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Radar Assisted Fast Neighbor Discovery for Wireless Ad Hoc Networks

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ABSTRACT In machine-type communication (MTC) consisting high-mobility machines, such as vehicles, aircrafts, robots, etc., there is a strong demand for fast wireless networking. With radars extensively applied in these machines for environment awareness, radar assisted fast neighbor discovery (ND) for wireless ad hoc networks is proposed to realize fast wireless networking for MTC. Four neighbor discovery algorithms are designed according to the accuracy level of prior information provided by radar. Then, the performance of neighbor discovery algorithms is analyzed theoretically. Simulation results are further provided to compare neighbor discovery algorithms with and without the prior information from radar. The results demonstrate that the time consumption of neighbor discovery is greatly reduced with prior information of radar. Moreover, the time consumption with prior information from radar increases with the number of nodes. However, the increasing speed is much slower than the neighbor discovery without prior information from radar. This paper proves the advantages of radar assisted neighbor discovery, which may motivate the study of radar assisted wireless networking schemes in the future.

INDEX TERMS Neighbor discovery, wireless ad hoc networks, Radar-Communication Integration.

I. INTRODUCTION

Machine-type communication (MTC) is widely deployed in the era of the 5th generation (5G) mobile networks [1]. In some MTC applications, such as vehicular networks and flying ad-hoc networks (FANETs), due to their high mobility and dynamic topology, there is a strong demand for fast wireless networking to realize cooperation among machines. Neighbor discovery, as a critical early step for wireless networking [2], has attracted wide attention in academia and industry. Hence, the fast neighbor discovery plays an essential role in the wireless networking for MTC.

Radars are extensively implemented in machines, such as vehicles, unmanned aerial vehicles (UAVs), aircrafts, robots, etc., to realize environment awareness. Even in wearable devices, mobile phones, smart speakers, etc., radars are implemented to recognize hand gestures [3]. Machines mounted with radars can collect prior information from environment, which will boost wireless networking. For example, Gonźalez-Prelcic *et al.* studied the radar assisted beam alignment for millimeter wave (mmWave) enabled vehicle-to-infrastructure (V2I) communications, where the prior information from radar improves the spectrum efficiency of V2I communications [4]. In the perspective of wireless networking, prior information obtained from radar can accelerate the speed of neighbor discovery. Burghal *et al.* [5] proved that the prior information of the set of neighbors can accelerate the speed of neighbor discovery. Li *et al.* [6] proposed a neighbor discovery algorithm called SBA-RA, where the prior information of neighbors obtained from radar is applied to reduce the time of neighbor discovery. Liu *et al.* [7] applied the double-face phased array radar to improve the efficiency of neighbor discovery.

However, neighbor discovery algorithms depending on the accuracy of prior information obtained from radar have be rarely studied in existing literatures. In this paper, the stop and reply mechanisms are applied in neighbor discovery algorithms according to the accuracy of the number of neighbors within the beam derived from radar detection. Firstly, we analyze the probability density function (PDF) of the number of neighbors in each beam when the nodes follow uniform distribution. Then, four neighbor discovery algorithms are

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designed according to the accuracy level of the prior information provided by radar. Numerical results demonstrate that compared with algorithms without prior information from radar, time consumption of the proposed neighbor discovery is significantly reduced with the prior information from radar. Moreover, the neighbor discovery speed can be further accelerated with more accurate prior information. The neighbor discovery schemes in this paper require the intergation of radar and communication. With cooperation between radar and communication, the prior information of radar can be applied in accelerating neighbor discovery.

The remainder of this paper is organized as follows. In Section II, the system model is introduced. In Section III, the radar assisted neighbor discovery algorithms are designed. In Section IV, the performance analysis for the proposed neighbor discovery algorithms is provided. The numerical results and analysis are revealed in Section V. Finally, we summarize this paper in Section VI.

II. SYSTEM MODEL

An ad hoc network with nodes uniformly distributed in a two-dimensional (2D) plane is considered. Each node has a unique ID, such as its MAC address. The node adopts directional transmission and directional reception (DTDR) mechanism. A node can point its transmit beam to a number of fixed directions. All nodes are in a clique that any two nodes can mutually cover each other. Since the neighbor discovery process occurs in a short time, the movement of nodes can be ignored. For a typical node A, there are N neighboring nodes uniformly distributed around it. The number of beams of node A is B. The beam having i neighboring nodes is defined by "i-node" beam. The probability that there are k i-node beams with N neighboring nodes and B beams is defined by $P(k, B, N, i)$. The expectation of the number of i-node beams is denoted as E_i. In Lemma 1, 2 and 3 of the appendixes, E_0, E_1 and E_i $(i \geq 2)$ are derived.

With radar function implemented at nodes, the prior information from radars can be applied to accelerate the process of neighbor discovery. For example, the radar can detect the existence of neighboring nodes in each beam. If the accuracy of radar detection is sufficiently high, it is even possible to accurately estimate the number of neighboring nodes in each beam. According to the accuracy level of the prior information, the neighbor discovery algorithms can be classified as the following two cases.

1) If the radar has low accuracy performance that only the existence of neighboring nodes in each beam can be determined, the node can selectively communicate in the beams with neighboring nodes to accelerate the neighbor discovery.
2) If the radar has high accuracy performance that the number of neighboring nodes in each beam can be determined, the node can stop communicating in a beam when all the neighboring nodes in this beam are discovered.

Besides, if node A and node B have discovered each other, the node B can choose not to reply the hello packet from node A [9]. This mechanism can reduce the collision probability, especially in the scenarios with a large number of neighboring nodes. According to the accuracy of the prior information and the reply mechanism, four radar assisted neighbor discovery algorithms are proposed as follows.

1) Reply and non-stop (RnS) algorithm: The neighboring nodes reply the hello packet of a node even though it has been discovered. If the radar has low accuracy performance, one node can not determine whether its neighbors have been fully discovered or not. Hence, the neighbor discovery process within a beam will not stop even when the nodes in this beam are all discovered.
2) Non-reply and non-stop (nRnS) algorithm: The neighboring node does not reply the hello packet of a node when it is discovered. Besides, the neighbor discovery process within a beam will not stop even when the nodes in this beam are all discovered.
3) Reply and stop (RS) algorithm: The neighboring node reply to the hello packet of a node even though it is discovered. If the radar has high performance, it is possible for one node to know whether the neighbors are fully discovered or not. Hence, the neighbor discovery process within a beam will stop when the nodes in this beam are all discovered.
4) Non-reply and stop (nRS) algorithm: The neighboring node does not reply the hello packet of a node when it is discovered. Besides, the neighbor discovery process within a beam will stop when the nodes in this beam are all discovered.

