An optimal location allocation by multi-user cooperative mobility for maximizing throughput in MANETs

JIQUAN XIE¹, (Graduate Student Member, IEEE), TUTOMU MURASE², (Member, IEEE)

¹Graduate School of Informatics, Nagoya University, Nagoya, Japan (e-mail: xiejq@net.itc.nagoya-u.ac.jp)
²Information Technology Center, Nagoya University, Nagoya, Japan (e-mail: tom@itc.nagoya-u.ac.jp)

Corresponding author: Jiquan Xie (e-mail: xiejq@net.itc.nagoya-u.ac.jp).

A part of the research in this paper is supported through Grants-in-aid for Scientific Research (19H04093)(20H00592).

ABSTRACT User cooperative mobility is a new approach to improve system throughput in mobile ad hoc networks (MANETs). Compared with traditional technologies such as expanding link bandwidth and promoting transmission protocol efficiency, this new method significantly reduces the cost of communication infrastructure, protocol complexity, and energy consumption through the mobility of helpers or collaborators. Nevertheless, diverse challenges, especially multiple user cooperative mobility in practical application, become a significant issue. Currently, most of the propositions assume a single mobility user and do not interpret the multiple user cooperative mobility scenarios. This paper proposes a new algorithm, called Maximum Throughput algorithm for Optimal Position (MTOP), based on the known geographic location information of fixed users. In this algorithm, the lower and upper bounds are derived to determine the search space domain based on feasible location assemblies. Furthermore, we define a conflict set of locations graph (CSLG) to prove this proposition that the domain includes the optimal location-allocation. Finally, the simulation results show that the throughput of MTOP is increased by 298.81%, 37.91%, and 23.04%, respectively, compared with the intuitive method, simulated annealing algorithm, and game theory method. Our proposed algorithm is confirmed to be effective in improving throughput, reducing complexity, and overhead in multiple user cooperative mobility systems.

INDEX TERMS MANETs, multiple user cooperative mobility, system throughput, Maximum Throughput algorithm for Optimal Position, conflict set of locations graph, computation cost.

I. INTRODUCTION

In recent years, mobile ad hoc networks (MANETs) have attracted massive attention from researchers with the rapidly growing mobile devices in the 5G era. Ad hoc network protocol is widely adopted in the small-scale area (hotel, house, etc.) and population gathering community (business center, commercial office, etc.) for assisting in individual and commercial usage [1]. With the widespread of 5G, the increasing demand for ad hoc networks for high transmission rate, low latency, and quality of service (QoS) [2] is a significant issue that requires further exploration. For supporting high QoS, system throughput is a vital parameter to advance the transmission rate; that is, the data rate per unit time in the entire wireless communication system [3].

There are a number of traditional approaches to improve throughput in the wireless communication system. Most of them are implemented by using expanded transmission bandwidth [4], increased efficiency of network or media access control (MAC) layer protocols [5], etc. However, these methods always consume a substantial amount of physical media resources or add a great deal of complexity to protocol standards. The user cooperation idea has been demonstrated as a low-cost approach to provide high throughput, allowing users to cooperate by forwarding the overheard data from source to destination [6].

Those users whose QoS is not guaranteed or cannot meet steady demand can request other users to act as intermediaries or helpers to relay. In this case, the user cooperative mobility approach is proposed to improve the throughput in practical application, which utilizes collaborators’ mobility to move to a feasible location for boosting the transmission rate [7], [8]. After the movable users move to the best
location, the interference can be reduced. The system signal-to-noise ratio (SINR) is the largest, and ultimately the final throughput improvement effect is the best.

At present, most of these previous approaches are only centered on single-user mobility strategies, which are limited in mobility distance and energy consumption. Moreover, multiple user mobility leads to the NP-hard problem and high complexity in traditional algorithms. In practical application, the effective algorithm of multi-user cooperative mobility strategy has not been proposed.

This paper concentrates on improving system throughput by multiple movable user mobility in the ad hoc networks. Different from previous mobility strategies, we utilize the coordinate information of cooperative users to propose a new heuristic algorithm, which not only maximizes system throughput but also reduces computation cost and communication overhead. Through our promotion, the contribution of the paper can be summarized as follows:

- We employ the Poisson point process (PPP) and calculate the cumulative distribution function to present the property of fixed nodes positions. From this, the Decode-and-Forward (DF) transmission technique is exploited in our formulation of system throughput maximization problem, which is a mixed-integer with non-linear and non-convex problem aimed at finding the optimal location for multiple moveable users.
- For solving this NP-hard problem, we define a domain concept in which the optimal locations for movable nodes can definitely be found. Furthermore, we classify this domain as two boundaries, called as lower and upper bounds, to delineate the domain scope.
- A conflict set of locations graph (CSLG) is proposed to clarify and calculate the values of lower bound and upper bound. Different with the previous conflict graph methods, we allocate the feasible location partitions as exploitable resources to movable nodes in CSLG. Moreover, we specify the allocation policy based on the conflict conditions of the SINR.
- We prove that the optimal locations for movable nodes must be located in the domain, and propose Maximum Throughput algorithm for Optimal Position (MTO). Finally, we introduce the previous methods, including intuitive method, simulated annealing, game theory method, and exhaustive global search algorithm as performance comparison. We evaluate the throughput, computing cost and communication overhead of these methods by NS3.

The remainder of this paper is organized as follows. The related work is discussed in Section II, and then section III presents the system model, problem formulation. In section IV, movable nodes’ location domain is defined, including the concept of domain, lower and upper bounds. Section V proposes the MTOP algorithm and introduces conventional methods. Performance simulation results are provided in Section VI to verify the performance of the proposed algorithm. Section VII presents the analytical results to validate the correctness of the simulation results. Finally, Section VIII concludes the paper.

II. RELATED WORK

This section describes a brief overview of system throughput improvement in ad hoc networks, user cooperative mobility technique, and application of graph theory in wireless networks.

A. SYSTEM THROUGHPUT IMPROVEMENT IN AD HOC NETWORKS

Some related works on improving system throughput in ad hoc networks are presented below. More recently, traditional approaches focus on physical (PHY) MAC layer mechanisms to improve network throughput performance. For the PHY layer, the primary augmentations are advanced modulation methods such as high-frequency bonding techniques, multiple large-scale input multiple-output (MIMO) antenna support, orthogonal frequency division modulation (OFDM), and single carrier (SC) techniques [9]. The MAC layer plays the most critical role for throughput enhancement since it is a medium for communication and support of other layer services, especially service differentiation, minimum latency, and fairness in bandwidth allocation [10]. Overall, we mainly discuss the proposed MAC mechanisms that lead to achieving high throughput.

Providing QoS through an enhanced MAC layer, Sandip et al. [11] proposed a design for achieving gain in transmission control protocol (TCP) throughput for different congestion control schemes, which combines 802.11e Hybrid Coordination Function (HCF) and 802.11n frame aggregation schemes. The proposed design includes several QoS mechanisms such as admission control, calculation of the transmission opportunity (TXOP), and a scheduler that aims to increase the throughput of best-effort traffic. However, this design only guarantees that this QoS mechanism supports small real-time traffic, and no consideration was given to the different interference and noise levels. Zhiqun et al. [12] focused on bandwidth allocation schemes for distributed wireless LANs based on the IEEE 802.11ac contention mechanism. For this purpose, they proposed Markov chains under non-saturated conditions, but they only consider ideal channel conditions, and all the enhanced PHY/MAC characteristics are not included.

MAC scheduling mechanism aims to design an effective scheduler for frame aggregation to achieve high throughput at the upper layer. Aajami et al. [13] proposed a TXOP sharing mechanism based on throughput awareness. In this method, the ant colony optimization mechanism is applied to achieve the scheduling and joint link adaptation of the TCP downlink, but this TXOP does not support dynamic channel management. In [14], Mourir et al. proposed a method that proposes a method that can transmit to multiple users simultaneously and provide appropriate transmission parameters for selected users. Then, it is helpful to select different transmission
parameters and improve user throughput. However, the interference of noise and the fairness of channel bonding is not considered. In [15], Mustafa et al. implemented the block acknowledgment of frame aggregation and tuning the TCP congestion algorithm to improve the algorithm’s performance and increase the packet transmission rate. Yet, the authors did not consider the different channel conditions while implementing the TCP congestion algorithm. In brief, most algorithms or mechanisms did not consider different channel access conditions, as well as sacrifice significant bandwidth or management resources to boost limited throughput. Hence, they are sometimes inefficient in practical applications.

B. USER COOPERATIVE MOBILITY APPROACH

B. Baron et al. [16] presented that the mobility of these storage-capable entities can create a communication channel that could help overcome the limitations or deficiencies of traditional data network scenarios and enhance throughput. By studying the per-session throughput of applications with loose latency constraints, M. Grossglauser et al. [17] find that user mobility makes the topology vary with packet delivery time scale. Then, [17] proved that when nodes are mobile rather than fixed, the throughput per user can be greatly increased. Tutomu Murase [18] presented that cooperative user mobility can reduce resource consumption for the network operator or service provider to improve QoS. In reference [19], A. Chaintreau. et al. proposed that an opportunistic forwarding algorithm can be designed according to human mobility under the background of human carrying devices, so as to improve the throughput.

Fig. 1 depicts the scenario and operation of the user cooperative mobility approach. Around the city, the QoS of many users cannot be satisfied to meet the typical requirements due to the distance away from AP. When many nodes are far away from AP, the transmission rate is low due to the signal attenuation, especially for remote nodes. According to the abnormal performance, the lower rate nodes will seriously affect the system throughput.

To improve the throughput and transmission rate, some users can act as relays (helpers) and have mobility. Considering the effects of interference and SINR between all users, these movable relays can move to the best location within a limited range to help the fixed users and increase the throughput performance, especially in the earthquake, fire, and other emergencies.

In recent years, many researchers focused on algorithms for improving system throughput through user mobility methods. To reduce the complexity of mobility control algorithms, some researchers introduced the intuitive method. It means that these movable cooperators move to an intermediate location between the two assisted users for connecting each link. J. Li et al. [20] analyzed ad hoc wireless networks’ capacity. They discovered a reasonable location scheduling; that is, the average distance between the source node and the destination node must be equal to make the network expands total throughput. R. Ohmiya et al. [21] investigated the throughput properties of three different ad hoc network topologies and revealed that the best locations are in the middle of two users. These papers verified that the intuitive method could improve throughput. However, only interference among parts of users, Signal-to-noise ratio (SNR), and communication coverage distance are to be taken into consideration.

