Reliable Data Transmission Scheduling for UAV-Assisted Air-to-Ground Communications

Guixian Qu, Ailing Xie, Shiyi Liu, Jianshan Zhou, and Zhengguo Sheng, *Senior Member, IEEE*

***Abstract*—Reliability is significant for unmanned aerial vehicle (UAV)-assisted air-to-ground (A2G) communications. In this letter, we address the reliability optimization problem by properly scheduling data transmissions under Non-Line-of-Sight (NLoS) channel fading. We capture the channel fading effect by the Rayleigh distribution and then formulate the A2G communication reliability from a probabilistic perspective. We propose a constrained optimization model that jointly takes into account the impacts of the aerial and ground nodes' mobility, the stochastic fading characteristics of the A2G channel, and the transmission constraints. From the model, we derive a closed-form reliability-optimal solution for data transmission scheduling and theoretically characterize the optimal reliability that is achievable. Simulation results verify our theoretical results and show the superior performance of the proposed scheduling solution over benchmark methods.**

***Index Terms*—Air-to-ground communication, NLoS radio propagation channel, Rayleigh fading model, reliability-oriented optimization, unmanned aerial vehicle.**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have been playing a more and more important role in a wide range of wireless networks and communication systems, such as aerial Internet of Things (IoT), Aerial-Ground Cooperative Vehicular Networks (AGCVNs), and software-defined Space-Air-Ground Integrated Networks (SAGINs). In these existing or envisioned information network architectures, UAV-assisted air-to-ground (A2G) communications are considered a key enabling technology supporting a massive number of mobile users' pervasive connectivity and high transmission rates. However, there exist some significant challenges to be addressed for the practical realization of UAV-assisted A2G communications, such as topological dynamic nature, large-scale Non-Line-of-Sight (NLoS) path loss and severe radio fading, and intense contention for channel access. In particular, the A2G communication links usually experience intermittent connectivity resulting from the high mobility of flying UAVs and ground mobile nodes. Hence, it is of paramount significance to guarantee the A2G communication reliability in the presence of external dynamic and stochastic effects.

This work was supported in part by the National Key Research and Development Program of China (Grant No. 2022YFC3803700) and the National Natural Science Foundation of China (Grant No. 52202391 and U20A20155). (Corresponding author: Ailing Xie)

Guixian Qu is with the Aero-engine System Collaborative Design Center, Research Institute of Aero-Engine, Beihang University, Beijing 100191, China (e-mail: guixianqu@foxmail.com).

Ailing Xie, Shiyi Liu, and Jianshan Zhou are with Beijing Key Laboratory for Cooperative Vehicle Infrastructure Systems & Safety Control, the School of Transportation Science and Engineering, Beihang University, Beijing 100191, China (e-mail: xieailing@buaa.edu.cn; sy2113305@buaa.edu.cn; jianshanzhou@foxmail.com).

Zhengguo Sheng is with the Department of Engineering and Design, University of Sussex, Richmond 3A09, U.K. (e-mail: z.sheng@sussex.ac.uk).

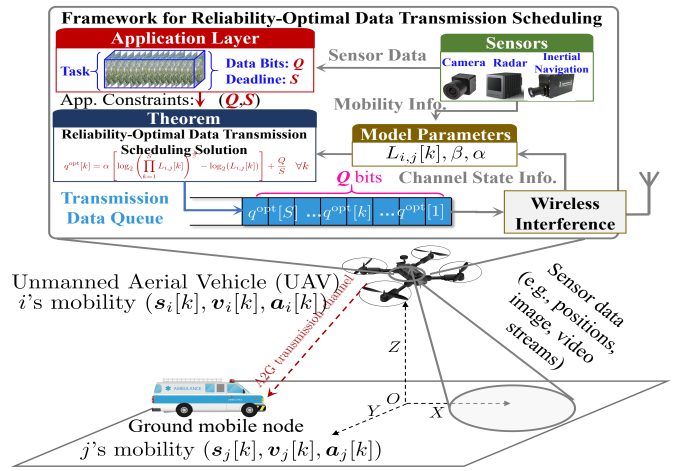


Fig. 1. The implementation framework for reliability-optimal data transmission scheduling.

In most of the current studies in the field of UAV-assisted networking, communication, aerial caching, and edge computing, researchers are engaged in developing novel solutions for the joint optimization of UAVs' deployment positions, trajectories and resource allocation, such as these works [1]–[20] and the references therein. Considerable system models and optimization algorithms are reported on either the maximization of system-level throughput [1]–[4], energy-efficiency [5]–[7] and computation rate [8], [9] or the minimization of overall energy consumption [10]–[16] and application-specified cost [17], [18]. Reference [19] uses Q-learning algorithms with power allocation to optimize the sum capacity of the UAV communication system. Reference [20] discusses the challenges and solutions for achieving ultra-reliable IoT communications with UAVs in a swarm scenario. However, limited research efforts have been made and few results have been presented to reliability-optimal data transmission scheduling for the UAV.