Details for the above four algorithms are described in Section III.

III. RADAR ASSISTED NEIGHBOR DISCOVERY ALGORITHMS

In the ad hoc network, the node adopts synchronous and half-duplex working mode. Time is divided into slots and each slot is divided into 3 sub-slots. The length of each sub-slot is long enough for the node to send its data package. The node adopts 3-way interactive mode to discover other nodes. The handshake succeeds only if transmitter and receiver are mutually covered without collision. However, a collision occurs when more than one node sends hello message or feedback message to a certain node at the same time. Once collision occurs, the handshake fails. All nodes obtain the prior information of neighboring nodes via radars, which means that a node knows the existence or the number of neighboring nodes in each beam. In each time slot, nodes only select the beams that have neighbors to communicate.

In a time slot, each node selects transmitting state or receiving state. Then the node selects a direction to communicate. The node that selects transmitting state will send a hello package in the first sub-slot and keep receiving in the second sub-slot. If it receives a feedback package from the receiving

node, it will send an acknowledgement packet in the third sub-slot and update its neighbor list. Otherwise, it keeps silent in the remaining time of this slot. The node that selects receiving state will maintain receiving in the first sub-slot. If it receives a hello packet from the transmitting node, it will send a feedback packet in the second sub-slot and then keep receiving in the third sub-slot. If the receiving node receives the acknowledgement packet of the transmitting node in the third sub-slot, it will update its neighbor list. Otherwise, it keeps silent in the remaining time of this slot. When the number of discovered neighbors reaches the total number of neighbors, the neighbor discovery process stops.

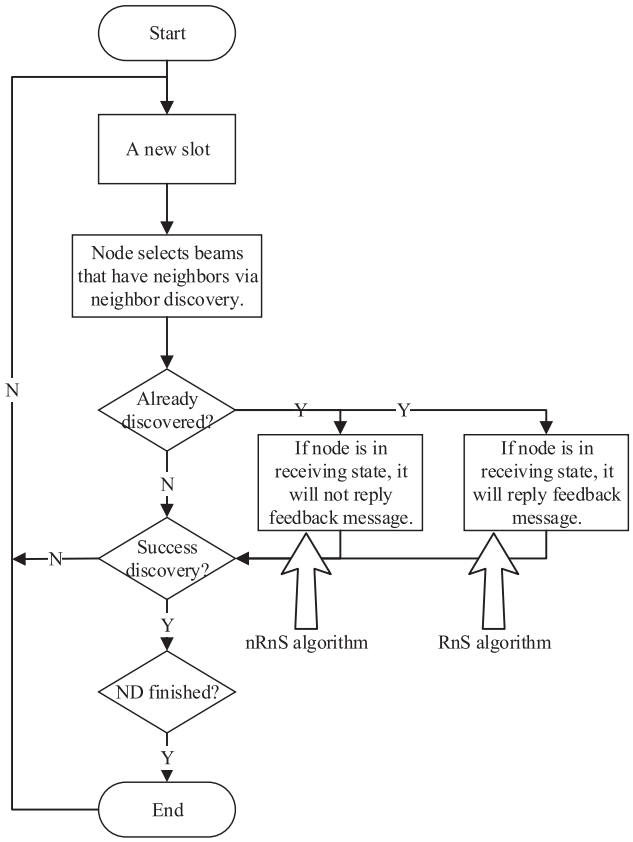

FIGURE 1. RnS and nRnS algorithms.

As illustrated in Fig. 1, for RnS algorithm and nRnS algorithm, in a new time slot, nodes select the beams with neighbors to communicate regardless of whether the beams are fully discovered or not. The difference between RnS algorithm and nRnS algorithm is that if two nodes have already discovered each other, when one node receives a hello packet from the other node, the node using RnS algorithm will still reply a feedback package, while the node using nRnS algorithm will not reply a feedback package.

As illustrated in Fig. 2, for RS algorithm and nRS algorithm, in a new time slot, nodes only select beams that have not been fully discovered. The difference between RS algorithm and nRS algorithm is the same as that of RnS and

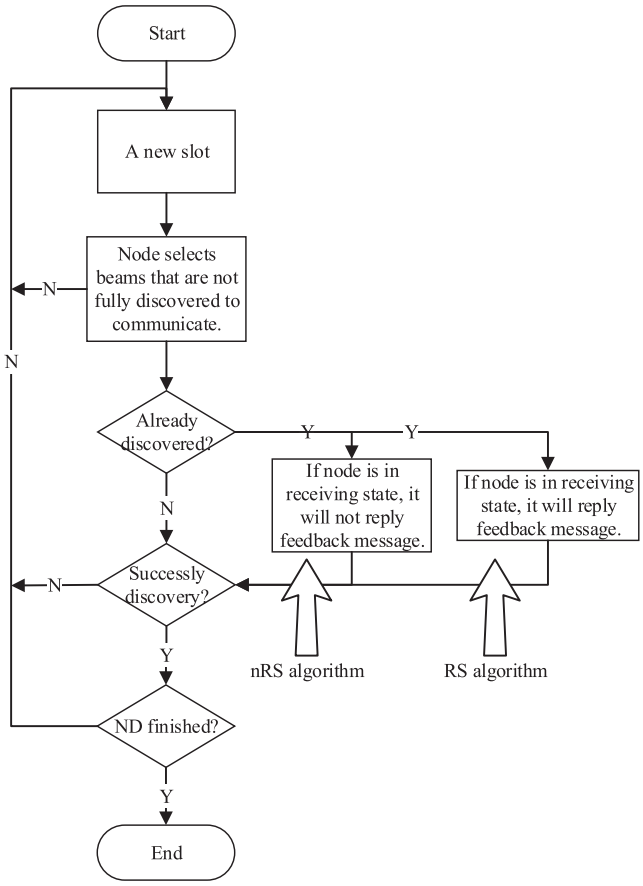

FIGURE 2. RS and nRS algorithms.

nRnS algorithms. When a node receives a hello packet, the node using RS algorithm will still reply a feedback package, while the node using nRS algorithm will not reply a feedback package.

IV. PERFORMANCE ANALYSIS

The prior information from radar can boost the neighbor discovery algorithm. In this section, the performance of radar assisted neighbor discovery algorithms is analyzed.

A. RnS ALGORITHM

In RnS algorithm, a node will select the beams with neighbors to communicate with equal probability. Hence, the 0-node beams are removed in the derivation of the probability of i-node beams P_i, which is

$$P_i = \frac{E_i/B}{1 - E_0/B} = \frac{E_i}{B - E_0}, \tag{1}$$

where $i \geq 1$.

