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Study on optimization of communication network for multi-unmanned aerial vehicles

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Abstract

The unmanned aerial vehicles (UAV) base station is most widely used as the emergency communication in response to emergencies. However, the performance improvement is in great demand at communication network. To improve the performance between the UAVs and the users, a novel method is proposed based on *k*-means++ algorithm and antenna adjusting. The established simulation platform and models are credible and reliable according to the very excellent approximation capability and the strong correlation between the simulation results and the Shannon's formula. The transmission success rate for the three conditions (using only *k*-means++, antenna pointing optimization and antenna downtilt angle optimization) dramatically increases with an increase in *k* and all reach the maximum when *k* is equal to 5. The fan throughput of the proposed method is almost two times than that of the other two conditions after the *k* value exceeds 5. Meanwhile, the edge users' rate and average user rate of the proposed method are all markedly increased. Overall, a novel method is provided for optimizing the performance between multi-UAVs and users, and the performance communication network for multi-UAVs is optimized by using the proposed method in this paper.

Keywords: Unmanned aerial vehicles, Ad hoc network, Communication networking, Capability

1 Introduction

In the future, there will be more and more wireless communication service data exchanges, and more ground communication systems can provide stable and reliable communication connections to a certain extent. However, in complex terrain, considering the influence of mountain, jungle and other shelter, channel quality of traditional ground base station is poor, which leads to poor network performance [1, 2]. Moreover, the existing ground base station is too heavy to meet the communication when the presence of large conference or sports events is hold, and ground base station is damaged in natural disasters such as earthquake or debris flow. To deal with the above problems, the unmanned aerial vehicles (UAV) base station is most widely used as the emergency communication in response to emergencies [3, 4].

UAV has widely attracted the attention of countries around the world because of the good mobility, low cost, convenient operation and other advantages [5, 6]. Particularly, the UAV can communicate with the ground cellular networks as an aerial terminal in the field of wireless communication [7, 8]. On the other hand, the UAV can be used as an air base station or a relay station to achieve the wireless network coverage of the target area [9, 10]. For the coverage problem, most of the research works focused on uncouple 3D placement problem of UAV, and they simplify the 3D space placement problem to the direction of horizontal and vertical [11]. Li et al. [12] demonstrated the problem of maximizing network throughput under the constraint of UAV base station capacity and proposed a UAV artificial bee colony algorithm to solve the problem of UAV base station, which can calculate the optimal flight position of each UAV base station and maximum network throughput. Bor-Yaliniz et al. [13] and Yanikomeroglu [14] focused on the properties of the UAV base station placement problem, and they formulated it as a 3D placement problem. They finally proposed a computationally efficient numerical solution with the objective of maximizing the revenue of the network. Huang et al. [15] focused on an optimization problem to find the optimal 3D positions for UAV base stations and developed a greedy algorithm with computational complexity analysis. Khuwaja et al. [16] studied the use of the UAV as the aerial base stations to provide wireless communication services in the form of UAV-based small cells; they find that the coverage area performance is dependent on the number of UAVs, deployment coordinates or network formation, and separation distance between UAVs and so on, and they concluded that a proper adjustment of the UAV separation distance can balance the co-channel interference.

The coverage may not meet the coverage requirements, because a single drone is limited by its hardware and software. In the future information and network environment, UAV clustering will have better robustness and viability [17]. Thus, in order to meet the actual demand of wide coverage and high bandwidth service, multi-UAV communication network is an inevitable trend of wireless communication network [18, 19]. Wang et al. [20] modeled the deployment problem as minimizing the number of UAVs and maximizing the load balance among them under two main constraints of robust backbone network and the fixed base stations, and they decomposed the problem into two subproblems and proposed a hybrid algorithm to solve this optimization problem with low complexity. Lyu et al. [21] proposed a polynomial-time algorithm with successive UAV base station placement to minimize the number of UAV base stations' wireless coverage, and the proposed algorithm performs favorably compared with other schemes in terms of the number of UAV base stations. Fotouhi et al. [22] designed UAV mobility algorithms to improve the spectral efficiency and proposed a range of practically realizable heuristics with varying complexity and performance, which can readily improve spectral efficiency by 34%. Mohamadi et al. [23] proposed an approach for efficient coverage using UAVs, and the proposed algorithms outperformed the benchmarking techniques and showed a high success rate, accuracy and consistency. Dai et al. [24] proposed a reinforcement learning-based approach to solve the multi-objective deployment problem, which considers the optimization problem of multiple performance metrics with various types of optimization variables. Zhao et al. [25] proposed a smart UAV base station placement mechanism to improve the mobile network operations in flash crowd and emergency situations, and they obtained network connectivity and system performance and resolved it with a genetic algorithm. Yang et al. [26] presented a reinforcement learning algorithm based on intrinsic rewards to provide the stable communication guarantee for multiple mobile users. Masroor et al. [27] optimized a multi-objective problem of UAV placement, users–UAV connectivity, distance and cost, so as to efficiently place UAVs in emergency situations where infrastructure is devastated with features of minimum distance, cost and number of UAVs. Nemer et al. [28] introduced a mathematical formulation for evaluating the payoff values based on a set of actions for each UAV; the UAVs' altitudes were adjusted by using the minimum number of UAVs to cover the candidate geographical region.

For UAV deployment problems, many studies used artificial intelligence technology [29, 30], such as clustering algorithms [31], deep learning (DL) [32], reinforcement learning (RL) [19] and so on. Zhang et al. [33] adopted the coverage probability as an evaluation index to find the 3D position of UAVs using particle swarm optimization, and they achieved the optimization purpose of maximizing the coverage probability. Aissa et al. [34] proposed UAV-centric machine learning (ML) solutions to satisfy network requirements. Sun et al. [35] studied the deployment method based on K-means clustering, which divided the target area into K convex subareas, and the mixed integer nonlinear problem was solved in each subarea to improve coverage. Lu et al. [36] present a deep reinforcement learning version to avoid exploring dangerous policies that lead to the high outage probability of the UAV messages by using three deep neural networks. To solve the problems of information eavesdropped during the UAV edge computing, the security of the UAV carrying mobile edge computing (MEC) has been studied [37, 38]. Lu et al. [39] utilized the reinforcement learning to optimize the secure offloading to reduce the information eavesdropping by a flying eavesdropper.

