Social Recommendations Using Dynamic Profiles in Mobile Social Networks

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Abstract

Mobile Social Networks (MSNs) enable their users to communicate in an ad-hoc infrastructure-less environment. Therefore, it is considered a very promising means of communication in cases of disasters and emergencies. However, because of the restricted radio coverage, network versatility and device power constraints, MSNs do not have continuous end-to-end connectivity between nodes. Information dissemination is one of the highly requested applications of MSNs. Multicast routing protocols are implemented to help disseminate data to target destinations. Their objective is to maximize the delivery ratio and reduce end- to-end latency. In this paper, directed multicast protocols are addressed, in which message forwarding is conditional on predefined criteria. One of the key factors to improve routing performance in MSNs is to carefully select candidate relays. In this paper, we exploit users' social profile and their interactions to improve relay recommendation and find target destinations. Our proposed protocol, Time-based Encounter of Socially Similar nodes, TESS, uses the social proximity between nodes taking into consideration the time at which nodes encounter. The proposed protocol reduces power consumption and network overhead, while increasing delivery ratios compared to related protocols.

Key Words: MSN, routing protocol, social recommendation, social profile, connection time.

1 Introduction

In the time of the pandemic, social distancing is highly advised, and may even be forced. However, social networking, through electronic devices, becomes highly requested and recommended. Connecting people, anywhere and anytime, is the main goal of mobile networking. The technological advancement of mobile devices and internet infrastructure enabled and helped the provision of diverse communication applications, in addition to the traditional phone calls, including text, voice, and video chatting applications [12] and [1]. However, relying on the internet connectivity, in addition to being costly, may not be always available in all places.

For local communities, such as residents of nearby buildings, employees in a company building, or students and staff members of an education campus, it is possible to utilize the geographic proximity, and connect people without internet infrastructure. Using the connectivity capabilities of current mobile devices, such as Bluetooth and WiFi direct, people can exchange data if they are within communication range of each other. A group of related people with smartphones or tablets that meet and contact with each other constitutes a mobile social network (MSN) [4] and [10].

Information dissemination to selected network users is one of the most requested applications in MSNs. Multicast routing is used to spread data messages to selected users. Multicast routing can be categorized as blind routing and criteria-based routing. Blind routing broadcasts the messages independent of the unique users' characteristics. Blind routing could be limited to a predefined number of receivers, or full broadcasting.

The epidemic routing is an example of full-broadcasting blind routing, often used as a reference benchmark [25]. This protocol considers all nodes to be relays to scan the destinations. Epidemic is suffering from extremely high network costs, which renders the protocol inefficient.

Criteria-based routing attempts to select appropriate relays to reach destinations to reduce overloading the network. Mobile social networks exploit the social features and interests of users to route the messages [8, 18] and [26]. MSN's major purpose is to improve relay selection to increase delivery ratio using the lowest percentage of relay candidates possible. Repetitive packet transfers will consume battery power and cause network overload because MSN is mostly dependent on mobile phones.

Our proposed protocol, Time-based Encounter of Socially Similar nodes, TESS, uses the social features of mobile nodes to identify the destinations and recommend the proper relays to reach those destinations. The main contribution is to improve MSN routing protocol performance metrics. The protocol assumes that users with similar social feature values, tend to meet each other more frequently. For each social feature value, the protocol records, in each node profile, the number of node connections having the same feature value, and the time of encounter. TESS works in two phases; the first phase, it broadcasts a small message containing a destination profile to

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find the target relays and destinations. In the second phase, it multicasts the data messages to the recommended relays or target destinations.

Simulation results show that in terms of network latency and delivery ratio, the proposed protocol outperforms the related ones.

The remainder of this paper is organized as follows: The related work is cited in Section 2. In Section 3, we introduce our proposed algorithm. Section 4 presents the results and analysis of the experiments. Conclusions are discussed in Section 5.

2 Related Work

Routing protocols can be categorized, based on relay selection, into two types: blind and criteria-based routing. In this section, we explain and discuss the criteria-based routing with their references and mention the well-known papers in the blind routing.

2.1 Blind Routing Protocols

This kind of routing protocol broadcasts messages regardless of individual node characteristics. The disadvantages of this routing are that it consumes mobile and network resources. The source nodes sent multiple copies of the messages to all nodes that they encountered. Epidemic routing [25] is the most well-known and benchmark protocol of this class. In epidemic routing, nodes broadcast messages to all encountered nodes identified by the network. Therefore, if given unlimited resources, it improves the delivery ratio, and the end-to-end latency. However, practically, resources are limited. Therefore, storage buffers are greatly exhausted. Besides, the energy consumption of mobile phones is a big concern, especially that they are battery-powered.

The authors in [23] and [24] proposed Spray-and-Wait (SnW) routing protocol to reduce the number of duplicated messages introduced to the network. Reducing the number of messages, significantly saves energy by reducing transmissions and receptions.