There are averagely M neighbors in one of the beams and we have

$$M = \sum_{i=1}^{N} iP_i. \tag{2}$$

The probability that node i discovers node j in a time slot is [9]

$$P_d^{RnS} = 2P_t\,(1-P_t)\left(\frac{1}{B_o}\right)^2 \times \left(1-(1-P_t)\,\frac{1}{B_o}\right)^{M_i-1}\left(1-P_t\frac{1}{B_o}\right)^{M_j-1}, \quad (3)$$

where M_i and M_j are the numbers of neighboring nodes in the beams of node i and node j, respectively. We replace M_i and M_j with the average number of neighbors in a beam, which means $M_i \approx M_j \approx M$. P_t is the probability of a node choosing to be a transmitter. $B_o = \sum_{i=1}^{N} E_i$ is the number of beams with neighboring nodes. The expected number of time slots to discover all nodes adopting RnS algorithm is

$$E^{RnS} = \sum_{i=1}^{N} \frac{1}{(N-i+1)\,P_d^{RnS}}. \quad (4)$$

Comparing with [10], the derivation of P_d^{RnS} is modified.

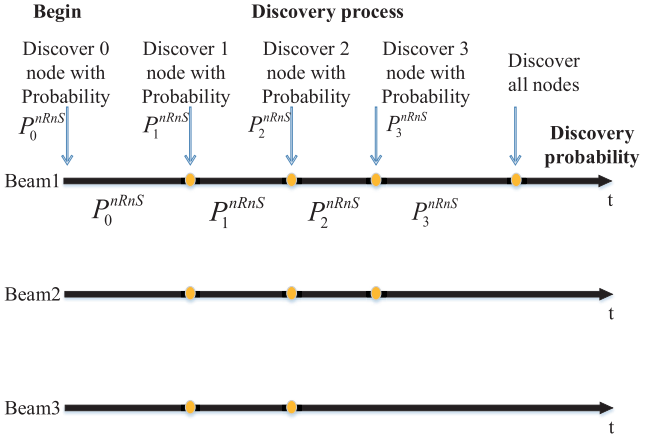

FIGURE 3. The change of discovery probability in nRnS algorithm.

B. nRnS ALGORITHM

Comparing with RnS algorithm, nRnS algorithm avoids repeated feedbacks. For example, if node i and node j are mutually discovered, node j will not reply the hello packet of node i. This mechanism was proposed in [9]. Fig. 3 depicts the discovery process. Each beam has a unique time-varying axis which represents the discovery probability. For instance, P_0^{nRnS} denotes the discovery probability when no neighbor is discovered. The dot denotes that a neighbor in the beam is discovered. Since the interference in this beam decreases, the discovery probability increases from P_0^{nRnS} to P_1^{nRnS}. With $u(t)$ representing the number of discovered neighbors of node i in the beam that covers node j until t-th time slot, the probability that node i discovers node j in a time slot is

$$P_u^{nRnS} = 2P_t\,(1-P_t)\left(\frac{1}{B_o}\right)^2 \times \left(1-(1-P_t)\,\frac{1}{B_o}\right)^{M_i-u(t)-1}\left(1-P_t\frac{1}{B_o}\right)^{M_j-1}. \quad (5)$$

Comparing with the fixed P_{dis} in RnS algorithm, the P_u in nRnS algorithm is time-varying since the term

$$t_1 = \left(1-(1-P_t)\,\frac{1}{B_o}\right)^{M_i-u(t)-1} \quad (6)$$

in (5) depends on time t. However, when the number of beams is large, the term t_1 is close to 1. Hence although P_u^{nRnS} is time-varying, the average P_u^{nRnS} can be used to estimate the expected number of time slots to discover all neighbors. Taking an i-node beam as an example, during the process of neighbor discovery, the average P_u^{nRnS} is as follows.

$$\overline{P_i} = \frac{1}{T}\int_0^T P_u^{nRnS}\,dt = \frac{1}{T}\sum_{u=0}^{i-1}\int_{T_u}^{T_{u+1}} P_u^{nRnS}\,dt, \quad (7)$$

where T is the total time to discover i nodes. T_u is the time between discovering the u-th node and the $(u+1)$-th node. When u neighbors are discovered, the P_u^{nRnS} remains unchanged until the next neighbor is discovered and the probability of discovering a node is $(i-u)\,P_u^{nRnS}$. The number of time slots to discover a node follows geometric distribution and its expectation is

$$\overline{N_u} = \frac{1}{(i-u)\,P_u^{nRnS}}. \quad (8)$$

Hence the $\overline{P_i}$ can be derived as

$$\overline{P_i} = \frac{1}{T}\sum_{u=0}^{i-1}\overline{N_u} = \frac{1}{T}\sum_{u=0}^{i-1}\frac{1}{(i-u)\,P_u^{nRnS}}P_u^{nRnS} = \frac{\sum_{u=0}^{i-1}\frac{1}{i-u}}{\sum_{u=0}^{i-1}\frac{1}{(i-u)P_u^{nRnS}}}. \quad (9)$$

For the i-node beam, we have derived $\overline{P_i}$. Then the average $\overline{P_i}$ is derived as follows.

$$\overline{P_{dis}} = \sum_{i=1}^{N}\overline{P_i}\cdot B\cdot E_i. \quad (10)$$

Then the expected time of neighbor discovery is

$$E^{nRnS} = \sum_{i=1}^{N}\frac{1}{(N-i+1)\,\overline{P_{dis}}}. \quad (11)$$

C. RS ALGORITHM

Define P_d^{RS} as the probability to discover a neighbor when nodes have already discovered i beams. Then we have

$$P_d^{RS} = 2P_t\,(1-P_t)\left(\frac{1}{B_o^{RS}}\right)^2 \times \left(1-(1-P_t)\,\frac{1}{B_o^{RS}}\right)^{M_i-1}\left(1-P_t\frac{1}{B_o^{RS}}\right)^{M_j-1}. \quad (12)$$

In RS algorithm, B_o^{RS} is the number of beams that still have undiscovered neighbors and it will decrease over time. The reduction of B_o^{RS} in (12) improves the probability of discovering a neighbor. The upper and lower bounds for the time of neighbor discovery are derived. The analysis is discussed under two cases, where $N \geq B$ and $N < B$.

