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Energy Efficient Estimation in Wireless Sensor Network With Unmanned Aerial Vehicle

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ABSTRACT Distributed estimation is a typical application of wireless sensor network (WSN), where a set of sensor nodes (SNs) collaboratively estimate some parameters of interest from noisy measurements. Recently, unmanned aerial vehicle (UAV) enabled WSN has attracted significant interest since the UAV can collect data energy-efficiently due to its high mobility. In this paper, we consider the joint optimization of UAV trajectory design and SNs' transmission bits allocation for estimating an unknown parameter in UAV-enabled WSN, and the objective is to minimize the total energy consumption of all SNs under the constraint that the mean square error (MSE) of estimation is below a target threshold. The joint optimization problem is formulated with mixed-integer non-convex programming, which is difficult to solve in general. As such, an efficient iterative algorithm is proposed to solve it by applying the block coordinate descent and successive convex optimization techniques. A low-complexity and systematic initialization scheme is also proposed for the trajectory design and transmission bits allocation based on the trade-off structure on the number of visited SNs for estimation. The extensive simulation results are provided to demonstrate the significant performance gains in terms of total energy consumption of all SNs as compared with other benchmark schemes.

INDEX TERMS Energy efficient, distributed estimation, unmanned aerial vehicle, wireless sensor network.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Recently, a revolution has been witnessed in the scientific research and various applications on wireless sensor network (WSN). WSN typically consists of large number of battery-powered tiny sensor nodes (SNs), which are deployed (systematically or randomly) over a certain physical area and can sense, process, and transmit processed information. Due to the collaborative working manner and flexible deployment of SNs, WSN has many applications, such as detecting events [1], monitoring environment [2], etc.

The spatially distributed SNs are able to monitor a physical phenomenon with some desired attribute (e.g., temperature, pressure, sound intensity, radiation levels, etc.), and then transmit their observations to a Fusion Center (FC) [3]. A fundamental problem in WSN is the estimation of an unknown parameter, which has many practical applications (e.g., temperature, pressure) [4]–[6]. Specifically, each SN makes a noisy observation of the parameter and then transmits the processed information to the FC, where a final estimate is conducted via fusing the collective information received from the SNs such that the mean square error (MSE) for estimation is minimized.

Energy efficiency is important in the design of WSN since recharging of batteries in SNs is inconvenient and costly [7]. In the traditional WSN, sensing data are forwarded to the FC via single-hop or multi-hop transmission, where SNs consume more energy when the size of network becomes larger. The reason is that longer transmission distance between SN to FC requires more transmit power, and a large number of SNs will result in a huge packet collision and retransmission [8]. Therefore, to prolong the lifetime of WSN, unmanned aerial vehicle (UAV) has been introduced as a key enabler for faster data gathering [9]–[11], where the main purpose is to provide a faster, reliable and energy efficient data collection.

With the rapid development in smart antennas, sensors, and wireless networking technologies, UAV has been incorporated in many network applications such as WSN, cooperative aerial communication networks, etc [12]. Specifically, with on-board wireless transceivers, UAV is more likely to establish line-of-sight (LoS) communication link for ground-to-air

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communication, and is capable of flying closer to SN to achieve better channel quality, thus collecting data from a wider area with UAV can be more energy efficiently [13]. Other promising features of the UAV include on-demand communication, cost-effective, environmental flexibility, and especially autonomous and unmanned nature. Therefore, it is suitable to deploy the UAV as the FC to conduct estimation task.

There are two critical issues in distributed estimation for UAV-enabled WSN. First, the number of transmission bits for each SN should be appropriately allocated. Intuitively, if the SN transmits more information to the UAV, the MSE for estimation will be smaller while the energy consumption of the SN will be larger. Therefore, there exists a trade-off between MSE and the energy consumption of all SNs with transmission bits allocation. Second, the UAV trajectory should be appropriately designed. If the UAV can approach to the SN closely, the energy consumption of the SN will be smaller with given transmission bits allocation since the channel quality between the UAV and the SN is better. However, the UAV may not be able to fly close enough to all SNs due to the limited endurance of UAV, where the MSE performance will be smaller. Therefore, the above similar trade-off exists with UAV trajectory design. The joint design of transmission bits allocation and UAV trajectory for UAV-enabled distributed estimation is challenging, and has not been investigated before to the best of authors' knowledge.

B. RELATED WORK AND CONTRIBUTION

Distributed estimation in WSN has received significant research interest due to its achievable estimation diversity with low implementation cost and reliability [6], [14]–[16], [18]. In [6], the authors investigated distributed estimation of an unknown deterministic scalar parameter in WSN with a learning-based approach, where there is no prior information on the local sensing modes. The optimal power allocation for distributed estimation in a power-constrained WSN was studied in [14], where the WSN is appropriately clustered and collaboration is allowed within the same cluster. In [15], the authors considered the distributed sequential estimation in dynamic WSN, where the estimation structure is designed to minimize the MSE in an online setting. Power allocation for distributed estimation of an unknown scalar parameter in WSN with a multiple-antenna FC was studied in [16], where SNs are equipped with radio-frequency-based energy harvesting technology. Energy-efficient delay-constrained transmission and sensing for cognitive radio systems was studied in [17], to minimize the average cost (including both energy consumption and delay cost) of users to finish a target traffic payload. The authors in [18] studied transmit power and quantization rate allocation schemes to minimize the MSE for distributed estimation with a linear observation model in an inhomogeneous WSN. In summary, most of the previous works aim to minimize the MSE for estimation in traditional WSN without UAV under the total energy consumption constraints of SNs.

In general, utilizing UAV can collect sensed data energy-effectively in WSN and thus prolong the lifetime of the SNs. It is interesting to investigate the distributed estimation with help of UAV in WSN. Recently, UAV enabled communication has gained many research interests, and UAV trajectory optimization has been extensively studied in the UAV control and navigation literature. In [19], the total throughput of UAV-served edge users was maximized by optimizing the UAV trajectory in each flying cycle, subject to the users' rate requirements. The authors in [20] aimed to minimize the multicast completion time via UAV trajectory design, while ensuring that the file is recovered successfully by each ground terminal. To achieve fair performance among users, the minimum throughput over all ground users was maximized in [21] with multiple UAVs via optimizing the multiuser association and transmission schedule jointly with power control and UAV's trajectory. An energy-efficient UAV communication scheme was proposed in [22] via optimizing the UAV's trajectory, where the communication throughput and the UAV's energy consumption were joint optimized. The trajectory of UAV and the transmit power of UAV were optimized in [25] by minimizing the outage probability of the UAV-enabled relay network. In summary, most of the previous works focus on optimizing the communication performance via UAV trajectory. However, there is little work considering the performance by utilizing UAV in WSN from the application aspect, e.g., estimation for an unknown parameter.

In this paper, we propose an energy efficient distributed estimation framework in WSN with the help of UAV, where the UAV is employed as a FC supporting fusing the collective information received from the SNs. In this case, our objective is to minimize the total energy consumption of all SNs, while satisfying the MSE requirement of estimation, via jointly optimizing the UAV trajectory and the number of transmission bits for each SN. The main contributions of this paper are summarized as follows:

- First, we propose a distributed estimation framework in WSN with the help of UAV. In this framework, we formulate the optimization problem to minimize the total energy consumption of all SNs while satisfying the MSE requirement of estimation, via jointly optimizing the UAV trajectory and the number of transmission bits for each SN. Since the formulated problem is difficult to be directly solved, we propose efficient iterative algorithms to find locally optimal solution based on successive convex optimization and block coordinate descent techniques, where the convergence of the proposed algorithm is analyzed.
- Second, as the converged result of the proposed algorithm critically depends on the initial UAV trajectory assumed, we propose new method to design the initial trajectory by fully exploiting the location information of the SNs. Specifically, as the UAV typically has better communication link when it is near SNs, the initial UAV trajectory should be designed so as to approach each SN as much as possible. To this end, we analyze the trade-off

structure on the number of visited SNs for estimation and propose the trajectory initialization design based on the Traveling Salesman Problem (TSP) solution. Compared to the existing UAV initial trajectory designs such as the straight-line, the main novelty of the proposed trajectory initialization lies in the optimized waypoints design and their order of visiting based on the trade-off structure on the number of visited SNs, as well as the UAV's practical mobility constraints such as its maximum speed.