2.2 Criteria Based Routing Protocol

This class of routing protocols is implemented to overcome the problems encountered with the blind routing protocols. The criteria for selecting successful relay candidates would help the source nodes in delivering messages to destinations with the lowest number of created message copies and the lowest rate of network overload possible. However, it still has its complications of measuring and verifying the criteria values.

Lindgren [14] used a probabilistic metric to determine if a node should forward the message to the nodes encountered and calculate the transitivity for the nodes. Li [13] determined that there is a similarity between users by location history and the interest values. Their protocol was based on establishing a connection between nodes if there are similar interests, or in cases where geographical positions were quite like each other. When the direct path between the two nodes was unavailable, friends of friends are used to relay messages. Deng [2] proposed a protocol to select the static social features in user profiles to create a social profile multicast (SPM). These social features have been used to pick the key relays for multicast routing. Two social properties were used: a range of associations, and common languages. The selection of these two social features was done according to the Infocom06 trace reports. Xu and Zhang [29] presented the EncoCent approach, where each node has multiple weighted features. The similarity between the encountered nodes was calculated based on the betweenness centrality of the nodes. Fujii [5] measured the similarity between the two encounters based on the number of common friends if there was direct link between them. Luo [16] proposed an algorithm to measure a simple intimacy-based relationship between two encountered nodes based on the type of relationship between them. Zhang [31] studied the integration between online and offline social networks. The encountering possibility between two nodes increased if they had common interests, or had the same social community, or they met occasionally. The meeting of the two nodes could have also occurred because they have common friends, or like the same events or groups. Socievole [21] implemented a centralized distribution scheme, Energy-aware Centrality-based Forwarding (ECF) to measure the centrality based on two values, degree and betweenness, at its current level of energy. ECF excluded the central nodes that have a low energy threshold. Soelistijanto [22] introduced a comparison between two forwarding strategies: social-aware forwarding and social-oblivious forwarding, in Social Opportunistic Networks (SONs). The social-aware forwarding strategy chose the next relay node based on its ranking. The node ranking was measured by the degree and betweenness centrality. The Social- oblivious forwarding strategy ignored the node ranking, and the next relay node is chosen randomly. Moreira [17] introduced a Social-aware Content-based Opportunistic Routing Protocol (SCORP) to measure the interests and the daily life routine of mobile nodes. Main principles of centrality and social community used to multicast the messages in the network.

The use of central nodes and social community structures as a community-based multicast routing system was suggested by Geo [6], where the central nodes selected based on the high ranked nodes instead of the most frequent contact nodes.

Xiao [28] introduced the definition of home-conscious culture in MSN. They implemented an algorithm for community-conscious opportunistic routing (CAOR), and the opportunistic routing relied on a few nodes in the network. Didwania [3] focused on analyzing the community detection method and the appropriate MSN community based on two factors, the complexity and the type of community detected.

Xu [30] proposed a social similarity-based multicast algorithm (Multi- Sosim). They measured nodes' dynamic social features and contact behavior. A compare- split scheme is used to separate nodes into communities based on the proximity between nodes. Thus, each community included nodes with shared values of social features.

Shang [20] enhanced their work in [30], and proposed two multicast algorithms, Destination nodes only in community (Multi-CSDO), and Destination nodes and Relay candidates in community detection (Multi-CSDR). The social characteristics of the nodes were included to split the nodes and destinations to communities. In CSDO, the destinations were divided into two communities to make the destinations more like each other. In CSDR, the nodes were distributed among the communities of the destination to be responsible of delivering the messages. Euclidean is used for determining accuracy in the multi-cast routing because its measurements are better than Tanimoto and Cosine.

Igarashi [9] used the concept of centrality and community to limit repeated messages in the network, as the mobile nodes have battery and storage constraints. Liu [15] discussed the modern mobility-assisted routing method, which meets both the scalability and privacy criteria. They quantify a global predictive model that predicts routing decisions for each post, such as machine learning.

A previous version of this work, TESS (Time-based Encounter of Socially Similar Nodes), is published in [7]. The current version is an enhancement of the older one. These enhancements are summarized as follows:

1) The similarity metrics, used to socially recommend relay candidates, are changed to achieve better performance.
2) Number of test cases are increased to measure the impact of more parameters on the proposed protocol.
3) More related work is included and compared with TESS to prove its superiority over them.

Pandemic-related applications that utilize mobile networks have been released. For example, the COVID-19 epidemic has motivated the development of many applications [19]. In [27], the authors provide exhaustive responses to a lot of questions about the COVID-19 tracking algorithms.

A summarized comparison between the related works is presented in Table.1.

