Toward Zero-Touch Provisioning in Smart Green Agriculture Driven by Mobile Sensor Stations

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***Abstract*—Smart Green Agriculture (SGA) is currently undergoing a substantial transformation facilitated by the integration of cutting-edge technologies, such as 5G, Artificial Intelligence (AI), and Internet of Things (IoT) devices, including sensors and Unmanned Vehicle Area (UAV). This integration is revolutionizing agricultural practices, making them more sustainable and efficient. For instance, sensors gather crucial data like temperature, humidity, and wind levels, while UAVs capture images and videos of crop fields. These devices can seamlessly communicate via a 5G model, reducing the need for extensive human intervention in SGA operations. We propose a system model that harmoniously coordinates and integrates various technologies in such a case. This includes leveraging UAV and its mobility to deploy a set of sensors for gathering sensing data. Our study illustrates the potential of orchestrated in integrated systems by cooperating among computing server, UAV, sensors and human. This approach is a promising solution for zero-touch system for the next generation of green agriculture. In such a case, our study demonstrates the significance of smart green agriculture driven by mobile sensors station as a viable solution for orchestration in agriculture. It also sets the stage for further advancements at the intersection of technology and sustainable farming practices, emphasizing the pivotal role of these innovations in shaping the future of agriculture.**

***Index Terms*—Smart Green Agriculture, Internet of things (IoT), Edge computing, UAV.**

I. Introduction

The vast adaptation of Internet of Things (IoT) devices has spurred significant advancements in science, technology, industry, and agriculture [1]. In particular, it has significantly enhanced the quality of monitoring systems in a wide range of applications, e.g., smart factories, smart buildings, smart agriculture, etc. In such applications, smart green agriculture is one of the critical aspects of a sustainable system that gained a tremendous amount of interest in both academia and industry. Recognizing the potential for sustainable development, numerous smart green agricultural projects are being rigorously developed and implemented in a structured manner. In particular, the application of innovative technologies such as smart sensors, automated irrigation systems, and data-driven decision-making platforms has produced impressive results. By employing these technology we can increase crop fields area, significant save water for cultivation, and increasing precision in pet, nutrient monitoring system. These advancements pave the way for a future of sustainable agriculture, where technology empowers farmers to optimize resources and ensure food security for generations to come.

Furthermore, the exponential increase in population has led to a higher demand for food in recent years [2]. However, farmland area is decreasing due to climate change, agricultural-to-industrial land-use change, housing demand, etc. This requires an improvement in agricultural productivity and quality in the near future. To address this pressing challenge, accurate monitoring of soil parameters is crucial for effective and targeted interventions in SGA [3], [4]. To facilitate informed decision-making, it is important to measure temperature, humidity, water levels, pests, nitrate, and many other properties. By doing so, we can allow for a confident selection of remedial measures, such as water and fertilizer regulation, or the selection of crop cultivars best suited to specific soil conditions.

While numerous researchers have explored the benefits of IoT devices for data collection, management, and monitoring in smart agriculture, achieving seamless integration and automation remains a challenge [5], [6]. Despite promising results reported by various authors, many systems still exhibit limitations due to the lack of interoperability between IoT devices, hindering their ability to function autonomously and requiring significant human intervention for decision-making [7]–[9].

Therefore, in this paper, we proposed a novel system model where IoT devices are cooperatively and automatically executing tasks from collecting, processing, and making decisions for

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smart green agriculture. Our contributions can be summarized as follows:

We proposed a novel system model of integration and cooperation among IoT devices for collecting, processing data, and making decisions, i.e., deciding location and duration to collect data, analyzing collected data by Multi-acess Edge computing. We proposed a novel idea of exploiting UAV to collect data over crop fields with multiple type of sensor networks to improve the mobility and simplicity of deployment and maintenance activity. We then, formulate an optimization problem of sensor activation and bandwidth allocation to minimize the total energy consumption of the network. We decompose the original into two subproblem such as communication resource allocation and sensing data collection problem.