From the above research works, we can know that many researchers conducted the studies to calculate the optimal position of UAVs base station and maximum performance by using position optimization algorithms. Meanwhile, researchers decomposed 3D positions problem into two subproblems to solve this position optimization problem with low complexity. The above studies have optimized the performance to some extent. However, there is comparatively huge rise space for performance improvement. To improve the performance between the UAVs and the users, a novel method is proposed based on k-means++ algorithm and antenna adjusting. The proposed method firstly takes advantage of k-means++ to calculate the value of k. Then, the performance parameters were optimized by adjusting the antenna lobe pointing. Finally, the performance was further improved by adjusting the antenna downtilt angle, especially for fan throughput which rises as much as two times than the other two conditions. For UAV deployment problems, many studies use artificial intelligence technology. Although the performance between the UAVs and users is improved to a certain extent, the promotion of the performance is limited. Different from some existing studies, this paper proposed a method not only using the k-means++ algorithm but also adjusting the antenna to improve the performance between the UAVs and the users. Comparably, the performance is further improved by using the proposed method, especially for fan throughput which rises as much as two times.

2 Methods

The simulation system with low cost and convenient configuration is generally used due to the high equipment deployment cost and the complex system assembly and disassembly in the field of wireless communication. The platform built in this paper is a dynamic system-level simulation platform, which can simulate the actual passage of time and then mobile switching and power control. The dynamic system-level simulation platform of UAV communication network is constructed on OPNET dynamic simulation software, which includes central control node, user node and UAV node. The central control node includes the scene initialization module and the time propulsion module, UAV nodes include UAV wireless resource management module and UAV mobile module, and user nodes include user wireless resource management module. The operation process of the UAV communication networking system-level simulation platform is shown in Fig. 1. The multi-UAV coverage scenario map is shown in Fig. 2.

Parameter input and network initialization functions were implemented in the scene initialization module. Parameter inputs can be modified through an external interface based on the simulation scenarios and the research problem. Network initialization acquits parameters from the platform to complete the relevant parameter initialization in the UAV network. Functions such as time propulsion, parameter update, access

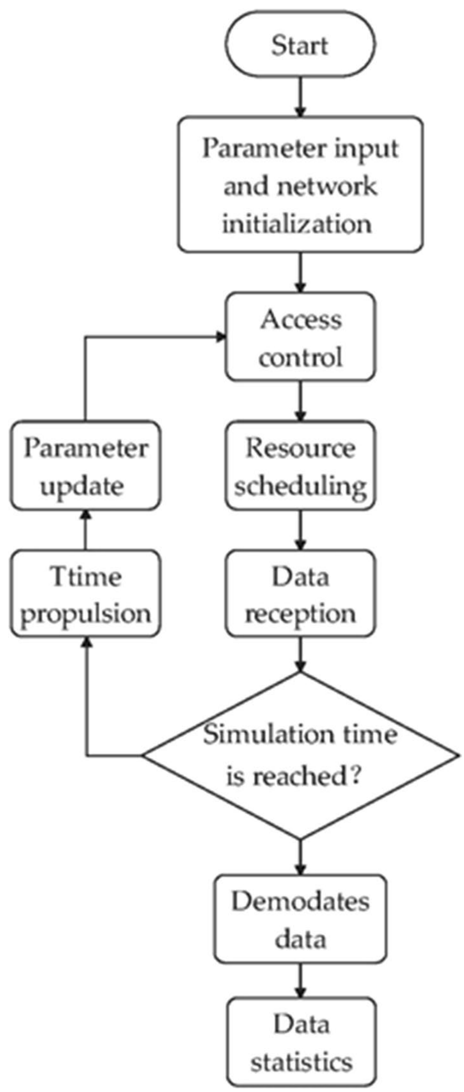

Fig. 1 Flowchart of the simulation process

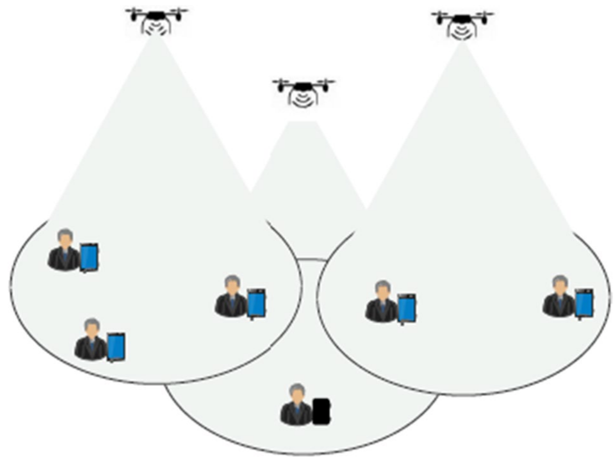

Fig. 2 Multi-UAV coverage scenario map

control and result statistics are implemented in the time propulsion module. After the initialization completion, the initialization completion interrupt is sent to the time propulsion module, and the initialization module enters the waiting state. Resource scheduling, data reception and demodulation are implemented in the UAV wireless resource management module. After the time propulsion module receives the interrupt information, it sends the scheduling interrupt to the base station wireless resource management module in a time slot and sends the self-interrupt in a subframe for channel state update. After the user receives the interruption, it sends a service message and sends the interruption to the base station, and the base station demodates data after receiving the interruption. When the simulation time is reached, the system sends interrupted to the time propulsion module. Finally, the data statistics module performs the relevant index statistics, and the simulation ends after the result statistics are completed. Position update is implemented in the UAV mobile module.