The remainder of this paper is organized as follows. Section II introduces the system model and presents the problem formulation for the distributed estimation in WSN with the help of UAV. Section III presents the proposed algorithm based on successive convex optimization and block coordinate descent techniques, where the convergence of the algorithm is analyzed. In Section IV, we propose en efficient trajectory initialization design scheme. Numerical results are presented in Section V to evaluate the performance of the proposed design. Finally, we conclude this paper in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a WSN consisting of K SNs on the ground, denoted by $U = \{u_1, u_2, \ldots, u_K\}$. The two dimensional (2D) coordinate of each SN u_k is denoted by $\mathbf{w}_k \in \mathbb{R}^{2\times 1}$, $1 \le k \le K$. We assume that the SNs need to estimate an unknown deterministic parameter θ within an period T with a UAV serving as a flying FC. In practices, T can be selected to satisfy the requirement for limited battery size of UAV. During the estimation period, each SN observes, quantizes, and transmits the quantized observation to the flying UAV. Based on the received messages, the parameter θ is jointly estimated by the UAV, as shown in Fig. 1.

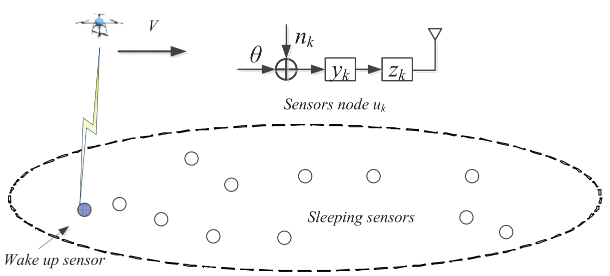

FIGURE 1. A UAV-enabled wireless sensor networks.

A. DISTRIBUTED ESTIMATION MODEL

For each SN u_k, the real value observation y_k can be modeled as

$$y_k = \theta + n_k, \tag{1}$$

where n_k is the observation noise spatially uncorrelated with zero mean and variance σ_k^2. The above model (1) is equivalent to the one where sensors observe with different attenuation, namely, $y_k = h_k\theta + n_k$. Indeed, if we let $y'_k = y_k/h_k$ and $n'_k = n_k/h_k$, then $y'_k = \theta + n'_k$, which is identical to (1) with equivalent noise variances $\sigma'^2_k = \sigma_k^2/h_k^2$.

Quantization scheme is typically used in the estimation, since it is inherent with the discrete nature of the communication between the sensors and the FC. We assume that each SN u_k performs a local probabilistic quantization scheme [5] to obtain the quantized message z_k from observation y_k. Suppose $[-W, W]$ is the signal range that sensors can observe, where W is a known constant that is typically determined by the sensor's dynamic range. In other words, $y_k = \theta + n_k \in [-W, W]$. With the probabilistic quantization, the interval $[-W, W]$ is divided into sub-intervals with identical length $\Delta = \frac{2W}{2^{S_k}-1}$, with S_k being the number of quantization bits. The observation y_k is then round to one of the two neighboring interval endpoints in a probabilistic manner. Suppose $-W+i\Delta \le y_k < -W+(i+1)\Delta$, where $0 \le i \le 2^{S_k}-2$. The observation y_k is quantized as z_k according to the following rules,

$$\mathbb{P}\{z_k = -W + i\Delta\} = 1 - r,$$
$$\mathbb{P}\{z_k = -W + (i+1)\Delta\} = r,$$

where $r = (y_k + W - i\Delta)/\Delta$.

Therefore, the quantized message z_k can be represented as

$$z_k = \theta + n_k + v_k$$

with $v_k = z_k - y_k$ denoting the quantization noise, which is independent across SNs since quantization is performed locally at each SN without coordination. It is shown in [26] that $\mathbb{E}(z_k) = \theta$, and $\mathrm{Var}(z_k) \le \sigma_k^2 + \delta_k^2$, where δ_k^2 is an upper bound of the quantization noise variance,

$$\delta_k^2 \triangleq \left(\frac{W}{2^{S_k}-1}\right)^2. \tag{2}$$

We assume that the uncoded Multiple Quadrature Amplitude Modulation (MQAM) is used for the transmission of the quantized information, where the number of bits per symbol is $\log_2 M$, similar as in [5], [26]. Moreover, we assume that the QAM symbol rate is approximately equal to B with appropriately Nyquist pulse shaping adopted, such that the symbol duration is $1/B$ [5], where B is the transmission bandwidth. Therefore, each SN u_k transmits its quantized message z_k to the UAV, based on which the fusion center at the UAV can performs the linear combination of its received messages to recover θ using the Quasi Best Linear Unbiased Estimators (Quasi-BLUE) [26], i.e.,

$$\hat{\theta} = \left(\sum_{k=1}^{K} \frac{1}{\delta_k^2 + \sigma_k^2}\right)^{-1} \sum_{k=1}^{K} \frac{z_k}{\delta_k^2 + \sigma_k^2}. \tag{3}$$

The quality of the estimator at the UAV can be typically measured by the mean square error (MSE), which is defined as $\mathrm{MSE}(\hat{\theta}) \triangleq \mathbb{E}\left(|\hat{\theta} - \theta|^2\right)$. With the probabilistic quantization scheme, it is shown in [26] that with transmission channel distortion, though obtaining the closed form expression of

MSE($\hat{\theta}$) is difficult, the associated MSE could be upper-bounded by MSE^u,

$$\mathrm{MSE}(\hat{\theta}) \leq (1+p_0)^2 \left(\sum_{k=1}^{K} \frac{1}{\delta_k^2+\sigma_k^2}\right)^{-1}$$
$$= (1+p_0)^2 \left(\sum_{k=1}^{K} \frac{1}{\left(\frac{W}{2^{S_k}-1}\right)^2+\sigma_k^2}\right)^{-1} \triangleq \mathrm{MSE}^u, \tag{4}$$

where $p_0 = \max_{1\leq k\leq K} \frac{8W}{\sigma_k}\sqrt{\frac{Kp_b}{3}}$, p_b is the target bit error rate of the sensor-FC transmission, and the term $(1+p_0)^2$ is a constant penalty compared to the case without demodulation error. It is not difficult to find that the lower bound of MSE^u can be deduced as $(1+p_0)^2\left(\sum_{k=1}^{K}\frac{1}{\sigma_k^2}\right)^{-1}$ as S_k approach to infinity, $\forall k$.

B. UAV DATA COLLECTION MODEL

The UAV is assumed to fly at a fixed altitude H and the maximum speed is denoted as $V_{\max}$. The initial and final UAV locations are denoted as $\mathbf{q}_0, \mathbf{q}_F \in \mathbb{R}^{2\times 1}$, respectively, where we assume that $\|\mathbf{q}_F-\mathbf{q}_0\| \leq V_{\max}T$ such that at least one feasible trajectory exists for the UAV to move from $\mathbf{q}_0$ to $\mathbf{q}_F$ with time T. We denote the UAV's flying trajectory projected on the ground as $\mathbf{q}(t) \in \mathbb{R}^{2\times 1}, 0 \leq t \leq T$. For convenience, the time horizon T is discretized into N time slots, i.e., $T = N\delta_t$, where δ_t denotes the elemental slot length chosen to be sufficiently small such that the UAV's location is considered as approximately unchanged within each time slot even at the maximum speed. To this end, we usually have $V_{\max}\delta_t \ll H$. We approximate the UAV trajectory $\mathbf{q}(t)$ as the sequence $\{\mathbf{q}[n], 1 \leq n \leq N\}$, where $\mathbf{q}[n] \triangleq \mathbf{q}(n\delta)$ denotes the UAV's horizontal location at time slot n. Therefore, the time-varying distance from the UAV to the SN u_k can be expressed as $d_k[n] = \sqrt{\|\mathbf{q}[n]-\mathbf{w}_k\|^2+H^2}, \forall n, k$. We assume that the doppler effect caused by the UAV mobility is well compensated at the receivers, similar as in [20]–[24].