Next, we present our system model.

II. System Model

In this paper, we consider a network model consisting of a crop field (CF) that can be represented as a grid size $M \times N$, where (m, n) represents the location of a point in the crop field, i.e., m is longitude, and n is latitude; a set of sensors $\mathcal{S}$, and a set of UAVs $\mathcal{V}$, which is demonstrated in Fig. 1.

In a typical monitoring system, sensors are deployed in fixed locations to collect real-time data. This can be achieved using a fixed sensor station, where the data is transmitted via wired or wireless networks. The station is powered either by a built-in battery or connected to the electrical grid. These sensor are monitoring the information of soils such as temperature, moisture, pH, nutrient, insect, etc. The effectiveness and accuracy of fixed sensor systems have been well established through practical use across various fields, particularly in agriculture. However, deploying fixed sensor stations poses significant challenges in terms of maintenance and operation. For instance, maintaining these systems requires personnel to visit each station to inspect equipment conditions, such as battery levels, and perform routine cleaning. Additionally, fixed stations are vulnerable to external factors like weather conditions and natural disasters, as well as operational risks from farming machinery, such as plows or harvesters.

Therefore, in this paper, we proposed a novel system model that is mobile sensor station(MSS) where sensors are carrying by an UAV. Consider a scenario where a farmer has a large area of land that needs preparation for the upcoming cultivation season. To improve plant productivity and quality, the farmer must gather various types of information, such as soil conditions, groundwater levels, and water table data. Traditionally, the farmer would need to travel across the land, using multiple tools to collect this information. On a small plot, this might take a few hours or a day, but on a larger scale, it could take several days, weeks, or even months.

Instead of manually performing these tasks, we can leverage advancements in technology, such as IoT devices, to streamline the process and complete it in just a few hours. For instance, we can use MSS to carry the necessary measurement tools, fly to different locations, gather data, and transmit it back to a central server (CS). The collected information can then be analyzed to help the farmer make informed decisions. The more MSSs deployed, the shorter the time needed to complete the tasks. However, this also increases the cost of deployment. Therefore, the farmer must carefully assess the cost-effectiveness of the approach, deciding how many MSS units to deploy and identifying the critical areas where data collection is most essential.

A. MSS model

In this section, we define our MSS[1] model. In which, an UAV is equipped with several type of sensors. And fly to predefined locations or real-time decision ordered by the CS. Let $H_v = \{i, i \in S\}$ be the set of sensors equipped at MSS v, where i represents sensor type-i. For instance, $i = 1$ represents moisture sensor, $i = 2$ represents nutrient sensor, etc. Let $|H_v|$ be the total number of sensors at MSS v.

In reality, the process of gathering data, sending data to the CS, data processing, receiving mission orders from the CS, and trajectory and sensor activation optimization is repetitive. However, by optimizing for a single mission, we can apply the same optimization strategy to various missions, and the system pertain optimized. We assume that a single mission has a total of T time slots, which could be minutes, seconds, hours, or other units. In each time slot t, the MSS can perform multiple actions, including hovering, flying, activating sensors, transmitting data, and receiving orders from the CS. In this paper, we assume that the MSS v has a built-in and rechargeable battery with a maximum capacity of $E_v^{\max}$. The MSS consumes energy not only for its own activities but also for sensor operations. Let $E_v^0[t]$ be the base-load energy of MSS v at time slot t. Let $E_v^{\text{hov}}[t]$, $E_v^{\text{active}}[t]$, $E_v^{\text{com}}[t]$, and $E_v^{\text{fly}}[t]$ represent the energy consumption for hovering, sensor activation, communication, and flying, respectively. Furthermore, during data collection missions, MSS may not always be flying. It may need to hover and gather data before transmitting it to the CS. Therefore, we define decision variable $x_v[t]$ The total energy consumption of MSS v during mission can be define as follows:

$$E_v^{\text{total}} = \sum_{t=1}^{T} \left(E_v^{\text{base}}[t] + E_v^{\text{fly}}[t] + E_v^{\text{hov}}[t] + E_v^{\text{active}}[t] + E_v^{\text{com}}[t] \right) \tag{1}$$

In the next section, we will further define each term in Eq. (1). Firstly, we define the communication model and its energy consumption which is defined as $E_v^{\text{com}}[t]$.