Table 1: Comparison of MSN routing protocols

Routing Category	Reference number	Characteristics	Forwarding criteria
Blind routing	A. Vahdat [25]	• Traditional Routing • Broad and casting messages	Network layer information
	T. Spyropoulos [23]	• Spray messages then wait • Try to save resources. • no criteria discoursed	
	T. Spyropoulos [24]		
Criteria – based	A. Lindgren [14]	• Delivery predictabilities factor to user's profile • The predicted chance of this node to deliver a message Save movement patterns	Probability delivery predictabilities Matrix
	He Li [13]	• Expect the interests of users - Location history from mobile users	Geographic proximity And Similar interests
	X. Deng [2]	• Nodes with small average gap to association or a high common language ratio had selected.	Static Social Profile
	F. Xu, H. Zhang [29]	• Weight given to the social features Importance prioritization	
	S. Fujii [5]	• Create wireless communications between the friends • Find the intimacy of the users	Static Social Profile-social relationship
	T. Luo [16]	• Relationship of a friend's friend • Find the intimacy of the users	
	Y. Zhang [31]	• Common friends, interests, community, or group either online or offline to be a relay candidate.	
	A. Socievole [21]	• The degree and betweenness of the social profiles of the nodes measured	Static Social Network / Centrality and Community-based perspective
	B. Soelistijanto[22]	• Compare two concepts to select the relay: Ranked nodes by the degree and betweenness or oblivious node	
	W. Geo[6]	• Nodes in the same community with high betweeness values selected to multicast the message centrality	

	M. Xiao [28]	• High intra-community centrality to the nodes and High inter-community to the set node selected to multicast the messages	
	Y. Xu [30]	• Compare-split scheme to create social communities	
	Charles Shang [20]	• Compare-split scheme for nodes and destinations • Communities for nodes and communities for destinations • Similarity between communities	
	Y. Igarashi [9]	• Location-based • Connection history to each node Contact graph created • Calculate the group communities - Central nodes	

3 Proposed Protocol: Time-Based Encounter of Socially Similar Nodes (TESS)

We can deduct from the comparative study, summarized in Section 2, that there is a need to utilize social characteristics of network users to enhance routing. In this section, we explain our proposed protocol, TESS, which utilizes social characteristics to find and recommend relay and destination nodes. We also show its added value to the previous related protocols.

A message is transmitted from a source node to a relay node once a predefined criterion is achieved. Every node maintains a connection history with each other node, which includes their common features and times of encounter. Our proposed protocol is supported by two main features: the routing control message, and a time-based feature-proximity calculation, discussed in the following subsections.

3.1 The routing Control messages

A source node carries two types of messages: A short (control) message containing the values of the social features of the target destinations; and the main data message. Each control message carries three main pieces of information: Origin, End, and TTL, illustrated as follows:

1) Origin: The generator of the message.
2) End: The destination.
3) Time-To-Live (TTL): The life span of the message, after which the message becomes useless and should be deleted.

The control message is sent to all the encountered nodes in an epidemic style. Each node receiving the control message calculates the proximity between its features and the features carried by the message. Control messages are sent back to the sending nodes. Based on the proximity measures, the relays are selected. Then the main data message is sent to the recommended relays and destinations. As a result of this process, the network's overload decreased because the size of the generated messages was smaller than the main messages.

The communication protocol between two encountered nodes: node1 and node2, is illustrated in Table 2: This connection is repeated between all the network's nodes.

3.2 Time-Based Feature-Proximity Calculation

After receiving the control message, we calculate a feature proximity weight of the encountered node against the destination feature profile. If the proximity weight is one, then the encountered node is a target destination. If the proximity weight is less than one, then it is compared to the proximity weight of the sending node. The node with the higher proximity weight will carry the message. The communication protocol between the two encountered nodes is illustrated in Algorithm 1.

Each node receiving the control message calculates the proximity weight using the following steps:

1) Extract the common social features between its feature profile and the target destination profile.
2) Calculate the feature weight according to the recorded encountering history of these features. This means all nodes having this feature and had a connection

with this node before. Use the following equation (1):

$$W_f = \frac{\sum_{j=1}^{d}(t_s - t_j)}{d} \quad (1)$$

where,
W_f : the weight of social feature f , t_s: System time (current time), t_j: The encounter times of the node with other nodes having the same value of feature f, d: the number of encountered nodes having the same value of feature f

1) Calculate the total proximity weight, including all common features, using equation (2):

$$W_{n/Dest} = \frac{\sum_{f=1}^{k} W_f}{c} \quad (2)$$

Table 2: The detailed scenario in active connection between two nodes

Time ↓	At Node	Action
	node1	Send a short message containing the feature profile of target destination
	node2	1-Receive the short message, 2-Calculate the proximity weight between its feature profile and the target profile, 3-Send acknowledgement, Ack, to node1 containing the proximity weight.
	node1	1-Receive the Ack, 2- Calculate the proximity weight between its feature profile and the target profile, 3- Compare between its proximity weight and the received proximity weight. 4- If the received proximity weight is one, node2 is a target destination, send the main data packet. 5-If the received proximity weight is less than one, but greater than its own proximity weight, send a copy of the main data packet. 6- If the received proximity weight is less than its own proximity weight, ignore sending to node2.
	node2	1-Receive the message, 2-If it is a destination send Ack, 3-If it is relay, multicast the message to find the target destinations
	node1 and node2	1-Update the connection history, if there are common social features between the two nodes,

Where, W_{n-Dst} : is the node n proximity weight with the target destination profile, k: number of common social features between the node n and the target destination, and c: the number of all previous encounters, including nodes with and without common features, in a predefined time window T.

