Optimizing Energy Consumption in UAV-Assisted IoT Networks

Subjects: Automation & Control Systems | Telecommunications

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Quadrotor unmanned aerial vehicles (UAVs) have emerged as ubiquitous and agile robots and data carriers within the framework of the future Internet of Things (IoT) and mobile wireless networks. Yet, the insufficient onboard battery necessitates the optimization of energy consumption for both the UAV and IoT devices while ensuring that communication requirements are met.

trajectory planning UAV IoT network

1. Introduction

Due to low cost, high mobility, and vertical take-off and landing advantages [1][2], unmanned aerial vehicles have found widespread application in mobile communication networks [3], such as UAV-aided ubiquitous coverage [4], UAV-aided relaying [5], and UAV-aided information dissemination and data collection [6]. Generally, UAVs are deployed to fly within certain wireless sensor networks (WSNs), which consist of numerous IoT devices distributed throughout space to collect or transmit data [7][8]. Several protocols have been developed for generating UAV flight trajectories to facilitate mobile data collection tasks [9]. With the extensive research and development in UAV technology, various effective controllers have been designed to ensure precise UAV trajectory tracking. These controllers include simple PID control, LQ control, backstepping control, and sliding mode control [10][11][12]. Recent advancements in controller design have further enhanced UAV flight agility and trajectory tracking capabilities. Lee et al. introduced the renowned geometric tracking control method, enabling highly accurate tracking even for aggressive trajectories [13][14]. Quan et al. developed a practical distributed controller that enables UAVs to accurately navigate through virtual tubes, enhancing trajectory tracking performance [15]. Additionally, Zhu et al. designed a nonlinear integral sliding mode attitude controller using the triple-step method to enable UAVs to withstand unknown disturbances [16].

Nevertheless, despite the significant breakthroughs achieved in UAV controllers, effective trajectory planning for UAV-assisted networks remains an area of active exploration and growing interest [17]. Specifically, due to the limited onboard battery capacity of UAVs, there is a pressing need for trajectory optimization concerning both energy consumption and completion time [3]. Furthermore, when ground nodes are disposable with limited power supplies, the optimization of the UAV's trajectory must take into account the energy consumption of these ground nodes [18]. In light of these challenges, extending the lifespan of UAV-aided wireless communication networks becomes imperative. Consequently, the optimization of energy-efficient and time-effective trajectory planning for UAVs has emerged as a critical component of network management [3][17]. The following parts provide a comprehensive review of related works, with a primary focus on energy consumption models and optimal trajectory design.

2. Energy Consumption Model

Before designing energy-optimized trajectories for UAVs within mobile networks, it is essential to develop an accurate energy consumption model for quadrotor UAVs. Current UAV energy consumption models can be classified into three types.

The first is data fitting with empirical power data obtained under various flight conditions using an onboard power sensor [19]. Subsequently, an energy consumption curve is fitted against user-defined variables, such as flight speed [20]. Note that the resulting energy consumption model is highly contingent upon experimental conditions and physical attributes, rendering it non-universal across all UAV models. The second type is based on classical helicopter theory [21][22]. Zeng et al. derived an energy consumption model for rotary-wing UAVs based on this theory. It comprehensively considered the profile power, induced power, and parasite power [23]. However, it is worth noting that helicopters and quadrotor UAVs differ in their physical structures, which may lead to inaccurate energy consumption results. The third type considers the unique structure of a quadrotor UAV. Caitlin et al. established the dynamic equations of quadrotor UAVs using the Newton–Euler equation, taking into account the influence of relative wind speed, ground effects, and interferences from nearby UAVs [24]. Bouabdalla et al. deduced the thrust, hub force, and torque coefficients of small quadrotor UAVs based on the blade element theory. This model considers the differences in blade structure between quadrotors and helicopters, resulting in a more comprehensive and accurate deduction of the influence of aerodynamics [25]. Hoffmann et al. studied the influence of three aerodynamic effects, namely, vortex ring state, blade flapping, and the interference caused by the fuselage, resulting in a complex thrust analysis [26]. While the above works focused on the impact of aerodynamics on quadrotor UAVs, they did not derive the energy consumption from the perspective of quadrotor UAVs' fundamental actuators, namely, BLDC motors.