Define $L_k[n]$ as the number of bits transmitted by u_k at time slot n, then $\sum_{n=1}^{N} L_k[n] = S_k$, $L_k[n] \in \mathbb{Z}$. At each time slot, the SNs transmit their quantized observations to the UAV via time division multiplexing access (TDMA), similar as in [21], [23]. Since uncoded MQAM is used for the transmission with symbol rate B, the maximum number of bits that can be communicated by the channel from u_k to UAV at each time slot can be defined as $\Delta_{\max} \triangleq \delta_t B \log_2 M$, and we have $\sum_{k=1}^{K} L_k[n] \leq \Delta_{\max}, \forall n$. Once the flying trajectory $\mathbf{q}[n]$ and the number of transmission bits $L_k[n]$ are determined, the UAV will inform the corresponding SNs the optimized transmission bits $L_k[n]$ over time slots via the downlink control links along its trajectory.

Denote $h_k[n]$ as the channel coefficient between the SN s_k and the UAV at time slot n. Thus, $h_k[n]$ can be modeled as $h_k[n] = \sqrt{\beta_k[n]}\rho_k[n]$, where $\rho_k[n]$ accounting for small-scale fading and $\beta_k[n]$ accounts for the large-scale channel attenuation. $\rho_k[n]$ is a complex-valued random variable with $\mathbb{E}[|\rho_k[n]|^2] = 1$, and $\beta_k[n]$ depends on the distance $d_k[n]$ between s_k and the UAV, i.e., $\beta_k[n] = G_1 d_k^{-\alpha}[n] = \frac{G_1}{(H^2+\|\mathbf{q}[n]-\mathbf{w}_k\|^2)^{\alpha/2}}$, where G_1 represents the channel power gain at 1 m, and $\alpha \geq 2$ is the path loss exponent.

Let $p_k[n]$ denote the transmit power for s_k at time slot n. As such, the achievable rate between s_k and UAV at time instant t is expressed as $\tilde{R}_k[n] = B\log_2\left(1+\frac{p_k[n]|h_k[n]|^2}{\sigma^2}\right)$, where B is the channel bandwidth and σ^2 is the noise power. Note that the channel coefficient $h_k[n]$ is a random variable, then $\tilde{R}_k[n]$ is also a random variable. Moreover, it is challenging to obtain the probability distribution of $\tilde{R}_{m,k}[n]$. Similar as in [27], we are interested in the average rate, defined as $\mathbb{E}[\tilde{R}_k[n]]$, which can be approximated as $\mathbb{E}[\tilde{R}_k[n]] \approx B\log_2\left(1+\frac{p_k[n]\beta_k[n]\mathbb{E}[|\rho_k[n]|^2]}{\sigma^2}\right) = B\log_2\left(1+\frac{p_k[n]\beta_k[n]}{\sigma^2}\right) \triangleq R_k[n]$. Such approximation can be verified to achieve high accuracy [27], especially for rural or suburban environment, which is the typical environment for data collection and estimation in WSNs.

Based on the above average rate, for uncoded MQAM, if $L_k[n] > 0$, then the energy consumption for transmitting $L_k[n]$ bits from u_k to the UAV at time slot n can be approximated as [28],

$$E_k[n] = 2N_f N_0 G_k^d[n]\left(\ln\frac{2}{p_b}\right)\left(\frac{M-1}{\log_2 M}\right)L_k[n], \tag{5}$$

where N_f is the receiver noise figure, N_0 is the single-sided receiver thermal noise spectral density, p_b is the target bit error rate, and $G_k^d[n] = G_1 d_k[n]^\alpha M_l$ with $d_k[n]$ the transmission distance from u_k to UAV at time slot n. M_l is the system constant, which represents the link margin compensating the hardware process variations and other additive background noise or interference.

Therefore, based on (5), the total energy consumption for SN u_k could be approximated as

$$E_k = \sum_{n=1}^{N} E_k[n] = \beta\sum_{n=1}^{N} L_k[n]d_k^\alpha[n]$$
$$= \beta\sum_{n=1}^{N} L_k[n](\|\mathbf{q}[n]-\mathbf{w}_k\|^2+H^2)^{\alpha/2}, \tag{6}$$

where we denote $\beta \triangleq 2N_f N_0 G_1 M_l (M-1)\left(\ln\frac{2}{p_b}\right)/\log_2 M$ as the power gain factor. Note that we ignore the circuit power and consider only the dominant transmission power of the SNs in this paper, as in [23], since the circuit power is typically much smaller than the dominant transmission power. The general design framework can also be applied to other modulations, such as QPSK, by simply changing the energy consumption expression in (5).

C. PROBLEM FORMULATION

Let $\mathbf{L} = \{L_k[n], \forall k, n\}$, $\mathbf{Q} = \{\mathbf{q}[n], \forall n\}$. Let $D_{\max} \triangleq V_{\max}\delta_t$ in meter, $S_k \triangleq \sum_{n=1}^{N} L_k[n]$ in bit, $\forall k$, and $\Delta_{\max} \triangleq \delta_t B\log_2 M$

in bit. We formulate joint optimization of SNs' transmission bits and UAV's trajectory for minimizing the total energy consumption of all SNs, with the MSE constraints as follows,

$$\begin{aligned}
\text{(P1)}: \min_{\mathbf{L},\mathbf{Q}} \quad & \beta \sum_{k=1}^{K}\sum_{n=1}^{N} L_k[n](\|\mathbf{q}[n]-\mathbf{w}_k\|^2+H^2)^{\alpha/2} \\
\text{s.t.} \quad & L_k[n] \geq 0, L_k[n] \in \mathbb{Z} \quad \forall k, n, && (7)\\
& \frac{(1+p_0)^2}{\Gamma(\mathbf{L})} \leq \mathrm{MSE}_0 && (8)\\
& \sum_{k=1}^{K} L_k[n] \leq \Delta_{\max}, \quad \forall n, && (9)\\
& \sum_{n=1}^{N} L_k[n] = S_k, \quad \forall k, && (10)\\
& \|\mathbf{q}[n]-\mathbf{q}[n-1]\| \leq D_{max}, \quad \forall n \geq 2, && (11)\\
& \mathbf{q}[1] = \mathbf{q}_0, \quad \mathbf{q}[N] = \mathbf{q}_F, && (12)
\end{aligned}$$

where

$$\Gamma(\mathbf{L}) \triangleq \sum_{k=1}^{K} \frac{1}{\delta_k^2+\sigma_k^2} = \sum_{k=1}^{K} \frac{(2^{S_k}-1)^2}{(2^{S_k}-1)^2\sigma_k^2+W^2}. \quad (13)$$

In constraints (8), MSE_0 denotes a target MSE for the estimating of θ at the FC. To ensure that the achieved MSE is less than MSE_0, we use the upper bound MSE^u in (4), and let $\mathrm{MSE}^u \leq \mathrm{MSE}_0$. The objective is to minimize the total energy consumption of all SNs. Note that the lower bound of MSE^u is $(1+p_0)^2\left(\sum_{k=1}^{K}\frac{1}{\sigma_k^2}\right)^{-1}$, then we have $\mathrm{MSE}_0 > (1+p_0)^2\left(\sum_{k=1}^{K}\frac{1}{\sigma_k^2}\right)^{-1}$ to ensure that problem (P1) is feasible.