Let us clarify the calculations with an example. Assume two nodes, Node1 and Node2, having the profiles shown in Table 3. Each node has three social features: job title, gender, and activity. Each social feature is linked to a vector of encounter times updated when a connection occurs between two nodes with the same value of this feature. In this example, Node1 has been connected to nodes that have same social feature value (job title="Doctor").

Let us assume that each of the two nodes, Node1 and Node2, was connected to a total of 20 nodes in the recorded time window, T, so c=20.

The proposed algorithm works in the following steps:

Table 3

	Feature name	Vector time
1	Job title=Doctor	12,13,14,17
2	gender="Male"	9:00, 10:00
3	activity="Reading"	10:00, 11:00

(a) Profile of node1

	Feature name	Vector time
1	Job title=Doctor	12,13
2	gender="Female"	11:00, 15:00
3	activity="3D printing"	

(b) profile of node2

1. Update the vector of encounter times. The vector of encounter times is updated by adding the system time, t_s=18:00, to the vector of the extracted common social features values "job title" between the two nodes. The updated profiles are shown in Table 4.

2. Measure the proximity weight between the two nodes and the target destination. The profile of the target destination, *Dst*, is {job title ="Doctor", gender = "Male", activity = "3D printing"}.

(a) For Node1, the common social feature values with *Dst* are: job title="Doctor", and gender="Male",

Using (1)
W_{Doctor}=18:00-18:00)+(18:00-17:00)+(18:00-14:00)+(18:00-13:00)+(18:00-12:00)/ 5=3.2
W_{Male}= (18:00-10:00)+(18:00-9:00)/2=9.5
Using Eq.(2), the proximity weight of Node1 with *Dst*,
$W_{Node1-Dst}$ = (3.2+9.5)/20=0.635

(b) For Node2, the common features are ¡job title="Doctor", activity="3D printing"¿.

Using (1)
W_{Doctor}= (18:00-18:00)+(18:00-13:00)+ (18:00-12:00)/3=3.6
$W_{3Dprinting}$=0
Using (2), the proximity weight of Node2 with *Dst*,
$W_{Node2-Dst}$ = (3.6+0)/20=0.18,

The calculations showed that the weight between Node1 and *Dst* is higher than that between Node2 and *Dst*. Therefore, Node1 is preferred to be a relay than Node2.

3.3 Time-Based Encounter of Socially Similar Nodes Example

Several mobile apps have been created to deal with the COVID-19 epidemic. These apps rely on the internet networks.

Table 4

	Feature name		Vector time
1	Job title=Doctor		12,13,14,17,**18**
2	gender="Male"		9:00, 10:00
3	activity="Reading"		10:00, 11:00

(a) Updated profile of node1

	Feature name	Vector time
1	Job title=Doctor	12,13,**18**
2	gender="Female"	11:00, 15:00
3	activity="3D printing"	

(b) Updated profile of node2

We can introduce these apps to be implemented on ad-hoc networks to take the advantages of the infrastructure-less and the location-based features. A static social profile is created for each user who uses the app.

To ensure the information quality, users' data are gathered from the medical healthcare to be used, for example:

- COVID-19 Health status: This feature has a color identifying the health status of the user. (Green-good health / yellow-infected in quarantine / Grey-exposed / Red-confirmed).
- Job title: This feature shows the user's job title.
- Case history: A case history essentially refers to a file containing the relevant information pertaining to the user, such as chronic diseases.
- Age: the user's age.

The following examples show the importance of creating a user profile with these features, and the need for this app.

- Pharmaceutical companies can use these apps to get their infected users identified by COVID-19 health status or the case history features for the advertising of medicinal products.
- In case of contact with infected users, the app can send alerts to all users who are near to the infected users.
- If the user needs urgent medical help, the app will help reach the nearest doctor in the connected network, and so on.

For example, assume that a source node creates a short message with a social profile: COVID-19 health status="red", Age=22. This means that the user wants to reach other users who are infected with the COVID-19 and their age is 22.

The app tries to reach these users in a short time with high performance measurement values.

4 Simulation Results

We compared our proposed protocol, TESS, to Multi-CSDOCSDR [20], EncoCent [29] and Epidemic [25]. All protocols utilize encounter history, and forward multiple copies of the same message. With three proximity measures, we test the algorithm by [28].

Simulations are conducted using the Opportunistic Network Environment (ONE) simulator [11]. The ONE simulator helps to create a virtual environment for various node movements so that routing messages between nodes can be tested using various routing protocols. In the ONE simulator, we set the properties of TESS as follows:

1) Size of one message = 1MB.
2) The nodes are clustered into regions, and each area has a social feature value, based on the assumption that nodes with similar social features meet each other more frequently than other nodes.
3) Messages are generated randomly every 25 to 35 seconds.
4) The duration of each simulation is 23200 seconds (about 6.44 hours).

To check the impact of increasing the buffer size and Time-to-live (TTL), we ran multiple simulations.

