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TSIRP: A Temporal Social Interactions-Based Routing Protocol in Opportunistic Mobile Social Networks

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ABSTRACT With the increasing number of smart device users, data transmission between users is becoming more important, and a network architecture called opportunistic mobile social network (OMSN) is gaining attention. However, routing in OMSNs is a challenging problem due to the frequent disconnection between nodes and the absence of paths from the source to the destination. It results in a complex topology and a low packet transmission success rate. Therefore, we propose a novel routing algorithm called the temporal social interactions-based routing protocol (TSIRP) for solving the problem of low network performance due to the improper selection of message relay nodes. First, we focus on the temporal context of social interactions. Specifically, at a certain time of the day, a person has specific people with whom the person usually interacts (e.g., workers usually meet co-workers during working hours; students usually meet their classmates during class). Based on temporal social interactions between nodes, potential forwarding metrics are proposed and calculated for each time of the day to make forwarding decisions. Second, we propose a new scheme to control the message spreading rate, which allows achieving a balance between delivery latency and overhead ratio. In addition, an analytical model is also designed using an absorbing Markov chain to estimate the performance of TSIRP. Simulations were also conducted, and the results indicate that TSIRP can achieve better performance than existing routing protocols in terms of packet delivery ratio, delivery latency, network overhead ratio, and average hop count.

INDEX TERMS Forwarding token, opportunistic mobile social network, potential forwarding metric, spreading rate control value.

I. INTRODUCTION

In recent years, because of the evolution of mobile communication technologies, people can easily access a lot of useful information through smart devices such as smartphones and tablets, which gradually became an integrated part of people's daily life. This strongly promoted the development of opportunistic mobile social networks (OMSNs) [1]–[3], which consist of human-carried mobile devices that exchange data with each other via short-range wireless communications. The major advantage of OMSNs is that it requires a low cost and does not rely on any infrastructure. In the application of opportunistic mobile social networks [4], [5], user experience is the most important. However, the connection between nodes is intermittent due to nodes' mobility in OMSNs, and delivering messages becomes a challenging issue. Therefore, a lot of routing protocols have been proposed to address this issue.

A few routing protocols are based on the flooding technique [6]. However, this approach causes high resource consumption and a high network overhead ratio because messages are spread as much as possible with the flooding strategy. To reduce the overhead ratio, the spray-and-wait routing protocol [7] limits the number of replications, but the selection of relay nodes is not considered, which results in a low packet delivery ratio and long latency.

A lot of studies [8]–[10] have considered relay selection by using information about the nodes, such as the communities

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that nodes belong to, the degree centrality, and betweenness centrality. For instance, in social-based epidemic-based (EPSoc) routing protocol [10], the degree centrality (the number of links to a node) is used. A node with a large value for degree centrality is preferred for a relay node. However, information on communities is difficult to obtain with a large number of nodes, because it requires information about all the nodes in the network, and forwarding messages to central nodes leads to a long delay as well as congested traffic around those nodes.

To find a better forwarding metric for relay selection, several studies have used a history of encounters [11], [12]. For example, in probabilistic routing (PRoPHET) [11] and probabilistic routing algorithm based on transmission capability of nodes (PRoPHET-TC) [12], the delivery predictability metric, which represents how likely a node will be able to deliver a message to the destination, is estimated by using encounter information. Specifically, if a node has already encountered the destination, delivery predictability increases; otherwise, delivery predictability is reduced. However, temporal social interactions are not fully taken into account in those protocols. For instance, workers usually encounter their family members in the morning, and then encounter their co-workers during working hours. In other words, which people a person frequently encounters depends on the time. In those protocols, when people meet their family members in the morning, they have high delivery predictability for their family members. When people are moving from home to the workplace, they still have high delivery predictability for their family members, and the delivery predictability for their co-workers is low because they do not have recent contacts. However, in this case, the delivery predictability for the family members should be low and the delivery predictability for their co-workers should be high. Therefore, the best relay nodes could not be selected. Based on temporal social interactions, a better forwarder can be selected to achieve a high packet delivery ratio and a low delivery delay (latency), which has not been considered in existing studies.

In this paper, to address limitations in the existing routing protocols in relay selection, which causes high overhead, long delays, and a low packet delivery ratio, we propose a novel routing protocol called the temporal social interactions-based routing protocol (TSIRP). Under TSIRP, the movement history of the nodes is analyzed, and temporal social interactions are used to obtain potential forwarding metrics (PFMs), which are then used to select relay nodes. Specifically, the encounter probabilities between nodes are estimated for each time of day based on the encounter information between nodes from the past. Then, by using the encounter probabilities and inter-contact time between nodes, three PFMs are determined, which are the expected delivery delay, the number of time slots to satisfy the meeting probability condition, and the mean value of inter-contact time.

Moreover, under TSIRP, the message spreading rate is controlled based on the state of the message in order to achieve a balance between delivery latency and network overhead. Specifically, when a message has just been generated, it should be quickly spread to increase the number of copies in the network, which leads to a shorter latency. After the message spreads enough, the message spreading rate should be decreased to reduce network overhead. Based on the forwarding token[1] and the residual lifetime of the message, in our work, a metric called the spreading rate control value is proposed to adjust the message spreading rate. Specifically, when the forwarding token is large (i.e., only a few copies are in the network) and the residual lifetime of a message is long, the message is quickly forwarded to neighboring nodes via broadcast without performing relay selection. When the forwarding token is low (i.e., sufficient copies are in the network) and the residual lifetime of the message is short, the node only forwards the message to selected relay nodes, i.e., the message spreading rate is decreased.

Also, using an absorbing Markov chain, we design an analytical model for the proposed routing algorithm, in which the message spreading rate control, the meeting probability, and the forwarding token are studied. The proposed analytical model can estimate the network performance in terms of the delivery latency and the packet delivery ratio with high accuracy.

To evaluate the performance of TSIRP, we compared it with other routing protocols. The simulation results indicate that our routing protocol can outperform other protocols in terms of latency, packet delivery ratio, network overhead ratio, and average hop count.

In summary, the main contributions of this paper are as follows.

- First, we propose three temporal social interaction-based forwarding metrics (i.e., the mean value of inter-contact time, the expected delivery delay, and the number of time slots to satisfy the meeting probability condition) in order to select better relay nodes.
- Second, we propose a scheme to control the message spreading rate in order to achieve a balance between delivery latency and network overhead. The message spreading rate control can reduce latency and the overhead ratio. Based on the residual lifetime of messages and the forwarding token of the messages, a spreading rate control value is calculated to control the message spreading rate.
- Third, we propose an analytical model to estimate the network performance of the routing algorithm using an absorbing Markov chain.
- Fourth, various experiments are conducted to validate the proposed routing protocol using a real road map and realistic human mobility. Network performance is analyzed in terms of packet delivery ratio, delivery latency,

[1]To reduce the network overhead ratio, a value, called forwarding token [7], is assigned to each generated message. When a node forwards a message to a relay node, it also hands over a half of the forwarding token to the relay node and keeps a half of the forwarding token for itself. If the forwarding token value equals one, the node stops forwarding the message and waits until meeting the destination.

overhead ratio, and average hop count. The simulation results indicate that TSIRP can outperform existing routing protocols.

The rest of this paper is organized as follows. First, Section II presents the related work. Then, Section III describes the proposed routing protocol in more detail. The analytical model is presented in Section IV. Then, the simulation results from the proposed routing protocol are evaluated in Section V. Finally, in Section VI, we conclude this paper.

II. RELATED WORK

In this section, we briefly describe the existing routing protocols in opportunistic mobile social networks (OMSNs) and compare them with our work.

OMSNs [1]–[3] are defined as networks that include mobile nodes. The mobile nodes exchange data with each other via short-range wireless communications when they come into contact. The communication takes place on the establishment of opportunistic contacts between mobile nodes. Therefore, human social relationships have a great effect on the forwarding messages. OMSNs do not require any additional infrastructure. The connection between nodes in OMSNs is intermittent and the end-to-end paths for message exchange may not exist. Therefore, delivering messages to the destinations is challenging in OMSNs.

In earlier work, several routing protocols were based on the flooding technique [6]. Under those routing protocols, messages are spread as much as possible in the network. Nodes constantly replicate messages for newly discovered contacts that have not already processed a copy of the messages, which leads to a high overhead ratio. To reduce the overhead ratio, some studies limit flooding of a message to a certain number of replications [7], [13]. However, since the selection of relay nodes was not considered, it is possible to replicate for nodes that have no interaction with the destination. Therefore, network performance may be degraded in terms of packet delivery ratio and latency. In order to address this problem, our routing protocol not only limits the number of replications but also performs relay selection to find better nodes for relaying packets.

Recently, a lot of relay selection schemes have been studied [14]–[20]. For instance, the spray-and-focus routing protocol [14] modifies the spray-and-wait routing protocol [7]. A message is forwarded to a certain number of nodes in the spray phase, and in the focus phase, last-encounter timers with the destination are used as metrics to select relay nodes. Nodes with lower values in the last-encounter timer are preferred as relay nodes. In an adaptive spray-and-wait routing algorithm based on capability of node (ASNW) [15], this study attempted to improve the spray-and-wait routing protocol by considering a node's own performance. Specifically, during the spray phase, a relay node with a high capability receives many copies of a message. In the wait phase, a node with a higher capability is selected to forward the message. Several studies have been proposed based on the physical positions of nodes [16], [17]. The distances between nodes are used to select a node for forwarding. A node with a shorter distance to the destination is preferred as a relay node. However, the metrics used in those routing protocols (e.g., the last-encounter timer with the destination, the capabilities of nodes, and the distances between nodes) do not much affect the probability that a node will encounter the destination in the future. Therefore, the possibility of delivering messages to the destination is low. Unlike those studies, our work analyzes the social interactions between nodes to estimate the probability that a node will encounter the destination in the future. Then, that probability is used to select relay nodes.