III. PROPOSED SOLUTION

Problem (P1) is a mixed-integer non-convex problem, which is difficult to solve such problem optimally in general. Therefore, an efficient sub-optimal solution to (P1) is needed. We first relax the integer variables in (7) into continuous variables. The relaxed problem of (P1) can be written as follows,

$$\begin{aligned}
\text{(P2)}: \min_{\mathbf{L},\mathbf{Q}} \quad & \beta \sum_{k=1}^{K}\sum_{n=1}^{N} L_k[n](\|\mathbf{q}[n]-\mathbf{w}_k\|^2+H^2)^{\alpha/2} \\
\text{s.t.} \quad & L_k[n] \geq 0, \quad \forall k, n, \\
& (8)--(12). && (14)
\end{aligned}$$

Note that the resulting objective value of (P2) serves as a lower bound for that of problem (P1), since any solution of (P1) satisfies all constraints of (P2) and is also a feasible solution of (P2). After solving (P2), we use the rounding operation similar as in [5] to obtain a feasible solution of (P1) since the number of quantized bits is an integer.

However, problem (P2) is still a non-convex optimization problem since the function $\frac{(1+p_0)^2}{\Gamma(\mathbf{L})}$ in (8) is a non-convex function with respect to $\mathbf{L}$. In the following, we propose an efficient solution to (P2) based on successive convex optimization and block coordinate descent techniques. Specifically, for given UAV trajectory $\mathbf{Q}$, the transmission bits $\mathbf{L}$ is optimized by employing the successive convex optimization technique. For any given transmission bits $\mathbf{L}$, we optimize the UAV trajectory $\mathbf{Q}$ by solving a convex quadratically constrained quadratic program (QCQP). We use the block coordinate descent method to optimize the two sets of variables in an alternating manner until the objective value converges.

A. TRANSMISSION BITS OPTIMIZATION WITH FIXED TRAJECTORY

For any given UAV trajectory $\mathbf{Q}$, the MSE minimization transmission bits can be obtained by solving the following problem,

$$\begin{aligned}
\text{(P3)}: \min_{\mathbf{L}} \quad & \beta \sum_{k=1}^{K}\sum_{n=1}^{N} L_k[n](\|\mathbf{q}[n]-\mathbf{w}_k\|^2+H^2)^{\alpha/2} \\
\text{s.t.} \quad & (8), (9), (10), (14).
\end{aligned}$$

Note that in problem (P3), the objective function and all the constraints are linear except the non-convex function $\frac{(1+p_0)^2}{\Gamma(\mathbf{L})}$ in (8), thus (P3) is still a non-convex optimization problem. To tackle this non-convex function, a local convex approximation is applied. For any local point $\mathbf{L}^l = \{L_{k,l}[n]\}$ obtained at the l th iteration, denote $S_{k,l} \triangleq \sum_{n=1}^{N} L_{k,l}[n]$ in bit, $\forall k$, and $S_k \triangleq \sum_{n=1}^{N} L_k[n]$ in bit, $\forall k$, we define the function

$$\Gamma_{lb}(\mathbf{L}) = \sum_{k=1}^{K}\left[A_{k,l} - I_{k,l}\left(\sigma_k^2 + \frac{W^2}{(2^{S_k}-1)^2}\right)\right] \quad (15)$$

where

$$A_{k,l} = \frac{2(2^{S_{k,l}}-1)^2}{\sigma_k^2(2^{S_{k,l}}-1)^2+W^2}, \quad (16)$$

$$I_{k,l} = \frac{(2^{S_{k,l}}-1)^4}{\left(\sigma_k^2(2^{S_{k,l}}-1)^2+W^2\right)^2}. \quad (17)$$

Note that $\Gamma_{lb}(\mathbf{L})$ is a concave function with respect to $\mathbf{L}$, since we find that the term $\frac{W^2}{(2^{S_k}-1)^2}$ is a convex function with respect to S_k by checking the second-order derivative, and composition with an affine mapping preserves convexity. In addition, we have the following theorem,

Theorem 1: For any give $\{L_{k,l}[n]\}$, we have

$$\Gamma(\mathbf{L}) \geq \Gamma_{lb}(\mathbf{L}), \quad (18)$$

where the equality holds at the point $\mathbf{L} = \mathbf{L}^l$. Furthermore, at the point $\mathbf{L} = \mathbf{L}^l$, both $\Gamma(\mathbf{L})$ and $\Gamma_{lb}(\mathbf{L})$ have identical gradient, i.e., $\nabla\Gamma(\mathbf{L}) = \nabla\Gamma_{lb}(\mathbf{L})$.

Proof: The proof of Theorem 1 follows the similar arguments in [22]. We define the function $f(z) \triangleq \frac{1}{F+z}$ with constant $F > 0$, which can be shown to be convex when $F+z > 0$. Note that the first-order Taylor expansion of a convex function is a global under-estimator, for any given z_0, we have $f(z) \geq f(z_0) + f'(z_0)(z-z_0)$, $\forall z$, where

$f'(z_0) = -\frac{1}{(F+z_0)^2}$ is the derivative of $f(z)$ at point z_0. By letting $z_0 = 0$, we have the following inequality,

$$\frac{1}{F+z} \geq \frac{1}{F} - \frac{z}{F^2}, \quad \forall z. \tag{19}$$

Therefore, let $F = \sigma_k^2 + \frac{W^2}{(2^{S_{k,l}}-1)^2}$, $z = \frac{W^2}{(2^{S_k}-1)^2} - \frac{W^2}{(2^{S_{k,l}}-1)^2}$, the inequality in (18) thus follows. Furthermore, it can be obtained from (15) that for any k, n, the gradient of $\Gamma_{lb}(\mathbf{L})$ with respect to $L_k[n]$ is

$$\nabla_{L_k[n]}\Gamma_{lb} = -I_{k,l}\nabla_{L_k[n]}\left(\sigma_k^2 + \frac{W^2}{(2^{S_k}-1)^2}\right), \quad \forall k, n. \tag{20}$$

The gradient of $\Gamma(\mathbf{L})$ in (13) can be obtained as

$$\nabla_{L_k[n]}\Gamma = \frac{-(2^{S_k}-1)^4\nabla_{L_k[n]}\left(\sigma_k^2 + \frac{W^2}{(2^{S_k}-1)^2}\right)}{\left(\sigma_k^2(2^{S_k}-1)^2 + W^2\right)^2}, \quad \forall k, n. \tag{21}$$

The two gradients in (13) and (15) are identical when evaluated at $\mathbf{L} = \mathbf{L}^l$. □

Theorem 1 can be used to approximate the non-convex function in (13) to a concave function in (15) that has the identical gradient, based on which the successive convex approximation methods can be utilized. Specifically, for any given local point $\mathbf{L}^l$, define the following optimization problem,

$$\begin{aligned}(\text{P4}): \min_{\mathbf{L}} \quad & \beta\sum_{k=1}^{K}\sum_{n=1}^{N} L_k[n](\|\mathbf{q}[n]-\mathbf{w}_k\|^2 + H^2)^{\alpha/2} \\ \text{s.t.} \quad & \frac{(1+p_0)^2}{\Gamma_{lb}(\mathbf{L})} \leq MSE_0 \\ & (9), (10), (14).\end{aligned} \tag{22}$$

Since $\Gamma_{lb}(\mathbf{L})$ is a concave function with respect to $\mathbf{L}$, (P4) is a convex optimization problem, which can be solved efficiently with the standard convex optimization techniques or existing solvers (e.g., CVX). Therefore, (P3) can be solved by optimizing (P4) iteratively with the local point $\mathbf{L}^l$ updated at each iteration, and we summarize the details in Algorithm 1.

Algorithm 1 Successive Optimization for Problem (P3)

1: Initialize the number of transmission bits as $\mathbf{L}^0$;
2: $l \leftarrow 0$; tolerance $\kappa > 0$;
3: **repeat**
4: Given $\mathbf{L}^l$, solve the convex optimization problem (P4) to obtain the optimal solution as $\mathbf{L}^{l+1}$;
5: $\mathbf{L}^l \leftarrow \mathbf{L}^{l+1}$;
6: $l \leftarrow l+1$;
7: **until** The fractional decrease of the objective value of (P4) is below tolerance κ.