The performance parameters measured are:

1) Relay count: number of nodes that hold the messages to be delivered to the destinations,
2) Delivery ratio: the ratio of messages delivered to their destinations to the total number of generated messages.
3) Overhead ratio: The ratio of redundant messages to the total number of generated messages,

Algorithm 1 TESS

Require: first node n_1 and its target destinations D_{n1} = [set of social profiles carried by n_1]

[A connection is established between two encountered nodes n_1 and n_2 nodes]

[n_1 and n_2 have set of social features (f)]

[Each node has initial battery power value (PW)]

[extract list of common social features (CF) between each node and the target destination d by the short message]

if CF_{n2} in D_{n1} **then**

  [n_2 is one of the target destinations, so a copy of its original message is sent to n_2]

else

  [Calculate the weight of each f in CF, n_1 and n_2, using 1 as discussed above]

end if

[Calculate the weight of n_1 , W_{d-n1} and n_2 , W_{d-n2}, using 2 as discussed above]

if $W_{d-n1} \leq W_{d-n2}$ **then**

  if $(PWn1 \geq 1)$ and $(PWn2 \geq 1)$ **then**

    [send a copy of the main message to n_2]

  end if

end if

4) Hop-count average: the ratio of the sum of hops traversed by all delivered messages to the number of delivered messages,
5) Drop packet ratio: number of packets discarded by the network.

We studied the impact of changing the buffer capacity and the TTL for different network sizes, N=20, 50, 100, 150, 200, where N is the total number of nodes in the network.

4.1 The Impact of Changing the Buffer Capacity

Increasing a node's buffer capacity will help hold additional packets, and thus increase the probability of delivering the packet, otherwise, the mobile node becomes a dead node.

As shown in Figure 1, increasing the buffer capacity for all protocols improves the delivery ratio. Epidemic has the worst delivery ratio, while TESS proved to achieve the best results in low buffer capacity and high TTL packets.

The delivery ratio for all protocols converges after a buffer capacity of 40 MB, because nodes are spatially close to each other and the buffer can hold more packets.

This is clarified by the decreasing of dropped packets when the maximum buffer capacity is reached, as shown in Figure 2(a).

4.2 The Impact of Changing the Packet Lifetime (Time to Live, TTL)

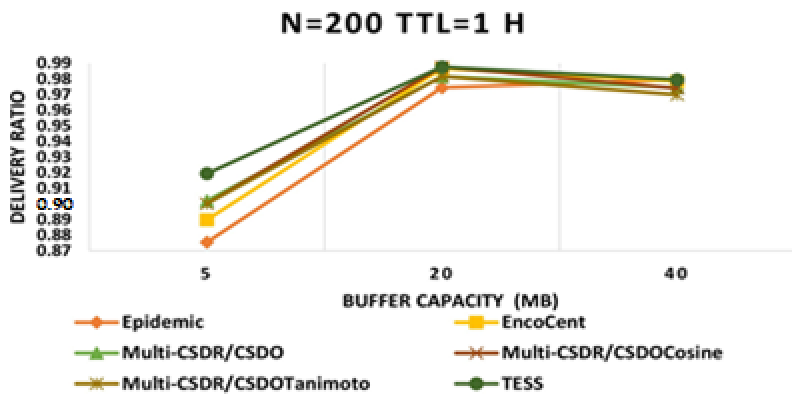
In Figure 2(b), increasing the packet lifetime, reduces the number of dropped packets, because packets have a longer time, and therefore higher possibility, to reach destinations.

We summarize our results as follows:

- Our approach improves overall performance measures when the buffer capacity and packet TTL are varied.
- Selecting the relays that matches or are a close match to the target profile, reduces the dropped packets, relay count, Figure 3, and hop count, Figure 4.
- TESS reduces the number of message copies in the network, and thus it reduces the transmission of packets between nodes. Therefore, TESS uses minimum network resources, and achieves good results in the overhead ratio, Figure 5.

5 Conclusion

Mobile Social Networks are being paid a lot of attention in the recent years. In this paper, we proposed TESS, a time-based encounter of socially related nodes. TESS utilizes the history of connections done by each node in the network to measure social similarities. The recommended relays and destinations are determined based on these measurements. Using the ONE simulator, simulation experiments using real data sets are conducted to evaluate our protocol performance. From the presented results, our approach proved to achieve better results than the related ones: Multi-CSDO, EncoCent, and Epidemic, increases the delivery ratio and decreases the delivery overhead, average latency, and average hop count as compared to the epidemic protocol. Generally, we manage to exploit the advantage of mobile social networks to improve the recommendation of relays that help reach target destinations.