The cooperative approach was proposed to boost SINR and throughput significantly. It requires the movable users to consider the interference between all the devices interacting with each other, not just to increase their own transmission rate or reduce others’ interference, i.e., the mobility nodes have to behave cooperatively concerning system throughput, rather than with selfish or greedy incentives. Sumiko Miyata et al. [22] proposed an optimal AP selection algorithm for maximizing throughput while keeping newly arrived user throughput stable. In [22], this algorithm should be applied within the movable distance and acceptable throughput threshold. Ryo Hamamoto et al. [23] introduced an AP selection method based on collaboration among APs and user’s mobility under the single user and the limited distances. In addition, Tianran Luo et al. [24], [25] evaluated system throughput features of the single movable user and validated the best location under capture effect or dynamic back-off time.

In [26], our previous work proposed an interaction position game to achieve high throughput and decrease computation costs in the multiple user mobility systems. However, the method’s completion time is also relatively long, and the communication overhead is so high that it is sometimes not efficient in the existing communication system. Nevertheless, the relevant practical algorithms for cooperative multi-user mobility schemes have not been explored due to the complex transmission strategies and optimization conditions.

C. APPLICATION OF GRAPH THEORY IN WIRELESS NETWORKS

A significant work in using graph theory to solve wireless network problems is reported in [27]. S. Ramanathan et al. proved that directed graph can be used for near-optimal
scheduling and can be extended to any network. The length of the scheduling is proportional to the graph thickness multiplied by the optimal color number. Kamal Jain et al. [28] first proposed using a conflict graph to determine the optimal throughput boundaries for a given network and workload. Lijun Chen et al. [29] presented using contention graph and contention matrix to formulate resource allocation in the network with joint congestion control and media access control.

For the conflict perspective, based on [28], Shaohe Lv et al. [30] introduced a conflict set graph to characterize the interference and define interference degree to measure a link’s interference. Jun Luo et al. [31] employed a practical interference model based on SINR, which is used to make the link transmission coordinate without conflict. In [31], a graph network model, and the SINR calculation algorithm for spatial reuse time division, multiple access link scheduling is proposed. Unlike the previous time-scheduling concept, we split the feasible location partitions into mobile nodes by using cooperative behavior to maximize throughput performance.

In summary, few research papers have jointly considered the issue of interference in ad hoc networks in multi-user cooperative mobility. Further, a suitable algorithm has not yet been proposed and adopted for a multi-user cooperative mobility system, i.e., to maximize throughput while ensuring low complexity and low communication overhead.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we demonstrate a detailed system modeling of multiple user cooperative mobility. Besides, we formulate the maximizing system throughput as a mixed-integer with a non-linear and non-convex problem.

A. SYSTEM MODEL

We model an ad hoc network as a set $H$ of nodes $h_i$, which consists of a set $F$ of fixed nodes $f_i$, a set $M$ of movable nodes $m_i$, with $H = F \cup M$. The number of fixed and movable nodes are $|F|$ and $|M|$, respectively. Each node $h_i \in H$ is associated with a geographical location, whereas each movable node $m_i \in M$ could move within a limited two-dimensional circle $C$, radius $R_c$. The multiple user cooperative mobility system is shown in Fig. 2, where transceivers pairs form communication links by Device-to-Device technique.

We hypothesize the following:

1) Each node is equipped with a single-antenna and cannot send and receive packets simultaneously.
2) All nodes have the same transmission power due to the same antenna performance and a slight convergence radius change, both of which generate data traffic, and all of the links are saturated.
3) The topology of the data flow remains a multi-hop chain. It does not change to star or tree type with node mobility because stable relationships between nodes, such as friends and collaborators, ensure that the transmission path remains unchanged.

The application scenario of the cooperative mobility communication system, which is depicted in Fig. 2. Initially, these fixed and movable nodes are randomly located in a limited circular space. Several nodes are far away from AP, and they ask other movable helpers or partners to become intermediaries and relay the data traffic. We assume that a virtual central controller distributed in the AP, such as Google Maps Navigation, which can run the proposed algorithm and arrange each movable node’s location. The AP sends control messages through the control channel at the physical layer to arrange each movable node’s geographic location. The frame header of data traffic contains the control information, so two-hop or multi-hop nodes can also receive it. This method of sending a control message is similar to "beacon."

During the transmission period, these collaborators transmit by the User Datagram Protocol (UDP) service. To facilitate analysis system throughput, we calculate the uplink data generated from all users to the AP while all links are saturated. Based on this consideration, system throughput is defined as the amount of data per unit time received by the AP, i.e., the average harmonic of all users’ transmission rates [32].

This work aims to assign each movable node a suitable location within the limited circle space while assuring the system throughput performance as better as possible. Specifically, the best strategy for maximizing system throughput is to attain the best position for them deliberating mutual interference. The best geographical positions maintain the maximum throughput keeping desirable SINE. However, it is a combinatorial optimization problem of exorbitant complexity considering mobility user locations’ diversity and inter-user interference. Solving this optimization problem will result in a tradeoff between the accuracy of the best throughput performance and the allowed computation cost [26]. We deduce and propose an effective algorithm.
by analyzing the relationship between SINR, the location of movable nodes, and system throughput. The virtual control center executes the algorithm to efficiently allocate the best location to the movable nodes, which improves the overall throughput of the system. Before the problem formulation, we present the location model’s definition and the location distribution function of fixed nodes.

We deploy polar coordinates to define the positions and the distance between two nodes. Let the position coordinate of node $h_i \in H$ be expressed as $h_i (\rho_i, \Theta_i)$, where $\rho_i$ is the polar diameter, $\rho_i \leq R_c$, and $\Theta_i$ is called as the polar angel. Then, we define the set of nodes $H$ as $H (\rho, \Theta) = \{h_i (\rho_i, \Theta_i) | h_i \in H, \rho_i \in \rho, \Theta_i \in \Theta, |\rho| \leq R_c, 0 \leq |\Theta| \leq \pi\}$ where $\rho$ and $\Theta$ denote the set of polar position and angle, respectively. Correspondingly, for fixed and movable nodes $f_i \in F$, $m_i \in M$, the position sets can be expressed as $F (\rho_f, \Theta_f) = \{f_i (\rho_f, \Theta_f) | f_i \in F, f_i \in \rho_f, f_i \in \Theta_f\}$, $M (\rho_m, \Theta_m) = \{m_i (\rho_m, \Theta_m) | m_i \in M, \rho_m \in \rho_m, \Theta_m \in \Theta_m\}$. The polar coordinate unit is defined as $1$. As for arbitrary two nodes $h_1 (\rho_1, \Theta_1)$ and $h_2 (\rho_2, \Theta_2)$, the distance $d_{h_1, h_2}$ can be given by

$$d_{h_1, h_2} = ||h_1 (\rho_1, \Theta_1) - h_2 (\rho_2, \Theta_2)|| = \sqrt{\rho_1^2 + \rho_2^2 - 2\rho_1 \rho_2 \cos(\Theta_1 - \Theta_2)}$$

(1)

Here, we define that all of the nodes should not locate at the same line, i.e., $\Theta \neq 0$. This is because that the best position for movable users is at the bisection position if $\Theta = 0$, which makes no sense to calculate. In order to better fit the practice and simulate fixed nodes, we utilize the Poisson point process (PPP) [33] to present the property of positions. In the limited circle $C : r (\Theta) = R_c$, the positions of these fixed nodes $f_1 (\rho_1, \Theta_1), f_2 (\rho_2, \Theta_2), \ldots, f_F (\rho_F, \Theta_F)$ are independent of each other.

**Definition 1:** Fixed nodes set $F$ is located at the region spaces set $X, f_i \rightarrow \chi_i, f_i \in F, \chi_i \subseteq \chi$, which is a space homogeneous Poisson point process, the following two conditions are satisfied.

1. For a random region $\chi_i$ lies in the space of the restricted circle $C : r (\Theta) = R_c, \chi_i \subseteq \chi \subseteq C$, $X = \delta (\chi_i)$ obeys Poisson distribution with mean value of $\lambda \nu_r (\chi_i)$, which can be expressed as

$$P [\delta (\chi_i) = k] = [\lambda \nu_r (\chi_i)]^k \exp \left[\frac{(-\lambda \nu_r (\chi_i))}{m!}\right]$$

(2)

where $\delta (\chi_i)$ is the number of points in the bounded region $\chi_i$, $\lambda$ is a constant, which is denoted as the average number of points per unit area, and $\nu_r (\chi_i)$ is the area of the bounded region $\chi_i$.

2. Random bounded region $\chi_1, \chi_2, \ldots, \chi_F$ do not intersect each other, then $\delta (\chi_1), \delta (\chi_2), \ldots, \delta (\chi_F)$ are independent of each other.

Accordingly, the fixed nodes in space are completely random, and the expectation of the number of points $\delta (\chi_i)$ per unit area is constant $\lambda$, which is unchanged with the area and position of the limited circle space $C$. In that case, random variable of the distance between any two fixed nodes, $d_{f_i, f_j}$, is independent and identically distributed, which can be subject to exponential distribution with $\lambda$. The probability that no fixed nodes exists in the bounded region $\chi_i$ is $P [\delta (\chi_i) = 0] = e^{-\lambda \nu_r (\chi_i)}$. Then, the cumulative distribution function $F (d_{f_i, f_j})$ can be derived as

$$F (d_{f_i, f_j}) = 1 - e^{-\lambda \nu_r (\chi_i)}$$

(3)

where $F (d_{f_i, f_j} \leq r)$ denotes the probability that the distance between fixed node $f_i$ and $f_j$ is less than $r$. Therefore, the expectation of $d_{f_i, f_j}, E [d_{f_i, f_j}]$, we have

$$E [d_{f_i, f_j}] = \int_0^{R_c} 2\pi r^2 \exp (-\lambda \pi r^2) dr$$

$$= \frac{2e^{-\lambda \pi R_c^2}}{\sqrt{\lambda}}$$

(4)

In this model, We analyze the inter-signal interference between users at the physical layer, rather than analyzing the specific frame slot scheduling and multiple packet processing conflicts at the link-layer MAC frame’s perspective. There are packet frame conflicts in the actual transmission. Still, we assume that the data stream is saturated, i.e., the performance degradation due to data frame conflicts on each link has less impact on our results.