1) $N \geq B$

In RS algorithm, the complete discovery of the neighbors in a beam will accelerate the neighbor discovery. In the derivation of the upper bound of the time for neighbor discovery, the nodes are uniformly distributed in all beams and the neighbor discovery consists of two stages. In the first stage, the neighbors in all beams can not be discovered completely and there is exactly one undiscovered neighbor in each beam in the end of the first stage, as shown in Fig. 4. Since B_o^{RS} remains unchanged in the first stage, the probability of discovering a neighbor remains unchanged during the first stage. In the second stage, the neighbors in each beam are discovered one by one.

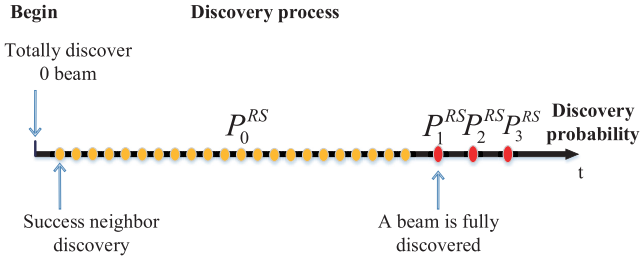

FIGURE 4. The change of discovery probability in RS algorithm: upper bound.

There are averagely $\lfloor \frac{N}{B} \rfloor$ or $\lfloor \frac{N}{B} \rfloor + 1$ neighbors in each beam since the nodes are uniformly distributed within the beams. By the end of the first stage of neighbor discovery, to achieve the upper bound of neighbor discovery, each beam needs to remain one undiscovered neighbor and the remaining $N - B$ neighbors are discovered in this stage. The probability that node i discovers node j in a time slot is

$$P_0^{RS} = 2P_t\,(1-P_t)\left(\frac{1}{B_o^{RS}}\right)^2 \times \left(1-(1-P_t)\,\frac{1}{B_o^{RS}}\right)^{M-1}\left(1-P_t\,\frac{1}{B_o^{RS}}\right)^{M-1}. \quad (13)$$

The time for neighbor discovery in the first stage is

$$t_1 = \sum_{i=0}^{N-B-1} \frac{1}{(N-B-i)\,P_0^{RS}}. \quad (14)$$

In the second stage, the probability of neighbor discovery is

$$P_d^{RS} = 2P_t(1-P_t)\left(\frac{1}{B_o^{RS}-i}\right)^2 \times \left(1-(1-P_t)\frac{1}{B_o^{RS}-i}\right)^{\underbrace{(M-1)\frac{B_o^{RS}-i}{B_o^{RS}}}_{\text{interference term}}} \times \left(1-P_t\frac{1}{B_o^{RS}-i}\right)^{\underbrace{(M-1)\frac{B_o^{RS}-i}{B_o^{RS}}}_{\text{interference term}}}. \quad (15)$$

Since $N \geq B$ and the nodes are uniformly distributed, we have $B_o^{RS} \approx B.\left(\frac{1}{B_o^{RS}-i}\right)^2$ due to the fact that the choice of beams is reduced with i discovered beams. As to the interference terms in (15), we have the following analysis.

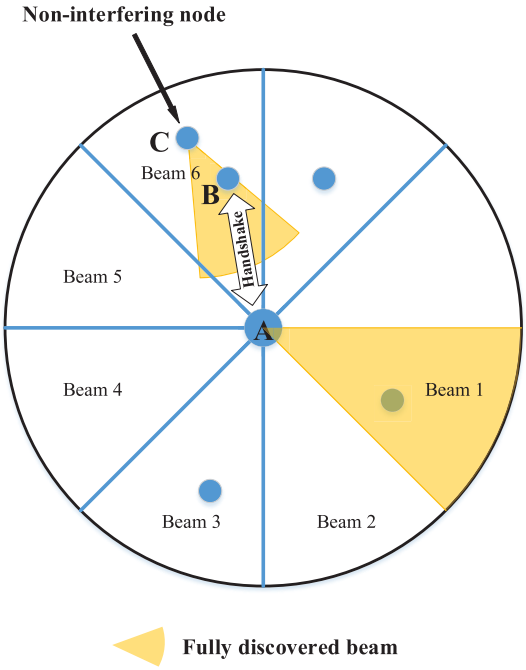

FIGURE 5. The mechanism of RS algorithm.

Supposing that a node has not discovered any neighbor in a certain beam, apparently there are $M-1$ interference nodes inside this beam. We assume that the progress of neighbor discovery for each node is the same, which means that every node has exactly discovered i of B_0 beams in the i-th stage. As a result, nodes will never choose these fully discovered beams for transmission or reception in the remaining slots. As shown in Fig. 5, node A attempts to communicate with node B through beam 6. If another node C in beam 6 has already fully discovered the beam which contains node A, the node C will not become an interfering node with regard to node A. The probability that a certain beam is not fully discovered when i beams have been fully discovered can be expressed as

$$P_s^{RS} = \frac{\binom{i-1}{B_o^{RS}}}{\binom{i}{B_o^{RS}}} = \frac{B_o^{RS}-i}{B_o^{RS}}. \quad (16)$$

Because there are $(M-1)$ interference nodes, the expression of the total interference term is $(M-1)\,P_s^{RS}$.

In the second stage, the time for neighbor discovery is

$$t_2 = \sum_{i=0}^{B-1} \frac{1}{(B-i)\,P_d^{RS}}. \quad (17)$$

Hence, the upper bound of the time for neighbor discovery is

$$E_{up}^{RS} = t_1 + t_2 = \sum_{i=0}^{N-B-1} \frac{1}{(N-B-i)\,P_0^{RS}} + \sum_{i=0}^{B-1} \frac{1}{(B-i)\,P_d^{RS}}. \quad (18)$$

Then, we derive the expression of lower bound. For comparison, the distribution of nodes is the same as that in the derivation of upper bound. It is known that to reduce the neighbor discovery time, increasing the discovery probability is of most importance. The earlier a beam is fully discovered, the earlier the discovery probability will increase. Therefore, the neighbor discovery process should be consecutive, which means that nodes have to discover neighbors belonging to the same beam until that beam is fully discovered, as shown in Fig. 6. Besides, the beam that includes less neighbors should be completely discovered earlier.

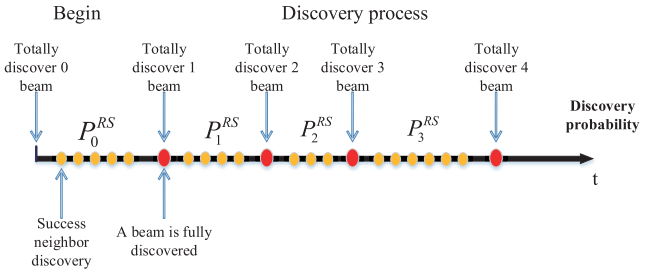

FIGURE 6. The change of discovery probability in RS algorithm: lower bound.

