Faculty of Computer Science and Information Technology

Enhanced Social-based Routing Protocols in Opportunistic Mobile Social Network

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Enhanced Social-based Routing Protocols in Opportunistic Mobile Social Network

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

……………………………

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ABSTRACT

An Opportunistic Network (OppNet) is a new paradigm of the Delay Tolerant Network (DTN). The dynamic topology of the OppNet degrades the efficiency of data dissemination. To cope with this challenge, exploiting the social features of the mobile users is a strong and effective research trend for efficient routing in OppNet. Opportunistic Mobile Social Networks (OMSN) has emerged as a new communication paradigm of OppNet, where social information is exploited for data dissemination purposes. The challenges are which social features to be exploited, how to combine the social features with other routing-related factors, and how multiple social features can be integrated to improve routing performance in OMSN. In this thesis, social information is combined with the Epidemic protocol to grab the advantages of Epidemic protocol in terms of high delivery ratio and low latency, and to decrease the overhead by exploiting social information. Messages' Time to Live (TTL) is decreased according to nodes' social degree when forwarding it. Experimental results show that the proposed protocol, Epidemic Social-based protocol (EpSoc), decreases the delivery overhead ratio and average hop count significantly. The reduction is up to 72%, 44% in overhead ratio and up to 41%, 56% in average hop count compared with Epidemic and Bubble Rap respectively. In addition, this thesis investigates exploiting the similarity between the users' social characteristics and the regularity of the people's social behaviour in daily life to improve routing performance in OMSN. Based on this, a Social-based Ranking protocol (SOR) is proposed. It ranks social characteristics according to nodes' social activity and exploits them to forward messages in OMSN. SOR has the highest delivery ratio compared with the benchmark protocols; the increase is up to 150%, 24%, and 65% compared with Epidemic, PRoPHET, and Bubble Rap respectively for the scenarios of low buffer size and high TTL value. SOR also decreases overhead ratio with 75%, 45%, and decreases the average hop count with 64% and 23% on average compared with Epidemic and PRoPHET respectively, while it has a slightly higher average hop count compared with Bubble Rap. Finally, this thesis explores exploiting multiple social metrics with the consideration of the mutual impacts and the correlation among them. Multipliable Social Metrics-based (MSM) routing protocol is proposed based on this idea. In MSM, social activity, similarity, and degree centrality and their mutual impacts are utilized to form the message's forwarding decision. Results show that MSM outperforms the benchmark protocols in terms of overhead ratio and average hop counts, and has competitive achievements regarding delivery ratio and average latency. The reduction in overhead ratio is ,on average, 95%, 93%, and 90% , and up to 81%, 60%, and 42% in average hop counts compared with Epidemic, PRoPHET, and Bubble Rap respectively. According to this study, social information plays a critical role in enhancing the efficiency of information sharing in the new emerged communication paradigms such as OMSN and device-to-device (D2D) networks.

Keywords: Social-based routing, social features, opportunistic networks, overhead control.

Penghalaan Berasaskan-sosial dalam Rangkaian Sosial Mudah Alih Oportunistik

ABSTRAK

Rangkaian Opportunistik (OppNet) adalah paradigma baru dalam rangkaian toleran kelewatan (DTN). Keadaan topologi yang dinamik ini menyebabkan penurunan kadar kecekapan dalam penyebaran data. Dalam menangani cabaran ini, mengeksploitasi ciri-ciri sosial peranti pengguna adalah sumber yang kukuh dan trend efektif yang cekap dalam penyebaran data dalam rangkaian OppNet. Rangkaian sosial mudah alih oportunistik (OMSN) telah muncul menjadi sebagai paradigma baru dalam rangkaian oportunistik OppNet, dimana penyebaran maklumat dieksploitasi untuk tujuan penyebaran data. Antara cabarannya ialah yang manakah ciri-ciri sosial yang perlu dieksploitasikan, bagaimanakah menggabungkan ciri-ciri sosial dengan elemen lain dalam penghalaan, dan juga bagaimanakah ciri-ciri pelbagai sosial boleh diintegrasikan bagi meningkatkan prestasi penghalaaan dalam OMSN. Di dalam tesis ini, maklumat sosial diintegrasikan dengan penghalaan secara Epidemic bagi mengambil kira kelebihan penghalaan Epidemic dari aspek kadar penghantaran data yang tinggi dan latensi yang rendah dan untuk mengurangkan lebihan dengan mengexploitasikan maklumat sosial. Masa untuk hidup (TTL) bagi sesuatu mesej akan berkurangan berdasarkan tingkatan sosial nod apabila mesej tersebut dihantar. Keputusan eksperimen menunjukkan bahawa skim cadangan protokol berasaskan sosial wabak (EpSoc) mengurangkan nisbah overhed penghantaran dan purata kiraan hop secara ketara. Masing-masing pengurangan berlaku sehingga 72%, 44% pada nisbah overhed dan sehingga 41%, 56% pada purata kiraan hop berbanding dengan Epidemik dan Buble Rap. Tambahan pula, tesis ini mengkaji bagaimana mengeksploitasi persamaan antara tingkah laku masyarakat dalam kehidupan seharian dan persamaan antara ciri-ciri sosial pengguna untuk meningkatkan prestasi penghalaan di OMSN.

Berdasarkan ini, penghalaan berdasarkan sosial yang dikenali sebagai protokol ranking berasaskan sosial (SOR) dicadangkan. SOR meletakkan kedudukan ciri-ciri sosial berdasarkan aktiviti sosial nod dan menggunakannya untuk penyebaran mesej dalam OMSN. SOR mempunyai kadar penghantaran yang tinggi berbanding dengan protokol penanda aras; peningkatan sehingga ke 15%, 24% dan 65% berbanding dengan Epidemic, PRoPHET dan Bubble Rap secara berasingan bagi situasi saiz penampan yang rendah dan nilai TTL yang tinggi. SOR juga mengurangkan kadar nisbah overhed dengan kadar 75%, 45% dan mengurangkan purata kiraan hop dengan kadar 64% dan 23% secara puratanya berbanding dengan Epidemic dan PRoPHET secara berasingan, sementara SOR mempunyai sedikit tinggi purata kiraan hop berbanding dengan Bubble Rap. Akhirnya, tesis ini meneroka bagi mengeksploitasikan pelbagai sosial metrik dengan mengambil kira impak bersama dan kolerasi antara mereka. Kepelbagaian asas penghalaan sosial skema yang dikenali sebagai MSM dicadangkan berdasarkan idea ini. Dalam MSM, aktiviti, persamaan dan tahap ketepatan serta kesan persamaan digunakan untuk membentuk keputusan penghantaran mesej. Keputusan experimen menunjukkan MSM mengatasi penanda aras protokol dari aspek nisbah overhed dan purata kiraan hop, serta juga mempunyai pencapaian daya saing berdasarkan kadar penghantaran dan purata latensi. Masing-masing pengurangan berlaku pada nisbah overhed, secara puratanya, 95%, 93% dan 90%, dan sehingga 81%, 60% dan 42% pada kiraan hop berbanding dengan Epidemic, PRoPHET dan Bubble Rap. Berdasarkan kajian ini, informasi sosial memainkan peranan yang penting dalam meningkatkan kecekapan perkongsian dan pertukaran maklumat dalam era komunikasi paradigma baru seperti rangkain OMSN dan peranti ke peranti (D2D).

Kata kunci: *Penghalaan berdasarkan-sosial, ciri-ciri sosial, rangkaian oportunistik, kawalan overhed.*

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AD	Average end-to-end Delay
AHC	Average Hop Counts
AO	Average Overhead
AODV	Ad hoc On-demand Distance Vector protocol
ASDM	Anycast Social-Distance Metric
CA	Cultural Algorithm
CAMF	Context-Aware Message Forwarding
CAMF	Context-Aware Message Forwarding
CAOR	Community-Aware Opportunistic Routing
CAR	Context-aware Adaptive Routing
CGrAnt	Cultural Greedy Ant
CiPRO	Context Information Prediction for Routing in OppNets
CRAWDAD	Community Resource for Archiving Wireless Data At Dartmouth
DC	Degree Centrality
DSR	Dynamic Source Routing protocol
DTN	Delay Tolerant Network
EpSoc	Epidemic Social-based

FCNS	Fuzzy routing Comprehensive Node Similarity
HiBOP	History-Based routing protocol
HS	Homing Spread
HSBR	Hybrid Social Based Routing
HSFR	Hypercube-based Multipath Social Feature
IoT	Internet of Things
IPAD	Interactive Personal Application Device
IR4.0	Industry Revolution 4.0
LASS	Local-Activity and Social-Similarity
LocalCom	Local Community protocol
MANET	Mobile Ad Hoc Networks
ML-SOR	Multi-layer Social Network based Routing
MSM	Multipliable Social Metrics
MSN	Mobile Social Network
OMSN	Opportunistic Mobile Social Network
ONE	Opportunistic Network Environment
OppNet	Opportunistic Network
PIS	Proximity-Interest-Social
PRoPHET	Probabilistic Routing Protocol using History of Encounters and Transitivity

SACC	Socially Aware Congestion Control protocol
SANE	Social Aware NEtworking
SARP	Social-Acquaintance based Routing Protocol
SCF	Store Carry Forward
SDR	Successful Delivery Ratio
SGRB	Social Groups-Based Routing
SimBet	Similarity Betweenness routing protocol
SIoT	Social Internet of Things
SMART	Social- and Mobile-Aware Routing strategy
SnW	Spray and Wait Routing
SOR	Social-based Ranking protocol
SPRINT-SELF	Social-Based Routing and Selfish Node Detection
SRAMSW	Social Relationship Based Adaptive Multi-Spray-and-Wait
TTL	Time To Live
VSNs	Vehicular Social Networks

CHAPTER 1

INTRODUCTION

1.1 Background

The usage of mobile devices becomes very pervasive. The global mobile data traffic reaches 28.56 (exabytes per month) in 2019 and it is expected to reach 77.49 (exabytes per month) by 2022 (https://www.statista.com).The diversity in its types; mobile smart phones, laptops, tablets, iPads, etc. and the plenty in the offered services and applications provided in electronic stores such as Apple, Google stores increase its popularity dramatically. The popularity of the mobile devices and the rapid and wide range development in its technologies emits new domains of knowledge and enlightens different ways of utilizing these devices. As mobile devices are relatively related to human social behavior, integrating human social activities into mobile devices result in new network paradigm i.e. mobile social network (MSN). In MSN, end users with similar social properties or common interests can come together and form virtual social communities using their mobile devices.

In general, MSN can be classified into two main categories; infrastructure and infrastructure-less network (Csobin et al., 2016). In infrastructure MSN, there are remote servers that host and provide the social services. Mobile users access the service providers for sharing and exchanging information. On the other hand, in infrastructure-less MSN or called Opportunistic Mobile Social Network (OMSN), there is no central server, and mobile devices use opportunistic network paradigm to communicate directly. In opportunistic network all mobile nodes contribute to disseminate information using store-carry-forward mechanism (Hu et al., 2015). Both infrastructure and infrastructure-less MSN have several services and applications in various fields of humans' daily lives.

A wide range of MSN services and applications have been deployed covering the benefits of many aspects of people daily lives. Advertising, information sharing, health care, entertainment, education and so forth are examples of the domains that MSN applications serves.

Although OMSN provides many advantages such as low-cost deployment and maintenance, they also post many challenges such as routing, privacy and security. In this research, the study focuses on the routing challenge. Routing messages is vital issue in OMSN because of the high dynamic topology and intermittent connectivity.

1.2 Routing in OMSN

Different techniques are used to forward data between intermediates nodes to convey information from source to destination. Flooding the network with copies of the message is the simplest approach (Tseng et al., 2002). However, it consumes high network and node resources and generate more congestion. Epidemic is introduced to control message forwarding by choosing the rely only from the not infected nodes based on the previous message (Vahdat & Becker, 2000). Epidemic achieves a high delivery ratio and low delivery latency when the resources are not a constraint. Due to the high delivery cost, Epidemic is not practical to be implemented in OMSN.

To overcome Epidemic drawbacks, probability-based routing protocol exploits the connection history with other peer's information in forwarding decision to reduce resources consumption (Lindgren et al., 2007). Moreover, selecting a node that has a high probability to encounter the destination when forwarding the message increases the delivery ratio.

Because of MSN is a combination of social information and communication technologies, social relations and behavior of the mobile users can be exploited to improve routing performance. This emitted new routing approach that is called social-based routing.

The main reasons that motivate researchers to utilizes social information for routing purposes are:

The characteristics of the social behaviors of people are long-term attributes. Humans follow regular social patterns in their daily lives. Therefore, such relatively stable properties can be exploited to deal with the dynamics and intermittent nature of OMSN topology.

- People tend to be organized in clusters or groups based on their similar social characteristics such as interests, hobbies. The encountering probability among people who belong to the same community is higher than with users in different communities. Clustering properties can also be utilized for efficient information provision in OMSN.
- Social information in the user's profile (affiliation, interests, languages) identifies the behavior and social activities of the mobile user in the social network. Therefore, it can be exploited to enhance message routing performance.

Social information can be collected or deducted from different sources. These sources can be classified into self-reported and detected sources. A user profile is an example of self-reported sources; by filling questionnaires or logging into the online social networks (Twitter, Facebook) this information can be acquired. For detected sources, social information is extracted using different ways such as analyzing contacting traces, monitoring the forwarded messages, and observing the mobility patterns. The collected social information can be processed later to enhance information provision in OMSN.

Based on social information, several social metrics can be formed and evaluated. Social ties, centrality, similarity, friendship, selfishness, community are examples of these metrics. Some of these metrics have a positive impact on routing performance such as centrality, similarity, friendship. That is because they contribute to giving a better prediction of the future encounter and then making forwarding decisions more efficient. On the contrary, other metrics for example selfishness worsen the performance because selfish users focus on self-utility ignoring the community utility. Consequently, selfish nodes in OMSN will decrease the forwarding efficiency due to poor collaboration. However, both positive and negative social features can be exploited to design social-based routing protocols in OMSN (Zhu et al., 2013).

Social based routing is one of the strong and active tends for developing more efficient routing schemes in opportunistic networking scenarios. Social information increases the accuracy of the predicted knowledge about network topology and also alleviates the negative impact of the high frequency of links breakage on routing performance. So, it is very important to study how social metrics can be exploited and combined with other networking related features to improve routing efficiency in OMSN.

All social-based routing approaches have the general main goal which is improving communication quality by exploiting the knowledge of the social networks. However, the way how to exploit user’s social information, which the social metrics to be selected, and how performance metrics are affected are still challenges.

Delivery cost is one of the main concerns of routing performance in the opportunistic network. The high intermittent connectivity of the opportunistic networks causes routing protocols to incur high delivery costs. Social information could be a fruitful source to effectively control the delivery overhead. This is the research focus of this thesis. Thus, the main concern of this study is to answer the research question: to what extent the exploiting of social information can minimize the overhead costs while not negatively affecting other performance metrics in opportunistic networks. Furthermore, this study aim to investigate how combining social aware forwarding technique and other forwarding protocols such as epidemic and probability can produce more efficient routing protocol. The investigation of different social aspects such as regularity of routine life, the exploiting of multiple social metrics and the relation of different social properties, also enclosed in this study to improve information provision in OMSN.

In this thesis, the focus is on studying the different social features that can be used for routing improvement in the opportunistic network. The thesis studies how social information can be acquired from different sources and how to evaluate it in measurable social metrics. In addition, this thesis explores how to exploit social metrics for developing an efficient social-based routing protocol that mainly reduces the delivery overhead to avoid resources exhausting and as well as achieving good delivery ratio and low latency. Furthermore, further insight will be conducted into selecting important social features and to explore the interconnection between social features when utilizing multiple social metrics.

1.3 Problem Statement

Routing is one of the key challengeable issues to be addressed in OMSN. This network paradigm incurs high mobility patterns, frequent links breakage and non-guaranteed existence of end to end path between source and destination (Xia et al., 2015; Mao et al., 2017). For efficient routing, the delivery cost needs to be decreased in terms of overhead ratio and average hop count while not negatively affects the delivery ratio and average latency in the network. Social information can be exploited to cope with the uncertainty and dynamism in the network topology of OMSN because people mostly carry mobile devices while they are moving around, and generally human has relatively stable social activities and follow similar interaction patterns (Xia et al., 2016).

Social based forwarding schemes are a strong trend in routing data in OMSN (Tsugawa, 2019). However, what the social features to be exploited, how to exploit the social features with other routing related issues for efficient routing strategies, and how multiple social features can be integrated for routing purposes, are all important research questions.

Social features can be exploited to adjust messages' TTL in the Epidemic-based forwarding protocol to decrease the negative impact of high message duplication and hence decrease delivery cost in OMSN. In addition, utilizing the social information available in the user's profile, and exploiting the regulating of people's social behavior, and considering the interconnection among multiple social metrics can make the forwarding decision more accurate and improve routing efficiency.

1.4 Research Objectives

The main goal of this research is to improve information provision efficiency in opportunistic mobile social networks by utilizing social features. The following objectives are designed to fulfill the aforementioned goal of this research:

1. To investigate the social features and its impact on the routing performance in OMSN.
2. To develop new social-based routing protocols to control the overhead and increase the data dissemination efficiency based on nodes' social features.
3. To evaluate the performance of the proposed dissemination protocols in the opportunistic network with selected benchmarks.

1.5 Scope of Research

This thesis concentrates on investigating social features to decrease delivery cost in OMSN. Therefore, the study focuses on decreasing the deliver overhead ratio and average hop counts while not negatively affecting the delivery ratio and average latency in the network.This study focuses on identifying the most common and effective social features which are used in the literature for performance enhancement of routing in OMSN. Three real traces datasets; Cambridge, INFOCOM05, and INFOCOM06, are used for performance evaluation because this study concentrates on the utilization of people's social information for improving routing efficiency in OMSN. In addition, three benchmarks from different routing protocols classes; flooding-based (Epidemic), prediction-based (PRoPHET), and socially-based (Bubble Rap) are used for performance comparison.

1.6 Research Approach and Contributions

The main objective of this thesis is to improve the routing performance in OMSN by exploiting mobile user's social information. Overhead is an important factor that impacts performance significantly. The main contribution of this thesis is to control the overhead and produce efficient social based forwarding schemes in OMSN. The significant contributions include:

1. The analysis of the different social features that impact the forwarding process and deduce the predominant ones to be exploited for efficient routing protocols.
2. Propose a social-based mechanism to control the overhead of Epidemic routing protocol in OMSN. Social degree centrality is integrated with Epidemic forwarding strategy to enhance the routing efficiency of Epidemic protocol. Consequently, Epidemic-based Social-based (EpSoc) routing protocol is proposed. In EpSoc, message replications are controlled socially by adjusting message's Time To Live (TTL) value according to the popularity of the mobile user. EpSoc decreases the overhead ratio significantly while achieving good performance in terms of delivery ratio and average latency.
3. Propose a social aware forwarding protocol based on ranked social characteristics. The proposed protocol, which called Social-based Ranking protocol (SOR), utilize the social characteristics of the user profile; it also considers the regularity of social behavior and the relative importance of the social features over different day periods. SOR increases the delivery ratio and decreases the overhead significantly in OMSN.
4. Propose Multipliable Social Metrics (MSM) routing protocol. This protocol combines three social features; social activity, social similarity, and degree centrality, where the interconnection between these features is used to form the forwarding decision. The experiment results show a great reduction in the overhead with good delivery ration and average latency.

The significance of this study includes the following:

- Decreasing the delivery cost in Opportunistic Mobile Social Networks (OMSN) makes it more efficient and consequently increases the trust of mobile users to utilize it to share and disseminate information.

- Cost-effective routing in OMSN helps to reserve the resources of nodes and network.
- From an economic perspective, OMSN can be utilized to decrease the overloads over the telecommunication, where OMSN can carry the personal-created contents.

All these points keep pace with the new interests of the fourth generation of the industry (IR 4.0) to provide high-quality services and trustworthy solutions.

1.7 Structure of This Thesis

After this chapter (introduction), the contributions are outlined as follows:

Chapter 2 discusses the related literature to routing protocols and the techniques of forwarding messages in the opportunistic network. It focuses on the social-based routing approaches and the social metrics that can be exploited to improve routing in OMSN.

Chapter 3 investigates decreasing the delivery cost of Epidemic-based routing protocol by integrating social information into its messages' forwarding strategy.

Chapter 4 provides a study of ranking people's social characteristics according to their social activities during their daily life and then exploiting the ranked social features to enhance routing performance in OMSN.

Chapter 5 presents the utilization of multiple social metrics and the interconnections among the social properties to control delivery overhead in OMSN. The social metrics: activity, similarity, and degree centrality are exploited for messages' routing.

Chapter 6 discusses an evaluation of the three social-based protocols proposed in this thesis. This chapter shows the differences among them according to the four evaluation metrics used in OMSN; delivery ratio, overhead ratio, average latency, and average hop count. In addition, it shows suitable scenarios for applying them.

Chapter 7 concludes the work in this thesis. It discusses the contribution and the significance of this research and presents the future works that can extend this research study.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the works related to the research scope of this thesis. Firstly, Section 2.2 discusses the basic concept of Opportunistic Networks (OppNet) and Opportunistic Mobile Social Networks (OMSN) as these two concepts are inter-related. Then one of the most challengeable issues of these networks is defined, that is, the messages routing in OMSN. Section 2.3 reviews in detail the different types of routing schemes used in OMSN. This section classifies the routing protocols according to the applied forwarding strategies where the subsections of this section present the features of each routing protocol.

The focus in this thesis is on the social aware routing in OMSN, so Section 2.3.5, Section 2.3.6 and Section 2.3.7 present comprehensively the related social-based routing schemes. Section 2.3.5 introduces the social-based routing in OMSN. Section 2.3.6 defines the most common social features that are exploited to improve routing performance in OMSN. Section 2.3.7 classifies the social-based routing schemes from the perspectives of the exploited social features. By this, the aim is to give a deep insight into what and how social metrics can be exploited to enhance routing in OMSN. The following sections (from Section 2.3.7.1 to Section 2.3.7.4) present the social-based approaches according to the proposed classification.

For more investigation, Section 2.4 deduces the main orientations of the social-based schemes. Section 2.5 presents some statistical analyses and inferred indications based on the literature review. Hence, Section 2.5.1 presents the deduced relative importance of the social features according to the number of research works that exploit the feature. While Section 2.5.2 presents the most common key performance metrics that are used to evaluate the performance of the social-based routing schemes. Lastly, Section 2.6 concludes this chapter.

2.2 Background

In recent years, the rapid and wide-range development in mobile devices technologies emits new domains and enlightens different ways of utilizing the technology and exploiting these advanced devices for various services. Opportunistic Networks (OppNets) (Khabbaz et al., 2012; Wu et al., 2017) and Mobile Social Networks (MSNs) are examples of these new networking paradigms for data distributing and content sharing (Kayastha et al., 2011).

Opportunistic network emerges as a new paradigm of Mobile Ad Hoc Networks (MANET); it is a highly disconnected MANET network (Csobin et al., 2016). There is no guaranteed, long-lasted path between source and destination. This is due to high mobility, low node density and a short coverage range of mobile nodes. Intermittent and disruptive connectivity are the main characteristics of OppNets. However, in this situation, to forward data from one point to another, mobile nodes cooperate to ensure the accurate deliverance of the data to destinations. The Store Carry Forward (SCF) mechanism is applied for information delivery (Zhu et al., 2015). In SCF, when there is no opportunity for forwarding data, mobile node stores contents in its buffer and then forward it later to a target recipient or population when there is an opportunity.

The high technical capabilities of modern mobile devices give the ability to utilize them for social activities, which results in a new network paradigm i.e. mobile social network (MSN), MSN is the communication structure that combines mobile communications networks with social networks (Wang et al., 2014; Hu et al., 2015). Communication techniques equipped in smart devices such as Bluetooth, ZigBee, Wi-Fi are utilized for communication. In addition, social interactions and relations among individuals like friendship and popularity are exploited for disseminating data efficiently and effectively. Figure 2.1 shows the relation between mobile communication, social relations in MSN.

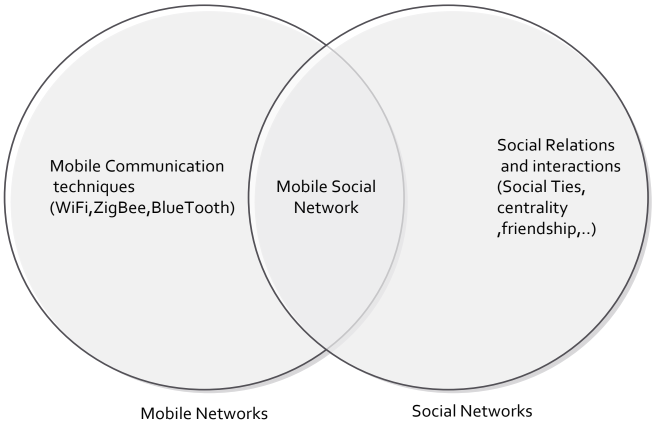


Figure 2.1: Mobile Social Network (Hu et al., 2015)

MSN involves two types of networks, the mobile communication network that connects cyber world devices, and the social network that connects humans. Modern mobile devices such as smartphones, tablets, IPADs are high technical capable devices; they are equipped with high-speed processors, large memories, communicating technologies, sensing devices. Adding to this the plenty of applications and software services available for these mobile devices (Google Play, Apple Store, Windows Phone Store). On the other hand, human beings are social beings that have their own communities, social activities, and relationships. People move around carrying their mobile devices. Consequently, by combining the two worlds, cyber and human, mobile devices can be exploited to serve the increasing of human social demands. As a result, in the context of the intersection between human space and mobile communications space the mobile social network (MSN) has emerged.

MSN networks deploy the communication paradigm of delay tolerant networks (DTNs) where nodes are mobiles and end to end paths between sources and destinations are not exist always (Zhou et al., 2014; Zhu et al., 2015). Consequently, in MSN networks, mobile users can access, share, and distribute data by exploiting their social relations.

From the structure perspective, MSN networks can be classified into two groups, i.e., centralized and decentralized (Wang et al., 2014; Csobin et al., 2016) . In centralized MSN, a central source hosts the information and provides services. Mobile devices connect to the centralized server using a mobile web-based application to acquire the required information. Examples of these applications are Facebook App (https://www.facebook.com), twitter app (https://twitter.com/download). On the other hand; mobile nodes in decentralized MSN are independent. There no central server but distributed data in mobile nodes' buffers. Mobile nodes catch the opportunity of coming in contact with each other to forward data using wireless technologies such as Bluetooth and Wi-Fi. The social behavior and the advantages of social features are exploited in choosing the next forwarder to disseminate contents. This type of MSN is called Opportunistic Mobile Social Network (OMSN) in this thesis, where this study is focused on this network paradigm. Some researches use a hybrid content dissemination strategy, by utilizing the available networking infrastructure as replicators, and then leverages these replicators to propagate the contents on smartphones to others via opportunistic communications (Thilakarathna et al., 2014).

There are several domains for applications of the MSN network (Mao et al., 2017). It is applied in domains such as social networking in rural regions, location-based and proximity services, disaster relief and vehicular networks (Vegni & Loscrí, 2015).

Examples of these applications are Peoplenet (Motani et al., 2005), Spiderweb (Sapuppo, 2010), vehicular ad-hoc networks (Ott & Kutscher, 2005), Twitter (https://www.twitter.com) and Facebook (https://www.facebook.com) for social networking, Blackboard (https://www.blackboard.com) for education, Glucose Buddy (https://www.glucosebuddy.com) for e-Health applications, and Triposo for travel and tourism (https://www.triposo.com/) .

OppNet is defined as a sparse and d high-dynamic topology mobile wireless network, therefore data dissemination in such an intermittent and uncertain connectivity environment is a challenging issue (Cao & Sun, 2013; Yuan et al., 2016). Traditional routing protocols used in wired networks like TCP/IP protocol or wireless MANET such as Ad hoc On-demand Distance Vector protocol (AODV) proposed by Perkins and Royer (1999), and Dynamic Source Routing protocol (DSR) proposed by Johnson et al. (2007) are unsuitable for routing in OppNet. Therefore, particular information exchange protocols are developed to enable nodes to route data from source to destination. Mobile nodes utilize the interaction periods with others to forward data contents. Hence, selecting the optimal forwarder in OppNet is the main challengeable issue when routing data. Efficient routing protocols in an intermittent and dynamically variant scenario such as OppNet should satisfy the performance requirement in terms of high delivery ratio, low network and node overhead, and low end to end delay (Alajeely et al., 2018; Rahim et al., 2018; Tahouri & Derakhshanfard, 2019).

In this thesis, the main aim is to enhance the routing performance for efficient data dissemination and information sharing in the OMSN network. The next section discusses the routing issues in opportunistic and MSN networks

2.3 Routing in OppNet and MSN Networks

In the literature, the issue of routing and data forwarding has been widely addressed (Chakchouk et al., 2015; Csobin et al., 2016; Alajeely et al., 2018). Different solutions have been suggested to solve this problem. The existing routing protocols in OppNet are classified in this thesis into five main categories. There are Flooding-based, Epidemic-based, Probabilistic-based, Context-based, and Social-based Routing protocolsg.

2.3.1 Flooding-based Routing

All Flooding is a naïve replication forwarding strategy. Each node forwards the received messages when meets a neighbor. There is no consideration of selecting candidate next forwarder. So, information is spread in the network as a broadcast storm. Unlimited replicas of messages in Flooding-based protocols result in exhausting network and nodes resources (bandwidth, buffer), thus causing congestion (Tseng et al., 2002). However, flooding-based routing is an effective approach when the movement of mobile nodes is unpredictable and network topology is very dynamic. Also, it can be applied for very disastrous scenarios such as earthquakes and storms where the main concern is to deliver messages to their destinations through consecutive forwardings between intermediate nodes when linkages are available.

2.3.2 Epidemic-based Routing

Epidemic routing protocol is an improved flooding-based protocol (Vahdat & Becker, 2000). Epidemic protocol reduces the duplication of the message’s copy. In

Epidemic, each host maintains an indexed list of originated and buffered messages, and each message is associated with a unique identifier. Based on this indexed information, a bit vector called summary vector is built to indicate which information has been seen by the sender. When two mobile nodes come into their communication range, they exchange summary vectors and determine which messages have not been seen previously. Eventually, using this pairwise information exchange messages are delivered to destinations.

Epidemic has upper bound for message delivery and a lower bound for the end-to-end delay (if no buffer constraints are applied). However, it has the highest overhead ratio because it still uses flooding strategy. Hence, the main drawback of the Epidemic protocol is the excessive usage of resources such as memory and bandwidth.

In this thesis, the Epidemic protocol is used as the benchmark for the proposed protocols. This is because it presents the fundamental knowledge of the flooding-based protocols, where it is a dominant routing protocol in terms of low delivery latency and low overhead ratio in the unconstrained-resources scenario. In addition, it is the best solution for data dissemination in some disaster situations such as flooding and earthquake. also it is used widely in the literature as a reference such as Xia et al. (2016), Abdelkader et al. (2016), Guan et al. (2017) and Liu et al. (2018), and is available online at ONE simulator web site (https://akeranen.github.io/the-one/) for researchers.

Some Epidemic-based approach approaches applies a control policy to decrease the delivery cost by limiting the number of messages replicas. Examples of these approaches Spray and Wait Routing (SnW) proposed by Spyropoulos et al. (2005), the works proposed by Chen et al. (2014), and by Aung et al. (2017). Social metrics are also exploited to control replications in Epidemic routing protocol. Community structuring or grouping is utilized to decrease the network overhead; Local Community protocol (LocalCom) proposed by F.Li and Wu (2009) and Social Groups-Based Routing (SGRB) proposed by Abdelkader et al. (2013) are examples of these protocols. LocalCom and SGRB, use local information to detect community and to route the message to reach the destination. This improves significantly the performance by decreasing network overhead.

Unlike these approaches, this thesis aim not only to decrease the overhead but to get the advantages of Epidemic and the social features to maintain effective information delivery in terms of low latency and high delivery ratio like Epidemic, and to reduce overhead significantly. The details of this protocol are presented in Chapter 3.

2.3.3 Probabilistic Routing

Probabilistic-based routing is an advanced version of Epidemic based routing protocol. Inspired by the non-randomness mobility of real users and to improve routing performance in networks with scarce resources (bandwidth and buffer) such as OppNet probabilistic routing was developed.

The most important protocol in this category is PRoPHET (Lindgren et al., 2007). In PRoPHET, a probabilistic metric called delivery predictability is defined, $p(a,b) \in [0,1]$ at every node a for each known destination b. Calculation of probabilistic metric has three dimensions; firstly, encountering, nodes that are often encountered have high delivery predictability. Secondly, aging, if a pair of nodes do not encounter each other in a while, the delivery probability for each other is decreased. Finally, transitive property, if node A frequently encounters node B, and node B frequently encounters node C, then node C probably is a good forwarder for messages destined for A.

2.3.4 Probabilistic Routing

The context describes the status information of the user and his own environment. Context information may be personal properties such as physical location, profession, email, or the reality of the surrounded environment such as node mobility, encounter history, formed communities, etc. Examples of these approaches: History-Based routing protocol (HiBOP) proposed by Boldrini et al. (2008), Gently proposed by Musolesi et al. (2008), Context Information Prediction for Routing in OppNets (CiPRO) proposed by Nguyen and Giordano (2012), Context-Aware Message Forwarding (CAMF) proposed by Wei et al. (2015) and Context-aware Adaptive Routing (CAR) proposed by Chen and Lou (2016). Context-based approaches exploit the knowledge acquired from context information to drive the forwarding process. Context information should be stored in nodes' memories and updated to reflect the real state of the underlying scenario and to benefit better forwarding decision.

2.3.5 Social-based Routing

Consideration and exploitation of social features of mobile nodes is a recent and active trend in the research area of routing and data dissemination (Ahmed et al., 2018). The main objective is to make the optimal decision when to select relay nodes with the highest probability to meet the destination node. Therefore, different social features and social metrics are investigated to improve the routing and dissemination process. There are different social properties such as centrality, similarity, and social ties that can be exploited. There are different and various trends in utilizing social features. Also, there are different objectives for exploiting social metrics.

This study focuses on the social-based routing. Therefore, in Section 2.3.6 defines the most common social features that are exploited in the literature for enhancing routing performance in MSN network, Section 2.3.7 categorizes the reviewed social-based routing protocols and provide a comprehensive review of these categories.

2.3.6 Social Features in OMSNs

Human social structures are at the core of opportunistic networking (Conti et al., 2012), whereas encounters between people during social activities give the opportunity to contact and exchange common interests. In recent years, the trend to exploit social behaviors of mobile nodes in OMSN for routing and data dissemination enhancement has drawn tremendous interests (Mao et al., 2017; Tsugawa, 2019). OMSNs depend on the cooperation between nodes to forward data, and it employs the store-carry-forward paradigm to allow intercommunication between them. Therefore, regarding the impact of social characteristics on performance of OMSNs, social characteristics are divided into two types: positive and negative (Zhu et al., 2013). The positive social characteristics, which increase collaboration in the network (such as community and friendship), and the negatives social characteristics, that decrease packet forwarding capability (example selfishness). Based on this division many researchers focus their efforts to get advantages from utilizing the positive social characteristics in data dissemination and routing (Rahim et al., 2017; Tahouri & Derakhshanfard, 2019). On the other hand, other researches study the negative effects of social features on routing and data dissemination algorithms and how to relieve their impacts (Mei & Stefa, 2012; Rahim et al., 2018; Socievole et al., 2019).

There are several social features exploited to enhance the data dissemination in OMSNs. The following section discusses the social features that are used in the discipline of social networks.

2.3.6.1 Centrality

Centrality in network analysis is a quantification of the relative importance of a vertex within a graph (Daly & Haahr, 2007). The node centrality can be measured by three metrics degree, closeness and betwenness (Freeman, 2006; Moreira et al., 2012).

i. Degree centrality

It is the number of direct ties that involve for a given node (Rahim et al., 2018). The node that has a high degree is an active node; this means that high data traffic flow through it. Some data dissemination and routing exploits such nodes to improve data dissemination, for example, Bubble Rap (Hui et al., 2011). Degree centrality of a node equals the number of all direct link connects it

Degree centrality for a given P_i node is calculated as follows:

$$C_D\,(P_i) = \sum_{k=1}^{N} a(p_i, p_k) \qquad \text{Equation 2.1}$$

Where N is number of nodes in the network, and $a(p_i, p_k)$ =1 if a direct link exists between two peer nodes p_i and p_k and $i \neq k$

ii. Closeness Centrality

It measures the reciprocal of the mean geodesic distance, which is defined as the shortest path between a node and all other reachable nodes (Hu et al., 2015). The closeness centrality can be regarded as a measure of how long information takes to spread from a given node to other nodes in the network. Consequently, if a node is near to the center of the graph, it has higher closeness centrality and is good for quickly spreading messages over the network. Closeness centrality of a node equals the reciprocal of the average distance to all other nodes in the social graph.

Closeness centrality for a given P_i node is calculated as follows:

$$C_c\,(P_i) = \frac{N-1}{\sum_{k=1}^{N} d(p_i, p_k)} \qquad \text{Equation 2.2}$$

Where N is number of nodes in the network, $d(p_i, p_k)$ is the distance (number of hops) between the two peer nodes p_i and p_k , and $i \neq k$.

iii. Betweenness Centrality

It measures the extent to which a node lies on the geodesic paths linking other nodes (Vastardis & Yang, 2013; Hu et al., 2015). Betweenness nodes control over information flowing between others. Betweenness nodes connect separate nodes and communities. A node with high betweenness centrality is a bridge for connections. Betweenness centrality of a node equals the number of shortest paths flow through it.

Betweenness centrality for a given P_i node is calculated as follows:

$$C_B\,(P_i) = \sum_{j=1}^{N} \sum_{k=1}^{j-1} \frac{g_{jk}(p_i)}{g_{jk}} \qquad \text{Equation 2.3}$$

Where g_{jk} is the total number of geodesic paths linking p_j and p_k and $g_{jk}(p_i)$ is the number of those geodesic paths that include P_i.

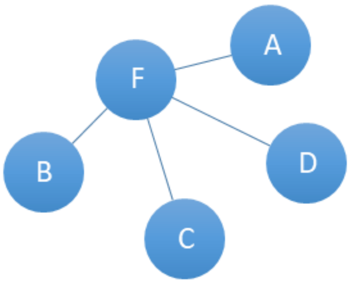


Figure 2.2: Three types of centrality measurement

For degree centrality calculation, Just one direct link incidents upon each of nodes A ,B,C and D, while four direct links incident upon nodes F. The degree centrality values are:

node (A)	1
node (B)	1
node (C)	1
node (D)	1
Node (F)	4

To calculate closeness centrality, sum the shortest distances from the node to all other nodes in the networks, then divide by the number of them. In this example, for nodes A, B,C and D:

$$\big((A-b)+(A-C)+(A-D)+(A-F)\big)/4=\frac{7}{4},$$

The closeness is the inversed value = $\frac{4}{7} \approx 0.57$

For nodes F:

$$\big((F-A)+(F-B)+(F-C)+(F-D)\big)/4=\frac{4}{4}=1$$

The closeness is the inversed value =1, The closeness centrality values are:

node (A)	4/7
node (B)	4/7
node (C)	4/7
node (D)	4/7
Node (F)	1

Regarding betweenness centrality, there are four shortest paths for each of node A, B, C, D and F. All the shortest paths flow only through node F. Therefore, the betweenness centrality values are:

node (A)	0
node (B)	0
node (C)	0
node (D)	0
Node (F)	6

The centrality measures clarify the importance of a node in the network from three perspectives: node activity (traffic issue), nodes location (shortest path) and node linkage (bridging). However, the centrality measures do not take into account the social interactions and strength of the links between nodes. Two nodes that link connects can be friends or coworkers, they may contact frequently and have common interests.

2.3.6.2 Similarity

It is a measurement of the degree of separation (Xia et al., 2015). The social similarity indicates the grouping of nodes depending upon common interests or contacts which can be calculated according to the number of common neighbors that two nodes have (Hu et al., 2015). There are other ways to define the similarity beyond common neighbors, for example, Li et al. (2015) define similarity based on user location while Shi et al. (2019) depend on user interest to define it.

2.3.6.3 Social Ties

They are the social interactions between individuals. Different types of social ties may describe different social relationships between people such as friends, relatives, colleagues. The strength of the tie is defined as "The strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding) and the reciprocal services which characterize the tie" (Granovetter, 1973). For example, Friendship is defined in general as a regular and long-lasting social tie between pair users. Related to the friendship concepts what is called homophily phenomenon (Bisgin et al., 2010), where people who have common interests and share similar activities be friends (McPherson et al., 2002). Therefore, the friendship in DTNs can be roughly determined by using either contact history between two nodes (Bulut & Szymanski, 2010) or common interests/contents claimed by two nodes (Zhang & Zhao, 2009). When friends meet, common interests are exchanged first, on the contrary when strangers (not friends) meet non-common interests are diffused first. Friendship and homophily phenomenon is exploited to diffuse data in OMSN (Bisgin et al., 2010; Guan et al., 2017; Fernandes et al., 2018).

2.3.6.4 Social Influence

It means influencing others to join (or leave) a community (Takaffoli et al., 2011; Hung et al., 2016). A high influence score indicates that when the node joins a community, a large number of follower nodes will also join that community or leave it.