2.1 User deployment model

For the user deployment of the UAV communication networks, the Poisson point process theoretical model is used. The Poisson point process has been widely used in the performance evaluation of cellular networks, and the network performance modeled by the Poisson point process is very close to the real base station deployment performance [40]. The user position is represented by the polar coordinates, such as (r_i, θ_i). The user positions satisfy a mean of a $\lambda\pi R^2$-Poisson distribution, where λ is expectations and variance, and R is the radius of UAV-covered area (Table 1). The algorithm implementation method within the simulation platform is as follows:

2.2 Propagation models

The propagation model is usually an abstract model of the propagation characteristics of electromagnetic waves between both ends of the sending and receiver, which can reflect the fading of the wireless signal in space. The fading of wireless channels can be divided into large-scale fading and small-scale fading. Pathway loss and shadow fading are the main causes of large-scale loss.

Table 1 User positions deployment implementation method

The algorithm of user positions deployment in a circular area.
Input: Number of users and circular area center and radius.
Output: User location.
1. Generate two random numbers independently: $u_1 \sim$ U(0,1), $u_2 \sim$ U(0,1).
2. Calculate the range of the user i: $r_i = R \cdot \sqrt{u_1}$, the angle of the user i: $\theta_i = 2\pi u_2$, where r_i is the polar radius, R is the radius of UAV-covered area, and θ_i is the polar angle.
3. The polar coordinates of user i: (r_i, θ_i).
4. Repeat steps 1 to steps 3 until all users generate the polar coordinates.
5. End.

The road loss model, derived from the external field measurement data, is applied in this paper. It is suitable for the UAV altitude from 500 to 5000 m, shown as follows:

$$\begin{aligned} PL(dB) = {} & 46.30 + 26.16\log_{10}(f) - 15\log_{10}(h_{bs}) \\ & - [(1.1\log_{10}(f) - 0.7)h_{ue} - 1.56\log_{10}(f) \\ & + 0.8] + [44 - 0.8\log_{10}(h_{bs})]\log_{10}(2d_{2d}) \\ & + 0.84[\log_{10}(h_{bs})]^2 \end{aligned} \tag{1}$$

where f is the carrier frequency, h_{ue} denotes the height of the user, h_{bs} denotes the height of the UAV, d_{2d} denotes the horizontal distance of the transceiver.

According to the movement of the UAV or the user, the shadow fading formula at time t is

$$\begin{aligned} L_s(t) = {} & \exp(-d/d_{\mathrm{cor}}) \cdot L_s(t-1) \\ & + x \cdot \sqrt{1 - \exp(-2d/d_{\mathrm{cor}})} \end{aligned} \tag{2}$$

where d is the distance between the current user and the UAV and d_{cor} expresses correlation distances.

Small-scale fading is the fading of the signal level at short times or short distances. Multipath propagation and the Doppler effect are the main causes of small-scale fading.

2.3 Antenna model

The UAV base station, such as the ground base station, follows the three-sector topology. The user adopts the omnidirectional antenna, and the UAV base station adopts the directional antenna. Vertical radiation direction of antenna model is expressed as

$$A_{E,V}(\theta) = -\min\left[12\left(\frac{\theta - 90^\circ}{\theta_{3dB}}\right)^2, SLA_V\right] \tag{3}$$

where θ is the angle of pitch, °. θ_{3dB} denotes the half-power angle of vertical direction, θ_{3dB}=65°. SLA_{V} expresses sidelobe limitation, SLA_{V}=30.

Horizontal radiation direction of antenna model is expressed as

$$A_{E,H}(\varphi) = -\min\left[12\left(\frac{\varphi}{\varphi_{3dB}}\right)^2, A_m\right] \tag{4}$$

where ϕ is the angle of azimuth, °. ϕ_{3dB} denotes the half-power angle of horizontal direction, $\phi_{3dB}=65°$. A_m expresses rear flap limitation, $A_m=30$.

Single-component direction of antenna model is expressed as

$$A''(\theta,\varphi) = -\min\left\{-[A_{E,V}(\theta) + A_{E,H}(\varphi)], A_m\right\} \tag{5}$$

where the maximal value of A'' is 80 dBi.

2.4 Adaptive coded modulation

Adaptive coded modulation (ACM) is an effective way to promote spectral efficiency in wireless channels. Since the existence of interference and fading, the channel has strong time variation, so it is necessary to adjust the relevant parameters according to the channel state. Adaptive coded modulation obtains the link adaptation purpose through rate control. Under the 5G network, the user channel conditions are generally good; thus, the platform supports 28 modulation encoding modes. The received demodulation part can be implemented through a joint link-level interface in a system-level simulation.

3 Results and discussion

When the target area increases, multiple UAVs are required to cover the wireless network. UAV location deployment is the primary task of using UAV for data communication services, and its deployment performance is directly related to the quality of system service and the effective utilization of resources. The UAV deployment algorithm is mainly divided into static deployment algorithm and dynamic deployment algorithm. Static deployment algorithm obtains ground user information and gives the best deployment results after global calculation, and the dynamic deployment algorithm found the users by UAV automatically and gradually. In this paper, the static deployment algorithm is applied, which first obtains the ground user information and then gives the best deployment results after the global calculation. The solution of the existing static deployment research is usually to cluster the users in the target area and to set the horizontal deployment position of the UAV as the center of the geometric position of the cluster (Table 2).

3.1 Simulation verification

To verify the correctness of the platform, refer to the standard of 3GPP TS36.942, the modem throughput with a link-adaptive function can be approximated by the boundary decay and truncation of Shannon's formula, which presents the following:

$$\mathrm{THR} = \begin{array}{ll} 0 & \mathrm{SINR} < \mathrm{SINR_{min}} \\ \alpha \cdot S(\mathrm{SINR}) & \mathrm{SINR_{min}} < \mathrm{SINR} < \mathrm{SINR_{max}} \\ \mathrm{THR_{max}} & \mathrm{SINR} > \mathrm{SINR_{max}} \end{array} \tag{6}$$

where α is the attenuation factor, $\mathrm{SINR_{min}}$ denotes the minimum signal-to-interference plus noise ratios (SINR) value of adaptive encoding, $\mathrm{SINR_{max}}$ denotes the maximum signal-to-interference plus noise ratios (SINR) value of adaptive encoding. S(SINR) presents the maximum throughput achievable at the value of SINR, which can be calculated as follows:

Table 2 Simulation conditions

Simulation parameters	Value
Simulation area/km	40 × 40
Carrier frequency/GHz	2.4
Bandwidth/MHz	10
User transmitting power/dBs	23
Sub-carrier interval/kHz	30
UAV height/m	3000
Antenna downward inclination/°	20
Coverage of users	200
Link-level interface	Maximum support level is 256 QAM
Pilot overhead/%	35
Business model	Full buffer

$$S(\mathrm{SINR}) = W \log_{10}(1 + \mathrm{SINR}) \tag{7}$$

where W is the transmission bandwidth.