Since the nodes are uniformly distributed, the average number of nodes in each beam is $\left\lfloor \frac{N}{B_o^{RS}} \right\rfloor$ or $\left\lfloor \frac{N}{B_o^{RS}} \right\rfloor + 1$. Similar to the derivation of upper bound, the lower bound of the time for neighbor discovery is

$$E_{down}^{RS} = \sum_{u=0}^{B-R-1} \sum_{i=0}^{m-1} \frac{1}{(N-i-mu)P_u^{RS}} + \sum_{u=B-R}^{B-1} \times \sum_{i=0}^{m} \frac{1}{(N-i-(B-R)m-(u-(B-R)(m+1)))P_u^{RS}}, \quad (19)$$

where $R = N \bmod B$.

2) $N < B$

In this scenario, the most representative node distribution is selected, namely, every node is distributed in a different beam. Hence, there are N beams containing 1 node and $B-N$ beams containing 0 node. Since each successful neighbor discovery results in the change of neighbor discovery probability, the analysis of upper bound and lower bound is the same in this scenario. Similar to the condition where $N \geq B$, the average neighbor discovery time is

$$t_{RS} = \sum_{i=0}^{N-1} \frac{1}{(N-i)\,P_d^{RS}}, \quad (20)$$

where $P_d^{RS} = 2P_t\,(1-P_t)\left(\frac{1}{N-i}\right)^2$ and N is the total number of neighbors.

D. nRS ALGORITHM

Combining the advantages of non-reply and stop-discovery mechanisms, we have nRS algorithm. Since the theoretical analysis of this algorithm is too complicated, we only analyze the simulation results in the next section.

V. SIMULATION RESULTS AND ANALYSIS

A. THE DISTRIBUTION OF NODES IN A BEAM

In order to verify Lemma 1, Lemma 2 and Lemma 3, the simulation results of the node distribution are obtained. As shown in Fig. 7, the figure illustrates how the number of beams (ranging from 6 to 34) and the number of neighbors (ranging from 5 to 83) affect the value of the probability that a beam contains exactly one node (E_1/B).

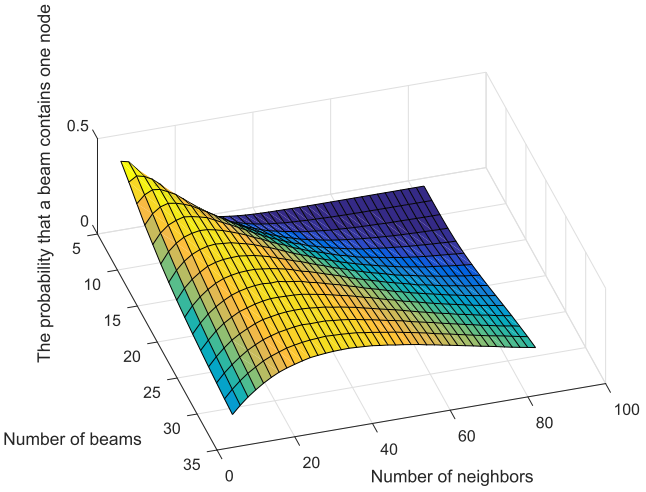

FIGURE 7. The probability that a beam contains one node.

Fig. 8 is the overlooking view of Fig. 7. By connecting the largest values in the graph into a line, we can find that when the number of beams and the number of neighbors are the same, the largest probability can be achieved. This is reasonable since the nodes are uniformly distributed. Similarly, when the number of neighbors is 2 times the number of beams, the probability that a beam contains exactly 2 nodes reaches maximum value.

Then we verify Lemma 1, Lemma 2 and Lemma 3. Fig. 9 shows the relation between the probabilities of different types of beams and the number of neighbors, where the beam number is 15. The curves contain both simulation results and theoretical results. For 0-node beam, its probability decreases monotonically. For the probabilities of 1-node beam and 2-node beam, before sliding down to zero, they rise to peak values when the numbers of neighbors are 15 and 30 respectively, which is reasonable since the nodes follow uniform distribution. The simulation curves fit well with the theoretical results, which verifies the correctness of Lemma 1, Lemma 2 and Lemma 3. Fig. 9 only verifies the beams that

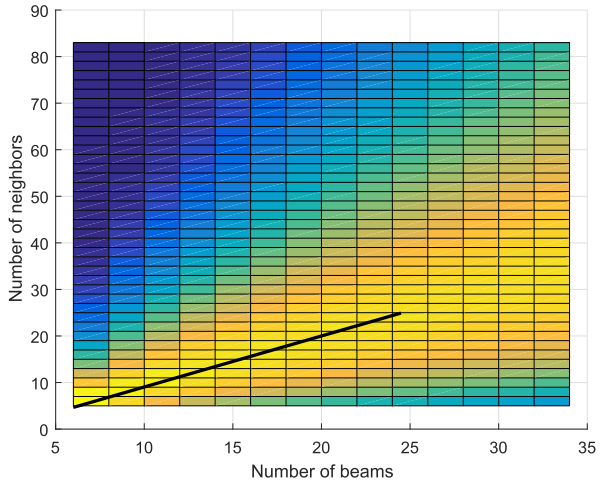

FIGURE 8. The overlooking view of Fig. 7.

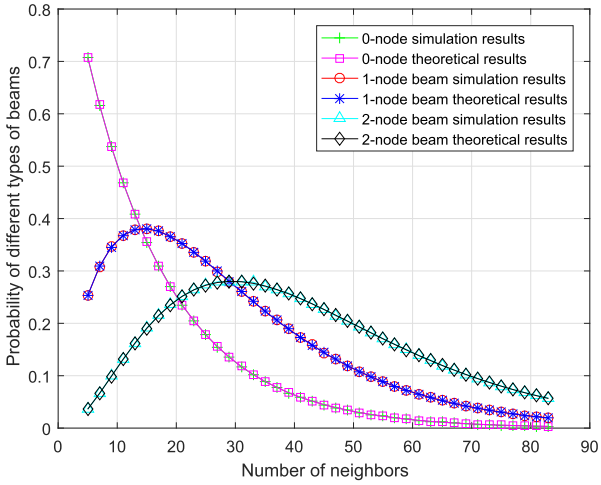

FIGURE 9. The probability of *i*-node beam.

contain 0, 1 and 2 nodes. However, the theory can also be applied to the beams containing up to N nodes.

The curves in Fig. 9 are the cross-section of Fig. 7. Hence, by adjusting the beam number, the theoretical results can be obtained in three-dimensional (3D) diagram. As shown in Fig. 10, the theoretical results fit well with the simulation results.