2.3.6.5 Selfishness

Actions that aim for the maximization of personal profit, against the common good (Vastardis & Yang, 2013; Socievole et al., 2019). Selfishness can be in two types, personal selfishness: where the user focuses on personal utility with no care about common benefits with all peers in the network, and social selfishness: where user behaves selfishly in a social sense, so just willing to forward data for nodes in the same community and drops packets for others.

It can be concluded that more metrics can be inferred depending on how well the understanding of the social aspects and how the social features are exploited. Table 2.1 summarizes the common social characteristics of MSN.

Table 2.1: Social Features for OMSNS

Centrality	The importance of node	
	Closeness centrality	Location , it has shortest path to others
	Betweenness centrality	Connect separated nodes or communities
	Degree centrality	Traffic , it is active node
Similarity	Common interests or contacts between nodes	
	Community structure	Frequently contacting nodes
Social Ties	Social relation, its strength determined by frequency and duration of contact	
	Friendship	regular and long-lasting contacts
Social influence	Influence node push others to joint or leave community	
Selfishness	Node just concerns about personal or community utility.	

The following section presents the routing schemes form the exploited social features perspective.

2.3.7 Social-based Routing in OMSNs: Exploited Social Features Perspective

Consideration and exploitation of social features of mobile nodes is a recent and active trend in the research area of routing and data dissemination in OMSN. The main objective is to make an optimal decision when to select relay nodes with the highest probability to meet the destination node. Therefore, different social features and social metrics are investigated to improve the routing and dissemination process.

As it is aforementioned in Section 2.3.6 (social features in OMSN), there are different social properties such as centrality, similarity, and social ties that can be exploited. There are different and various trends of utilizing social features and different objectives for exploiting social metrics. Some routing methods utilized one of them, and others combine multiple social features. The social based routing protocols are classified in this thesis according to the exploited social features; see Figure 2.3 for the proposed classification.

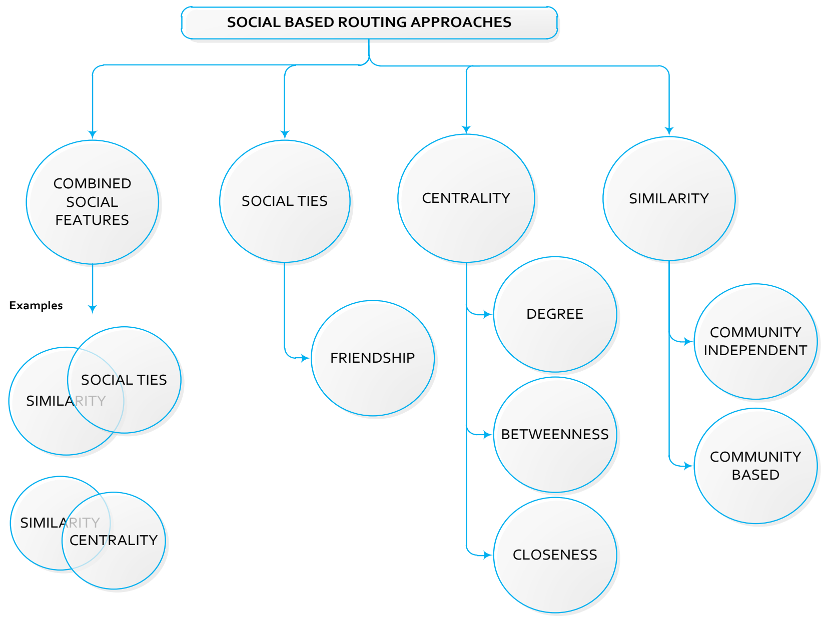


Figure 2.3: Classification of social-based routing protocols.

2.3.7.1 Similarity (Community-Independent) Approaches

The similarity in OMSN is an indication of grouping between nodes depending on common contacts (neighbors), interests, or locations. Consequently, nodes with a high similarity have high probability of contact.

According to literature review in this thesis, some similarity-based protocols use community detection algorithms to identify the community that a node belongs to. The community detection process is complex and time-consuming. So, similarity-community-independent approaches overlook community detection issue and depend directly on the similarity between individuals. In the following sections, the similarity (community-independent) works are reviewed.

Mostly, the information exists in node profiles (user and device information) is the source of community-independent methods to calculate similarity and then exploit it for enhancement. For examples, Social-greedy proposed by Jahanbakhsh et al. (2010) , HSFR proposed by Wu and Wang (2014), SANE proposed by Mei et al. (2015) are methods depend on the user social information stored in node profile, while approaches such as HiBOP proposed by Boldrini et al. (2008), CiPRO proposed by Nguyen and Giordano (2012), SPRINT-SELF proposed by Ciobanu et al. (2015) and CAMF peoposed by Wei et al. (2015) consider both user and device (buffer size, remaining energy) for similarity calculation and exploiting. Other community-independent methods depend on common properties such as contacts (neighbors) and location, for example, K. Chen and Shen (2014) proposed SMART protocol which uses contact history to measure similarity based on the common contacts.

Context-aware and social-aware concepts are combined to enhance routing in OMSN. The similarity metric is exploited with several of context-aware protocols to enhance their performance. These approaches focus on the nodes’ context for the best forwarding data. HiBOP and CiPRO are examples of these methods.

Users update their social profiles through social media. Some routing protocols in OMSN consider the time evolving in social information. The similarity is exploited also in these methods. These protocols dynamic-social information-aware in this thesis. Dynamic-social-information ware is more applicable but incur high overhead. HiBOp and HSFR consider the dynamism in context of social information. On the other hand, this study found other methods for example Social-greedy, derive social distance from people's social profiles (offline information). This information is utilized to route messages. So, it is called a static social information approach in this thesis. Nodes profiles are used for showing the effectiveness of using various social dimensions, particularly for media sharing applications. They define a social distance between a pair of nodes depending on the similarity of their interests. The more common attributes, the closer the two nodes are. The message is forwarded to the next node which socially closer to the destination.

The similarity is utilized with stateless approaches that do not need knowledge about network topology. Stateless approaches have profound performance in terms of network overhead. SANE, SMART and CAMF are examples of these methods. SANE combines the advantages of both social-aware and stateless approaches (for example Epidemic). The aim is to overcome the storage capacity problem with existing social aware approaches such as LABEL which proposed by Hui and Crowcroft (2007) and Bubble Rap proposed by Hui et al. (2011).

SPRINT-SELF protocol combines the social-based routing and the node behavior prediction to decrease the network and node overhead. Social community information is exploited for efficient routing where existing social information such as Facebook-provided data is used. In addition, the authors predict future node behavior by analyzing the node’s past encounters and using a Poisson distribution.

Liu et al. (2018) propose FCNS which is a fuzzy routing-forwarding algorithm exploits comprehensive node similarity (the social and mobile similarities) in opportunistic social networks. Information about the state of the network is collected and updated to evaluate the social and mobile similarities of nodes in the network, and then transmission preference for each node is calculated through the fuzzy evaluation. The forwarding strategy depends on comparing the transmission preference of the nodes where the node with higher transmission preference will be selected as a message relay.

2.3.7.2 Similarity (Community-Detection) Approaches

These approaches consider the social structure and grouping of people. So that, communities are declared or detected in the network. Routing approaches try to exploit social communities to get better performance. Most of the community-based routing protocols depend on historical contacts between users (frequently contacts, long contacts), common locations (called homes) or common social properties (for example interests) to detect communities. In addition, labeling is also used by some of the community-based schemes for defining and declaring communities in the network. LABEL and Gently are examples of schemes that use the labeling technique to define communities in the network.

LABEL proved that using small labels to identify users' community improve forwarding performance. Gently follows the same technique to define the communities, but try to overcome the drawback of LABEL that source needs to wait until the community members of the destination or the destination itself are at one hop distance from the source to start forwarding.

Community structuring or grouping is utilized for control flooding and decrease the network overhead. LocalCom and SGRB are examples of these protocols. LocalCom and SGRB, also use local information to detect community and to route the message to reach the destination. This improves significantly performance by decreasing network overhead.

People tend to visit some places frequently. Communities are formed based on the common location and utilized in social ware routing approaches in OMSN to improve performance. HS proposed by Wu et al. (2013) and LASS proposed by Li et al. (2015) are examples of these schemes.

In HS, frequently visited locations which are called homes are used to quickly deliver the message to the destination. Messages are delivered to the destination using zero-knowledge routing protocol while the copies of each message are no more than a given threshold. Although HS achieves well regarding average delivery ratio and delay, it incurs also high node and network cost due to home forming and information exchanges through the different home phases.

Nodes have different local activities within their communities, LASS addresses the importance of local activity and its impact on the performance. The similarity feature is defined as the inner product of local activity vectors of the mobile nodes for each community in a dynamic weighted network.

The community concept is utilized with prediction techniques in CAR, it is a community aware protocol proposed to improve routing efficiency in delay tolerant network. Each community can be considered as a unit such as a virtual big node during the routing procedure. Intra and inter-community routing phase are adopted in CAR. The inter-community routing will be triggered when the node does not belong to any of the message's destination communities. While intra-community routing will be triggered when the message already arrives at one of its destination communities, that is, the node belongs to one of the message's destination communities.

It can be concluded that all community-based protocols exploit the community concept to get an efficient routing protocol. Different protocols focus on different sides for enhancement, for example, HS focuses on delivering the contents quickly while SGRB aims to reduce the resources consumption. The features that are utilized to form the community are different from one to another. LABEL and Gently depend on labels, LocalCom and SGRB depend on similarity in contact frequency, while in HS the locations are utilized to form the homes. Most of these methods put Epidemic as its benchmark; this is because it achieves the highest delivery ratio. However, Epidemic incurs very high cost and overhead, so community-based protocols aim to converge to Epidemic in terms of delivery ratio and to solve the problems related to cost and resource consumption.

2.3.7.3 Social Ties-based Routing Approaches

Social ties-based schemes concern and focus on interacting between nodes in OMSN. They exploit the aspects related to the social relations and interaction between individuals such that contact frequency, contact duration, and relation strength.

Pujol et al. (2009) proposed FairRoute protocol that utilizes the social ties to get rid of the congestion problem around central nodes and to apply load distribution. This method relies on perceived interaction strength and assortativity (homophily phenomenon (Bisgin et al., 2010) to guide the forward decision upon contact. Although FairRoute achieves fair load distribution, other more important performance metrics such as delivery ratio and cost are not enhanced.

Social ties are also used to decrease the overhead in social based protocols. In PeopleRank protocol (Mtibaa et al., 2010) , the relative importance of a node in a social graph is measures and people are tagged as “important” when they are linked (in a social context) with many other “important” people (popular). Only neighbors in the social graph have an impact on the ranking. The message forwarding decisions can then follow a non-decreasing rank rule, where socially well-connected nodes become the best forwarders for message delivery. In this way, the number of message replicas is reduced significantly. However, PeopleRank is considered a state-full routing protocol in OMSN, because it depends on social interaction between nodes and their contact frequency to compute the probability distribution for node ranking. Consequently, it implies nodes and network overhead.

Friendship relationship is a special type of social relations. Some researchers exploit this relation to enhancing data forwarding in OMSN. Bulut and Szymanski (2010) (2012) proposed friendship-based routing protocol to analyze social relations between people, they define friendships in terms of people behavior. In this protocol, contact history between two nodes is utilized to indicate the tie strength of the virtual link and to form friendship community.

Matis et al. (2016) proposed HSBR protocol to exploit social relations and combine them with the main features of both routing protocols of traditional MANET protocol (DSR) (Johnson et al., 2007). This approach is applicable in the networks where the separate solutions of MANET or DTN are useless or ineffective. Nodes' profiles are utilized to evaluate the social relations between users.

In ASDM protocol proposed by Le and Gerla (2016), the social tie is utilized to consider the anycast routing problem in DTN. Novel forwarding metric, Anycast Social-Distance Metric (ASDM), is proposed. ASDM is defined as the probability of successfully delivering a packet to any members of an anycast group based on the social distances to members of the group. It is based on the multi-hop delivery probability over the most probable path from the source to the destinations. Exploiting social features in this protocol results in a robust and efficient anycast routing protocol.

Liu et al. (2017) developed a socially aware congestion control protocol called (SACC) to control the congestion. They evaluate the strength of the social link between the relay node and the destination and also define the congestion level to drop messages when the congestion takes place in the network. Therefore, the applied forwarding strategy drops the message with the minimum social link rather than random dropping.

2.3.7.4 Combined Social Features-based Approaches

The combination of different social features to enhance the performance of OMSN is a strong trend in the literature. Different social features are combined in different ways and for different goals. The following section reviews the current schemes that combine different social features for routing and data dissemination improvement in OMSN.

Daly and Haahr (2007) proposed SimBet protocol. In this protocol, the ego network analysis technique is used to estimate the values of the betweenness centrality and the similarity for each node. SimBet performs well with regard to message delivery. However, suffer from high delay as well as congested traffic around central nodes.

Visiting common places frequently is inherent and important social properties of people. Different social features are combined and exploited to improve routing in location-based approaches. CAOR proposed by Xiao et al. (2014) , SMART proposed by Zhu et al. (2014) and ML-SOR proposed by Zhu et al. (2015) are examples of these methods.

CAOR exploits similarity (community-based) and degree centrality to improve routing. In contrary to other social aware methods that tend to forward the message to the nodes with locally optimal social characteristics, they propose a new protocol, which is a home-aware community model. Since the number of communities is far less than the number of nodes in magnitude, the computational cost and maintenance cost of contact information is greatly reduced.

ML-SOR exploited social features (Degree centrality and betweenness) to solve the throwbox placement problem. Deploying thowboxes is well-known scheme to improve data dissemination in OppNet, the problem is where to place the thowboxes in a large-scale throwbox-assisted mobile social DTN. Based on the knowledge of social characteristics of mobile users and candidate locations a smart social-based protocol is proposed to pick the deployment locations of thowboxes.

In SMART, similarity, centrality and community social features are combined to confront the blind-point and dead-end problems exist in utility-based routing protocols such as Simbet, Bubble Rap, and PRoPHET. Blind-point happens when the source node and all its neighbors have similar utility values near to zero. So, it is difficult to determine the relay node. While dead-end occurs in the scenario when the source node has a higher utility of all its neighbors causing messages to stick in the source node. Based on the observation that the movements of mobile users are strictly restricted to the local area (locality property), the authors proposed a new method for community portioning. In addition, they apply convolution and decay operation on utility computation to get rid of the causes of blind-spot and dead-end.

The concept of ranking nodes socially to improve routing performance is applied using multi social features. In Bubble Rap clustering and grouping of users are considered together with the degree centrality social feature. Bubble Rap focuses to overcome the problems of previous routing methods such as Epidemic which are cost ineffective due to the partial capture of the transient network behavior. Bubble Rap exploits two social and structural metrics, namely centrality and community. Nodes belong to different sized communities and have different levels of popularity (i.e. rank). Each node is assumed to have two rankings: global denotes the popularity (i.e. connectivity) of the node in the entire society, and local denotes popularity within its community. Messages are forwarded to nodes having higher global ranking until a node in the destination's community is found. Then, the messages are forwarded to nodes having a higher local ranking within the destination's community.

Social features are also combined and utilized to consider the dynamism of people's behavior result from their daily routine. These approaches are more close to the reality of people life and their social activities. DLifecomm proposed by Moreira et al. (2012) utilizes the community structure and the social relation between mobile nodes. In dLifecomm it is assumed that contact duration can provide more reliable information than contact history, or frequency when it comes to identifying the strength of social relationships. The objective of this method is to consider the dynamism of users' behavior resulting from their daily routines. Users' daily routines are considered to quantify the time-evolving strength of social interactions and so to foresee more accurately future social contacts than with proximity graphs inferred directly from inter-contact times. The benchmark of DLifecomm is Bubble Rap which is similar in terms of exploiting community and centrality, but not considering dynamism of user behavior. The difference between Bubble Rap and dLifecome is that Bubble Rap considers a fixed social structure, while dLifeComm is aware of its dynamics: the network is still a fixed collection of linked individuals, but now users' daily routines influence the way links are used.

Another method that considers the dynamic in social structure and user behavior is ML-SOR**.** Node centrality, community structure, and social tie; all these three social features are exploited in ML-SOR where more than one kind of connection can exist between two individuals. This module is called a multilayer social network model. This model is constructed by combining offline (temporal) and online (static) social information. Offline social information is detected from the encounters between nodes in the network while online social information is acquired from social networks such as Facebook, Twitter. The relationship between these layers is investigated in terms of node centrality, community structure, social tie, and link prediction to effectively select the forwarding nodes and hence improving routing performance.

Xia et al. (2015) proposed Int-Tree protocol which combines three social features (similarity, social tie, and community) to study the relationship between the interests and evaluate the similarity between users interests. Three kinds of relationships between user's interests are presented; interest inclusion, cross-layer interests, and interest intersection. The interrelations between users' interests are considered to form the communities in the network, and the node can belong to different communities. Combining three social concepts provide a better forwarder node selection. However, it suffers from higher latency due to the required time to select the best forwarder.

In CGrAnt protocol proposed by Vendramin et al. (2016), social metrics are exploited with other optimization approaches to design a social aware routing protocol for opportunistic networks. Cultural Algorithm (CA), Ant Colony Optimization (ACO) and social connectivity between users are combined to address the routing problem. Social metrics of nodes including degree and betweenness centralities are analyzed to support forwarding decision in opportunistic network environment. In CGAnt exploiting social metrics with other opportunistic and complex information (such as frequency and duration and mobility features) resulted in an adaptive and tolerated forwarding approach in different mobility scenarios.

Guan et al. (2017) combine three social features in SRAMSW, that is, similarity, betweenness centrality and friendship to enhance the forwarding process and to avoid the dead-end problem. In addition, a buffer management mechanism is combined with social features to enhance spray-based routing.

In SARP, Rahim et al. (2017) proposed a social-based routing protocol for data dissemination in Vehicular Social Networks (VSNs).The proposed protocol, named Social-Acquaintance based Routing Protocol (SARP), exploits multiple social metrics; community acquaintance, social activeness, and degree centrality. Each node maintains and updates the values of these metrics and a priority value is calculated based on them. When a message carrying node encounters another node, messages will be forwarded if the encountered node has a higher priority value than the relay.

Xia et al. (2016) developed PIS which is a multi-dimensional routing protocol exploits three social factors, that is, physical proximity, social interests, and social relationship for efficient message delivery. The ego network is considered to maintain the physical proximity of the nodes where the frequent and direct contact information is included. Regarding user interest, two kinds of interest are considered; self-interest, which is the interest of the user himself, and the contact interest, which is the interest of the encountering nodes. In addition, both direct (user' friend) and indirect social relationships (friends of friends) are utilized. PIS compares the similarities of the candidate forwarders to the destination node with respect to the three exploited dimensions. Then, it calculates the similarity utility function and node with a higher similarity metric will be selected as the appropriate forwarding.

Table 2.2 provides a summary of the social-based routing schemes arranged according to the exploited social features; the key field of this table is the used social features. In addition, there is denotation if other related features such as mobility patterns or context are also exploited in the work.

Table 2.2: Summary of Social Based Routing Algorithms in OMSN

Date	**Proposed approach**	**Description**
Similarity Community-independent		
2008	(HiBOP) (Boldrini et al., 2008)	• Store context information just related to the node's community • Looking for nodes that show an increasing match with the context attributes of the destination
2009	Social-greedy (Jahanbakhsh et al., 2010)	• Forwarding is made by closeness and social distance • Closeness is calculated by the common attributes (address, school,..) of two nodes • Depends on closeness when forward data If forwards message to the next node if it is socially closer to the destination.

Table 2.2 continued

2012	CiPRO (Nguyen & Giordano, 2012)	• Similarity in context information of source and destination • Calculate the probability to deliver message to destination based on temporal and spatial context of the user • Predict the mobility pattern of nodes • Temporal and spatial user's context is used to predict the mobility pattern
2014	SMART (Chen & Shen, 2014)	• Each node build its social map depending on Encounter history (frequently meeting) • Social map contain many hops (long relay path) • Packet Delivery probability is calculated based on encountering frequency and social closeness • Links are weighed to reflect the delivery probability between the two nodes. • Packets are forwarded to nodes have high delivery probability to their destination • It is better because of having broader view
	Similarity Community-independent	
2014	HSFR (Wu & Wang, 2014)	• Uses internal social features of each node including affiliation , language , ... • Use two unique processes : entropy to extract the most informative social features , and multi path routing • Common social features (affiliation, language ,..) • Convert routing problem from mobile space (M-space) to static space or structured space (F-space)
2015	SANE (Mei et al., 2015)	• Similar interests, nodes exchange their interest profiles • Focus on tackle with the problem of storage large amount of information at nodes • Stateless approach like Epidemic For data dissemination uses utility concept
2015	CAMF (Wei et al., 2015)	• Stateless approach is adopted to measure encounter opportunities • The acquired encounter opportunities and nodes selfishness are combined. • Forwarding and receiving capabilities of mobile nodes are considered. • Similarities between nodes' property profiles are exploited to calculate encounter probabilities.

Table 2.2 continued

2015	SPRINT-SELF (Ciobanu et al., 2015)	• Exploit community social information • Use prediction algorithm based on the contact history • Detect selfish node in the network and apply avoidance mechanism • Concerns about node and network resources
2018	FCNS (Liu et al., 2018)	• Use fuzzy logic • Considers the similarity degree between nodes, which is a combination of mobile and social similarities. • Apply feedback mechanism for better more stable forwarding strategy.
Similarity Community-detection		
2007	LABEL (Hui & Crowcroft, 2007)	• Uses labels to form communities • Depends on community affiliation to forward data • Delivery ratio is very low when TTL is low because of using On-hope delivery to just nodes in destination's community
2008	Gently (Musolesi et al., 2008)	• Uses labels to identify communities like LABEL • Use CAR (community aware routing) and LABEL routing strategies • When no node of the destination community is in reach, it uses CAR . • When meet node of destination community, it adopts LABEL strategy • In destination community it uses CAR to deliver message to destination
2009	LocalCom (Li & Wu, 2009)	• Encounter history is used to form communities • In inter-community routing use flooding control, and in intra-community use single hop routing
2013	SGRB (Abdelkader et al., 2013)	• Uses social relation between nodes (nodes with frequent contacts belongs to same group) • Excludes nodes that don't add significant value to the node carrying the message this improve performance and reduce overhead.

Table 2.2 continued

2013	HS (Wu et al., 2013)	• Base on flooding in forwarding like Epidemic • Nodes have Common interests and visit common locations forms community homes • Each home supports throwbox. • It has Three phases: homing , spreading, and fetching • Forward message from source to home, then forward between homes, then in the community flood the community
2015	LASS (Li et al., 2015)	• Take into account the difference of members' activity within each community • The common interest are used to consider the similarity • To gain the node local activity of node within the community, new community detection algorithm is proposed (SAWD) • Similarity of two nodes is the inner product of their local activity victors.
2016	CAR (Chen & Lou, 2016)	• Community is considered as virtual big node when routing. • Two phases of routing are considered Inter and intra community. • Contact expectation and community aware concepts are combined to decrease overhead resulted from information exchange between nodes.
2009	FairRoute (Pujol et al., 2009)	• Depends on social strength relation to forward data • It is congestion-aware protocol • Based on interaction strength between nodes in short and long time scale to make fair load balancing • Fully distributed algorithm
2010	PeopleRank (Mtibaa et al., 2010)	• Fully distributed algorithm • Rank nodes depending on social interaction between nodes • forward data based on stable social information between nodes (non-decreasing rank)

Table 2.2 continued

2012	Friendship-based routing (Bulut & Szymanski, 2010; Bulut & Szymanski, 2012)	• Two nodes are friends if they have frequent, long-lasting and regular contacts. • Use friendship relation to forward data towards the destination
2016	HSBR (Matis et al., 2016)	• hybrid method for complicated and diversified MANET-DTN environment with different level of velocities of mobile devices • Fully decentralized combines main features of both Dynamic Source Routing (DSR) and Social Based Opportunistic Routing (SBOR) algorithms. • Nodes' profiles and contact history are considered for social tie evaluation.
2016	ASDM (Le & Gerla, 2016)	• The aim is to design efficient and robust anycast routing protocol in DTN networks • Frequency and recency of nodes contacts are considered to evaluate social ties • Social ties are utilized to construct social graph in each node based on local observation and knowledge exchange. • Social metric (ASDM) is proposed which is multi-hop social distances to anycast group
2017	SACC (Liu et al., 2017)	• The main aim is controlling congestion in the network • Exploit the strength of the social links (frequently encountering) • Apply social aware message dropping mechanism (messages with minimum social link are dropped)
Combined social features: Degree & Community		
2011	Bubble Rap (Hui et al., 2011)	• Consider different sized community • Focus on centrality • Uses popularity (rank) local and global for data forwarding • Predict path from source to destination by including nodes with strong social connection
Combined social features: Closeness and Community		
2014	CAOR (Xiao et al., 2014)	• Use the centrality to form homes inside communities • Star-shaped communities homes are the centers· • Firstly Rout data between homes , then inside community use shortest path (lowest delay)

Table 2.2 continued

Combined social features: Similarity and Betweenness		
2007	SimBet (Daly & Haahr, 2007)	• Use ego network concept where just local information are considered. • Depends on betweenness centrality to forward data towards the destination
Combined social features: Social Tie and Community		
2012	DLifecomm (Moreira et al., 2012)	• Use time-involving social structure to model dynamism of daily life • Uses time nodes spend together to measure the strength of social tie • Use social strength and node Importance or degree for data forwarding • Use two complementary utility function TECD (Time Evolving Contact Duration) and TECDi for forwarding data
Combined social features: Similarity , Centrality and Community		
2014	SMART (Zhu et al., 2014)	• Exploit similarity , centrality ,community social features. • Distributed community partitioning method based on locality property of mobile nodes is used to form communities • The blind-spot and dean-end problems are defined and significantly alleviated using decay function. • Effective Intra and inter community communication methods are used to improve routing performance.
Combined social features: Social Tie and Community density		
2015	Int-Tree (Xia et al. 2015)	• Social ties, community density, similarity of interests are exploited to improve routing performance • Recognize different kinds of user's interests and exploit them to partition network and form communities • Based on the interest a tree of communities is formed to save the constrained resources of mobile nodes.
Combined social features: Degree and Betweenness		
2015	Social based throwbox placement (Zhu et al., 2015)	• Exploit social feature to place hrowboxes in mobile social DTN • Social properties of both mobile users and locations are utilized • Degree and betweenness centrality are exploited • Significant improvement is achieved when social features are exploited to solve throwbox placement problem.

Table 2.2 continued

2016	CGAnt (Vendramin et al., 2016)	• Analysis mobility patterns in DTN and the understanding of how mobile nodes interact socially. • Based on (1) Cultural Algorithms (CA) and Ant Colony Optimization (ACO) and (2) operational metrics that characterize the opportunistic social connectivity between wireless users. • Adaptive and tailored to match forwarding decisions to different mobility conditions.
Combined social features: Centrality, community similarity and social ties		
2015	ML-SOR (Socievole et al., 2015)	• Both temporal social features (detected social properties from encountering history) and static social features (online social information from social network such as facebook and twitter) are considered • Multi-layered complex network combining online and offline social relationships is studied. • Social features: node centrality (different types of centralities), similarity between communities and social ties all are exploited to effectively select the forwarding node. • Social features and link prediction scheme are utilized to forward messages.
Combined social features: Similarity and social ties		
2016	PIS (Xia et al., 2016)	• Consider the regularity of people social behavior and activities • Physical proximity, interests, social relations are considered for forwarding strategy • Copy control method is applied for more effective forwarding scheme.
Combined social features: centrality, similarity and friendship		
2017	SRAMSW (Guan et al., 2017)	• Combine buffer management and social aware routing • Intend to solve the problem of blind spots or dead end problems of the existing spary-based routing protocols.
Combined social features: Community acquaintance, centrality and activeness		
2017	SARP (Rahim et al., 2017)	• Aim to reduce End-to-End delay and improve packet delivery ratio in VSNs • Consider the global and local community acquaintance of nodes.

Each social-based scheme depends on specific attributes such as contact history, user profile and social relations to evaluate the social metrics. Table 2.3 shows the attributes that are utilized in each of the reviewed social-based schemes.

Table 2.3: Social Attributes Used for Exploiting Social Features

Proposed approach	**The attributes used for exploiting social features**
Similarity Community-independent	
(HiBOP) (Boldrini et al., 2008)	-User's profile -user's behavior (contacts with others in some context) -common attributes & common user behavior
Social-greedy (Jahanbakhsh et al., 2010)	-User's profile - common interests
CiPRO (Nguyen & Giordano, 2012)	-node's profile (device, user) -common attributes Temporal and spatial user's context
SMART (Chen & Shen, 2014)	-Contacts history - common contacts (friends)
HSFR (Wu & Wang, 2014)	-User profile (most informative social features) - common social features
SANE (Mei et al., 2015)	-User profile - common interests
CAMF (Wei et al., 2015)	-user properties profiles -nodes' forwarding and receiving capabilities (remaining energy and buffer size)
SPRINT-SELF (Ciobanu et al., 2015)	- User social relationships - Contacts history
FCNS (Liu et al., 2018)	- Social attributes - mobility trajectories
Similarity Community-detection	
LABEL (Hui & Crowcroft, 2007)	-small labels
Gently (Musolesi et al., 2008)	- small labels - Context-aware
LocalCom (Li & Wu, 2009)	- Local information (contact frequency and duration , irrigation :variance of the separation period) - Betweennes are used for inter-community forwarding
SGRB (Abdelkader et al., 2013)	Groups base on contact frequency
HS (Wu et al., 2013)	Common locations
DLifecomm (Moreira et al., 2012)	- Contact frequency (K-CLIQUE) - links between communities change over time

Table 2.3 continued

LASS (Li et al., 2015)		- Common interests - Local activity (contact frequency) of users within the communities.
CAR (Chen & Lou, 2016)		- Contact frequencies - Contact duration
Social Ties		
FairRoute (Pujol et al., 2009)		- Message is forwarded to nodes have similar social status
PeopleRank (Mtibaa et al., 2010)		-The relative importance of the node (social context)
Friendship-based routing (Bulut & Szymanski, 2010; Bulut & Szymanski, 2012)		- Contact history : frequent, long-lasting and regular contacts
HSBR (Matis et al., 2016)		-Nodes' profiles -encounter history
ASDM (Le & Gerla, 2016)		- Frequency and recency of nodes contacts
SACC (Liu et al., 2017)		- frequency and encountering time period
Combined social features		
Degree & Community	Bubble Rap (Hui et al., 2011)	- Popularity (people meeting) - Contact frequency (K-CLIQUE algorithm) - Contact duration (WNA algorithm)
Closeness & Community	CAOR (Xiao et al., 2014)	-User profile -Common interest
Similarity & Betweenness	SimBet (Daly & Haahr, 2007)	- Number of nodes indirectly connected - Common acquaintances
Social Tie & Community	DLifecomm (Moreira et al., 2012)	- Contact frequency (K-CLIQUE) - Links between communities change over time
Similarity & Centrality& Community	SMART (Zhu et al., 2014)	- Common friends between pair of nodes -The relative importance of node in the community (sum of direct links/number of nodes in the community) -Locality property of mobile nodes is utilized to partition network into communities
Social ties & community density & similarity	Int-Tree (Xia et al. 2015)	- Common interests -The contact time over period is used to measure the social tie - Community density is calculated based on the number of contacts (node activities)

Table 2.3 continued

Degree & Betweenness	Social based throwbox placement (Zhu et al., 2015)	- Common places between users - Frequently visited places
Degree & Betweenness	CGAnt (Vendramin et al., 2016)	- Encounter frequency - Duration of contacts between users
Centrality& similarity of communities & social ties	ML-SOR (Socievole et al., 2015)	- Encounter frequency - Number and duration of contacts between users - Common interests - Social ties are extracted from online social networks (social links)
centrality, similarity, and friendship	SRAMSW (Guan et al., 2017)	- Common neighbors - Contact history
Community acquaintance, centrality, and activeness	SARP (Rahim et al., 2017)	- Contact history
Similarity, Social ties	PIS (Xia et al., 2016)	- Contact history - User profile to get interests list

Based on the reviewed approaches, there are main orientations in the researches of social-based routing in OMSN. The next section presents it.

2.4 Orientations in Social-based Routing

- **Flooding:** Flooding-based methods, for example, Epidemic protocol is the benchmark for most of the recent protocols; that is because of their dominant performance in terms of delivery ratio and delivery delay. However, flooding and control flooding approaches have high delivery costs and overhead. Based on this, corresponding social based routing approaches try to decrease the cost and the overhead without significantly affects the delivery ratio and delay. It can be said that the good performance of the flooding and controlled-flooding protocols refers also to their simplicity, which decreases the overhead from the nodes' perspective. Therefore, social-based approaches should take into account the simplicity of the design.

- **Combination:** The combination of different social features (similarity and betweenness, social tie and similarity) enhances the performance of data dissemination in OMSN. This is shown in SimBet ,Bubble Rap, CAOR , PIS, and SARP. Another type of combination is the combining between the social features and the other features of the OMSN such as context information, contact frequency and temporal sides achieved better performance. It can be seen in works such as CiPRO (social features, Temporal and spatial user's context), HiBOP (social features , context information), FCNS (mobility and social features) and SRAMSW (social features and buffer management techniques).
- **Network information:** According to acquiring information about the network or other peers, social-based approaches can be classified into state-full approaches or stateless ones. LABEL, Gently, BUBBLE Rap, HiBOP, are examples of state-full approaches. Stateless approaches such as SANE, SMART and HS are free of network information. For state-full approaches, the available network information enables choosing a better path or intermediate nodes towards the destination which increases the delivery ratio and decreases the delay. However, these approaches suffer from nodes and networks overhead refer to network information collecting and exchanging, consequently need computations of complex metrics either on the whole network by the nodes. On the other hand, stateless approaches have low network overhead but they make pressure on the nodes' resources because they just depend on local information and nodes' profiles for forwarding.
- **Time evolving:** According to considering of time evolving of user behavior and network situation, there are static and dynamic social-based approaches. Dynamic approaches take into account the context of the network and users' behavior along the time, while

static approaches consider offline information about the network. Dynamic approaches provide a more accurate vision of network topology, consequently choosing more optimal next nodes when forwarding data. However, dynamic approaches require a lot of forwardings among nodes (information updating) which increases the network overhead. Static approaches require less computational cost and achieve lower network overhead but incur lower delivery and higher delay. Social-Gready ,HiBOP, CIPRO, dLifeComm, Friendship are examples of Dynamic approaches and, Bubble Rap and SimBet are examples of static approaches.

- **Abstraction:** the main reason for exploiting social features for data dissemination in OMSN is that the social properties of users are more stable and less volatile than other features like mobility patterns. Some social based methods such as CAOR, HS and HSFR decrease more the effects of the changes in users' mobility on forwarding strategy in OMSN. HS and CAOR depend on homing concepts (users visit some places called homes more frequently) and convert routing from node to node into home to home. Also, they exploit homing concepts to spread the data to the users which decrease the delay significantly. HSARF converts routing from dynamic and changeable nodes mobility patterns to routing and data forwarding to static social features space. Abstraction technique is effective in term of delivery ratio and delay but require more complex processing and computations which consume nodes resources.
- **Ranking:** tagging nodes with rank according to their importance or their social status in the network is a common concept in socially based approaches in OMSN. BUBBLE Rap , People Rank , dLifeComm are examples of these approaches. Using ranking is a reflection of the reality of the social behavior of people. In people society, the social activity of the persons varies widely. Some peoples are active and others not. So that,

exploiting this social concept to deliver data in OMSN results in a good enhancement in terms of delivery ratio and delivery cost. However, high ranked nodes will be exhausted and the network will suffer from congestion especially in heavy load scenarios and in case of the undistributed load. Table 2.4 presents a summary of the observed orientations for social-based routing in OMSN.

Table 2.4: Orientations of Social Schemes in OMSN

Schemes type	Examples	Exploited social features
Context aware social - based	(HiBOP) (Boldrini et al., 2008) CiPRO (Nguyen & Giordano, 2012) CAMF (Wei et al., 2015) Gently (Musolesi et al., 2008)	Similarity (community-independent) Similarity (community-independent) Similarity (community-independent) Community
Based on static (offline) social information	Social-greedy (Jahanbakhsh et al., 2010) SPRINT-SELF (Ciobanu et al., 2015)	Similarity (community-independent) Similarity (community-independent)
Consider dynamism in social properties	(HiBOP) (Boldrini et al., 2008) CiPRO (Nguyen & Giordano, 2012) HSFR (Jie Wu & Wang, 2014) Friendship-based routing (Bulut & Szymanski, 2010; Bulut & Szymanski, 2012) DLifecomm (Moreira et al., 2012) ML-SOR (Socievole et al., 2015) FCNS (Liu et al., 2018) SARP (Rahim et al., 2017) PIS (Xia et al., 2016)	Similarity (community-independent) Similarity (community-independent) Similarity (community-independent) Social-ties Community & Social ties Community & Social ties Similarity Community acquaintance, centrality, and activeness Similarity and social tie

Table 2.4 continued

Location social-based	CiPRO (Nguyen & Giordano, 2012) HS (Wu et al., 2013) Social-based throwbox placement (Zhu et al., 2015) CAOR (Xiao et al., 2014) SMART (Zhu et al., 2014)	Similarity (community-independent) Community Similarity & Betweenness Community & Degree Community & Degree
State-full network information	(HiBOP) (Boldrini et al., 2008) LABEL (Hui & Crowcroft, 2007) PeopleRank (Mtibaa et al., 2010) SimBet (Daly & Haahr, 2007) Social-based throwbox placement (Zhu et al., 2015) CAOR (Xiao et al., 2014) Int-Tree (Xia et al. 2015) FCNS (Liu et al., 2018)	Similarity (community-independent) Community Social Ties Similarity & Betweenness Similarity & Betweenness Community & Degree Community & Degree Community & Degree Similarity
State-less network information	SANE (Mei et al., 2015) CAMF (Wei et al., 2015) SGRB (Abdelkader et al., 2013) HS (Wu et al., 2013) Bubble Rap (Hui et al., 2011)	Similarity (community-independent) Similarity (community-independent) Community Community Community & Degree

Table 2.4 continued

Concern nodes and network resources	(HiBOP) (Boldrini et al., 2008) CiPRO (Nguyen & Giordano, 2012) SMART (K. Chen & Shen, 2014) SANE (Mei et al., 2015) FairRoute (Pujol et al., 2009) CAMF (Wei et al., 2015) SPRINT-SELF (Ciobanu et al., 2015) SACC (Liu et al., 2017) SRAMSW (Guan et al., 2017)	Similarity (community-independent) Similarity (community-independent) Similarity (community-independent) Similarity (community-independent) Social Ties Similarity (community-independent) Similarity (community-independent) Social Ties Centrality, similarity, and friendship
Ranking and node activity –aware	PeopleRank (Mtibaa et al., 2010) Bubble Rap (Hui et al., 2011) LASS (Li et al., 2015)	Social Ties Community & Degree Community
Consider the relation between social features	Int-Tree (Xia et al. 2015)	Community & Degree
Exploit social features to decrease routing overhead	CAR (H. Chen & Lou, 2016) SPRINT-SELF (Ciobanu et al., 2015)	Similarity (community-based) Similarity (community-independent)

2.5 Statistical Analysis and Inferred Indication

In this section, a statistical analysis of the reviewed social-based researches is presented. The objective of this analysis is to get derived indications from the recent researches in social-based routing and data dissemination. Moreover, it explains and assures the benefits of exploiting the social features in forwarding strategy in OMSN. The statistical analysis covers the relative importance of social features and the performance metrics used for evaluation.

2.5.1 The Relative Importance of Social Features

For each social feature, the research approaches that used it are counted; that is to get an indicator of the frequency of using the different social features. The different using percentages of the exploited social features are shown in Figure 2.4. The graph gives an indicator of the relative importance of the social features in the recent social-based approaches. Thirty-five social-based routing approaches are reviewed, it is clear that methods that utilize the similarity have the highest percentage: (80%) of the reviewed approaches. The methods that combine different social features and the schemes that exploit social ties score (36%) and (32%) respectively. The methods that exploit the centrality features (degree, betweenness) are (12%). All these percentages are calculated based on the number of the reviewed approaches in this thesis.

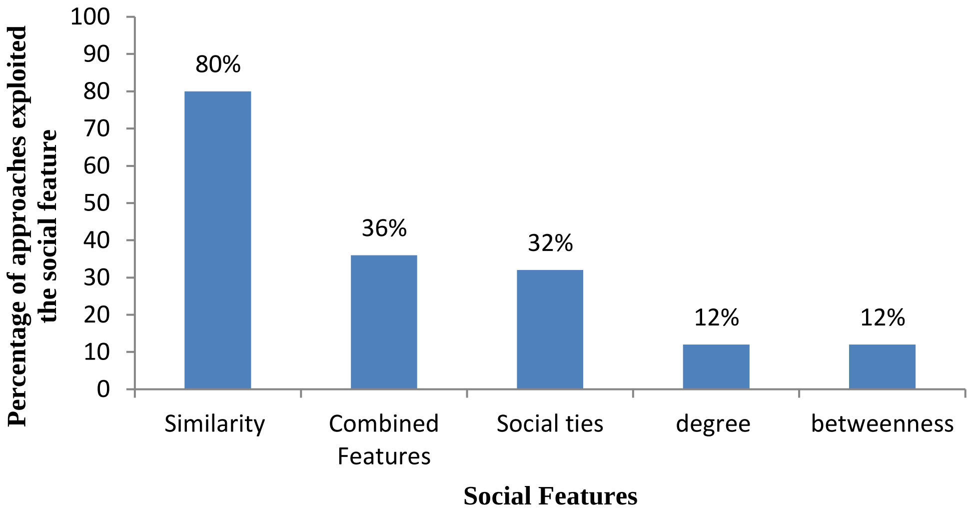


Figure 2.4: Approaches according to the exploited social feature

The highest percentage of the methods that utilize similarity (community detection - based and non-community detection-based methods) points to the high positive effect of the similarity on the performance of the social-based algorithms and also indicates the relative importance of the similarity feature among the other social features. The lower percentage of methods that exploit social ties or combine multiple features is because they require updated information about the network topology and the users' social activities. Regarding approaches that utilize centrality features such as degree or betweenness suffer from congestion around the nodes with centrality.