**B. PROBLEM FORMULATION**

![FIGURE 3. Mathematical model. (a) Transmission of data flow between nodes; (b) Fixed and movable nodes transfer via Decode-and-Forward.](image)

As shown in Fig. 3(a), fixed location users satisfy the Poisson space point process and are distributed around the AP. Considering that the practical application is in a large square or park, we set the propagation model as the non-line-of-sight (NLOS), and the obstacles might distort the radio waves. In addition, multi-path signals are superimposed,


TABLE 1. Notation used for problem formulations.

| Parameters | Description |
|------------|-------------|
| $F$        | Set of fixed nodes |
| $M$        | Set of movable nodes |
| $|F|$       | Number of fixed nodes |
| $|M|$       | Number of movable nodes |
| $R_c$      | Radius of circle space |
| $P_{tx}$   | Transmission power |
| $F(\rho_f, \Theta_f)$ | Set of fixed nodes positions |
| $f_i(\rho_f, \Theta_f)$ | Fixed node $f_i$ position |
| $\varphi(I_{f_i, f})$ | Distance function between fixed nodes |
| $d_0$      | Reference distance |
| $K$        | Constant, which is related to the antenna gain and average channel attenuation |
| $\alpha$   | Path loss exponent |
| $\beta$    | SINR threshold |
| $M(\rho_m, \Theta_m)$ | Set of movable nodes positions |
| $\Phi_1[f_i(\rho_f, \Theta_f), m_i(\rho_m, \Theta_m)]$ | Distance function between fixed node $f_i$ and movable node $m_i$ |
| $\Phi_2[f_{i+1}(\rho_{i+1}, \Theta_{i+1}), m_i(\rho_m, \Theta_m)]$ | Distance function between fixed node $f_{i+1}$ and movable node $m_i$ |
| $\Phi_3[m_i(\rho_m, \Theta_m), m_j(\rho_j, \Theta_j)]$ | Distance function between movable nodes $m_i$ and $m_j$ |
| $\Gamma_1[\Phi_1(x), \Phi_2(x)]$ | Angle function between fixed node $f_i$ and movable node $m_i$ |
| $\Gamma_2[\Phi_1(x), \Phi_2(x)]$ | Angle function between fixed node $f_{i+1}$ and movable node $m_i$ |
| $\gamma_{f_i, f_{i+1}}$ | SINR of link $f_i \rightarrow f_{i+1}$ for receiver $f_{i+1}$ |
| $\gamma_{m_i, f_{i+1}}$ | SINR of link $m_i \rightarrow f_{i+1}$ for receiver $f_{i+1}$ |
| $\gamma_{f_i, m_i}$ | SINR of link $f_i \rightarrow m_i$ for receiver $m_i$ |
| $P_{DF,i}$ | Maximum combining transmission rate of link $f_i \rightarrow f_{i+1}$ and $f_i \rightarrow m_i \rightarrow f_{i+1}$ |
| $\varepsilon_1[m_i(\rho_m, \Theta_m)]$ | SINR function of link $f_i \rightarrow f_{i+1}$ |
| $\varepsilon_2[m_i(\rho_m, \Theta_m)]$ | Combining SINR function of link $f_i \rightarrow m_i \rightarrow f_{i+1}$ |

and the strength of the attenuation coefficient approximately obeys the Rayleigh distribution.

Under Decode-and-Forward (DF) [35], the cooperative relay node $m_i$ decodes the received signal from node $f_i$, and reencodes it before forwarding it to the destination node $f_{i+1}$, which could maximize the utilization of spatial diversity. Thus, we make use of the DF with diversity combining [36] between nodes transmission to expound the system throughput and extrapolate the best position, which is presented in Fig. 3(b). Assume fixed node $f_i$ sends data packets to $f_{i+1}$ relaying by movable node $m_i$, the received power $P_{m_i}$ of movable node $m_i$ can be given by

$$P_{m_i} = P_{tx}K\left(\frac{l_{f_i, m_i}}{d_0}\right)^{-\alpha}$$

(5)

where $P_{tx}$ is the transmission power of fixed node $f_i$, $l_{f_i, m_i}$ is the distance between node $f_i$ and $m_i$, $d_0$ is the reference distance, $K$ is a constant related to the antenna gain and average channel attenuation, and $\alpha$ is the path-loss exponent. The constant $K$ can be calculated by the empirical average of the received power at the distance $d_0$. The reference distance $d_0$ varies from 10 to 100 meters at outdoor space, here, we set it as 20 [34]. The value of path loss exponent $\alpha$, which depends on the propagation, usually ranges from 2 and 4.

Consider the outdoor or urban shadowed space, $\alpha = 4$ [37]. Then, (5) can be simplified as $P_{m_i} = P_{tx}K\left(\frac{l_{f_i, m_i}}{d_0}\right)^{-4}$.

To jointly consider the path loss and shadowing effects, the relationship between $P_{m_i}$ and $P_{tx}$ is measured in dB, which can be presented as follows [38],

$$\left(\frac{P_{m_i}}{P_{tx}}\right)_{\text{dB}} = 10\log_{10} K - 40\alpha \log_{10} \left(\frac{d}{20}\right) + \Delta$$

(6)

where $\Delta$ is a Gaussian random variable with zero mean and standard deviation $\sigma$. At the urban microcells, the value of $\sigma$ is from 4 to 12. This implies that the constant $K$ can be calculated by (6).

In the DF relay transmission, fixed node $f_{i+1}$ not only receive the signal from node $f_i$ but also combine with the signal sent by relay node $m_i$, i.e., it makes $f_{i+1}$ receive two copies of the signal due to the diversity combining. Let the receive power node for $f_{i+1}$ from $m_i$ and $f_i$, denote as $P_{f_{i+1}, m_i}$ and $P_{f_{i+1}, f_i}$, respectively. Similarly, we can obtain $P_{f_{i+1}, m_i} = P_{tx}K\left(\frac{l_{f_i, m_i}}{d_0}\right)^{-4}$ and $P_{f_{i+1}, f_i} = P_{tx}K\left(\frac{l_{f_i, f_{i+1}}}{d_0}\right)^{-4}$, where $l_{f_i, m_i}$ and $L_{f_i, f_{i+1}}$ denote the distance between node $f_{i+1}$ and nodes $m_i$, $f_i$, respectively. $L_{f_i, f_{i+1}}$ can be considered as a known quantity due to fixed nodes location information, $L_{f_i, f_{i+1}} = ||f_i(\rho_f, \Theta_f) - f_i(\rho_{i+1}, \Theta_{i+1})|| \equiv \varphi(I_{f_i, f_{i+1}})$, where $\varphi(x)$ is the distance function of between
\[ \text{SINR}_{f_{i+1}} = \gamma_{f_i,f_{i+1}} + \gamma_{m_i,f_{i+1}} \]

\[ \gamma_{f_i,f_{i+1}} = \frac{1}{N_0 + \frac{\Phi_2(f_{i+1}, m_i)}{20}} \left( \frac{\psi(f_{i+1}, f_{i+1})}{20} \right)^4 + \frac{1}{N_0 + \frac{\Phi_2(f_{i+1}, m_j)}{20}} \left( \frac{\psi(f_{i+1}, f_{i+1})}{20} \right)^4 + \sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_{i+1}, m_j)}{\Phi_2(f_{i+1}, m_j)} \right)^4 \]

\[ \gamma_{m_i,f_{i+1}} = \frac{1}{N_0 + \frac{\Phi_2(f_{i+1}, m_i)}{20}} \left( \frac{\psi(f_{i+1}, f_{i+1})}{20} \right)^4 + \sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_{i+1}, m_j)}{\Phi_2(f_{i+1}, m_j)} \right)^4 \]

\[ \text{SINR}_{m_i} = \gamma_{f_i,m_i} = \frac{1}{N_0 + \frac{\Phi_1(f_i, m_i)}{20}} \left( \frac{\psi(f_i, f_i)}{20} \right)^4 + \sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, m_j)}{\Phi_1(f_i, m_j)} \right)^4 \]

\[ C_{DF,i} = R_{DF,i} \leq \frac{1}{2} \min \{ \log_2 (1 + \text{SINR}_{m_i}), \log_2 (1 + \gamma_{f_i,f_{i+1}} + \gamma_{m_i,f_{i+1}}) \} \]

\[ (R_{DF,i})_{\text{max}} = \frac{1}{2} \min \{ \varepsilon_1 [m_i (\rho_i, \Theta_i)], \varepsilon_2 [m_i (\rho_i, \Theta_i)] \} \]

\[ \varepsilon_1 [m_i (\rho_i, \Theta_i)] \triangleq \log_2 \left( 1 + \frac{N_0 + \frac{\Phi_1(f_i, m_i)}{20}}{\sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, m_j)}{\Phi_1(f_i, m_j)} \right)^4 + \sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, m_j)}{\Phi_1(f_i, m_j)} \right)^4} \right) \]

\[ \varepsilon_2 [m_i (\rho_i, \Theta_i)] \triangleq \log_2 \left( 1 + \frac{N_0 + \frac{\Phi_2(f_i, f_{i+1})}{20}}{\sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, f_{i+1})}{\Phi_2(f_i, f_{i+1})} \right)^4 + \sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, f_{i+1})}{\Phi_2(f_i, f_{i+1})} \right)^4} \right) \]

The distance \( l_{f_i,m_i} \) and \( l_{f_{i+1},m_i} \) are derived as follows,

\[ l_{f_i,m_i} = \| f_i (\rho_i, \Theta_i) - m_i (\rho_i, \Theta_i) \| \]

\[ \phi_1(f_i, \rho_i, \Theta_i) = \phi_1(f_{i+1}, \rho_i, \Theta_i) \]

\[ \phi_2(f_i, f_{i+1}, \rho_i, \Theta_i) = \phi_2(f_{i+1}, f_{i+1}, \rho_i, \Theta_i) \]

\[ \theta_1(f_i, f_{i+1}, \rho_i, \Theta_i) = \theta_1(f_{i+1}, f_{i+1}, \rho_i, \Theta_i) \]

\[ \theta_2(f_i, f_{i+1}, \rho_i, \Theta_i) = \theta_2(f_{i+1}, f_{i+1}, \rho_i, \Theta_i) \]

\[ \text{SINR}_{m_i} = \gamma_{f_i,m_i} \]

\[ C_{DF,i} = R_{DF,i} \leq \frac{1}{2} \min \{ \log_2 (1 + \text{SINR}_{m_i}), \log_2 (1 + \gamma_{f_i,f_{i+1}} + \gamma_{m_i,f_{i+1}}) \} \]

\[ (R_{DF,i})_{\text{max}} = \frac{1}{2} \min \{ \varepsilon_1 [m_i (\rho_i, \Theta_i)], \varepsilon_2 [m_i (\rho_i, \Theta_i)] \} \]

\[ \varepsilon_1 [m_i (\rho_i, \Theta_i)] \triangleq \log_2 \left( 1 + \frac{N_0 + \frac{\Phi_1(f_i, m_i)}{20}}{\sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, m_j)}{\Phi_1(f_i, m_j)} \right)^4 + \sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, m_j)}{\Phi_1(f_i, m_j)} \right)^4} \right) \]

\[ \varepsilon_2 [m_i (\rho_i, \Theta_i)] \triangleq \log_2 \left( 1 + \frac{N_0 + \frac{\Phi_2(f_i, f_{i+1})}{20}}{\sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, f_{i+1})}{\Phi_2(f_i, f_{i+1})} \right)^4 + \sum_{k=1}^{M} \sum_{j=1}^{M} \left( \frac{\psi(f_i, f_{i+1})}{\Phi_2(f_i, f_{i+1})} \right)^4} \right) \]
of for link \( f_i \to f_{i+1} \), \( W \) is physical channel bandwidth, which can be normalized as 1. Substituting (7), (8), (9) and (10) into (11), the transmission rate \( R_{DF,i} \) can be rewritten as (12).