B. Communication Model

In this paper, communication model take place between MSS and the CS, involving two types of data transmission: i) real-time data and ii) semi-real-time data. For example, an MSS equipped with a camera can monitor insects by capturing real-time images and sending them to the CS. The CS then analyzes the images and identifies the next location

[1]We use MSS v and UAV v interchangeably.

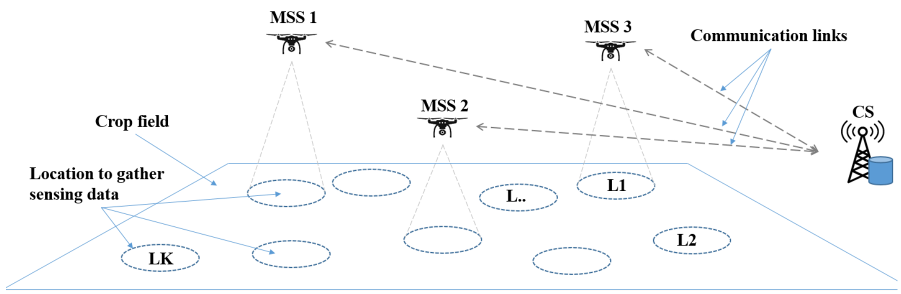

Fig. 1: Illustration of our system model.

for further data collection. This process is considered real-time data transmission. Other sensing data, such as humidity, water levels, and soil nutrients, can be sent to the CS after the MSS returns to its home station. This can be considered as semi-real-time data. For simplicity, we assume that the semi-real-time data can be transmitted via wireless LAN or M2M protocol, thus, we omitted to analysis this case. In the real-time data transmission, we employed the Air-to-Ground (A2G) communication technology. Let $R_v[t]$ be the achievable data rate between MSS $v \in V$ and BS at time slot t. $R_v[t]$ can be modeled as follows:

$$R_v[t] = \beta_v[t] W[t] \log_2\left(1 + \frac{P_v[t]G_v[t]}{I_0}\right), \forall t \in T, \forall v \in V, \tag{2}$$

where $\beta_v[t]$ is the fraction of bandwidth that is allocated to MSS v at time slot t, $W[t]$ is the total system bandwidth, $P_v[t]$ is the transmit power of MSS v, $G_v[t]$ is the channel gain between the CS and MSS v. In this model, we assume that communication methodology base Orthogonal Multiple Access technique (OMA), and thus, there is no co-tier interference among MSS. Consequently, according to [10], [11], $G_v[t]$ can be define as follows:

$$G_v[t] = 10^{-(\ \ _v + \ \ _{LoS})/10}, \forall v \in V, \tag{3}$$

where $\ \ _{LoS}$ is the additional attenuation factor for LoS link, and Ψ_{v0} is the path-loss component between MSS v and the CS, given by:

$$\Psi_v[t] = 20\log_{10}(d_v[t]) + 20\log_{10}(f_c) + 10\log_{10}(\frac{2\pi}{c})^2, \tag{4}$$

where f_c is the carrier frequency, $d_v[t]$ is the distance between UAV v and the BS, c is the speed of light. Furthermore, let $\alpha_v[t]$ be the size of sensing data of MSS v that transmitted to CS at time slot t. In this paper, we assume that $\alpha_v[t]$ is not extremely large, thus, it will not exceed the transmission to another time slot. As a result,the energy consumption of communication can be define as follows:

$$P_v[t] = \frac{I_0}{G_v[t]}\left(2^{R_v[t]/\beta_v[t]W[t]} - 1\right). \tag{5}$$

Let $z_v[t]$ denote the decision variable of communication at time slot t of MSS v, whether MSS v need to communicate with CS or not. $z_v[t]$ can de modeled as follow:

$$z_v[t] = \begin{cases} 1, & \text{if MSS vneed to communicate with CS,} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Thus, the energy consumption for communication of MSS v can be formulated as follow:

$$E_v^{\text{com}}[t] = P_v[t] z_v[t]. \tag{7}$$

Next we define our energy consumption model for flying and hovering of MSS v.