2.5.2 Key Performance Metrics for Social-based Protocol Performance Evaluation

Different performance metrics are used to evaluate the social-based routing schemes. The relative importance of the performance metrics are studied by counting –for each used performance metric- the number of social-based approaches the concerns in it. First, the definition of these performance metrics is presented as follows:

a) **Delivery Ratio:** The ratio between the number of delivered messages and total number of created messages.

b) **Delivery Delay (latency):** The time elapsed between message creation and delivery.

c) **Cost:** it can be defined in several ways as follows:

- **Total Delivery cost:** the total number of messages (including duplications) transmitted across the network.
- **Routing cost or network overhead or Average delivery cost:** the additional data are sent for successfully delivering a message to a destination.
- **Number of replicas (duplicates or copies):** the number of copies of the message that the node is allowed to forward to other relays
- **Number of Forwardings:** the average number of forwardings of each packet before the destination is reached. Another metric has the same meaning is the

number of forwarding hops where it is the number of hops a message must take in order to reach the destination.

- **Distribution of the total amount of forwards or handovers:** an indicator of the distribution of the number of forwards between the mobile nodes in the network.

Figure 2.5 shows the relative importance of the different performance metrics based on the number (percentage) of the social-based approaches.

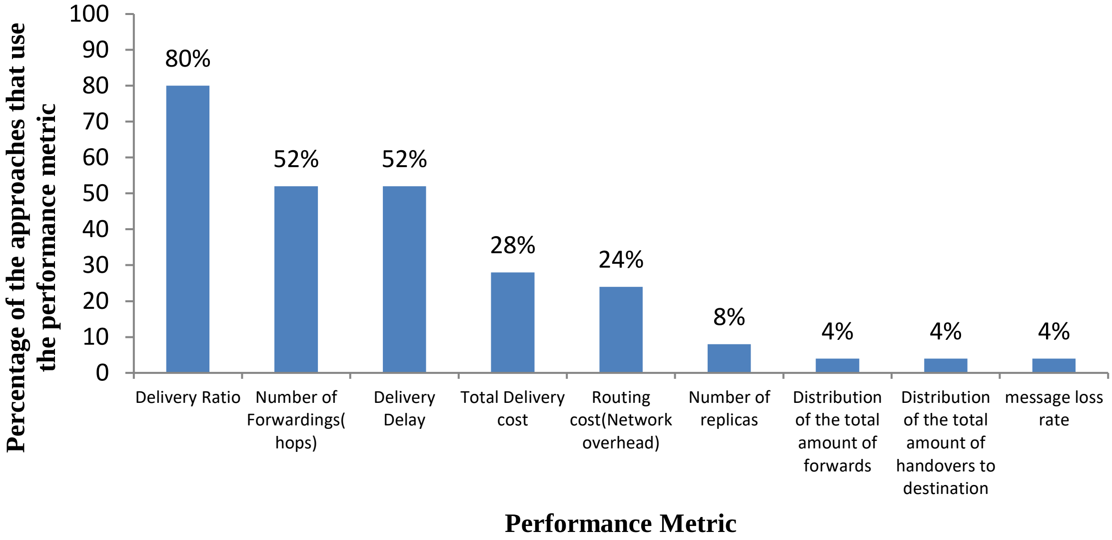


Figure 2.5: Relative importance of performance metrics

In Figure 2.5, the delivery ratio is the performance metric that scores the highest concerns of social-based approaches (80%), this result is logical because the common objective of routing protocols is to deliver contents to the destination. However, OMSN is a special paradigm of MSN, consequently, it owns identical performance metrics such as the number of forwardings and number of replicas. Regarding the delivery delay, decreasing delay increases the reliability and applicability of the proposed algorithms from the users' perspectives. Most of the reviewed approaches -excluding (HiBOP) and FairRoute do not focus explicitly on preserving nodes resources.

2.6 Conclusion

In this chapter, an extensive literature review has been conducted about routing in OMSN networks, which is one of the key challengeable issues of these types of wireless networks. The main categories of the routing protocols in OMSN has been defined, and the social-based routing has been reviewed in detail because this thesis focuses on the investigation of the social-based routing protocols for better performance efficiency in OMSN.

The most common social features in the literature and the metrics that can be evaluated based on them have been defined. Furthermore, new classification of the social-based routing protocols has been proposed according to the social metrics which are exploited to enhance routing efficiency in OMSN.,

Based on the reviewed approaches, the main orientations in the current researches about social-based routing in OMSN have been discussed. In addition, a statistical analysis has been performed to deduce an indicator of the relative importance of exploiting the different social features and the key performance metrics that are used for performance evaluation of routing in OMSN.

The general objective of this thesis is providing efficient routing in OMSN by exploiting social metrics. The next chapter discusses the first proposed social-based protocol to enhance routing in OMSN.

CHAPTER 3

SOCIAL AND EPIDEMIC BASED ROUTING

3.1 Introduction

The purpose of this chapter is to investigate the effect of integrating social information with Epidemic routing protocol in OMSN. In unlimited resource scenarios, Epidemic protocol has superiority over other routing protocols in terms of high delivery ratio and low average latency. However, because of the flooding nature of Epidemic, it exhausts the resources of both nodes and network. Getting the advantages of the robustness and simplicity of Epidemic, which is suitable for disruptive networking scenarios as opportunistic networks, while decreasing the delivery overhead are vital issues to be investigated. To meet these purposes, a hybrid routing protocol named EpSoc is proposed in this chapter.

EpSoc is a social and Epidemic based routing protocol. In EpSoc, degree centrality is exploited to decrease the delivery cost by adapting messages' Time To Live (TTL) value socially, also the Epidemic data forwarding stategy is adopted for good delivery performance. The rest of the chapter is organized as follows. Section 3.2 explains in detail the motivation of forming EpSoc and the used data forwarding strategy and its pseudo code. Section 3.3 shows the performance evaluation of EpSoc. It presents the characteristics of the real datasets used to get the social properties of individuals and to do routing experiments. In addition, it presents the simulation software and the settings used to achieve the experiments and to evaluate the work. The experiments and results are presented in Section 3.4. The conclusion of this chapter is provided in Section 3.5.

3.2 Hybrid Routing Protocol (EpSoc)

In EpSoc, a social-based protocol is designed to produce an efficient Epidemic-based routing protocol in the Opportunistic Mobile Social Network (OMSN). The main objective is to benefit from the advantages of both Epidemic and social approaches, where Epidemic contributes to providing high delivery ratio and low latency, while social information can be exploited to control the overhead.

In order to achieve this objective, social features i.e. nodes' degree centrality, are embedded in the routed messages by employing two mechanisms; first, the message's Time To Live (TTL) is adjusted based on the degree centrality of the nodes. If a message is forwarded to a node that has a higher degree centrality (active node), its' TTL value will be decreased according to the active node's degree centrality value. The second mechanism is a message blocking technique. Epidemic forwards messages to all encountered nodes that did not receive the message before, therefore, replications of the expired TTL messages will be received again in the active nodes. A message blocking technique is employed to prevent active nodes from receiving these replicas again. The next subsections present the components of the proposed protocol and the forwarding strategy.

3.2.1 Degree Centrality

Degree centrality is one of three types of centrality social metrics as it was explained in (Section 2.3.6). Node's degree centrality indicates the popularity of a node in the network. In other words, the degree centrality of a person in a social network is the reflection of his relative social importance, where nodes with high degree centrality are considered socially active nodes in the network. Degree centrality can be calculated using the Equation (3.1).

$$DC_i = \sum_{k=1}^{N} a(i,k) \qquad \text{(Hui et al., 2011)} \qquad \text{Equation 3.1}$$

Where N is the number of nodes in the network, and $a(\mathrm{i},\mathrm{k}) = 1$ if a direct link exists between node i and node k and $i \neq k$

EpSoc adopts the algorithm used in Bubble Rap (Hui et al., 2011) to calculate the global degree centrality of a node. Degree centrality metric is calculated based on the contact history of mobile nodes, where global centrality is the number of peers a mobile user encountered them previously in the whole network.

3.2.2 Forwarding Strategy of EpSoc

Figure 3.1 depicts the forwarding process in EpSoc, where the two mechanisms are applied.

In Figure 3.1, Node $N1$ encountered three nodes $N2$, $N3$, and $N4$. $N2$ has Degree Centrality (DC) higher than $N1$, thus the TTL value of the forwarded messages to $N2$ is decreased by dividing it by the DC value of $N2$. These messages are called socially infected messages. Node $N2$ registers the ID of these messages as seen messages in its blocking register. Node $N2$ will drop the infected socially message when it expires but will still maintain their IDs in the blocking register.

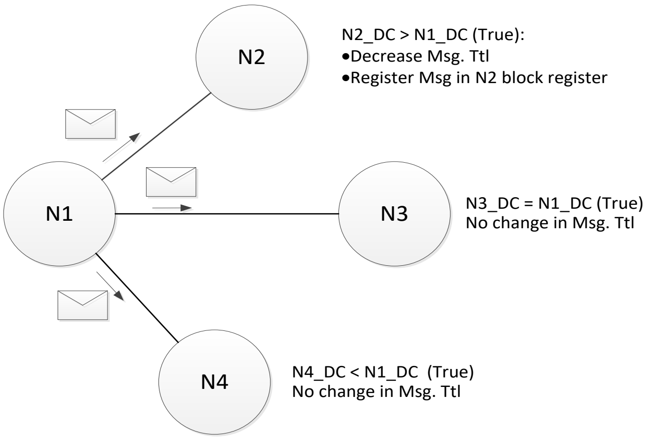


Figure 3.1: Adjusting TTL according to degree centrality

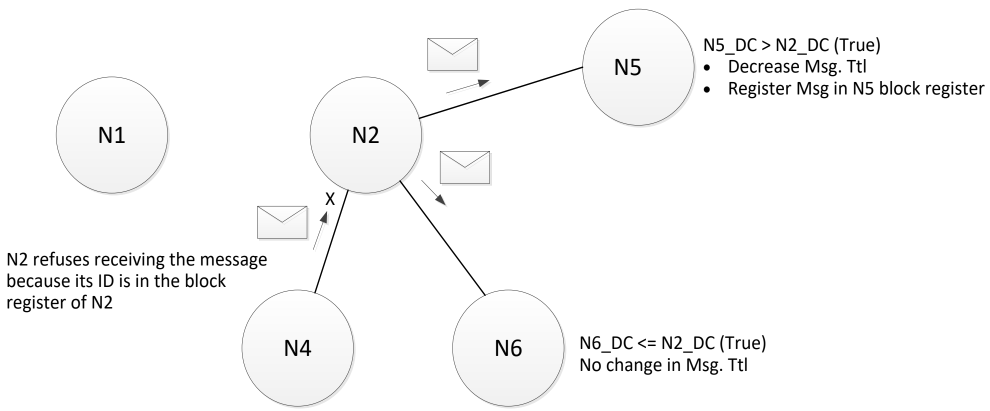


Figure 3.2: Blocking re-sent message

In Figure 3.2, Epidemic forwarding strategy which is adopted in EpSoc causes replications of socially infected messages to be re-sent to node $N2$ from other nodes such as 4 . In this case, node $N2$ will reject receiving the message with the reason that it is a seen message (its ID is stored in the blocking register).

Accordingly, the forwarding strategy of EpSoc is as follows: when node N_i encounters N_j , the TTL value of the messages will be adjusted if the degree centrality (DC_j) of N_j is greater than the degree centrality (DC_i) of N_i using the following proposed equation:

$$TTL_{new} = \frac{TTL_{old}}{DC_j} \qquad \{if \quad DC_j > DC_i\} \qquad \text{Equation 3.2}$$

Where DC_j , DC_i are the degree centralities of nodes N_j , N_i respectively. TTL_{new} value range is based on TTL_{old} and DC_i values. The value of TTL_{new} is integer.

The two mechanisms are combined and adopted in EpSoc to enhance routing performance. If a node is socially more active, it meets more nodes in the network and has a higher potential to deliver more messages. Decreasing messages' TTL value in active nodes results in releasing space in their buffers and increases the ability to deliver more messages. This will increase the delivery ratio in the network. To decrease the delivery cost, the blocking mechanism controls the replications by preventing decreased TTL messages from hitting again the previously traversed active nodes. For more explanation, each active node in the network registers the IDs of all the received messages in its blocking register. This is because there is a higher probability that active nodes deliver the message or send a copy of the received message to a relay with higher social activity. Consequently, for an active node N when the TTL value of a message MSG in N's buffer reaches zero, MSG is dropped. If a copy of MSG is sent again to N from another node as a result of the applied Epidemic-based forwarding strategy, N will reject receiving the copy because its ID exists in N's blocking register. This decreases the forwardings in OMSN and hence the overhead ratio in the network.

Regarding average latency, the messages that are delivered by active nodes have a shorter end-to-end delay (delivery latency) comparing to other messages delivered by lower activity nodes, so average latency will also be decreased.

It is concluded that decreasing message life socially and combine it with messages blocking protocol can affect positively the performance of Epidemic routing protocol in OMSN.

3.2.3 Pseudo-code of EpSoc Message Forwarding

The global degree centrality is used to calculate the centrality of the node. Each node N_i records the encounters nodes in the network. When node N_i encounters N_j , the degree centrality values are calculated. Then, centrality values are exchanged between both nodes. N_i compares its centrality value DC_i with N_j centrality value DC_j . If DC_j is greater than DC_i which means that N_j is socially more active than N_i, then for each message m_i in N_i buffer Buf_{N_i} , the TTL value $m_{i_{TTL}}$ is decreased by dividing it by the node N_j centrality value DC_j. The ID of each socially infected message is registered in N_j blocking register $Block_{N_j}$. Figure 3.2 shows the flowchart of the forwarding strategy of EpSoc, and Algorithm 1 shows the complete Pseudo-code of EpSoc.

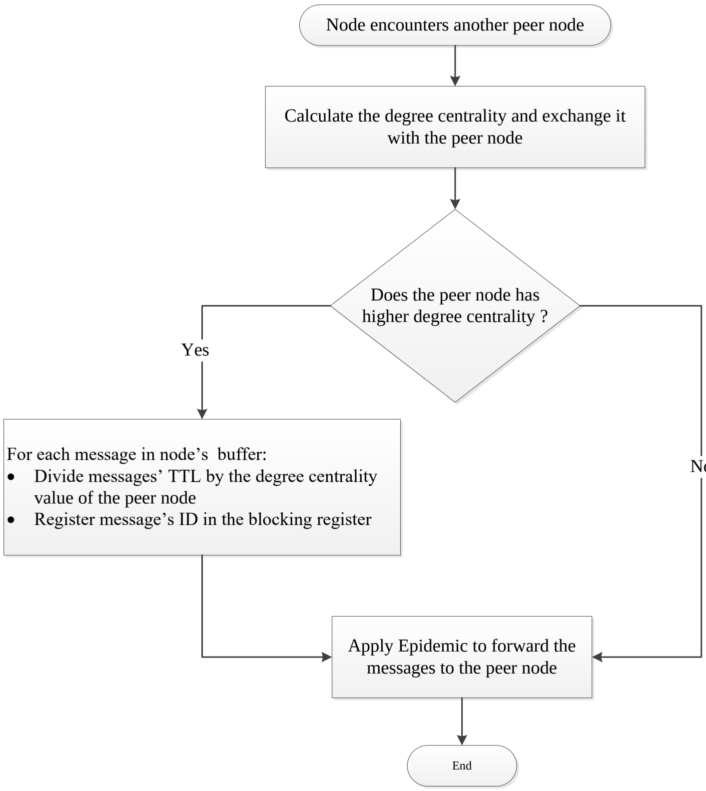


Figure 3.3: Flowchart of EpSoc forwarding strategy

Algorithm 1 : Pseudo-code of forwarding strategy in EpSoc

For all $N_i \in N$
  if N_i encounter N_j
    Calculate DC_i, DC_j
    $DC_i \leftrightarrows DC_j$
    For all $m_i \in Buf_{N_i}$
      if $m_{i_{ID}} \notin Block_{N_j}$
        if $DC_j > DC_i$
          $m_{i_{TTL}} \leftarrow m_{i_{TTL}}$ / DC_j
          $Buf_{N_j} \leftarrow m_i$ forward message to N_j
          $Block_{N_j} \leftarrow m_{i_{ID}}$
        End if
      End if
    End for
  End if
End for

3.3 Performance Evaluation

This section provides a detailed evaluation of EpSoc protocol and a comparison with two benchmarks; Epidemic and Bubble Rap. First, the experimental real datasets are defined, where these datasets are used in the evaluation of the routing protocols (EpSoc ,Epidemic, and Bubble Rap).

3.3.1 Experimental Dataset

This study focus on exploiting people's social information to improve routing performance in OMSN. Therefore, real information about human's social properties and behavior are required. From the literature, there are real traces datasets used for evaluating social-based routing protocols in OMSN. In this study, three datasets, well known and widely used in the literature, are used in the experiments. They are: Cambridge, INFOCOM05, and INFOCOM06. All of these datasets are real traces collected from real-life scenarios; university campus and conferences. There are various datasets for opportunistic networks, the three used datasets are chosen for their different scales and environments. Also, all are available online for public use through the CRAWDAD web site which is Community Resource for Archiving Wireless Data at Dartmouth.

The Cambridge experimental data set includes traces of Bluetooth sightings by groups of users (36) carrying small devices (iMotes) for a number of days in campus environments. The experiments used to collect this dataset are conducted in a computer laboratory that includes the undergraduate first-year and second-year students, and also some Ph.D. and postgraduate students. The experiment lasted for almost 11 days.

INFOCOM05 conducted during the IEEE INFOCOM 2005 conference in Miami where 41 iMotes were carried by attendees for 3 to 4 days. Mobile users in the experiment mainly consisted of students from Cambridge University who were asked to carry these iMotes with them at all times for the duration of the experiment

INFOCOM06 dataset is collected during IEEE INFOCOM 2009 conference. In this dataset, there are 78 mobile iMotes have a wireless range around 30 meters and using Bluetooth technology for communication. Bluetooth encounters between 78 short-range nodes are tracked and stored. The experiment lasted for 1 day and 16 Hours. All these datasets are available online (Website of CRAWDAD project, available at http://crawdad.org/cambridge/haggle).

3.3.2 Simulation Setup

Opportunistic Network Environment (ONE) (Keränen et al., 2009) simulator is used to evaluate EpSoc. Also, comparison with Epidemic and Bubble Rap routing protocols is included to measure the performance of the proposed protocol EpSoc. The simulator settings are tabulated in Table 3.1.

Table 3.1: Simulation Settings

Simulation setting	Value
Simulation end Time:	
(Cambridge dataset)	274 (Hour)
(INFOCOM05 dataset)	70 (Hour)
(INFOCOM06 dataset)	40 (Hour)
Number of nodes	
(Cambridge dataset)	36
(INFOCOM05 dataset)	41
(INFOCOM06 dataset)	78
Transmit Speed	250 kBps (2 Mbps)
Mobility	Real trace datasets
Buffer Size	1,2,5,15,25,35,45,55 (MB)

Table 3.1 continued

Routing Protocols	Epidemic, EpSoc, BubbleRap
Message Size	128k
Event Interval	30 to 40 seconds
Initial Message TTL	
(Cambridge dataset)	10 (Minute), 30 (Minute), 1 ,3, 5,12, 24, 36, 60, 72, 96, 186
(INFOCOM05 dataset)	10 (Minute), 30 (Minute) , 1, 4, 8, 16, 20, 24, 28, 32, 36, 38.4
(INFOCOM06 dataset)	10 (Minute), 30 (Minute) , 1, 4, 8, 16, 20, 24, 28, 32, 36, 38.4

3.3.3 Performance Evaluation Metrics

Buffer size and message TTL value are considered as evaluation factors in the conducted experiments. These two features have a high impact on routing performance in OMSN. In this work, these two features are affected directly; where the TTL value of the messages are adapted socially according to the node popularity while the blocking mechanism is used to control the buffering in the active nodes. Consequently, the conducted experiments are to evaluate the performance of EpSoc when varying TTL and buffer size.

Two protocols are used as a benchmark of EpSoc, they are the Epidemic and Bubble Rap. Epidemic is selected as a benchmark because EpSoc adopts its strategy in forwarding messages and also EpSoc integrates social features to overcome its drawbacks. So, it is important to investigate the impacts of integrating social features into Epidemic on routing performance.

Regarding Bubble Rap, it is a well-known effective social based routing protocol used as a benchmark for other routing schemes in the literature. In addition, Bubble Rap also uses the degree centrality as EpSoc wherein Bubble Rap employs local and global centrality to forward messages inside the community and between the different communities.

In opportunistic networks, there are common performance evaluation metrics used to measure the performance of a routing protocol. These are the successful delivery ratio (SDR), average overhead (AO), average delay or latency (AD), and average hop counts (AHC). In this chapter, these metrics are used to perform the evaluation and comparison of the proposed routing protocol EpSoc with the selected benchmarks routing protocols. The following subsections define these evaluation metrics.

1) Successful Delivery Ratio (SDR)

It is the ratio between the number of successfully delivered messages to the destinations and the total number of created messages by sources (Equation 3.3). The ideal value of the Successful Delivery ratio (SDR) is 1.0 when all created messages are delivered to their destinations.

$$SDR = \frac{Delivered\ messages}{Created\ messages} \qquad \text{Equation 3.3}$$

2) Average Delay (AD)

It is the average of the time elapsed between message creation and delivery. AD is calculated as in equation (3.4).

$$AD = \frac{\sum_{Delivered\ Messages}(\ delivered\ time - \ creation\ time)}{Delivered\ messages} \qquad \text{Equation 3.4}$$

3) Overhead Ratio (OR)

It is the additional messages (relayed messages – delivered messages) are sent for successfully delivering a message to a destination. It is calculated as in (Equation 3.5).

$$OR = \frac{Relayed(transformed)\ messages - \ delivered\ messages}{Delivered\ messages} \qquad \text{Equation 3. 5}$$

4) Average Hop Count (AHC)

It is the average of the number of hops that messages must take in order to reach the destination. AHC is calculated as in (Equation 3.6).

$$AHC = \frac{\sum_{Delivered\ Messages}(the\ number\ of\ traversed\ nodes)}{Delivered\ messages} \qquad \text{Equation 3. 6}$$

3.4 Experiments and Results

The experiments are carried out for different sizes of buffer and different values of TTL to investigate the impact of varying buffer size and TTL on EpSoc performance. That is because they affect the forwarding strategy of EpSoc as has been aforementioned in Section 3.3.3. First, buffer size varies while TTL is constant, and then the buffer size is set to a constant value when changing TTL.

3.4.1 Varying Buffer Size

For varying the buffer size, the value of TTL is set to 2.5 days for the Cambridge dataset, and 10 Hours for both INFOCOM05 and INFOCOM06 datasets. These values are selected as a medium value, neither low nor high, according to the recorded time of the real traces experiments. Also, it is selected based on the experiments of varying TTL value where the three experimented protocols have good performance for these TTL values.

In the simulation settings, message size is set to 128KB. Accordingly, there are three considered levels of buffer size in this study; low, medium, and high. Increasing the buffer size means increasing the maximum number of the messages that a mobile node can carry which in turn affects the routing performance in OMSN. Table 3.2 shows the maximum number of buffered messages for each buffer size level.

Table 3.2: Maximum Number of Buffered Messages

Buffer Level	Buffer Size (MB)	Max No of the buffered messages
Low	1	8
	2	16
	5	40
Medium	15	120
	25	200
	35	280
High	45	360
	55	440

The following tables and figures show the performance evaluation and comparisons between EpSoc, Epidemic, and Bubble Rap. The figures show the change in the performance metrics; delivery ratio, overhead ratio, average latency, and average hop count with buffer size. Tables present the protocols achievements and the performance difference, in percentage, between EpSoc and the two benchmark protocols i.e. Epidemic and Bubble Rap. Positive (+) and negative (-) signs will be used within the tables inside the difference field to indicate the increase (+) and decrease (-) in performance metric value.

3.4.1.1 Delivery Ratio vs. Buffer Size

Buffer size has a clear impact on data delivery in OMSN. The increase in buffer size gives intermediate nodes the opportunity to carry more messages and vice versa. This eventually increases the delivery ratio (high buffer size) or decreases it (low buffer size).

Table 3.3 shows the relation between delivery ratio and buffer size for Cambridge dataset experiment. Figure 3.4 depicts the change of delivery ratio with the buffer size and

Figure 3.5(a) and Figure 3.5(b) show the performance achievement and the differences in percentage between EpSoc, Epidemic and Bubble Rap.

Table 3.3: Delivery Ratio vs. Buffer Size (Cambridge dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	0.04	0.05	0.05	+25%	0%
2	0.06	0.07	0.08	+34%	+15%
5	0.1	0.12	0.13	+30%	+9%
15	0.19	0.2	0.22	+16%	+10%
25	0.23	0.24	0.27	+18%	+13%
35	0.27	0.26	0.31	+15%	+20%
45	0.3	0.28	0.34	+14%	+22%
55	0.33	0.31	0.36	+10%	+17%

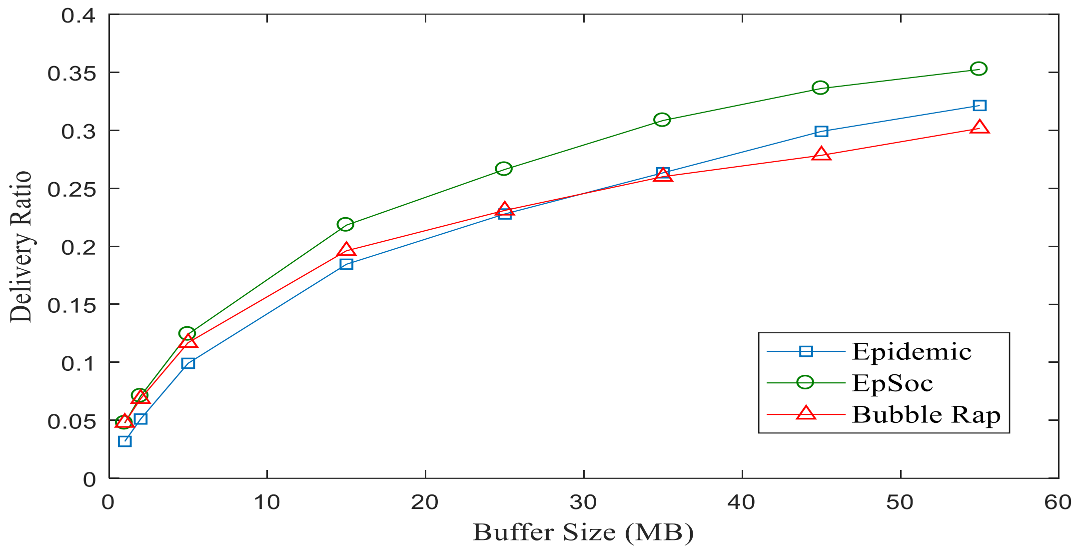
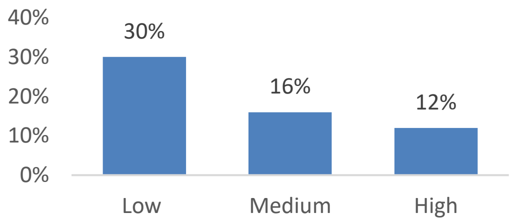
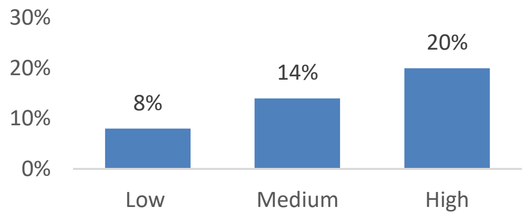


Figure 3.4: Delivery Ratio vs. Buffer Size (Cambridge dataset)



(a): Performance difference: **EpSoc vs. Epidemic** EpSoc increases the delivery ratio over Epidimic for all buffer size scenarios



(b): Performance difference: **EpSoc vs. Bubble Rap** EpSoc increases the delivery ratio over Bubble Rap for all buffer size scenarios

Figure 3.5: Performance Differences (Cambridge dataset)

EpSoc increases the delivery ratioby 20% and 13% on average as compared to Epidemic and Bubble Rap respectively. It can be observed that, EpSoc has the highest superiority over Epidemic in low buffer size scenarios, where the average increase is about 30%. This is because Epidemic consumes more resources i.e. buffer size due to high redundancy. Compared to Bubble Rap, EpSoc outperforms Bubble Rap more in high buffer size scenarios where the difference is, on average, 20%. This is because EpSoc utilizes buffer size more efficiently than Bubble Rap by decreasing messages' TTL in the active nodes and employing the blocking mechanism.

In Table 3.4, Figure 3.6, Figure 3.7(a) and Figure 3.7(b), the relation between the delivery ratio and buffer size is depicted for INFOCOM05 dataset experiment. EpSoc also achieves higher delivery ratio than Epidemic and Bubble Rap.

Table 3.4: Delivery Ratio vs. Buffer Size (INFOCOM05 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	0.07	0.09	0.12	+72%	+34%
2	0.11	0.13	0.18	+64%	+39%
5	0.13	0.2	0.24	+85%	+20%
15	0.3	0.3	0.35	+17%	+17%
25	0.39	0.36	0.4	+3%	+12%
35	0.43	0.41	0.44	+3%	+8%
45	0.47	0.44	0.47	0%	+7%
55	0.49	0.47	0.49	0%	+5%

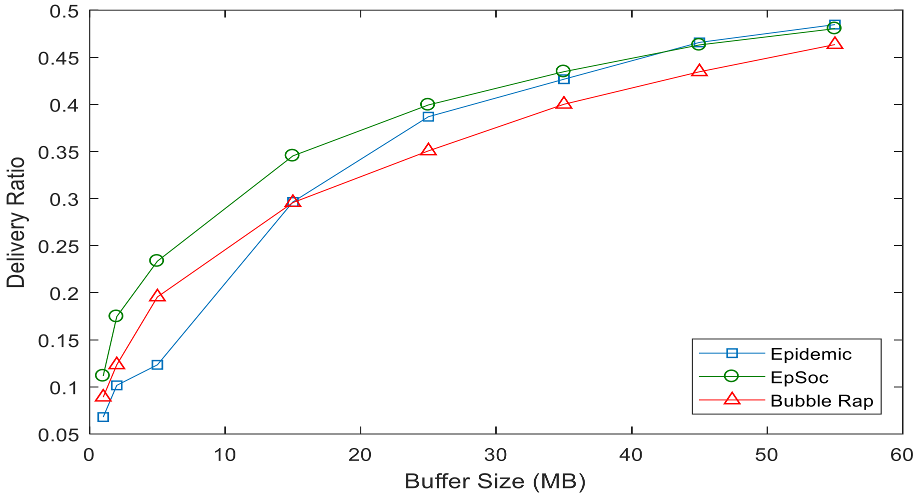
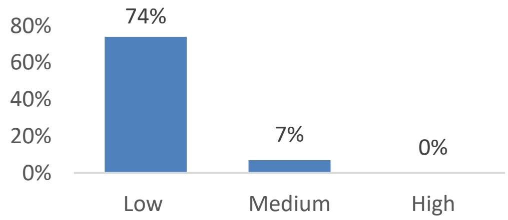
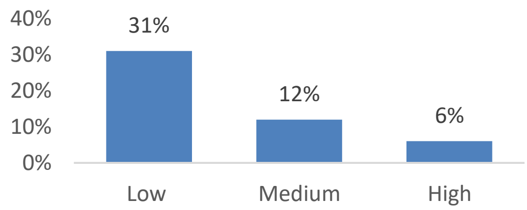


Figure 3.6: Delivery Ratio vs. Buffer Size (INFOCOM05 dataset)



(a): Performance difference: **EpSoc vs. Epidemic** EpSoc increases the delivery ratio over Epidimic for low and medium buffer size scenarios, while has similar achievement for high scenario.



(b): Performance difference: **EpSoc vs. Bubble Rap** EpSoc increases the delivery ratio over Bubble Rap for all buffer size scenarios

Figure 3.7: Performance Differences (INFOCOM05 dataset)

In this experiment, EpSoc has also the best achievement in low buffer size scenarios, where it increases the delivery ratio over Epidemic and Bubble Rap ,on average, by 74% and 31% respectively. This is because when buffer size is low, messages will be dropped shortly due to the buffer overflow, which affects negatively the delivery ratio. Therefore, there is a need for utilizing the constrained size carefully. Both Epidemic and Bubble Rap do not deploy any mechanism to address this. On the contrary, EpSoc does this by decreasing TTL when the relay has higher degree centrality and also employing the messages blocking. This results in utilizing the low size of the buffer for messages that have higher probability to be delivered by the active nodes. Consequently, the delivery ratio will be increased.

In this dataset, the number of nodes is higher than Cambridge dataset. So, increasing the buffer size i.e. medium and high-level scenarios, alleviates the negative impact of dropping messages because of replication. This enables Epidemic to deliver more messages and also enables Bubble Rap to carry more messages and to deliver more. So that, the superiority of EpSoc over Epidemic and Bubble Rap becomes lower than low buffer size scenarios. Table 3.5, Figure 3.8 and Figure 3.9 show the change in delivery ratio with buffer size for INFOCOM06 dataset experiment.

Table 3.5: Delivery Ratio vs. Buffer Size (INFOCOM06 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	0.1	0.16	0.23	+130%	+44%
2	0.12	0.22	0.27	+125%	+23%
5	0.19	0.28	0.33	+74%	+18%
15	0.33	0.41	0.41	+25%	0%
25	0.44	0.48	0.47	+7%	-3%
35	0.52	0.52	0.52	0%	0%
45	0.6	0.58	0.56	-7%	-4%
55	0.64	0.62	0.58	-10%	-7%

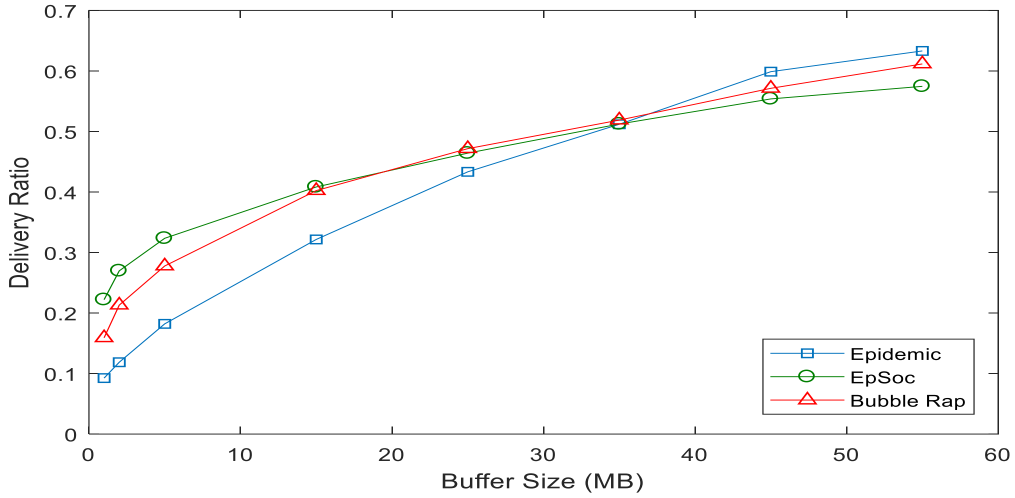
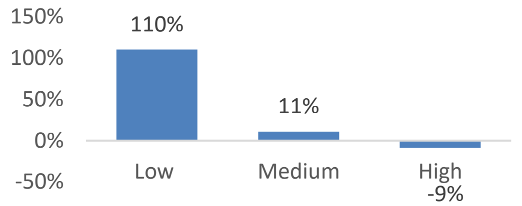
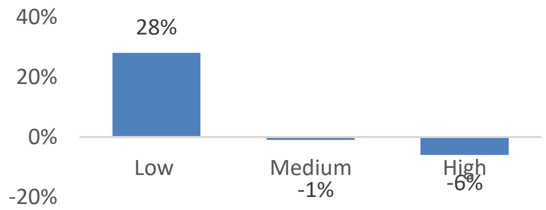


Figure 3.8: Delivery Ratio vs. Buffer Size (INFOCOM06 dataset)



(a): Performance difference: **EpSoc vs. Epidemic** EpSoc increases the delivery ratio over Epidimic for low and medium buffer size scenarios, while has lower achievement for high scenario.



(b): Performance difference: **EpSoc vs. Bubble Rap** EpSoc increases the delivery ratio over Bubble Rap for low buffer size scenario, while has lower achievement for medium and high scenarios.

Figure 3.9: Performance Differences (INFOCOM06 dataset)

EpSoc has a higher delivery ratio than Epidemic and Bubble Rap in low buffer size scenarios, on average it is 110% over Epidemic and 28% over Bubble Rap. For medium buffer size, the delivery ratio is 10% more than Epidemic and 1% lower than Bubble Rap. For high buffer size, EpSoc has a lower delivery ratio than Epidemic and Bubble Rap, it is -6% and -4% respectively. The reason is that, in the scenarios of the high number of mobile nodes (INFOCOM06) and higher buffer size, the overflow probability will be lower and the encountering between nodes will be higher. Therefore, the applied strict control mechanism of EpSoc will be less effective.

It can be summarized that in EpSoc, blocking run out TTL messages form been received in active nodes results in more space in the buffers, which enables nodes to carry more messages when encountering other nodes and later deliver them to target destinations. In addition, the decreasing value of TTL of the messages, which are forwarded to active nodes, results in better utilization of buffers space. This is because low value of TTL enables nodes to drop messages earlier and hence carrying more new messages. Moreover, the active node has a high delivery ratio. Therefore, the number of delivered messages is increased over time.

3.4.1.2 Overhead Ratio vs. Buffer Size

Table 3.6 and Figure 3.10 show the results of the overhead ratio metric for Cambridge dataset experiment. Figure 3.10 presents the change of overhead ratio with buffer size and Table 3.6 shows the performance achievement and the performance differences in percentage between EpSoc, Epidemic and Bubble Rap.

Table 3.6: Overhead Ratio vs. Buffer Size (Cambridge dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	622.68	54.83	479.01	-24%	+774%
2	595.14	70.1	361.86	-40%	+417%
5	392.07	82.59	220.59	-44%	+168%
15	240.68	98.28	132.11	-46%	+35%
25	199.78	104.36	114.85	-43%	+11%
35	173.19	103.18	101.63	-42%	-2%
45	151.35	103.21	98.62	-35%	-5%
55	139.6	97.14	95.86	-32%	-2%

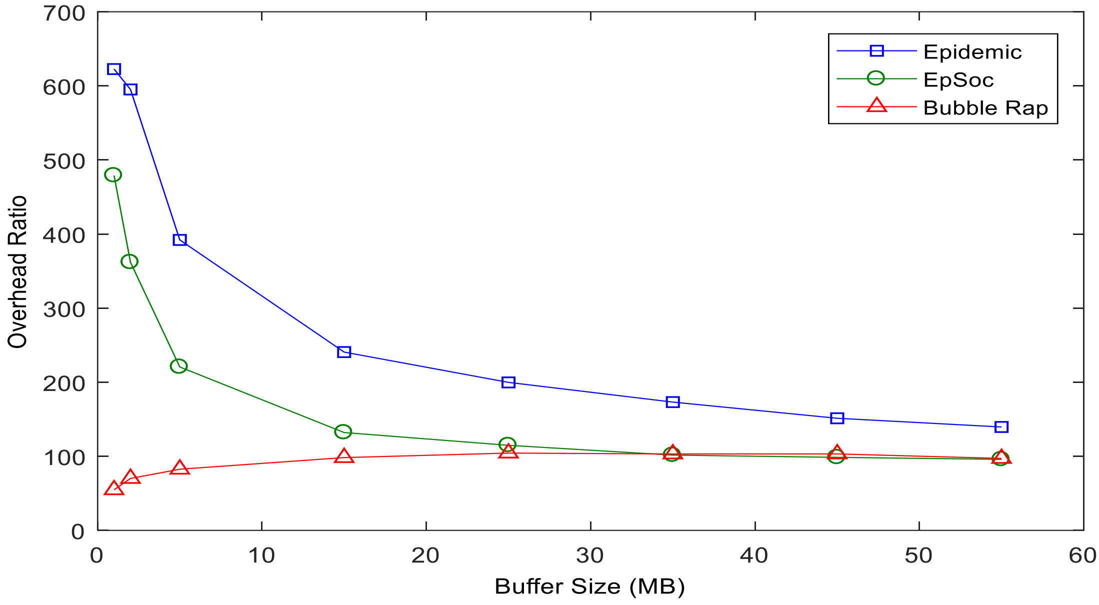


Figure 3.10: Overhead Ratio vs. Buffer Size (Cambridge dataset)

It can be observed that EpSoc and Epidemic are affected by the change in buffer size more than Bubble Rap. This is because they are flooding-based forwarding approaches where they forward messages to any non-infected encountered node; hence they utilize the buffer more than Bubble Rap. In Bubble Rap, the forwarding strategy is more conservative where messages are forwarded based on the social metrics i.e. local and global centrality. This makes the buffering rate in Bubble Rap lower than Epidemic and EpSoc.