B. TRAJECTORY OPTIMIZATION WITH FIXED TRANSMISSION BITS

For any given transmission bits $\mathbf{L}$, the UAVąŕs trajectory is optimized to minimized the total energy consumption of all SNs. Specifically, the problem can be simplified as

$$\begin{aligned}(\text{P5}): \min_{\mathbf{Q}} \quad & \beta\sum_{n=1}^{N} L_k[n](\|\mathbf{q}[n]-\mathbf{w}_k\|^2 + H^2)^{\alpha/2} \\ \text{s.t.} \quad & (11), (12).\end{aligned} \tag{23}$$

Since $\|\mathbf{q}[n]-\mathbf{w}_k\|^2$ is a convex quadratic function with respect to $\mathbf{q}[n]$, (P5) is a convex quadratically constrained quadratic program (QCQP), which can also be solved by standard convex optimization techniques or existing solvers (e.g., CVX).

C. OVERALL ALGORITHM AND CONVERGENCE

The overall iterative algorithm for the integer-relaxed problem (P2) is obtained by optimizing the transmission bits $\mathbf{L}$ and trajectory $\mathbf{Q}$ alternately via solving problem (P3) and (P5) respectively, which is summarized in Algorithm 2.

Algorithm 2 Overall Iterative Optimization Algorithm

1: Initialize the trajectory as $\mathbf{Q}^0$;
2: Initialize the transmission bits as $\mathbf{L}^0$;
3: $\nu \leftarrow 0$;
4: tolerance $\kappa > 0$;
5: **repeat**
6: Solve (P3) for given $\{\mathbf{Q}^\nu, \mathbf{L}^\nu\}$ to obtain the solution $\mathbf{L}^{\nu+1}$ with Algorithm 1;
7: Solve (P5) for given $\mathbf{L}^{\nu+1}$, and denote the optimal solution as $\mathbf{Q}^{\nu+1}$;
8: $\nu \leftarrow \nu+1$;
9: **until** The fractional decrease of the objective value of (P3) is below κ.

The convergence analysis of our proposed algorithm is shown as follows. First, let us consider the convergence of Algorithm 1. Define $\eta(\mathbf{L}, \mathbf{Q})$ and $\eta^{ub}(\mathbf{L}, \mathbf{Q})$ as the objective values of problem (P3) and (P4) respectively for $\mathbf{L}$ and $\mathbf{Q}$. For any given $\mathbf{Q}$, we can obtain the following inequalities

$$\eta(\mathbf{L}^l, \mathbf{Q}) \overset{(a)}{=} \eta^{ub}(\mathbf{L}^l, \mathbf{Q}) \overset{(b)}{\geq} \eta^{ub}(\mathbf{L}^{l+1}, \mathbf{Q}) \overset{(c)}{\geq} \eta(\mathbf{L}^{l+1}, \mathbf{Q}), \tag{24}$$

where (a) holds since the first-order Taylor expansion is tight at the given local point $\mathbf{L}^l$; (b) holds since (P4) is solved optimally with solution $\mathbf{L}^{l+1}$; (c) holds due to the fact that for any iteration l, $\Gamma_{lb}(\mathbf{L})$ is always a lower bound of $\Gamma(\mathbf{L})$. Furthermore, the objective value of problem (P3) is lower bounded by a finite value, then Algorithm 1 is guaranteed to converge. Let us consider the convergence of Algorithm 2. We denote $\eta(\mathbf{L}^\nu, \mathbf{Q}^\nu) = \eta^\nu$. It follows that

$$\begin{aligned}\eta^\nu &= \eta(\mathbf{L}^\nu, \mathbf{Q}^\nu) \overset{(d)}{\geq} \eta(\mathbf{L}^{\nu+1}, \mathbf{Q}^\nu) \\ &\overset{(e)}{\geq} \eta(\mathbf{L}^{\nu+1}, \mathbf{Q}^{\nu+1}) = \eta^{\nu+1},\end{aligned} \tag{25}$$

where (d) holds due to (24); (e) holds since $(\mathbf{L}^{\nu+1}, \mathbf{Q}^{\nu+1})$ is the optimal solution of (P5). Thus, $\eta^{\nu+1} \leq \eta^\nu$. Moreover, the objective value of (P3) is lower bounded by a finite value, thus Algorithm 2 converges.

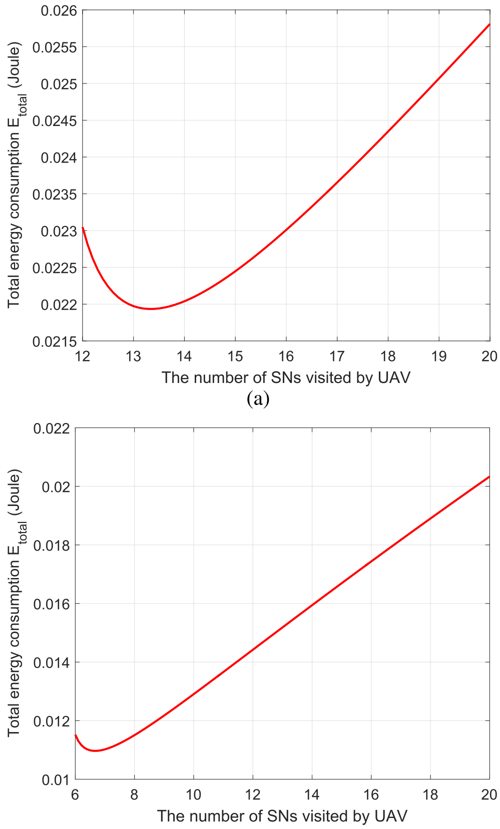

FIGURE 2. **Total transmission energy consumption E_{total} V.S. m (ideal scenario). (a) $\sigma_k^2 = 0.01, MSE_0 = 0.05$. (b) $\sigma_k^2 = 0.01, MSE_0 = 0.1$.**

IV. TRAJECTORY AND TRANSMISSION BITS INITIALIZATION

Note that for locally optimal algorithms with successive convex optimization, the converged solution and the system performance depend on the initialization schemes. In this section, we first analyze the main trade-off structure based on the ideal scenario that the UAV has enough time to fly to the top of each SN. Based on the insight obtained from the ideal scenario, we propose a low-complexity initialization scheme for the trajectory and transmission bits allocation in Algorithm 2.

A. TRADE-OFF ON THE NUMBER OF VISITING SNS

Note that in (P1), the total energy consumption objective function requires smaller $L_k[m]$ while MSE constraints (8) requires larger $L_k[m]$, then in the optimal solution of (P1) the MSE constraints in (8) are all satisfied with equality. Therefore, $\sum_{k=1}^{K} \frac{1}{\delta_k^2+\sigma_k^2} = \frac{(1+p_0)^2}{MSE_0}$. Consider the ideal scenario that the time horizon T is sufficiently large so that the UAV can fly to the top of each SN and collects data with the minimum link distance H (or best channel quality), where the channel quality between UAV and all SNs are the same. Assume that the UAV collects data from m SNs with the same number of transmission bits, $m \leq K$. Denote the set of SNs visited by UAV as $U(m)$, $U(m) \subseteq U$, $|U(m)| = m$, then $\frac{1}{\delta_k^2+\sigma_k^2} = \frac{(1+p_0)^2}{mMSE_0}$, $u_k \in U(m)$. Therefore, $S_k = \log_2\left(1 + \frac{W}{\sqrt{\frac{mMSE_0}{(1+p_0)^2} - \sigma_k^2}}\right)$, $u_k \in U(m)$. The total energy consumption can be expressed as follows,

$$E_{total} = \beta m H^{\alpha} \log_2\left(1 + \frac{W}{\sqrt{\frac{mMSE_0}{(1+p_0)^2} - \sigma_k^2}}\right). \tag{26}$$

Therefore, the optimization problem for the ideal scenario can formulated as follows,

$$\begin{aligned} \text{(P6)}: \min_{m} \quad & \beta m H^{\alpha} \log_2\left(1 + \frac{W}{\sqrt{\frac{mMSE_0}{(1+p_0)^2} - \sigma_k^2}}\right) \\ \text{s.t.} \quad & \frac{mMSE_0}{(1+p_0)^2} > \sigma_k^2, \quad \forall k, \end{aligned} \tag{27}$$

where constraints (27) ensure that (26) is feasible.