In this paper, we propose a novel data transmission scheduling method to maximize the reliability for a UAV-assisted A2G communication network. Specifically, we first model the mobility of the UAV and ground nodes. We then use the well-known Rayleigh fading model to capture the statistical effect of NLoS radio propagation channels and characterize the UAV-assisted A2G communication reliability, which takes into account the network mobility and application requirements. Upon the reliability modeling, we propose a constrained optimization model to maximize the overall reliability. From this model, we derive a closed-form reliability-optimal solution for data transmission scheduling. Overall, the novel contribution of this paper is twofold: 1) The proposed constrained optimization model jointly considers the coupled effects of the aerial and ground nodes' mobility, the stochastic fading characteristics of the A2G wireless channel, and the transmission constraints imposed by an upper-layer application, and 2) a closed-form reliability-optimal scheduling solution is analytically obtained and the optimal reliability of the

UAV-assisted A2G communications is also derived, thus the achievable upper bound on the overall probability of successful data transmissions during limited time slots can be theoretically characterized. Finally, the advantages of the proposed scheduling solution in transmission capacity over benchmark methods are verified by the numerical simulation results.

II. System Model and Problem Formulation

In general, the fundamental requirements of an upper-layer application can be abstracted into two key parameters, the total amount of data bits, Q, that need to be transmitted from the flying UAV to the ground mobile node [1] and the limited number of time slots allocated for UAV-assisted A2G transmissions, S. In order to successfully transmit all the application data within the limited duration in the presence of high mobility, path loss, and channel fading, the UAV should partition the whole data content, Q, into a sequence of smaller-size data pieces, $\{q[k], k = 1, 2, \ldots, S\}$, and properly schedule the size of each data piece, $q[k]$, to be transmitted in each time slot k. For notation simplicity, let $\boldsymbol{q} = \operatorname{col}\{q[k], k = 1, 2, \ldots, S\} \in \mathbb{R}^{S\times 1}$ denote a solution for data transmission scheduling. At this point, the following application-specified constraints should be met so as to guarantee the data transmission integrity

$$\mathcal{Q}(Q, S) := \left\{\boldsymbol{q} \in \mathbb{R}^{S\times 1} : \mathbf{1}^{\mathrm{T}}\boldsymbol{q} = Q; \boldsymbol{q} \geq \mathbf{0}\right\}, \tag{1}$$

where $\mathbf{1}$ and $\mathbf{0}$ are two $S \times 1$ column vectors, all of whose elements are 1 and 0, respectively. Indeed, $\mathcal{Q}(Q, S) \subset \mathbb{R}^{S\times 1}$ denotes the feasible region consisting of all the scheduling solutions satisfying the constraints in (1).

We follow [6] to plan the trajectory of the aerial node before a certain mission period. Similar to [8], [22], [23], we adopt a time-discrete double-integral kinematics model to effectively describe the motion state of the UAV. We capture the time-varying spatial position, $\boldsymbol{s}_l[k]$, velocity, $\boldsymbol{v}_l[k]$, and acceleration, $\boldsymbol{a}_l[k]$, of a node l as

$$\begin{cases} \boldsymbol{s}_l[k+1] = \boldsymbol{s}_l[k] + \tau\boldsymbol{v}_l[k] + \frac{\tau^2}{2}\boldsymbol{a}_l[k],\ l \in \{i, j\}; \\ \boldsymbol{v}_l[k+1] = \boldsymbol{v}_l[k] + \tau\boldsymbol{a}_l[k],\ l \in \{i, j\}, \end{cases} \tag{2}$$

where i and j denote the UAV and the ground mobile node, respectively, and τ denotes the duration of a time slot. Using (2), the time-dependent relative distance between the aerial and the ground nodes, $L_{i,j}[k]$, can be expressed as

$$L_{i,j}[k] = \|\boldsymbol{s}_i[k] - \boldsymbol{s}_j[k]\|_2 . \tag{3}$$

Besides, according to the existing literature [5]–[7], we adopt the well-known orthogonal channel access model to calculate the number of data bits that can be transmitted per time slot via the A2G communication link as follows

$$\pi[k] = \frac{B}{N}\log_2\left(1 + \frac{p_i\delta_j g^2\left(L_{i,j}[k]\right)}{n_0^2}\right), \tag{4}$$

[1]We follow the existing works such as [5] and focus on a single UAV scenario. However, our proposed model and solution can be naturally extended to a multi-node application scenario without altering our methodology proposed here. For example, we can further combine the time division multiple access (TDMA) protocol to extend our method to multi-UAV or multi-node scenarios [15], [21]. We leave extending our system model as future work.

where B is the total bandwidth available for the A2G communication channel, N denotes the number of nodes accessing the same channel at the same time, and $g\left(L_{i,j}[k]\right)$ represents the random channel gain that is related to the mobility-dependent relative distance, propagation path loss, and channel fading characteristics. According to [24]–[26], we consider that the aerial-ground channel follows quasi-static fading, in which the channel is considered static within each time interval while varies across different time intervals. In addition, p_i denotes the transmission power of the UAV i, $\delta_j \in [0, 1]$ denotes the portion of the transmission power that can be allocated to the ground mobile node j, and n_0^2 is the average noise power in the environment.