EpSoc decreases the overhead ratio, on average, by 38% compared to Epidemic. This is because EpSoc applies two mechanisms to control replication socially: blocking messages and decreasing messages TTL in the active nodes. This increases the number of delivered messages and decreases the number of replications and hence decreases the forwardings number. As a result, the overhead ratio is decreased in the network.

Comparing to Bubble Rap, EpSoc has higher overhead ratio for the low and medium buffer size scenarios. This is for two reasons; first, the replication and epidemic strategy adopted in EpSoc. Second, lower buffer sizes cause dropping relayed messages early due to the buffer overflow. However, with the increase in the buffer size, the efficiency of EpSoc becomes better and it achieves a similar and slightly lower overhead ratio than Bubble Rap at large buffer size scenarios. In Table 3.7 and Figure 3.11 the results of INFOCOM05 dataset experiment are presented.

Table 3.7: Overhead Ratio vs. Buffer Size (INFOCOM05 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	382.21	85.63	185.34	-52%	+117%
2	398.13	114.29	173.24	-57%	+52%
5	349.61	129.75	146.32	-59%	+13%
15	254.46	122.46	130.87	-49%	+7%
25	200.44	107.08	111.94	-45%	+5%
35	184.04	91.66	97.82	-47%	+7%
45	173.38	79.93	80.99	-54%	+2%
55	165.75	68.58	70.11	-58%	+3%

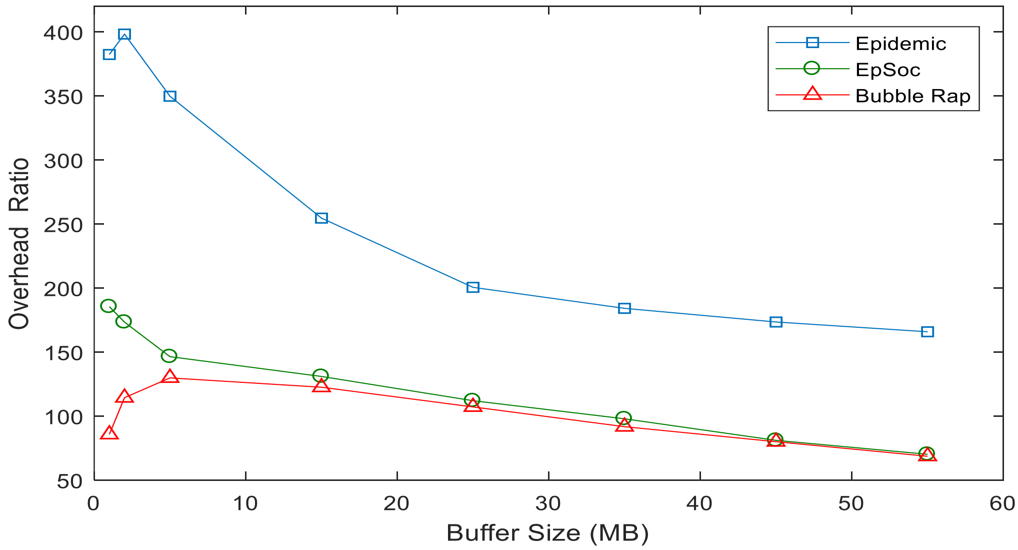


Figure 3.11: Overhead Ratio vs. Buffer Size (INFOCOM05 dataset)

Similar to Cambridge experiment, increasing the buffer size decreases the overhead ratio significantly for Epidemic and EpSoc while it has a lower impact on Bubble Rap. EpSoc outperforms Epidemic significantly where it decreases the overhead ratio by 53% on average because of socially overhead control.

Compared to Bubble Rab, increasing buffer size decrease the performance difference between EpSoc and Bubble Rap. For low buffer size scenarios, EpSoc has lower efficiency due to the adopted Epidemic-based forwarding strategy. However, it has similar achievement at medium and high buffer size scenarios. The results of INFOCOM06 dataset experiment are shown in Table 3.8 and Figure 3.12.

Table 3.8: Overhead Ratio vs. Buffer Size (INFOCOM06 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	2292.54	388.56	295.2	-88%	-25%
2	1993.36	509.63	322.28	-84%	-37%
5	1487.05	567.25	332.36	-78%	-42%
15	917.88	405.31	266.06	-72%	-35%
25	674.04	326.39	212.99	-69%	-35%
35	549.61	272.65	173.99	-69%	-37%
45	454.25	227.47	145.01	-69%	-37%
55	410.42	196.59	124.95	-70%	-37%

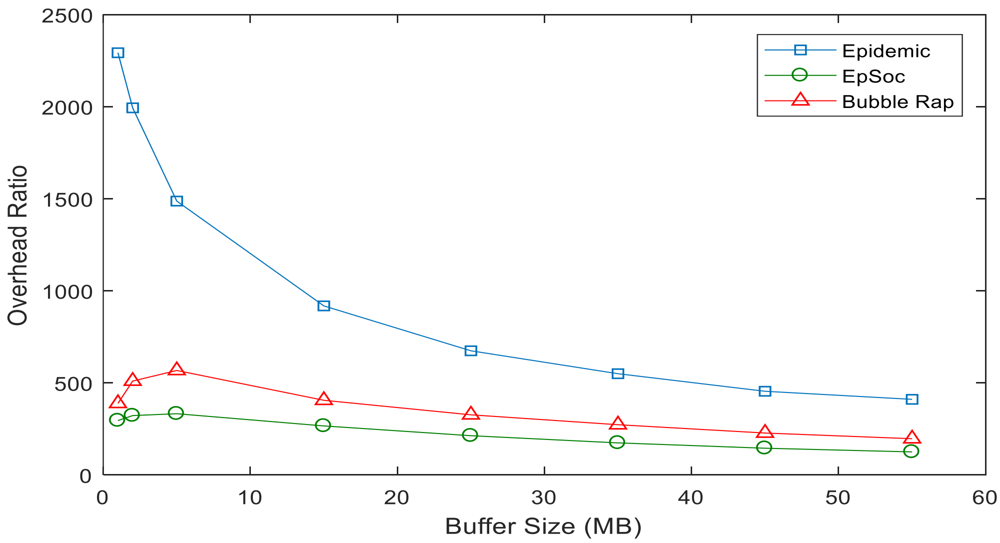


Figure 3.12: Overhead Ratio vs. Buffer Size (INFOCOM06 dataset)

In this dataset, the number of mobile nodes is greater than the two other datasets. So, the impact of exploiting the popularity of the nodes will be more effective. As a result, EpSoc outperforms both Epidemic and Bubble Rap protocols. The reduction in the overhead ratio is 75% and 36%, on average, compared to Epidemic and Bubble Rap respectively.

In general, based on the results, it can be said that EpSoc as a hybrid forwarding approach in OMSN; Epidemic and Social, it decreases the overhead significantly compared to Epidemic protocol because of employing social-based replication control methods. Also, compared to Bubble Rap, EpSoc can achieve close or might lower overhead ratio for high buffer size scenarios and when the number of nodes is high in OMSN.

3.4.1.3 Average Latency vs. Buffer Size

Average latency increases when the buffer size is increased. This is because if there is no opportunity for the relay node to forward the message, increasing the buffer size allows messages to be carried for a longer time before dropping due to the buffer overflow. Therefore, the average delivery time of the all delivered messages will be increased and hence results in a higher average latency in OMSN. On the other hand, when the buffer size is low, only messages that reach their destinations quickly will not be dropped. So, the average end-to-end delay of the delivered messages i.e. average latency in the network which will be low.

Table 3.9 and Figure 3.13 show the results of Cambridge dataset experiment. Figure 3.11 presents the change of the average latency with buffer size and Table 3.9 shows the performance achievement and the performance differences in percentage between EpSoc, Epidemic and Bubble Rap.

Table 3.9: Average Latency vs. Buffer Size (Cambridge Dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	2260.07	2294.15	1283.44	-44	-45
2	5715.01	5859.19	3651.03	-37	-38
5	17732.31	17185.44	10865.5	-39	-37
15	42086.3	45347.09	21014.95	-51	-54
25	51926.42	57793.32	25071.66	-52	-57
35	54214.09	59587.79	28821.02	-47	-52
45	58507.1	63586.74	31211.97	-47	-51
55	59872.71	65920.79	34100.81	-44	-49

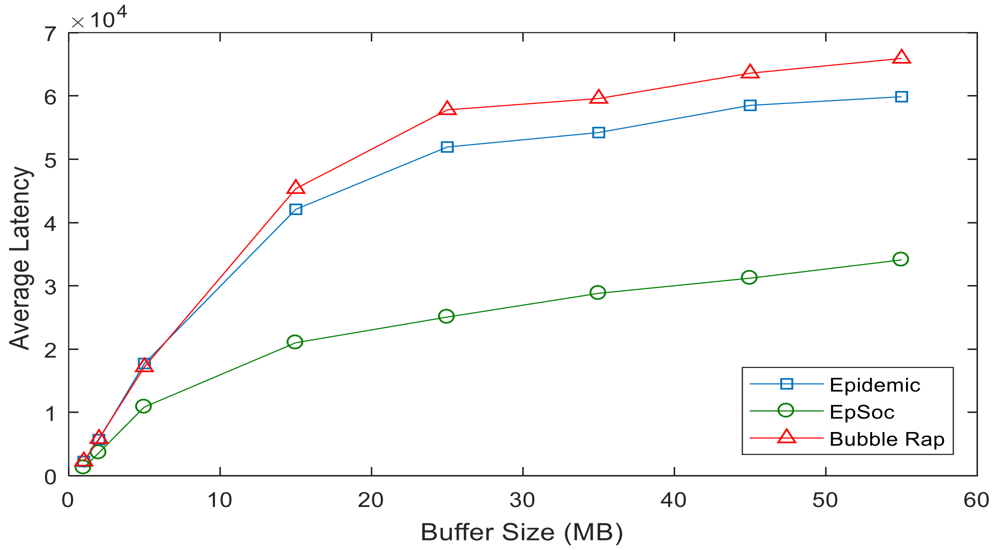


Figure 3.13: Average Latency vs. Buffer Size (Cambridge dataset)

It is clear that EpSoc decreases the average latency significantly compared to Epidemic and Bubble Rap. The decrement is on average 45% and 48% compared to Epidemic and Bubble Rap respectively. In EpSoc, the messages forwarded to the active nodes will have low TTL values as a result of adapting TTL value according to the user's popularity. Therefore, messages in the active nodes can be dropped faster, this releases more space in the buffers and enables active nodes to relay more new messages. Active nodes meet a higher number of nodes in the network and hence can deliver messages faster than the other nodes in the network. Consequently, the average latency in the network will be lower.

In Table 3.10, Figure 3.14 and Figure 3.15, the results of the INFOCOM05 dataset experiment are presented. It can be observed that EpSoc has better achievement in terms of average latency than Epidemic and Bubble Rap.

Table 3.10: Average Latency vs. Buffer Size (INFOCOM05 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	2418.41	2401.1	1199	-51%	-51%
2	5830.57	5146.19	3645.24	-38%	-30%
5	10196.92	10164.55	6422.86	-38%	-37%
15	11720.8	12296.67	10150.64	-14%	-18%
25	13526.75	13107.22	11313.52	-17%	-14%
35	13566.85	13427.27	11819.9	-13%	-12%
45	13869.74	13568.89	11930.68	-14%	-13%
55	13791.9	13544.13	12140.62	-12%	-11%

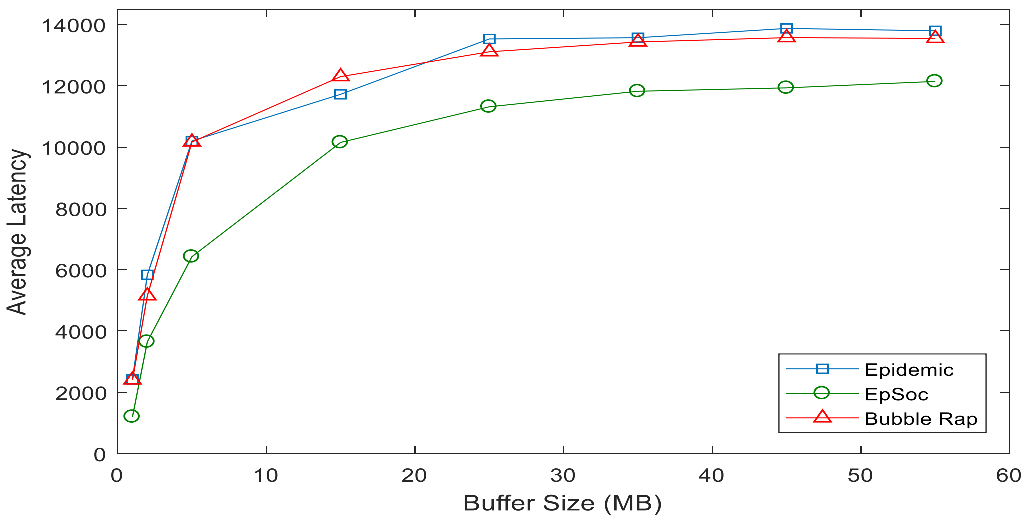
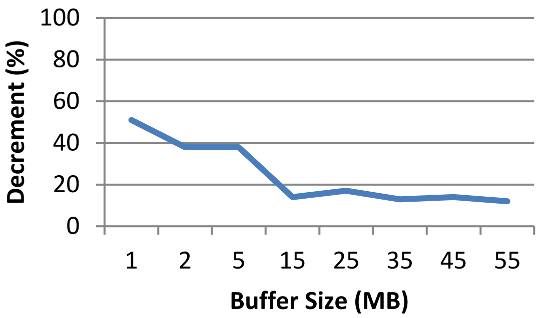
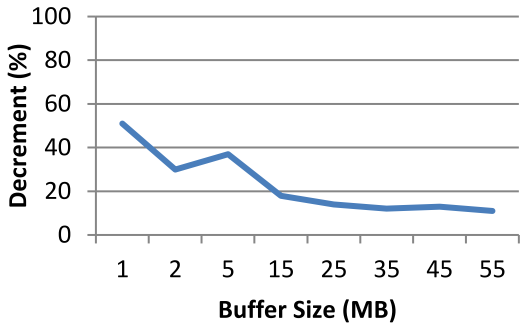


Figure 3.14: Average Latency vs. Buffer Size (INFOCOM05 dataset)



(a): Average Latency Decrement (%): **EpSoc vs. Epidemic** EpSoc decreases the average latency by 42% (low buffer size scenarios) and by 14% (medium and high buffer size scenarios).



(b): Average Latency Decrement (%): **EpSoc vs. Bubble Rap.** EpSoc decreases the average latency by 39% (low buffer size scenarios) and by 14% (medium and high buffer size scenarios).

Figure 3.15: Average Latency Decrements (INFOCOM05 dataset)

Compared to Epidemic it can be seen in Figure 3.13(a) that average latency is decreased by 42% on average for low buffer size scenarios and by 14% on average for medium and high buffer size scenarios. While compared to Bubble Rap Figure 3.13(b) shows that the decrement percentage is 39% on average for low buffer size scenarios and 14% on average for medium and high buffer size scenarios.

For INFOCOM06 dataset, the experimental results are presented in Table 3.11, Figure 3.16 and Figure 3.17. As for Cambridge and INFOCOM05 dataset, EpSoc also outperforms Epidemic and Bubble Rap in this experiment. It decreases the average latency compared to Epidemic by 47% on average for low buffer size scenarios and by 16% on average for medium and high buffer size scenarios as depicted in Figure 3.15(a). Figure 3.15(b) shows the decrement percentage compared to Bubble Rap where it is 61% on average for low buffer size scenarios and 16% on average for medium and high buffer size scenarios.

Table 3.11: Average Latency vs. Buffer Size (INFOCOM06 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	3053.17	4406.27	1284.6	-58%	-71%
2	5328.41	8135.41	2852.43	-47%	-65%
5	7551.84	9525.47	4972.4	-35%	-48%
15	9502.89	10714.87	7847.67	-18%	-27%
25	11185.78	11005.5	8848.58	-21%	-20%
35	11744.43	11213.16	9729.51	-18%	-14%
45	11930.6	11380.06	10328.05	-14%	-10%
55	11803.24	11309.35	10628.63	-10%	-7%

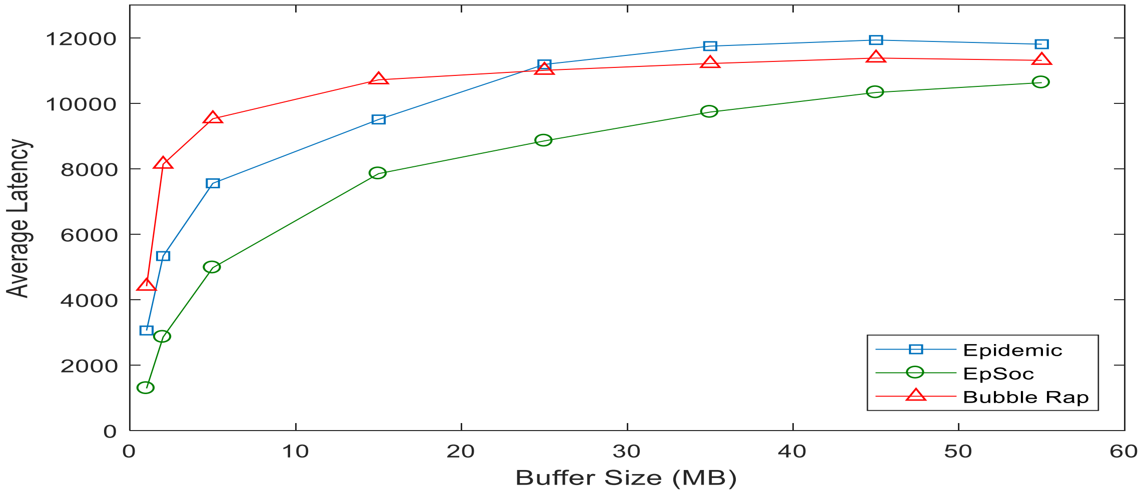
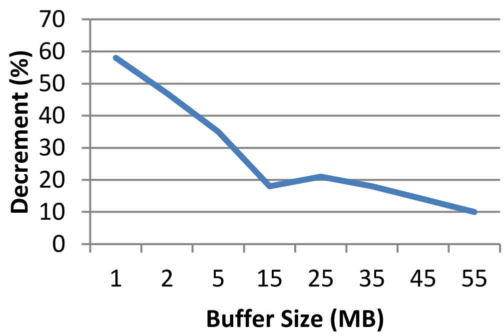
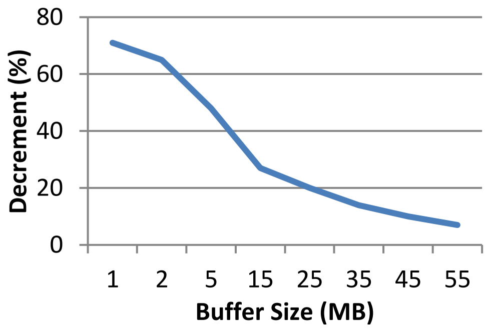


Figure 3.17: Average latency vs. Buffer size (INFOCOM06 dataset)



(a): Average Latency Decrement (%): **EpSoc vs. Epidemic** EpSoc decreases the average latency 74% (low buffer size scenarios) and 16% (medium and high buffer size scenarios) .



(b): Average Latency Decrement (%): **EpSoc vs. Bubble Rap.** EpSoc decreases the average latency by 61% (low buffer size scenarios) and by16% (medium and high buffer size scenarios)

Figure 3.16: Average Latency Decrements (INFOCOM06 dataset)

It is clear that EpSoc decreases the average latency significantly as compared to Epidemic and Bubble Rap for all datasets scenarios especially when buffer size is low.

3.4.1.4 Average Hop Count vs. Buffer Size

In this section the average hop count metric for EpSoc , Epidemic and Bubble Rap is evaluated. Table 3.12 and Figure 3.18 show the results of Cambridge dataset.

Table 3.12: Average Hop Count vs. Buffer Size (Cambridge dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	5.67	1.99	2.91	-49%	+47%
2	7.38	2.09	2.94	-61%	+41%
5	7.36	2.2	2.92	-61%	+33%
15	6.34	2.2	2.97	-54%	+35%
25	5.83	2.24	3.12	-47%	+40%
35	5.82	2.24	3.08	-48%	+38%
45	5.24	2.27	3	-43%	+33%
55	4.93	2.27	2.95	-41%	+30%

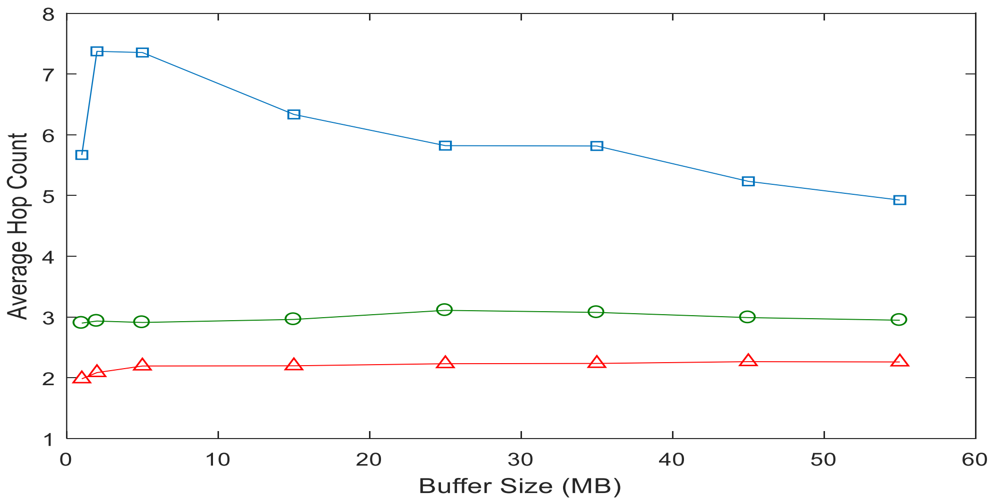


Figure 3.18: Average Hop Count vs. Buffer size (Cambridge dataset)

It can be observed from the results that the change in buffer size has lower impact on EpSoc and Bubble Rap as compared to Epidemic. This is due to the high replication rate in Epidemic where it is flooding-based protocol. On the other hand, EpSoc controls the replication socially and Bubble Rap adopts strict social based forwarding protocol. For low buffer size scenarios (1, 2, 5 MB) the buffer overflows is more frequent, so increasing buffer size decreases the rate of messages dropping rate due to buffer overflow and enables messages to traverse more nodes. So, the average hop count increase with buffer size increase for Epidemic, EpSoc and Bubble Rap. For high buffer size scenarios (15 MB and above), buffer overflow has lower impact, so increasing buffer size enables relays node to carry more messages and forward it to encountered peers, which results in higher probability to deliver the messages and hence decreases the average hop counts required to deliver messages for Epidemic and EpSoc.

EpSoc outperforms Epidemic significantly; the reduction in average hop count is 51% on average. This is because of the message blocking mechanism where it decreases the replication rate in the network and hence decreases the message forwarding.

Comparing to Bubble Rap, EpSoc has higher average hop counts; 37% on average. The reason is that in Bubble Rap there is no message replication because it is a pure social based approach while in EpSoc adopting the Epidemic forwarding protocol results in messages replication in the network. This increases the number of forwardings and contributes to a higher average hop count. Similar results can be seen in the experiment of INFOCOM05 dataset in Table 3.13 and Figure 3.19.

Table 3.13: Average Hop Count vs. Buffer Size (INFOCOM05 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	5.74	2.2	3.04	-48%	+39%
2	8.31	2.31	3.11	-63%	+35%
5	7.79	2.43	3.14	-60%	+30%
15	6.9	2.53	3.01	-57%	+19%
25	5.66	2.52	2.92	-49%	+16%
35	4.92	2.5	2.79	-44%	+12%
45	4.72	2.51	2.79	-41%	+12%
55	4.37	2.49	2.74	-38%	+11%

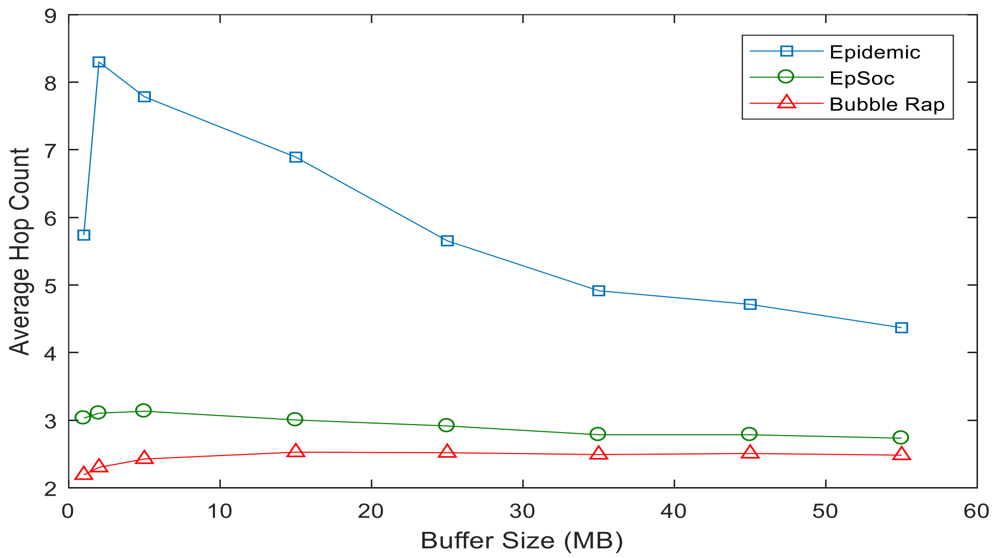


Figure 3.19: Average Hop Count vs. Buffer size (INFOCOM05 dataset)

As in Cambidge dataset, EpSoc has better efficiency than Epidemic but higher hop count compared to Bubble Rap. EpSoc decreases the average hop count by 50% on average compared to Epidemic. While compared to Bubble Rap, it is observed that for low buffer size scenarios it has 35% increase on average, and for medium and high buffer size scenarios the increase is 14% on average. Table 3.14 and Figure 3.20 show the results of INFOCOM06 dataset experiment.

Table 3.14: Average Hop Count vs. Buffer Size (INFOCOM06 dataset)

Buffer Size (MB)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
1	12.55	2.67	3.41	-73%	+28%
2	13.04	2.75	3.36	-75%	+23%
5	10.82	2.85	3.37	-69%	+19%
15	8.39	2.93	3.13	-63%	+7%
25	7.58	3.08	3.01	-61%	-3%
35	6.75	3.03	2.94	-57%	-3%
45	5.83	3.08	2.91	-51%	-6%
55	5.29	2.97	2.89	-46%	-3%

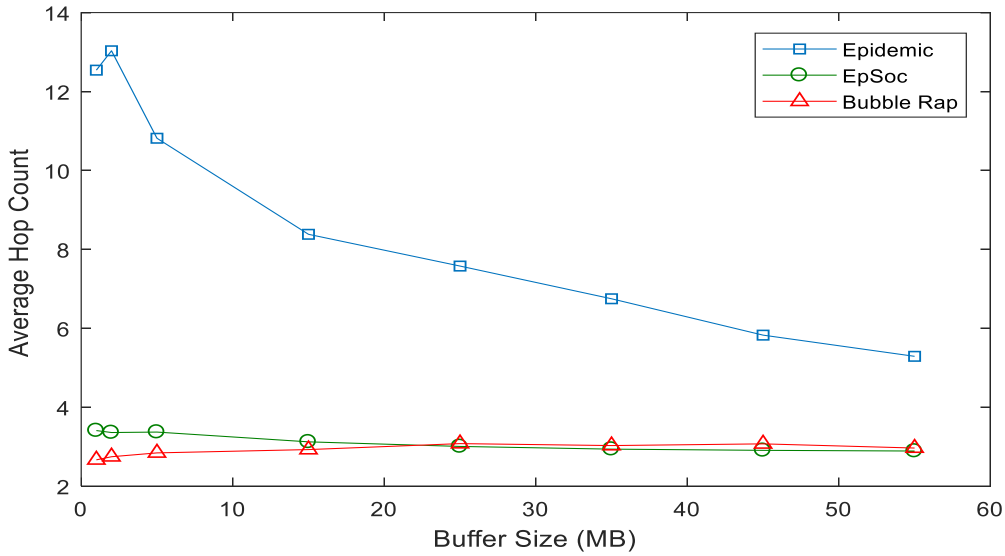


Figure 3.20: Average Hop Count vs. Buffer Size (INFOCOM06 dataset)

EpSoc outperforms Epidemic significantly in this experiment because it controls the messages replication socially. It reduces the average hop count 62% on average.

Compared to Bubble Rap it can be observed that, for low buffer size scenarios, EpSoc has lower efficiency; the average hop count is 23% higher on average. But the efficiency of EpSoc becomes better with increasing buffer size where at 25 MB EpSoc starts having better efficiency i.e. lower average hop count than Bubble Rap.

In the INFOCOM06 dataset the number of mobile nodes is higher than Cambridge and INFOCOM05 datasets. This enables EpSoc to benefit more from the higher number of active nodes in the network and hence has better efficiency.

3.4.2 Varying Initial TTL

TTL determines the life of the messages forwarded in the network. A high value of TTL gives a higher chance of the messages to be delivered to destinations before dropping and vice versa. To vary the initial TTL value, the buffer size is set to 5MB though out the experiment scenarios. This value was selected based on the previous experiments conducted for different buffer size scenarios, where 5MB scenario provides better in the performance of the protocols.

3.4.2.1 Delivery Ratio vs. TTL

Increasing messages' TTL gives the opportunity to deliver more messages before dropping due to run out TTL value, so it increases the delivery ratio in the network. Table 3.15 and Figure 3.21 show the relation of delivery ratio with TTL for Cambridge dataset.

Table 3.15: Delivery Ratio vs. TTL (Cambridge dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	0.05	0.03	0.04	-20%	+34%
30	0.07	0.05	0.06	-15%	+20%
60 (1Hour)	0.08	0.07	0.07	-13%	0%
180 (3 Hours)	0.1	0.1	0.1	0%	0%
300 (5 Hours)	0.11	0.12	0.12	+10%	0%
720 (12 Hours)	0.14	0.15	0.15	+8%	0%
1440 (1Day)	0.16	0.18	0.18	+13%	0%
2160 (1.5Day)	0.16	0.17	0.18	+13%	+6%
3600 (2.5Day)	0.16	0.17	0.19	+19%	+12%
4320 (3Day)	0.17	0.17	0.19	+12%	+12%
5760 (4Day)	0.16	0.17	0.19	+19%	+12%
10080 (1Week)	0.16	0.17	0.2	+25%	+18%

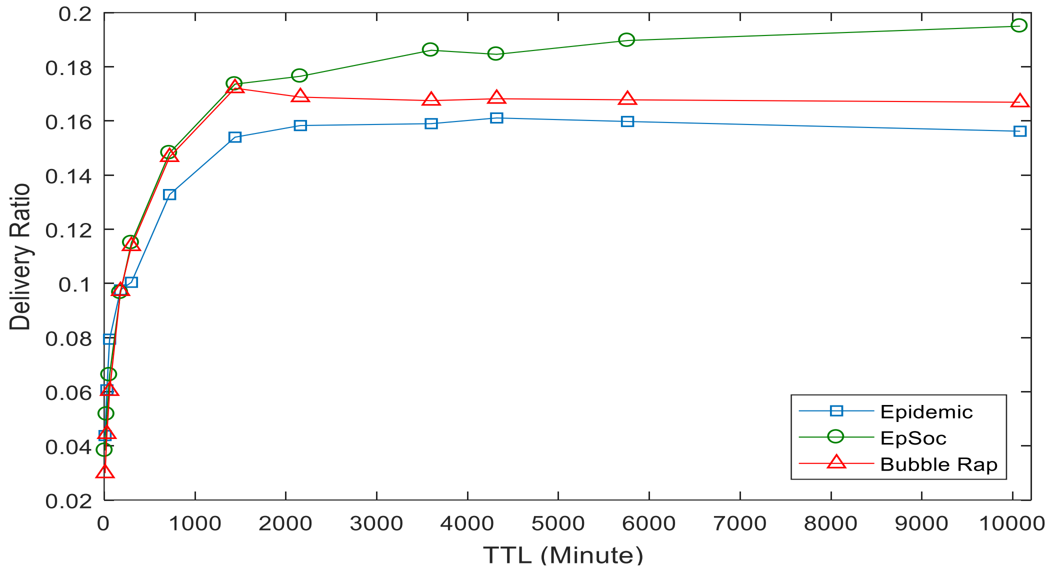


Figure 3.21: Delivery Ratio vs. TTL (Cambridge dataset)

It can be seen that the efficiency of all the protocols increased by increasing TTL until reaching a plateau. For a low TTL (10m, 30m, 60m) scenario, the delivery ratio of EpSoc is slightly lower than Epidemic (16% on average). The reason is, Epidemic employs messages' replication (flooding-based strategy) to increases the number of the delivered messages hence to increase the delivery ratio. In EpSoc exploiting social features will not be a very effective strategy due to quickly messages' dropping because of low TTL value. However, by increasing TTL value, the achievement of EpSoc becomes better, and at 300 minutes EpSoc starts outperforming Epidemic as a result of exploiting active nodes to forward messages and utilizing social features to control replication and decrease overhead.

Comparing to Bubble Rap, EpSoc outperforms Bubble Rap for a low (10m, 30m) and a high (more than 1.5 days) TTL value, while has the same achievement for other scenarios. When TTL value is low, EpSoc adopts Epidemic-based forwarding strategy, it delivers more messages than Bubble Rap before messages are expired due to low TTL value.

In high TTL scenarios, EpSoc shortens the life of the messages forwarded to the active nodes; also, it blocks the replicas of the expired messages from hitting again active nodes.

This results in an increment in the delivered messages, and at the same time decreases the forwardings number in the network. Therefore, the delivery ratio is increased. Table 3.16 and Figure 3.22 show the relation of delivery ratio with TTL for INFOCOM05 dataset experiment.

Table 3.16: Delivery Ratio vs. TTL (INFOCOM05 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	0.1	0.06	0.08	-20%	+34%
30	0.15	0.11	0.12	-20%	+10%
60 (1Hour)	0.17	0.15	0.16	-6%	+7%
240 (4 Hours)	0.17	0.18	0.21	+24%	+17%
480 (8 Hours)	0.17	0.19	0.24	+42%	+27%
960 (16 Hours)	0.17	0.2	0.26	+53%	+30%
1200 (20 Hours)	0.19	0.2	0.26	+37%	+30%
1440 (1 Day)	0.18	0.2	0.26	+45%	+30%
1680 (1Day4Hours)	0.18	0.2	0.25	+39%	+25%
1920 (1Day8Hours)	0.17	0.2	0.26	+53%	+30%
2160 (1.5 Day)	0.17	0.19	0.26	+53%	+37%
2400 (1Day16Hours)	0.18	0.2	0.26	+45%	+30%

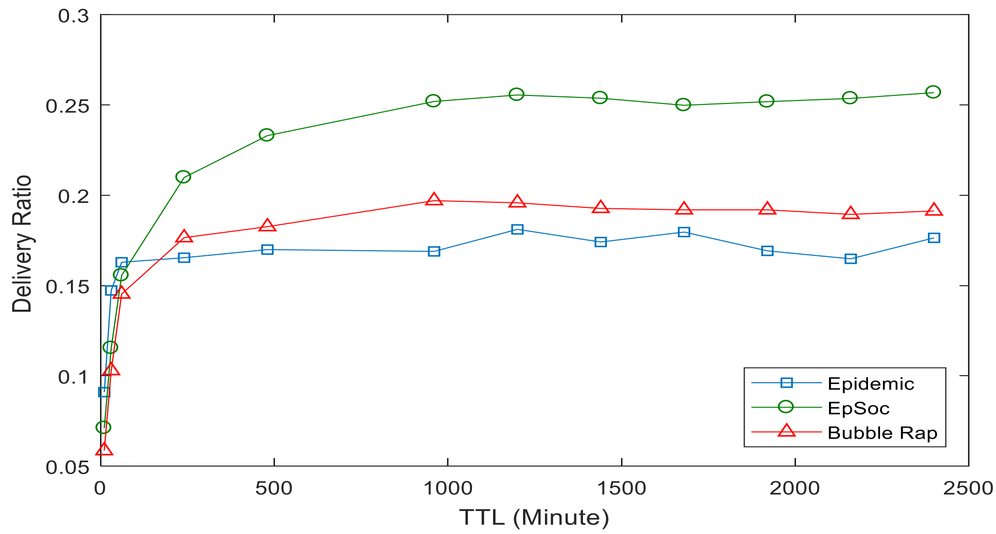


Figure 3.22: Delivery Ratio vs. TTL (INFOCOM05 dataset)

As Cambridge experiment and for the same reasons; EpSoc has also slightly lower delivery ratio than Epidemic (15% on average) for low TTL value scenarios (10, 30 and 60 Minutes), and by increasing TTL value, EoSoc outperforms Epidemic and increase the delivery ratio by 43% on average. EpSoc outperforms Bubble Rap in this experiment for all TTL value scenarios. The average increment in the delivery ratio is 26%. Deploying a socially controlled Epidemic-based forwarding strategy and exploiting the popularity of active nodes enables EpSoc to achieve this.

For INFOCOM06 dataset experiment, Table 3.17 and Figure 3.23 show the performance evaluation in term of delivery ratio metric.

Similar results, as Cambridge and INFOCOM05 experiments, can be observed when comparing EpSoc with Epidemic. EpSoc has lower delivery ratio than Epidemic in low TTL scenarios (10, 30, and 60 Minutes) and better achievement when increasing TTL value above 60 minutes.

Table 3.17: Delivery Ratio vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	0.2	0.13	0.13	-35%	0%
30	0.27	0.19	0.17	-38%	-11%
60 (1Hour)	0.26	0.22	0.21	-20%	-5%
240 (4 Hours)	0.19	0.25	0.29	+53%	+16%
480 (8 Hours)	0.18	0.26	0.32	+78%	+24%
960 (16 Hours)	0.16	0.26	0.33	+107%	+27%
1200 (20 Hours)	0.15	0.25	0.34	+127%	+36%
1440 (1 Day)	0.15	0.24	0.34	+127%	+42%
1680 (1Day4Hours)	0.15	0.24	0.34	+127%	+42%
1920 (1Day8Hours)	0.14	0.24	0.35	+150%	+46%
2160 (1.5 Day)	0.15	0.24	0.35	+134%	+46%
2400 (1Day16Hours)	0.14	0.23	0.36	+158%	+57%

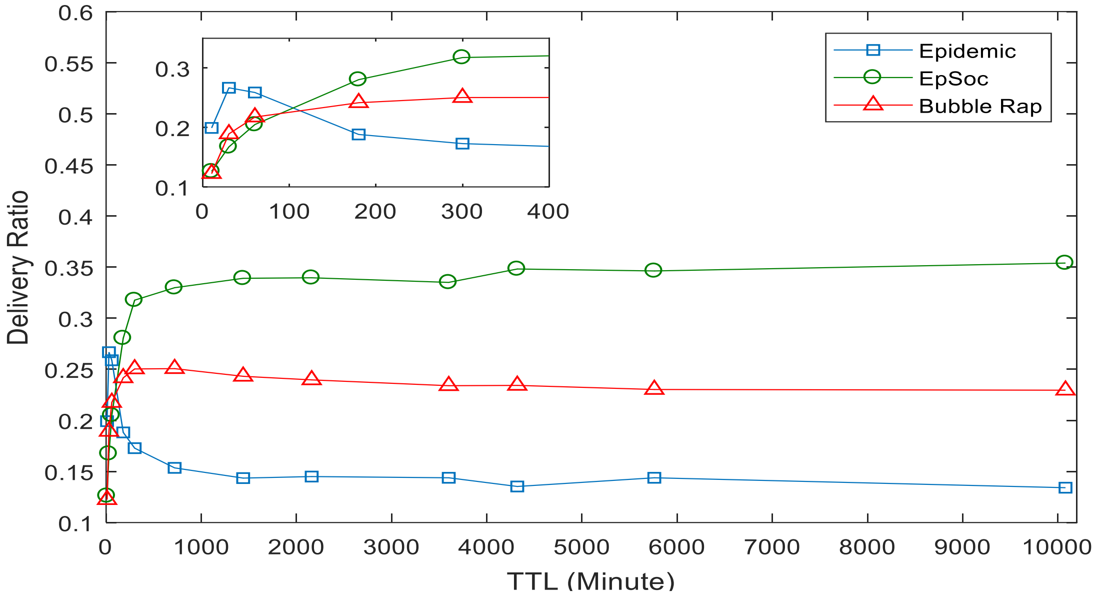


Figure 3.23: Delivery Ratio vs. TTL (INFOCOM06 dataset)

Comparing to Bubble Rap, in low TTL value scenarios (10, 30, and 60 Minutes), EpSoc has a slightly lower delivery ratio (5% on average) than Bubble Rap. This is because this dataset has a higher number of nodes than Cambridge and INFOCOM05 datasets. However, for higher TTL values scenarios (more than 60 Minutes), EpSoc outperforms Bubble Rap by 40% on average.