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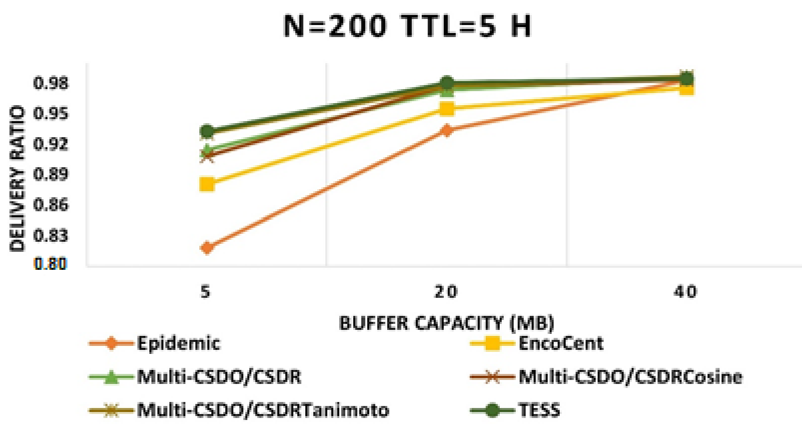
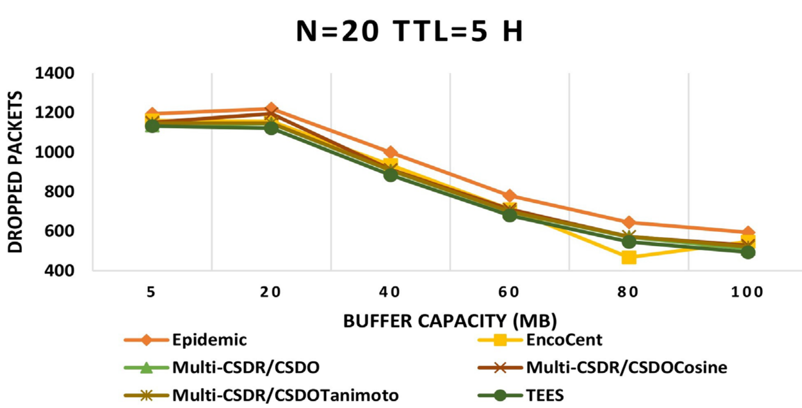


(b)

Figure 1: Impact of changing the buffer capacity on delivery ratio, N=200 (a) TTL= 1 H (b) TTL= 5 H



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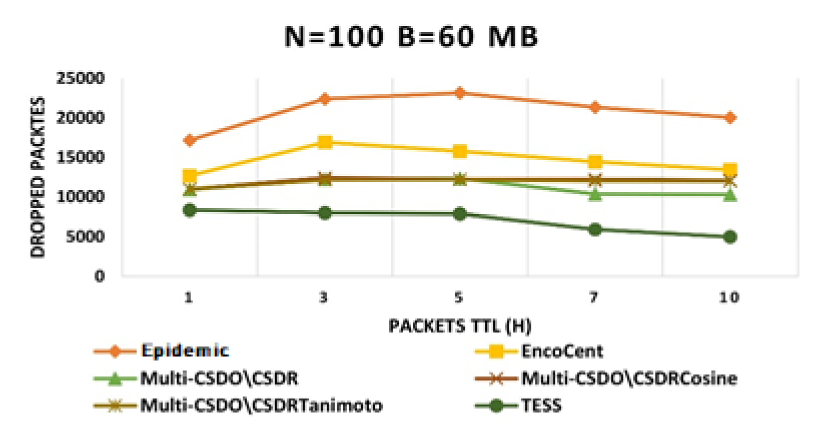
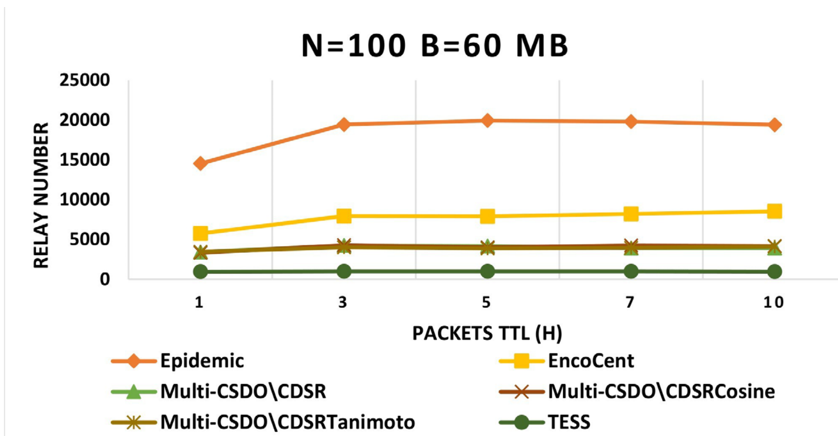


(b)

Figure 2: Impact of changing the buffer capacity on dropped packets (a) N= 20, TTL= 5 H (b) N= 100, B= 60 MB