We focus on a heavily built-up urban scenario where the UAV flight is often conducted at a low height or some others where there are many obstacles that can scatter the UAV's radio signal before it arrives at the ground mobile node. The well-known Rayleigh distribution can be used to model channel stochastic fading in the above NLoS radio propagation environment [27]–[32]. In such a Rayleigh fading channel, the squared channel gain $g^2\left(L_{i,j}[k]\right)$ usually follows an exponential distribution with the parameter $L_{i,j}^{\beta}[k]$ where β denotes the path loss exponent. Therefore, the probability that the UAV can successfully transmit the data piece $q[k]$ scheduled in time slot k to the ground mobile node can be derived from the probabilistic perspective as follows

$$\begin{aligned} \Pr(q[k]) &= \Pr\left\{\pi[k] \geq \frac{q[k]}{\tau}\right\} \\ &= \Pr\left\{\frac{B}{N}\log_2\left(1 + \frac{p_i\delta_j g^2\left(L_{i,j}[k]\right)}{n_0^2}\right) \geq \frac{q[k]}{\tau}\right\} \\ &= \Pr\left\{g^2\left(L_{i,j}[k]\right) \geq \frac{2^{\frac{q[k]N}{B\tau}}n_0^2 - n_0^2}{p_i\delta_j}\right\} \\ &= \exp\left(-\frac{2^{\frac{q[k]N}{B\tau}}n_0^2 - n_0^2}{p_i\delta_j L_{i,j}^{-\beta}[k]}\right). \end{aligned} \tag{5}$$

Based on the multiplication principle in probability theory, we establish the mathematical definition of UAV-assisted A2G communication reliability as follows.

Definition 1: The reliability of UAV-assisted A2G communications under large-scale NLoS channel fading is defined as the total probability of the UAV successfully transmitting all the Q-bit data to the ground mobile node during the given S time slots as follows

$$\Pr(Q, S) = \prod_{k=1}^{S}\Pr(q[k]) = \exp\left(\sum_{k=1}^{S}\frac{n_0^2 - 2^{\frac{q[k]N}{B\tau}}n_0^2}{p_i\delta_j L_{i,j}^{-\beta}[k]}\right). \tag{6}$$

Furthermore, the reliability-oriented optimization model for data transmission scheduling is proposed under the upper-layer application constraints presented in (1) as follows

$$\begin{aligned} \max_{\boldsymbol{q}} :\ & \Pr(Q, S) = \exp\left(\sum_{k=1}^{S}\frac{n_0^2 - 2^{\frac{q[k]N}{B\tau}}n_0^2}{p_i\delta_j L_{i,j}^{-\beta}[k]}\right) \\ \text{s.t. } & \boldsymbol{q} \in \mathcal{Q}(Q, S). \end{aligned} \tag{7}$$

III. Main theoretical results

In the following, we first analyze the convexity of (7), and further obtain the closed-form optimal scheduling solution.

Lemma 1: The maximization model (7) is concave with respect to the decision variable $\boldsymbol{q}$. A local optimum of (7) is a globally optimal solution.

Proof: Note that application-specified constraints (1) contains equality and inequality constraints, and both of them are linear constraints. At this point, the convexity of the optimization model depends on the objective function. Let

$$F(q[k]) = \frac{n_0^2 - 2^{\frac{q[k]N}{B\tau}} n_0^2}{p_i \delta_j L_{i,j}^{-\beta}[k]}. \tag{8}$$

The objective function $\Pr(Q, S)$ is a composite function formed by the sum of $F(q[k])$ and an exponential function, so its convexity depends only on the convexity of $F(q[k])$. The second-order derivative of $F(q[k])$ with respect to $q[k]$ is expressed as

$$\frac{d^2 F(q[k])}{d(q[k])^2} = -\frac{N^2 n_0^2 (\ln 2)^2 L_{i,j}^{\beta}[k]}{B^2 \tau^2 p_i \delta_j} 2^{\frac{q[k]N}{B\tau}} \le 0, \forall k, \tag{9}$$

which implies that the function $F(q[k])$ is concave w.r.t. all $p[k]$. So $\Pr(Q, S)$ is also concave w.r.t. $\boldsymbol{q}$, and (7) is concave. According to convex optimization theory, a local optimum of (7) is a globally optimal solution. ■

We further derive a closed-form solution for data transmission scheduling and the optimal analytical reliability as in the following theorem. The closed-form solution is guaranteed to be a globally optimal solution for (7) based on Lemma 1. The optimal analytical reliability can provide the maximum achievable reliability bound on the UAV communication system.