Generally, based on the achieved results of all three datasets, it can be concluded that for a low TTL (10, 30 and 60 Minutes) scenario, the delivery ratio of Epidemic is slightly higher than EpSoc and Bubble Rap in all the datasets experiments. The reason is, for a short TTL value it will not be very effective due to quickly messages' dropping. In addition, the replicating of Epidemic increases the number of delivered messages hence increase the delivery ratio. However, When TTL is increased, EpSoc and Bubble Rap outperform Epidemic due to utilizing the social features.

It is noticed also that in low TTL (10 , 30 , 60 Minute) scenarios, EpSoc outperforms Bubble Rap in the first two experiments (Cambridge and INFOCOM05) while achieves lower, but close, performance in INFOCOM06 scenario. Increasing the number of the nodes in the INFOCOM06 experiment gives Bubble Rap this advantage over Epsoc where the low TTL values prevent EpSoc from contributing better.

For high TTL values scenarios (more than 60 Minute), EpSoc outperforms Epidemic and Bubble Rap in all the datasets experiments. This is due to that EpSoc shorten the life of the messages forwarded to the active nodes, also blocks the replicas of the expired messages from hitting again active nodes. This results in an increment in the delivered messages and a decrease in the forwardings. Therefore, the delivery ratio is increased.

3.4.2.2 Overhead Ratio vs. TTL

TTL value determines the life of a message in a network. Therefore, if it is low, the overhead will decrease because of the quickly dropping of messages due to expiration. On the contrary, increasing TTL value extends message life, which enables relays to forward and deliver more messages before dropping, and hence rises up the overhead ratio in the network.

The following sections show the performance evaluation of the protocols in terms of overhead ratio for the three real dataset experiments. Table 3.18 and Figure 3.24 show the change of overhead ratio with TTL for Cambridge dataset.

Table 3.18: Overhead Ratio vs. TTL (Cambridge dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	33.26	11.69	30.18	-10%	+159%
30	32.5	11.18	34.19	+6%	+206%
60 (1Hour)	35.97	11.1	34.01	-6%	+207%
180 (3 Hours)	343.25	30.35	142.52	-59%	+370%
300 (5 Hours)	391.87	56.23	160.02	-60%	+185%
720 (12 Hours)	309.55	80.45	156.01	-50%	+94%
1440 (1Day)	272.73	84.47	145.62	-47%	+73%
2160 (1.5Day)	267.97	90.41	149.25	-45%	+66%
3600 (2.5Day)	267.41	92.28	151.06	-44%	+64%
4320 (3Day)	263.55	91.59	153.32	-42%	+68%
5760 (4Day)	263.73	92.18	156.15	-41%	+70%
10080 (1Week)	271.15	92.65	150.03	-45%	+62%

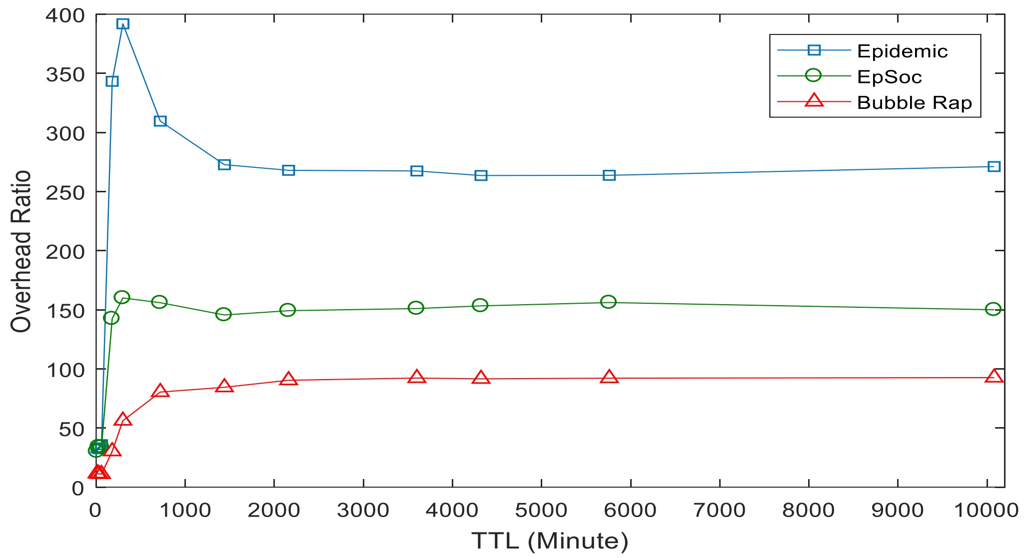


Figure 3.24: Overhead ratio vs. TTL (Cambridge dataset)

From the results, it is clear that the overhead ratio increases when the TTL value increases until the change in overhead ratio reach a plateau for all the protocols. EpSoc outperforms Epidemic significantly, where the decrement in the overhead ratio is about 50% on average. This is because, in EpSoc, decreasing messages' TTL value at active nodes results in dropping messages rapidly and hence decrease the replication rate.

Compared with Bubble Rap, EpSoc has a higher overhead ratio for this dataset. Flooding-based forwarding employed in EpSoc in addition to the lower scale of nodes' number in the Cambridge dataset contributes to increasing the overhead ratio for EpSoc. The results of the INFOCOM05 dataset are presented in Table 3.19 and Figure 3.25.

Table 3.19: Overhead Ratio vs. TTL (INFOCOM05 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	36.26	15.22	32.49	-11%	+114%
30	53.56	16.45	34.97	-35%	+113%
60 (1Hour)	213.26	32.4	58.55	-73%	+81%
240 (4 Hours)	341.27	107.18	138.51	-60%	+30%
480 (8 Hours)	351.52	132.11	137.41	-61%	+5%
960 (16 Hours)	369.03	137.5	135.29	-64%	-2%
1200 (20 Hours)	344.99	140.34	138.23	-60%	-2%
1440 (1 Day)	357.01	144.25	138.28	-62%	-5%
1680 (1Day4Hours)	352.88	144.15	152.04	-57%	+6%
1920 (1Day8Hours)	375.55	144.14	143.04	-62%	-1%
2160 (1.5 Day)	380.27	146.61	148.83	-61%	+2%
2400 (1Day16Hours)	364.03	145.75	146.15	-60%	+1%

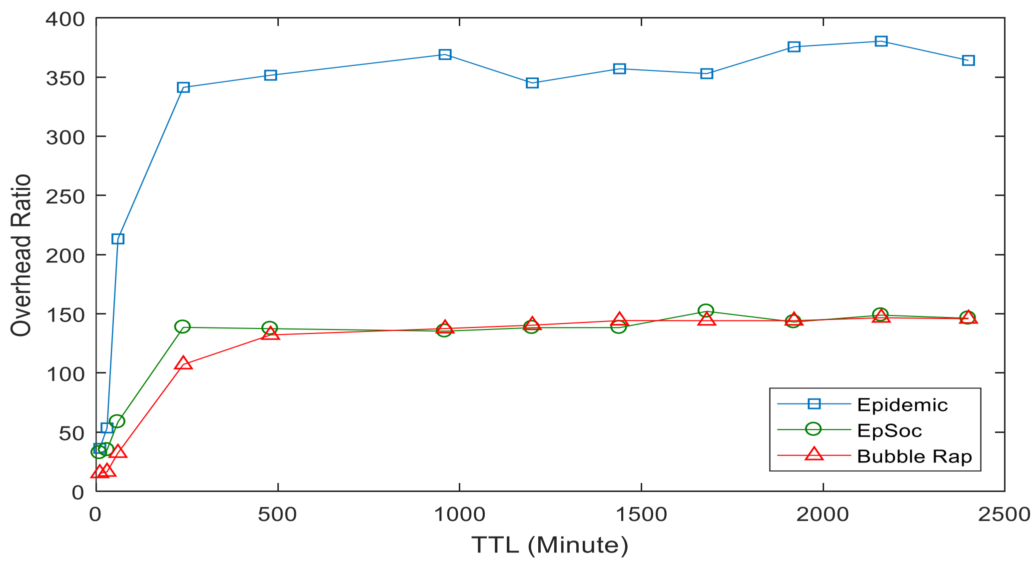


Figure 3.25: Overhead Ratio vs. TTL (INFOCOM05 dataset)

EpSoc decreases the overhead ratio by 56% on average compared to Epidemic and has almost the same achievement as Bubble Rap. In this dataset, the number of nodes is higher than in Cambridge dataset, so the interconnections and social activities among mobile users are higher. This increases the efficiency of EpSoc because it will exploit the higher number of active nodes in the network. Consequently, EpSoc has a better performance than Cambridge dataset.

Table 3.20 and Figure 3.26 show the results of INFOCOM06 dataset experiment EpSoc outperforms Epidemic significantly where the reduction in the overhead ratio is 72% on average.

Table 3.20: Overhead Ratio vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	73.53	26.46	56.48	-24%	+114%
30	105.04	28.2	60.43	-43%	+115%
60 (1Hour)	764.14	108.86	95.95	-88%	-12%
240 (4 Hours)	1214.33	450.26	253.05	-80%	-44%
480 (8 Hours)	1312.79	552.92	271.83	-80%	-51%
960 (16 Hours)	1378.56	585.2	302.82	-79%	-49%
1200 (20 Hours)	1373.26	586.81	297.96	-79%	-50%
1440 (1 Day)	1309.78	579.51	307.33	-77%	-47%
1680 (1Day4Hours)	1309.93	596.95	317.2	-76%	-47%
1920 (1Day8Hours)	1391.22	596.49	306.44	-78%	-49%
2160 (1.5 Day)	1310.41	608.12	322.57	-76%	-47%
2400 (1Day16Hours)	1392.04	599.75	316.18	-78%	-48%

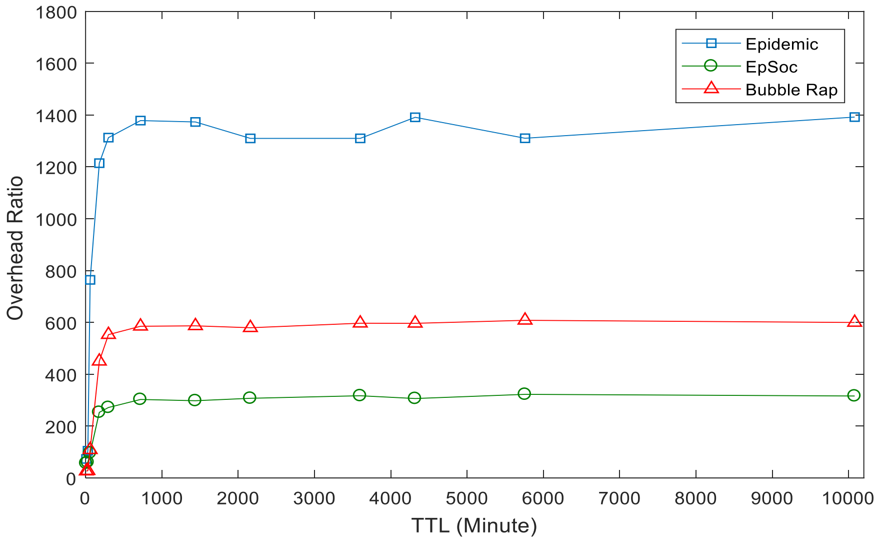


Figure 3.26: Overhead Ratio vs. TTL (INFOCOM06 dataset)

EpSoc outperforms Bubble Rab when TTL value greater than 1 hour. The average reduction in the overhead ratio is 44%. The number of nodes in INFOCOM06 is higher than in both INFOCOM05 and Cambridge datasets, so the social-based techniques employed in EpSoc are more efficient in reducing delivery overhead.

Generally, based on the figures and tables, it is clear that the overhead ratio increases when the TTL value increases until the change reaches almost a stable rate. Epidemic has the worst achievement due to its flooding nature. EpSoc outperforms Epidemic significantly. The decrement in the overhead ratio is about 50%, 60%, and 77% for Cambridge, INFOCOM05, and INFOCOM06 datasets respectively. This is a result of decreasing messages' TTL value in the active nodes and consequently decrease the replication rate in the network.

Comparing EpSoc with Bubble Rab, EpSoc outperforms Bubble Rap in the INFOCOM06 experiment, and achieves slightly higher, but very close, performance for the INFOCOM05 dataset, while it has higher overhead ratio than Bubble Rap in Cambridge experiment. The social-based techniques employed in EpSoc are more efficient when the number of nodes in the network is higher, as for INFOCOM06 experiment, while in lower nodes number scale datasets like Cambridge dataset, flooding-based forwarding employed in EpSoc contributes to increasing the overhead ratio. Consequently, Bubble Rap outperforms it.

For a low TTL scenario (10, 30, 60 Minute), all the protocols achieve low overhead. The reason is that messages are dropped quickly and hence the message delivery rate is very low. Increasing TTL value provides the opportunity to forward and later to deliver more messages. Consequently, the difference between the performance of the protocols becomes more significant.

3.4.2.3 Average Latency vs. TTL

Changing the TTL values affects the average latency in the network in OMSN. In a low TTL value scenarios, only messages that are forwarded quickly will be delivered before dropping due to TTL exhaustion. Therefore, the average end-to-end (latency) in the network will be low. Increasing TTL value allows messages that are forwarded in a lower time to be delivered, which in turn increases the average latency in the network. However, when most messages have enough life to reach the destination, the increase in TTL will become ineffective, and other factors play the key impact on messages delivery ratio in OMSN.

The following tables and figures show the relationship between TTL and average latency. Table 3.21 and Figure 3.27 present the results of Cambridge dataset experiment.

Table 3.21: Average Latency vs. TTL (Cambridge dataset)

TTL (Minutes)	Epidemi c	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	71.09	77.35	53.87	-25%	-31%
30	378.84	422.99	284.95	-25%	-33%
60 (1Hour)	926.61	1028.91	740.66	-21%	-29%
180 (3 Hours)	3694.71	3606.83	2654.6	-29%	-27%
300 (5 Hours)	6268.56	6268.11	5488.4	-13%	-13%
720 (12 Hours)	15957.46	15535.2	9681.8	-40%	-38%
1440 (1Day)	28885.69	29108.8	16058.	-45%	-45%
2160 (1.5Day)	32595.8	32477.6	16332.	-50%	-50%
3600 (2.5Day)	33792.01	33122.4	17921.	-47%	-46%
4320 (3Day)	33523.49	33163.9	18403.	-46%	-45%
5760 (4Day)	33702.22	33374.7	20051.	-41%	-40%
10080 (1Week)	33172.08	33356.3	23241.	-30%	-31%

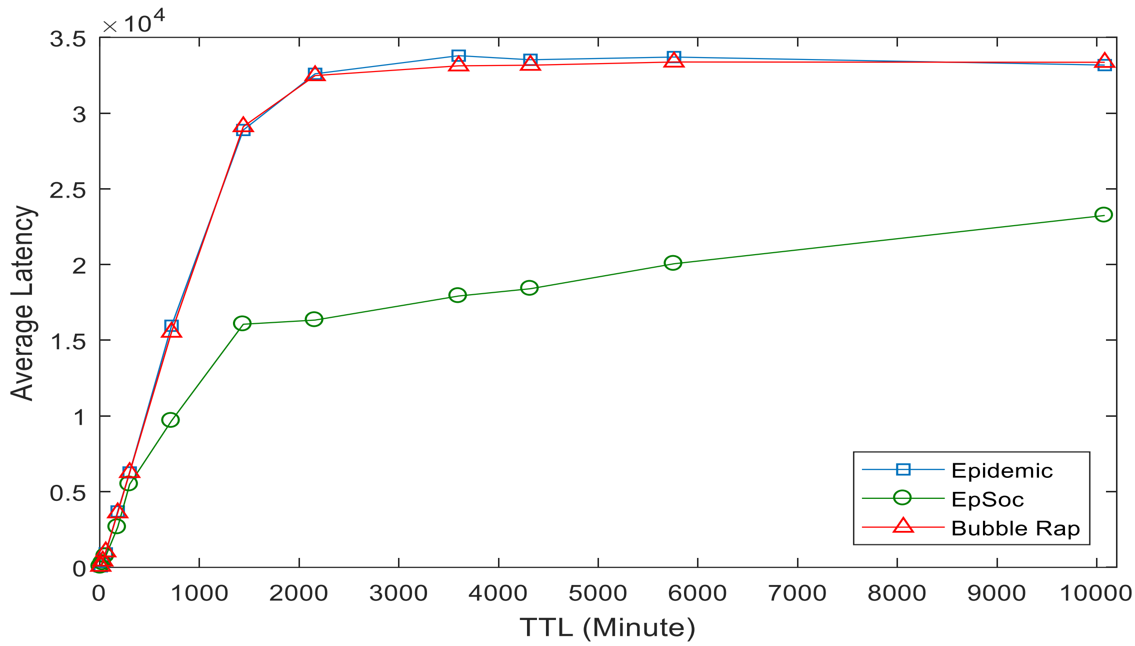


Figure 3.27: Average Latency vs. TTL (Cambridge dataset)

EpSoc outperforms Epidemic and Bubble Rap significantly. The average percent decrease in the delivery latency compared with Epidemic and Bubble Rap is 34% and 37% respectively. This is because EpSoc reaps the advantages of both social-based and flooding-based approaches to decrease the average latency in the network by deploying two techniques: First, adopting the Epidemic forwarding strategy allows more intermediate nodes to be involved in the message forwarding and hence there is a higher probability to deliver messages faster. Second, decreasing messages' TTL in the active nodes enables them to carry more messages and deliver them in a lower latency because of their high popularity.

Similar results can be seen in Table 3.22 and Figure 3.28 which show the results of INFOCOM05 dataset experiment. The decrease in delivery latency is 36% and 33% against Epidemic and Bubble Rap respectively.

Table 3.22: Average Latency vs. TTL (INFOCOM05 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	156.29	159.24	150.2	-4%	-6%
30	542.94	566.87	527.06	-3%	-8%
60 (1Hour)	1248.73	1271.19	1136.6	-9%	-11%
240 (4 Hours)	4279.31	4334.13	3589.3	-17%	-18%
480 (8 Hours)	8084.25	7995.32	5877.2	-28%	-27%
960 (16 Hours)	13340.56	14443.71	8310.4	-38%	-43%
1200 (20 Hours)	15968.62	15021.16	8664.4	-46%	-43%
1440 (1 Day)	14790.14	14758.11	8124.4	-46%	-45%
1680 (1Day4Hours)	16157.64	14564.82	8037.5	-51%	-45%
1920 (1Day8Hours)	15614.99	14614.21	7594.9	-52%	-49%
2160 (1.5 Day)	15723.31	14880.05	7652.9	-52%	-49%
2400 (1Day16Hours)	16883.66	14869.83	7490.8	-56%	-50%

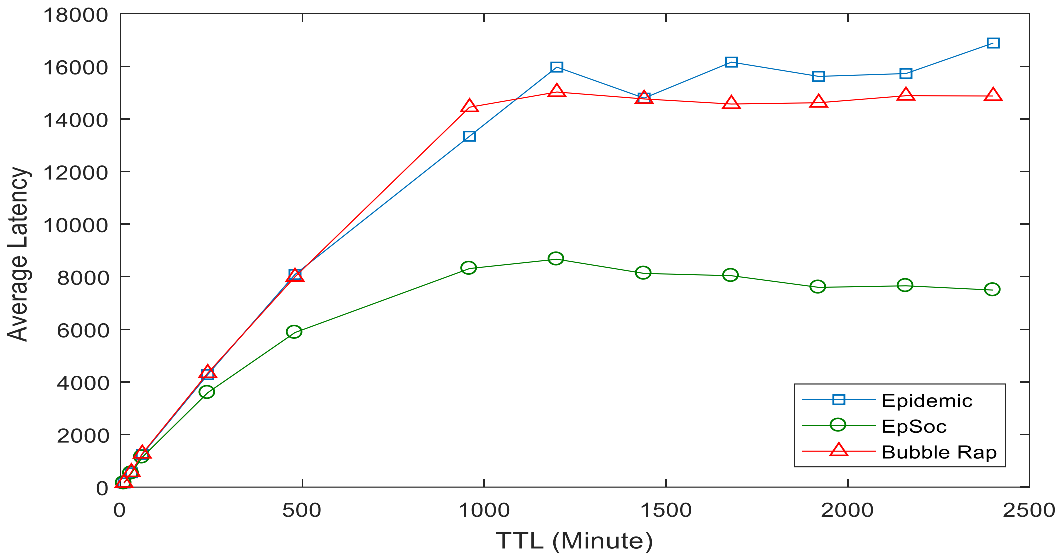


Figure 3.28: Average Latency vs. TTL (INFOCOM05 dataset)

It is also clear in INFOCOM06 dataset experiment, Table 3.23 and Figure 3.29, that EpSoc outperforms both Epidemic and Bubble Rap. It decreases average latency significantly with 41% compared to Epidemic and 56% compared to Bubble Rap. In this experiment, EpSoc has higher performance compared with Cambridge and INFOCOM05 datasets. This is because of the higher number of nodes in the network, i.e. more number of socially popular nodes. This contributes a more effective forwarding strategy in EpSoc.

Table 3.23: Average Latency vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	87.63	141.76	93.95	8%	-34%
30	370.31	466.65	347.23	-7%	-26%
60 (1Hour)	1078.01	981.59	749.86	-31%	-24%
240 (4 Hours)	4127.79	4556.68	2878.5	-31%	-37%
480 (8 Hours)	6908.7	8437.62	4594.7	-34%	-46%
960 (16 Hours)	9957.36	14167.7	5126.0	-49%	-64%
1200 (20 Hours)	9690.14	15235.98	4749.1	-51%	-69%
1440 (1 Day)	9534.43	15991.08	4389.5	-54%	-73%
1680 (1Day4Hours)	11330.41	15824.08	3892.9	-66%	-76%
1920 (1Day8Hours)	9774.35	15787.54	4124.7	-58%	-74%
2160 (1.5 Day)	10043.48	15486.53	4277.1	-58%	-73%
2400 (1Day16Hours)	9255.37	15568.04	4029.2	-57%	-75%

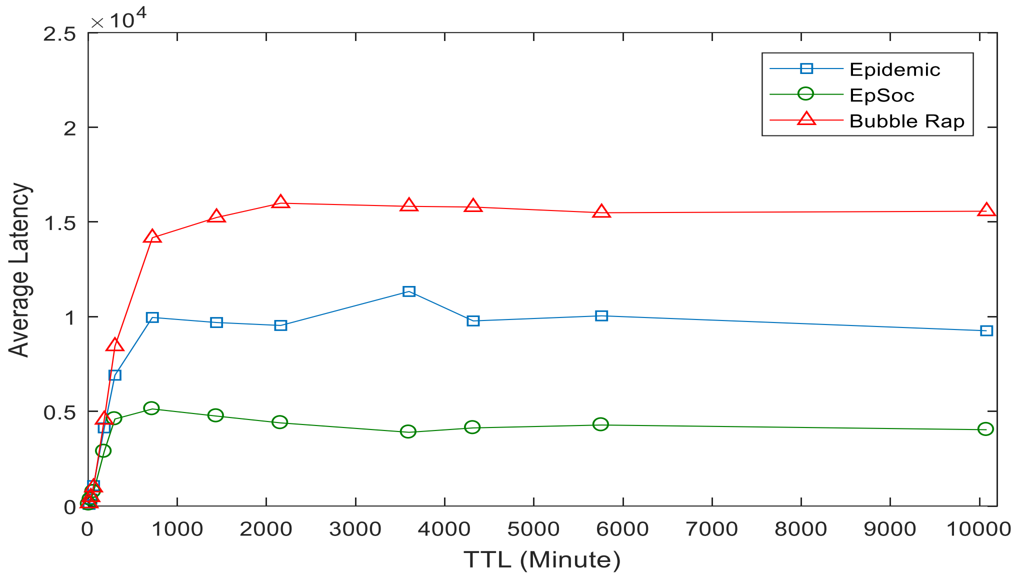


Figure 3.29: Average Latency vs. TTL (INFOCOM06 dataset)

3.4.2.4 Average Hop Count vs TTL

There is an inverse relationship between TTL value and average hop count (the number of traversed nodes to reach the destination). Low TTL values result in a lower number of forwardings between nodes due to the quickly exhausting of message life. On the contrary, increasing TTL enables messages to traverse more intermediate nodes to the destination. The following tables and figures present this relation in the experiments.

Table 3.24 and Figure 3.30 show the change in average hop count with TTL for Cambridge dataset.

Table 3.24: Average Hop Count vs. TTL (Cambridge dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	2.64	1.88	2.31	-13%	23%
30	2.81	1.96	2.5	-12%	28%
60 (1Hour)	2.85	2.02	2.55	-11%	27%
180 (3 Hours)	5.09	2.14	2.71	-47%	27%
300 (5 Hours)	6.61	2.18	2.79	-58%	28%
720 (12 Hours)	6.41	2.22	2.79	-57%	26%
1440 (1Day)	6.37	2.19	2.8	-57%	28%
2160 (1.5Day)	6.63	2.15	2.87	-57%	34%
3600 (2.5Day)	6.55	2.19	2.99	-55%	37%
4320 (3Day)	6.54	2.2	2.91	-56%	33%
5760 (4Day)	7.25	2.19	3.03	-59%	39%
10080 (1Week)	7.08	2.2	3.12	-56%	42%

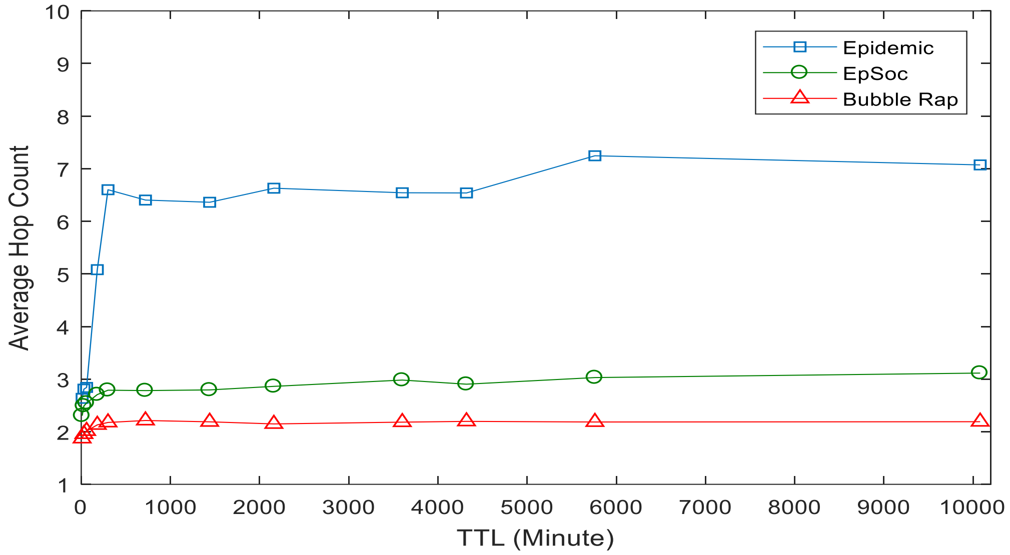


Figure 3.30: Average Hop Count vs. TTL (Cambridge dataset)

It is observed that if TTL is low (10, 30 and 60 Minute) all routing protocols have low average hop count because most messages are dropped. With the increase in TTL, EpSoc and Bubble Rap achieve low average hop counts and almost stable performance. This is because the forwarding process is guided by the social features which result in utilizing a fewer number of intermediate nodes to deliver the message. Regarding Epidemic, the average hop count increases significantly with TTL increase because of the adopted flooding-based forwarding strategy.

EpSoc decreases the average hop count significantly compared to Epidemic. In EpSoc, messages are forwarded to the nodes that have higher popularity. These active nodes encounter others more frequently so they deliver messages in a lower number of hops.

Comparing to Bubble Rap, EpSoc has higher average hop counts. This is due to adopting the Epidemic-based forwarding strategy, which involves a higher number of intermediate nodes in the routing process compared with Bubble Rap.

Table 3.25 and Figure 3.31 show the result of INFOCOM05 dataset. It can observe similar results to Cambridge dataset where EpSoc outperforms Epidemic and has lower performance than Bubble Rap in terms of average hop counts.

Table 3.25: Average Hop Count vs. TTL (INFOCOM05 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	3.2	1.82	2.38	-26%	31%
30	3.5	2.06	2.49	-29%	21%
60 (1Hour)	4.67	2.25	2.66	-44%	19%
240 (4 Hours)	6.94	2.4	3.1	-56%	30%
480 (8 Hours)	7.46	2.45	3.28	-57%	34%
960 (16 Hours)	8.97	2.48	3.43	-62%	39%
1200 (20 Hours)	9.37	2.45	3.48	-63%	43%
1440 (1 Day)	9.36	2.43	3.53	-63%	46%
1680 (1Day4Hours)	9.72	2.43	3.5	-64%	45%
1920 (1Day8Hours)	9.22	2.42	3.33	-64%	38%
2160 (1.5 Day)	8.76	2.42	3.47	-61%	44%
2400 (1Day16Hours)	9.64	2.42	3.53	-64%	46%

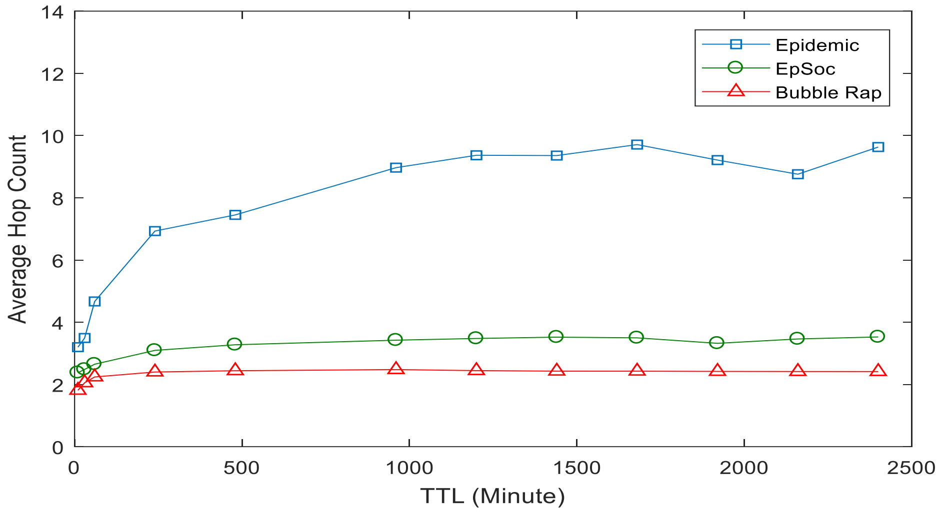


Figure 3.31: Average Hop Count vs. TTL (INFOCOM05 dataset)

Table 3.26 and Figure 3.32 show the results of INFOCOM06 dataset. EpSoc also outperforms Epidemic while it has lower performance than Bubble Rap.

Table 3.26: Average Hop Count vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	Bubble Rap	EpSoc	EpSoc VS Epidemic	EpSoc VS Bubble Rap
10	4.04	2.54	2.63	-35%	+4%
30	4.27	2.64	2.66	-38%	+1%
60 (1Hour)	5.65	2.73	2.76	-52%	+2%
240 (4 Hours)	8.59	2.74	3.06	-65%	+12%
480 (8 Hours)	10.5	2.76	3.21	-70%	+17%
960 (16 Hours)	11.75	2.86	3.24	-73%	+14%
1200 (20 Hours)	12.5	2.94	3.32	-74%	+13%
1440 (1 Day)	13.25	2.92	3.33	-75%	+15%
1680 (1Day4Hours)	12.73	2.94	3.38	-74%	+15%
1920 (1Day8Hours)	12.19	2.93	3.34	-73%	+14%
2160 (1.5 Day)	12.66	2.92	3.43	-73%	+18%
2400 (1Day16Hours)	12.16	2.9	3.45	-72%	+19%

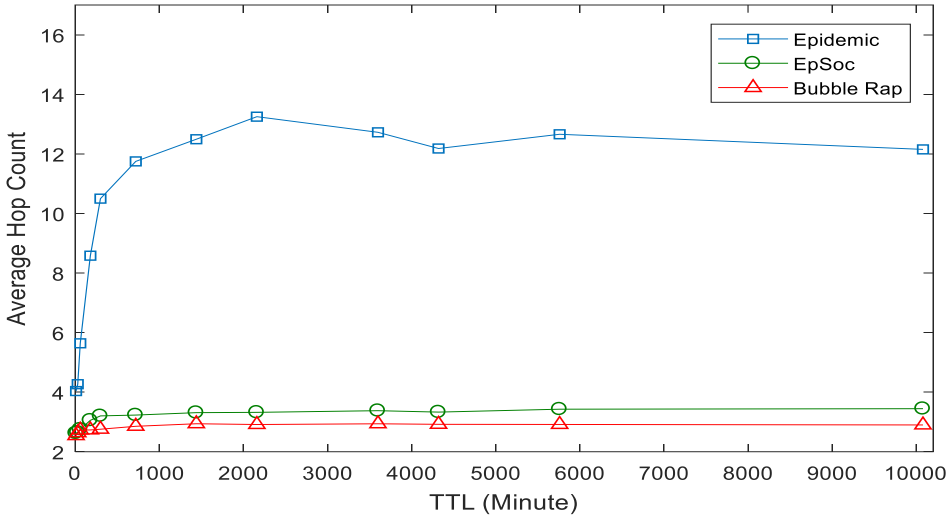


Figure 3.32: Average Hop Count vs. TTL (INFOCOM06 dataset)

However, in this experiment, the superiority of Bubble Rap over EpSoc decreases. The reason is that the number of nodes in the network is higher than Cambridge and INFOCOM05, so exploiting social features in EpSoc will be more effective with additional active nodes.

3.5 Conclusion

This chapter investigated the integration of social features with flooding-based forwarding strategy i.e. Epidemic in OMSN. Hybrid Social-Epidemic based routing protocol named EpSoc is proposed. EpSoc adopts the message forwarding strategy of Epidemic and exploits degree centrality to decrease resources exhaustion. Two mechanisms were employed in EpSoc; first adjusting the message's TTL according to the nodes' social popularity. Second; blocking messages in the socially active nodes.

The experiments were conducted based on three real datasets: Cambridge, INFOCOM05, and INFOCOM06. In each experiment, the buffer size and the initial value of the message's TTL were varied in a wide range to evaluate EpSoc under different scenarios. Four key performance metrics i.e. delivery ratio, delivery overhead, latency and average hop count are used for measurement.

Results show that EpSoc outperforms Epidemic routing protocol for all considered Key Performance Indicators (KPIs) in all the experiments. Delivery ratio is increased significantly, the increase in INFOCOM 06 experiment reaches, on average, 110% for low buffer and 118% for high TTL scenarios. Regarding overhead ratio, average latency, and average hop counts, EpSoc reduces them also. The decrease ratio increases with the increase in the number of the nodes in the network, for INFOCOM 06 experiment, which has the highest number of nodes compared with Cambridge and INFOCOM05, the reduction reaches 75%, 47%, 62% in overhead ratio, average latency, and average hop counts respectively.

Regarding Bubble Rap, which is a complex and a reference social-based routing protocol for other schemes in the literature, EpSoc outperforms it in terms delivery ratio and average latency. EpSoc increases delivery ratio with 40%, and decreases average latency with 56% on average for low buffer size and high TTL scenarios in INFOCOM 06 experiment. The results of Cambridge and INFOCOM05 dataset experiments shown that EpSoc has lower performance than Bubble Rap in terms of overhead ratio and average hop count. because adopting Epidemic-based forwarding strategy in EpSoc.

In conclusion, combining social information with Epidemic decreases the delivery overhead and latency significantly compared with Epidemic. However, EpSoc has its drawbacks in terms of exhausting nodes and network resources due to the inherited Epidemic-based forwarding strategy. In addition, EpSoc has lower efficacy in terms of overhead and average hop count against the social-based routing benchmark i.e. Bubble Rap.

Therefore, there is a need for further investigating the benefits of exploiting social features. It is worthy to study the impact of other social metrics such as similarity and the regularity in people's social activities to improve routing performance in OMSN. Also, it is very important to investigate how combining social features with other related factors such as contact history and user behavior will affect the routing performance. These challenges will be considered in Chapter 4.

CHAPTER 4

ROUTING BASED ON RANKED SOCIAL FEATURES

4.1 Introduction

This chapter explores the different relative impacts of the social characteristics stored in users' profile such as research topics, languages and nationality on the routing in OMSN. Also, it investigates how to rank these social characteristics based on their different impacts on user activities during the regular daily life. Ranked social characteristics are exploited to develop a social aware forwarding protocol to provide an efficient message forwarding strategy in OMSN.

People have different social characteristics such as nationality, spoken languages, and interests. These characteristics have high impacts on how they socialize. This is to the fact that individuals with common social characteristics tend to meet each other more frequently than others. In addition, most people follow a regular mobility pattern and have repeated social activities in their daily lives, i.e. there is a life routine for most people.

So, it is important to answer the question: how to measure the different impacts of the social characteristics on the user social behavior during different time periods of daily life, and can these differences be exploited to enhance routing in OMSN.

In this chapter, the user's social profile is considered as a source of the user's social characteristics, where all the social characteristics in the profile are utilized to develop an efficient forwarding protocol. Furthermore, to consider the relation between the temporal dimension and social behavior of the mobile user during his/her daily life, a time slicing mechanism of the user's day is designed. For each time period, nodes contacts are maintained and updated in a specific profile called period contacts profile. Based on period contacts profile, for each period, a ranking algorithm is used to rank the different social features according to its impact (namely the number of encounters with other nodes have the same social characteristic). The proposed protocol examines the similarity between the ranked social features of the intermediate nodes and the destination to make an efficient forwarding decision for the messages. Based on this, a new social-based routing protocol called SOR is developed. The details of SOR protocol and the related algorithms are presented in the next section.

4.2 SOR Routing Protocol

SOR is a social based routing protocol ranks social characteristics and exploits them for efficient message forwarding and data dissemination in OMSN. Several social characteristics can be stored in a user profile such as nationality, language, interest topics, membership, and hobbies. Social behavior and activities of the people are the reflection of these social characteristics during routine life. For example, researchers with similar interesting research topics encounter each other and make a discussion for a long time during conference activities, students with common hobbies tend to form groups and interconnect regularly in the campus life. These simple examples indicate that social features have an impact on the individual's social behavior during their daily life routine.

To consider the change in people social behavior during the different periods in a day, in the proposed protocol, the day is sliced into six periods, each is four hours long as it is depicted in Figure 4.1. This division is chosen because it is used in the literature (Moreira et al., 2012; Xia et al., 2016) and is common in people social lifestyle such as employees working style in companies, student's life in the university campus and activities in scientific events like a conference.

In SOR, for each node and for each period, ranking algorithm ranks the social characteristics of the user based on the encountering with the other peers. The ranked social features during day periods are exploited for the forwarding process.

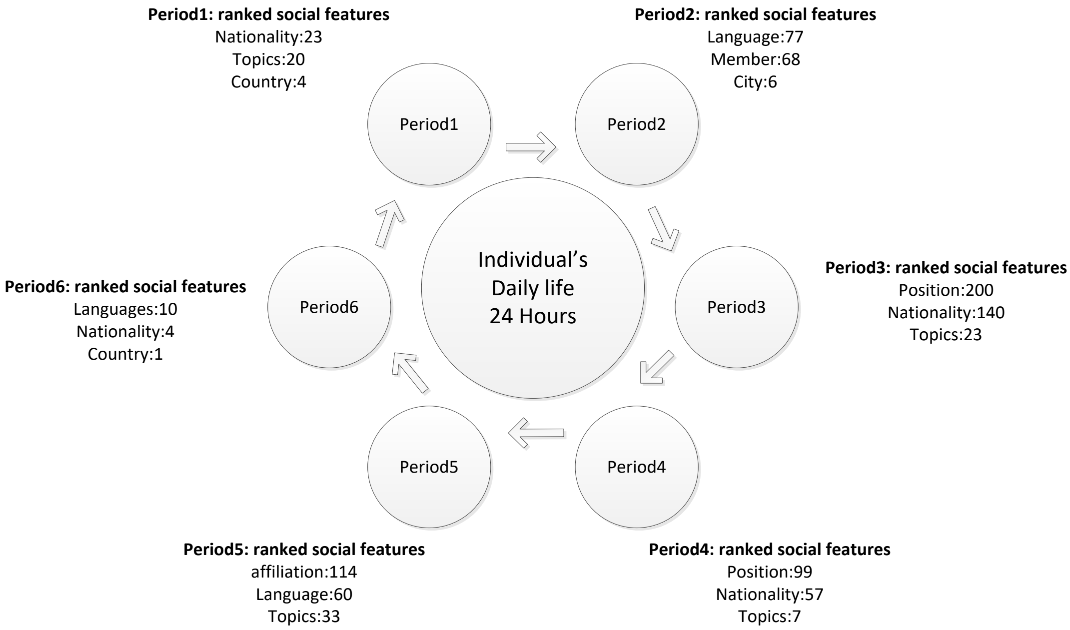


Figure 4.1: SOR social feature for a node over day periods

4.2.1 Updating Nodes' Contacts Per Period

People follow almost stable patterns of social behavior in their daily life, it is the daily routine. Inspiring by this notation, a proposed mechanism is designed to divide the day into six time periods and maintain the contacts between nodes in each period. These contacts information will be exploited in the proposed ranking algorithm to rank the social features, which reflects their relative importance in the proposed routing protocol. Ranked social features are used as a metric to select the best relay. The number of contacts of a node $Node_i$ with $Node_j$ in a period p_m is calculated based on the following proposed equation:

$$C_{p_m}^{ij} = \sum_{k=1}^{k=N} en(i,k) \quad : k = j\,, k \neq i \qquad \text{Equation 4.1}$$

Where $en(i,k) = 1$ if there is a direct connection between i and j in the period p_m

So that the total number of contacts of node $Node_i$ in the period p_m is calculated as following proposed equation:

$$C_{i,p_m} = \sum_{j=1}^{j=N_{p_m}} C_{p_m}^{ij} \qquad \text{Equation 4.2}$$

Where N_{p_m} is the number of encountered nodes in the period p_m.