To address these gaps, a novel energy consumption model considering quadrotor dynamics, aerodynamics, and BLDC motor dynamics has previously been developed by the authors [27], which is more suitable for energy-efficient trajectory planning for UAV-assisted networks.

3. Trajectory Optimization Method

Subsequently, an optimal trajectory can be intricately designed to conserve UAV energy through the application of suitable energy consumption models. In the context of the mobile communication network, classification can be made based on the number of UAVs and IoT users, resulting in three distinct configurations: the one-to-one scenario [28], the one-to-multi scenario [29], and the multi-to-multi scenario [30]. The one-to-one scenario aims to minimize the flight distance required to complete the communication task, effectively transforming it into a traveling salesman problem [31]. The one-to-multi scenario, which involves more optimization constraints compared to the one-to-one scenario, has garnered greater interest and can be readily extended to the multi-to-multi scenario.

Considering the multi-channel communication capabilities of a UAV within a wireless network, IoT devices can be clustered based on their locations, a problem akin to the disk cover problem [32]. K-means is a widely adopted and practical algorithm for clustering multiple objects. Galkin et al. employed the K-means algorithm to partition airborne access points into K clusters and subsequently deployed the UAV at the center of each cluster, thereby alleviating the load on macrocells and achieving superior signal strength compared to static picocell alternatives [33]. Li et al. introduced the BTK-means algorithm, which addresses the issue of millimeter-wave signal blockage and facilitates the clustering of ground users and UAV deployment [34]. Qu et al. proposed the UBK-means algorithm, which considers user bandwidth requirements to determine the number of centers, resolving bandwidth limitations in emergency scenarios [35]. However, one limitation of the classical K-means algorithm is its sensitivity to the initial random selection of cluster centers. Consequently, intelligent clustering of IoT devices is imperative to enhance the performance of both the UAV and the IoT network, with a focus on energy efficiency.

Mozaffari et al. employed the circle packing algorithm to determine the minimum number of disks [36][37]. However, this method’s primary focus on achieving complete coverage of circular areas results in significant cross-coverage issues, as it does not consider the location information of IoT devices. Lyu et al. proposed an algorithm for placing UAV base stations along a spiral line, utilizing the maximum coverage radius of a UAV to cover IoT devices, with the objective of minimizing the number of disks [32]. Zeng et al. applied this spiral algorithm to cluster IoT devices, and the traveling salesman problem (TSP) algorithm was integrated to minimize completion time [30]. Nevertheless, the coverage radius of the disk was chosen as the maximum value of the UAV’s communication range. In cases where some IoT devices are highly aggregated and distant from others, this additional coverage radius results in energy wastage.

To address this aforementioned gap, this paper introduces a variable-radius disk cover method based on the GAK-means algorithm, which dynamically clusters IoT devices based on their locations. This approach enables the design of better-optimized trajectories to achieve efficient energy consumption for both the UAV and IoT devices.

References

1. Boursianis, A.D.; Papadopoulou, M.S.; Diamantoulakis, P.; Liopa-Tsakalidi, A.; Barouchas, P.; Salahas, G.; Karagiannidis, G.; Wan, S.; Goudos, S.K. Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. Internet Things 2022, 18, 100187.
2. Sony, S.; Laventure, S.; Sadhu, A. A literature review of next-generation smart sensing technology in structural health monitoring. Struct. Control. Health Monit. 2019, 26, e2321.