We can find that the transmission rate \( R_{DF,i} \) is a function of the node \( m_i \)'s position variable \( m_i (\rho_i, \Theta_i) \), \( m_i (\rho_i, \Theta_i) \in M (\rho_m, \Theta_m) \). For all links in this ad hoc network, the system throughput \( T_{h.sys} \) is defined as the reciprocal of the sum of harmonic means of each node [32].

\[
T_{h.sys} = \frac{1}{2} \frac{|M|}{\sum_{i=1}^{M} \frac{1}{R_{DF,i}}} \tag{13}
\]

Then, the maximizing system throughput \( T_{h.sys} \) problem can be converted to minimize \( \sum_{i=1}^{M} \frac{1}{R_{DF,i}} \). The global objective is to find the optimal movable nodes position to maximize network throughput. Summarizing from (7) to (12) into (13), the throughput optimization problem is as follows,

\[
\min_{M (\rho_m, \Theta_m)} \quad \sum_{m \in M} \left\{ \frac{1}{|M|} \arg \min_{\varepsilon \in [1,2]} \right\}
\]

\[
s.t. \quad 0 < |\rho_m| \leq R_c \quad 0 \leq |\Theta_m| \leq \pi \\
\gamma_{f_i, f_{i+1}} \geq \beta \\
\gamma_{f_i, m_i} \geq \beta \\
\gamma_{m_i, f_{i+1}} \geq \beta \\
E [\varphi (l_{f_i, f_{i+1}})] = E [l_{f_i, f_j}]
\tag{14}
\]

where \( E [\varphi (l_{f_i, f_{i+1}})] \) is a constant, and \( \varphi (l_{f_i, f_{i+1}}) \) can be calculated by known location information \( f_i \). Note that \( M (\rho_m, \Theta_m) \) is the optimization variable to determine the mobility-optimal scheduling. In particular, the objective function is mixed-integer with non-linear and non-convex constraints variable functions \( \Phi_1 (f_i, m_i) \), \( \Phi_2 (f_{i+1}, m_i) \) and \( \Phi_3 (m_i, m_{i+1}) \). This causes this problem to be a Mixed-Integer with Non-Linear and Non-Convex Problem (MINLCP), which is NP-hard generally. This problem can be solved by using exhaustive search, but has intractable and prohibitive complexity \( O \left( C_r R_{c_i}^2 \right) \), where \( |R_{c_i}^2| \) denotes the number of selection position profiles (number of nodes per unit area is 1). Conventional heuristic methods are alternative approaches, like simulated annealing, game theory method, etc. However, they cannot guarantee that the optimal solutions can be obtained. High computation complexity and low accuracy of solutions are also significant constraints to these heuristic algorithms’ practical application.

In the following sections, we introduce the concept of domain and then illuminate the search region of movable nodes, including upper and lower bounds. The original exhaustive problem is decomposed into two-step problem, namely deducing the domain of upper and lower bound by conflict graph method and location allocation for movable nodes considering interference. Moreover, we design the Maximum Throughput algorithm for Optimal Position (MTOP) based on the derived domain. Finally, we compare MTOP with conventional heuristic methods and obtain analytical results.

IV. LOCATION DOMAIN OF MOVABLE NODES

This section presents the domain concept, which is a certain search region for movable nodes considering the interference. And then, we prove the upper and lower bounds invoked by the conflict graph. In addition, we provide algorithms for obtaining these two bound values.

A. CONCEPT OF DOMAIN

Notice that general heuristic algorithms cannot obtain the resolution of MINLCP. Our idea is to explore a small enough domain and contain the optimal position assemblies to reduce redundant computation and improve search accuracy. Please refer to Table 2 for a summary of additional notation pertaining to the Definitions and Propositions to follow.

| Parameters | Description |
|------------|-------------|
| \( G \) | Domain, which represents the range of \( M^* (\rho_m, \Theta_m) \) |
| \( G_{Upper} \) | Upper bound of the domain |
| \( G_{Lower} \) | Lower bound of the domain |
| \( D_I \) | Determination of upper bound range |
| \( D_L \) | Determination of lower bound range |
| \( \Omega \) | All profiles of movable nodes locations |
| \( G_p (V, E) \) | Communication graph |
| \( G (V, \bar{E}) \) | Conflict graph |
| \( U \) | Set of satisfying the upper bound |
| \( I \) | Set of satisfying the lower bound |

Conforming to (14), the optimization problem is related to the variable \( M (\rho_m, \Theta_m) \), which can be expressed in terms of distance functions \( l_{f_i, m_i} \) and \( l_{f_{i+1}, m_i} \). We define a domain \( G \) as the desirable range of \( M^* (\rho_m, \Theta_m) \) which is the optimal locations, given by (15).

\[ \Omega_1 \text{ and } \Omega_2 \text{ denote circular regions with fixed nodes } f_i \text{ and } f_{i+1} \text{ as centers, respectively. } \Omega_0 \text{ is the intersection of regions both } \Omega_1 \text{ and } \Omega_2, \text{ i.e., the moveable range for } m_i \text{ on each link } f_i \to f_{i+1}. \text{ If the range of } G \text{ can be determined, then it is easier to attain the approximate optimal solution of (16) by using iterative approaches. However, } G \text{ cannot be directly resolved because of interfering interactions and the randomness of mobility. Hence, we further define upper and lower bounds to obtain an interval to estimate the fetch space of } G, \text{ defined as follows.}

Definition 2: In a limited two-dimensional circle \( C \) with radius \( R_c \), arbitrary fixed nodes \( f_i \) and \( f_{i+1} \) transfer data packets by DF with diversity combining, then the set of all movable nodes \( m_i \in M \) exist boundaries in the domain space, called as upper bound and lower bound.
information of fixed nodes. In the propositions, we derive and prove the key properties of \( D_U \) and \( D_L \) find the algorithm’s borders.

### B. LOWER BOUND

To characterize the interference at different positions for movable nodes and simultaneous conflict-free operation of links, we define a conflict set of locations graph (CSLG) model. Note that a conflicting concept for the edge-based physical interference model is first introduced in [28].

The conflict graph is more effective than the traditional model. Note that a conflicting concept for the edge-based physical interference model is first introduced in [28]. The author focused on the weighted degree of the directed graph to indicate the interference and noise intensity. However, this model is only from the perspective of the linear programming approach, i.e., two adjacent edges cannot share the same endpoint.

Further, [39] proposed the conflict set graph concept to characterize and measure the interference degree. The fundamental difference between our CSLG and the conflict graph of [39] is that our CSLG model schedules the locations to the movable nodes, while [39] concentrated on allocating the number of slot times to each link. Compared with [28], [39], CSLG considers the conflict condition based on SINR according to different locations. Hence, in order to incorporate interference and obtain the bound range, we define the conflict graph as follows:

**Definition 3** (Conflict set of locations graph (CSLG)): Within the limited circle space \( \Omega \), we define the accessible profiles of locations for movable nodes \( M(\rho, \theta) \) as \( \Omega = \{\tau_1, \tau_2, \tau_3, ..., \tau_{|\Omega|}\} \), then \( m_l (\tau_l) \) denotes the position assigned to node \( m_l \) is at location \( \tau_l \). Movable nodes by assigning locations with fixed nodes together form a communication graph as \( G_p = (V, E) \), where \( V \) is the set of movable nodes, \( m_l (\tau_l) \in V \), and edge \( E \) denote the existence of a communication link between two vertices.

- **A conflict set of positions graph (CSLG)** \( \mathcal{G}(V, E) \), where the set of vertices \( V \) denotes the links in the communication graph \( G_p \), and the edge \( E \) means that if two vertices conflict with each other, then they can be connected by an edge. Concerning the edge \( E \), the conflict property is present.

- **Conflict:** Let \( \xi \subset V \) denote a set of vertices, given a vertex \( l \) such that \( l \not\in \xi, \xi \) is a conflict set of vertex \( l \) if and only if \( \mathcal{C}_l = \{ \xi | \text{SINR}_l (\xi \cup \{l\}) < \beta, \text{SINR}_l (\xi) \geq \beta \} \), where \( \mathcal{C}_l \) is the collection of conflict sets at one of location assembles \( \Omega \).

Revisiting MINLNC/F’s limitation in (16), we can assert...
that the ideal situation for movable nodes is that there exists no location conflict that makes each node’s SINR less than the threshold. In other words, it could make
\[
P_r \{\gamma_{f_i,m_i} \geq \beta\} \equiv 1,
\]
\[
P_r \{\gamma_{f_i,m_i} \geq \beta\} \equiv M(p_m, \theta_m) \rightarrow M^*(p_m, \theta_m)
\]
and
\[
P_r \{\gamma_{f_i,m_i} \geq \beta\} \equiv 1 \text{ valid in this case.}
\]
Therefore, the concept is transferred to the conflict graph corresponding to the proposition that there are no occurring edges for each vertex in CSLG. The domain of lower bound can be defined as follows.

**Proposition 1:** An allocation composed of assemblies of locations is feasible for the lower bound if and only if the following condition is satisfied:

- There’s no link between arbitrary two vertices for the set of positions assigned to movable nodes, i.e., no edges exist in \(G(V,E)\). For \(\forall v_1 \subset V, \forall v_2 \subset V,\)
\[
\mathcal{I} = \{v_1,v_2 | \text{SINR}(v_1,v_2) \geq \beta, v_1 \leftrightarrow v_2\}
\]

**Proof 1:** The lower bound can search all of the feasible locations for movable nodes satisfying the SINR larger than threshold \(\beta\). Mapping to the CSLG means that the in-degree and out-degree of vertices in the CSLG are both zero. Then, there’s no link, and edges exist in \(G(V,E)\).