Theorem 1: Suppose that there exists an optimal solution of (7) that is an interior feasible point, denoted by $\boldsymbol{q}^{\text{opt}} = \text{col}\{q^{\text{opt}}[k], k = 1, 2, \ldots, S\} \in \text{int}(\mathcal{Q}(Q, S))$. The globally optimal solution $\boldsymbol{q}^{\text{opt}}$ is expressed as

$$q^{\text{opt}}[k] = \alpha \left[\log_2 \left(\prod_{k=1}^{S} L_{i,j}[k] \right)^{\frac{1}{S}} - \log_2(L_{i,j}[k]) \right] + \frac{Q}{S}, \tag{10}$$

for $k = 1, 2, \ldots, S$, where $\alpha = B\tau\beta/N$. By using the locally optimal solution $\boldsymbol{q}^{\text{opt}}$, the achievable optimal reliability of the UAV-assisted A2G communications can be expressed as

$$\Pr{}^{\text{opt}}(Q, S) = \exp\left(\frac{\sum_{k=1}^{S} n_0^2 L_{i,j}^{\beta}[k] - S 2^{\frac{Q\beta}{S\alpha}} n_0^2 \left(\prod_{k=1}^{S} L_{i,j}^{\frac{\beta}{S}}[k] \right)}{p_i \delta_j} \right). \tag{11}$$

Proof: Let $f(\boldsymbol{q}) = \sum_{k=1}^{S} L_{i,j}^{\beta}[k] 2^{\frac{\beta q[k]}{\alpha}}$ in the objective function of (7). Since only $f(\boldsymbol{q})$ involves the decision variables $\boldsymbol{q}$, solving (7) boils down to dealing with the following minimization problem

$$\boldsymbol{q}^{\text{opt}} = \text{argmin} \left\{ f(\boldsymbol{q}) : \boldsymbol{q} \in \mathcal{Q}(Q, S) \right\}. \tag{12}$$

From (12), the corresponding Lagrangian function is

$$\mathcal{L}(\boldsymbol{q}, \boldsymbol{\lambda}, \sigma) = f(\boldsymbol{q}) - \boldsymbol{\lambda}^{\text{T}} \boldsymbol{q} - \sigma \left(\mathbf{1}^{\text{T}} \boldsymbol{q} - Q \right), \tag{13}$$

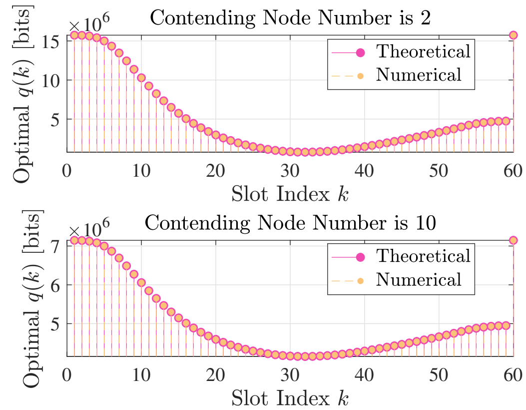


Fig. 2. The analytical and numerical optimal scheduling solutions.

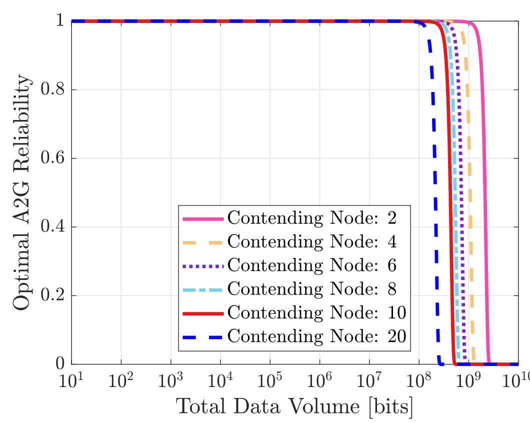


Fig. 3. The impacts of the requirements and the contending nodes on the optimal reliability.

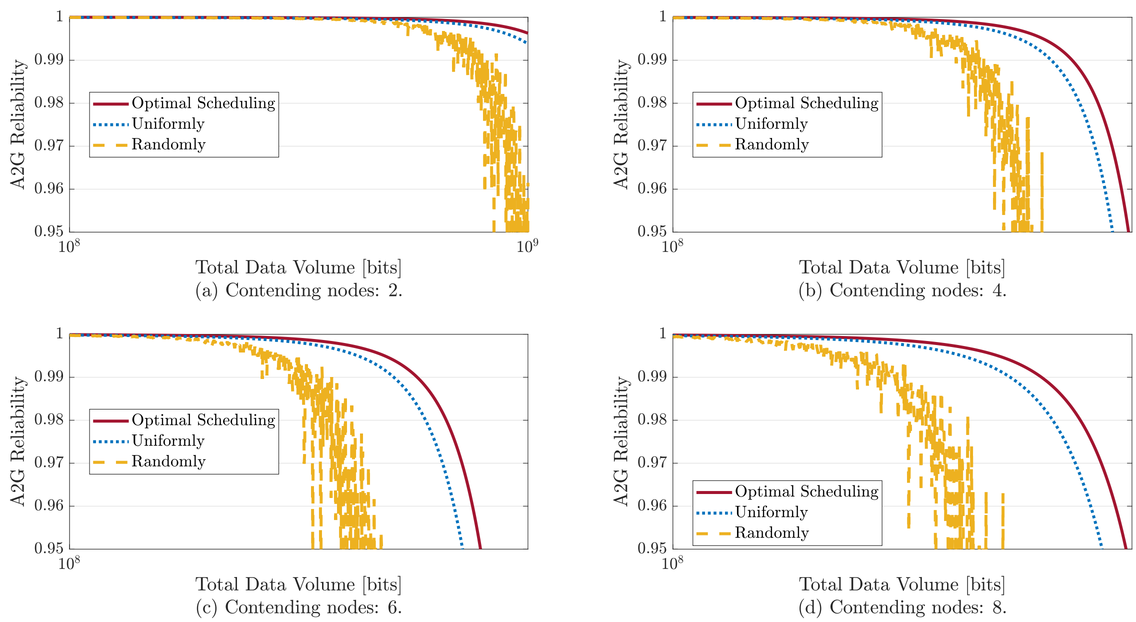
where $\boldsymbol{\lambda} = \text{col}\{\lambda[k] \in \mathbb{R}_{\ge 0}, k = 1, 2, \ldots, S\}$ are the nonnegative Lagrangian multipliers while $\sigma \in \mathbb{R}$ is an unconstrained Lagrangian multiplier. Thus, the Karush-Kuhn-Tucker (KKT) conditions for a feasible point of (7) to be locally optimal can be established as follows