A number of routing protocols have been inspired by the centrality measurements of the social network and communities of people [8]–[10], [18], [23], [24]. In [8], nodes are separated into communities, and a message is forwarded to nodes that have the same community as the destination. In social-based epidemic-based routing protocol (Epsoc) [10], centrality measurements of the social network (e.g., degree centrality and betweenness centrality) are used as metrics to select relay nodes. Messages are forwarded towards the node with higher centrality values. The bubble rap routing protocol (BUBBLE Rap) [9] considers both betweenness centrality (which measures the number of times a node lies on the shortest path between two other nodes) and the community for relay selection. Under bubble rap, each node maintains two betweenness centrality values. The betweenness centrality of a node, which is calculated with all nodes in the network, is used as the global ranking, and the betweenness centrality of the node, which is calculated with nodes in its community, is used as the local ranking. A message is forwarded to nodes with better ranking values. The global ranking is used until a node in the destination's community is found. Then, the local ranking is used. Under the social energy–based routing (SEBAR) routing protocol [18], a social metric based on node encounters (called social energy) is presented. A node that frequently encounters other nodes has higher social energy. The forwarding strategy is similar to the bubble rap routing protocol [9]. The social energy of a node in the network and the social energy of a node in its community are used as the global ranking and the local ranking, respectively. In message routing using multi-layer social networks in opportunistic communications (ML-SOR) [23], the social network is detected from the history of encounters between nodes. In the detected social network (DSN), the link between two nodes exists if they encounter each other. The degree centrality of nodes is obtained on the DSN graph. Moreover, the friendship information between nodes on online social networking websites, such as Facebook, LinkedIn is used to calculate tie strength between two nodes. The tie strength between two nodes is the number of online social networks where they are friends. The interest of nodes is also collected and used to form an interest network where there is a link between two nodes if they have at least one common interest. The number of common neighbors over the total neighbor of two nodes in the interest network is considered as the link predictor between them. Based on the degree centrality, the tie strength, and the link predictor, a metric is proposed for relay selection. A node with a higher value of relay selection metric is preferred to become a relay node. In exploiting online and offline activity-based metrics for opportunistic forwarding (EOOF) [24], the history of encounters is also used to obtain DSN graphs for each time slot of a day, in which the weight of links is the number of contacts between nodes in a time slot. In addition, they define a dynamic online social network (DOSN), in which there is a link between two nodes if they are online friends (e.g., Facebook friends) and the weight between two nodes is calculated based on common interest and the number of encounters between them in a time slot. Two nodes with a lot of common interest and a larger number of encounters have a stronger weight. From the DSN graph and DOSN graph, weighted degree centralities (the weighted degree is the sum of weights to the node's direct connections) are obtained for nodes. Based on those weighted degree centralities, the temporal fused degree centrality is proposed. A node with high values of weighted degree centralities has a high value of the temporal fused degree centrality. The forwarding strategy is based on the bubble rap routing protocol [9] with the temporal fused degree centrality, which is used as the ranking of nodes. Under those protocols, to determine network communities, a node needs to know information about all the other nodes in the network. That is difficult. The friendship information on online social networking websites and the interest of nodes are helpful information for routing. However, in a large network size such as urban sensing networks, it is also hard to require a node to know the interest of all other nodes and share their personal information with other nodes. Moreover, when the centrality measurements such as degree centrality are used for relay selection, central nodes are preferred to be selected as relay nodes. It may be effective when the network traffic is low. However, for the high network traffic, forwarding a lot of messages to central nodes leads to long delays and congested traffic around those nodes. To resolve those issues, TSIRP focuses on social interactions between nodes with the destination, instead of using centrality measurements. Specifically, a node, which has high social interaction with the destination, is preferred to become a relay node. In other words, a node that has more chances to meet the destination is selected, instead of selecting central nodes that have more chances to meet all other nodes in the network (i.e., a relay node is more specifically chosen in TSIRP). That can avoid long delays and congested traffic around central nodes.

Several routing protocols were proposed that explore the history of encounters between nodes [11], [12], [19]–[22]. In [11], [12] those protocols, delivery predictability, which represents how likely a node will be able to deliver a message to the destination, is estimated based on a history of encounters. A node replicates messages if the encountered node has a greater value for delivery predictability to the destination. In [19]–[22], they also use the delivery predictability for relay selection. Moreover, the number of replications is controlled and limited to reduce the overhead ratio. In [25], a community-based opportunistic routing protocol (CORP) is proposed. The network communities are determined and a communication probability value between two communities is defined. A community has a high community probability with another community if nodes in the community frequently meet nodes in the other community. Then, if the source and the destination are in the same community, a node with high delivery predictability and high energy is selected as a relay; otherwise, nodes in the destination's community and nodes in the communities, which have higher community probabilities with the destination community, are selected. However, updating the community probability is difficult since a node needs to know the encounter information of all other nodes. In those routing protocols, the sociality is based on social interactions between nodes without considering the effect of time. For example, if two nodes frequently encounter in the morning, they are considered a close relationship. Therefore, they will be selected as the relay nodes of messages sent to their close friend. However, they rarely encounter in the afternoon. If a message is sent in the afternoon, it will be delayed to morning on the next day. To address this problem, in our routing protocol, the temporal context of social interaction is taken into account. The social relationship between nodes is considered for each certain time of the day. For instance, if two nodes frequently encounter in the morning and rarely encounter in the afternoon, they will have a close relationship in the morning and a weak relationship in the afternoon. Moreover, controlling the message spreading rate, which allows reducing latency and overhead ratio, is not considered in those studies. In our work, the rate for spreading messages is controlled based on the state of the messages. A message is quickly spread when it has just been generated, and if the message is spread wide enough, the message spreading rate is reduced to decrease the overhead.

In this work, the system model for a city-wide network is considered. There are some available real data such as [26]. However, these data are collected for the people in certain events such as a workshop and a conference. That could not reflect the relatively long-term interactions between people in a city-wide network. In [27], the data of 35 students (15 students participate and they detected also 20 external devices) are gathered for 7 days on the campus of the University of Calabria. Please note that, in our model, the people in the network should come from various organizations (e.g, companies, universities, hospitals) to reflect the real contexts. Hence, the data [27], in which participants are only some students of a university, could not reflect the real contexts for a city-wide network. Moreover, the available real data is usually collected in a short time that is not enough to detect the temporal social interaction of people. Therefore, we use a synthetic mobility model for generating movements of nodes.

A comparison of routing protocols is summarized in Table 1.

TABLE 1. Comparison of routing protocols.

Routing protocols	No. of replications	Relay selection based on	Controlling the message spreading rate
Epidemic [6]	Not limited	Randomness	No
Spray-and-Wait [7], Home spread [13]	Limited	Randomness	No
Spray-and-Focus [14]	Limited	Last-encounter timer	No
ASNW [15]	Not limited	Node's capability	No
PEGRS [16], GLARP [17]	Not limited	Physical position of nodes	No
EFREP [8]	Not limited	Node's community	No
Epsoc [10]	Not limited	Node's centrality	No
BUBBLE Rap [9]	Not limited	Node's community and centrality	No
SEBAR [18]	Not limited	No. of encounters	No
PRoPHET [11], PRATC [12]	Not limited	Delivery predictability obtained by using previous encounter information	No
ADRP [19], PSNW [20], PRoPHET-L [21], ESCW [22]	Limited	Delivery predictability obtained by using previous encounter information	No
ML-SOR [23], EOOF [24]	Not Limited	History of node's encounters, Friendship information on online social network, and node's interest	No
CROP [25]	Not Limited	Node's community, the community probability, delivery predictability obtained by using previous encounter information, and node's energy	No
TSIRP	Limited	Potential forwarding metrics obtained by considering movement history and temporal social interactions	Yes

III. THE PROPOSED ALGORITHM

In this work, a city-wide network is considered. Specifically, N nodes move in a city area and communicate with each other via wireless interfaces (e.g., Bluetooth 5.0) when they come within the communication range of each other. The buffer size and bandwidth of all nodes are assumed to be the same. The movement history of nodes is collected over D days. In the movement history, the positions of the nodes are recorded every 30 seconds. Each day is divided into 36 time slots. Two nodes are considered as encountering each other when they are within transmission range for 30 seconds. Each packet includes three attributes: source, destination, time to live (TTL). TTL is a time value in seconds that limits the lifetime of the packet in the network. After TTL expires, the packet is dropped.

First, we describe the potential forwarding metrics, and how to calculate them. Then, the spreading rate control value is discussed. Finally, the TSIRP forwarding scheme is described.

A. POTENTIAL FORWARDING METRIC

In this work, movement history is analyzed to obtain potential forwarding metrics (PFMs), which are used for relay selection. A node with a lower PFM value is preferred as a relay node. Based on the inter-contact time, the expected delivery delay, and the meeting probability condition, three PFMs are proposed.

1) THE MEAN VALUE OF INTER-CONTACT TIME ($\overline{ICT}$)

The inter-contact time (ICT) represents the elapsed time between two successive contacts for a given pair of nodes. Let u and v denote two arbitrary nodes in the network. The mean value of ICTs between node u and node v is denoted $\overline{ICT}_{u,v}$. Let η be the number of ICT samples between node u and node v obtained from the movement history. For example, suppose that in the movement history, node u and node v encounter three times. We will obtain two ICT samples (i.e. $\eta = 2$). The elapsed time between the first encounter and the second encounter is the first sample of ICT. The elapsed time between the second encounter and the third encounter is the second sample of ICT. The i^{th} ICT sample is denoted $ICT^i_{u,v}$. $\overline{ICT}_{u,v}$ is calculated as follows:

$$\overline{ICT}_{u,v} = \frac{\sum_{i=1}^{\eta} ICT^i_{u,v}}{\eta} \tag{1}$$

A low value of $\overline{ICT}_{u,v}$ means that node u frequently meets node v. Therefore, the node that has the lower mean value for inter-contact time with the destination is preferred as a relay node. $\overline{ICT}_{u,v}$ is used as a potential forwarding metric.

2) THE EXPECTED DELIVERY DELAY (ED)

Note that the movement history of nodes is collected over D days, and one day in the movement history is divided into 36 time slots. To determine whether two nodes encounter each other or not in a time slot, the encounter state is used. Let $e^{u,v}_{d,i}$

denote the encounter state between node u and node v in time slot i of day d, such that $e_{d,i}^{u,v}$ equals 1 if node u encounters node v in time slot i of day d; otherwise, $e_{d,i}^{u,v}$ is zero.

We define $P_i^{u,v}$ as the probability that node u meets node v in time slot i of a new day. Based on the social interactions between two people at a certain time, $P_i^{u,v}$ is estimated as follows:

$$P_i^{u,v} = \frac{1}{D}\sum_{d=1}^{D} e_{d,i}^{u,v} \tag{2}$$

Equation (2) indicates that if node u has frequently encountered node v in time slot i in the past, $P_i^{u,v}$ will have a large value (i.e., node u has a high possibility to encounter node v in time slot i in the future).