The comparison of transmission rate from the user to the base station between the simulation and Shannon's formula is shown in Fig. 3, in which the resource block is equal to 1. As the resource block is equal to 5, the comparison of transmission rate from the user to the base station between the simulation and Shannon's formula is shown in Fig. 4. It can be seen from Figs. 3a and 4a that the simulation results of the two conditions are almost the same as the results of Shannon's formula, which means that the approximation capability of the simulation results is excellent.

Simulation fitting analysis of transmission rate between the user and the base station is shown in Figs. 3b and 4b; it can be seen that the transmission rate between the user and the base station is bigger for the simulation results than that of Shannon's formula; this is because of the parameter setting of the simulation. However, it can be seen that the correlation coefficients (R) are 0.99778 and 0.99944, respectively. These indicate that the correlation between the simulation results and the Shannon's formula is strong for both the two conditions. Therefore, the simulation plat and models are credible and reliable, and these can be used for further research work.

3.2 Horizontal position optimization based on *k*-means++

The k-means++ is improved on the basis of the k-means, which not only considers the number of clusters k, but also selects the initial cluster center. The main idea of the k-means++ is that the selection of kth cluster center needs to refer to the location of the k-1 th cluster center, and the point farther away from the k-1 cluster center, the greater the chance that it can be selected as a new cluster center. It makes the clustering effect improve greatly (Table 3). The UAV location deployment algorithm based on k-means++ is given in Table 3.

The k value determination is generally given by empirical values or by the dataset itself. Three reference indexes, such as sum of the squared errors, profile coefficient method and Calinski–Harabasz, are used to obtain the k value from the dataset itself.

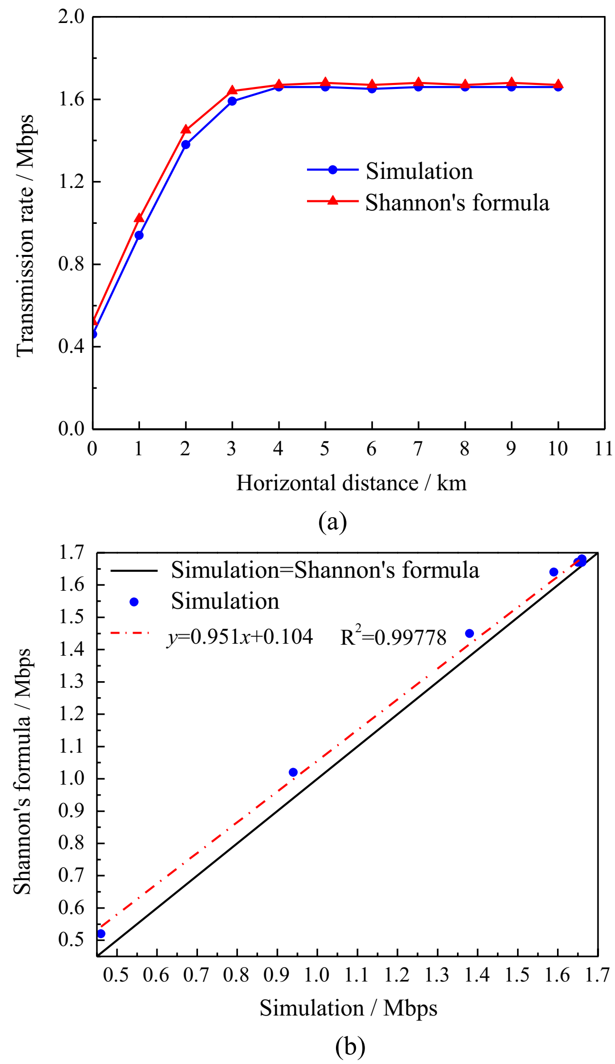

Fig. 3 Transmission rate between the user and the base station (resource block = 1). **a** Comparison of the transmission rate between the simulation and Shannon's formula; **b** fitting analysis of simulation

The sum of the squared errors (SSE) is calculated as

$$\mathrm{SSE} = \sum_{i=1}^{k} \sum_{p \in C_i} (p - m_i)^2 \tag{8}$$

where p is the data points in the cluster center; C_i expresses the i th cluster; m_i expresses cluster center.

When k is less than the threshold, the aggregation degree increases rapidly and the SSE drops rapidly; when k is more than the threshold, the aggregation degree increases slowly and the SSE decreases slowly. This threshold is the best k value for this spatial dataset.

