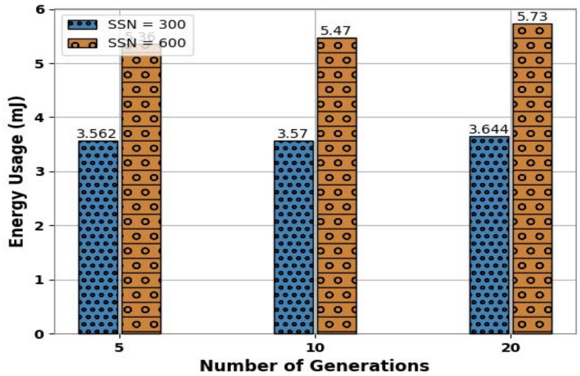

Fig. 2. Energy usage with number of generations when radius $r = 30$

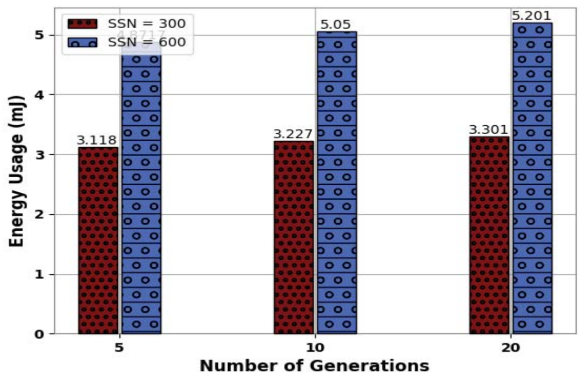

Fig. 3. Energy usage with number of generations when radius $r = 40$

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