It is observed that if m is larger, then S_k is smaller, the individual energy consumption is smaller, but the number of visited SNs is larger. Thus, m should be appropriately selected to tradeoff the effect between the quantization noise and the average observation noise shown in (26). Given σ_k^2 and MSE_0, the curve of E_{total} with respect to m in (26) can be shown in Fig. 2.

It is observed from Fig. 2 that visiting all SNs may not be the best choice, there exists a balance between the effect of quantization noise and the observation noise. Although there is no tractable closed-form solution for the optimal m to minimize the above E_{total}, it is easy to numerically evaluate (26) for different m values and then obtain the optimal m by comparing the resulting total transmission energy

Algorithm 3 Trajectory Initialization Algorithm

Solve (P6) to obtain the optimal m with numerical methods;
Given m, determine $U(m)$ with bisection method on ellipse region $\Omega(r)$;
tolerance $\kappa > 0$;
$l \leftarrow 0$; $u \leftarrow MAX$;
while $u - l > \kappa$ **do**
    $c \leftarrow (l + u)/2$;
    Obtain VBS locations based on $U(m)$ and c with spiral BS placement algorithm;
    Find a trajectory $\mathbf{Q}$ to visit these VBS locations with *NoReturn-GivenOrigin-ArbitraryEnd* TSP method;
    if $\mathbf{Q}$ is feasible within T **then**
        $u \leftarrow c$;
        $\mathbf{Q}_0 \leftarrow \mathbf{Q}$;
    else
        $l \leftarrow c$
    end if
end while
Output:$\mathbf{Q}_0$;

TABLE 1. **Parameters settings.**

Parameters	Explanation	Value
H	The altitude of UAV (m)	100m
δ_t	The elemental time slot length (s)	0.5s
V_{max}	The maximum speed of UAV	50m/s
B	Channel bandwidth (Hz)	1MHz
α	Path loss exponent	2.2
W	The range of the observation	1
M	MQAM	8
G_1	The gain factor at $d = 1$m	30dB
N_f	The receiver noise figure	10dB
N_0	Receiver thermal noise spectral density	-170 dBm/Hz
M_l	The link margin	10dB
p_b	Target BER	10^{-3}
κ	Algorithm tolerance threshold	10^{-3}

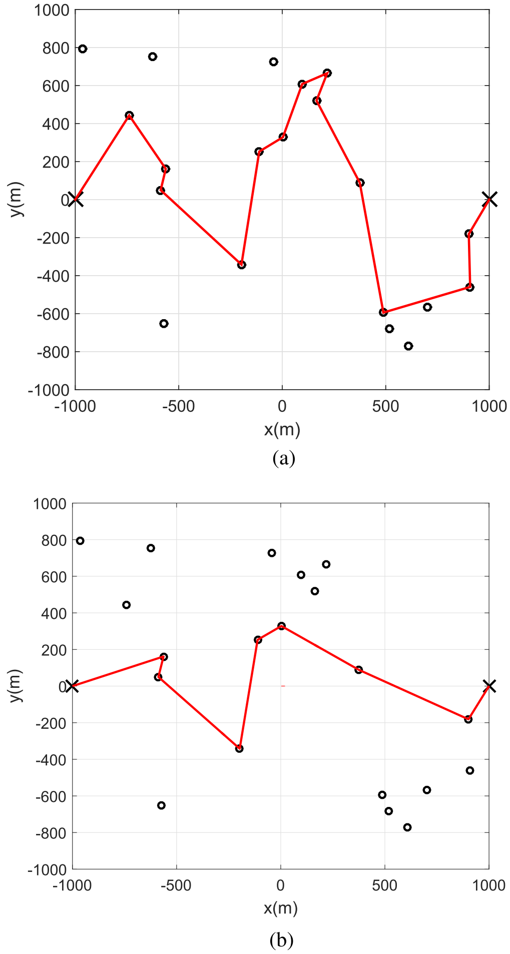

FIGURE 3. **Trajectory with large T ($T = 300$s). (a) $\text{MSE}_0 = 0.05$. (b) $\text{MSE}_0 = 0.1$.**

consumption, given the single dimensionality and the integer nature of m.

B. TRAJECTORY INITIALIZATION SCHEME

From the above discussion, we find that visiting all SNs may not be the best choice, and there exists an optimal value m. Inspired by the insight obtained from the ideal scenario, we propose a trajectory initialization scheme based on the optimal value m.

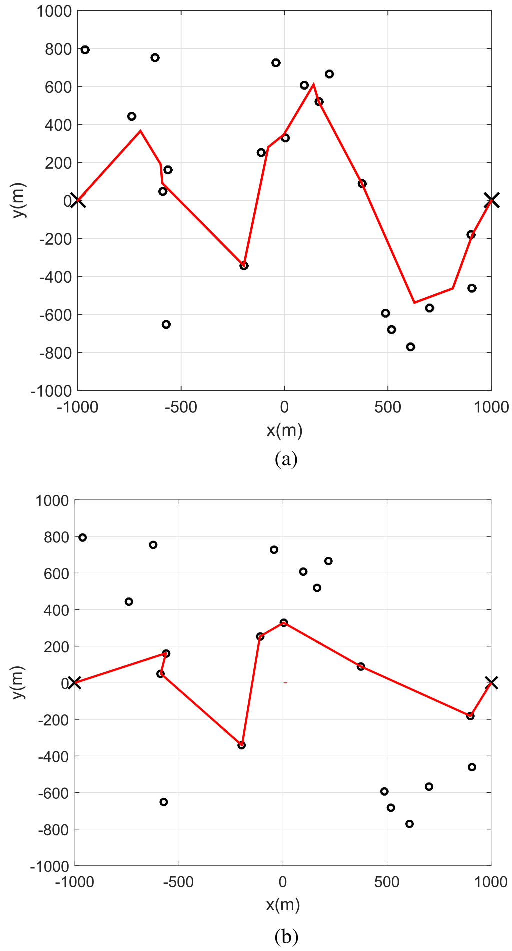

FIGURE 4. **Trajectory with small T ($T = 100$s). (a) $\text{MSE}_0 = 0.05$. (b) $\text{MSE}_0 = 0.1$.**

Given the optimal m, $m \leq K$, we need to select which SNs should be visited. Note that the initial and final locations of UAV are pre-determined as $\mathbf{q}_0$ and $\mathbf{q}_F$, we would like to select m SNs near $\mathbf{q}_0$ and $\mathbf{q}_F$. We can define an ellipse region $\Omega(r)$ with parameter r, $\Omega(r) = \{\mathbf{q} \mid \|\mathbf{q} - \mathbf{q}_0\| + \|\mathbf{q} - \mathbf{q}_F\| \leq r, \mathbf{q} \in \mathbb{R}^{2\times 1}\}$, $r \geq \|\mathbf{q}_F - \mathbf{q}_0\|$. Bisection method can be used to identify the appropriate r so that $\Omega(r)$ just contains m SNs, which outputs the set of visited SNs, $U(m)$.