In time slot, t, the expected delivery delay between node u and node v within k time slots is denoted as $ED_t^{u,v}$. $ED_t^{u,v}$ is the estimated latency to deliver packets from node u to node v. In other words, $ED_t^{u,v}$ is the expected duration from the time slot t to the time when node u encounters node v. This value is obtained as follows:

$$ED_t^{u,v} = \sum_{i=t+1}^{t+k}((i-t)\times P_i^{u,v}\times\prod_{j=t+1}^{i-1}(1-P_j^{u,v})) \tag{3}$$

where $(i-t)$ is the delivery latency if node u and node v encounter at time slot i. $P_i^{u,v}$ is the estimated probability that node u encounters node v at time slot i. $\prod_{j=t+1}^{i-1}(1-P_j^{u,v})$ is the estimated probability that node u and node v have not encountered (and hence have not delivered packets) before time slot i. Based on those two probabilities, the probability that node u delivers a packet to node v in time slot i, and has not delivered the packet to node v in previous time slots (i.e., time slot $t+1$ to time slot $i-1$) is calculated, and then $ED_t^{u,v}$ is obtained. The expected delivery delay within k time slots of the two nodes is used as a potential forwarding metric. A node with a lower expected delivery delay to the destination is the better forwarder

3) THE NUMBER OF TIME SLOTS TO SATISFY THE MEETING PROBABILITY CONDITION ($\hat{x}$)

In current time slot, t, $P^{u,v}(x)$ denotes the probability that node u meets node v during x time slots, $P^{u,v}(x)$ is calculated as:

$$P^{u,v}(x) = 1-\prod_{i=t}^{t+x}(1-P_i^{u,v}) \tag{4}$$

Given a required meeting probability, θ, we find the minimum value of x that satisfies the condition $P^{u,v}(x) \geq \theta$. Let $\hat{x}$ be the minimum value of x that satisfies the meeting probability condition:

$$\hat{x} = \{\min(x)|P^{u,v}(x) \geq \theta\} \tag{5}$$

$\hat{x}$ is used as a potential forwarding metric. A lower value for $\hat{x}$ means the required meeting probability between the two nodes can be obtained in a shorter time. Thus, a node is selected as the relay node if it has a lower value of $\hat{x}$ with the destination.

B. SPREADING RATE CONTROL VALUE

In this subsection, the forwarding token for packets is discussed first. Then, we propose a spreading rate control value to control the message spreading rate.

In TSIRP, the number of replications is limited by using a forwarding token. When a node generates a packet, it also assigns a forwarding token for the packet in a similar way to spray-and-wait [7]. The initial value of the forwarding token is C. When a node replicates a packet, it also appends half of the current token value to the copy of the packet. When the token value is less than or equal to 1, the node stops spreading the packet and waits until meeting the destination.

Now, we describe the proposed spreading rate control value based on the forwarding token value and the residual lifetime of a packet. Suppose that node u wants to send packet p to node v. The current forwarding token value for packet p at node u is denoted c_p^u. When node u tries to replicate packet p to its neighbor, c_p^u is checked. If $c_p^u \leq 1$, node u stops spreading the packet and waits until meeting the destination; otherwise, relay selection is performed and the spreading rate control value is used.

Let t_p be the residual lifetime of packet p. The spreading rate control value for packet p of node u is denoted as SC_p^u. SC_p^u is calculated as follows:

$$SC_p^u(c_p^u, t_p) = e^{-[\alpha\times\frac{c_p^u}{C}+(1-\alpha)\times(\frac{t_p}{TTL})]} \tag{6}$$

where a tunable parameter, $\alpha \in [0, 1]$, modifies the balance between the residual lifetime and the forwarding token. From Equation (6), we see that $SC_p^u \in [1/e, 1)$ and higher values of t_p and c_p^u lead to a lower value for SC_p^u.

The spreading rate control value is used in the forwarding scheme to control the message spreading rate. Specifically, a low value of SC_p^u means that packet p has just been generated (i.e., the residual lifetime of the packet is long), and the token value for forwarding it is large. Therefore, packet p should quickly spread through the network. When the packet is spread wide enough (i.e., SC_p^u is large), the rate for spreading the packet should be reduced to decrease the overhead.

Let ρ ($\rho \in [1/e, 1]$) denote the threshold value for the spreading rate control. When $1/e \leq SC_p^u \leq \rho$, node u replicates packet p to all neighbor nodes without considering any metrics. That increases the rate for spreading packet p. If $SC_p^u > \rho$, relay nodes are selected and node u only replicates packet p to those relay nodes, which reduces the rate for spreading packet p.

C. FORWARDING SCHEME

The proposed forwarding scheme based on PFMs and the spreading rate control value is presented in Algorithm 1. The notations in the algorithm are defined in Table 2.

Algorithm 1 The Forwarding Scheme

1: Node u wants to send packet p to node v

Input: $\mathbb{S}_u^{NB} = \{n_i | 1 \leq i \leq n_u^{NB}\}$, SC_p^u, ρ, $PFM_{u,v}$ $\overline{C_D(u)}$, t_p, d_t, c_p^u

Output: select relay nodes, forward packet p to relay nodes, and update token value for forwarding

2: Initialize $i = 1$;

3: **while** $i \leq n_u^{NB}$ and $c_p^u > 1$ **do**

4:   **if** $\frac{1}{e} \leq SC_p^u \leq \rho$ **then**

5:     Node n_i is selected as a relay node for packet p

6:   **else if** $PFM_{n_i,v} < PFM_{u,v}$ **then**

7:     Node n_i is selected as a relay node for packet p

8:   **else if** $TTL - t_p > d_t$ and $\overline{C_D(n_i)} > \overline{C_D(u)}$ **then**

9:     Node n_i is selected as a relay node for packet p

10:   **end if**

11:   **if** node n_i is selected as a relay node for packet p **then**

12:     Node u forwards a copy of packet p to node n_i

13:     $c_p^{n_i} = \frac{c_p^u}{2}$

14:     $c_p^u = \frac{c_p^u}{2}$

15:   **end if**

16:   $i = i + 1$

17: **end while**

TABLE 2. Definitions of notations in algorithm 1.

n_u^{NB}	The number of neighbors of node u
$\mathbb{S}_u^{NB} = \{n_i \| 1 \leq i \leq n_u^{NB}\}$	The neighbor set of node u after sorting in increasing order of values for PFMs between the neighbor nodes and the destination
SC_p^u	The spreading rate control value for packet p of node u
$\rho \in [1/e, 1]$	The threshold value for the spreading rate control
$PFM_{u,v}$	The potential forwarding metric between node u and node v
$\overline{C_D(u)}$	The mean value of degree centrality for node u
t_p	The residual lifetime of packet p
d_t	The time threshold for determining a long-delayed packet
c_p^u	The forwarding token for packet p of node u

Suppose that a person (node u) wants to share a photo (packet p) with a friend (node v) by interfacing with an application. The routing for the message is processed in the network layer. Specifically, the neighbor list of node u is checked. If the destination is in its neighbor list, the packet is delivered to the destination. If not, the forwarding scheme is executed.

As described in Table 2, the neighbors of node u are sorted in increasing order of PFM values between the neighbor nodes and the destination. Recall that a node with a lower PFM value is considered better for relaying packet p. Therefore, packet p should be forwarded to the node with a lower PFM value. For this, relay selection is performed with each neighbor n_i, where i is from 1 to n_u^{NB}.

For each node n_i, the packet forwarding token of node u, c_p^u, is checked in line 3. If $c_p^u \leq 1$, node u stops forwarding and waits until meeting the destination; otherwise, relay selection begins and the spreading rate control value (SC_p^u) is checked in line 4. If SC_p^u is a low value (i.e., $1/e \leq SC_p^u \leq \rho$), in line 5, node u selects node n_i as the relay node for packet p without considering any other metrics. With a high SC_p^u value (i.e., $SC_p^u > \rho$), the relay node is selected based on PFMs.

PFM values are compared in line 6. In particular, if node n_i has a lower PFM with the destination than node u (i.e., $PFM_{n_i,v} < PFM_{u,v}$), node n_i is selected as the relay node for packet p in line 7.

In our forwarding scheme, if a packet cannot be delivered to the destination for a long time, degree centrality is also used to create more chances to deliver the packet to the destination. Specifically, the residual lifetime of packet p is taken into account in line 8. $TTL - t_p > d_t$ indicates that packet p is experiencing a long delay. For such packets, degree centrality, which is the number of links to a node, is used. Degree centralities of nodes are obtained for each day in the movement history, and then, the mean value of degree centrality is calculated. A node with a higher mean value for degree centrality shows that it has many neighbors and more chances to meet better relay nodes. Therefore, if $\overline{C_D(n_i)} > \overline{C_D(u)}$, node u will select node n_i as the relay node for packet p.

Finally, if node n_i is selected as the relay node for packet p, in lines 12-14, node u will forward a copy of packet p to node n_i, and a half of the forwarding token value is assigned to the copy of packet p at node n_i.

IV. THE ANALYTICAL MODEL

In the analytical model, it is assumed that N nodes are in the network, each with a finite transmission range, and moving in a closed area. Two nodes encounter when they come within the transmission range of each other, at which point they can exchange packets. It is assumed that each node has enough buffer to store all packets that it has received. A packet has the time to live (TTL) and it is dropped if TTL expires.

To design a feasible mathematical model, yet obtain an analytical insight into the proposed routing protocol, the behavior of TSIRP is slightly simplified. Specifically, the meeting probability is used instead of using PFMs and the degree centrality in case of long delay packets is not considered. For example, node u wants to send packet p to node v. Let n_i be a neighbor of node u. After checking the forwarding token value (i.e, $c_p^u > 1$) and the spreading rate control value (i.e., $SC_p^u > \rho$), if node n_i has a higher meeting probability with the destination than u, it will be selected as the relay node for packet p.

In order to obtain the analytical model, first, the network state is discussed. Then, the state transition is described. Finally, an absorbing Markov chain is used to obtain the network performance. The meaning of notations, which are used in the analytical model, are shown in Table 3.

A. NETWORK STATE SPACE

Let us focus on a single packet p from source node u to destination v. A bit is used to represent the state that a node

TABLE 3. Important notation in section 4.