$$\begin{cases} \nabla_{\boldsymbol{q}} \mathcal{L}(\boldsymbol{q}, \boldsymbol{\lambda}, \sigma) = \nabla_{\boldsymbol{q}} f(\boldsymbol{q}) - \boldsymbol{\lambda} - \sigma \mathbf{1} = \mathbf{0}; \\ \boldsymbol{\lambda} \odot \boldsymbol{q} = \mathbf{0}; \\ \boldsymbol{q} \in \text{int}(\mathcal{Q}(Q, S)); \\ \boldsymbol{\lambda} \in \mathbb{R}_{\ge 0}^{S \times 1}, \end{cases} \tag{14}$$

where $\odot$ represents the Hadamard product that operates the element-wise multiplication between any two matrices with the same size. In (14), the first equation denotes the stationarity, the second denotes the complementary condition, the third denotes the primal feasibility, and the last denotes the dual feasibility. That is, $\boldsymbol{q}^{\text{opt}}$ must satisfy the above conditions.

Note that $\boldsymbol{q}^{\text{opt}}$ is a feasible interior point, i.e., $\boldsymbol{q}^{\text{opt}} > \mathbf{0}$. At this point, combining the complementary condition and the dual feasibility implies $\boldsymbol{\lambda} = \mathbf{0}$. Based on this result and the stationarity in (14), we obtain

$$\sigma = \frac{\partial f(\boldsymbol{q})}{\partial q[k]} = \frac{\beta L_{i,j}^{\beta}[k]}{\alpha} 2^{\frac{\beta q[k]}{\alpha}} \ln 2 \tag{15}$$



(a) Contending nodes: 2.
(b) Contending nodes: 4.
(c) Contending nodes: 6.
(d) Contending nodes: 8.

Fig. 4. The A2G communication reliability of our method, the uniform and the random schemes under different numbers of contending nodes.

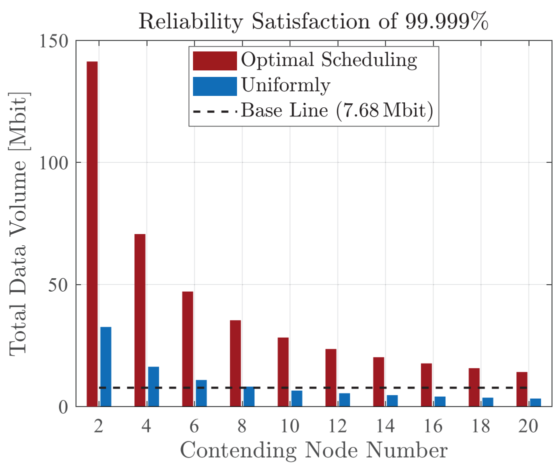


Fig. 5. The transmitted data volume achieved by different methods under the reliability satisfaction of 99.999%.

and thus

$$q[k] = \frac{\alpha}{\beta}\log_2\left(\frac{\sigma\alpha}{\beta L_{i,j}^{\beta}[k]\ln 2}\right) \tag{16}$$

for $k = 1, 2, \ldots, S$. Substituting (16) into the equality constraint $\mathbf{1}^{\mathrm{T}}\boldsymbol{q} = Q$ can obtain

$$Q = \frac{\alpha}{\beta}\log_2\left(\left(\frac{\sigma\alpha}{\beta\ln 2}\right)^{S}\prod_{k=1}^{S} L_{i,j}^{-\beta}[k]\right), \tag{17}$$

which derives a closed-form σ as follows

$$\sigma = \left(\prod_{k=1}^{S} L_{i,j}^{\frac{\beta}{S}}[k]\right)\frac{\beta 2^{\frac{\beta Q}{\alpha S}}\ln 2}{\alpha}. \tag{18}$$

Therefore, substituting (18) into (16) can immediately obtain (10). Similarly, substituting (10) into (6) can get (11). According to Lemma 1, (10) is a globally optimal solution for data transmission scheduling. ■

Based on the proposed theorem above, we develop the implementation framework of reliability-optimal data transmission scheduling for the UAV-assisted A2G communications as illustrated in Fig.1. As shown in the figure, by using the closed-form scheduling solution, the flying UAV can dynamically adapt its application-specified transmission data at each time slot to guarantee communication reliability even under a high-mobility scenario.