C. Energy consumption model

In this section we define the energy consumption model for each scenario such as activating sensor, flying and hovering of MSS, respectively. Let $x_v[t]$ be the decision variable of MSS v at time slot t. $x_v[t]$ can be define as follow:

$$x_v[t] = \begin{cases} 1, & \text{if MSS v is flying,} \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

Moreover, based on the work in [12] and the kinetic energy, the energy consumption of MSS v for flying at time slot t can be formulated as follow:

$$E_v^{\text{fly}} = \frac{1}{2} m_v \nu_v[t]^2. \tag{9}$$

On the other hand, according the work in [13] energy consumption for hovering of MSS v at time slot can be define as follows:

$$E_v^{\text{hov}}[t] = \frac{\eta\sqrt{\eta}}{\ \ _v\sqrt{0.5\pi j r^2 \varkappa}}, \tag{10}$$

where η, $\ \ $, j, r, and $\varkappa$ are the proportional to the MSS's mass, power efficiency, number of rotors, and air density, respectively. Moreover, we consider the energy consumption for activating a subset of sensors that are built-in the MSS v at time slot t. Let $y_{v,s}[t]$ be the decision variable that denoted whether sensor s is activated at time slot t or not. $y_{v,s}[t]$ can be define as follow:

$$y_{v,s}[t] = \begin{cases} 1, & \text{if sensor s is activated,} \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

As a results, the energy consumption for energy consumption of sensors activating at time slot t of MSS v can be define as follows:

$$E_v^{\text{activate}}[t] = \sum_{s \in H_v} E_{v,s} y_{v,s}[t], \tag{12}$$

where $E_{s,v}$ is the energy consumption of sensor type s. Consequently, the total energy consumption of MSS v at time slot t can be formulated as follows:

$$E_v^{\text{total}}[t] = E_v^{\text{fly}} x_v[t] + (1 - x_v[t])\left(E_v^{\text{hov}} + E_v^{\text{activate}}[t]\right) + E_v^{\text{base}} + E_v^{\text{com}}[t]. \tag{13}$$

D. Sensing data model

In this paper, our sensing data model is the amount of data gathered by MSS during a mission. Furthermore, we assume that during the gathering process, each location L_i, one sensor at least gathered π_s records of data. For instance, at mission i-th, nutrient sensor must gathered $\pi_s = 10$ records of data about nutrient at location L_i, s is the nutrient sensor. Let κ_s be the base load energy to active of each type of sensor s to gather sensing data. For simplify, we assume that this based energy consumption is the same for any type of sensor. In practical settings, it must be different, however, it will not effect too much in the optimization problem of our model. Let C_{v,s_i} be the number of record of sensor s_i in MSS v. It must satisfy the following:

$$C_{v,l_i,s_i} \geq \pi_s, \forall v \in V, \forall s_i \in S_v. \tag{14}$$

Thus, $E_{v,s}$ can be formulate as follows:

$$E_{v,s} = \sum_{t=1}^{T} \kappa_s C_{v,l_i,s}, \forall s \in S_v, \forall v \in V. \tag{15}$$

Based on the aforementioned equations, we will formulate our optimization problem in the next section.