$S=\{0,1\}$	The node state space
Ω	The network state space
p_i^C	The probability that $c_p^i > 1$
$p_t^R(i,j)$	The probability that node j receives packet p from node i at time slot t
Ω_X	The set of potential next states with current state X
$\mathbb{R}_X$	The set of relay nodes in state X
$p_t^R(j)$	The probability that node j receives packet p at time slot t
$p(X,Y)_t$	The probability that the network state switches from X to Y at time slot t
$\mathbb{S}^{TR}$	The set of transient states
n^{TR}	The number of transient states
$\mathbb{S}^{AB}$	The set of absorbing states
n^{AB}	The number of absorbing states
$\mathbf{Q}_i^t$	The transition matrix between transient states at time slot t with $t_p = TTL - i$
$\mathbb{Q}^t$	The set of all transition matrix $\mathbf{Q}_i^t$ at time slot t
$\mathbf{R}_i^t$	The transition matrix from transient states to absorbing states at time slot t with $t_p = TTL - i$
$\mathbb{R}^t$	The set of all transition matrix $\mathbf{R}_i^t$ at time slot t
$\mathbf{N}^t$	The fundamental matrix for packets, which is generated at time slot t
$\mathbf{B}^t$	The absorbing probabilities matrix for packets, which are generated at time slot t
$p_t^I(Z)$	The probability that the initial network state is state Z
$p_d(X^*)$	The probability that the final network state is absorbing state X^*
p_d	The packet delivery ratio
δ_{i,X^*}^t	The expected number of steps until absorbing state X^*, when starting at state i
τ	The duration of a time slot
ED	The delivery delay

carries the packet or not. If the node carries the packet, the state bit is set to 1; otherwise, the state bit is set to 0. Let $S = \{0, 1\}$ be the node state space. For N nodes in the network, the space of network state is a set of N - element vectors, possibly restricted by a number of constraints. Let $\Omega \subseteq S^N$ denote the network state space.

$$\Omega = \{X|X = (x_1, x_2, x_3, \ldots, x_N)\}, \quad x_i \in S \tag{7}$$

where x_i represent the state of node i in the network.

The number of replications is limited by forwarding token value C. Therefore, the network state space has a constraint as follow:

$$\sum_{i=1 (i \neq v)}^{N} x_i \leq C \tag{8}$$

B. STATE TRANSITION

We assume that the network is in a state during a time slot, and the network state transition is considered when the time slot changes. Specifically, the state transition happens if the packet is forwarded to new nodes in the next time slot. An example of state transitions for six nodes in the network with the initial forwarding token $C = 4$ is shown in Fig. 1. The network state switches from state X_1 to state X_2 when node 2 forwards the packet to node 5, and from state X_2 to X_3 when the packet is forwarded to node 4. In TSIRP, the state transition from X_3 to state X_1 is impossible.

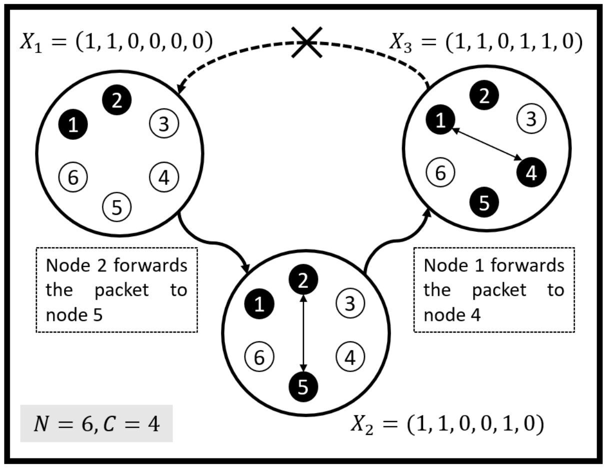

FIGURE 1. Example of state transitions for six nodes with initial forwarding token $C = 4$.

To study state transition, first, the probability that a relay node i forwards packet p to node j is discussed. Then, the transition between network states is presented.

Now, it is assumed that there is a contact between relay node i and node j. In the case that node j is the destination, packet p is delivered to node j. Otherwise, the forwarding scheme is taken into account. Specifically, the forwarding token value is checked. Recall that c_p^i is the forwarding token for packet p of node i. For node i to transfer packet p to node j, the first condition is $c_p^i > 1$. The number of relay nodes in state X is defined as n_X^R ($n_X^R = \sum_{i=1}^N x_i$). Let p_i^C denote the probability that $c_p^i > 1$, which is approximated one if n_X^R is lower than $\frac{C}{2}$. Otherwise, p_i^C is approximated as:

$$p_i^C = \frac{C - n_X^R}{n_X^R} \tag{9}$$

In the case that $c_p^i > 1$, let $p_t^R(i,j)$ be the probability that node j receives packet p from node i at current time slot t. Then, $p_t^R(i,j)$ is obtained as follow:

$$p_t^R(i,j) = \begin{cases} P_t^{i,j}, & \text{if } j = v \\ p_i^C \times P_t^{i,j}, & \text{if } j \neq v \text{ and} \\ & (\frac{1}{e} \leq SC_p^i \leq \rho \text{ or } P_t^{j,v} > P_t^{i,v}) \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where if node j is the destination (i.e., $j = v$), $p_t^R(i,j)$ is equal to the probability that node i encounters node j at time slot t ($P_t^{i,j}$). In the case of $j \neq v$, the spreading rate control value and the meeting probability are checked. Specifically, if $\frac{1}{e} \leq SC_p^i \leq \rho$ or $P_t^{j,v} > P_t^{i,v}$, $P_t^{i,j}$ is calculated based on p_i^C and $P_t^{i,j}$. Otherwise, the packet is not be forwarded.

Now, we consider the transition between network states. Let $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n)$ be two network states in Ω, and also let X be the current network state. For Y to be a potential next state from current state X, y_i should be equal to 1 if x_i is 1. Let Ω_X be the set of potential next states from current state X. We assume that $Y \in \Omega_X$. $\mathbb{S}^D_{X,Y}$ defines a set of nodes, which have the different state between X and Y. Specifically, $x_j = 0$ and $y_j = 1, \forall j \in \mathbb{S}^D_{X,Y}$. Every contact between a relay node i ($x_i = 1$) and node $j \in \mathbb{S}^D_{X,Y}$ offers the chance for transiting from current state X to state Y. Let $\mathbb{R}_X$ be the set of relay nodes in state X and $p^R_t(j)$ be the probability that node j receives packet p at time slot t. $p^R_t(j)$ is calculated as:

$$p^R_t(j) = 1 - \prod_{i \in \mathbb{R}_X} (1 - p^R_t(i, j)) \tag{11}$$

where the probability that node j has not received the packet from any nodes in $\mathbb{R}_X$ is computed. Then, the $p^R_t(j)$ could be obtained as Eq. (11).

If the packet is transferred to all nodes in $\mathbb{S}^D_{X,Y}$ and was not transferred to any other nodes, then the network transition from state X to state Y happens. Let $\mathbb{R}_Y$ be the set of relay nodes in state Y. The probability that the network state switches from X to Y at current time slot t is defined as $p(X, Y)_t$, which is obtained as follow:

$$p(X, Y)_t = \begin{cases} \prod_{i \in \mathbb{S}^D_{X,Y}} p^R_t(i) \\ \times \prod_{j=1 (j \notin \mathbb{R}_Y)}^{N} (1 - p^R_t(j)), & \text{if } X \neq Y \\ 1 - \sum_{Z \neq X} p(X, Z)_t, & \text{if } X = Y \end{cases} \tag{12}$$

where if $X \neq Y$, the probability that all nodes in $\mathbb{S}^D_{X,Y}$ receive the packet and the probability that all nodes, which are not relay nodes in state Y, do not receive the packet are calculated. Then, $p(X, Y)_t$ is obtained. In the case of $X = Y$, which means that the network state is not be changed, $p(X, Y)_t$ is calculated based on the probability that the state transition does not happen.

C. NETWORK PERFORMANCE

In this subsection, the routing protocol is transformed into an absorbing Markov chain. Then, network performance metrics such as packet delivery ratio and delivery latency in routing are obtained.

An absorbing Markov chain is a Markov chain in which every state can reach an absorbing state after some number of steps. An absorbing state is a state that, once entered, is impossible to leave. States, which are not absorbing states, in an absorbing Markov chain are defined as transient states. To transform the routing protocol into an absorbing Markov chain, a network state is considered as a state in the absorbing Markov chain. From the network state space (Ω), states, in which the destination has not received the packet, are defined as transient states, and states, in which the packet was delivered to the destination, are considered as absorbing states. When the network state is a transient state, it may switch to another transient state or an absorbing state. When the network state is an absorbing state, further transitions are no longer considered. The transition matrix between transient states and the transition matrix from transient states to absorbing states are obtained from the probability of state transitions. Based on those matrices, the fundamental matrix and the absorption probabilities matrix for the absorbing Markov chain are calculated. Then, network performance is obtained using those matrices.

Specifically, we consider the network state when transferring packet p from source node u to destination v. Any state $X \in \Omega$, with $x_v = 0$ and $x_i = \{0, 1\}, \forall i \neq v$, is considered as the transient state. The set of transient states is denoted as $\mathbb{S}^{TR}$. The desired network state is any $X^* \in \Omega$, with $x_v = 1$ and $x_i = \{0, 1\}, \forall i \neq v$. These states are absorbing states. Let $\mathbb{S}^{AB}$ be the set of absorbing states. n^{TR} and n^{AB} denote the number of transient states and the number of absorbing states, respectively.

Now, the transition matrix between transient states is considered. It is assumed that TTL of packet p is k time slots. Note that t_p is the residual lifetime of packet p, and the spreading rate control value depends on t_p. The value of t_p decreases from k to 0. For each time slot t, a set of matrices $\mathbb{Q}^t = (Q^t_0, Q^t_1, \ldots, Q^t_{k-1})$ is obtained. Where Q^t_i is the transition matrix between transient states at time slot t, with $t_p = TTL - i$. An element $q^t_{n,m}$ in matrix Q^t_i represents the probability that a state transits from transient state n to transient state m at time slot t. The size of matrix Q^t_i is $n^{TR} \times n^{TR}$.

For the transition matrix from transient states to absorbing states, another set of matrices $\mathbb{R}^t = (R^t_0, R^t_1, \ldots, R^t_{k-1})$ is also obtained. R^t_i is a $n^{TR} \times n^{AB}$ matrix, which is the transition matrix from transient states to absorbing states at time slot t with $t_p = TTL - i$. Each element $r^t_{n,m}$ in matrix R^t_i shows the probability that state switches from transient state n to absorbing state m at time slot t.

Now, the fundamental matrix for the absorbing Markov chain can be defined. Let N^t be the fundamental matrix for the packet, which is generated at time slot t and has the $TTL = k$. N^t is calculated as:

$$N^t = I + \sum_{i=t}^{t+k-1} \prod_{j=t}^{i} Q^j_{j-t} \tag{13}$$

where I is the identity matrix. N^t is a $n^{TR} \times n^{TR}$ matrix whose element $n^t_{n,m}$ is the expected number of times the network is in state m, starting from state n, before getting absorbed. Therefore, the sum of a row in matrix N^t is the expected number of steps until absorption, when starting from the respective state at time slot t.