**Proposition 2:** The range for \(D_L\) satisfies the following inequality,
\[
(D_L)_{\text{max}} = \frac{\varphi(l_{f_i,f_{i+1}}) \beta^\frac{1}{2}}{|M|(|M| - 1) - \beta^\frac{1}{2}}
\]

**Proof 2:** For the node \(m_i\), the interference-to-signal ratio (ISR) can be expressed as (20). In order to ensure that transmit without conflict, ISR \(\geq \frac{1}{2}\), then we have
\[
\sum_{j=1,j \neq i}^{\lfloor M \rfloor - 1} \Phi_3(m_i,m_j) < \varphi(l_{f_i,m_i}) - \sum_{k=1}^{\lfloor F \rfloor - 1} \Phi_2(f_k,m_i)
\]

**Remark 1:** The lower bound comes from the necessary condition: even though there exist interferences among nodes in the communication graph, the optimal location in the lower bound can guarantee SINR for each node larger than the threshold, i.e., no edges in CSLG. For allocation locations to movable nodes, the domain can be repeated search from 0 to \((D_L)_{\text{max}}\) until any two vertices have no edges in CSLG.

The lower bound calculation can be executed iteratively as Algorithm 1.

**Algorithm 1 Lower bound calculation**

1. **input:** Communication graph \(G_p = (V,E)\), Geographical information of fixed nodes \(\mathcal{F}(l_{f_i,f_{i+1}}), (D_L)_{\text{max}}\).
2. **output:** \(G_{\text{Lower}}\).
3. for \(D_L = 0 \rightarrow (D_L)_{\text{max}}\) do
4. \(G \leftarrow G_p\) generates the domain of movable nodes locations.
5. \(\mathcal{I} \leftarrow G_p\) integrates each link as a dot.
6. for arbitrary two vertices in \(\mathcal{I}, v_1 \subset V, v_2 \subset V\) do
7. if \(\mathcal{I} = \emptyset\) then \(G_{\text{Lower}} \leftarrow G\)
8. else \(D_L = D_L + \Delta D_L, \Delta D_L = \frac{(D_L)_{\text{max}}}{|M|}\) end if
9. end for
10. end for
11. return \(G_{\text{Lower}}\)

**C. UPPER BOUND**

Under extreme scenarios, we sometimes cannot discover the optimal location in the lower bound due to the limitations of moving conditions or noise influence; that is, an outage can occur. Then, we characterize this status that there exist location conflicts that make SINR of someone less than the threshold, i.e., the edges can be allowed in CSLG. It implies that the prerequisite of finding the optimal location for maximum throughput is to ensure two aspects. On the one hand, it is necessary to ensure the normal transmission of each DF link. On the other hand, we also need to minimize

\[
\text{ISR} = \sum_{k=1}^{\lfloor F \rfloor - 1} P_{tx} K \left(\frac{l_{f_i,f_{i+1}}}{20}\right)^{-4} + \sum_{j=1,j \neq i}^{\lfloor M \rfloor - 1} P_{tx} K \left(\frac{\Phi_3(m_i,m_j)}{20}\right)^{-4}
\]

\[
\leq \left[\sum_{k=1}^{\lfloor F \rfloor - 1} \Phi_2(f_k,m_i) + \sum_{j=1,j \neq i}^{\lfloor M \rfloor - 1} \Phi_3(m_i,m_j)\right]^{-4}
\]
(DU)min ≤ DU ≤ (DU)max

(DU)max = \frac{\sqrt{2}}{\sqrt{2|\Omega| + 1} - 1} \cdot \tau_c

(DU)min = \arg \max \left\{ 20 \left[ \frac{P_{tx} \cdot K}{N_0} \left( \frac{1}{\beta} - 20 \right) \right]^{-\frac{1}{2}}, \rho 1 \right\}

Proposition 3: An allocation composed of assembles of \( \Omega = \{ \tau_1, \tau_2, \tau_3, \ldots, \tau_\pi \} \) is feasible for the upper bound if and only if the following condition is satisfied:

- For the set of positions assigned to movable nodes, the upstream and downstream links that contain the public nodes cannot influence each other in the communication graph \( G_p \). Assume the three connection nodes in the DF link, \( \forall v_1 \subset V, \forall v_2 \subset V, \forall v_3 \subset V \) in \( G_p = (V, E) \), the vertices can be denoted as \( v_1v_2 \in V, v_1v_3 \in V, \) and \( v_2v_3 \in V \) in \( G \) respectively. Then, there's no vertices \( v_i \subset V \) that make \( v_1v_i, v_2v_i \) and \( v_3v_i \) such that

\[
U = \{ v_1v_i, v_2v_i, v_3v_i \mid U \neq \emptyset \}
\]

\[
U = \{ u1 < \beta \} \land \{ u2 < \beta \} \land \{ u3 < \beta \}
\]

\[
u1 = \text{SINR} (v_1v_2, v_1v_i)
\]

\[
u2 = \text{SINR} (v_2v_3, v_2v_i)
\]

\[
u3 = \text{SINR} (v_1v_3, v_3v_i)
\]

Proof 3: According to the DF protocol, the premise for smooth transmission is that the DF upstream and downstream communications do not conflict with each other; that is, they can be transmitted simultaneously. Because if they are conflicting, it will produce data congestion, resulting in a sharp decrease in throughput. Hence, note that the upper bound means that there exist edges in CSLG \( G \), but should ensure that DF transmits smoothly. Indeed, the principle of obtaining an optimal location in the upper bound is that the less conflict, the better. The reason is that the more conflicting edges, the stronger the interference. Hence, we should minimize the number of vertices that are not included in the adjacent DF links.

Proposition 4: The range for \( D_U \) satisfies inequality (26).

Proof 4: Consider the fixed and movable nodes connect to form a large lattice, which is located in the limited circle. Let each side of lattice has \( n \) nodes, \( (n + 1)^2 \geq 2 |\Omega| + 1 \), which means the lattice contains all the nodes sets. The maximal side length of this lattice is \( \sqrt{2}R_c \), then \( nD_U \leq \sqrt{2}R_c \). We can derive that

\[
\frac{\sqrt{2}R_c}{n} \leq R_c \frac{\sqrt{2}}{\sqrt{2|\Omega| + 1} - 1}.
\]

It should guarantee that the SINR for DF transmission both \( \gamma_{f_i, f_{i+1}} \) and \( \gamma_{m_i, f_{i+1}} \) are larger than the threshold, then we can obtain

\[
\frac{N_0}{P_{tx} K} \left( \frac{\varphi (f_{i+1}, m_i)}{20} \right)^4 + \sum_{k=-1, k \neq i}^{i+1} \left( \frac{\varphi (f_{i+1}, m_i)}{\varphi (f_{k+1}, f_{i+1})} \right)^4 + \sum_{j=-1, j \neq i}^{i+1} \left( \frac{\varphi (f_{i+1}, m_i)}{\varphi (f_{j+1}, f_{i+1})} \right)^4 \leq 1 \beta
\]

Since \( \Phi (f_{i+1}, m_i) \leq \arg \max \{ \Phi (f_{i+1}, m_k) \} \), we simplify (27) and (28) to derive (29).

Consider \( \gamma_{f_i, m_i} \) also satisfies the above rule, it can be derived as follows,

\[
\frac{N_0}{P_{tx} K} \left( \frac{\varphi (f_{i+1}, m_i)}{20} \right)^4 + \sum_{k=-1, k \neq i}^{i+1} \left( \frac{\varphi (f_{i+1}, m_i)}{\varphi (f_{k+1}, m_i)} \right)^4 + \sum_{j=-1, j \neq i}^{i+1} \left( \frac{\varphi (f_{i+1}, m_i)}{\varphi (f_{j+1}, m_i)} \right)^4 \leq 1 \beta
\]

\[
(29)
\]

\[
\rho 1 \triangleq \varphi (f_{i+1}, m_k) \left\{ \frac{1}{2} \left[ \frac{1}{\beta} - \left( \frac{N_0}{P_{tx} K} \left( \frac{\varphi (f_{i+1}, m_k)}{20} \right)^4 + \left( \frac{\varphi (f_{i+1}, m_k)}{\varphi (f_{i+1}, m_k)} \right)^4 + \left( \frac{\varphi (f_{i+1}, m_k)}{\varphi (f_{i+1}, m_k)} \right)^4 \right) \right] \right\}^{-\frac{1}{2}}
\]

\[
\rho 2 \triangleq \left( \frac{1}{\beta} - 2 \right) \left[ \frac{N_0}{P_{tx} K} \left( \frac{1}{20} \right)^4 + \frac{2}{\varphi (f_{i+1}, m_k)^4} \right]^{-\frac{1}{2}}
\]

VOLUME 14, 2020

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/
then we obtain
\[
20 \left[ \frac{P_{tx} K}{N_0} \left( \frac{1}{\beta} - 20 \right) \right]^{-\frac{1}{2}} \leq \arg \max \left\{ \Phi_1 (f_i, m_i), \Phi_3 (m_i, m_j) \right\} \tag{31}
\]
Due to \( D_U \geq \arg \max \{ \Phi_2 (f_{i+1}, m_j) \} \) and \( D_U \geq \arg \max \{ \Phi_1 (f_i, m_i), \Phi_3 (m_i, m_j) \} \), hence, \( D_U \) can be derived as
\[
D_U \geq \arg \max \left\{ 20 \left[ \frac{P_{tx} K}{N_0} \left( \frac{1}{\beta} - 20 \right) \right]^{-\frac{1}{2}}, 0 \right\} \tag{32}
\]

Remark 2: As for the upper bound, it must be ensured that adjacent DF links cannot exist conflict, i.e., there are no edges between each adjacent DF vertices in CSLG. In addition, we update \( \mathcal{G} \) by minimizing the number of conflict vertices that are not comprised in the neighboring DF links. As illustrated in Algorithm 2, the upper bound calculation can be executed iteratively.

**Algorithm 2 Upper bound calculation**

1. **input**: Communication graph \( G_p = (V, E) \), Geographical information of fixed nodes \( \varphi (f_i, f_{i+1}) \), \( (D_U)_\min \) and \( (D_U)_\max \).
2. **output**: \( \mathcal{G}_{Upper} \).
3. **for** \( D_U = (D_U)_\min \) to \( (D_U)_\max \) **do**
4. \( \mathcal{G} \leftarrow G_p \) generates the domain of movable nodes locations.
5. \( \mathcal{F} \leftarrow G_p \) integrates each link as a dot.
6. **for** \( \forall v_1 \in V, \forall v_2 \in V, \forall v_3 \in V \) in a DF link at \( G_p \) **do**
7. Generate vertices in \( \mathcal{F} \), \( v_1 v_2 \in V \), \( v_1 v_3 \in V \) and \( v_2 v_3 \in V \)
8. **if** \( \exists v \in V \) make \( v_1 v_2 v_3 \) and \( v_3 v_1 \) such that \( \{ u_1 < \beta \} \wedge \{ u_2 < \beta \} \wedge \{ u_3 < \beta \} \neq \emptyset \)
9. **then**
10. \( D_U = D_U + \Delta D_U \)
11. \( \Delta D_U = \frac{|M| (D_U)_\min}{|M|} \)
12. \( \min \{ \sum_i |M| \} \)
13. **else** \( \mathcal{G}_{Upper} \leftarrow \mathcal{G} \)
14. **end if**
15. **end for**
16. **end for**
17. **return** \( \mathcal{G}_{Upper} \)

In summary, we present the upper and lower bound range and calculation algorithm. It is convenient to estimate and search the optimal locations of movable nodes for best throughput. In the next section, we propose a new algorithm, the Maximum Throughput algorithm for Optimal Position (MTOP), based on the upper and lower bounds to determine the optimal locations. Besides, we also introduce several conventional algorithms or proposed methods as a comparison.