IV. Main simulation results

We conduct simulations to validate our theoretical results and the proposed scheduling solution. In the simulations, the total bandwidth is set to $B = 10\,\mathrm{MHz}$, the path loss exponent is $\beta = 2.75$ to simulate the effect of the large-scale NLoS channel fading, and the slot duration is $\tau = 0.5\,\mathrm{s}$. The UAV's power p_i is specified as $p_i = 30\,\mathrm{dBm}$ along with the environmental noise power of $n_0^2 = -100\,\mathrm{dBm}$. The power allocation ratio is $\delta_j = 1$. Additionally, the number of available time slots is given as $S = 60$ such that the scheduling time horizon is $0.5 \times 60 = 30\,\mathrm{s}$, while the application data load is set to $Q = 300\,\mathrm{Mbit}$. For the sake of the case study, the mobility of the UAV and the ground mobile node are configured according to specific trajectory planning data. First, two case studies under different numbers of contending nodes, $N = 2, 10$, are used to compare the scheduling results obtained by our closed-form expression in Theorem 1 and by a numerical constrained optimization algorithm based on the well-known sequential quadratic program (SQP). From Fig. 2, it is observed that both optimization methods can provide the

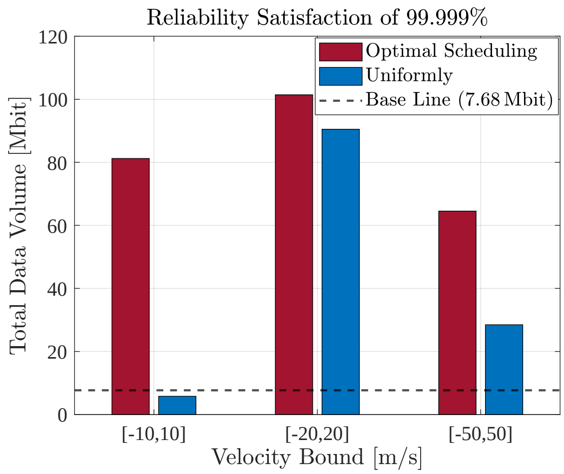


Fig. 6. Comparison results for different UAV velocity constraint bounds.

same scheduling solution. This fact confirms the correctness of our theorem and numerically verifies the proposed closed-form solution.

Besides, in Fig. 3, the impacts of the data volume required to be transmitted and the number of contending nodes on the optimal reliability is analyzed by using our theoretical model. It is seen that increasing the transmission load or channel contention can reduce communication reliability. Nevertheless, even though under severe channel contention, $N = 20$, and a large transmission load, $Q = 10^8$ bits, the A2G communication reliability can be guaranteed above 0.99 by using our transmission scheduling solution. Fig. 3 sheds light on the high-reliability region for designing the total transmission load under different numbers of contending nodes, e.g., $Q \in [0, 10^9]$ (bits) under $N = 2$.

Furthermore, Fig. 4 compares the A2G communication reliability of our transmission scheduling method to other baselines, including the uniform and the random schemes under different numbers of contending nodes. It is noted that these two conventional schemes are widely used as the benchmark methods in the literature such as [33]–[35]. It can be seen that the random allocation performs the worst. Our method maintains higher transmission reliability, which ensures more than 0.996 despite the transmission load reaching 10^9 bits (Fig. 4(a)). Meanwhile, our method improves the reliability by about 2.38% and 2.52% in Fig. 4(c) and Fig. 4(d), respectively, compared to the uniform scheme. This is because our proposed method is adaptive to the network mobility, which enables the UAV to dynamically schedule the data volume in each transmission slot in order to maximize the reliability. In contrast, the random and the uniform schemes can not adapt to the mobility.

In addition, to verify the advantage of the proposed scheduling solution, we compare it to a benchmark solution, i.e., the conventional method that uniformly schedules the data bits in each time slot, in Fig. 5. We also show the baseline ultra-reliable and low-latency communications (URLLC), which is one of the most important requirements for 5G. As required by the 5G URLLC specification, the 32-byte user-plane data should be transmitted per $1\,\mathrm{ms}$ with the reliability requirement of 99.999%, i.e., the required data volume is equivalent to $32 \times 8 \times 10^3 \times 30\,\mathrm{bits} = 7.68\,\mathrm{Mbit}$ over the total time horizon of $30\,\mathrm{s}$. From Fig. 5, it can be seen that the conventional solution fails in achieving the required data volume when the contending node number is higher than $N = 10$, while our scheduling solution can transmit much larger data meanwhile satisfying the 5G URLLC reliability requirement. The data volume achieved by our solution is about 3.3369 times larger than that achieved by the conventional method on average. In particular, even with a large contending node number, $N = 20$, our solution improves the transmitted data volume by about 84.0% than the 5G URLLC-required baseline. These comparative results confirm the advantage of our reliability-optimal scheduling solution in terms of transmission capacity.