Now, the absorbing probabilities matrix can be obtained. B^t is defined as the absorbing probabilities matrix for packets, which are generated at time slot t. B^t is calculated as:

$$B^t = \frac{1}{k} \sum_{i=t}^{t+k-1} (N^t \times R^i_{i-t}) \tag{14}$$

where each element $b^t_{n,m}$ is the probability of being absorbed in an absorbing state m during k time slots, given that we start at a transient state n.

We assume that the initial network state is one of the state in $\mathbb{S}^{TR}$. When source node u generates packet p at time slot t, the network state is $X = (0, 0, \ldots, x_u = 1, \ldots, 0, 0)$. Let $p^I_t(Z)$ be the probability that the initial network state is state Z ($Z \in \mathbb{S}^{TR}$). In our model, $p^I_t(Z)$ is set to $p(X, Z)_t$, with $t_p = k$.

Let $p_d(X^*)$ denote the probability that the final network state is absorbing state X^*. From the probability that the initial network state is state $X \in \mathbb{S}^{TR}$ and the probability of being absorbed in state X^*, given that the initial state is state X, $p_d(X^*)$ is obtained as:

$$p_d(X^*) = \frac{1}{36}\sum_{t=1}^{36}\sum_{X\in\mathbb{S}^{TR}}(p^I_t(X) \times b^t_{X,X^*}) \tag{15}$$

where $p_d(X^*)$ is the average value of 36 time slots in a day.

Now, the packet delivery ratio of packets from source node u to the destination v is denoted by p_d. $p_d(X^*)$ is calculated for all $X^* \in \mathbb{S}^{AB}$. Then, p_d is the sum of those values.

$$p_d = \sum_{X^*\in\mathbb{S}^{AB}} p_d(X^*) \tag{16}$$

In order to obtain the delivery latency, first, assume that the network ends up absorbing state X^*. Now, there is only one absorbing state in the set of absorbing states (i.e., state X^*). The set of transient states is also updated. Specifically, states that are impossible to switch to X^* are removed. Let $\mathbb{S}^{AB}_{X^*}$ and $\mathbb{S}^{TR}_{X^*}$ denote the set of absorbing states and the set of transient states for this case, respectively. All conditional transition probabilities, given that the process ends up in state X^* are computed to update $p^I_t(X)$. $\mathbb{Q}^t$ and $\mathbb{R}^t$ are also updated based on those probabilities. A new fundamental matrix N^{t*} is obtained for new transition matrices. Let the vector $N^{t*}_i = (n^{t*}_{i,1}, n^{t*}_{i,2}, \ldots, n^{t*}_{i,n^{TR}})$ denote the row i^{th} in matrix N^{t*}. The expected number of steps until absorbing state X^*, when starting at state i is defined as δ^t_{i,X^*}, whose value is the sum of all elements in N^{t*}_i. The values of δ^t_{i,X^*} are obtained for all absorbing state $X^* \in \mathbb{S}^{AB}$.

Let τ be the duration of a time slot. Note that each step corresponds to a time slot. *ED* is defined as the delivery delay of packets from source node u to destination v. Then, *ED* is computed as:

$$ED = \tau \times \frac{1}{36}\sum_{t=1}^{36}\sum_{X^*\in\mathbb{S}^{AB}}\left(\frac{p_d(X^*)}{p_d}\sum_{X\in\mathbb{S}^{TR}_{X^*}}(p^I_t(X) \times \delta^t_{i,X^*})\right) \tag{17}$$

where using the initial probabilities, $p^I_t(X)$, and the law of total expectation, *ED* is obtained and it is also the average value for 36 time slots in a day.

D. COMPARING WITH THE SIMULATION

In this subsection, the analytical model is compared with the simulation. First, a part of Helsinki map [28], with a size of $2,000$ meter $\times$ $2,000$ meter was used for the simulation. We generate the movements of 20 nodes for 100 days by using the social relationship-aware human mobility model (SRMM) [29], which reflects the characteristics of human movement (i.e., flight lengths, inter-contact times, the radius of gyrations, and pause times) and the social context. In SRMM, people are partitioned into social groups based on information from a social graph. People in the same group have several common places where they frequently visit. Then, the movements of the people are determined by considering the distances from people to places, and social relationships between people. For instance, people prefer visiting nearby places, as well as places where many of their friends are. In SRMM, people are assumed to move 12 hours per day. The movements from day 1 to day 98 were used to obtain the meeting probability between nodes in the network. The simulations of routing protocols were performed on days 99 and 100 with 24 hours simulation time and an opportunistic networking environment (ONE) simulation tool [28] was used.

The *TTL* is set to 3 hours ($k = 9$ time slots). The initial value of forwarding token C is 4. ρ and α are set to 0.6 and 0.5, respectively. The packet generation interval is randomly set at between 25 and 30 seconds.

One source and destination pair is randomly chosen for simulation. The result is the average over five-times simulations with five different pairs of source and destination. The analytical model also obtains the results for five pairs of source and destination, respectively.

Figure 2 shows the network performance obtained from the analytical model and the simulation with the various number of nodes in the network. The results of the packet delivery ratio are presented in Figure 2(a). For a larger number of nodes in the network, packets have more chances to forward to a better relay, which leads to a higher packet delivery ratio. That is reflected in both the analytical model and the simulation. Specifically, Figure 2(a) indicates that the packet delivery ratio increases as the number of nodes increases. Overall, the obtained results show that the packet delivery ratio from the analytical model coincides well with the simulation.

Figure 2(b) shows the results of the delivery latency. The trends between the analytical model and the simulation match. Specifically, the delivery latency was reduced when the number of nodes increased since, with a larger number of nodes, the possibility of meeting and forwarding packets to nodes that have higher meeting probabilities with the destination is increased. Figure 2(b) also indicates that the delivery latency, which is obtained by the analytical model, is slightly longer than the simulation results. It is partially because, in the analytical model, each step for state transition is processed at the end of a time slot. However, in the simulation, packets could be forwarded in the middle of a time slot.

V. EVALUATION RESULTS

In this section, the performance of the proposed routing protocol is evaluated in terms of packet delivery ratio, delivery

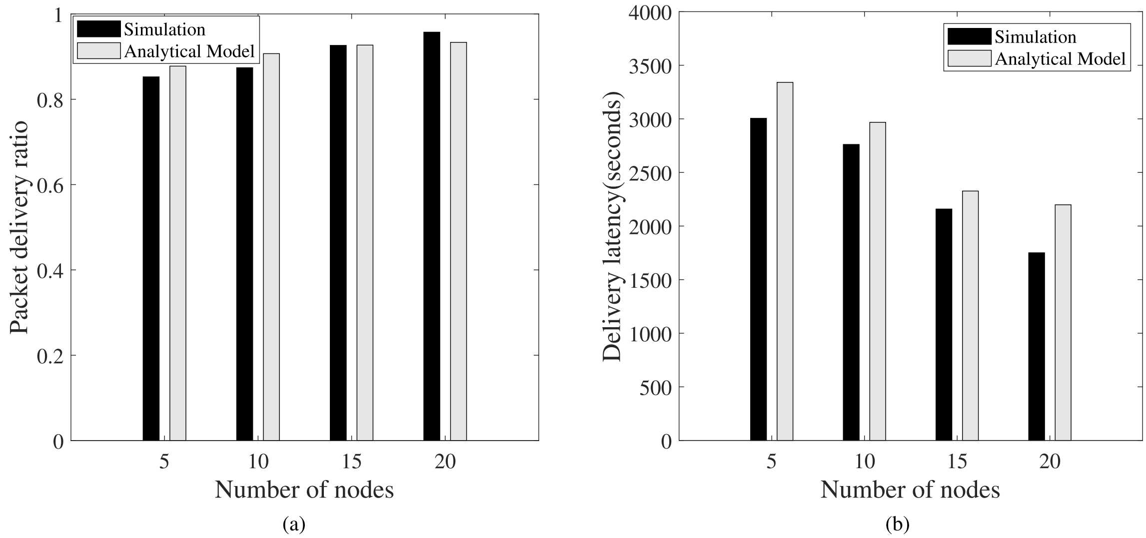

FIGURE 2. The results from the analytical model and the simulation with the various number of nodes in the network: (a) packet delivery ratio, (b) delivery latency.

latency, overhead ratio, and average hop count. The packet delivery ratio is the proportion of messages that have been delivered to their destinations out of all generated messages. The delivery latency is the delay in delivering messages from sources to destinations. The overhead ratio is the total number of replications divided by the total number of generated messages. Average hop count is the average number of intermediate nodes through which a message passes from the source to the destination.

First, TSIRP was validated with three PFMs. Then, TSIRP was compared with epidemic routing [6], the spray-and-wait routing protocol [7], PRoPHET [11], and CORP [25].

A. SIMULATION SETUP

A map of Helsinki [28], with a size of $8,300$ m $\times$ $7,310$ m was used as the simulation area. Let T denote the simulation time. In this paper, the movements of 150 nodes for 81 days were generated by SRMM. The movements from day 1 to day 80 were used to obtain PFMs in TSIRP and the delivery predictability in PRoPHET and CORP. The simulations of routing protocols were performed on day 81 with simulation time $T = 12$ hours. It is assumed that people move between places by car in the city. Based on car speeds from [30], the speed of node movement was set to follow a normalized distribution: $N(39, 5^2)$ km/h.

We used the media access control (MAC) layer of Bluetooth 5.0 with a node transmission range of 100 m, and a transmission rate of 2 Mbps. Packets were generated with a size of 500 bytes, and the generation interval was randomly set at between 25 and 30 seconds. The *TTL* for packets was set to three hours. Each node has a buffer that can store 100 packets. The initial value of forwarding tokens C and α were set to 32 and 0.5, respectively. In our simulation, a message can contain different information (e.g., an emergency alert, a traffic jam notification, or weather information). Depending on the information a message carries, the message should have a different value for d_t, which determines whether the message is experiencing a long delay or not. Therefore, the values of time threshold d_t were assumed to be $N(80, 10^2)$ minutes.

In addition, we also compared the proposed protocol with other routing protocols. Common parameters, such as the network area, the number of nodes, the mobility model, and the MAC layer were the same in all routing protocols. Under PRoPHET, the initialization constant of delivery predictability, P_{init}, the aging constant, γ, and the scaling constant, β, were set to 0.75, 0.98, and 0.25, respectively. For CORP, the maximum probability threshold P_{max} and minimum probability threshold P_{min} were set to 0.88 and 0.45, respectively. Under the spray-and-wait, the forwarding token was set to the same value as our routing protocol. A summary of simulation parameters is in Table 4.