B. RnS ALGORITHM

We first demonstrate the results of RnS algorithm. Fig. 11 shows the relation between the neighbor discovery time and the number of neighbors (ranging from 5 to 14), where the beam number is 10. Notice that the theoretical curve overlaps with the simulation curve, which verifies the theoretical results.

C. nRnS ALGORITHM

Fig. 12 compares the theoretical results and the simulation results of nRnS algorithm. The beam number is 10. In order

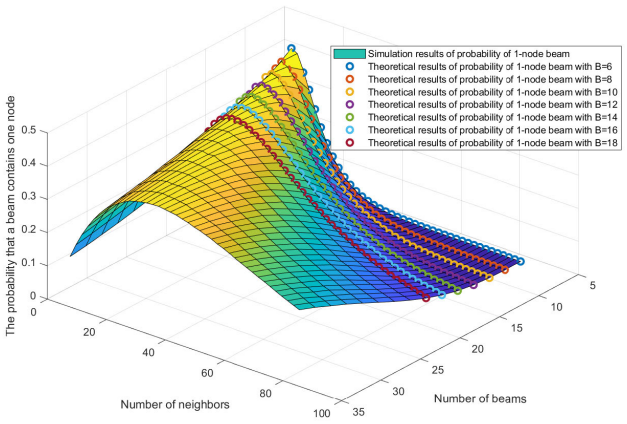

FIGURE 10. The probability of 1-node beam in 3D space.

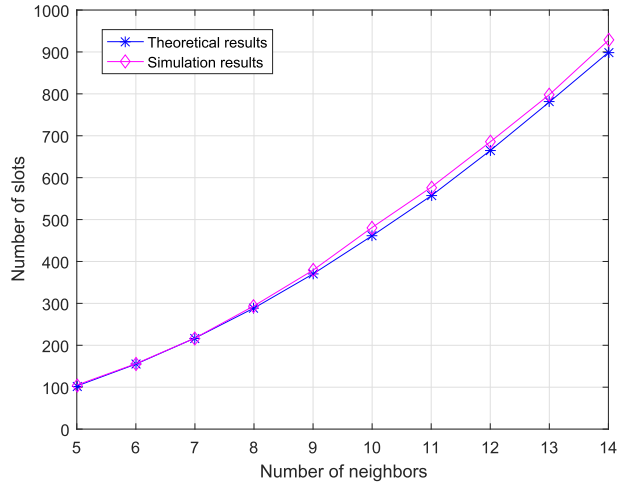

FIGURE 11. The time of complete neighbor discovery using RnS algorithm.

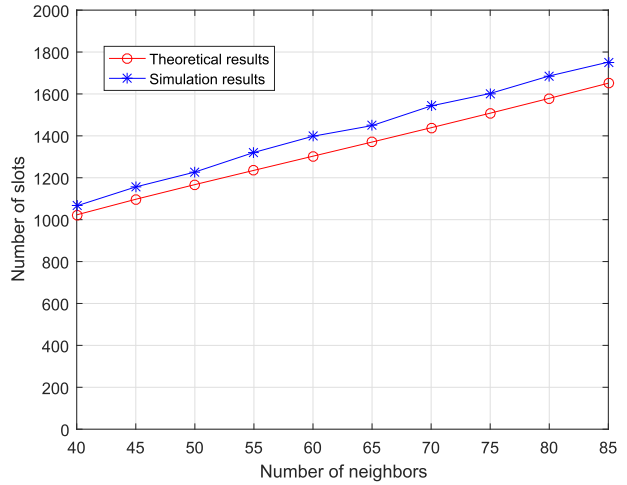

FIGURE 12. The time of complete neighbor discovery using nRnS algorithm.

to reveal the differences between RnS algorithm and nRnS algorithm, neighbor numbers are set within a high range from 40 to 85. This is reasonable because the two algorithms

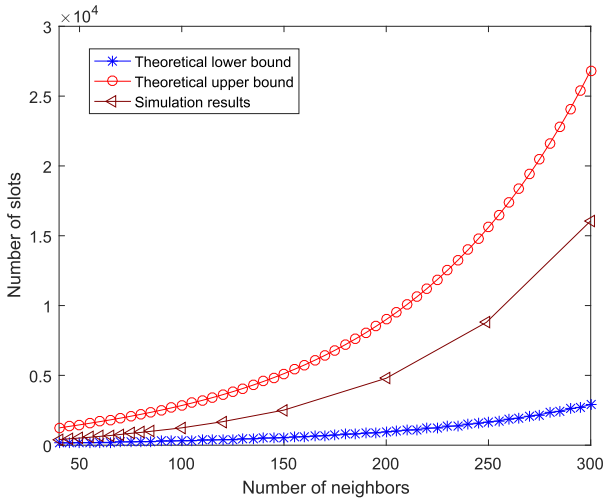

FIGURE 13. The time of complete neighbor discovery using RS algorithm.

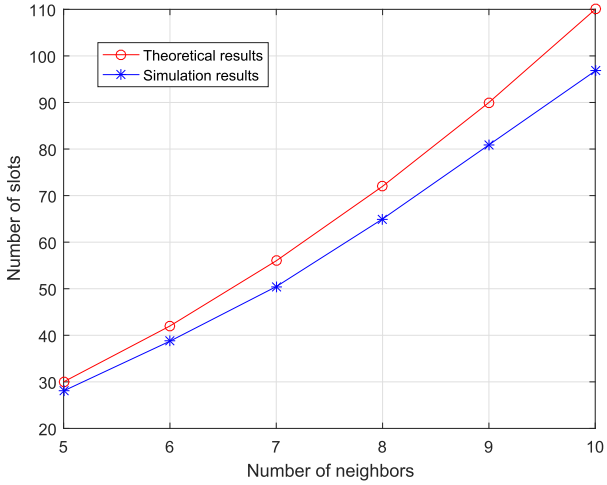

FIGURE 14. The time of neighbor discovery using RS algorithm when $N \leq B$.