The next notations are used in the updating algorithm.

- $ConP$: periods profile; node maintains the periods of contacting with other peers, where day is sliced into six equivalent time periods $P = \{p_1, p_2, p_3, p_4, p_5, p_6\}$
- $ConP_{Nodes}$: the set of the encountered nodes in a period
- C_p^{ij} : the contacts number between $Node_i$ and $Node_j$ in the current period *p*

The next section presents Algorithm 4.1 used to update node contacts for each period in the day and the flowchart of this process.

Algorithm 4.1: Updating the node's contacts during a period

1: $Node_i$ contacts $Node_j$
2: Get the current period *p*
4: If $p\ \exists\ ConP$
6:     If $Node_j\ \exists\ ConP_{Nodes}$
7:         C_p^{ij} =+1

Else
Add $Node_j$ to $ConP_{Nodes}$
C_p^{ij} =1
End if
Else
Add p to $ConP$
Add $Node_j$ to $ConP_{Nodes}$
C_p^{ij} =+1
End if

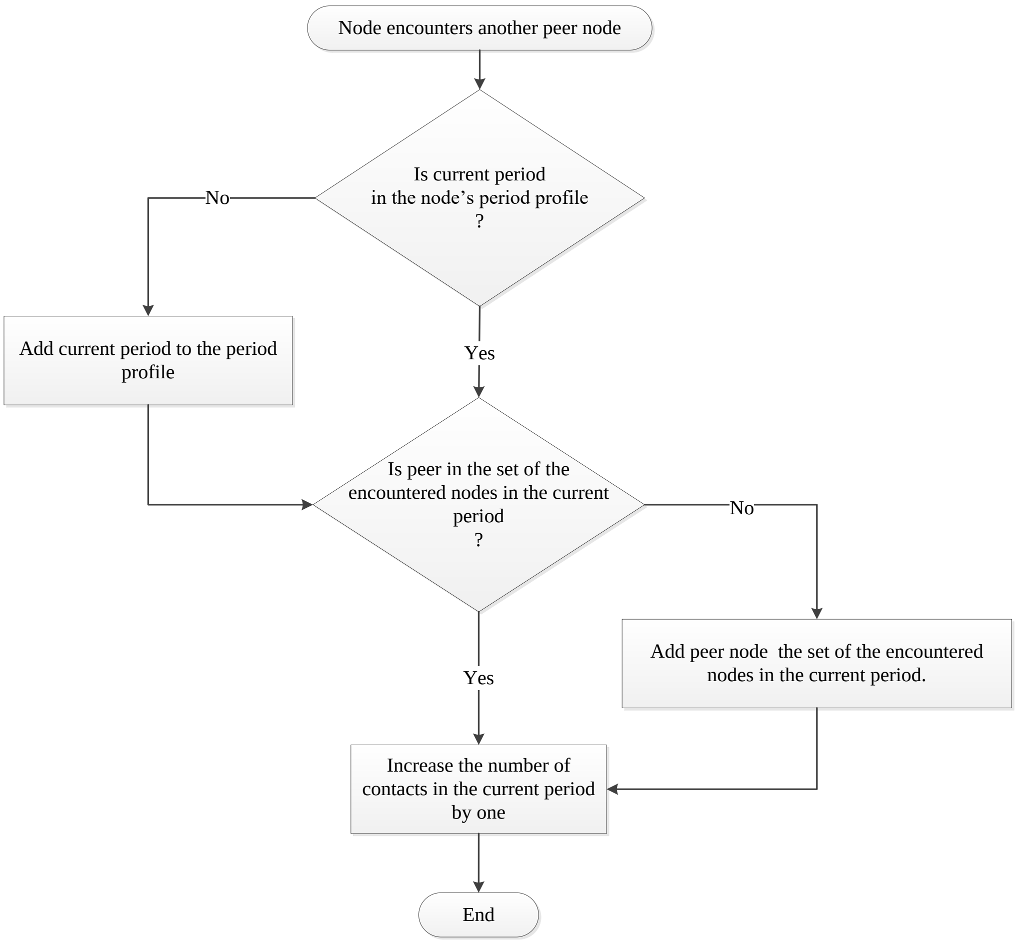


Figure 4.2: Flowchart of updating nodes' contacts per period

When $Node_i$ encounter another peer $Node_j$, the period profile, which maintains the number of node's contacts within each period, is updated to add the current period if it does not exist. If $Node_i$ encounters node $Node_j$ for the first time in this the current period, it adds it to it’s set of encountered nodes in the current period and set the number of contacts with $Node_j$ to one. If $Node_i$ encountered $Node_j$ previously in the current period, it only increases the number of contacts with $Node_j$ by one.

4.2.2 Ranking Social Features

As aforementioned, the day is divided into six periods where each period is 4 Hours long. In each period, the number of contacts between nodes is updated and maintained. Each node has several social features stored in the user's profile. Each social feature available in the user’s profile may have a single value like the country feature or multiple values such as the nationality and interesting topics. For every period in a day, the contacts with other nodes are recorded in the period contacts profile as it is mentioned in Section 4.2.1. Based on this, for each node, social features are ranked according to the number of contacts with other nodes that have a common social feature.

Let $F(fn, fv)$ be the set of the name/value pairs in the social profile of a user. A social feature may take one of several values. So that, for a particular social feature $f_x \in F$ there is only one value for fn_x and multiple values for fv_x. It can be writen that $fv_x \in V_x$, where V_x is the set of the values of feature f_x.

In a period p_m, for each social feature $f_{x,i}$ of the node $Node_i$, the number of contacts with other nodes that match $f_{x,i}$ values is counted, it is called $cont_{f_{x,i}}$ and is calculated using the proposed following equation:

$$cont_{f_{x,i}} = \sum_{j=1}^{j=N_{p_m}} p(i,j) \qquad \text{Equation 4.3}$$

Where $p(i,j) = 1$ if $fn_{x,i} = fn_{x,j}$ and $(V_{x,i} \cap V_{x,j}) \neq \emptyset$, N_{p_m} is the total number of the encountered nodes in the period p_m , $cont_{f_{x,i}}$ is an indicator of the importance of a social feature of a node in a particular period.

Using equation (4.3), during each period in a day, nodes calculate the importance of its social features. The importance value is used to rank the social features of a node and then they are maintained sorted ascending in the node's profile. The social feature that has the highest rank, called top-ranked social feature, is exploited for forwarding procedure.

For more explanation of the ranking algorithm, the following example clarifies its work. In period 1 node A has 20 contacts with node B, 14 contacts with node C, and 10 contacts with node D. Common features of nodes A and B are <Languages, Topics, Nationality >, common features of nodes A and C are <Topics, City, Member, Language >, and common features of nodes A and D are < Country, Languages, Nationality >. Thus, for node A, in period 1 the ranks of social features are < Languages: 44, Nationality: 30, Topics: 24, City: 14, Member: 14, Country: 10>. Consequently, the top-ranked social feature of node A in period 1 is the language feature.

Mobile nodes move and socialize with other peers in the OMSN network; hence, social features should be updated in the nodes' profile according to the nodes' encountering and their social activities in the OMSN network. Figure 3.4 shows the flowchart of how to update the number of contacts for each social feature and ranking then according to the number of their contacts.

When a node encounters another peer, it updates the number of contacts for its social features. For each social feature, if it matches any of the social features of the peers' features the number of contacts for this social feature is increased by one. Matching between two features means that they have the same name and there is one or more common value between them, for example, both social features are language and the two persons speak the English and Arabic languages. After updating the number of contacts of the social features, these features are ranked descending where the social feature that has the highest contacts rate is on the top of the features social features vector.

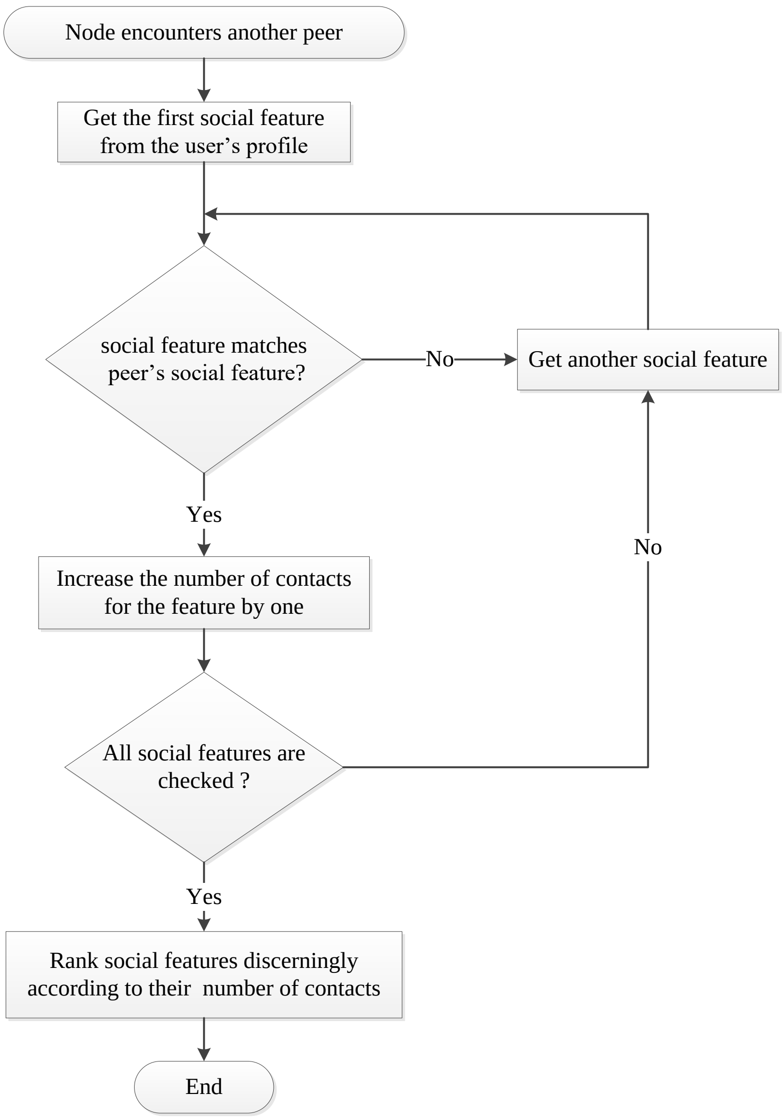


Figure 4.3: Flowchart of updating features' contacts and ranking

4.2.3 Forwarding in SOR

SOR protocol combines two concepts: first, dividing a day into equal periods to consider the repeated patterns of the mobile user's social behavior, and second, ranking social features to exploit social information in the forwarding decision. Based on the description in 4.2.1 and 4.2.2, every node ranks its social features per period using equation (4.4). Forwarding node selects the next relay node has the highest matching with the top-ranked social feature of the destination.

To explain more the proposed forwarding protocol Figure 4.2 shows an example of the forwarding process.

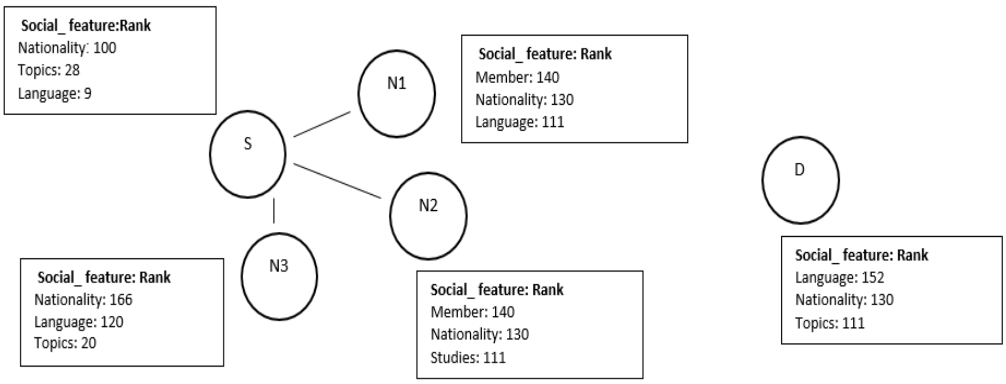


Figure 4.4: Forwarding process in SOR

Based on Figure 4.2, node S is the sender and Node D is the destination while nodes N1, N2, and N3 are intermediate nodes, and in addition, they are candidate messages' forwarders. Assume that in the current period, the top rank social feature of node D is language. Node S will select the next relay from among the intermediate nodes (N1, N2, N3) that have common languages, in this case, nodes N1 and N3. Node S will further choose the node that has the highest rank for language feature, i.e. N3 in this example.

Figure 4.5 shows the flowchart of the forwarding strategy of SOR and Algorithm 4.2. shows its pseudocode.

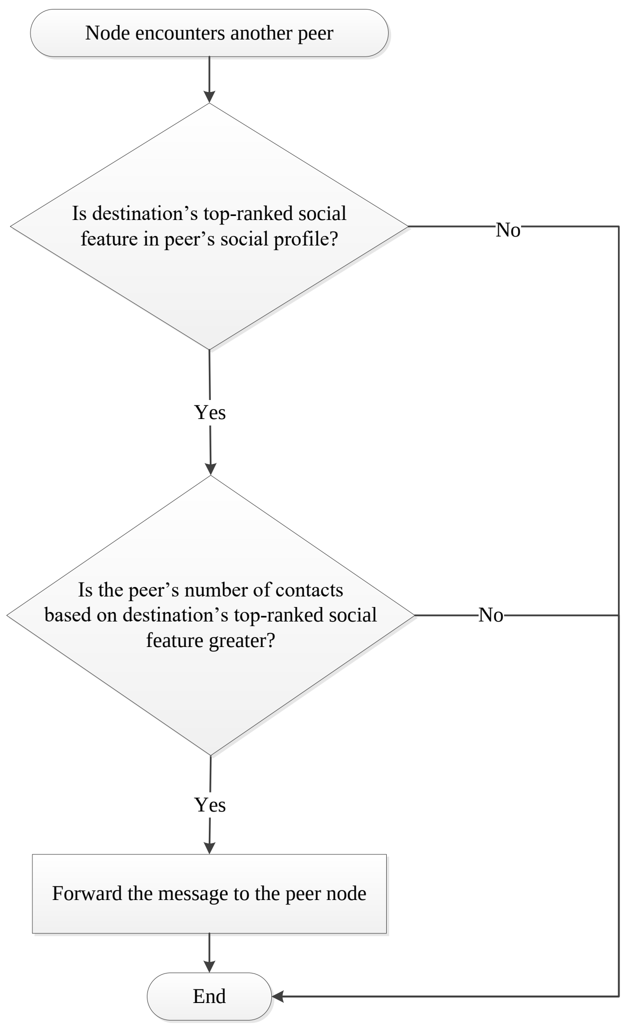


Figure 4.5: Flowchart of the forwarding strategy of SOR

When a node $Node_i$ encounters another peer node $Node_j$, it checks if $Node_j$ has the destination's top-ranked social feature in its social profile. If this, it compares the number of contacts based on this feature (the importance of this feature) of $Node_j$ with its value, if it is greater it will forward the message to $Node_j$, else it will still carrying the message.

The next notations are used to explain forwarding algorithm.

- Hf_d : highest ranked social feature of destination in the current period.
- F_j : set of the social features of $Node_j$
- $cont_{j,Hf_d}$: the number of contacts of $Node_j$ with other nodes that has similar Hf_d
- $cont_{i,Hf_d}$: the number of contacts of $Node_i$ with other nodes has that similar Hf_d

Algorithm 4.2: SOR Forwarding algorithm

$Node_i$ encounters $Node_j$

Get the current period

    If $Hf_d \ni F_j$

        If $cont_{j,Hf_d} > cont_{i,Hf_d}$

        Forward message to $Node_j$

        End if

    End if

End for

4.3 Performance Evaluations

4.3.1 Data Set

INFOCOM06, which is real dataset, is used to evaluate the proposed protocol. This dataset is chose because the social characteristics of the mobile users are provided where participants are asked for filling answers in a questionnaire about different social features. In this study, this social information is collected and attached as social profiles for mobile users in the experiments. All the available social characteristics are exploited. They are ten social features: nationality, studies, languages, affiliation position, city, country, stay, member and topics.

In the INFOCOM06 dataset, 78 mobile iMotes have a wireless range around 30 meters and using Bluetooth technology for communication. Bluetooth encounters between 78 short-range nodes are tracked and stored.

The experiment in the INFOCOM06 dataset lasts for 14400 seconds i.e. 1.67 Days. So, regarding the proposed time-slicing mechanism (periods of the day) there will be ten periods through the experiment. Social feature weight (importance) will be evaluated for each period of the day according to the proposed ranking algorithm.

4.3.2 Simulation Setup

Opportunistic Network Environment (ONE) are used to do the experiments and to evaluate the proposed protocols. SOR performance is compared with three benchmark routing protocols: Epidemic which is flooding-based routing protocol, PRoPHET which is prediction-based routing protocol and Bubble Rap which is social-based routing protocol.

Regarding simulation settings, the broadcast type is Bluetooth interface with the transmit speed of 2 Mbps for all the nodes. The message event generator in ONE simulator generates one new message in every 30 to 40 seconds. Message size is 124 KB. The simulation end time is varied from 4 Hours (14400 seconds) to 40 Hours (144000 seconds) by step 4 Hours. Also, TTL value is varied from low values (10, 30 minutes) to the end time of the experiment (1.6 days) by step 4 Hours. Table 4.1 shows the simulator settings of this experiment.

Table 4.1: Simulation Settings

Simulation Time	4,8,12,16,20,24,28,32,36,40 (Hour) (10 periods)
Interface	Bluetooth Interface
Number of nodes	78 short range devices
Transmit Speed	250 k (2 Mbps)
Mobility	Real trace data (INFOCOM06)
Buffer Size	5 MB
Routing Protocols	Epidemic , PRoPHET, BubbleRap, SOR
Message Size	128 KB
Event Interval	30 to 40 seconds
Message TTL	10 (minute), 30 (minute) , 1, 4, 8, 16, 20, 24, 28, 32, 36, 38.4 (Hour)

In each experiment, there is a comparison of the performance of the protocols SOR, Epidemic, Prophet and Bubble Rap based on the following metrics:

- Successful Delivery ratio: it is the ratio between the number of delivered messages and the total number of created messages. The ideal value of the successful delivery ratio is (1.0) when all created messages are delivered to their destinations.
- Overhead Ratio: it is the additional bytes are sent for successfully delivering a message to a destination.
- Average Latency: it is the average of the time elapsed between message creation and delivery.
- Average Hop Count: it is the average of the number of hops that messages must take in order to reach the destination.

4.4 Results and Discussion

To evaluate the performance of SOR against Epidemic, PRoPHET, and Bubble Rap, three factors are considered: experiment time, message TTL, and the buffer size.

Regarding experiment time, the aim is to evaluate the performance of the four protocols over the different day periods. In addition, to investigate if SOR can achieve good performance when the social activities varied over the daytime. TTL and the buffer size also has a high impact on the routing performance in MSN networks, this is because of the opportunistic nature of the communications among the mobile nodes and the adoption of the store-carry-forward mechanism for data distribution.

Depending on this, the simulation time, the TTL, and buffer size values will be varied and the output results of these different scenarios will be used for the evaluation.

4.4.1 Evaluation Over Time

In this experiment, messages' TTL value is set to 10 Hours and buffer size to 5MB, and change the simulation end time from 14400s (4 Hours) to 144000s (1.6 Days) with 4 Hours step. The following tables and figures show the performance comparisons between SOR, Epidemic, PRoPHET, and Bubble Rap in terms of delivery ratio, overhead ratio, average latency and average hop count respectively over the experiment time.

In Table 4.2 and Figure 4.6, the change in the delivery ratio over the experiment time is depicted. The experienced protocols have varied performance during the different periods of the experiment, because of the changing in the connectivity among mobile nodes and the message generation scenarios during the experiment time.

Table 4.2: Delivery Ratio vs. Simulation End Time (INFOCOM06 dataset)

Simulation end time (Seconds)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
14400 (4Hours)	0.11	0.25	0.28	0.3	+173%	+20%	+8%
28800 (8Hours)	0.09	0.19	0.21	0.24	+167%	+27%	+15%
43200 (12Hours)	0.07	0.14	0.16	0.18	+158%	+29%	+13%
57600 (16Hours)	0.18	0.34	0.24	0.44	+145%	+30%	+84%
72000 (20 Hours)	0.18	0.36	0.23	0.44	+145%	+23%	+92%
86400 (1day)	0.18	0.36	0.24	0.44	+145%	+23%	+84%
100800	0.16	0.31	0.21	0.39	+144%	+26%	+86%
115200	0.16	0.3	0.2	0.37	+132%	+24%	+85%
129600	0.16	0.31	0.2	0.37	+132%	+20%	+85%
144000	0.18	0.38	0.23	0.45	+150%	+19%	+96%

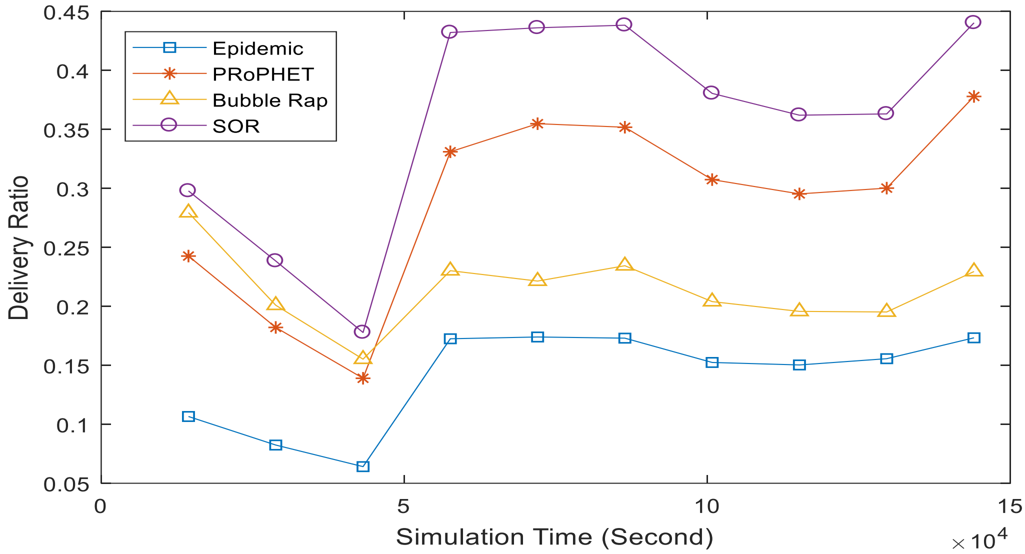


Figure 4.6: Delivery Ratio vs. Simulation End Time

It can be seen clearly that SOR outperforms all the other protocols. It increases the delivery ratio, on average, with 149%, 24% and 65% compared with Epidemic, PRoPHET and Bubble Rap respectively.

Ranking the social characteristics based on their importance makes the forwarding decision more efficient where nodes that are socially closer to the destination are selected as a message relay. This results in a productive utilizing of the node resources for routingpurposes. On the contrary, it can be seen for example Epidemic protocol, which is a flooding-based routing protocol, has the lowest achievement due to exhausting the limited resources of the nodes in MSN. Table 4.3 and Figure 4.3 show the performance evaluation in terms of overhead ratio.

Table 4.3: Overhead Ratio vs. Simulation End Time (INFOCOM06 dataset)

Simulation end time (Seconds)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
14400 (4Hours)	530.87	287.44	109.69	293.9	-45%	3%	+168%
28800 (8Hours)	551.65	304.01	104.86	233.7	-58%	-24%	+123%
43200 (12Hours)	511.36	277.69	94.95	218.3	-58%	-22%	+130%
57600 (16Hours)	978.05	446.05	431.29	317.6	-68%	-29%	-27%
72000 (20 Hours)	1465.3	705.06	709.4	431.1	-71%	-39%	-40%
86400 (1day)	1713.5	820.77	779.87	489.0	-72%	-41%	-38%
100800	1699.7	840.56	784.13	492.9	-72%	-42%	-38%
115200	1532.9	784.15	725.52	458.4	-71%	-42%	-37%
129600	1354.5	700.38	657	414.8	-70%	-41%	-37%
144000	1313.2	594.36	599.75	357.5	-73%	-40%	-41%

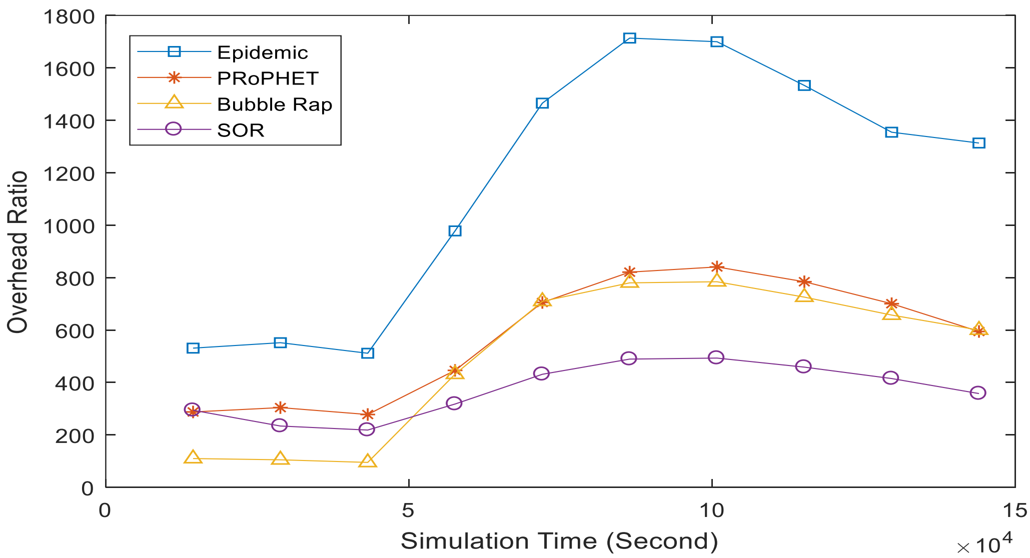


Figure 4.7: Overhead Ratio vs. Simulation End Time

Based on the results, it is clear that SOR achieves a low overhead ratio along the time of the experiment. It outperforms Epidemic significantly due to the flooding nature of

Epidemic resulting in a high overhead ratio. The reduction in the overhead ratio for SOR compared with Epidemic is 71% on average.

Also, SOR outperforms PRoPHET and decreases the overhead ratio, on average, with 39%. This is because SOR considers, in addition to the connectivity of the previous nodes like PRoPHET, the regularity of the social activities and the relative importance of the social characteristics. All this gives SOR the advantage over PRoPHET which only depends on the history of the contact to forward messages in MSN.

Comparing SOR with Bubble Rap, SOR starts with a higher overhead ratio than Bubble Rap for the first 3 periods of the experiment (the first 12 Hours). This is due to that SOR depends on the regularity of the social behavior for ranking social features which require some time to be detected and then making SOR more effective in routing messages. However, for all later time periods during the experiment SOR has a lower overhead ratio than Bubble Rap and decreases the overhead ratio, on average, with 37%. The reduction is resulted from decreasing the number of carried messages when routing messages by exploiting ranked social features, this makes the forwarding process more effective in terms of choosing the appropriate forwarders to deliver the message to its destination. The results of evaluating average latency metric are shown in Table 4.4 and Figure 4.8.

Table 4.4: Average Latency vs. Simulation End Time (INFOCOM06 dataset)

Simulation end time (Seconds)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
14400 (4Hours)	989.76	804.25	1153.2	726.0	-27%	-10%	-38%
28800 (8Hours)	2928.65	2679.57	2351.2	2529.	-14%	-6%	+8%
43200 (12Hours)	3319.54	4300.13	3906.1	3363.	+2%	-22%	-14%
57600 (16Hours)	8213.38	10335.12	7244.7	9763.	+19%	-6%	+35%
72000 (20 Hours)	6987.15	9351.49	6947.5	8511.	+22%	-9%	+23%
86400 (1day)	6439.84	8963.87	7557.7	8131.	+27%	-10%	+8%
100800 (1day4Hours)	6550.32	8951.04	7669.8	8119.	+24%	-10%	+6%
115200 (1day8Hours)	7179.52	9462.27	8172.3	8691.	+22%	-9%	+7%
129600	7638.5	10135.57	9571.4	9449.	+24%	-7%	-2%
144000	8122.76	11491.65	10331.	10201	+26%	-12%	-2%

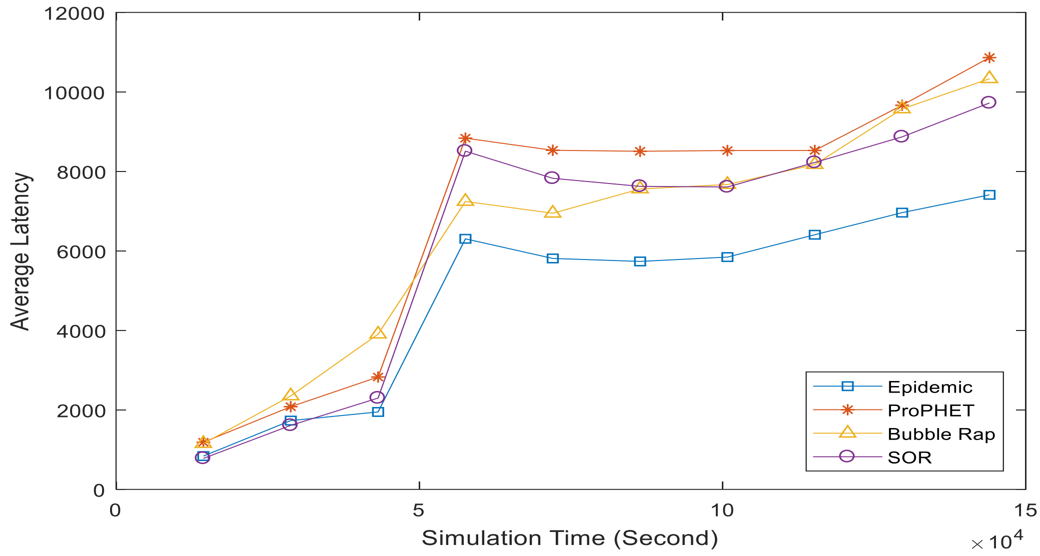


Figure 4.8: Average Latency vs. Simulation End Time.

It is seen that the average latency for all protocols increases as the experiment time passes. This is a result of socializing between people and the creation of new social relations, so the amount of the information exchanged between mobile users in the network increases during the experiment and consequently the average latency for all delivered messages in OMSN increases. Epidemic has the lowest average delivery latency. This is because it floods messages to all available neighbors which decreases the average time of delivering the messages in the whole network in OMSN.

SOR has a lower, but close, performance in terms of average latency compared to PRoPHET. Comparing to Bubble Rap, SOR has similar achievements during most of the experiment duration.

SOR outperforms PRoPHET because the messages are forwarded and carried by only the mobile nodes that have a close social relationship with the destination. In addition, exploiting the regularity of social behaviors contributes to a more efficient forwarding strategy. Consequently, the average latency will be lower in OMSN. Table 4.5 and Figure 4.6 show the results of the evaluation of the average hop count metric.

Table 4.5: Average Hop Count vs. Simulation End Time (INFOCOM06 dataset)

Simulation end time (Seconds)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
14400 (4Hours)	4.83	3.05	2.83	2.8	-43%	-10%	-3%
28800 (8Hours)	7.23	3.08	2.7	2.7	-64%	-14%	-2%
43200 (12Hours)	7.39	3.21	2.77	2.6	-66%	-20%	-7%
57600 (16Hours)	9.69	3.56	2.63	3.1	-69%	-13%	+18%
72000 (20 Hours)	10.87	3.64	2.74	3.2	-71%	-13%	+17%
86400 (1day)	11.36	3.78	2.87	3.3	-71%	-13%	+16%
100800	11.96	3.75	2.84	3.3	-73%	-13%	+16%
115200	12.03	3.75	2.88	3.2	-74%	-14%	+13%
129600	11.75	3.69	2.88	3.2	-73%	-14%	+11%
144000	11.35	3.78	2.9	3.3	-72%	-15%	+13%

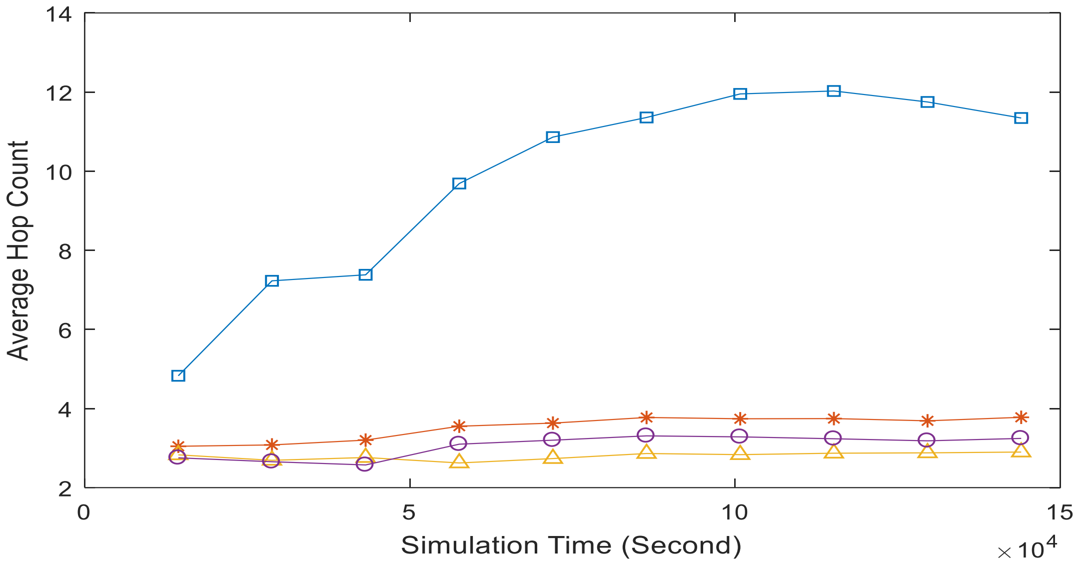


Figure 4.9: Average Hop Count vs. Simulation End Time

It is clear that SOR outperforms Epidemic significantly where the reduction in average hop count value is about 68% on average. The reason is SOR selects the relay based on a social aware routing algorithm, while Epidemic, which is a flooding-based routing approach, incurs redundancy of message replicas, so it has the worst achievement.

SOR, PRoPHET, and Bubble Rap have very close achievement in terms of average hop count, it is about 3 to 4 hops on average. This is because all these protocols apply strict rules to select the relay nodes. PRoPHET depends on the probability of encountering the destination to select the next forwarder, while both SOR and Bubble Rap exploit the social properties for forming the forwarding decision. As a result, the number of hops that a message traverses to reach the destination will be low. SOR outperforms PRoPHET where the reduction ratio in the average hop counts is about 14% on average. Comparing to Bubble Rap, SOR has a converge achievement, where the average of the hop counts is higher at 9%.

In SOR, exploiting ranked social features to forward messages reduces message replication substantially in the network. Also, ranking social features and exploiting the regularity of the social activities resulted in an efficient selection of the relay node.

4.4.2 Varying TTL

In this experiment, SOR performance is evaluated for different TTL values. The TTL value is ranged from very low value, 10 minutes, to the maximum time of the real dataset experiment time, which is 1.6 days. The following tables and figures show the change of delivery ratio, overhead ratio, average latency and average hop count versus TTL value. Table 4.6 and Figure 4.10 show the changes in delivery ratio with TTL for all schemes.

Table 4.6: Delivery Ratio vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	**Epidemic**	**PRoP HET**	**Bubble Rap**	**SOR**	**SOR VS Epidemic**	**SOR VS PRoP HET**	**SOR VS Bubble Rap**
10	0.2	0.18	0.13	0.16	-20%	-12%	+24%
30	0.27	0.25	0.19	0.23	-15%	-8%	+22%
60 (1Hour)	0.26	0.26	0.22	0.28	8%	8%	+28%
240 (4Hour)	0.19	0.32	0.25	0.38	100%	19%	+52%
480 (8Hour)	0.18	0.37	0.26	0.43	139%	17%	+66%
960 (16Hour)	0.16	0.36	0.26	0.44	175%	23%	+70%
1200 (20Hour)	0.15	0.35	0.25	0.44	194%	26%	+76%
1440 (1Day)	0.15	0.35	0.24	0.43	187%	23%	+80%
1680 (1Day	0.15	0.34	0.24	0.43	187%	27%	+80%
1920 (1Day	0.14	0.34	0.24	0.43	208%	27%	+80%
2160 (1Day	0.15	0.33	0.24	0.43	187%	31%	+80%
2400 (1Day	0.14	0.32	0.23	0.43	208%	35%	+87%

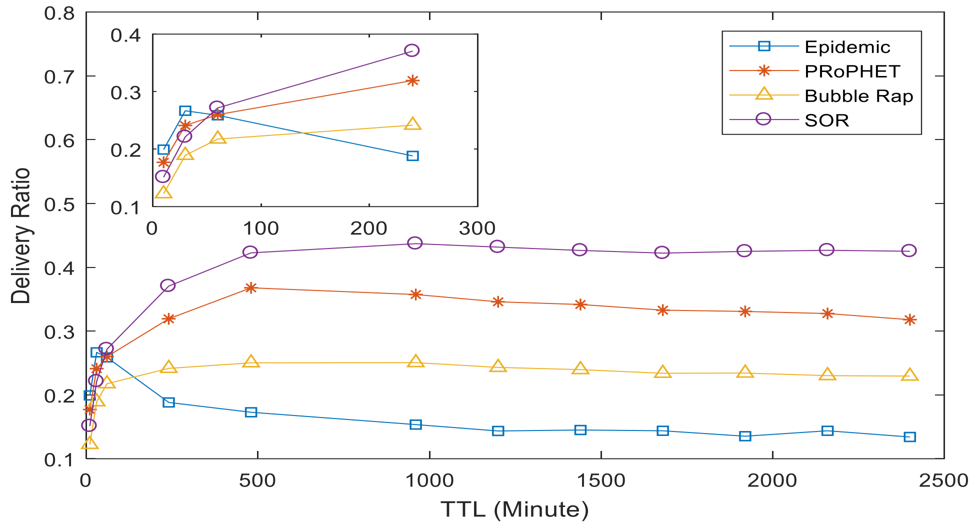


Figure 4.10: Delivery Ratio vs. TTL (INFOCOM06 dataset)

For low values of TTL (10 Minutes -1 Hour) the delivery ratio of all routing protocols is low due to the high ratio of dropping messages because of TTL exhaustion. Increasing TTL causes rising up the delivery ratio to maximum values at (8 Hours); this is because there is a higher probability for delivering more messages to the destinations before messages' TTL expiration. For high TTL values (16 Hours and up), the delivery ratio change is almost fixed, and varying the TTL value has no impact, while other features such as buffer size or message size play the important role in determining the performance.

SOR outperforms all other protocols for the scenarios of (8 Hours and up) TTL values. The increment in delivery ratio, on average, is 159%, 24% and 70% compared with Epidemic, PRoPHET, and Bubble Rap respectively. The reason is that messages with high TTL are carried by nodes that have strong social relations, this increases the number of delivered packets and decreases the forwardings in the network and hence increases the delivery ratio. In addition, SOR considers the regular patterns of the user's social activity during daily life, and further, it ranks the social characteristics based on the encountering rate in each time period.

As a result of all these strategies adopted in SOR for forwarding messages, the selected relay node has a higher probability to encounter the destination and this contributes to enabling SOR to achieve higher delivery ratio than other schemes. The relation between overhead ratio and message TTL is presented for all the schemes in Table 4.7 and Figure 4.11.