The profile coefficient (S) is calculated as

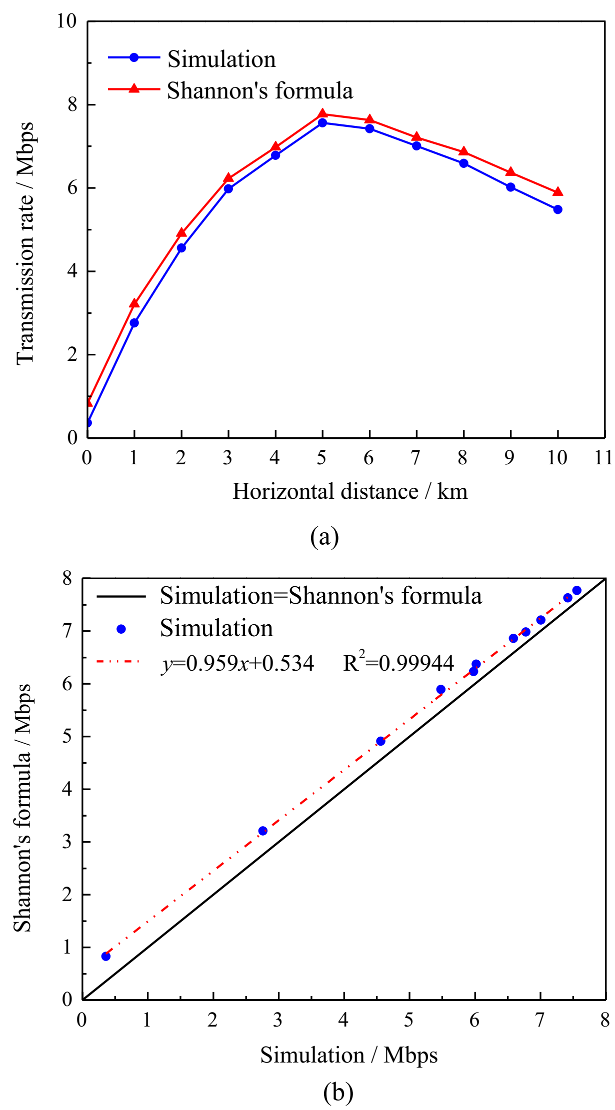

Fig. 4 Transmission rate between the user and the base station (resource block = 5). **a** Comparison of the transmission rate between the simulation and Shannon's formula; **b** fitting analysis of simulation

$$S = \frac{B - A}{\max(A, B)} \tag{9}$$

where A is expressed as the mean of the Euclidean distance from sample point p to all other sample points in this cluster; b represents the minimum of the mean Euclidean distance from sample points p to sample points in other clusters. The value of S is taken between [− 1,1], and the larger value of S indicates that the sample point is more fit in the cluster.

The Calinski–Harabasz (CH) is calculated as

$$\mathrm{CH} = \frac{\mathrm{SSB}}{\mathrm{SSW}} \cdot \frac{N - k}{k - 1} \tag{10}$$

Table 3 UAV location deployment algorithm based on k-means++

The algorithm of the UAV location deployment algorithm based on k-means++.
Input: Number of UAV and user location coordinates.
Output: Horizontal position coordinates of UAV.
1. Given the k value of UAV to be deployed.
2. Initializes the location coordinates of the user to be covered.
3. The location of a user was randomly selected as the location of the first cluster center.
4. Go through all users, and get the horizontal distance from all the users to current cluster centers, then select the shortest distance as L_i.
5. The probability of this user that can be selected as the cluster center is calculated as: $P_i = L_i^2/\Sigma L_i^2$.
6. The new cluster center is determined according to the probability P_i that the user is selected.
7. Perform steps from 4 to 6 until the k initial cluster centers are determined.
8. The distance between each user and the other cluster centers is calculated.
9. Select the cluster closest to the user and add the user to the list of the cluster.
10. All clusters were traversed and the average of the user coordinates within the cluster list was calculated.
11. The mean values of coordinate were taken as the new cluster center coordinates.
12. Return to step 8 until the cluster center coordinates unchanged or the number of iterations is reached.
13. End.

where N is the size of the dataset; SSB is the inter-class variance; and SSW represents the within-class variance. As same as S, the larger value of CH indicates that the sample point is more fit in the cluster.

The results of the reference indexes in two scenarios are shown in Fig. 5. Scenario 1 expresses that the users are evenly distributed in the simulation area, which means that the users are uniformly distributed in the area as simulating calculation. Scenario 2 expresses that the users are randomly distributed in the simulation area, which means that the users are stochastically distributed in the area as simulating calculation. It can be seen from Fig. 5a that the values of SSE for both scenarios decrease gradually from the maximum to stable values. For scenario 1, the value of SEE remains constant when k is equal to 8. However, the value of SEE remains unchanged when k is equal to 5 for scenario 2. According to the evaluation principle of SSE, the best value of k is obtained when the value of SSE basically remains constant. Thus, the best values of k are 8 and 5 for scenario 1 and scenario 2, respectively. The values of S for the two scenarios are shown in Fig. 5b. The values of S for scenario 1 varied little, and no significant maximum values occurred. The values of S for the scenario 2 reach the maximum when k is equal to 5. According to the evaluation principle of S, the best value of k is obtained as the value of S reaches maximum. Thus, it can be concluded that the method of profile coefficient is invalid for the scenario 1, and the best value of k is 5 for scenario 2 according to the method of profile coefficient. The values of CH for the two scenarios are presented in Fig. 5c. For scenario 1, the value of CH do not appear the maximum along with the increase in k, which indicates invalid in the method of Calinski–Harabasz to calculated the value of k. The value of CH achieves maximum at the value of k is 5 for scenario 2, which means the best value of k is 5 for scenario 2 according to the method of Calinski–Harabasz.

It can be concluded that the method of sum of the squared errors can be used to calculate k for both two scenarios; however, the other two methods, such as profile