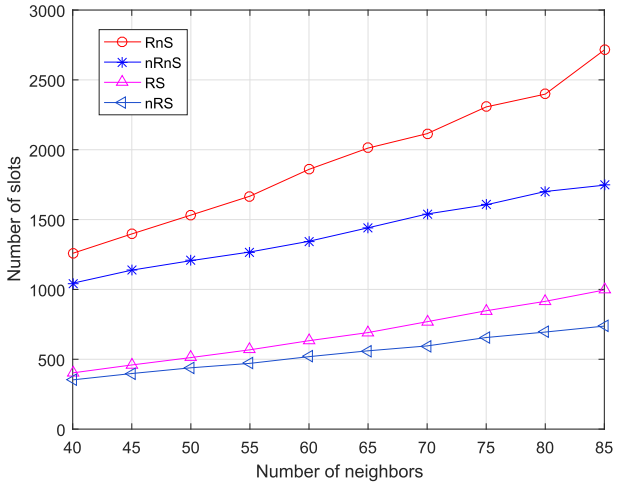

FIGURE 15. Comparison of four neighbor discovery algorithms.

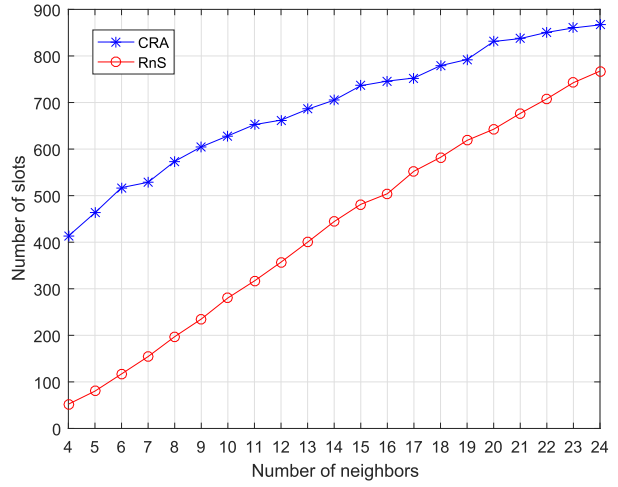

FIGURE 16. Comparison of RnS algorithm and CRA algorithm.

have similar results if neighbor numbers are not large enough compared with the beam number. Note that the theoretical curve is slightly lower than the simulation curve, which is due to the fact that we obtain a fixed expression of the discovery probability P_{dis}. However, the actual P_{dis} is changing in the process of neighbor discovery.

D. RS ALGORITHM

Fig. 13 shows the upper and lower bounds of RS algorithm, where the beam number is 10 and the neighbor numbers range from 40 to 300. The results show that the practical neighbor discovery time is in the middle part between the theoretical upper and lower bounds.

Fig. 14 is the verification of RS algorithm when $N \leq B$. The beam number is 10 and the neighbor numbers range from 5 to 10. It is shown that the theoretical curve is on the upper side of the simulation curve, which is reasonable since there may be more than one neighbor in a beam.

E. nRS ALGORITHM

Since the theoretical analysis of nRS algorithm is too complicated, we only give the simulation results here. According to the previous analysis, different accuracy of radar leads to different choices of neighbor discovery algorithms. Combining the four neighbor discovery algorithms, Fig. 15 plots the time these algorithms take to complete neighbor discovery.

In Fig. 15, the four algorithms can be divided into two categories according to one factor, namely, whether or not the nodes apply stop-discovery mechanism. Then each category can be classified into two sub-categories according to whether or not the non-response mechanism is applied. We discover that when the stop-discovery mechanism is applied, the time to complete neighbor discovery is significantly reduced. When the non-response mechanism is further applied, the time for neighbor discovery reveals a slight decline. This phenomenon shows that both the stop-discovery mechanism and the non-response mechanism can speed up neighbor discovery process. However, the effect of the stop-discovery

mechanism is more significant for accelerating neighbor discovery compared with the non-response mechanism.

Fig. 16 compares the discovery time of a traditional neighbor discovery algorithm called completely random algorithm (CRA) [6] and RnS algorithm. When the number of neighbors is less than the number of beams, RnS algorithm has its advantage of selecting non-empty beams. When the number of neighbors is large, almost every beam has neighbors, hence the advantage of RnS algorithm becomes smaller. Finally, when every beam has neighbors, the performance of these two algorithms is the same.

VI. CONCLUSION

This paper proposed the radar assisted fast neighbor discovery algorithms for wireless ad hoc networks. According to the feedback mechanism and the accuracy of the prior information provided by radar, four neighbor discovery algorithms are proposed in this paper. The performance of the neighbor discovery algorithms is analyzed and simulated. It is verified that the time consumption of neighbor discovery with the prior information of radar decreases significantly.

APPENDIX A
LEMMA 1

Lemma 1: The expectation of the number of 0-node beams is

$$E_0 = \begin{cases} \sum_{k=B-N}^{B-1} kP(k,B,N,0), & N < B, \\ \sum_{k=0}^{B-1} kP(k,B,N,0), & N \geq B, \end{cases} \tag{21}$$

where

$$P(k,B,N,0) = \binom{B}{k} E_{B-k}(N)/B^N, \tag{22}$$

$$E_m^0(j) = \begin{cases} m^j - \sum_{l=1}^{m-1} \binom{m}{l} E_{m-l}^0(j), & j \geq m, \\ 0, & j < m \text{ or } m = 1. \end{cases} \tag{23}$$

Proof: With N neighbors and B beams, we define $P(k,B,N,i)$ as the probability that there are k beams consisting i neighbors. Then we have

$$E_i = \sum_k k \cdot P(k,B,N,i), \tag{24}$$

where E_i is the expectation of the number of beams consisting i neighbors. Define $E_m^i(j)$ as the number of situations that j neighbors are placed into m beams without the beams consisting i neighbors. Then we have

$$P(k,B,N,0) = \underbrace{\binom{B}{k} E_{B-k}^0(N)}_{T_1} / B^N, \tag{25}$$

where $\binom{B}{k}$ is the number of methods to select k vacant beams from the total B beams. $E_{B-k}^0(N)$ is the number of methods to put the N neighbors into the remaining $B-k$ beams without vacant beams. B^N is the number of methods to put N neighbors into B beams. The term T_1 divided by B^N is the probability $P(k,B,N,0)$.

In the derivation of $E_m^0(j)$, when $j \geq m$, m^j is the number of methods to place j neighbors into m beams. $\binom{m}{l}$ is the number of methods to select l vacant beams from the m beams. $E_{m-l}^0(j)$ is the number of methods to put j neighbors into the $m-l$ beams and there are no vacant beams. Hence $\binom{m}{l} E_{m-l}^0(j)$ is the number of methods to put j neighbors into the m beams and there are l vacant beams. $m^j - \sum_{l=1}^{m-1} \binom{m}{l} E_{m-l}^0(j)$ is the number of methods to put j neighbors into m beams and there are no vacant beams, namely, the value of $E_m^0(j)$.