In practical applications, T may not be large enough. It may be impossible for the UAV to fly to the top of all SNs in $U(m)$ with small T. Virtual base station (VBS) placement as waypoint method [22] can be used to generate an initialization trajectory. Specifically, given the SN locations for $U(m)$ and communication range c of UAV, the VBS placement problem aims to find a minimum number of VBSs and their respective locations, so that each SN in $U(m)$ is covered by at least one VBS, i.e., the spiral BS placement algorithm [29]. Given $U(m)$ and c, we can find a trajectory $\mathbf{Q}$ to visit these VBS locations with *NoReturn-GivenOrigin-ArbitraryEnd* TSP method [22]. If $\mathbf{Q}$ is infeasible within time T, we can further reduce c. Therefore, given T, we can use bisection method to identify the appropriate c. It is not difficult to verify that if T is large, the result $\mathbf{Q}$ is the TSP

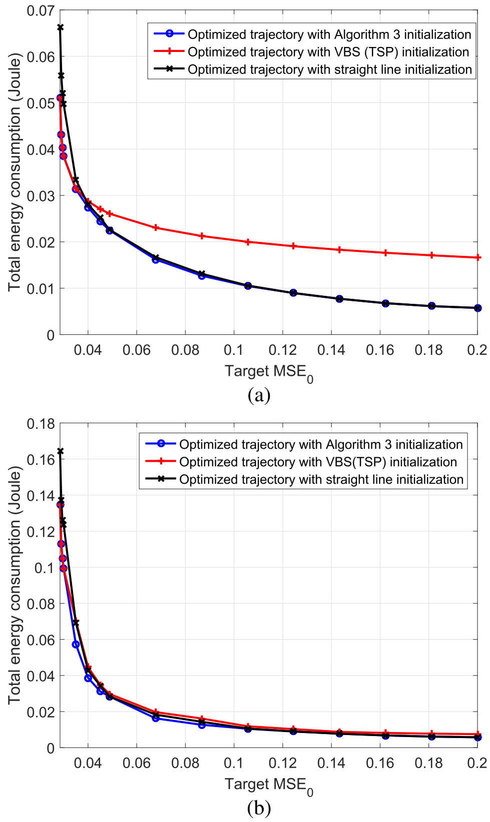

FIGURE 5. **Total energy consumption V.S. MSE_0. (a) Large T (T = 300s). (b) Small T (T = 100s).**

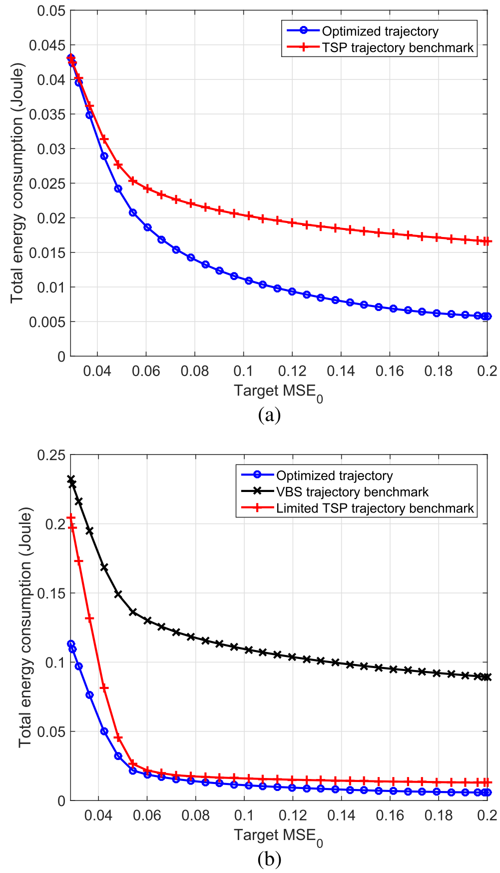

FIGURE 6. **Total energy consumption V.S. MSE_0. (a) Large T (T = 300s). (b) Small T (T = 100s).**

path since c is sufficiently small. Therefore, our algorithm is general for all scenario settings, which is summarized in Algorithm 3.

C. TRANSMISSION BITS INITIALIZATION SCHEME

Given the initial trajectory of UAV $\mathbf{Q}^0$ and $U(m)$, we need to obtain the initial transmission bits $\mathbf{L}^0$. We can set

$$S_k = \begin{cases} \log_2\left(1 + \dfrac{W}{\sqrt{\dfrac{mMSE_0}{(1+p_0)^2} - \sigma_k^2}}\right) & u_k \in U(m) \\ 0 & u_k \notin U(m) \end{cases}, \tag{28}$$

then the initial transmission bits $\mathbf{L}^0$ is obtained by solving the following linear programming (LP) problem,

$$\begin{aligned} \text{(P7)}: \min_{\mathbf{L}} \quad & \beta \sum_{k=1}^{K}\sum_{n=1}^{N} L_k[n](\|\mathbf{q}[n] - \mathbf{w}_k\|^2 + H^2)^{\alpha/2} \\ \text{s.t.} \quad & (10), (14), (28). \end{aligned}$$

V. NUMERICAL RESULTS

We consider a WSN with $K = 20$ SNs, which are randomly located within an area of size 2.0×2.0 km^2. The UAV's initial and final locations are set as $\mathbf{q}_0 = [-1000, 0]^T$ and $\mathbf{q}_F = [1000, 0]^T$ in meter, respectively. The observation range W are assumed to be equal to 1 [5]. The common parameters used in the simulation is summarized in Table 1.

A. OPTIMIZED TRAJECTORY

We set $\sigma_k^2 = 0.01, \forall k$. The optimized trajectories under different T are shown in Fig. 3 and Fig. 4. It is observed that even T is large, the UAV will not visit all the SNs, which reflects the trade-off structure discussed in Section IV-A. Specifically, it is observed in Fig. 2 of Section IV-A that the optimal number of visited SNs by UAV is about 13 when $MSE_0 = 0.05$, and about 7 when $MSE_0 = 0.1$. It is verified in Fig. (3)(a) and Fig. 4(a) that UAV visits 13 SNs when $MSE_0 = 0.05$. It is also observed that in Fig. (3)(a) UAV is able to fly to the top of each SN to gain better channel quality since $T = 300$ s is large enough, while in Fig. (4)(a) UAV cannot fly to the top of each SN since $T = 100$ s is small. In Fig. 3(b) and Fig. 4(b) when $MSE_0 = 0.1$, the UAV always visits 7 SNs as shown in Fig. 2, and the UAV can fly to the top of the 7 SNs when $T = 100$ s.

B. COMPARISON WITH DIFFERENT INITIALIZATION SCHEMES

Note that for locally optimal algorithm, the converged solution and the system performance depend on the initialization schemes. Thus, we compare the performance of our proposed

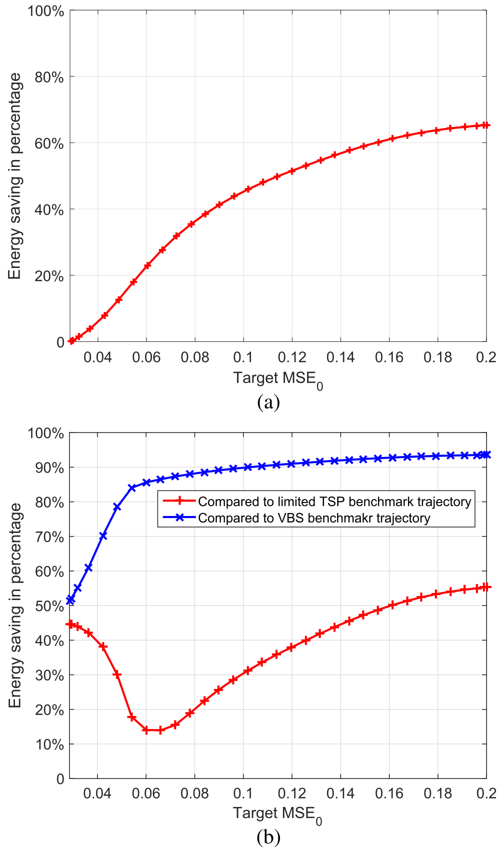

FIGURE 7. **Energy saving V.S. MSE_0. (a) Energy saving compared to TSP trajectory with large T ($T = 300$s). (b) Small T ($T = 100$s).**