3. Mozaffari, M.; Saad, W.; Bennis, M.; Nam, Y.H.; Debbah, M. A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. IEEE Commun. Surv. Tutor. 2019, 21, 2334–2360.
4. Zhao, N.; Lu, W.; Sheng, M.; Chen, Y.; Tang, J.; Yu, F.R.; Wong, K.K. UAV-assisted emergency networks in disasters. IEEE Wirel. Commun. 2019, 26, 45–51.
5. Ahmed, S.; Chowdhury, M.Z.; Jang, Y.M. Energy-efficient UAV relaying communications to serve ground nodes. IEEE Commun. Lett. 2020, 24, 849–852.
6. Zhan, C.; Zeng, Y. Aerial–ground cost tradeoff for multi-UAV-enabled data collection in wireless sensor networks. IEEE Trans. Commun. 2019, 68, 1937–1950.
7. Du, R.; Gkatzikis, L.; Fischione, C.; Xiao, M. Energy efficient sensor activation for water distribution networks based on compressive sensing. IEEE J. Sel. Areas Commun. 2015, 33, 2997–3010.
8. Ouyang, F.; Cheng, H.; Lan, Y.; Zhang, Y.; Yin, X.; Hu, J.; Peng, X.; Wang, G.; Chen, S. Automatic delivery and recovery system of Wireless Sensor Networks (WSN) nodes based on UAV for agricultural applications. Comput. Electron. Agric. 2019, 162, 31–43.
9. Baek, H.; Lim, J. Design of future UAV-relay tactical data link for reliable UAV control and situational awareness. IEEE Commun. Mag. 2018, 56, 144–150.
10. Bouabdallah, S.; Noth, A.; Siegwart, R. PID vs LQ control techniques applied to an indoor micro quadrotor. In Proceedings of the 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No. 04CH37566), Sendai, Japan, 28 September–2 October 2004; Volume 3, pp. 2451–2456.
11. Bouabdallah, S.; Siegwart, R. Backstepping and sliding-mode techniques applied to an indoor micro quadrotor. In Proceedings of the 2005 IEEE International Conference on Robotics and Automation, Barcelona, Spain, 18–22 April 2005; pp. 2247–2252.
12. Mahony, R.; Kumar, V.; Corke, P. Multirotor aerial vehicles: Modeling, estimation, and control of quadrotor. IEEE Robot. Autom. Mag. 2012, 19, 20–32.
13. Lee, T.; Leok, M.; McClamroch, N.H. Geometric tracking control of a quadrotor UAV on SE (3). In Proceedings of the 49th IEEE conference on decision and control (CDC), Atlanta, GA, USA, 15–17 December 2010; pp. 5420–5425.
14. Goodarzi, F.; Lee, D.; Lee, T. Geometric nonlinear PID control of a quadrotor UAV on SE (3). In Proceedings of the 2013 European Control Conference (ECC), Zurich, Switzerland, 17–19 July 2013; pp. 3845–3850.
15. Quan, Q.; Fu, R.; Li, M.; Wei, D.; Gao, Y.; Cai, K.Y. Practical distributed control for VTOL UAVs to pass a virtual tube. IEEE Trans. Intell. Veh. 2021, 7, 342–353.