### V. MTOP ALGORITHM AND CONVENTIONAL METHOD

#### A. MAXIMUM THROUGHPUT ALGORITHM FOR OPTIMAL POSITION

**Proposition 5:** The optimal locations \( M^* (\rho_m, \Theta_m) \) of movable nodes \( m_i \in M \) for the best throughput \( T_h^* \) must be located at the scope of the upper bound \( G_{Upper} \) and lower bound \( G_{Lower} \) areas.

**Proof 5:** As stated in (16), the limitation factors indicate that the range of domain \( \mathcal{G} \) should guarantee the transmission protocol regular operation. From the physical interference perspective, the SINR for fixed and movable nodes should be larger than the threshold \( \beta \). If the link can transfer without conflict, i.e., there are no edges in CSLG, it must satisfy the requirement of SINR. On the other hand, from the protocol interference viewpoint, Euclidean distance between transceivers should be no less than the interference range and be no more than the communication range. If the upstream and downstream links that contain the public nodes cannot influence each other, then transmission data by the DF link is satisfied.

All in all, the upper bound \( G_{Upper} \) meets the slight restrictions of (16). Moreover, the lower bound \( G_{Lower} \) satisfies the severe restrictions. Thus, the optimal locations for system throughput must be located at a range of the upper bound \( G_{Upper} \) and lower bound \( G_{Lower} \) areas.

**Remark 3:** The optimal locations for movable nodes within the range of \( G_{Upper} \) and \( G_{Lower} \) can significantly reduce the search coverage. From this, we propose a new heuristic algorithm based on the upper and lower bounds, called Maximum Throughput algorithm for Optimal Position (MTOP), which is clarified in Algorithm 3.

We describe the MTOP algorithm for constructing a feasible location-allocation as below. In phase 1 (line 3-6), it initializes system throughput and optimal location. Specifically, the MTOP performs proposing algorithms to calculate the upper and lower bound values. In phase 2 (line 7-26), it initializes initial locations by randomly selected in the \( \mathcal{G} \), and then refer to simulated annealing algorithm [40] to determine the optimal locations \( M_{\mathcal{G}} \) for each \( \mathcal{G} \). Here, we set the initial temperature \( T_{ini} \) as 1000 to maintain accuracy, and configure the number of iterations \( \kappa \) as 100 considering the computation cost.

Finally, in phase 3 (line 25-38), with the search area slowly expanding, it compares old and new throughput values that are newly generated from optimal locations. If the new throughput is larger than the old value, it updates the optimal throughput and continues to expand the search range \( \mathcal{G} \), where we define \( \Delta \mathcal{G} \) as a per expansion area. Otherwise, it is out of the loop and no longer enlarges \( \mathcal{G} \). There are two reasons as follows: i) considering the expansion of the search range and computing costs rising sharply, we make a trade-off to ensure lowest complexity and highest accuracy; ii) the lower bound we derived could guarantee that the optimal value with a high probability locate within its range. In that case, the worst case is that the search area is expanded until it reaches \( G_{Upper} \). Obviously, compared with searching directly...
Algorithm 3 Maximum Throughput algorithm for Optimal Position

1: **input:** Geographical information of fixed nodes \( \varphi (l_i, f_i, f_{i+1}) \)
2: **output:** Optimal locations \( M^* \), Maximal throughput \( T_{sys}^* \)
3: \( G_{Lower} \leftarrow \varphi (l_i, f_i, f_{i+1}) \) execute Algorithm 1.
4: \( G_{Upper} \leftarrow \varphi (l_i, f_i, f_{i+1}) \) execute Algorithm 2.
5: Initialize throughput solution \( T_{sys} = 0 \).
6: Initialize optimal location \( M^* = \emptyset \).
7: for \( G \leftarrow G_{Lower} \) to \( G_{Upper} \) do
8: \( M_G \leftarrow M \) Generate initial locations by movable nodes randomly selecting in \( G \).
9: Set initial status \( S \), temperature \( T_{int} = 1000 \), \( T_{min} = 1 \).
10: for \( T = T_{int} \) to \( T_{min} \) do
11: for \( \kappa = 1 \) to 100 do
12: Generate a new position allocation \( M_{new} = M + \Delta M \), where \( \Delta M \) is the new location \( G \).
13: \( \Delta T_{sys} = T_{sys} (M_{new}) - T_{sys} (M) \)
14: Compute acceptance probability \( T = \exp \left( \frac{\Delta T_{sys}}{\psi} \right) \).
15: Draw a random value \( \psi \in [0, 1] \).
16: if \( \psi < T \) then \( M \leftarrow M_{new}, \kappa = \kappa + 1 \)
17: else
18: Update \( M \leftarrow M \).
19: Update temperature parameter \( T \leftarrow T - 0.001 \times T \).
20: end if
21: if \( T_{sys} (M_G) < T_{sys} (M) \) then
22: Update \( M_G \leftarrow M \).
23: end if
24: end for
25: end for
26: return \( M_G \).
27: if \( T_{sys} (M_G) > T_{sys} (M^*) \) then
28: \( \Delta D = \frac{D_{max} - D_{min}}{|M|} \)
29: \( \Delta G \leftarrow \Delta D \)
30: \( G = G + \Delta G \)
31: \( M^* \leftarrow M_G \)
32: \( T_{sys} \leftarrow T_{sys} (M_G) \)
33: else break;
34: end if
35: end for
36: return \( M^* (\rho_m, \Theta_m) \).
37: Construct locations allocation: allocate the optimal locations for all movable nodes \( m_i \in M \) according to \( M^* (\rho_m, \Theta_m) \).
38: return \( T_{sys} \).

in the upper bound range, MTOP ensures the accuracy with the lowest computational cost.

If there are no movable nodes between fixed nodes, our proposed algorithm (MTOP) will not execute. In addition, we do not specify node types because there are already many predefined fixed and movable nodes in this model, i.e., we do not need to select and assign which nodes are fixed or movable. In this research, we care about moving these movable nodes at the given PPP distribution case of nodes. If there are more than one movable nodes in the same location, then the selection strategy is based on social routing with the MTOP. If several users are satisfied according to social routing, then choosing one of them will not affect the result. Because according to the harmonic mean method, the best result can be achieved by selecting one of the users as the relay.

B. CONVENTIONAL METHOD

Many conventional heuristic algorithms estimate and attain approximate optimum or sub-optimum for dealing with the NP-hard problem. Specifically, simulated annealing (SA) is an effective and general algorithm for solving NP-hard problems, widely applied in engineering optimization problems. The SA algorithm starts from a specific high initial temperature. It continues to iterate with the continuous decline in temperature parameters until the optimal solution is found by setting termination conditions [40]. During each cooling iteration, the Metropolis criterion is used to determine whether or not to accept the new solution as the optimal solution. However, The SA algorithm obtains the optimal solution concerning the Metropolis criterion [41].

In many cases, the optimal solution is unstable. In other words, a suboptimal solution is often found out as a result. Essentially, SA is a stochastic optimization algorithm based on the Monte Carlo iteration strategy to treat it as a comparison with the performance of our proposed MTOP.

In our previous work [26], we proposed an interaction position game (IPG) and investigated the Spatial Adaptive Play (SAP) algorithm to work out the optimum. In this game, we employ cooperative behavior among movable nodes instead of assuming selfishness as the traditional game model. Compared with the SA algorithm, this game theory method could achieve lower computation cost and higher throughput performance. Nevertheless, the SAP algorithm costs excessive communication overhead. In practical application, the SAP’s overhead and computation costs are not in line with actual current traffic and do not meet users’ requirements. Some researchers proposed an intuitive method to be close to engineering applications: the helper node moves to the middle position between the transmitter and receiver in a link. It has been verified in [20], [21], to be capable of improving throughput in one movable node system. However, the throughput performance of this method is insufficient in the multi-user mobility communication system. Thus, we compare the SAP algorithm and intuitive method with MTOP to interpret the performance variance.

Overall, in the next simulation results section, we compare the performance of the following algorithms:

(1) Intuitive Method (IM) [20], [21].
(2) Simulated Annealing (SA) [40].
(3) SAP algorithm of IPG (SAP) [26].
(4) Maximum Throughput algorithm for Optimal Position (MTOP).
(5) Exhaustive global search (ESG).

VI. SIMULATION AND NUMERICAL RESULTS

A. SIMULATION SCENARIO

In our simulation experiments, we set the radius \( R_c \) of limited circle space as 150m for matching with real-life scenarios, such as high-traffic malls, parks, or squares. Each movable node has four directions (east, west, south, and north) to move, and the per-unit step is 1m. We define the mobility speed as 1.5 m/s, which is the ordinary pedestrians’ average speed without generality loss. Our approach aims to find the best locations by the MTOP algorithm for movable nodes to maximize system throughput. Thus, different mobility speeds alter no more than the convergence time to achieve the optimum. In other words, mobility speed only changes the time for movable nodes to reach the optimal location, but it does not influence the throughput performance results.

\( \lambda \), which is the average number of fixed nodes per unit area, i.e., a parameter for the degree of sparsity, impacts system throughput [33]. The number of fixed nodes \(|F|\) is twice the number of movable nodes \(|M|\), \(|F| = 2|M|\). As \( \lambda = 1.5 \times 10^{-4} \), \(|F| = 10\), \(|M| = 5\), and as \( \lambda = 7 \times 10^{-4} \), \(|F| = 50\), \(|M| = 25\), respectively. We simulate the different values of \(|F|\) and \(|M|\) to evaluate these algorithms’ performance.

TABLE 3. Parameter values for simulation.

| Parameters                     | Value               |
|--------------------------------|---------------------|
| Radius of limited circle space, \( R_c \) | 150 m               |
| Communication Standard         | IEEE 802.11g        |
| Transport Protocol             | UDP                 |
| Path loss Exponent (\( \alpha \)) | 4.00                |
| Mobility Speed                 | 1.5 m/s             |
| Maximum transmission power     | 10 dBm              |
| White Gaussian Noise (\( N_0 \)) | -90 dBm             |
| Wave Frequency                 | 2.4 GHz             |
| Bandwidth                      | 2 MHz               |
| SINR threshold (\( \beta \))   | 24.56 dB, 10.79 dB  |
| Number of fixed nodes (\( |F|\)) | 10, 50              |
| Number of movable nodes (\( |M|\)) | 5, 25               |

Concerning the wireless communication configuration, we employ IEEE 802.11g as the communication standard and UDP as a transmission protocol in NS3. We set the path loss exponent as 4.00 due to the shadowing effect, and the wave frequency as 2.4 GHz. To verify the different performances of different SINR thresholds for these algorithms, thus we set two values, 24.56 dB and 10.79 dB [42]. The detailed parameter configuration is given in Table 3.