Finally, we also compare the performance of different methods under different UAV mobility. Specially, we set three cases of UAV velocity bounds, i.e. $[-10, 10]$, $[-20, 20]$, and $[-50, 50]$ $\mathrm{m/s}$. These different velocity bounds lead to different UAV trajectories and different flight velocities, which simulate low, medium, and high mobility scenarios, respectively. The UAV mobility can influence the time-varying relative distance between the aerial and ground nodes, thus affecting the channel quality. Fig. 6 shows the total data transmission volume that can be achieved by different methods when the transmission reliability reaches 99.999% under different mobility scenarios. In the case of low mobility, our method outperforms the other methods, making the data volume 13 times larger than that of the other methods on average. In the case of medium mobility, our method gets a 12.07% increase in the data volume when compared to the uniform scheme. In the high mobility scenario, the volume of data transmitted by the uniform scheme is less than half of our method. It shows that our method achieves the highest reliability and meets the URLLC requirement under different mobility scenarios.

V. Conclusion

This letter provides a closed-form reliability-optimal solution for scheduling UAV-assisted A2G data transmissions under large-scale NLoS channel fading and also theoretically characterizes the achievable optimal reliability from the probabilistic perspective. The theoretical results capture the effects of the aerial and ground nodes' mobility, the channel stochastic characteristics, and the application constraints on the A2G communication reliability. Simulation results show that the proposed scheduling solution achieves a much larger transmitted data volume than the conventional method when satisfying the same reliability requirement. Moreover, the proposed solution provides a considerable performance improvement over the 5G URLLC-required baseline. In the future, we can extend our method to multi-UAV or multi-node scenarios. While the current work focuses on the NLoS channel, it is necessary to extend the work to situations where the UAVs fly in rural areas with high altitudes and the A2G channels incorporate probabilistic LoS links.

References

[1] Z. Sun, Z. Wei, N. Yang, and X. Zhou, "Two-tier communication for uav-enabled massive iot systems: Performance analysis and joint design of trajectory and resource allocation," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 4, pp. 1132–1146, April 2021.

[2] W. Xu, Y. Sun, R. Zou, W. Liang, Q. Xia, F. Shan, T. Wang, X. Jia, and Z. Li, "Throughput maximization of uav networks," *IEEE/ACM Transactions on Networking*, pp. 1–15, 2021.

[3] Y. Che, Y. Lai, S. Luo, K. Wu, and L. Duan, "Uav-aided information and energy transmissions for cognitive and sustainable 5g networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 3, pp. 1668–1683, March 2021.

[4] W. Shi, J. Li, H. Wu, C. Zhou, N. Cheng, and X. Shen, "Drone-cell trajectory planning and resource allocation for highly mobile networks: A hierarchical drl approach," *IEEE Internet of Things Journal*, vol. 8, no. 12, pp. 9800–9813, June 2021.

[5] J. Zhou, D. Tian, Z. Sheng, X. Duan, and X. Shen, "Joint mobility, communication and computation optimization for uavs in air-ground cooperative networks," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 3, pp. 2493–2507, March 2021.

[6] M. Li, N. Cheng, J. Gao, Y. Wang, L. Zhao, and X. Shen, "Energy-efficient uav-assisted mobile edge computing: Resource allocation and trajectory optimization," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3424–3438, March 2020.

[7] L. Bai, R. Han, J. Liu, Q. Yu, J. Choi, and W. Zhang, "Air-to-ground wireless links for high-speed uavs," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 12, pp. 2918–2930, Dec 2020.

[8] Y. Liu, J. Zhou, D. Tian, Z. Sheng, X. Duan, G. Qu, and V. C. M. Leung, "Joint communication and computation resource scheduling of a uav-assisted mobile edge computing system for platooning vehicles," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–16, 2021.

[9] F. Zhou, Y. Wu, R. Q. Hu, and Y. Qian, "Computation rate maximization in uav-enabled wireless-powered mobile-edge computing systems," *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 9, pp. 1927–1941, Sep. 2018.

[10] Y. Zeng and R. Zhang, "Energy-efficient uav communication with trajectory optimization," *IEEE Transactions on Wireless Communications*, vol. 16, no. 6, pp. 3747–3760, June 2017.

[11] S. Chai and V. K. N. Lau, "Multi-uav trajectory and power optimization for cached uav wireless networks with energy and content recharging-demand driven deep learning approach," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 10, pp. 3208–3224, Oct 2021.

[12] C. Sun, W. Ni, and X. Wang, "Joint computation offloading and trajectory planning for uav-assisted edge computing," *IEEE Transactions on Wireless Communications*, vol. 20, no. 8, pp. 5343–5358, Aug 2021.

[13] J. Zhang, L. Zhou, Q. Tang, E. C.-H. Ngai, X. Hu, H. Zhao, and J. Wei, "Stochastic computation offloading and trajectory scheduling for uav-assisted mobile edge computing," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 3688–3699, April 2019.

[14] J. Ji, K. Zhu, C. Yi, and D. Niyato, "Energy consumption minimization in uav-assisted mobile-edge computing systems: Joint resource allocation and trajectory design," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 8570–8584, May 2021.

[15] Y. Liu, K. Xiong, Q. Ni, P. Fan, and K. B. Letaief, "Uav-assisted wireless powered cooperative mobile edge computing: Joint offloading, cpu control, and trajectory optimization," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 2777–2790, April 2020.