Table 4.7: Overhead ratio vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
10	73.53	52.45	26.46	29.26	-61%	-45%	+11%
30	105.04	74.03	28.2	31.92	-70%	-57%	+14%
60 (1Hour)	764.14	624.89	108.86	115.7	-85%	-82%	+7%
240 (4Hour)	1214.3	641.67	450.26	367.0	-70%	-43%	-19%
480 (8Hour)	1312.7	598.35	552.92	363.8	-73%	-40%	-35%
960 (16Hour)	1378.5	608.12	585.2	360.4	-74%	-41%	-39%
1200 (20Hour)	1373.2	588.09	586.81	364.4	-74%	-39%	-38%
1440 (1Day)	1309.7	578.08	579.51	366.6	-73%	-37%	-37%
1680 (1Day 4Hours)	1309.9	593.68	596.95	370.3	-72%	-38%	-38%
1920 (1Day 8Hours)	1391.2	598.39	596.49	368.3	-74%	-39%	-39%
2160 (1Day	1310.4	603.97	608.12	366.6	-73%	-40%	-40%
2400 (1Day	1392.0	609.94	599.75	366	-74%	-40%	-39%

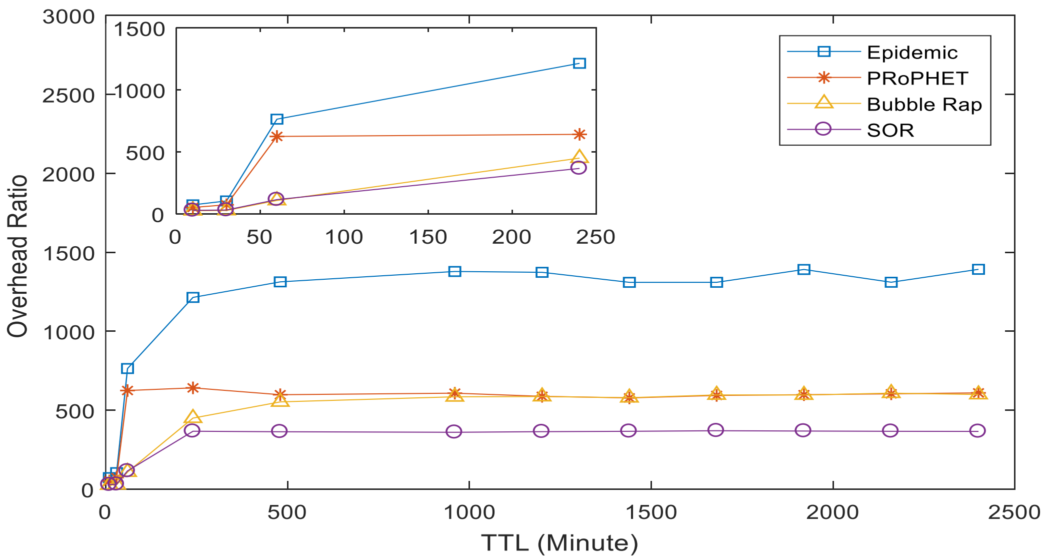


Figure 4.11: Overhead Ratio vs. TTL (INFOCOM06 dataset)

It can be seen that SOR outperforms all other schemes in terms of overhead ratio for all TTL values except for very low TTL values scenarios (10, 30 and 60 Minutes) it achieves lower, but very close, performance compared to Bubble Rap protocol only. In these scenarios, messages expire quickly, which obstructs SOR forwarding messages effectively because it depends on the nodes contacts history to rank the social characteristics in each time period. On the contrary, for the higher TTL values scenarios, ranking protocol becomes more efficient and SOR outperforms all other schemes.

SOR considers all social characteristics in the user's profile and ranks them according to the social activities of the mobile nodes for each period. As a result, nodes with strong social relationships with the destination in each time period are chosen as relays, this decreases the number of involved intermediate nodes in the forwarding process and increases the probability of delivering the message. Consequently, the overhead ratio is decreased substantially. The reduction in the overhead ratio is on average about 73%, 45%, and 36% compared to Epidemic, PRoPHET, and Bubble Rap respectively. Table 4.8 and Figure 4.12 show the evaluation results of average latency metric for SOR against other benchmark schemes.

Table 4.8: Average Latency vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
10	87.63	112.8	141.76	153.8	+76	+37	+9
30	370.31	390.8	466.65	458.7	+24	+18	-2
60 (1Hour)	1078.0	1012.5	981.59	921.0	-15	-10	-7
240 (4Hour)	4127.7	4723.1	4556.68	4199.	+2	-12	-8
480 (8Hour)	6908.7	9413.1	8437.62	8403.	+22	-11	-1
960 (16Hour)	9957.3	14602.	14167.7	1245	+26	-15	-13
1200 (20Hour)	9690.1	16028.	15235.9	1321	+37	-18	-14
1440 (1Day)	9534.4	16816.	15991.0	1306	+38	-23	-19
1680 (1Day 4Hours)	11330.	17134.	15824.0	1334	+18	-23	-16
1920 (1Day 8Hours)	9774.3	17146.	15787.5	1327	+36	-23	-16
2160 (1Day	10043.	17364.	15486.5	1326	+33	-24	-15
2400 (1Day	9255.3	16835.	15568.0	1333	+45	-21	-15

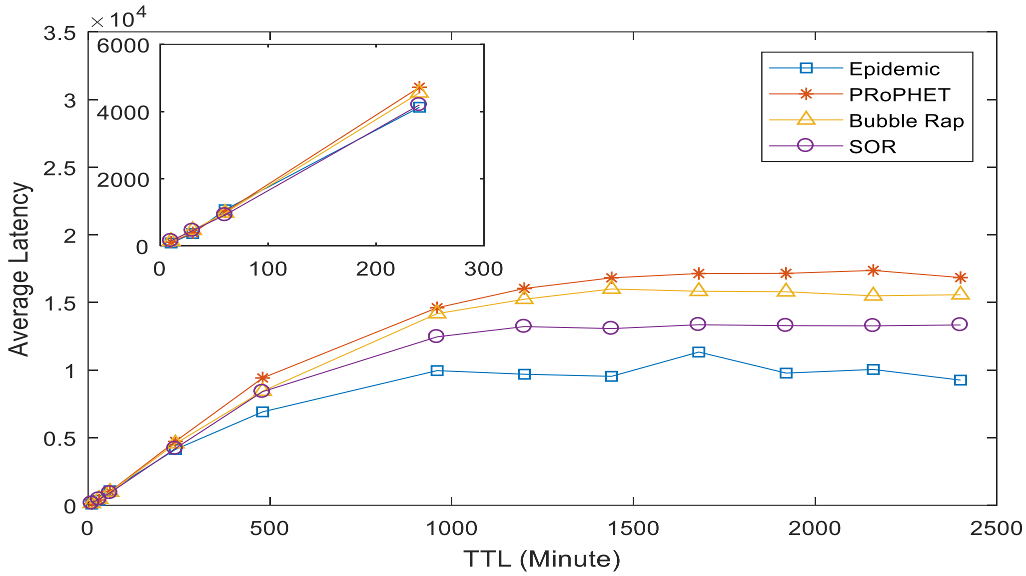


Figure 4.12: Average Latency vs. TTL (INFOCOM06 dataset)

It is noticed that the increase in a message's TTL gives the opportunity to the messages that follow a longer path to reach the destination. So, the more TTL increases the higher average end to end delay achieved.

For a very low TTL values scenario (10,30 Minutes), messages are expired quickly so the benefits of ranking the social characteristics based on the history of the contacts will less effective because of the messages dropping. As a result, SOR has very close, but lower, performance than Bubble Rap and also lower performance than PRoPHET. For scenarios of higher TTL values (higher than 30 Minutes), SOR outperforms all other schemes except Epidemic which is the dominant protocol for this evaluation metric because of its flooding-based forwarding strategy. In SOR, choosing the best relay based on the ranked social properties in each time period increases the probability to encounter the destination, and hence deliver messages to the destination in a shorter time. SOR decreases the average latency by about 18% and 10%, on average, compared to PRoPHET and Bubble Rap respectively. The evaluation of average hop count with TTL change is shown in Table 4.9 and Figure 4.13.

Table 4.9: Average Hop Count vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
10	4.04	3.48	2.54	2.77	-32	-21	+10
30	4.27	3.66	2.64	2.94	-32	-20	+12
60 (1Hour)	5.65	4.29	2.73	2.98	-48	-31	+10
240 (4Hour)	8.59	3.61	2.74	3.17	-64	-13	+16
480 (8Hour)	10.5	3.79	2.76	3.23	-70	-15	+18
960 (16Hour)	11.75	4.11	2.86	3.26	-73	-21	+14
1200 (20Hour)	12.5	4.15	2.94	3.24	-75	-22	+11
1440 (1Day)	13.25	4.2	2.92	3.25	-76	-23	+12
1680 (1Day 4Hours)	12.73	4.29	2.94	3.24	-75	-25	+11
1920 (1Day 8Hours)	12.19	4.27	2.93	3.2	-74	-26	+10
2160 (1Day	12.66	4.39	2.92	3.23	-75	-27	+11
2400 (1Day	12.16	4.21	2.9	3.24	-74	-24	+12

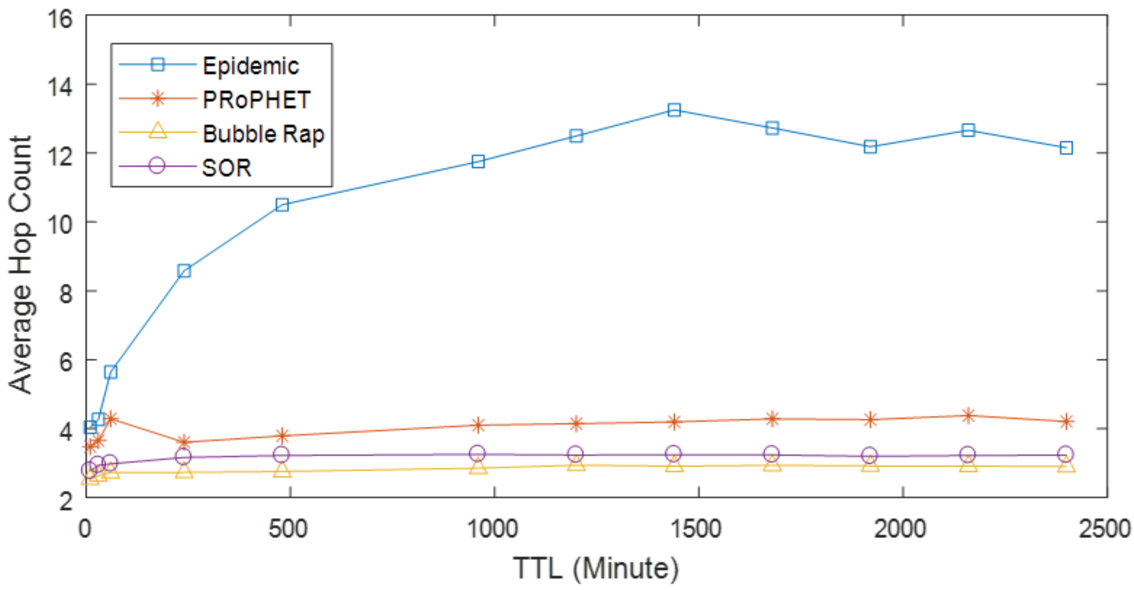


Figure 4.13: Average Hop Count vs. TTL (INFOCOM06 dataset)

It can be seen that, as the TTL values increases, hop counts increase for all protocols until reaches almost a stable level. Epidemic performance is affected by TTL value change more than other schemes because it is a flooding-based protocol whereby increasing in TTL value decreases the rate of dropping the expired message and hence gives it the opportunity to forward more replicas.

SOR outperforms the other none social-based protocols, it reduces the hop counts by 64%, 23%, on average, compared with Epidemic and PRoPHET respectively. The numbers of hop counts are reduced in SOR because exploiting social features limits the number of the candidate nodes as a relay, where the relay node is chosen only from the nodes that have the similar values of the top-ranked social feature of the destination. Comparing with Bubble Rap, the social-based protocol, SOR has higher but very close performance.

4.4.3 Varying Buffer Size

For varying the buffer size, the value of TTL is set to 10 Hours. This value is selected based on the experiments of varying TTL value where all experimented protocols have good performance at these TTL values.

In the simulation settings, message size is set to 128KB. So, there are three considered levels of buffer size in this study; low buffer size (1MB, 2 MB, 5 MB), middle buffer size (15 MB,25 MB,35 MB) and high buffer size (45 MB,55 MB). Increasing the buffer size means increasing the maximum number of messages that a mobile node can carry.

The following tables and graphs show the experimental results of evaluating SOR performance against the three benchmarks. Delivery ratio, Delivery overhead ratio, average latency, and average hop counts are evaluated for each experiment. Delivery ratio change against buffer size is depicted in Table 4.10 and Figure 4.14.

Table 4.10: Delivery Ratio vs. Buffer size (INFOCOM06 dataset)

Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
1	0.1	0.21	0.16	0.25	+150%	+20%	+57%
5	0.19	0.39	0.28	0.45	+137%	+16%	+61%
15	0.33	0.51	0.41	0.58	+76%	+14%	+42%
25	0.44	0.56	0.48	0.64	+46%	+15%	+34%
35	0.52	0.62	0.52	0.67	+29%	+9%	+29%
45	0.6	0.66	0.58	0.71	+19%	+8%	+23%
55	0.64	0.7	0.62	0.73	+15%	+5%	+18%

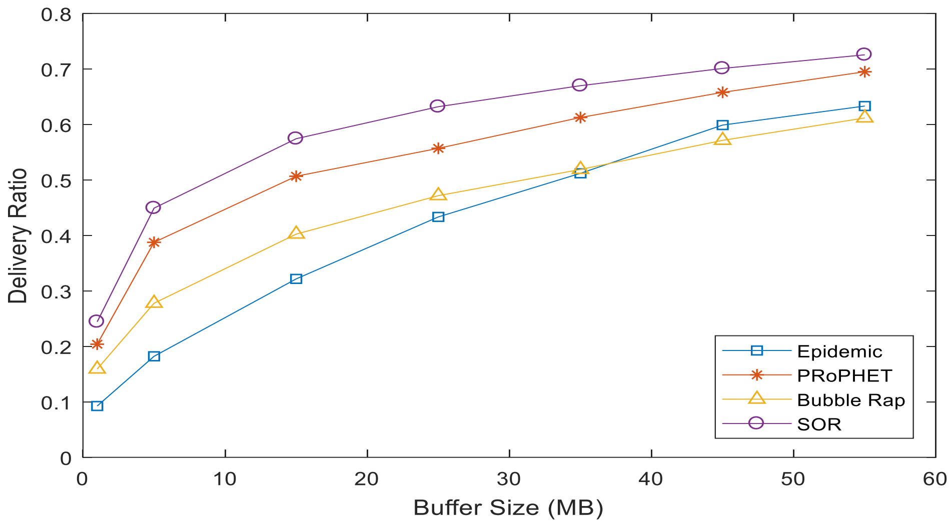


Figure 4.14: Delivery Ratio vs. Buffer Size (INFOCOM06 dataset)

From Figure 4.10, it can be seen that with the increase in buffer size the delivery ratio increases for all routing schemes and vice versa. The reason is that a higher buffer size enables mobile nodes to store and carry more messages and then deliver them later to the destinations.

SOR outperforms all other schemes for this evaluation metric, it achieves the highest delivery ratio for all buffer size scenarios. SOR increases the delivery ratio, on average, with 67%, 10%, and 38% compared with Epidemic, PRoPHET, and Bubble Rap respectively. Also, it can be noticed that the superiority of SOR over other routing schemes increases with the decrease in buffer size. For more explanation, for low buffer size level the increment in delivery ratio is 144% , 18%, and 59% , while for medium buffer size level the increment is 50% , 13%, and 35% and for high buffer size level it is 17% , 7%, and 21% compared with Epidemic, PRoPHET, and Bubble Rap respectively. This means that SOR utilizes the buffer size more effectively than other schemes for routing purposes.

SOR utilizes all the social characteristics of the mobile users and adopts ranking algorithm to choose the next relay node, this results in forwarding messages only to the nodes that have a higher probability to encounter the destination soon during each daily period. Consequently, the store-carry-forward mechanism will be very effective especially for constrained resource scenarios like a low buffer size of mobile nodes. Table 4.11 and Figure 4.15 show the results of evaluating delivery overhead ratio for SOR and the comparison with benchmark routing schemes.

Table 4.11: Overhead Ratio vs. Buffer Size (INFOCOM06 dataset)

Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
1	2292.54	1120.05	688.56	560.5	-76%	-50%	-19%
5	1487.05	684.31	567.25	402.2	-73%	-42%	-30%
15	917.88	533.68	405.31	338.7	-64%	-37%	-17%
25	674.04	463.23	326.39	294.8	-57%	-37%	-10%
35	549.61	397.31	272.65	267.1	-52%	-33%	-3%
45	454.25	343.47	227.47	249.1	-46%	-28%	+10%
55	410.42	316.11	196.59	228.7	-45%	-28%	+17%

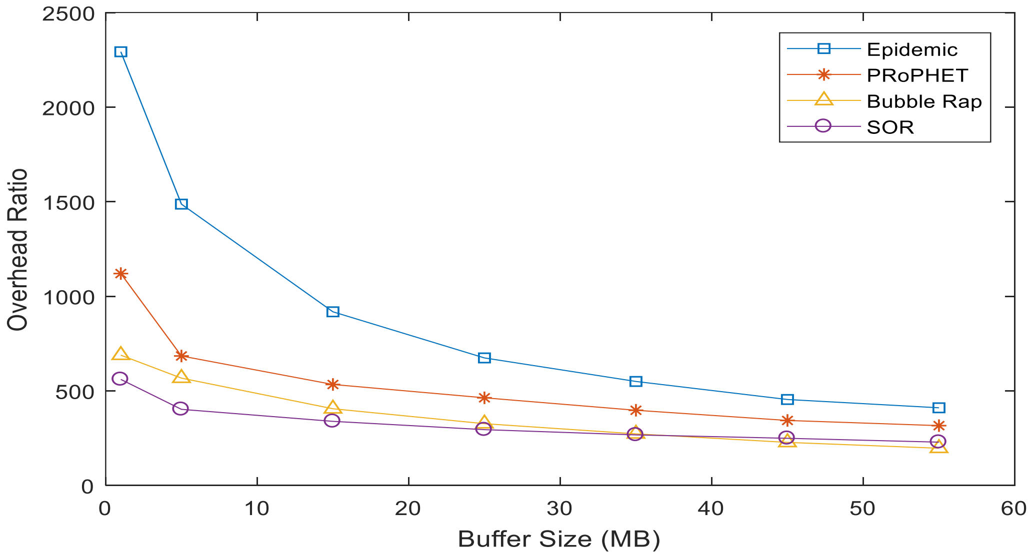


Figure 4.15: Overhead Ratio vs. Buffer Size (INFOCOM06 dataset)

It is clear that increasing buffer size results in decreasing the overhead ratio in the MSN network because it enables intermediate nodes to carry more messages for later delivery. SOR has a low overhead ratio in the MSN network. It outperforms other schemes, especially for low and medium buffer size scenarios. The decrease in the overhead ratio is 75%, 46% and 25% for low buffer size level and is 58%, 36% and 10% for medium buffer size level compared with Epidemic, PRoPHET, and Bubble Rap respectively. For a high buffer size scenario, SOR decreases overhead ratio with 46% and 28% compared with Epidemic and PRoPHET respectively, while has a slightly higher overhead ratio compared with Bubble Rap (14% higher), because Bubble Rap forwarding strategy is stricter in selecting the relay nodes by considering both degree centrality and community social metrics.

In Table 4.12 and Figure 4.16 the relation between average latency and buffer size is shown for SOR and other routing schemes.

Table 4.12: Average Latency vs. Buffer Size (INFOCOM06 dataset)

Buffer Size (MB)	**Epidemic**	**PRoPHET**	**Bubble Rap**	**SOR**	**SOR VS Epidemic**	**SOR VS PRoPHET**	**SOR VS Bubble Rap**
1	3053.17	4913.2	4406.27	3633.8	20%	-27%	-18%
5	7551.84	10921.	9525.47	9733.4	29%	-11%	3%
15	9502.89	11199.	10714.8	10782	14%	-4%	1%
25	11185.78	11288.	11005.5	10752.	-4%	-5%	-3%
35	11744.43	10913.	11213.1	10484.	-11%	-4%	-7%
45	11930.6	10498.	11380.0	10547.	-12%	1%	-8%
55	11803.24	10140.	11309.3	10589.	-11%	5%	-7%

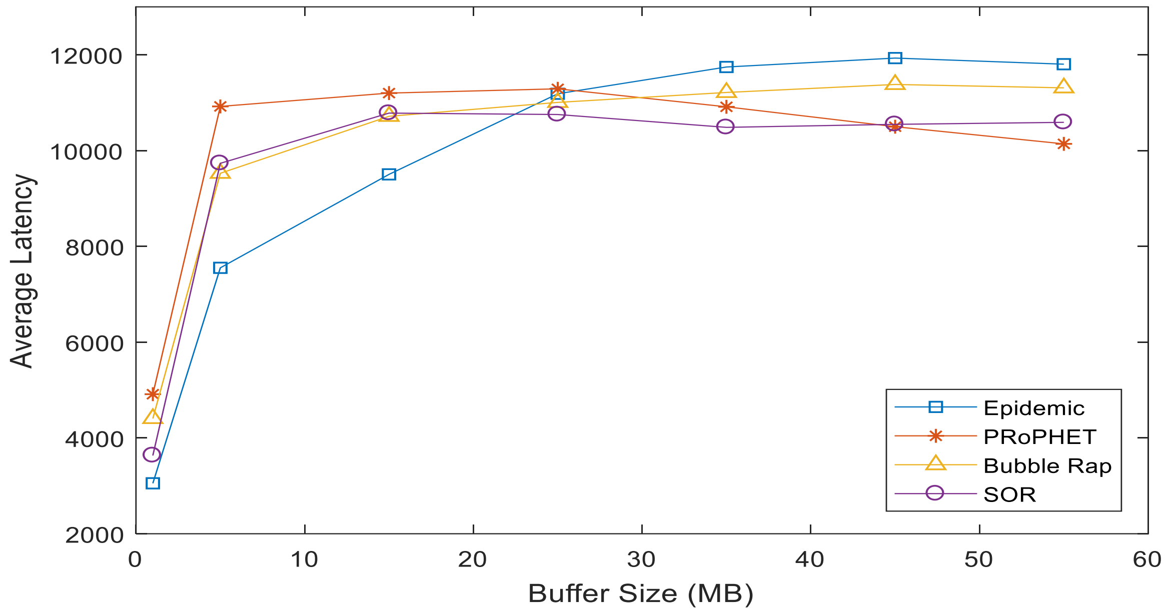


Figure 4.16: Average Latency vs. Buffer Size (INFOCOM06 dataset)

From the results, it is seen that increasing the buffer size of mobile nodes in the network results in an increment in the average latency because messages can be stored and carried for a longer time period without being dropped because of buffers overflow. Consequently, the delivered messages will have, on average, a higher value of end-to-end delay to reach the destinations.

For low buffer size scenarios, it is observed that SOR has lower average latency than ProPHET and Bubble Rap while Epidemic outperformance all other schemes in these scenarios because of its flooding-based forwarding strategy. Exploiting users' social characteristics and ranking them according to the social activities enable SOR to select forwarder nodes have a higher probability to encounter the destination, so to deliver messages in a lower end to end delay. With the increase in buffer size (25 MB and above), SOR, PRoPHET and Bubble Rap protocols achieve almost similar performance. They benefit from the ability to store more messages in the mobile nodes buffers and outperform

Epidemic protocol. The average hop count evaluation results are shown in Table 4.13 and Figure 4.17.

Table 4.13: Average Hop Counts vs. Buffer Size (INFOCOM06 dataset)

Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	SOR	SOR VS Epidemic	SOR VS PRoPHET	SOR VS Bubble Rap
1	12.55	3.76	2.67	3.21	-75%	-15%	+21%
5	10.82	3.9	2.85	3.27	-70%	-17%	+15%
15	8.39	3.63	2.93	3.22	-62%	-12%	+10%
25	7.58	3.48	3.08	3.13	-59%	-11%	+2%
35	6.75	3.52	3.03	3.1	-55%	-12%	+3%
45	5.83	3.48	3.08	3.11	-47%	-11%	+1%
55	5.29	3.56	2.97	3.1	-42%	-13%	+5%

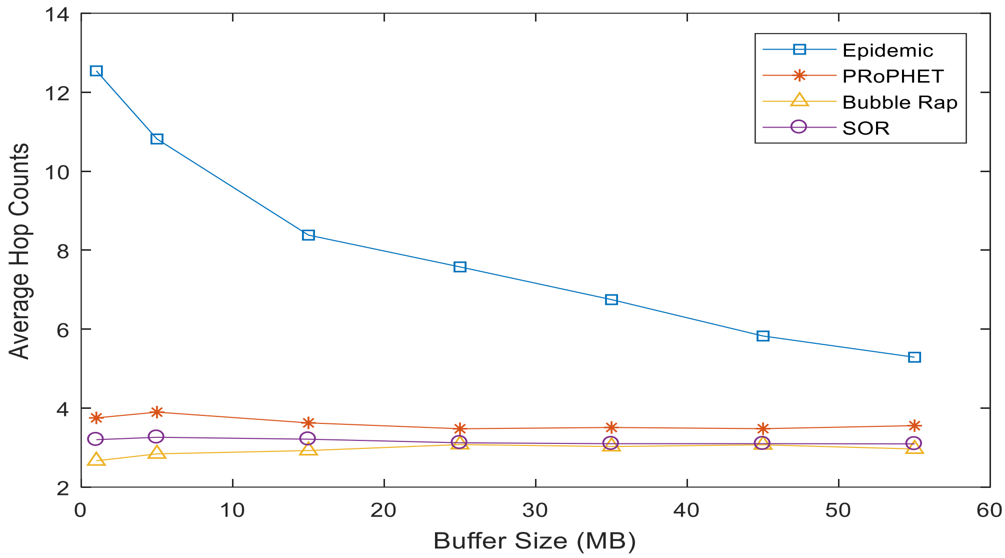


Figure 4.17: Average Hop Counts vs. Buffer Size (INFOCOM06 dataset)

SOR achieves low hop count when routing messages in MSN and outperforms Epidemic and PRoPHET schemes and reduces average hop count with 60% and 12%, on average, respectively compared with them. The reason is that only nodes that have similarity with the highest ranked social feature of the destination will be selected when forwarding a message. Hence, a low number of nodes corporate in delivery the messages in MSN network and this yields low average hop count in the MSN network. Comparing with Bubble Rap, which is also a social-based routing protocol, SOR has slightly higher average hop count especially for the scenarios of low buffer size values (1, 5, 15 MB). On average, SOR has 2.94 average hop count while Bubble Rap has 3.11 average hop count. The reason is, as aforementioned, Bubble Rap exploits community and degree centrality for relay selection which means decreasing the number of the nodes involved in relaying the message.

4.5 Conclusion

In this chapter, a context-aware social-based routing protocol (SOR) have been presented. It considered the context of mobile social networks in terms of the social routine activities of mobile users. The day is divided into six time periods, and for each time period, the social characteristics of mobile users are ranked based on their importance. SOR exploits the ranked social features to make the forwarding decision.

To evaluate the performance of the proposed protocol (SOR), three benchmarks from different routing categories are used: flooding-based protocol (Epidemic), probability-based protocol (PRoPHET), and social-based protocol (Bubble Rap). SOR has the highest delivery ratio comparing to all other protocols. For the scenarios of low buffer size and high TTL value, the increase in the delivery ratio reaches 150%, 24%, and 65% comparing with Epidemic, PRoPHET, and Bubble Rap respectively. Regarding overhead ratio, SOR decreases it with 75%, 45%, and 36% on average comparing with Epidemic, PRoPHET, and Bubble Rap respectively. SOR also decreases the average hop count with 64% and 23% on average compared with Epidemic and PRoPHET respectively, while it has a slightly higher average hop count compared with Bubble Rap.

In conclusion, in the opportunistic networks environment, the consideration of different dimensions of social properties and activities of mobile users is a fruitful approach to develop an efficient data dissemination protocol. To be more specific, the main advantage of considering different social factors in SOR is increasing the delivery ratio. However, in terms of overhead ratio and average hop count, which are indications of resource consuming, SOR does not decrease them effectively as compared with the social-base benchmark i.e. bubble Rap. The objective in the next chapter is to investigate how to exploit multiple social features and consider the mutual correlations among them to decrease the delivery cost significantly while achieving a competitive delivery ratio in OMSN.

CHAPTER 5

ROUTING BASED ON MULTIPLE SOCIAL METRICS

5.1 Introduction

It has been learned from Chapter 3 and Chapter 4 that developing an effective way to exploit the social aspects can enhance the routing efficiency in OMSN. In SOR, considering several different social properties results in an increase in the delivery ratio, and exploiting degree centrality in EpSoc decreases the delivery cost of the Epidemic protocol. Therefore, the main objective of this chapter is to introduce a new routing protocol, called multiple-social metrics routing protocol (MSM), to exploit multiple social metrics (various social factors as SOR) and (to control overhead as EPSoc) to decrease the delivery cost and increase the delivery ratio in OMSN.

MSM exploits three different social metrics, namely, degree centrality, social similarity, and social activeness. These three metrics are combined in a utility function used for taking the forwarding decision. For further investigation, the routing performance of MSM is evaluated against three benchmarks, they are Epidemic, PRoPHET and Bubble Rap.

The details of MSM routing protocol are presented in Section 5.2. The performance evaluation based on the KPIs is described in Section 5.3. Results and the related discussion are provided in Section 5.4. Finally, Section 5.5 concludes the chapter.

5.2 MSM Routing Protocol

In this study, social metrics are classified into two categories: network-side metrics and node-side metrics. Network-side metrics are the metrics that are calculated based on the interactions between the node and the other mobile nodes in the networks, while the node-side metrics are the metrics that are calculated based on the interactions between the node and particular nodes in the network. In this context, the social metrics: social centrality (degree, betweenness, and closeness) and social activity are classified as network-side metrics because they are evaluated based on the contact history of the node with the other nodes in the network. On the other hand, similarity and friendship are classified as node-side metrics, where its values are defined according to the social interactions and communicating with particular peers in the network.

MSM exploits social metrics that belong to different classifications (network-side and node-side) and considers their mutual impact for more effective routing in OMSN. MSM utilizes three social metrics; social activity, social similarity, and social centrality. The three social metrics are combined and the correlation among them is exploited to make the forwarding decision more accurate.

5.2.1 Social Metrics Exploited in MSM

Social activity, similarity, centrality are common social metrics in MSN as aforementioned in Section 3.3.7. The next subsections define them and present the way to evaluate them.

- **Social Activity**

In the opportunistic network the topology is dynamic, and the current neighbors of each node change frequently. The node that has a higher rate of meeting new peers is considered socially an active node. For example, if there are two nodes N_1 and N_2, and at time t_1: the neighbors of node N_1 are the nodes: N_2, N_4, N_3 and N_7, while the neighbor of node N_2 are the nodes: N_1 N_4 N_5 and N_9. Later, at time t_2 ($t_2 > t_1$): N_1 has the neighbors: N_3, N_4, N_5 and N_7, while the neighbors of N_2 are the nodes: N_8 N_{12} N_6 and N_9. In this example, node N_2 is socially more active than node N_1 because it has more new peers at t_2 (N_8 N_{12} and N_6), while N_1 has only one new neighbor: N_5. The social activity of a node is calculated as follows:

$$Act(N_i) = 1 - \frac{Nb_i^{t_l} \cap Nb_i^{t_p}}{Nb_i^{t_l} \cup Nb_i^{t_p}},$$ (Rahim et al., 2017) Equation 5.1

Where:

t_l : the time of the last change in the neighbors of N_i

t_p : the time of the previous change in the neighbors of N_i

$Nb_i^{t_l}$, $Nb_i^{t_p}$ are the set of the current neighbors of N_i at t_l and t_p respectively.

- **Social Similarity**

From social science, people tend to build clusters inside their social networks with peers who have common social characteristics, behaviors, or friends. People who belong to a cluster may meet each other more frequently than others, and hence the probability of the future meeting is high. The similarity between two nodes N_i and N_j is computed as following:

$$SimNb_{i,j} = Nb_i \cap Nb_j$$ (Guan et al., 2017) Equation 5.2

where Nb_i is the current neighbors of node N_i and Nb_j represents the current neighbors of node N_j.

- **Degree Centrality**

It is an indicator of the social importance (popularity) of a node in the social network. Node gets higher popularity when it encounters more other nodes in the network. Therefore, the increase in degree centrality results in a higher probability to deliver messages. The degree centrality of a node Ni is given by:

$$DC_i = \sum_{k=1}^{N} a(i,k), \qquad \text{(Hui et al., 2011)} \qquad \text{Equation 5.3}$$

Where N is the number of nodes in the network, and $a(\mathrm{i},\mathrm{k}) = 1$ if a direct link exists between node i and node k and $i \neq k$.

5.2.2 MSM Forwarding Policy

In the proposed protocol (MSM) the three social metrics: activity, degree centrality, and similarity are combined to make the forwarding decision in OMSN. An encounter node will be selected as a relay in two cases: first, if it is more socially active than the current node, and it has a similarity with the destination and its similarity is more than the current relay node. This condition is because there is a probability that, a node has higher social activity (meet more new people frequently) than the current relay but it is socially far from the destination. So that, forwarding messages to such a node is an unwise decision. Fulfilling this condition leads to select relays that are more socially closer to the destination and hence the probability to encounter the destination is higher. Second, the relay has a higher centrality metric than the current node and it has contacted the destination before and it has a similarity with the destination. This is because forwarding messages to nodes that have high centrality and strong social relation with the destination increases the probability of encountering the destination.

MSM combines the social impacts of the network-side and node-side metrics for efficient forwarding strategy. Accordingly, utility function is proposed where the value of the utility function of a node N_j is computed as follows:

$$U_{N_j} = simF \times Act(N_j) + cenF \times DC(N_j) \quad \text{Equation 5.4}$$

The factors $simF_{i,j}$ and $cenF_{i,j}$ are used to make a strict selection of the relay to the nodes that are socially closer to the destination. $Act(N_j)$ is calculated based on equation (5.1) and $DC(N_j)$ is calculated based on the equation (5.3).

According to the similarity metric, a node will be selected as a relay only if it has a similarity with the destination and if it has a higher similarity value than the current node. So, the value of the similarity factor $simF$ is:

$$\begin{cases} simF = 1 : \Delta sim_{i,j} = SimNb_{j,d} - SimNb_{i,d} > 0 \\ simF = 0 : \Delta sim_{i,j} = SimNb_{j,d} - SimNb_{i,d} \leq 0 \end{cases} \quad \text{Equation 5.5}$$

While for centrality metric the relay will be chosen only if it encountered the destination previously and it has a similarity with the destination. So, the value of the centrality factor $cenF$ is:

$$\begin{cases} cenF = 1 : SimNb_{j,d} > 0 \ and \ Enc_{j,d} \neq 0 \\ cenF = 0 : SimNb_{j,d} = 0 \ or \ Enc_{j,d} = 0 \end{cases} \quad \text{Equation 5.6}$$

Where similarities are calculated based on the equation (5.2). and $Enc_{j,d} \neq 0$ if the destination node exists in the contact history of node N_j.

When a node N_{i} encounters another node N_{j}, each node calculates the values of $Act(N_j)$ $Act(N_i)$,$SimNb_{j,d}$, $SimNb_{i,d}$ and $Enc_{j,d}$ metrics for each message stored in their buffers. Then based on these values, each node evaluates $simF$ using Equation (5.5), and $cenF$ using Equation (5.6). Finally, the utility of the two nodes U_{N_j} , U_{N_j} is calculated. If and only if the utility of the encountered node U_{N_j} is greater than the current node U_{N_i}, the message will be forwarded to the encountered node, else the current node continues carrying the message. Figure 5.1 shows the flowchart of the proposed forwarding policy of MSM and Algorithm 5.1 presents the pseudo-code of forwarding process in MSM.

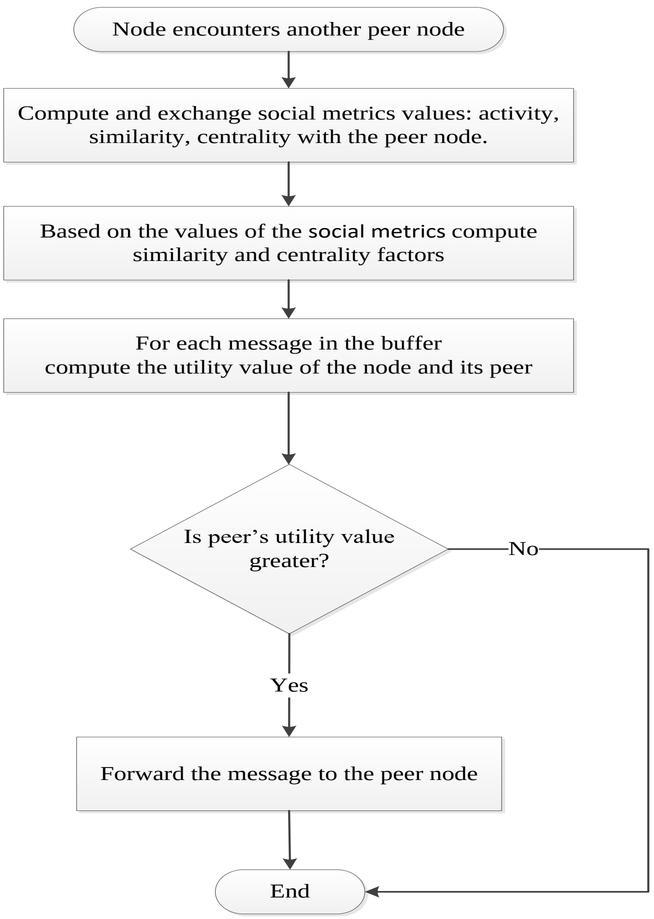


Figure 5.1: Flowchart of the forwarding process of MSM

Algorithm 5.1: Pseudo-code of forwarding process in MSM

```
$Node_i$ $encounters$ $Node_j$
$for$ $each$ $message$ in $Node_i$ buffer
$compute$ $Act(N_j)$ $Act(N_i)$ , $SimNb_{j,d}$ , $SimNb_{i,d}$ , $Enc_{j,d}$
$compute$ $simF$ , $cenF$
$compute$ $U_{N_j}$ , $U_{N_j}$
    $if$ $U_{N_j} >$ $U_{N_i}$
        $forward$ $message$ $to$ $Node_j$
    $End$ $if$
$End$ $for$
```

5.3 Performance Evaluation

The efficiency of MSM is investigated against three well-known routing protocols i.e. Epidemic, PRoPHET, and Bubble Rap. Each of them is from a different routing category; Flooding-based, Probabilistic, and social-based categories respectively. ONE simulator is used to study the MSM performance.

5.3.1 Datasets

The same three datasets used previously in Chapter 3 are used to evaluate MSM protocol: Cambridge, INFOCOM05, and INFOCOM06 datasets. As aforementioned in Chapter 3, these datasets have different scales and are suitable for evaluating social-based routing schemes.

5.3.2 Simulation Settings:

ONE simulator (Keränen et al., 2009) is used to conduct the experiments for performance evaluation of MSM. The real traces of the three datasets are used for simulation scenarios. Broadcast type is Bluetooth interface with the transmit speed of 2 Mbps for all the nodes. Message event generator in ONE simulator generates one new message in every 30 to 40 seconds. Message size is 124 KB. Simulation end time is varied from 4 Hours (14400 seconds) to 40 Hours (144000 seconds) by 4 Hours step. Also, the message's TTL value is varied from a low value (10, 30 Minutes) to the end time of the experiment by 4 Hours step. To study the impact of the buffer size, it is also varied as follows (1, 5, 15, 25, 35, 45, 55 MB). Table 5.1 shows the simulation settings.

Table 5.1: Simulation Settings

Simulation setting	Value
Simulation End Time:	
(Cambridge dataset)	274 (Hour)
(INFOCOM05	70 (Hour)
(INFOCOM06	40 (Hour)
Interface	Bluetooth Interface
No of nodes	
(Cambridge dataset)	36
(INFOCOM05 dataset)	41
(INFOCOM06 dataset)	78
Transmit Speed	250 k (2 Mbps)
Mobility	Real trace datasets
Buffer Size	1,2,5,15,25,35,45,55 (MB)
Routing Protocols	MSM , Epidemic , PRoPHET, BubbleRap
Message Size	128k
Event Interval	30 to 40 seconds
Initial Message TTL	
(Cambridge dataset)	10 (Minute), 30 (Minute), 1 ,3, 5,12, 24, 36, 60, 72, 96, 186
(INFOCOM05 dataset)	10 (Minute), 30 (Minute) , 1, 4, 8, 16, 20, 24, 28, 32, 36, 38.4
(INFOCOM06 dataset)	10 (Minute), 30 (Minute) , 1, 4, 8, 16, 20, 24, 28, 32, 36, 38.4

5.3.2 Key Performance Indicators (KPIs)

To evaluate the performance of the proposed protocol, the evaluation metrics used in Chapter 3 and Chapter 4 are used; they are Delivery ratio, Overhead ratio, Average latency and Average hop counts.

5.4 Results and Discussion

Three parameters are considered to evaluate the performance of the proposed protocol: buffer size, message's TTL values and experiment time. This is for investigating the efficiency of MSM for different TTL, buffer size levels, and to examine its achievement along the experiment time. The evaluation is applied for the three datasets: Cambridge, INFOCOM05, and INFOCOM06.

5.4.1 Performance Evaluation with Different Buffer Sizes

In OMSN, nodes employ the store-carry-forward mechanism for information provision, where nodes keep buffering the message when there is no opportunity to forward it. So that, buffer size plays a critical role in determining the routing performance.