B. SYSTEM THROUGHPUT

We first verify the distribution of positions of fixed nodes with different Poisson densities. Fig. 5(a) and Fig. 5(b) illustrate sparse distribution at the different number of fixed users, \(|F| = 10\), \(|F| = 50\). By comparing these two figures, we can see that the smaller the value of \(|F|\), the sparser the distribution of fixed nodes. In addition, there are some fixed nodes around AP (red triangle), and the nodes far away from AP increase with the number of nodes. This indicates that our preset expectation function \( E[I_{f_i,f_j}] \) is fixed and computable in (4). From this, the geographical distance information of fixed nodes \( \varphi(I_{f_i,f_j}) \) also can be calculated.

In the following throughput comparison figures, the X-axis denotes the number of iterations, and the Y-axis denotes the system throughput values. We compare the throughput performance of five algorithms, which contains MTOP, SAP, SA, IM, and ESG, under different \(|F|\) and \(|M|\) in Fig. 6. It can be noted that the performance curves, both IM and ESG, are all straight lines. For IM, the positions of movable nodes are located at the middle position between each transceiver, so the number of iterations is just one. REGARD TO ESG, we only perform a global search once and do not care how it loops internally. Therefore, the throughput remains...
unchanged after one iteration.

We can note that the execution of MTOP can obtain the best throughput value that is close to that of exhaustive global search (ESG) in these two figures. By analyzing the throughput value, the highest throughput by execution MTOP is 2.51 Mbps that occurred in Fig. 6(a) as $|M| = 5$, $|F| = 10$. The reasons are as follows: i) lower throughput benefits would be attained through cooperative mobility due to larger multi-hops and interference, which are caused by larger number of nodes; ii) the harmonic value of system throughput ensures that the benefits are stable when the proportion between fixed and movable nodes unchanged. Compared with IM, SA, and SAP, MTOP performs better than the former three algorithms and improves the maximum throughput ratio by 298.81%, 37.91%, and 23.04% in Fig. 6(a).

Moreover, the number of iterations MTOP is the smallest among these three algorithms (SA, SAP and MTOP). The number of iterations for all algorithms rise up as $|M|$ increases, because it should calculate more location options for movable nodes, and loops boost in MTOP algorithm operation. The minimum of number of iterations for MTOP is 120, and the minimum ratio of MTOP to SA and SAP is respectively, 37.5% and 15.38% in Fig. 6(a). Specifically, these two figures are summarized two key statements: i) the performance of MTOP is much better than SA and SAP in terms of throughput and iteration times; ii) the larger number of nodes would decrease the throughput and increase iteration times.

With the purpose of illuminating the effect of SINR, the throughput comparison of the MTOP algorithm under different $|F|$, $|M|$ and SINR is shown in Fig. 7. We simulate four cases to clarify the relationship between number of nodes and SINR threshold. This figure depicts that the best throughput performance is 2.51 Mbps as $|M| = 5$, $|F| = 10$, and $\beta = 24.56$ dB. The performance on throughput can be divided into four levels. The first and second level is as $|M| = 5$ and $|F| = 10$, because the small number of nodes and multi hops, the throughput attenuation and interference caused by performance anomaly are reduced, which makes the throughput larger.

As far as different SINR thresholds are concerned, it can be noted that the throughput of $\beta$ as 24.56 dB is larger than that of $\beta$ as 10.79 dB. Because the SINR sensed by the receiver must exceed the threshold $\beta$ to transmit successfully; otherwise, it causes an outage. Then, if the SINR determination criterion is raised, the link can maintain a higher transmission rate. Therefore, the transmission rate with $\beta = 24.56$ dB is higher than that with $\beta = 10.79$ dB. The ratio of iteration numbers maximum to a minimum is 5.72. The larger of $|M|$ and $|F|$, the more iterations are required.

### C. COMPUTATION COST

In this section, we evaluate the convergence behaviors with iteration numbers and computation cost in MTOP, SAP, and SA under different $|F|$ and $|M|$. The cumulative distribution function (CDF) of the iterations converging to the maximum is shown in Fig. 8. In this figure, X-axis denotes the number...
of iterations, and Y-axis denotes the CDF of convergence. Here, we set the SINR threshold for each receiver as 24.56 dB.

We can observe that the curve of convergence speed of MTOP ascends significantly more than the other two algorithms (SA and SAP) with the increment in the number of iterations. Notably, as the increment of $|F|$ and $|M|$, more iterations are needed to achieve convergence. The reason is that larger number of nodes would enlarge the computation of $G_{Upper}$ and $G_{Lower}$ for the MTOP algorithm with the number of fixed nodes increasing. In Fig. 8, compared with SAP and SA, the maximum convergence rate ratio of MTOP is increased by 2.63 and 4.80 times. With the growth of $|M|$, the gain of convergence rate from the MTOP algorithm is more noticeable. The detailed proof can be referred to as Lemma 2 in the analytical result section.

Turning to computation cost, the histogram Fig. 9 illustrates the comparison of completion time for MTOP, SAP, and SA under different $|F|$ and $|M|$. The CPU configuration of the simulation computer is Intel (R) core i7-8700 3.20 GHz. It is noted that MTOP costs the minimum completion time in these four cases compared with SAP and SA. The time complexity analysis and proof can be referred to as Lemma 1. The minimum completion time of MTOP is only 3.75 seconds and 7.838 seconds. For SAP, the completion time is 6.875 seconds and 18.38 seconds according to the X-axis order. Similarly, the completion time of SA is 11.88 seconds and 26.49 seconds respectively.

We can especially find that as the values of $|F|$ and $|M|$ scale up, the completion time ratio of SA and SAP to MTOP becomes increasingly higher. It means that the performance benefit from the MTOP algorithm is more significant with the raising in the number of movable nodes $|M|$. According to the qualitative perspective analysis, this is because the search domain of valid and feasible locations diminishes after we execute lower and upper bounds. For the quantitative proof, please refer to Lemma 2. The result shows that compared with SAP and SA, MTOP algorithm reduces the most computation time by 44.12% and 237.97%, respectively, as $|M| = 25$, $|F| = 50$.

D. OVERHEAD

In addition to deliberating the throughput performance and computation cost in the existing communication system, we also need to calculate the communication cost, i.e., communication overhead, in the process of algorithm execution. The comparison of communication overhead among MTOP, SAP, and SA is depicted in Fig. 10. In this figure, X-axis denotes the computation cost of the algorithms. Y-axis denotes the percentage of redundant data in total transmission data. We define the percentage of redundant data in total data as the evaluation index of overhead. In general, each packet contains redundant and valid data information. Redundant data refers to the center’s control information, mobile users’ location information, and mobile users’ adequate policy information. The communication overhead is the sum of the redundant communication data during the entire algorithm execution. If the percentage is higher, the algorithm will consume more overhead. Hence, this value reflects the algorithm costs during the control center, executing algorithms.

Fig. 10 illuminates that the proportion of redundant information becomes smaller and smaller to zero during completion. For MTOP, the reason is that the strategies and locations information required by the algorithm is decreasing until $G_{Upper}$ and $G_{Lower}$ are finally calculated. Similarly, for SAP and SA, the required locations information continuously drops off until they achieve the global or local optimum. In Fig. 10, we can detect that communication overhead represents the area around the curve and X-axis, which is the integration of curves. The communication overhead of MTOP, SAP, and SA is 18.916, 69.956, and 30.291. Then, it can be obtained that after three algorithms execution, the
communication overhead of MTOP is 72.96% lower than SAP, and is 37.55% lower than SA. The reasons are following: i) MTOP reduces the search domain based on the upper and lower bounds, then the transmission data only contains slight geographical location information of fixed nodes; ii) for SAP, it should cover the opponent’s available strategies and action information, and then meet Nash equilibrium; iii) for SA, it iterates under the defined temperature and the decision function. Therefore, MTOP only requires less redundant data than SAP and SA, resulting in less communication overhead to achieve optimal throughput performance.

VII. ANALYTICAL RESULTS

In this section, we quantitatively demonstrate the running time of SAP, SA, and MTOP through mathematical analysis. We derive and prove the following lemmas to verify and validate the correctness of the complexity simulation results.

**Lemma 1:** In terms of complexity, the running time for SAP, SA and MTOP are as follows:

- **SAP:**\( O\left(M^2 \left( R_c^{\text{SA}} + R_c^2 \right) \right) \)
- **SA:**\( O\left(10^5 \cdot R_c^{2\text{SA}} \right) \)
- **MTOP:**\( O\left(\frac{1}{2} |M|^2 \left( D_U^2 + D_L^2 \right) + \frac{1}{2} |M|^2 R^{\text{TM}} \right) \)

where \( R' \) is length parameter of the final domain, \( D_L < R' < D_U \) and \( D_L < D_U < R_c \).

**Proof 6:** Refer to [26], the SAP algorithm exchanges and collects information about opponents’ strategies. Each node calculates the utility function overall its available actions with strategies information received from opponents until Nash equilibrium and the predefined iteration is reached. The time complexity of the SAP algorithm consists of two components, one is the iteration of the choice within the circle radius \( O\left(\frac{1}{2} |M|^2 R_c^{\text{SA}} \right) \), and the other is the iteration of the individual nodes according to the range of the circle area \( O\left(\frac{1}{2} |M|^2 R_c^2 \right) \). Therefore, the running time for SAP is \( O \left[ \frac{1}{2} |M|^2 \left( R_c^{\text{SA}} + R_c^2 \right) \right] \). As for the SA algorithm, the complexity is \( O \left[ R_c^{2\text{SA}} (T_{\text{max}} - T_{\text{min}})^5 \right] \), where \( T_{\text{min}} \) and \( T_{\text{max}} \) denote the maximum and minimum temperature, respectively. In our simulation, in order to guarantee the accuracy, we set the value of \( (T_{\text{max}} - T_{\text{min}})^5 \) as \( 10^5 \). Hence, the time complexity of the SA algorithm is \( O \left(10^5 \cdot R_c^{2\text{SA}} \right) \).