When $j < m$ or $m = 1$, $E_m^0(j) = 0$ because there are no vacant beams in this situation. ■

APPENDIX B
LEMMA 2

Lemma 2: The expectation of the number of 1-node beams is

$$E_1 = \begin{cases} \sum_{k=1}^{B-1} kP(k,B,N,1), & N > B, \\ \sum_{k=1}^{N-2} kP(k,B,N,1) + \dfrac{\binom{B}{N} \cdot N \cdot N!}{B^N}, & N \leq B, \end{cases} \tag{26}$$

where

$$P(k,B,N,1) = \binom{N}{k}\binom{B}{k}(k!)\, E_{B-k}^1(N-k)/B^N. \tag{27}$$

And we have

- *When $j > m$,*

$$E_m^1(j) = m^j - \sum_{l=1}^{m-1} \binom{m}{l}\binom{j}{l} l! E_{m-l}^1(j-l). \tag{28}$$

- *When $j \leq m$,*

$$E_m^1(j) = m^j - \sum_{l=1}^{j-2} \binom{m}{l}\binom{j}{l} l! E_{m-l}^1(j-l) - \binom{m}{j} j!. \tag{29}$$

Proof: When $j > m$, the derivation of $E_m^1(j)$ is similar to the derivation of $E_m^0(j)$. There are three steps to derive $E_m^1(j)$.

- Step 1: Select l beams from the m beams and select l neighbors from the j neighbors. Then place the l neighbors into the l beams. There are $\binom{m}{l}\binom{j}{l} l!$ methods of placements.

- Step 2: Place the remaining $j-l$ neighbors into the $m-l$ beams and there are no 1-node beams. There are $E^1_{m-l}(j-l)$ methods of placements.
- Step 3: $E^1_m(j)$ is the number of methods to place j neighbors into m beams minus $\sum_{l=1}^{m-1}\binom{m}{l}\binom{j}{l}l!E^1_{m-l}(j-l)$.

When $j \le m$, if there are $j-1$ 1-node beams, all the j beams are 1-node beams. In the derivation of $E^1_m(j)$, when $l=j-1$, there are j 1-node beams. Hence we have

$$E^1_m(j) = m^j - \sum_{l=1}^{j-2}\binom{m}{l}\binom{j}{l}l!E^1_{m-l}(j-l) - \binom{m}{j}j!. \quad (30)$$

Notice that $E^1_1(j)=1$ with $j \ge 2$. With the results of $E^1_m(j)$, the $P(k,B,N,1)$ can be derived by two steps.

- Step 1: Select k nodes from the total N nodes and select k beams from the total B beams. Then put the k nodes into the k beams. The number of methods for this operation is $\binom{N}{k}\binom{B}{k}k!$
- Step 2: Put the remaining $N-k$ nodes into the remaining $B-k$ beams and there are no 1-node beams. The number of methods for this operation is $E^1_{B-k}(N-k)$.

The $P(k,B,N,1)$ is derived as (27), where the denominator B^N is the number of methods to put N neighbors into B beams.

With $P(k,B,N,1)$, the E_1 can be derived. Notice that when $N \le B$ and $k=N-1$, the number of 1-node beams is N. Hence the E_1 when $N \le B$ is

$$E_1 = \sum_{k=1}^{N-2} kP(k,B,N,1) + \frac{\binom{B}{N}\cdot N\cdot N!}{B^N}. \quad (31)$$

■

APPENDIX C
LEMMA 3

Lemma 3: The expectation of the number of i-node beams with $i \ge 2$ is

$$E_i = \begin{cases} \sum_{k=1}^{B-1}\frac{k}{B}P(k,B,N,i), & N > iB, \\ \sum_{k=1}^{B-2}\frac{k}{B}P(k,B,N,i) + \frac{\prod_{w=0}^{N-1}\binom{N-iw}{i}}{B^N}, & N = iB, \\ \sum_{k=1}^{\lfloor \frac{N}{i} \rfloor}\frac{k}{B}P(k,B,N,i), & N < iB, \end{cases} \quad (32)$$

where $i > 1$ and

$$P(k,B,N,i) = \binom{B}{k}\binom{N}{ik}\prod_{w=0}^{k-1}\binom{i(k-w)}{i}E^i_{B-k}(N-ik)/B^N. \quad (33)$$

And we have

- *When $j > im$,*

$$E^i_m(j) = m^j - \sum_{l=1}^{m-1}\binom{m}{l}\binom{j}{il}\prod_{h=0}^{l-1}\binom{i(l-h)}{i}E^i_{m-l}(j-il). \quad (34)$$

- *When $j = im$,*

$$E^i_m(j) = m^j - \sum_{l=1}^{m-2}\binom{m}{l}\binom{j}{il}\prod_{h=0}^{l-1}\binom{i(l-h)}{i}E^i_{m-l}(j-il) - \prod_{h=0}^{\frac{j}{i}-1}\binom{j-ih}{i}. \quad (35)$$

- *When $j < im$,*

$$E^i_m(j) = m^j - \sum_{l=1}^{\lfloor \frac{j}{i} \rfloor}\binom{m}{l}\binom{j}{il}\prod_{h=0}^{l-1}\binom{i(l-h)}{i}E^i_{m-l}(j-il). \quad (36)$$

Proof: When analyzing $E^i_m(j)$, three cases need to be considered.

- When $j > im$, there are at most $m-1$ i-node beams.
- When $j = im$, if there are $m-1$ i-node beams, all the m beams are i-node beams.
- When $j < im$, there are at most $\lfloor \frac{j}{i} \rfloor$ i-node beams.

The derivation of $E^i_m(j)$ needs three steps.

- Step 1: Select l beams from the total m beams and select il nodes from the total j nodes.
- Step 2: Divide the il nodes into l bunches. There are i nodes in each bunch. Then put the l bunches of nodes into l beams. There are $\prod_{h=0}^{l-1}\binom{i(l-h)}{i}$ methods for this operation.
- Step 3: Put the remaining $j-il$ nodes into the remaining $m-l$ beams and there are no i-node beams. There are $E^i_{m-l}(j-il)$ methods for this operation.

With $E^i_m(j)$, the $P(k,B,N,i)$ can be derived, which is provided in (33). With $P(k,B,N,i)$, E_i can be derived in (32). Notice that E_i is a piecewise function of N. ■

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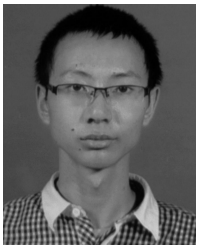

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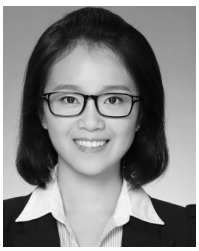

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