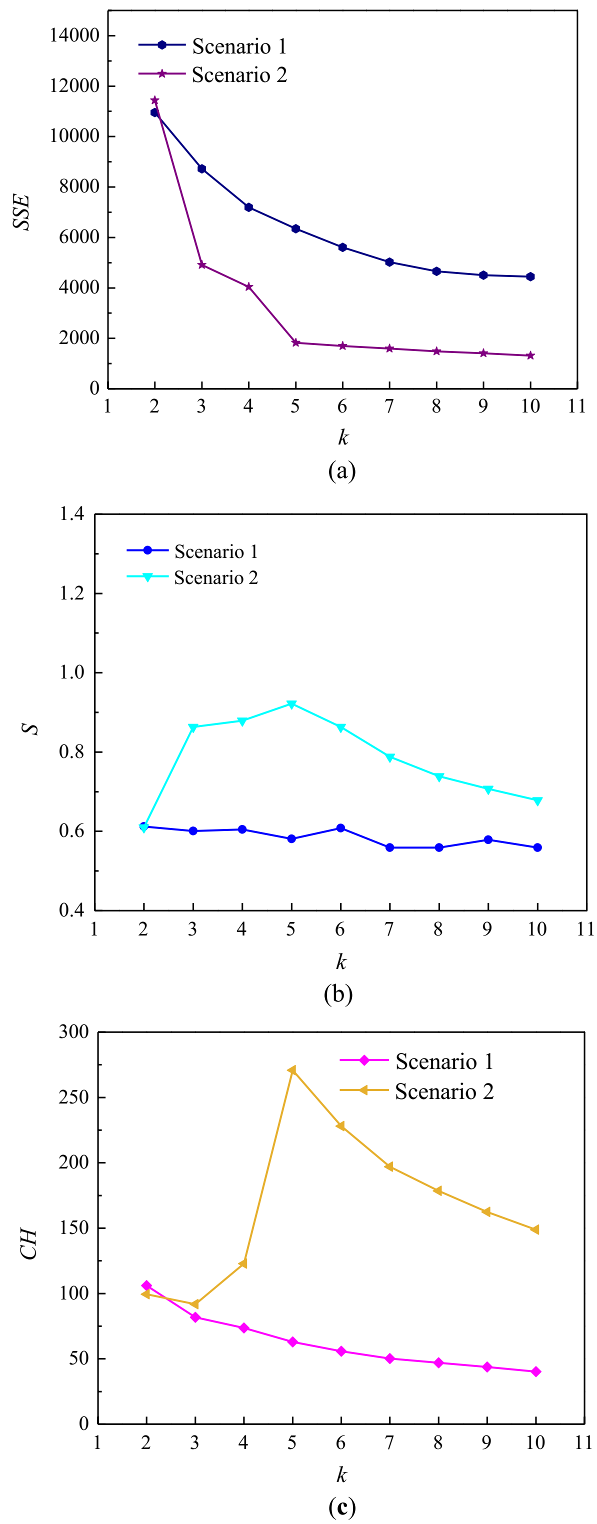

Fig. 5 Results of the reference indexes in two scenarios. **a** The value of SSE; **b** the value of S; **c** the value of CH

coefficient and Calinski–Harabasz, can not be applied only for scenario 2. Thus, the method of sum of the squared errors is more suitable to calculate *k*, and it will be used in this paper in the following study.

Four parameters, such as the transmission success rate, fan throughput, edge users rate and average users rate, are studied for the scenario 2, in which the users are randomly distributed in the simulation area. The transmission success rate and fan throughput between the UAV and users are shown in Fig. 6. It can be seen that the transmission success rate and fan throughput both increase with an increase in *k*. The transmission success rate reaches the maximum when *k* is equal to 5, and the fan throughput achieves the maximum when *k* is equal 8. The best value of *k* obtained according to the transmission success rate is the same as that achieved from *k*-means++ algorithm using the sum of the squared errors as reference index. However, the best value of *k* is 8 according to the fan throughput, which means that to achieve the maximum fan throughput needs an increase in the member of the UAV to 8. It is clear that the cost increases with an increase in the number of UAVs; hence, it is necessary to search a method to decrease the number of UAVs as much as possible. The edge users rate and average users rate between the UAV and users are shown in Fig. 7. It can be seen from Fig. 7 that the edge users rate and average users rate both increase continuously with the increase in *k*. It is indicated that the increase in UAVs is beneficial to both the edge users rate and the average users rate. Thus, it can be concluded that the more the number of UAVs the greater the edge users rate and average users rate.

3.3 Performance optimization based on *k*-means++ and antenna adjusting

According to the evaluation principle of *k*-means++, the best value of *k* is obtained when the value of SSE basically remains constant. Thus, the best value of *k* is 5 for scenario 2 based on *k*-means++. The best value of *k* obtained according to the transmission success rate which is the same as that achieved from *k*-means++ algorithm using the SSE as reference index. However, the best value of *k* is 8 according to the fan throughput.

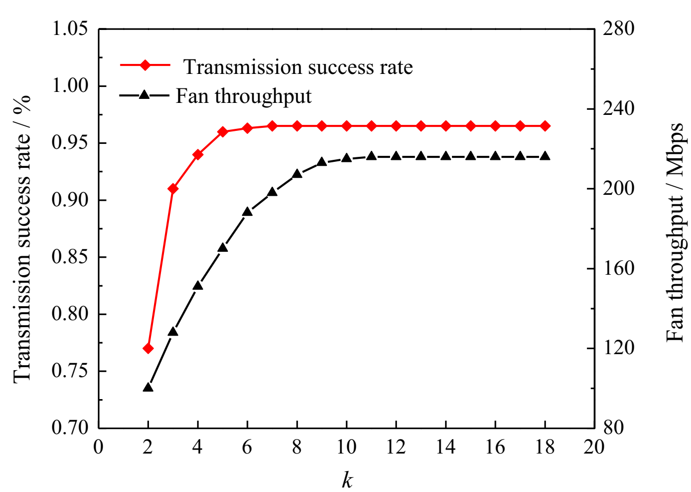

Fig. 6 Transmission success rate and fan throughput based on *k*-means++

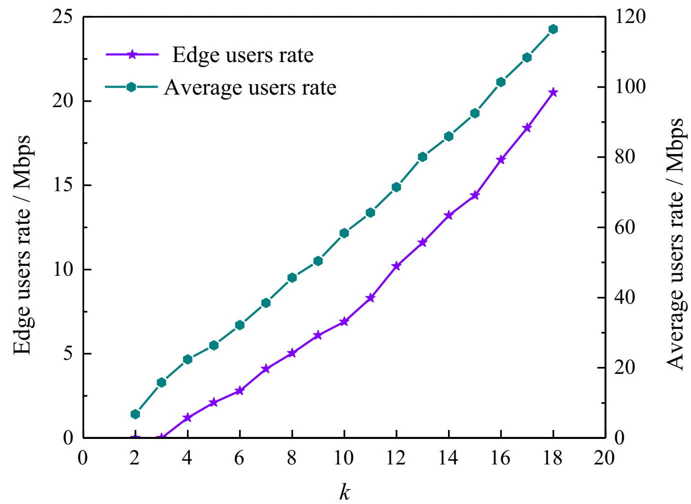

Fig. 7 Edge users rate and average users rate based on *k*-means++

It is clear that the cost increases with an increase in the number of UAVs; hence, it is necessary to search a method to decrease the number of UAVs as much as possible.