[16] T. Zhang, Y. Xu, J. Loo, D. Yang, and L. Xiao, "Joint computation and communication design for uav-assisted mobile edge computing in iot," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 8, pp. 5505–5516, Aug 2020.

[17] F. Lyu, P. Yang, H. Wu, C. Zhou, J. Ren, Y. Zhang, and X. Shen, "Service-oriented dynamic resource slicing and optimization for space-air-ground integrated vehicular networks," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–15, 2021.

[18] F. Tang, H. Hofner, N. Kato, K. Kaneko, Y. Yamashita, and M. Hangai, "A deep reinforcement learning-based dynamic traffic offloading in space-air-ground integrated networks (sagin)," *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 1, pp. 276–289, Jan 2022.

[19] Z. Kaleem, W. Khalid, A. Muqaibel, A. A. Nasir, C. Yuen, and G. K. Karagiannidis, "Learning-aided uav 3d placement and power allocation for sum-capacity enhancement under varying altitudes," *IEEE Communications Letters*, vol. 26, no. 7, pp. 1633–1637, 2022.

[20] Z. Yuan, J. Jin, L. Sun, K.-W. Chin, and G.-M. Muntean, "Ultra-reliable iot communications with uavs: A swarm use case," *IEEE Communications Magazine*, vol. 56, no. 12, pp. 90–96, 2018.

[21] Z. Wang, D. Hong, Z. Fan, X. Wan, Y. Xu, and B. Duo, "Resource allocation for uav-assisted backscatter communication," *EURASIP Journal on Wireless Communications and Networking*, vol. 2022, no. 1, p. 104, 2022.

[22] S. Shi and M. Lazar, "On distributed model predictive control for vehicle platooning with a recursive feasibility guarantee," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 7193–7198, 2017.

[23] M. Yan, W. Ma, L. Zuo, and P. Yang, "Dual-mode distributed model predictive control for platooning of connected vehicles with nonlinear dynamics," *International Journal of Control, Automation and Systems*, vol. 17, no. 12, pp. 3091–3101, 2019.

[24] P. Yang, X. Xi, T. Q. Quek, J. Chen, and X. Cao, "Power control for a urllc-enabled uav system incorporated with dnn-based channel estimation," *IEEE Wireless Communications Letters*, vol. 10, no. 5, pp. 1018–1022, 2021.

[25] L. Zhang, Z.-Y. Zhang, L. Min, C. Tang, H.-Y. Zhang, Y.-H. Wang, and P. Cai, "Task offloading and trajectory control for uav-assisted mobile edge computing using deep reinforcement learning," *IEEE Access*, vol. 9, pp. 53 708–53 719, 2021.

[26] X. Qi, M. Yuan, Q. Zhang, and Z. Yang, "Joint power-trajectory-scheduling optimization in a mobile uav-enabled network via alternating iteration," *China Communications*, vol. 19, no. 1, pp. 136–152, 2022.

[27] H. Lei, D. Wang, K.-H. Park, I. S. Ansari, J. Jiang, G. Pan, and M.-S. Alouini, "Safeguarding uav iot communication systems against randomly located eavesdroppers," *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1230–1244, 2019.

[28] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Mobile unmanned aerial vehicles (uavs) for energy-efficient internet of things communications," *IEEE Transactions on Wireless Communications*, vol. 16, no. 11, pp. 7574–7589, 2017.

[29] W. Khawaja, I. Guvenc, D. W. Matolak, U.-C. Fiebig, and N. Schneckenburger, "A survey of air-to-ground propagation channel modeling for unmanned aerial vehicles," *IEEE Communications Surveys Tutorials*, vol. 21, no. 3, pp. 2361–2391, thirdquarter 2019.

[30] R. Agrawal, A. Sehgal *et al.*, "Composite channel model for wireless propagation with wide-range signal variation using rayleigh–generalized inverse gaussian distribution," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. 46, no. 1, pp. 213–223, 2022.

[31] T. Taniguchi and T. Fujii, "Power control in local 5g/beyond systems utilizing spectrum database and monte carlo stochastic programming," in *2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC)*. IEEE, 2022, pp. 1098–1104.

[32] T. Shafique, H. Tabassum, and E. Hossain, "End-to-end energy-efficiency and reliability of uav-assisted wireless data ferrying," *IEEE Transactions on Communications*, vol. 68, no. 3, pp. 1822–1837, 2019.

[33] H. Yan, W. Bao, X. Zhu, J. Wang, G. Wu, and J. Cao, "Fairness-aware data offloading of iot applications enabled by heterogeneous uavs," *Internet of Things*, p. 100745, 2023.

[34] B. Li, S. Yu, J. Su, J. Ou, and D. Fan, "Computation offloading in multi-uav-enhanced mobile edge networks: A deep reinforcement learning approach," *Wireless Communications and Mobile Computing*, vol. 2022, 2022.

[35] Q. Luo, X. Chen, and G. Wu, "A data transmission scheduling method considering broken-point continuingly-transferring in vanets," *Wireless Networks*, vol. 27, no. 7, pp. 4461–4477, 2021.