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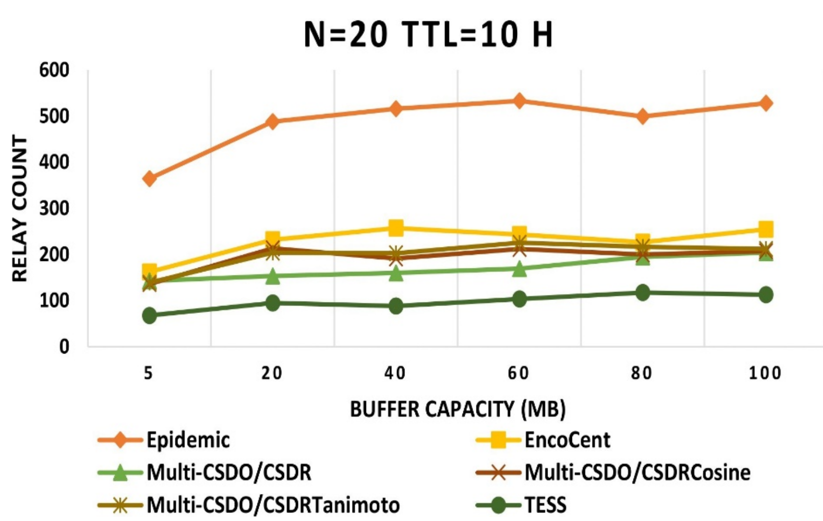

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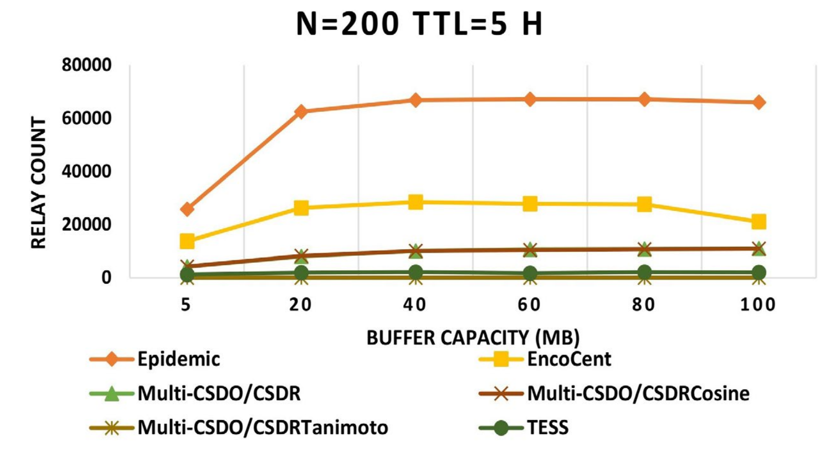
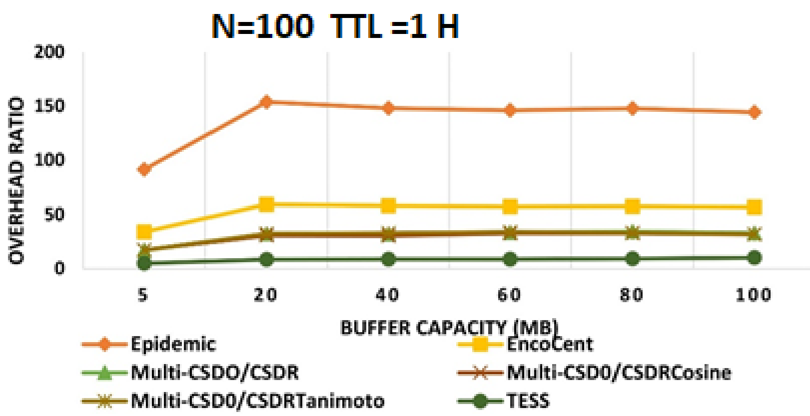


(c)

Figure 3: Impact of changing the packet lifetime on relay number (a) N= 20, B= 60 MB (b) N= 20, TTL= 10 (c) N= 200, TTL= 5 H



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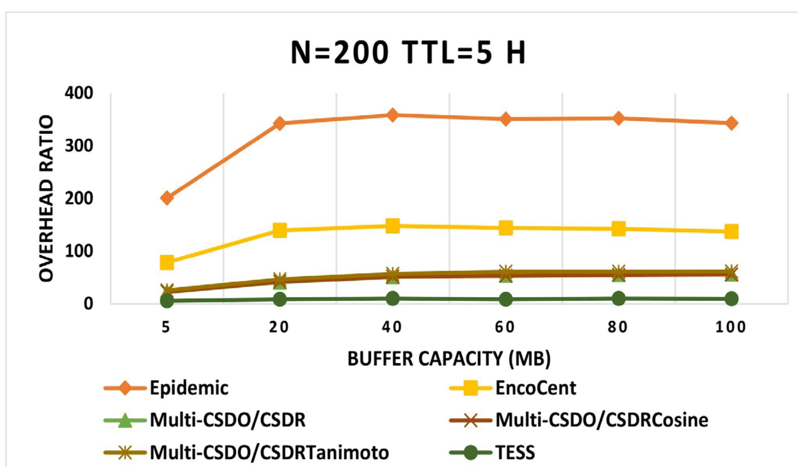