III. Problem Formulation

In this paper, our objective function is minimize the energy consumption of the system. The optimization problem can be formulated as follows:

$$\min_{\boldsymbol{\beta},\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}} \quad \sum_{v\in V} E_v^{\text{total}} \tag{16a}$$

s.t.

$$E_v^{\text{total}} \leq E_v^{\max}, \forall v \in V, \tag{16b}$$

$$C_{v,l_i,s_i} \geq \pi_s, \forall v \in V, \forall s_i \in S_v, \forall l_i \in L_v, \tag{16c}$$

$$0 \leq \beta_v[t] \leq 1, \forall v \in V, \forall t \in T, \tag{16d}$$

$$\sum_{v\in V} \beta_v[t] x_v[t] \leq 1, \forall t \in T, \tag{16e}$$

$$x_v[t] \in \{0,1\}, \forall v \in V, \forall t \in T, \tag{16f}$$

$$y_{v,s}[t] \in \{0,1\}, \forall v \in V, \forall s \in H_v, \forall t \in T, \tag{16g}$$

$$z_v[t] \in \{0,1\}, \forall v \in V, \forall t \in T, \tag{16h}$$

where, constraint (16b) represents the total energy consumption of MSS v should not exceed is capacity. Constraint (16c) guarantee that each sensor must gathered at least π record of data for each location l_i^v. Constraint (16d) represent the amount of bandwidth allocated to MSS v is linear and non-negative. Constraints (16f), (16g), and (16g) represents decision variables are binary. Due to the binary variables and coupling constraint (16e), the problem in (16) fall into NP-hard category, thus, it cannot be solve in polynomial time. Therefore, based on the work in [11], [14], we decouple problem (16) into two subproblem: i) communication resource allocation problem; ii) sensing data activation problem. The first subproblem can be derive as follow

$$\min_{\boldsymbol{\beta}} \quad \mathcal{F}_v(\beta_v[t], z_v[t]) \tag{17a}$$

s.t.

$$\mathcal{F}_v[t] \leq E_v^{\max}, \forall v \in V, \tag{17b}$$

$$0 \leq \beta_v[t] \leq 1, \forall v \in V, \forall t \in T, \tag{17c}$$

$$\sum_{v\in V} \beta_v[t] x_v[t] \leq 1, \forall t \in T, \tag{17d}$$

$$\tag{17e}$$

where the objective funtion $\mathcal{F}_v(\beta_v[t])$ can be define as follows:

$$\mathcal{F}_v(\beta_v[t]) = \sum_{t=1}^{T} \left(E_v^{\text{com}}[t]\right) + \bar{E}_v[t], \tag{18}$$

where

$$\bar{E}_v[t] = E_v^{\text{fly}} x_v[t] + (1 - x_v[t])\left(E_v^{\text{hov}} + E_v^{\text{activate}}[t]\right) + E_v^{\text{base}}. \tag{19}$$

It means that we fixed the other variables $\boldsymbol{x}, \boldsymbol{y}$, then solve the problem of bandwidth allocation w.r.t. β and $z = 1$, it mean that MSS v is active to request communication link to the BS. This principal of this method based on the decomposition technique [15] and Block Coordinate Descent (BCD) [14]. The optimal conditions and convergence analysis can be refer to the work in [11], [14], [16]. Similar to our work in [11], the close-form solution of (17) can be define as follows:

$$\beta_v^{(*)}[t] = \sqrt{\frac{1 + \zeta_v[t] P_v[t]}{\xi_v[t] W[t] \log_2\left(1 + \frac{P_v[t] G_v[t]}{I_0^2}\right)}}, \tag{20}$$

where $\zeta_v[t]$ and $\xi_v[t]$ is the non-negative Lagrangian multipliers, respectively.