From the antenna model in formulas (3)–(5), it can be obtained that the closer the user is to the antenna lobe, the greater the antenna gain obtained by the user. It is necessary to optimize the distance between the users and antenna lobe. Moreover, the antenna downtilt angle is more important to the performance of UAV. The optimal antenna downtilt angle is calculated by

$$\theta = \arctan(h/R) \tag{11}$$

where h is the height of the UAV; R represents the longest distance between the UAV and users.

Thus, the performance optimization method of UAV is proposed to improve the performance between users and UAV based on the *k*-means++ and antenna adjusting. The calculation process of the proposed method is presented in Table 4. It can be seen from Table 4 that the input and output of the proposed method is the number of UAVs, user location coordinates, antenna horizontal pointing and downtilt angle of UAV, respectively. The cluster center number of *k*-means++ algorithm is obtained firstly by using *k*-means++ algorithm, which is used as the location deployment center of UAV. Then, the optimal antenna lobe pointing is calculated by gradual adjusting of the antenna lobe pointing. Finally, the optimal downtilt angle is calculated by formula (11).

The transmission success rate of three conditions is calculated, which is presented in Fig. 8. It can be seen from Fig. 8 that the transmission success rate for the three conditions dramatically increases with an increase in k and all reach the maximum when k is equal 5. The transmission success rate calculated by antenna downtilt angle optimization (the proposed method) is biggest, and it is smallest by using only *k*-means++ method. Thus, it is can be concluded that the transmission success rate could be increased by using the proposed method when the number of UAVs is not increased.

The fan throughput of three conditions is shown in Fig. 9, which presents that the fan throughput for the three conditions all increases firstly with an increase in k and then

Table 4 Performance optimization algorithm based on *k*-means++ and antenna adjusting

The algorithm of performance optimization based on *k*-means++ and antenna adjusting.
Input: Number of UAVs and user location coordinates.
Output: Antenna horizontal pointing and downtilt angle of UAV.
1. The number and position of UAV are computed by the *k*-means++ algorithm.
2. Calculate the distance of all users to the antenna lobe of the UAV, and the average distance can be calculated.
3. Update the antenna lobe pointing with 5° as the step size.
4. Repeat step 2, the new average distance can be calculated.
5. If the new average distance is less than average distance, the average distance is replaced by the new average distance.
6. Repeat steps 3 to 5, until all the conditions are calculated, and the smallest average distance is obtained. Then, the antenna lobe pointing is obtained at the same time.
7. Select the longest distance between the UAV and users
8. Calculate the optimal downtilt angle by formula (11).
9. Adjust the antenna lobe pointing and downtilt angle.
10. End.

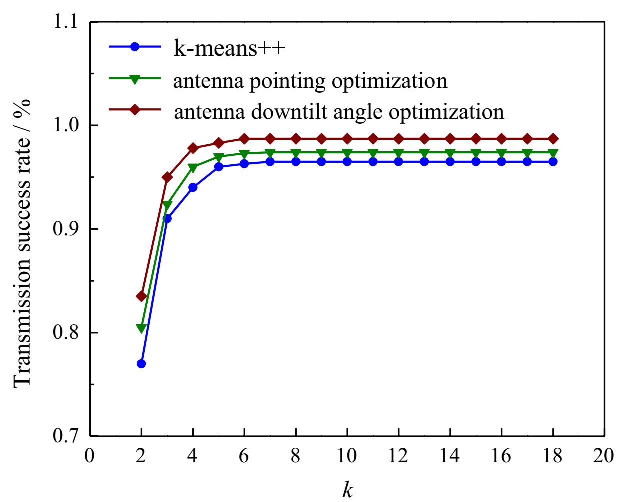

Fig. 8 Transmission success rate based on *k*-means++ and antenna adjusting

changes gradually with a continuous increase in *k* until *k* reaches 8. Moreover, the fan throughput based on *k*-means++ and antenna lobe pointing optimization has a small rise than that based on *k*-means++ only. The fan throughput of the proposed method is almost two times than that of the other two conditions after the *k* value exceeds 5. It can be concluded that the fan throughput improves obviously when the proposed method is used between the UAVs and the users. Therefore, the fewer the UAV is applied, the better the fan throughput could be obtained using the proposed method.

The edge users rate and average users rate of the three conditions are shown in Figs. 10 and 11, respectively. It can be seen that the edge users rate and average users rate of the three condition all increase with an increase in *k*. Meanwhile, the edge users rate and average users rate of the proposed method both increase observably than the other two conditions. Therefore, the proposed method has the obvious effect on improving performance between the UAV and the users. Furthermore, the cost of UAV decreases