B. EFFECTS OF THE SPREADING RATE CONTROL THRESHOLD (ρ) AND THE INITIAL VALUE OF THE FORWARDING TOKEN (C) ON THE PERFORMANCE FOR THREE PFMs

In this subsection, the effects of three potential forwarding metrics ($\overline{ICT}$: the mean value of inter-contact time, *ED*: the expected delivery delay, $\hat{x}$: the number of time slots to satisfy the meeting probability condition) are analyzed. *ED* between nodes was computed with $k = 100$ time slots. The required meeting probability, θ, was set to 0.2 when we calculated $\hat{x}$. For the three PFMs, network performance based on various values for ρ and C was collected.

Figure 3 shows the network performance for the three PFMs with various ρ values. In Fig. 3(a), the packet delivery ratio increased significantly when ρ increased from 0.4 to 0.6, and then slightly decreased if ρ kept increasing. For a low value of ρ, the message spreading rate is quickly reduced and packets are not spread widely enough. In contrast, if ρ is large,

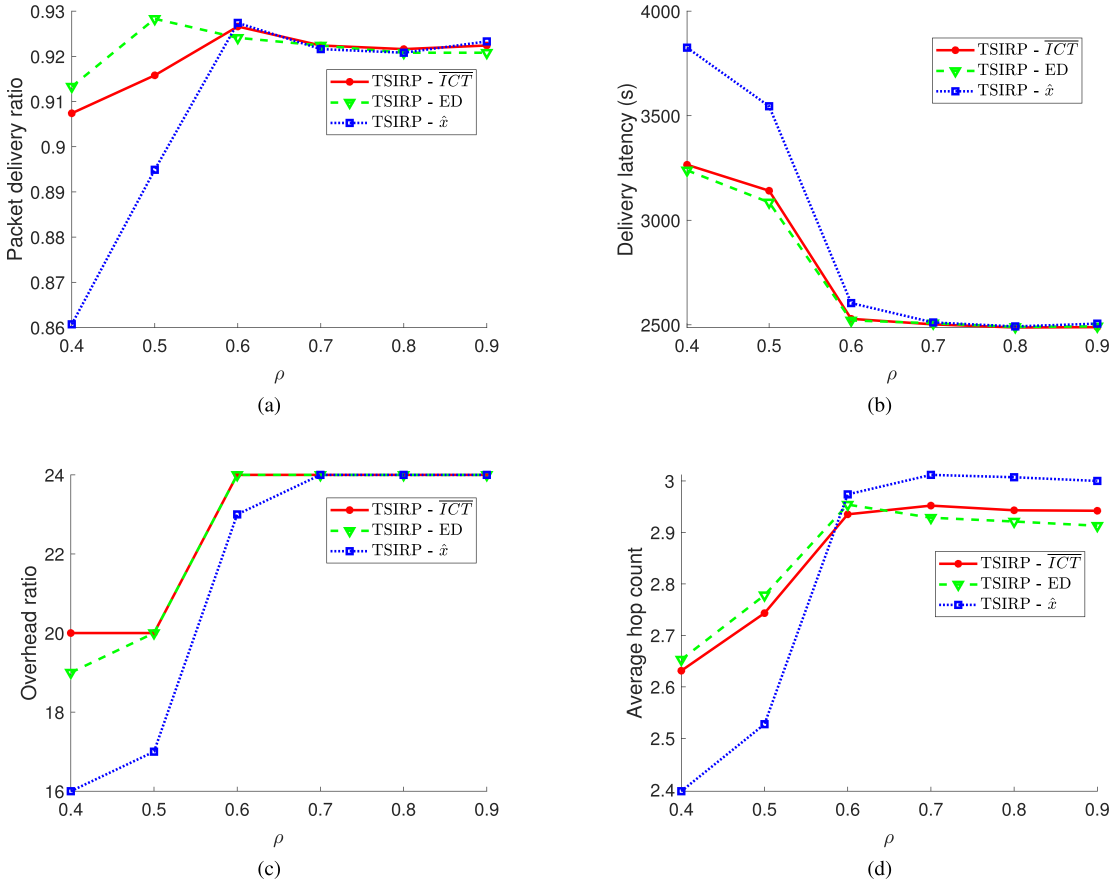

FIGURE 3. The network performance for three PFMs with various ρ values (the spreading rate control threshold): (a) packet delivery ratio, (b) delivery latency, (c) overhead ratio, and (d) average hop count.

TABLE 4. Simulation parameters.

Parameter	Value
Size of network area	8,300 m×7,310 m
Number of nodes (N)	150
Simulation time (T)	12 h
Mobility model	SRMM
The speed of node movement	$N(39, 5^2)$ km/h
MAC layer	Bluetooth 5.0
Transmission rate	2 Mbps
Transmission range	100 m
Packet TTL	3 h
Packet size	500 bytes
Packet generation interval	25-30s
Buffer size	100 packets
Initial value of forwarding token (C)	32
Time threshold for considering the mean value of degree centrality (d_t)	$N(80, 10^2)$ min

the relay selection will be performed too late. Those reasons led to a low packet delivery ratio. As shown in Fig. 3(a), the best packet delivery ratio was achieved when $\rho = 0.6$. For the three PFMs, when $\rho = 0.4$ and $\rho = 0.5$, higher packet delivery ratios were obtained by using *ED*. Then, when ρ was between 0.6 and 0.9, different PFMs obtained similar values for packet delivery ratio.

Figure 3(b) illustrates the delivery latency for the three PFMs. Overall, the results indicate that all three PFMs have a lower delivery latency from a larger value for ρ. *ED* achieved a lower delivery latency than $\overline{ICT}$ and $\hat{x}$ because, based on temporal social interactions, nodes that have lower values for *ED* were determined and selected as relay nodes.

The results for the overhead ratio are displayed in Fig. 3(c). It is clear that the overhead ratio increased to a certain point when ρ varied between 0.4 and 0.6, and did not change after that. With a large value for ρ (between 0.7 and 0.9), most of the message copies were forwarded to neighbor nodes without considering PFM, so the overhead ratio was high, and different PFMs obtained similar results. Figure 3(d) illustrates the results for average hop count, which also increased when we increased ρ from 0.4 to 0.6. When ρ was between 0.7 and 0.9, the lowest average hop count among the three PFMs was achieved by using *ED*.

The network performance for the three PFMs with various C values is shown in Fig. 4. The packet delivery ratio

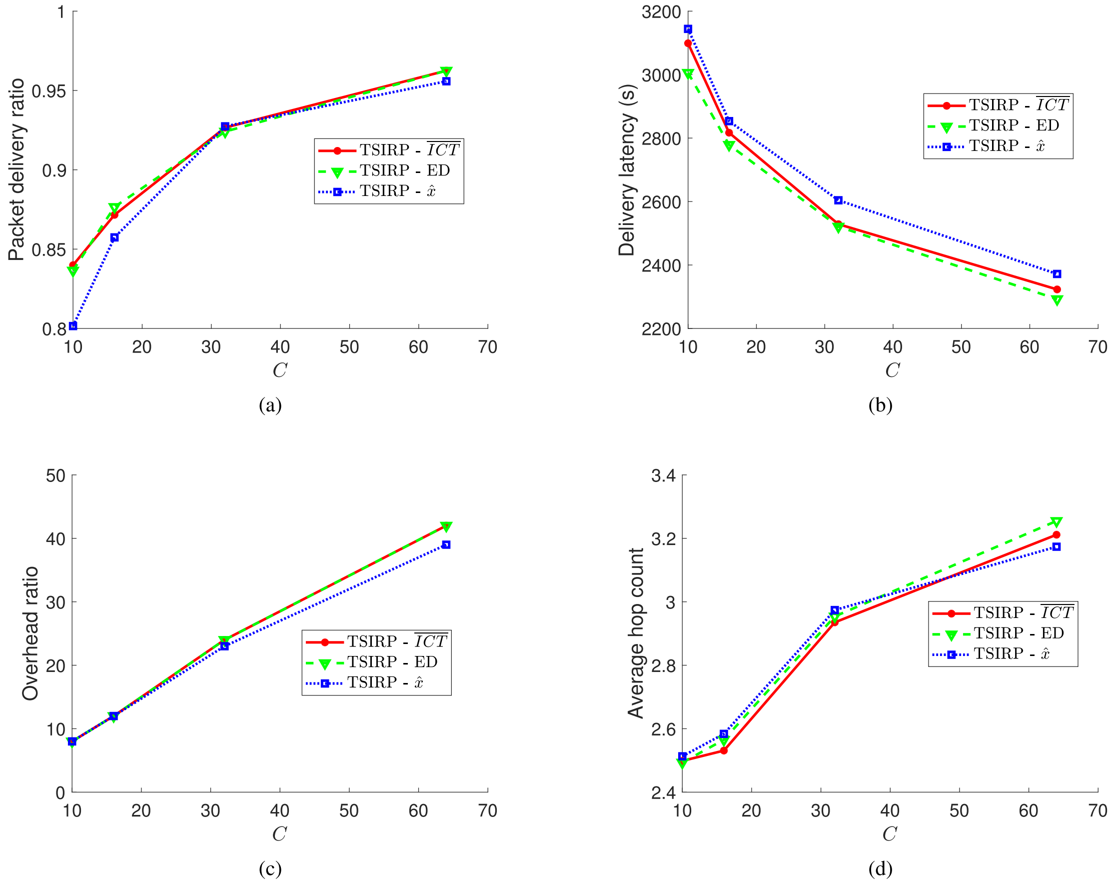

FIGURE 4. **The network performance for three PFMs with various C values (the initial value of the forwarding token): (a) packet delivery ratio, (b) delivery latency, (c) overhead ratio, and (d) average hop count.**

is presented in Fig. 4(a). We see that a larger C value achieves a better packet delivery ratio because, with a large C value, the number of copies of messages in the network was also large, and the messages had a high possibility of being delivered to the destinations. The obtained results with $\overline{ICT}$ and ED are similar and higher than the results with $\hat{x}$. Figure 4(b) presents delivery latency for various C values. Overall, latency decreased when there was an increase in C values; by selecting relay nodes with lower values for ED, the delivery latency based on ED was lower than with the other PFMs.

The results of the overhead ratio and the average hop count for various C values are displayed in Fig. 4(c) and Fig. 4(d), respectively. As shown in the figures, the overhead ratio and the average hop count increased as C increased, since a large C value means a large number of message replications. The results obtained for the different PFMs are similar in terms of overhead ratio and average hop count.

Based on the results of network performance in Fig. 3 and Fig. 4, the value of ρ was set to 0.6, and the expected delivery delay (ED) was used as the PFM to compare with other routing protocols.