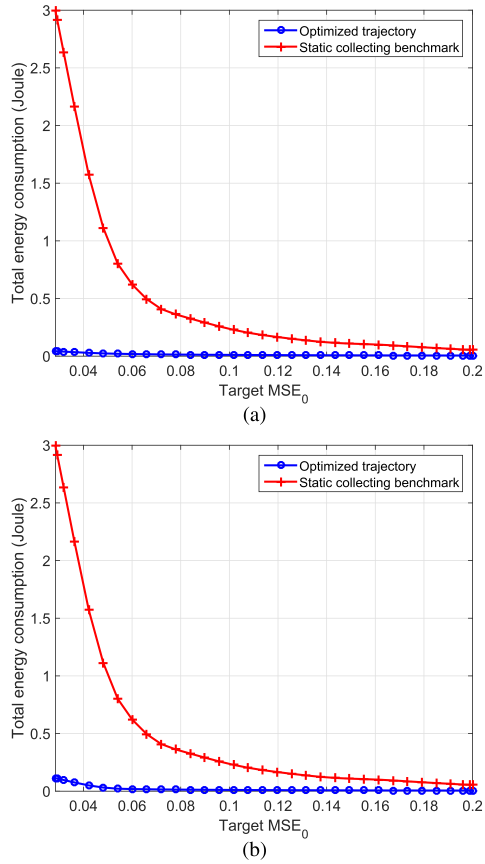

FIGURE 8. **Total energy consumption V.S. MSE_0. (a) Large T ($T = 300$s). (b) Small T ($T = 100$s).**

initialization scheme in Section IV with different benchmark initialization schemes in terms of total energy consumption in Fig. 5. To this end, we jointly optimize UAV trajectory as well as transmission bits allocation with iterative Algorithm 2 but with different initialization schemes. The benchmark initialization scheme includes *VBS initialization scheme* and *straight line initialization scheme*. The VBS initialization scheme and straight line initialization scheme generate a VBS trajectory and a straight line trajectory as $\mathbf{Q}_0$, separately, and then solve (P7) to obtain $\mathbf{L}_0$ with $U(m) = U$.

It is observed that the VBS initialization performs better than straight line initialization when MSE_0 is small, while it performs worse when MSE_0 is large, but the proposed initialization with Algorithm 3 always performs better, since it combines the advantages of both VBS initialization and straight line initialization. When T is small, the performances of the three initialization schemes are similar, which reflects that our optimization framework is robust enough that any initialization scheme can converge to the similar solution.

C. COMPARISON WITH DIFFERENT BENCHMARK TRAJECTORIES

In order to show the performance gain brought by the optimization framework, we compare the total energy consumption of our optimized trajectory with that of different benchmark trajectories in Fig. 6. Our optimized trajectory is obtained based on the initialization scheme with Algorithm 3 and iterative optimization Algorithm 2. The benchmark trajectories includes *VBS benchmark trajectory* and *limited TSP benchmark trajectory*. The VBS benchmark trajectory is that UAV collects data from all SNs along a VBS trajectory, and the transmission bits of all SNs are identical. When T is large, the VBS trajectory converges to a TSP trajectory. The limited TSP benchmark trajectory is a heuristic trajectory for small T. Since T is small, then UAV flies to the top of a subset of SNs and collects data from them along a TSP trajectory, and the transmission bits of each SN in the subset is identical. The subset of SNs can be determined by bisection method over the adjacent region of $\mathbf{q}_0$ and $\mathbf{q}_F$ based on T. When T is large, the limited TSP trajectory also converges to a TSP trajectory over all SNs.

It is observed that the optimized trajectory performs better than the benchmark trajectories, and the performance gain is more pronounced in Fig. 7. In Fig. 7, we show the *energy savings* of our optimized trajectory compared with the benchmark trajectories. The energy saving is defined as $\frac{E_b - E_o}{E_b} \times 100\%$, where E_o and E_b are the total energy consumptions with our optimized trajectory and benchmark trajectories, separately. It is observed that our optimized trajectory can save more energy compared to the benchmark trajectories. Note that compared to limited TSP benchmark trajectory, there exists a minimum point in the curve, which

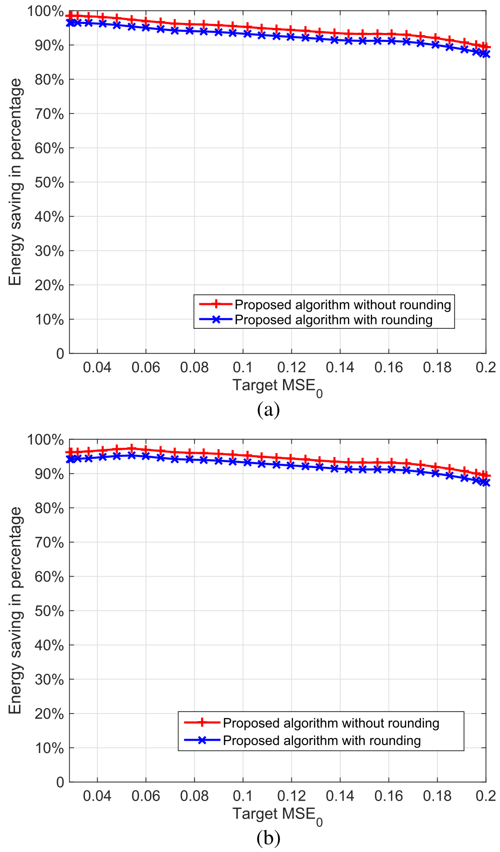

FIGURE 9. **Energy saving compared to static collecting scheme V.S. MSE_0. (a) Large T ($T = 300$s). (b) Small T ($T = 100$s).**

reflects that our optimized trajectory converge to the similar trajectory as limited TSP benchmark trajectory at that MSE_0 value.

D. COMPARISON WITH STATIC COLLECTING SCHEME

In order to show the performance gain brought by the mobility of UAV, we compare the total energy consumption of our optimized trajectory with that of conventional static collecting scheme in Fig. 8, where the fusion center is deployed in the fixed location at the geometric center of all SNs. For fair comparisons, the transmission bits of static collecting schemes are also optimized by Algorithm 2. It is observed that our proposed trajectory design significantly outperforms the static collecting scheme.

In Fig. 9, we show the *energy savings* of our optimized trajectory compared with the static collecting schemes. It is observed that compared to the static collecting scheme, distributed estimation with the mobility of UAV can save up to 90% energy consumption of all SNs, and the gain is more pronounced with the increase of T. The fundamental reason of the performance gain is that the energy consumption of all SNs can be reduced at the cost of the energy consumption of UAV, and charing for UAV is more convenient than charing for SNs. It is also shown in the simulation that the performance of the proposed algorithm is slightly poorer than that without rounding, and the gap between the two curves is relatively small, which reflects the accuracy of the adopted relaxation method.

VI. CONCLUSION

This paper proposes an energy efficient distributed estimation framework in WSN with the help of UAV. We formulate and solve the optimization problems to jointly design the UAV trajectory and transmission bits allocation for each SN to minimize total energy consumption of all SNs while satisfying the MSE requirement for estimation. We propose iterative algorithms by employing successive convex optimization and block coordinate descent techniques to find efficient locally optimal solution, which is guaranteed to converge. Furthermore, we design a TSP-based initial trajectory for the UAV based on the trade-off structure on the number of visited SNs for estimation. Simulation results show that significant energy savings for SNs are achieved by the proposed solution compared to that with other benchmark schemes.

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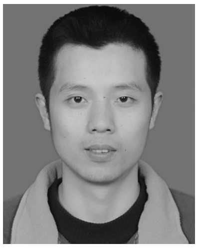

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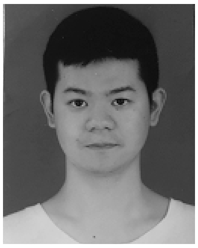

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