The second subproblem is determine whether to active sensor to collect data or not, and how long to hovering UAV at a location. It can be formulated as follows:

$$\min_{\boldsymbol{x},\boldsymbol{y}} \quad \mathcal{F}_v(\boldsymbol{x}[t], \boldsymbol{y}[t]) \tag{21a}$$

s.t.

$$\mathcal{F}_v(\boldsymbol{x}[t], \boldsymbol{y}[t]) + E_v^{\text{com}}[t] \leq E_v^{\max}, \forall v \in V, \tag{21b}$$

$$C_{v,l_i,s_i} \geq \pi_s, \forall v \in V, \forall s_i \in S_v, \forall l_i \in L_v, \tag{21c}$$

$$x_v[t] \in \{0,1\}, \forall v \in V, \forall t \in T, \tag{21d}$$

$$y_{v,s}[t] \in \{0,1\}, \forall v \in V, \forall s \in H_v, \forall t \in T. \tag{21e}$$

$$\tag{21f}$$

The second problem is non-convex nor con-cave which is Np-hard problem due to binary variables $\boldsymbol{x}$ and $\boldsymbol{y}$. Thus, obtain a solution in polynomial time is impossible in practical settings. And thus, it become intractable. Therefore, we firstly, employ

Algorithm 1 ADMM-based solution approach

Initialize: $i = 0$; $\beta_u^v(0)$, $\epsilon > 0$, $\zeta_u^v(0), \xi^v(0)$, and $\varrho_l(0) > 0, (l = 1, 2)$,
repeat
  $i \leftarrow i + 1$;
  $z \leftarrow 1$;
  Update β based on (20);
  Update $\boldsymbol{x}_v^{(i+1)}$ based on the ADMM method;
  Update $\boldsymbol{y}_v^{(i+1)}$ according to (47);
until $|\mathcal{F}_v(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\beta})^{(i+1)} - \mathcal{F}_v(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\beta})^{(i)}| \leq \epsilon$;
Then, set $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\beta}$ as the desired solution.

the relaxation method to approximate the binary variables into continuous variables. The solution of approximate problem is not the global optimum, however, in some sense it applicable and can be consider as a near-optimal solution [17]. Moreover, we define constraint (21b) as the projection condition into the feasible solution set, and thus, we omit this constraint in the approximate problem [16]. Similar to our works in [11], [16], [18], problem (21) can be approximate as follows:

$$\min_{\boldsymbol{x}, \boldsymbol{y}} \quad \mathcal{F}_v(\boldsymbol{x}[t], \boldsymbol{y}[t]) \tag{22a}$$

s.t.

$$\mathcal{F}_v(\boldsymbol{x}[t], \boldsymbol{y}[t]) + E_v^{\text{com}}[t] \leq E_v^{\max}, \forall v \in V, \tag{22b}$$

$$C_{v,l_i,s_i} \geq \pi_s, \forall v \in V, \forall s_i \in S_v, \forall l_i \in L_v, \tag{22c}$$

$$0 \leq x_v[t] \leq 1, \forall v \in V, \forall t \in T, \tag{22d}$$

$$0 \leq y_{v,s}[t] \leq 1, \forall v \in V, \forall s \in H_v, \forall t \in T. \tag{22e}$$

(22f)

As a result, problem (22) can be solvable via ADMM method [17]. The detail of proposed algorithm can be describe in Alg. 1. In which, we assume that, MSS always active to communicate with the BS, thus, z is set to one. The bandwidth allocation variable β can be obtain via Eq. (20), while $\boldsymbol{x}$ and $\boldsymbol{y}$ can be obtain via ADMM method and the cvxpy solver in python [19].The solution will convergence with criterial condition ϵ.

IV. Numerical Results

A. Simulations setup

In this paper we assume a scenario that CS generate a subset of location based on the grid size $M \times N$. For instance, $L = \{1, 2, \ldots, M \times N\}$, a subset of K location needed to gather sensing data can be define as $\mathcal{K} = \{L_1, L_2, \ldots, L_K\}$. Moreover, we assume that each mission MSS will get a subset of location that is different from the last mission. This will guarantee the Age of Information (AoI) of the system. Thus, for simplicity, we assume that CS employed a random permutation of $\mathcal{L}$ and extract a subset of K location. Moreover, we assume that the trajectory of MSS can be optimized via Deep Reinforcement Learning [20]–[22]. And thus, we omit this part in our numerical results. The main parameters used in our numerical results is stated in table. I.

TABLE I: Simulation parameters.