C. EFFECTS OF THE PACKET GENERATION INTERVAL ON THE PERFORMANCE OF ROUTING PROTOCOLS

The network performance for various values of the packet generation interval is presented in Fig. 5. The packet delivery ratio is shown in Fig. 5(a). We see that all five protocols achieved higher packet delivery ratios as the packet generation interval increased since the network traffic is lower with a longer packet generation interval. By controlling the message spreading rate and selecting relay nodes with lower values for ED, the packet delivery ratio under TSIRP is higher than the others. In PRoPHET and epidemic routing, the message spreading rate was not considered, and the number of replications was not limited. Thus, the buffer filled, and a lot of packets were dropped, which led to a low value for the packet delivery ratio. By using the network community information, the packet delivery ratio in CORP is higher than those in PRoPHET and epidemic routing. In the spray-and-wait routing protocol, by limiting the number of replications, the buffer overflow was reduced and the packet delivery ratio was greater than that in CORP.

Latency from various values for the packet generation interval is illustrated in Fig. 5(b). Based on the flooding

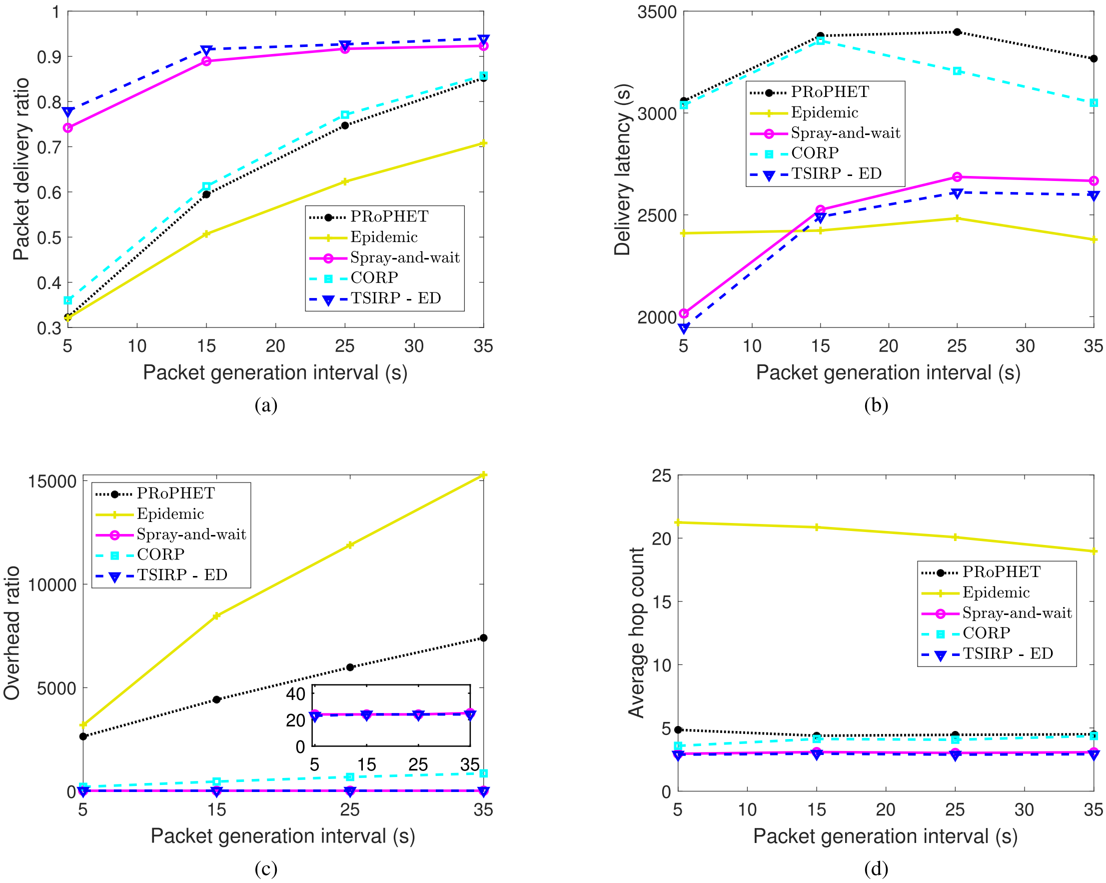

FIGURE 5. **The network performance for various values of the packet generation interval: (a) packet delivery ratio, (b) delivery latency, (c) overhead ratio, and (d) average hop count.**

strategy, epidemic routing provided a shorter delay than other routing protocols with less network traffic (i.e., a longer packet generation interval). Under TSIRP and the spray-and-wait routing protocol, delivery latency increased when we increased the packet generation interval because, with a short packet generation interval, the network traffic is heavy and the buffer overflows. Therefore, when new packets are generated and received, packets with long delays are removed from the buffer to store the new packets. As a result, there are only packets with short delays in the buffer. That creates low values for delivery latency. When the packet generation interval is longer, buffer overflow is reduced, and more packets with longer delays are in the buffer, which increases latency. Under PRoPHET and CORP, when a message has just been generated, the message is slowly spread due to nodes performing relay selection. Therefore, the delivery latency under PRoPHET and CORP is long. By controlling the message spreading rate, TSIRP resolves this problem, and nodes with lower values for *ED* are preferred as relay nodes. That reduces the latency. As shown in Fig. 5(b), TSIRP achieved a lower latency than PRoPHET and the spray-and-wait routing protocol.

Figure 5(c) displays the results for overhead ratio. Under TSIRP and the spray-and-wait routing protocol, low values for overhead ratio were obtained by limiting the number of replications, whereas epidemic routing and PRoPHET had very high values for the overhead ratio. In the CORP, by finding the node in the destination's community before finding the destination, the overhead ratio is also reduced. For example, when the packet generation interval is five seconds, the overhead ratios from TSIRP, the spray-and-wait routing protocol, and CORP were 23, 24, and 212, respectively, whereas epidemic routing and PRoPHET obtained 3194 and 2643, respectively. In Fig. 5(d), the average hop count is presented. As shown in the figure, the average hop count under TSIRP was lower than the others. In TSIRP, by using PFMs in relay selection and limiting the number of replications, the overhead ratio and the average hop count were reduced.

D. EFFECTS OF PACKET TTL ON THE PERFORMANCE OF ROUTING PROTOCOLS

In this subsection, we also collect and present the result of epidemic routing in the case of unlimited buffer size for various TTL values to show the theoretical maximal performance and compare it with our routing protocol.

In Fig. 6, the network performance for various values of *TTL* is illustrated. The packet delivery ratio is shown in Fig. 6(a). The results indicate that giving a longer lifetime

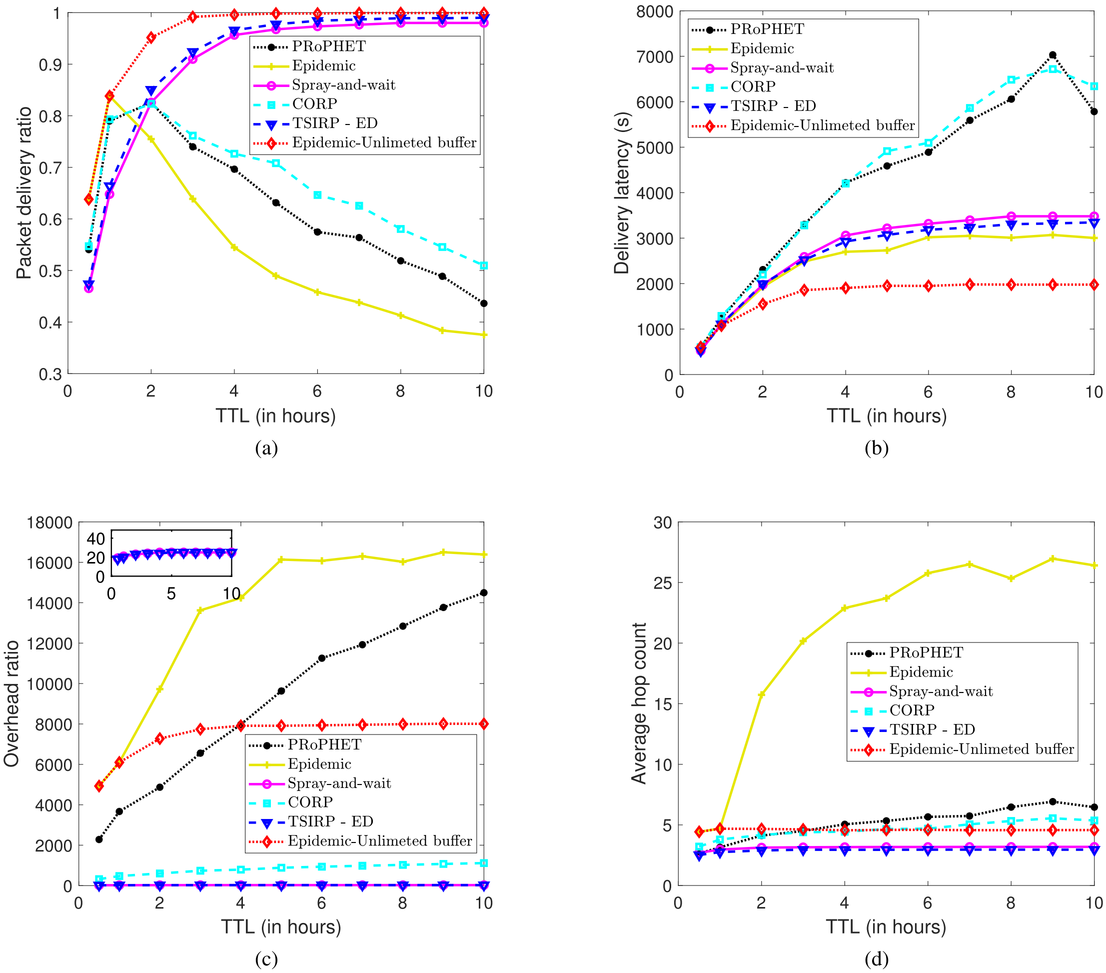

FIGURE 6. The network performance for various values of packet time to live: (a) packet delivery ratio, (b) delivery latency, (c) overhead ratio, and (d) average hop count.

to packets increases the packet delivery ratio up to a certain point, and then, the packet delivery ratio settles under TSIRP and the spray-and-wait routing protocol but decreases in epidemic routing, and PRoPHET due to buffer overflow. In CORP, by trying to forward the packet to the destination's community, the buffer overflow is reduced and the packet delivery ratio is slightly higher than PRoPHET. By considering packet spreading rate and relay selection, the packet delivery ratio from TSIRP is higher than from other routing protocols when *TTL* varies between 2 hours and 10 hours, and it close to the theoretical maximal value with a large value for *TTL* (e.g., *TTL* between 6 hours and 10 hours)

Delivery latency results are in Fig. 6(b). A large value for *TTL* means packets can be stored for a long time in the buffer, which leads to increased latency, as shown in the figure. Epidemic with unlimited buffer size obtained the lowest value. The results also indicate that the delivery latency under TSIRP is lower than under PRoPHET and the spray-and-wait routing protocol, and is slightly longer than epidemic routing.