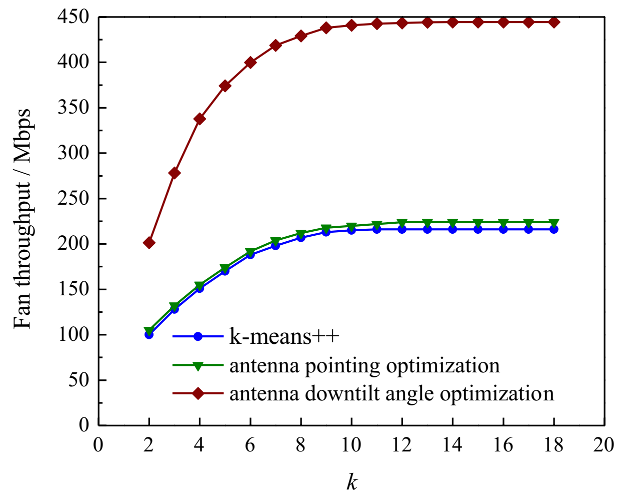

Fig. 9 Fan throughput based on *k*-means++ and antenna adjusting

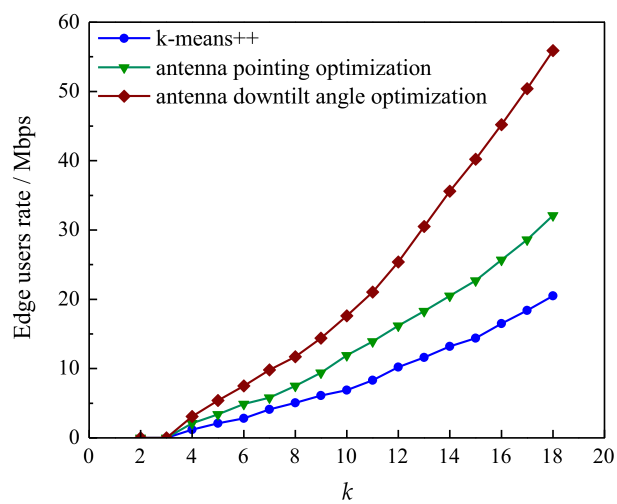

Fig. 10 Edge users rate based on *k*-means++ and antenna adjusting

dramatically when the proposed method is applied in communication network for multi-UAV.

3.4 Discussion

The platform built in this paper based on user deployment model, propagation models, antenna model and adaptive coded modulation is used to simulate the performance of communication network for multi-UAVs. To improve the performance between the UAVs and the users, a novel method is proposed based on *k*-means++ algorithm and antenna adjusting. The proposed method first takes the advantage of *k*-means++ to calculate the value of *k*, which is used as the number of UAVs and the center of the deployment location. Then, the performance parameters, such as transmission success rate, fan throughput, edge users rate and average users rate, were optimized by adjusting the antenna lobe pointing. Finally, the performance was further improved by adjusting the

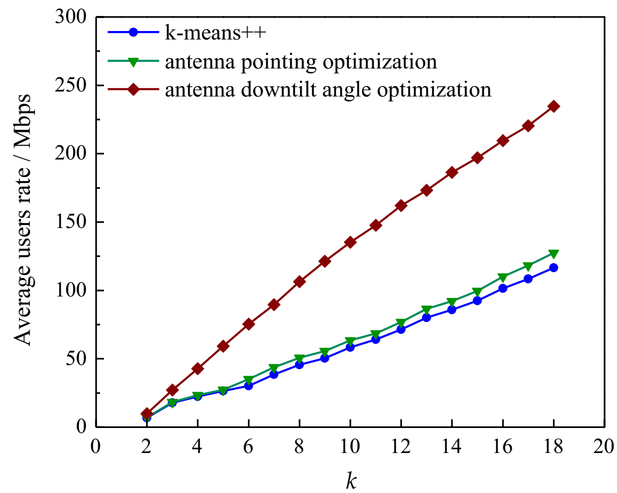

Fig. 11 Average users rate based on *k*-means++ and antenna adjusting

antenna downtilt angle, especially for fan throughput which increases as much as two times than the other two conditions.

Many researchers conducted the studies to calculate the optimal flight position of each UAV base station and maximum performance by using position optimization algorithms [15, 16]. Meanwhile, researchers decomposed 3D positions problem into two subproblems to solve this positions optimization problem with low complexity [20]. These methods are universal simulation technique to optimize the location of the UAVs and the performance between the UAVs and the users. In this paper, the study was conducted in view of the above research methods. Furthermore, it proposed own methods to improve the performance. Therefore, the result conducted from the simulation plat and its calculation model is believable and reliable.

For UAV deployment problems, many studies use artificial intelligence technology [29, 30], such as clustering algorithms [31], deep learning [32, 36], particle swarm optimization [33], reinforcement learning [19] and so on. Although the performance between the UAVs and users is improved to a certain extent, the promotion of the performance is limited. Different from the above studies, this paper proposed a method not only using the *k*-means++ algorithm but also adjusting the antenna to improve the performance between the UAVs and the users. The deployment method based on *k*-means clustering was studied, which divides the target area into *k* convex subareas, and the mixed integer nonlinear problem is solved in each subarea to improve coverage [35]. They presented that the simulation results achieved an up to 30% higher coverage probability when the *k*-means clustering method was used. Comparably, the performance was further improved by using the *k*-means++ and antenna adjusting, especially for fan throughput which rises as much as two times.

4 Conclusion

The unmanned aerial vehicles (UAV) base station is most widely used as the emergency communication in response to emergencies. However, the performance improvement is in great demand at communication network. The platform based on user deployment model, propagation models, antenna model and adaptive coded modulation is built in this paper to simulate the performance of communication network. To improve the performance between the UAVs and the users, a novel method is proposed based on k-means++ algorithm and antenna adjusting. The established simulation platform and models are credible and reliable according to the very excellent approximation capability and the strong correlation between the simulation results and the Shannon's formula. The sum of the squared errors is the best method to calculate the clustering center k than the other two methods, such as profile coefficient and Calinski–Harabasz, and it is used in the following study. The transmission success rate for the three conditions (using only k-means++, antenna pointing optimization and antenna downtilt angle optimization) dramatically increases with an increase in k and all reach the maximum when k is equal 5. The fan throughput of the proposed method is almost two times that of the other two conditions after the k value exceeds 5. It can be concluded that transmission success rate and the fan throughput improve obviously between the UAVs and the users when the proposed method is used. Therefore, the fewer the UAV is applied, the better the fan throughput could be obtained using the proposed method. Meanwhile, the edge users rate and average users rate of the proposed method are all markedly increased. The proposed method has the obvious effect on improving performance between the UAV and the users. It means that the cost used in UAV decreases dramatically when the proposed method is applied in communication network. Overall, the performance communication network for multi-UAVs is optimized by using the proposed method in this paper and a novel method is provided for optimizing the performance between multi-UAVs and users.

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Author contributions
GH contributed to the conception of the study, data analyses and experimental design and wrote the manuscript. YX participated in the design of the study and performed the statistical analysis. JQ carried out the intelligent algorithm studies. JX participated in the analysis with constructive discussions. KS conceived the study and participated in its design and coordination and helped to draft the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Competing interests
The authors declare that they have no competing interests.

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