Consider MTOP can be divided into three phases. In the first phase, the complexity of upper and lower bounds calculation is \( O \left(\frac{1}{2} |M|^2 D_U^2 \right) \) and \( O \left(\frac{1}{2} |M|^2 D_L^2 \right) \). In the second and third phases, the total complexity is \( O \left(\frac{1}{2} |M|^2 R^{\text{TM}} \right) \), where \( R' \) is length value which is related to the final domain. So, the time complexity is \( O \left(\frac{1}{2} |M|^2 (D_U^2 + D_L^2) + \frac{1}{2} |M|^2 R^{\text{TM}} \right) \).

**Lemma 2:** The descending order of algorithm complexity is that \( SA > SAP > MTOP \). In addition, with the increase in the number of movable nodes \( |M| \), the performance benefit from MTOP algorithm is much more obvious.

**Proof 7:** If \( |M| = 1 \), the time complexity for these three algorithms are respectively, \( O \left( R_c + R_c^2 \right) \), \( O \left(10^5 \cdot R_c^2 \right) \) and \( O \left(\frac{1}{2} (D_U^2 + D_L^2) + R' \right) \). Because \( D_L < R' < D_U \) and \( D_L < D_U < R_c \), it is noticeable that the time complexity of MTOP is smallest, and the algorithmic complexity of SAP is much less than that of SA.

If \( |M| \geq 2 \), we define the complexity ratio as follows,

\[
\eta_1 = \frac{O\left(\frac{1}{2} |M|^2 \left( D_U^2 + D_L^2 \right) + |M|^2 R^{\text{TM}} \right)}{O \left(10^5 \cdot R_c^{2\text{SA}} \right)}
\]

\[
\eta_2 = \frac{O\left(\frac{1}{2} |M|^2 \left( D_U^2 + D_L^2 \right) + |M|^2 R^{\text{TM}} \right)}{O \left(10^5 \cdot R_c^{2\text{SA}} \right)}
\]

\[
\eta_3 = \frac{O\left(\frac{1}{2} |M|^2 \left( R_c^{\text{SA}} + R_c^2 \right) \right)}{O \left(10^5 \cdot R_c^{2\text{SA}} \right)}
\]

where \( \eta_1, \eta_2 \) and \( \eta_3 \) denote the complexity ratio of SAP to SA, MTOP to SA and MTOP to SAP. It can be noted that as \( |M| \to \infty \), the time complexity of SA grows exponentially faster than that of SAP and MTOP, so \( \lim_{|M| \to \infty} \eta_1 = 0 \) and \( \lim_{|M| \to \infty} \eta_2 = 0 \). Due to \( R' < R_c \), derive \( \eta_3 < 1 \) and \( \lim_{|M| \to \infty} \eta_3 = 0 \). Obviously, the MTOP has the highest performance benefit as \( |M| \to \infty \).

VIII. CONCLUSION

In this paper, we illustrate the multiple user cooperative mobility system in mobile ad hoc networks. Firstly, we utilize the Poisson point process to present the features of fixed nodes positions. From this, we employ the DF transmission protocol to formulate a system throughput maximization problem, which is a mixed-integer with a non-linear and non-convex problem. After that, the lower and upper bounds are defined to delineate the domain scope. Furthermore, CSLG is proposed to clarify and calculate the values of...
two these bounds. Specifically, we propose the MTOP algorithm to obtain the optimal locations for movable nodes. The simulation results show that compared with SA, SAP, and IM, the throughput of MTOP is increased by 298.81%, 37.91%, and 23.04%, respectively. Compared with SAP and SA, MTOP reduces the computation cost by 44.12% and 237.97%, respectively; Besides, the communication cost of MTOP is reduced by 72.96% and 37.55%. It demonstrates that MTOP is a practical algorithm for improving system throughput and reducing computational costs and overhead in practical applications.

REFERENCES

[1] E. Huang, W. Hu, J. Crowcroft, and I. Wassell, “Towards commercial mobile ad hoc network applications: A radio dispatch system,” in Proceedings of the 6th ACM international symposium on Mobile ad hoc networking and computing, 2005, pp. 355–365.

[2] N. D. Han, Y. Chung, and M. Jo, “Green data centers for cloud-assisted mobile ad hoc networks in 5G,” IEEE Netw., vol. 29, no. 2, pp. 70–76, 2015.

[3] B. Alawieh, Y. Zhang, C. Assi, and H. Mouftah, “Improving spatial reuse in multihop wireless networks-a survey,” IEEE Commun. Surv. Tutorials, vol. 11, no. 3, pp. 71–91, 2009.

[4] F. Chen, H. Zhai, and Y. Fang, “Available bandwidth in multirate and multihop wireless ad hoc networks,” IEEE J. Sel. Areas Commun., vol. 28, no. 3, pp. 299–307, 2010.

[5] S. Moh and C. Yu, “A cooperative diversity-based robust MAC protocol in wireless ad hoc networks,” IEEE Trans. Parallel Distrib. Syst., vol. 22, no. 3, pp. 353–363, 2010.

[6] A. Ozgur, O. Lévêque, and N. C. David, “Hierarchical cooperation achieves optimal capacity scaling in ad hoc networks,” IEEE Trans. Inf. Theory, vol. 53, no. 10, pp. 3549–3572, 2007.

[7] Q. Zhang, Q. Chen, F. Yang, X. Shen, and Z. Niu, “Cooperative and opportunistic transmission for wireless ad hoc networks,” IEEE Netw., vol. 21, no. 1, pp. 14–20, 2007.

[8] F. Wang, L. Ruan, and M. Z. Win, “Cooperative Network Operation Design for Mobility-Aware Cloud Radio Access Network,” IEEE Trans. Wirel. Commun., vol. 17, no. 12, pp. 7819–7833, 2018.

[9] A. Argyriou, “Cross-layer and cooperative opportunistic network coding in wireless ad hoc networks,” IEEE Trans. Veh. Technol., vol. 59, no. 2, pp. 803–812, 2009.

[10] R. Karmakar, S. Chattopadhayay, and S. Chakraborty, “Impact of IEEE 802.11 n/ac PHY/MAC high throughput enhancements on transport and application protocol performance,” IEEE Commun. Surv. Tutorials, vol. 19, no. 4, pp. 2050–2091, 2017.

[11] J. Xie and T. Murase, “Multiple User Cooperative Mobility in Mobile Ad Hoc Networks: An Interaction Position Game,” IEEE Access, vol. 8, pp. 126297–126314, 2020.

[12] S. Lv, X. Wang, and X. Zhou, “Scheduling under SINR model in ad hoc networks with successive interference cancellation,” GLOBECOM - IEEE Glob. Telecommun. Conf., no. December 2010, 2010.

[13] J. Luo, A. Iyer, and C. Rosenberg, “Throughput-lifetime trade-offs in multihop wireless networks under an SINR-based interference model,” IEEE Trans. Mob. Comput., vol. 10, no. 3, pp. 419–433, 2010.

[14] K. Medepalli and F. A. Tobagi, “Throughput analysis of IEEE 802.11 wireless LANs using an average cycle time approach,” in GLOBECOM'05. IEEE Global Telecommunications Conference., 2005, vol. 5, pp. 1–5.

[15] S. P. Weber, X. Yang, J. G. Andrews, and G. D. Veciana, “Transmission capacity of wireless ad hoc networks with outage constraints,” IEEE Trans. Inf. Theory, vol. 51, no. 12, pp. 4091–4102, 2005.

[16] Y.-W. P. Hung, W.-J. Huang, and C.-C. J. Kuo, “Cooperative communications and networking: technologies and system design. Springer Science & Business Media, 2010, pp. 17–77. [Online]. Available: http://dl.merc.ac.ir/handle/Hannan/146#sthash.KzZwJ4wA.dpbs

[17] G. Kramer, M. Gastpar, and P. Gupta, “Cooperative strategies and capacity theorems for relay networks,” IEEE Trans. Inf. Theory, vol. 51, no. 9, pp. 3037–3063, 2005.

[18] D. Chen and J. N. Laneman, “Modulation and demodulation for cooperative diversity in wireless systems,” IEEE Trans. Wirel. Commun., vol. 5, no. 7, pp. 1785–1794, 2006.

[19] I. Stepanov, D. Herrscher, and K. Rothermel, “On the impact of radio propagation models on MANET simulation results,” in Proceedings of 7th International Conference on Mobile and Wireless Communications Networks (MWCN 2005), Marrakech, Morocco, 2005.

[20] P. Stuedi, O. Chinelati, and G. Alonso, “Connectivity in the presence of shadowing in 802.11 ad hoc networks,” in IEEE Wireless Communications and Networking Conference, 2004, vol. 4, pp. 2225–2230.

[21] G. Brar, D. M. Blough, and P. Santi, “Computationally efficient scheduling with the physical interference model for throughput improvement in wireless mesh networks,” Proc. Ann. Int. Conf. Mob. Comput. Networking, Mobicom, vol. 2006, pp. 2–13, 2006.

[22] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by simulated annealing,” Science (80–), vol. 220, no. 4598, pp. 671–680, 1983.

[23] H. E. Romeijn and R. L. Smith, “Simulated annealing for constrained global optimization,” J. Glob. Optim., vol. 5, no. 2, pp. 101–126, 1994.

[24] T. Y. Lin and J. C. Hou, “Interplay of spatial reuse and SINR-determined data rates in CSMA/CA-based, multi-hop, multi-rate wireless networks,” Proc. - IEEE INFOCOM, pp. 803–811, 2007.

Xie et al.: An optimal location allocation by multi-user cooperative mobility for maximizing throughput in MANETs
JIQUAN XIE received his B.S. and M.S. degrees from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 2013 and 2016, respectively. He is currently pursuing a Ph.D. degree with the Department of Information Engineering, Nagoya University, Nagoya, Japan. His research interests include the mobile ad hoc networking, mobile cloud computing, and edge computing.

TUTOMU MURASE was born in Kyoto, Japan, in 1961. He received his M.E. degree from the Graduate School of Engineering Science, Osaka University, Japan, in 1986. He also received his Ph.D. degree from the Graduate School of Information Science and Technology, Osaka University, in 2004.

He joined NEC Corporation Japan in 1986. He was a visiting professor at the Tokyo Institute of Technology from 2012 - 2014. He is currently a professor at Nagoya University, Japan.

Dr. Murase has been engaged in research on traffic management for high-quality and high-speed internet. His current interests include transport and session layer traffic control, wireless network resource management, and network security. He is also interested in user cooperative mobility research. He received the Best Tutorial Paper Award on his invited paper about QoS control for overlay networks in the IEICE Transactions on Communication in 2006. He has served as TPC for many IEEE conferences and workshops. He has more than 90 registered patents including several international patents. He was a secretary of the IEEE Communications Society Japan Chapter. He is a member of IEEE and a fellow of IEICE.