Parameter	Value
Total number of MSS (V)	3
White-noise (I_0)	-174 dBm/Hz [11]
Number of time slots (T)	100
Additional pathloss η_{LoS} and η_{NLoS}	2 and 20 dB[23]
Transmission power P_v	50 mW[23]
Moving energy consumption	1.0 $\sim$ 5.0 mAh/m[23]
Hovering energy consumption of UAV E_v^{hov}	20.0 mAh[23]
System bandwidth W_v	3 MHz [11]
The number of records (π)	10
The number of location (L)	100

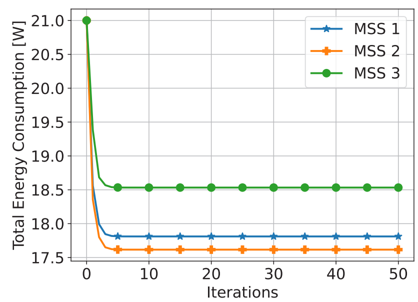

Fig. 2: Performance of proposed solution approach

In performance matrix, we compare our results with a trivial solution approaches is *Greedy Algorithm* (GRA), *Randomization Algorithm* (RDA), and *Exhausted Search Algorithm* (ESA).

1) Greedy Algorithm:: This approach tries to find the first best solution, which sometimes achieves a global optimum but mostly a local optimum. It is a naive approach to compare with this solution approach. However, it is reasonable to employ in an NP-hard category due to its complexity.

2) Randomization Algorithm:: This approach takes a random solution from the feasible solution set, which is the simplest and lowest complexity approach in the NP-hard category. It does not consider any sophisticated solutions, but sometimes, it can reach a reasonable solution through a probabilistic model.

3) Exhausted Search Algorithm:: This approach tries to find all possible solutions in the feasible set. This takes exponential time and is not suitable for large-scale settings. However, to measure the potential of our proposed solution approach, we employ ESA in small-scale settings to compare it with our approach.

B. Numerical results

Fig. 2 shows that our proposed solution approach converges after 10 iterations and has a stable performance. As shown in the figure, after reaching a stationary solution, it no longer fluctuates, demonstrating stability. This is due to the convexity properties of the relaxation problem (21), which is consistent with the theoretical analysis of the ADMM principle in [17].

Moreover, in Fig. 3, we compare our solution with the three aforementioned approaches to demonstrate the potential of the proposed approach. In this figure, we ran the simulation 100

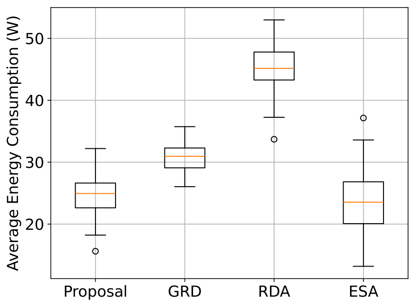

Fig. 3: Performance comparison

times and took the results to compare with the others under the same settings. As a result, our approximate problem can achieve a near-optimal solution in the ESA approach while outperforming the two naive approaches such as GRD and RDA. However, our proposed approach has a lower complexity of $O(KVT)$ compared to the ESA approach $(O(T2^{(KV)}))$. We choose only 3 MSS, which is too small; however, with a number of $T = 100$, $K = 50$, and $V > 3$, it remains a challenge to perform the ESA approach. In these results, the average energy consumption of our approach is 25(W), and the ESA approach is 23 (W), which is nearly 8% larger than the optimal solution.

V. Conclusion

In this paper, we propose a novel system model of mobile sensor stations involved in smart green agriculture. By leveraging improvements in technology such as the 5G communication model and UAVs, we have designed a robust model to make decisions on gathering sensing data and communication between UAVs and CS. By employing our proposed approach, we can reduce human effort in monitoring agricultural data and decision-making in smart agriculture models. The proposed approach demonstrates a potential solution for integrating UAVs, 5G technology, IoT and toward the zero-touch provisioning in SGA.

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