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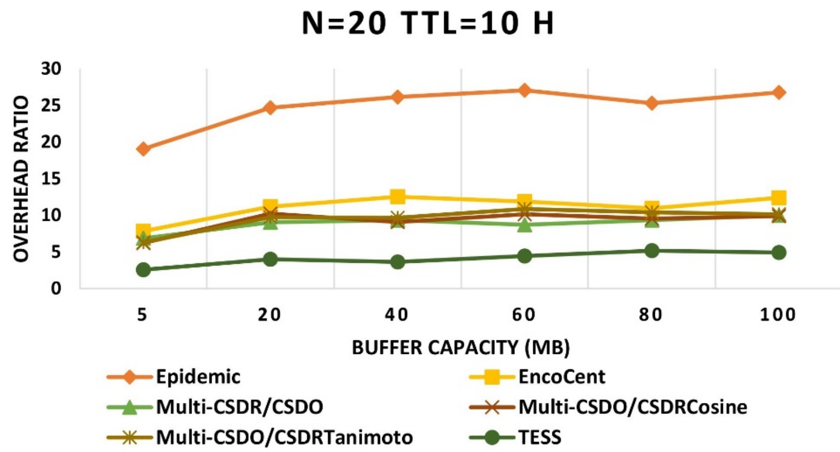
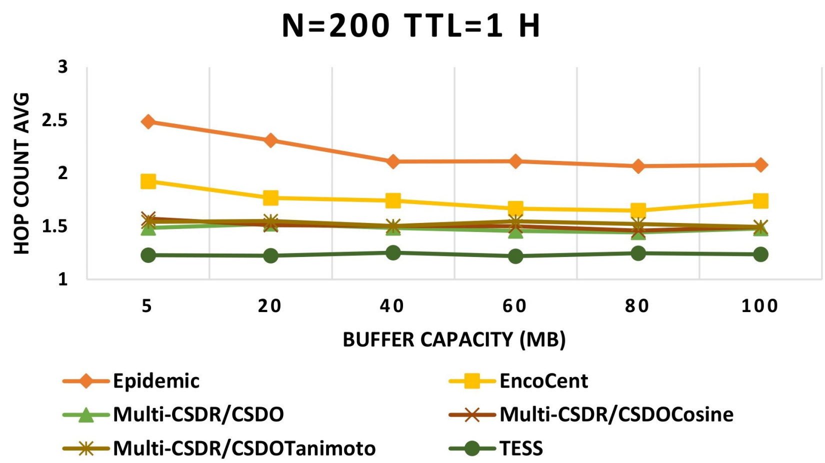


(c)

Figure 4: Impact of changing the buffer capacity on overhead ratio (a) N= 100, TTL= 1 H (b) N= 200, TTL= 5 H (c) N= 20, TTL= 10 H



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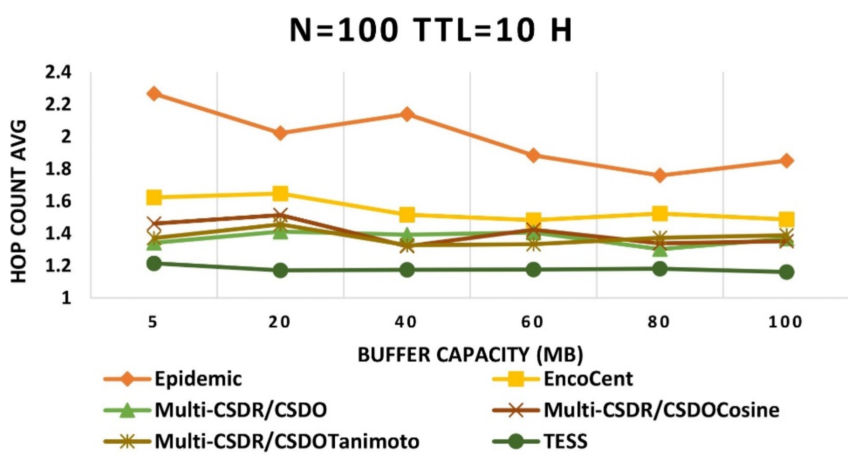
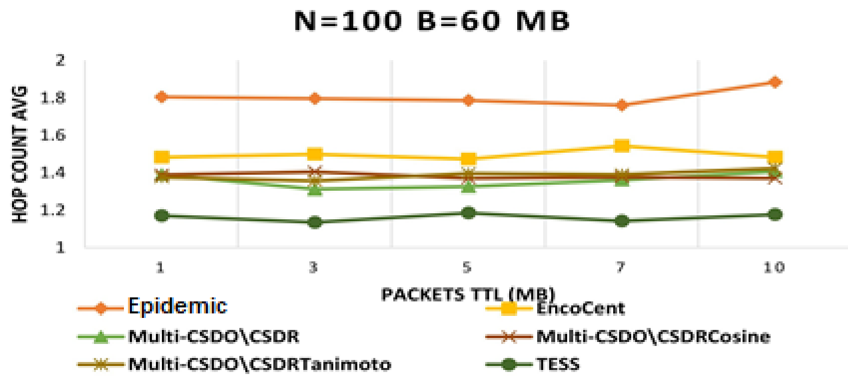


(b)



(c)

Figure 5: Impact of changing the packet lifetime on average hop-count (a) N= 200, TTL= 1 H (b) N=100, TTL=10 H (c) N= 100, B= 60 MB

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