16. Zhu, C.; Chen, J.; Zhang, H. Attitude control for quadrotors under unknown disturbances using triple-step method and nonlinear integral sliding mode. IEEE Trans. Ind. Electron. 2022, 70, 5004–5012.
17. Zeng, Y.; Zhang, R.; Lim, T.J. Wireless communications with unmanned aerial vehicles: Opportunities and challenges. IEEE Commun. Mag. 2016, 54, 36–42.
18. Zhan, C.; Zeng, Y.; Zhang, R. Energy-efficient data collection in UAV enabled wireless sensor network. IEEE Wirel. Commun. Lett. 2017, 7, 328–331.
19. Abeywickrama, H.V.; Jayawickrama, B.A.; He, Y.; Dutkiewicz, E. Empirical power consumption model for uavs. In Proceedings of the 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), Chicago, IL, USA, 27–30 August 2018; pp. 1–5.
20. Di Franco, C.; Buttazzo, G. Energy-aware coverage path planning of UAVs. In Proceedings of the 2015 IEEE International Conference on Autonomous Robot Systems and Competitions, Vila Real, Portugal, 8–10 April 2015; pp. 111–117.
21. Bramwell, A.R.S.; Balmford, D.; Done, G. Bramwell's Helicopter Dynamics; Elsevier: Amsterdam, The Netherlands, 2001.
22. Filippone, A. Flight Performance of Fixed and Rotary Wing Aircraft; Elsevier: Amsterdam, The Netherlands, 2006.
23. Zeng, Y.; Xu, J.; Zhang, R. Energy minimization for wireless communication with rotary-wing UAV. IEEE Trans. Wirel. Commun. 2019, 18, 2329–2345.
24. Powers, C.; Mellinger, D.; Kushleyev, A.; Kothmann, B.; Kumar, V. Influence of aerodynamics and proximity effects in quadrotor flight. In Experimental Robotics: The 13th International Symposium on Experimental Robotics; Springer: Berlin/Heidelberg, Germany, 2013; pp. 289–302.
25. Fay, G. Derivation of the Aerodynamic Forces for the Mesicopter Simulation; Standord University: Stanford, CA, USA, 2001.
26. Hoffmann, G.; Huang, H.; Waslander, S.; Tomlin, C. Quadrotor helicopter flight dynamics and control: Theory and experiment. In Proceedings of the AIAA Guidance, Navigation and Control Conference and Exhibit, Hilton Head, SC, USA, 20–23 August 2007; p. 6461.
27. Jia, G.; Li, C.; Li, M. Energy-Efficient Trajectory Planning for Smart Sensing in IoT Networks Using Quadrotor UAVs. Sensors 2022, 22, 8729.
28. Yang, D.; Wu, Q.; Zeng, Y.; Zhang, R. Energy tradeoff in ground-to-UAV communication via trajectory design. IEEE Trans. Veh. Technol. 2018, 67, 6721–6726.
29. Ning, Z.; Yang, Y.; Wang, X.; Guo, L.; Gao, X.; Guo, S.; Wang, G. Dynamic computation offloading and server deployment for UAV-enabled multi-access edge computing. IEEE Trans. Mob. Comput. 2021, 22, 2628–2644.

30. Zeng, Y.; Xu, X.; Zhang, R. Trajectory design for completion time minimization in UAV-enabled multicasting. IEEE Trans. Wirel. Commun. 2018, 17, 2233–2246.

31. Tran, D.H.; Vu, T.X.; Chatzinotas, S.; ShahbazPanahi, S.; Ottersten, B. Coarse trajectory design for energy minimization in UAV-enabled. IEEE Trans. Veh. Technol. 2020, 69, 9483–9496.

32. Lyu, J.; Zeng, Y.; Zhang, R.; Lim, T.J. Placement optimization of UAV-mounted mobile base stations. IEEE Commun. Lett. 2016, 21, 604–607.

33. Galkin, B.; Kibilda, J.; DaSilva, L.A. Deployment of UAV-mounted access points according to spatial user locations in two-tier cellular networks. In Proceedings of the 2016 Wireless Days (WD), Toulouse, France, 23–25 March 2016; pp. 1–6.

34. Li, F.; He, C.; Li, X.; Peng, J.; Yang, K. Geometric Analysis-Based 3D Anti-Block UAV Deployment for mmWave Communications. IEEE Commun. Lett. 2022, 26, 2799–2803.

35. Qu, H.; Zhang, W.; Zhao, J.; Luan, Z.; Chang, C. Rapid deployment of UAVs based on bandwidth resources in emergency scenarios. In Proceedings of the 2020 Information Communication Technologies Conference (ICTC), Nanjing, China, 29–31 May 2020; pp. 86–90.

36. Mozaffari, M.; Saad, W.; Bennis, M.; Debbah, M. Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs. IEEE Trans. Wirel. Commun. 2016, 15, 3949–3963.

37. Mozaffari, M.; Saad, W.; Bennis, M.; Debbah, M. Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage. IEEE Commun. Lett. 2016, 20, 1647–1650.