The overhead ratio and the average hop count with various values of *TTL* are presented in Fig. 6(c) and Fig. 6(d), respectively. The obtained results from TSIRP are better than from other routing protocols due to the small number of replications and from executing relay selection. Under PRoPHET and epidemic routing, when TTL increases, a lot of packets are dropped and re-transmitted due to the buffer overflow. In the case of epidemic routing with the unlimited buffer size, the buffer overflow does not happen and packets are not dropped. That is the reason why the overhead ratio from PRoPHET and epidemic routing higher than epidemic routing with unlimited buffer. The path from the source to the destination in the case of epidemic routing with unlimited buffer achieves the lowest delay. However, the path with the lowest delay may not be the path with the lowest number of hop counts. Therefore, the average hop count from epidemic routing with the unlimited buffer can be greater than from TSIRP.

E. EFFECTS OF BUFFER SIZE ON THE PERFORMANCE OF ROUTING PROTOCOLS

Figure 7 displays the network performance for various buffer sizes. First, the packet delivery ratio is shown in Fig.7(a).

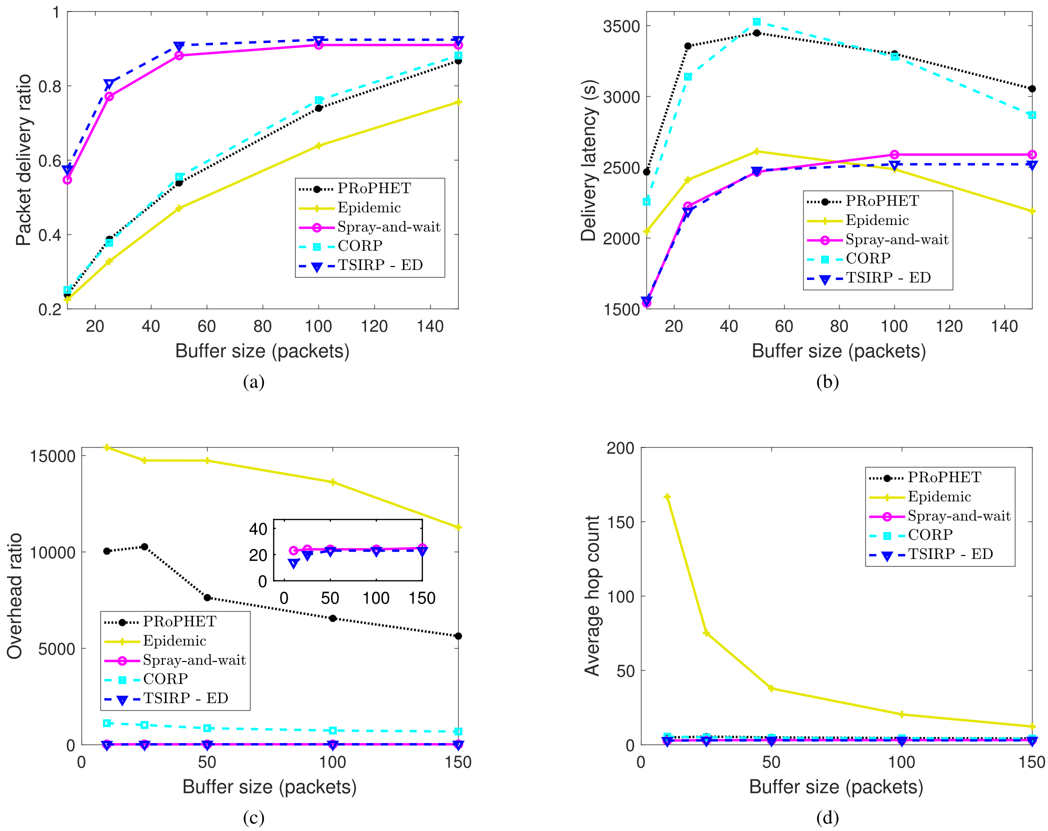

FIGURE 7. The network performance for various buffer sizes: (a) packet delivery ratio, (b) delivery latency, (c) overhead ratio, and (d) average hop count.

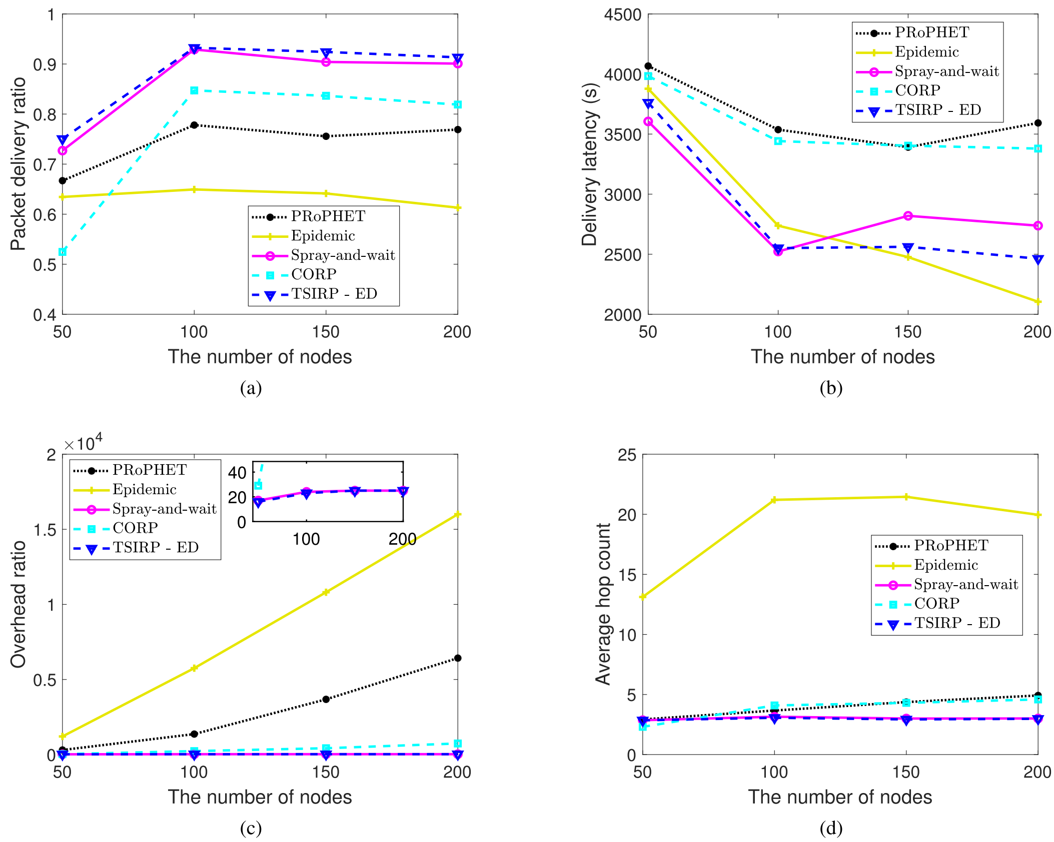

FIGURE 8. The network performance with various values for the number of nodes in the network: (a) packet delivery ratio, (b) delivery latency, (c) overhead ratio, and (d) average hop count.

We can see that the packet delivery ratio increased as the buffer size increased since a large buffer means more packets can be forwarded and stored in it. The packet delivery ratio in CORP is higher than PRoPHET and lower than the spray-and-wait routing. TSIRP always achieves the best packet delivery ratio with the various buffer sizes.

Delivery latency is in Fig. 7(b). When the buffer size is smaller than 100 packets, the proposed routing protocol delivered lower latency than the others. Note that a shorter latency was achieved under epidemic routing when the buffer size increased to 150 packets since a large buffer will reduce the packet loss rate in epidemic routing. However, with epidemic routing, the network overhead is huge, as shown in Fig.7(c), because of flooding. Figure 7(d) illustrates the average hop count, and the best result was also obtained under TSIRP.

F. EFFECTS OF THE NUMBER OF NODES ON THE PERFORMANCE OF ROUTING PROTOCOLS

Network performance from various values numbers of nodes in the network is illustrated in Fig. 8. The results for packet delivery ratio are presented in Fig. 8(a). In the case of 50 nodes, it is hard for a node to find the nodes in the destination's community which leads to a low packet delivery ratio in CORP. For various numbers of nodes, TSIRP outperformed the other routing protocols in terms of packet delivery ratio. In contrast, epidemic routing provided the worst result because the flooding strategy leads to the buffer overflow.

Latency is presented in Fig. 8(b). As shown in the figure, delivery latency was reduced when the number of nodes increased for all the routing protocols since, with a large number of nodes, the possibility of meeting nodes is higher. The delay under TSIRP was lower than PRoPHET, CORP, and the spray-and-wait routing protocol, and higher than epidemic routing when the number of nodes was between 150 and 200.

In terms of overhead ratio and average hop count, TSIRP was also better than the other routing protocols, as shown in Fig. 8(c) and in Fig. 8(d).

VI. CONCLUDING REMARKS

In this work, we proposed an efficient routing protocol for opportunistic mobile networks. Based on temporal social interactions and the history of social interactions between nodes, three PFMs were proposed for relay selection (i.e., the mean value of inter-contact time between nodes, the expected delivery delay, and the number of time slots to satisfy the meeting probability condition). In addition, a scheme to control the message spreading rate was proposed based on the state of the message in order to achieve a balance between delivery latency and network overhead. Specifically, based on the residual lifetime and the forwarding token, a spreading rate control value was proposed to control the message spreading rate. This scheme allows reducing both latency and the overhead ratio. Furthermore, in our forwarding scheme, if a packet is experiencing a long delay, degree centrality is also used to create more chances to deliver the packet to the destination. In addition, we design an analytical model to study the proposed routing algorithm and the proposed model can accurately estimate the network performance in terms of the packet delivery ratio and the delivery delay.

The network performance under TSIRP was evaluated by comparing it with other routing protocols (epidemic routing, spray-and-wait, PRoPHET, and CORP) in terms of delivery latency, packet delivery ratio, overhead ratio, and average hop count. The simulation results indicate that TSIRP can outperform existing routing protocols.

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