5.4.1.1 Delivery Ratio vs. Buffer Size

For each dataset, buffer size value is changed in the range from 1MB to 55MB to evaluate the routing performance according to all performance metrics. So, there are three levels of buffer size as in Chapter 3; low (1, 2, 5 MB), medium (15, 25, 35 MB), and high (45, 55 MB). Table 5.2 and Figure 5.2 show the results for Cambridge dataset.

Table 5.2: Delivery Ratio vs. Buffer Size (Cambridge dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM VS Epidemic	MSM VS PRoPHET	MSM VS Bubble Rap
low	1	0.032	0.058	0.048	0.05	+48%	-19%	-2%
	2	0.051	0.088	0.069	0.07	+40%	-19%	+4%
	5	0.099	0.146	0.117	0.12	+20%	-19%	+2%
Medium	15	0.185	0.193	0.196	0.17	-9%	-13%	-14%
	25	0.228	0.220	0.231	0.19	-15%	-12%	-16%
	35	0.263	0.240	0.260	0.21	-21%	-13%	-20%
High	45	0.299	0.254	0.278	0.22	-27%	-14%	-22%
	55	0.321	0.264	0.302	0.22	-31%	-15%	-26%

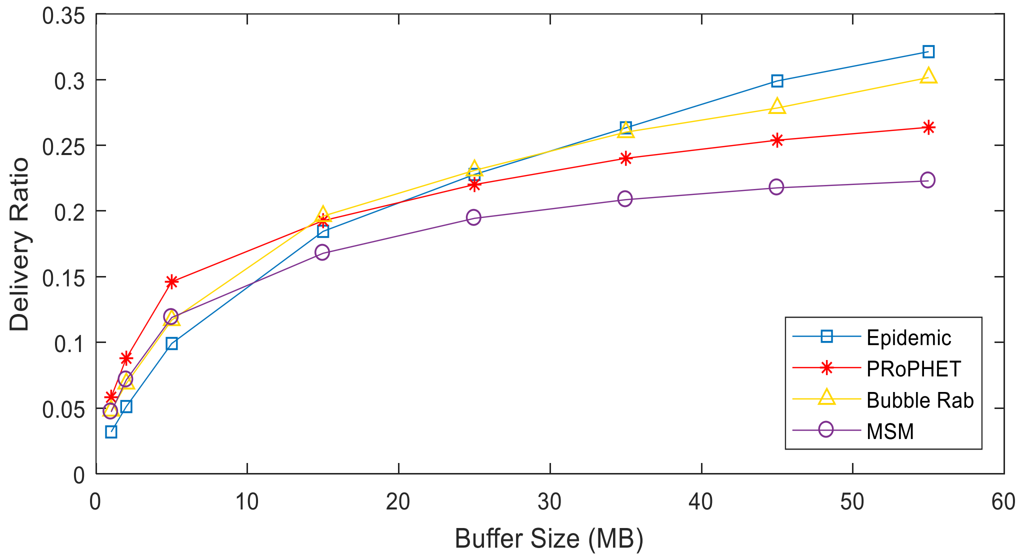


Figure 5.2: Delivery Ratio vs. Buffer Size (Cambridge dataset)

For low buffer size scenarios, MSM outperforms Epidemic with an average of 36%, while it has almost similar performance compared with the social based protocol i.e. Bubble Rap, and it achieves lower delivery ratio than PRoPHET with an average of 19%. For medium and high buffer size scenarios, MSM has lower delivery ratio compared with Epidemic, PRoPHET and Bubble Rap with averages of 21%, 13%, and 20% respectively. The reason is that, against the other examined protocols, MSM adopts a strict social-based strategy for selecting the next message's carrier; this decreases the forwardings in the networks and results in a lower number of delivered messages. This makes MSM more effective for low resource scenarios i.e. low buffer size. The results of INFOCOM05 experiment are shown in Table 5.3 and Figure 5.3.

Table 5.3: Delivery Ratio vs. Buffer Size (INFOCOM05 dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM VS Epidemic	MSM VS PRoPHET	MSM VS Bubble Rap
low	1	0.068	0.108	0.089	0.097	+43%	-10%	+9%
	2	0.102	0.166	0.123	0.140	+38%	-15%	+13%
	5	0.171	0.260	0.196	0.221	+29%	-15%	+13%
Medium	15	0.296	0.366	0.296	0.332	+12%	-9%	+12%
	25	0.387	0.423	0.351	0.397	+3%	-6%	+13%
	35	0.427	0.449	0.400	0.431	+1%	-4%	+8%
High	45	0.466	0.476	0.435	0.458	-2%	-4%	+5%
	55	0.485	0.492	0.464	0.478	-1%	-3%	+3%

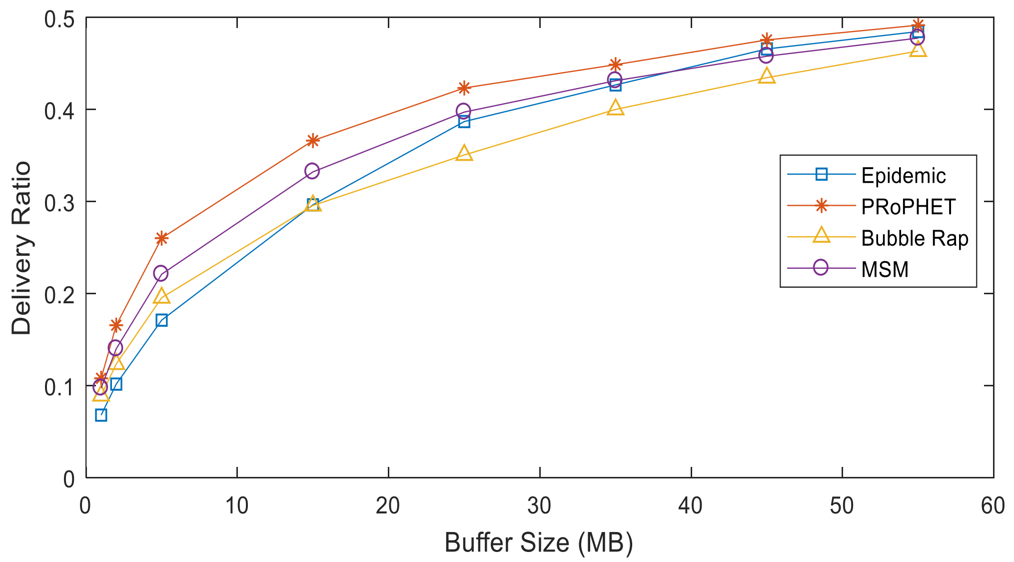


Figure 5.3: Delivery Ratio vs. Buffer Size (INFOCOM05 dataset)

It is clear that MSM outperforms both Epidemic and Bubble Rap for low and medium buffer size scenarios. The increase in the delivery ratio for low buffer size scenarios is on average 37% over Epidemic and 12% over Bubble Rap, and for the medium buffer size scenarios, the increase is, on average, 5% and 11% respectively. In the case of high buffer size scenarios, MSM has almost the same achievement as Epidemic and Bubble Rap.

Comparing with PRoPHET, MSM achieves lower delivery ratio but the difference decreases with the increase in buffer size. The average decrease in the delivery ratio is 13%, 6% and 4% for low, medium and high buffer size respectively.

MSM has better performance in this experiment compared with Cambridge dataset experiment because the number of mobile nodes in the network is higher so that the social information has a higher impact on enhancing routing performance in OMSN. The results of the third experiment, INFOCOM06 dataset, are presented in Table 5.4 and Figure 5.4.

Table 5.4: Delivery Ratio vs. Buffer Size (INFOCOM06 dataset)

Buffer Size Level	**Buffer Size (MB)**	**Epidemic**	**PRoPHET**	**Bubble Rap**	**MSM**	**MSM VS Epidemic**	**MSM VS PRoPHET**	**MSM VS Bubble Rap**
low	1	0.093	0.204	0.159	0.202	+118%	-1%	+27%
	2	0.119	0.277	0.213	0.297	+150%	+7%	+39%
	5	0.182	0.388	0.278	0.409	+125%	+6%	+47%
Medium	15	0.322	0.507	0.402	0.503	+56%	-1%	+25%
	25	0.433	0.557	0.472	0.536	+24%	-4%	+14%
	35	0.512	0.613	0.519	0.556	+9%	-9%	+7%
High	45	0.599	0.658	0.571	0.568	-5%	-14%	-1%
	55	0.633	0.695	0.612	0.572	-10%	-18%	-7%

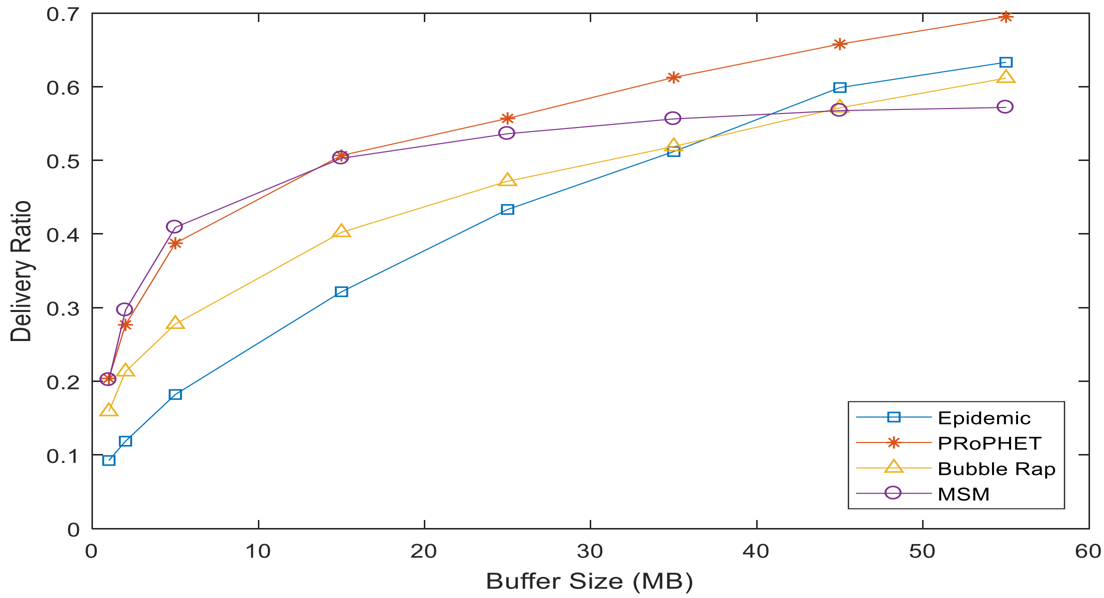


Figure 5.4: Delivery Ratio vs. Buffer Size (INFOCOM06 dataset)

In INFOCOM06 experiment, MSM outperforms Epidemic and Bubble Rap for low and medium buffer size scenarios, while it has very close achievement as PRoPHET. MSM increases the delivery ratio in an average of 131% and 38%, and at an average of 30% and 15% compared with Epidemic and Bubble Rap for the low, medium scenarios respectively. For high buffer size scenarios, MSM has a slightly lower delivery ratio than other protocols. This is because MSM does not utilize the increase in the buffer size effectively due to its high restriction on forwarding messages.

It can be summarized that the delivery ratio of MSM increases with the increase in buffer size like all the other protocols and for all datasets experiments. However, MSM is more efficient for low buffer size scenarios because of its strict forwarding policy. In addition, the efficiency of MSM increases with the increase in the number of nodes in the network; where the social features and social interactions among users have a higher impact on routing performance. The results have shown that the achievement of MSM is better in INFOCOM06 than INFOCOM05, and it is better in INFOCOM05 than Cambridge.

5.4.1.2 Overhead Ratio vs. Buffer Size

Table 5.5 and Figure 5.5 show the evaluation of overhead ratio with different buffer size for Cambridge experiment.

Table 5.5: Overhead Ratio vs. Buffer Size (Cambridge dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs Epidemic	MSM vs PRoPHET	MSM vs Bubble Rap
low	1	622.67	565.91	54.83	326.95	-47%	-42%	+496%
	2	595.13	418.78	70.09	233.14	-61%	-44%	+233%
	5	392.06	263.84	82.58	142.47	-64%	-46%	+73%
Medium	15	240.68	193.80	98.28	70.99	-71%	-63%	-28%
	25	199.78	156.17	104.36	36.29	-82%	-77%	-65%
	35	173.19	134.96	103.17	22.59	-87%	-83%	-78%
High	45	151.34	119.22	103.20	15.49	-90%	-87%	-85%
	55	139.59	97.75	97.14	11.94	-91%	-88%	-88%

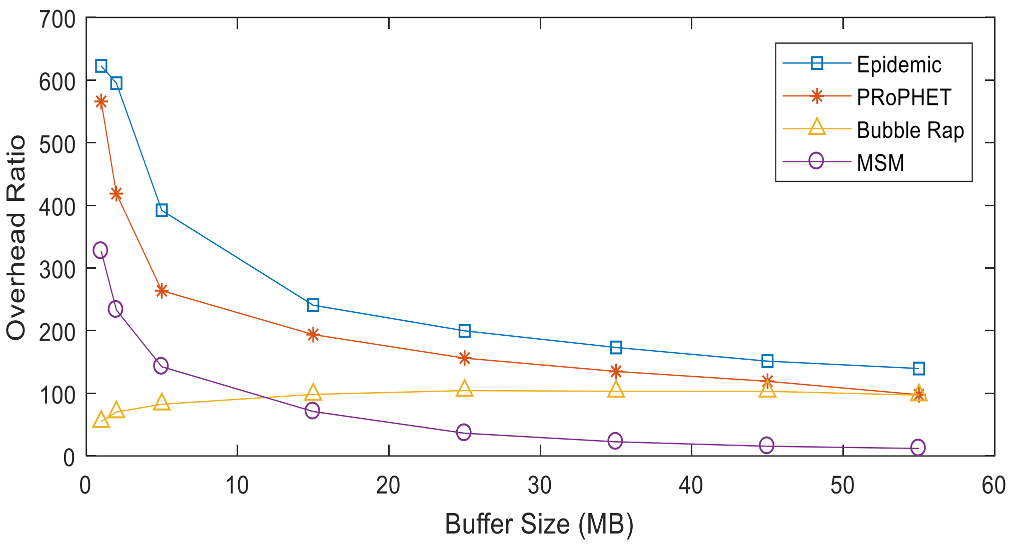


Figure 5.5: Overhead Ratio vs. Buffer Size (Cambridge dataset)

For Cambridge experiment, MSM outperforms Epidemic and PRoPHET for all buffer levels. The reduction in the overhead ratio is 74% and 66%, on average, respectively. Comparing with Bubble Rap, MSM has a higher overhead ratio for low buffer size scenarios but MSM outperforms it for medium and high buffer size scenarios with a decrement of 57%

and 82%, on average, respectively. This reason is, the high rate of message dropping in low buffer size scenarios affects the performance of MSM more than Bubble Rap due to the low number of the selected relay in MSM.

Table 5.6: Overhead Ratio vs. Buffer Size (INFOCOM05 dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM VS Epidemic	MSM VS PRoPHET	MSM VS Bubble Rap
low	1	382.21	384.56	85.63	195.1	-49%	-49%	+128%
	2	398.12	306.15	114.2	162.1	-59%	-47%	+42%
	5	349.60	224.42	129.74	112.3	-68%	-50%	-13%
Medium	15	254.46	175.84	122.46	71.60	-72%	-59%	-42%
	25	200.44	156.47	107.08	55.82	-72%	-64%	-48%
	35	184.03	151.13	91.66	45.67	-75%	-70%	-50%
High	45	173.37	144.38	79.92	37.73	-78%	-74%	-53%
	55	165.75	140.23	68.57	31.97	-81%	-77%	-53%

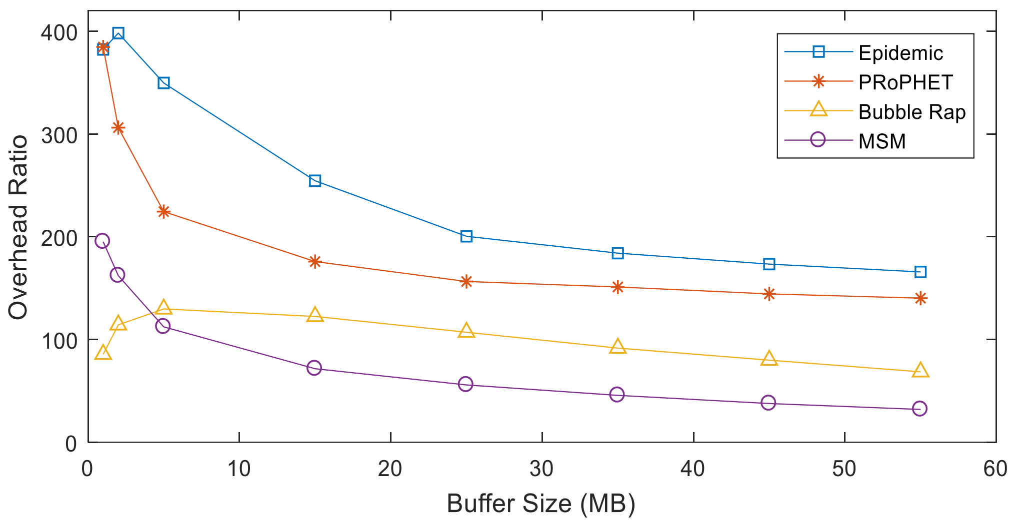


Figure 5.6: Overhead Ratio vs. Buffer Size (INFOCOM05 dataset)

Also, in INFOCOM05 experiment, MSM protocol outperforms Epidemic and PRoPHET for all buffer levels. On average, the reduction in overhead is 59% and 49% for low buffer size scenarios, 73% and 64% for medium buffer size scenarios, and 80% and 76% for high buffer size scenarios compared with Epidemic and PRoPHET respectively. Comparing with Bubble Rap, it outperforms MSM for low buffer size scenario but for medium and high buffer size scenario, MSM has a better performance where it reduces, on average, the overhead ratio with 47% and 53% respectively. The efficiency of MSM increases in this experiment because the increase in the number of nodes compared with Cambridge dataset, so exploiting social information contribute more enhancement.

Table 5.7: Overhead Ratio vs. Buffer Size (INFOCOM06 dataset)

Buffer Size Level	**Buffer Size (MB)**	**Epidemic**	**PRoPHET**	**Bubble Rap**	**MSM**	**MSM VS Epidemic**	**MSM VS PRoPHET**	**MSM VS Bubble Rap**
low	1	2292.53	1120.05	688.56	87.72	-96%	-92%	-87%
	2	1993.36	901.51	509.63	57.63	-97%	-94%	-89%
	5	1487.05	684.30	567.25	30.93	-98%	-95%	-95%
Medium	15	917.87	533.68	405.30	16.08	-98%	-97%	-96%
	25	674.04	463.22	326.39	13.36	-98%	-97%	-96%
	35	549.60	397.31	272.64	11.24	-98%	-97%	-96%
High	45	454.24	343.46	227.46	10.33	-98%	-97%	-95%
	55	410.41	316.11	196.58	10.07	-98%	-97%	-95%

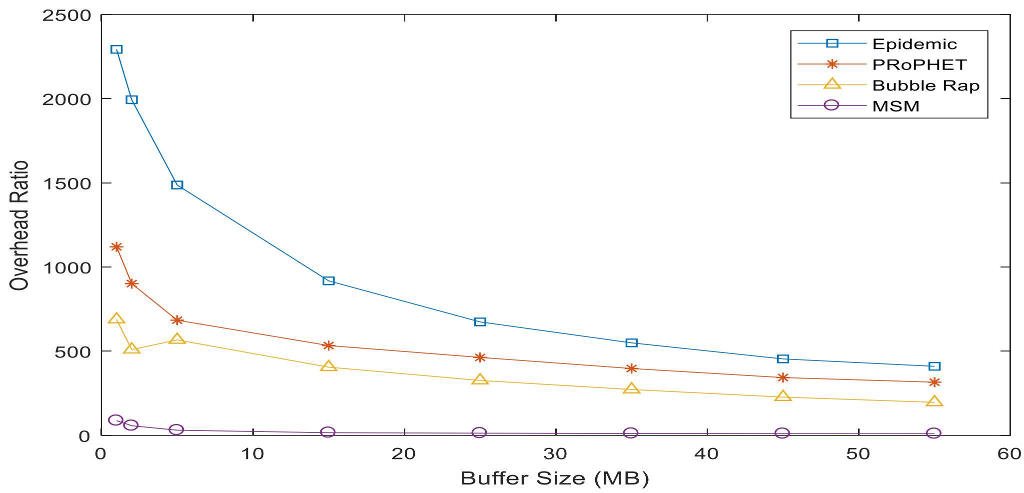


Figure 5.7: Overhead Ratio vs. Buffer Size (INFOCOM06 dataset)

In INFOCOM06, MSM protocol outperforms its benchmark routing protocols: Epidemic, PRoPHET and Bubble Rap for all buffer level scenarios. The average reduction in overhead ratio is, on average, 97%, 98%, and 98 %, for the low buffer size scenarios, 94%, 97%, and 97% for medium buffer size scenarios, and 90%, 96%, and 95% for high buffer size scenario compared with Epidemic, PRoPHET and Bubble Rap respectively.

It can be seen that the performance of MSM improves with the increase in buffer size. This is because the forwarding strategy of MSM depends on keep storing messages in the mobile node's buffer when the encountered nodes have not a stronger social relationship with the destination than the current messages' relay node. Also, it is noticed that for low buffer scenario, MSM performance is better in INFOCOM06 experiment than Cambridge and INFOCOM05 experiments. The reason is that the number of nodes in the network is higher in INFOCOM06, where this enables messages to be forwarded to another node before dropping due to the buffer overflow.

5.4.1.3 Average Latency vs. Buffer Size

As mentioned previously in Chapter 3, buffer size affects the overall end-to-end delay when delivering messages in OMSN network. Increasing buffer size results in an increase in the latency in the network and vice versa. Table 5.8 and Figure 5.8 present the experimental results for Cambridge dataset.

Table 5.8: Average Latency vs. Buffer Size (Cambridge dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	Epidemic	PRoPHET	Bubble Rap
low	1	2298.5	2620.4	2139	2660.7	+14%	+2%	+20%
	2	5827.7	6080.02	5390	6052.82	+4%	0	+11%
	5	11504.8	12904.2	11479	13110.6	+12%	+2%	+12%
Medium	15	13272.9	14094.9	13160	14492.3	+8%	+3%	+9%
	25	14398.3	14468.3	13835	14894.9	+3%	+3%	+7%
	35	15055.9	14665.7	14207	15019.4	0	+2%	+5%
High	45	15480.4	14717.8	14503	15022.5	-3%	+2%	+3%
	55	15417.4	14655.9	14411	15020.9	-3%	+2%	+4%

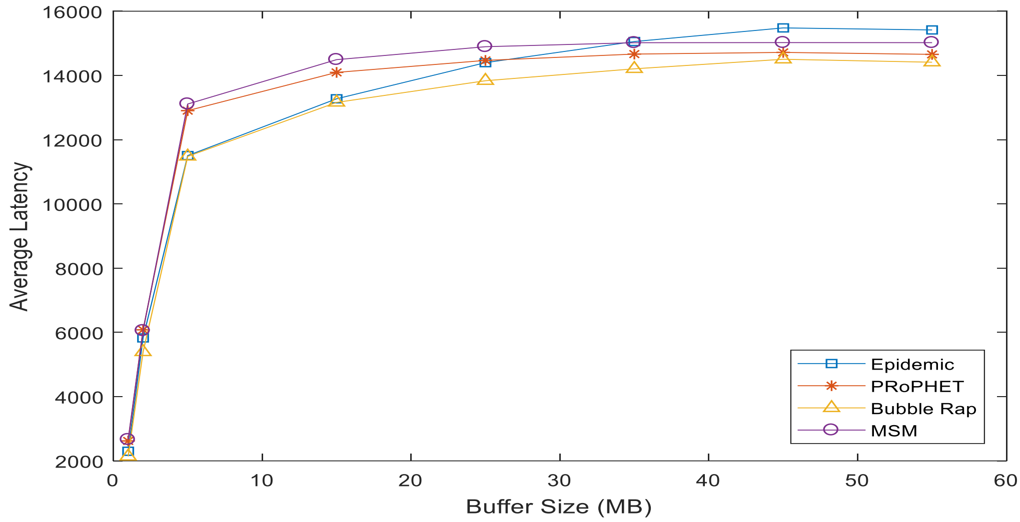


Figure 5.8: Average Latency vs. Buffer Size (Cambridge dataset)

MSM outperforms both Epidemic and Bubble Rap protocols in Cambridge Experiment, and its superiority increases with the increase in buffer size. On average, the reduction in average latency is 11%, 70% and 75% in low, medium and high scenarios respectively compared with Epidemic, and 11%, 73%, and 77% in low, medium and high scenarios respectively compared with Bubble Rap. Comparing with PRoPHET Protocol, MSM protocol almost has the same performance. In Table 5.9 and Figure 5.9, the evaluation of average latency with different buffer size is shown for INFOCOM05 dataset.

Table 5.9: Average latency vs. Buffer Size (INFOCOM05 dataset)

Buffer Size Level	**Buffer Size (MB)**	**Epidemic**	**PRoPHET**	**Bubble Rap**	**MSM**	**Epidemic**	**PRoPHET**	**Bubble Rap**
low	1	2418.40	3007.15	2401.10	2673.85	%11%	-11%	%11%
	2	5830.56	6479.27	5146.19	5589.07	-4%	-14%	%9%
	5	10196.9	11031.7	10164.5	10331.5	%1%	-6%	%2%
Medium	15	11720.7	12693.7	12296.6	12412.5	%6%	-2%	%1%
	25	13526.7	13299.9	13107.2	13131.0	-3%	-1%	0%
	35	13566.8	13309.4	13427.2	13288.3	-2%	0%	-1%
High	45	13869.7	13361.7	13568.8	13419.0	-3%	0%	-1%
	55	13791.9	13118.3	13544.1	13441.7	-3%	%2%	-1%

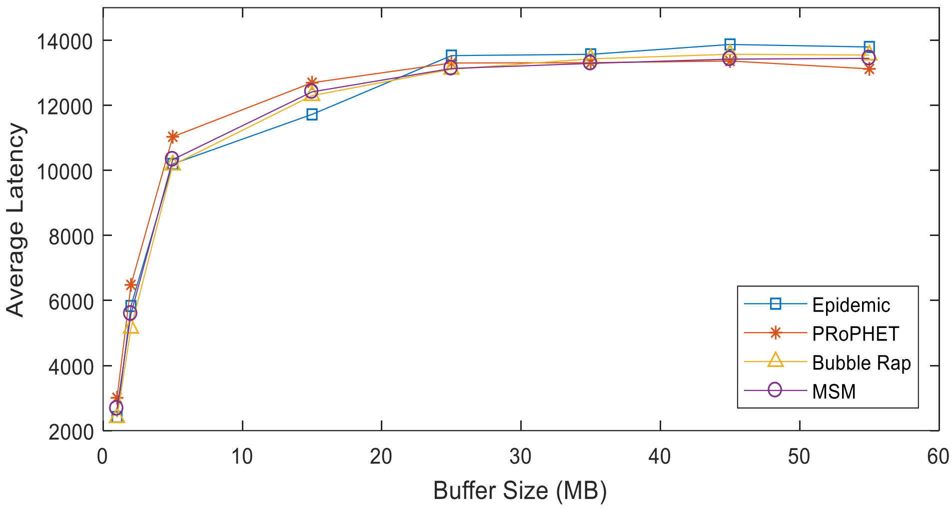


Figure 5.9: Average Latency vs. Buffer Size (INFOCOM05 dataset)

In INFOCOM05 experiment, MSM protocol has almost similar average latency with the other protocols. The achievement differences among the protocols is very small. Table 5.10 and Figure 5.10 show the evaluation results for INFOCOM06 dataset.

Table 5.10: Average Latency vs. Buffer Size (INFOCOM06 dataset)

Buffer Size Level	**Buffer Size (MB)**	**Epidemic**	**PRoPHET**	**Bubble Rap**	**MSM**	**Epidemic**	**PRoPHET**	**Bubble Rap**
low	1	3053.17	4913.27	4406.26	5366.43	+76%	+9%	+22%
	2	5328.40	9301.03	8135.40	9848.77	+85%	+6%	+21%
	5	7551.84	10921.5	9525.47	11714.2	+55%	+7%	+23%
Medium	15	9502.88	11199.9	10714.8	12769.8	+34%	+14%	+19%
	25	11185.7	11288.7	11005.5	12887.2	+15%	+14%	+17%
	35	11744.3	10913.2	11213.1	12848.6	+9%	+18%	+15%
High	45	11930.0	10498.0	11380.0	12967.1	+9%	+24%	+14%
	55	11803.3	10140.0	11309.3	13038.9	+10%	+29%	+15%

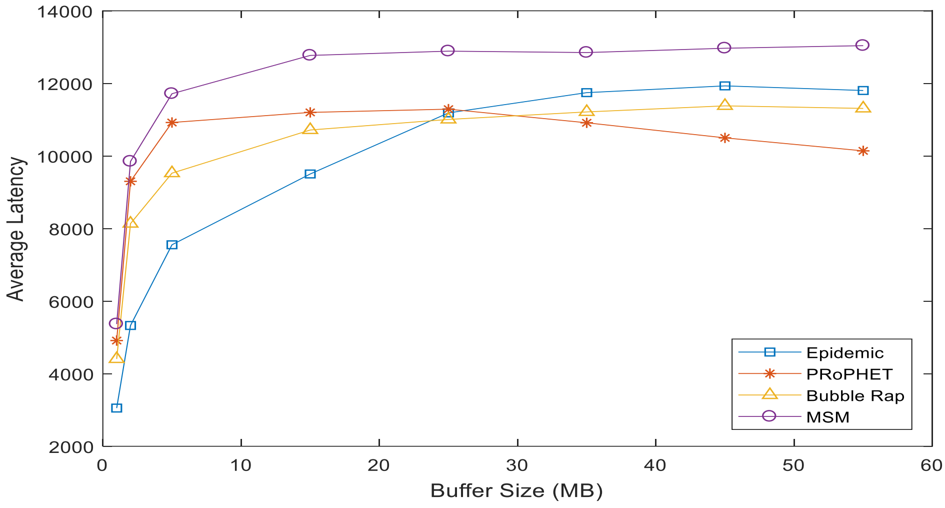


Figure 5.10: Average Latency vs. Buffer Size (INFOCOM06 dataset)

For INFOCOM06 experiment, MSM protocol has a higher average latency than Epidemic and Bubble Rap protocols for all buffer size scenarios. Comparing with Epidemic the increase in average latency is, on average, 72% for low buffer size scenario, 19% for medium buffer size scenario and 10% for high buffer size scenarios. Comparing with PRoPHET Protocol the increase in average latency is, on average, 7% for low buffer size scenario, 15% for medium buffer size scenario and 27% for high buffer size scenario. While against Bubble Rap, the increase in average latency is, on average, 22% for low buffer size scenario, 17% for medium buffer size scenario and 15% for high buffer size scenario respectively.

The increase in the average latency of MSM protocol compared with other routing schemes, which is clear in INFOCOM06 experiment, is a result of applying strict social based forwarding strategy, this leads to storing the messages for a longer time in intermediate nodes' buffers and hence increases the average latency in the network.

5.4.1.4 Average Hop Count vs. Buffer Size

In this section, the average hop metric is evaluated for MSM, Epidemic, PRoPHET and Bubble Rap routing protocols against different buffer size levels. Table 5.11 and Figure 5.11 show the experiment results for Cambridge dataset.

Table 5.11: Average Hop Count vs. Buffer Size (Cambridge dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM VS Epidemic	MSM VS PRoPHET	MSM VS Bubble Rap
low	1	5.67	2.56	1.98	1.79	-68%	-30%	-10%
	2	7.37	2.80	2.09	1.85	-75%	-34%	-11%
	5	7.35	2.88	2.19	1.93	-74%	-33%	-12%
Medium	15	6.33	3.29	2.20	2.04	-68%	-38%	-7%
	25	5.82	3.37	2.23	2.07	-64%	-39%	-7%
	35	5.82	3.34	2.24	2.06	-65%	-38%	-8%
High	45	5.23	3.27	2.27	2.06	-61%	-37%	-9%
	55	4.93	3.15	2.26	2.07	-58%	-34%	-8%

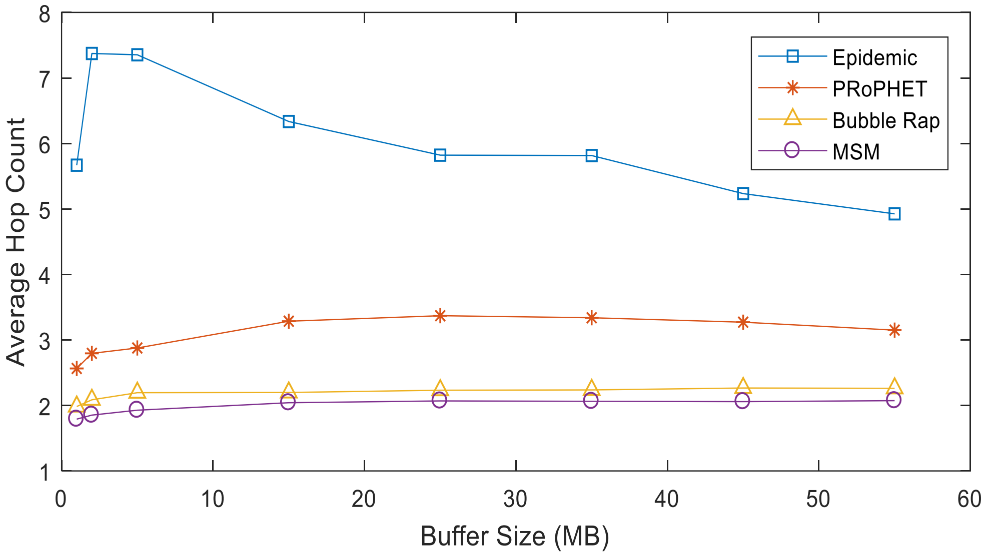


Figure 5.11: Average Hop Count vs. Buffer Size (Cambridge dataset)

For Cambridge experiment, MSM has the lowest average hop count compared with the other protocols. The average reduction percentage is 72%, 32% and 11% in low buffer size scenario and 66%, 38% and 7% in medium buffer size scenario and is 60%, 36% and 9%, compared with Epidemic, PRoPHET and Bubble Rap respectively.

Similar achievement can be seen also for INFOCOM05 dataset, its results are depicted in Table 5.12 and Figure 5.12.

Table 5.12: Average Hop Count vs. Buffer Size (INFOCOM05 dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM VS Epidemic	MSM VS PRoPHET	MSM VS Bubble Rap
low	1	5.74	3.31	2.19	1.89	-67%	-43%	-14%
	2	8.30	3.76	2.30	1.98	-76%	-47%	-14%
	5	7.79	4.09	2.43	2.05	-74%	-50%	-15%
Medium	15	6.89	3.74	2.53	2.09	-70%	-44%	-17%
	25	5.65	3.51	2.52	2.11	-63%	-40%	-16%
	35	4.92	3.34	2.49	2.11	-57%	-37%	-15%
High	45	4.71	3.29	2.51	2.11	-55%	-36%	-16%
	55	4.37	3.27	2.48	2.08	-52%	-36%	-16%

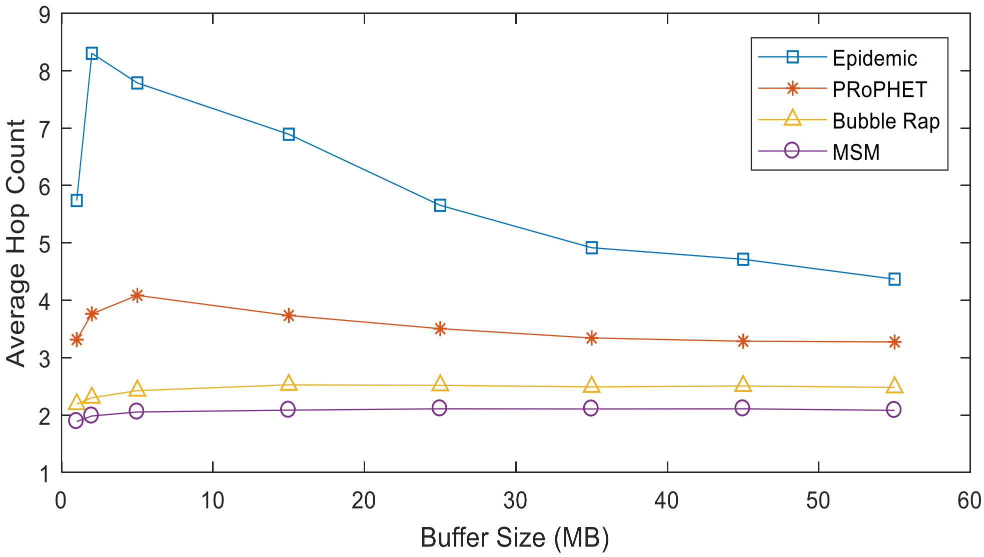


Figure 5.12: Average Hop Count vs. Buffer Size (INFOCOM05 dataset)

MSM outperforms all other protocols and reduces the average hop count in the network, on average, with 64%, 41%, and 15% compared with Epidemic, PRoPHET and

Bubble Rap respectively. Table 5.13 and Figure 5.13 show the evaluation result of the average hop count metric for INFOCOM06 dataset.

Table 5.13: Average Hop Count vs. Buffer Size (INFOCOM06 dataset)

Buffer Size Level	Buffer Size (MB)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM VS Epidemic	MSM VS PRoPHET	MSM VS Bubble Rap
low	1	12.54	3.75	2.67	1.58	-87%	-58%	-41%
	2	13.03	3.77	2.74	1.65	-87%	-56%	-40%
	5	10.82	3.90	2.84	1.70	-84%	-56%	-40%
Medium	15	8.38	3.63	2.93	1.77	-79%	-51%	-39%
	25	7.58	3.48	3.08	1.80	-76%	-48%	-41%
	35	6.75	3.51	3.03	1.81	-73%	-48%	-40%
High	45	5.83	3.48	3.07	1.82	-69%	-48%	-41%
	55	5.29	3.56	2.97	1.82	-66%	-49%	-38%

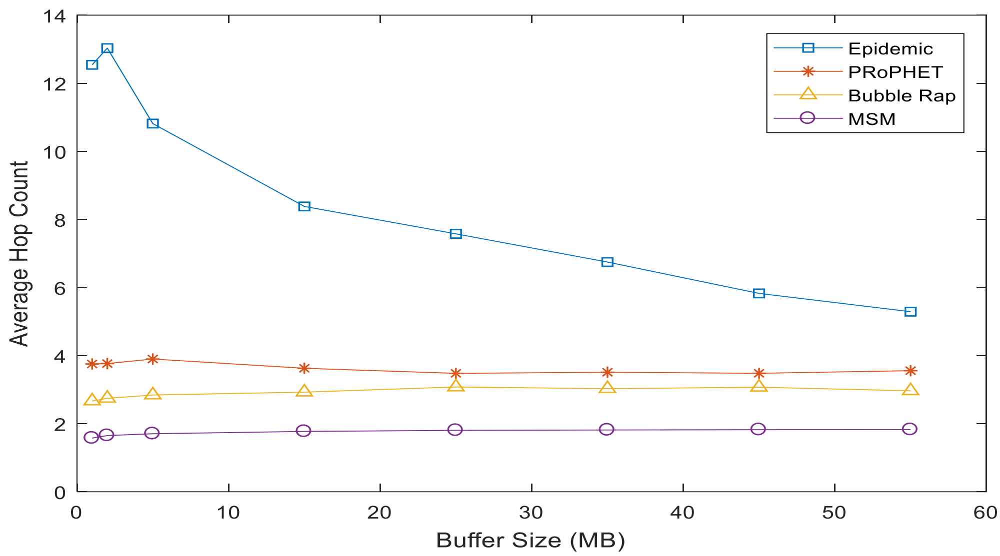


Figure 5.13: Average Hop Count vs. Buffer Size (INFOCOM06 dataset)

Also in this dataset, MSM achieves the lowest average hop count in MSN network. Comparing with Epidemic, PRoPHET and Bubble Rap, the reduction is, on average, 65%, 24%, and 6% respectively.

To understand these results, exploiting three social metrics and considering the mutual impacts among them enables MSM to decrease the number of forwardings in the network. Selecting the next forwarder in MSM depends on the strength of the social relationship with the destination; therefore, a lower number of mobile nodes will contribute to the forwarding process. The result is decreasing the overall average hop count in the MSN network and preserving the network and nodes resources.

5.4.2 Performance Evaluation over Time

This section studies the performance of the proposed protocol MSM along the experiment time. The aim is to study the achievement of MSM against its benchmark protocols over the times of the experiment. For this purpose, messages TTL is set to 600 minutes (10 Hours) and the buffer size to 5MB and change the simulation end time from 14400 seconds (4 Hours) to 144000 seconds (1.6Day) for INFOCOM06 dataset, and from 14400 seconds (4 Hours) to 254150 seconds (2.9 Days) for Cambridge and INFOCOM05 datasets with 4 Hours step. The following sections present the experimental results for the four-evaluation metrics.

The experimented protocols have a changed performance during the experiment time, this is up to the movement scenarios and the changing in the connectivity among mobile nodes and the message generation during the different time periods of the real dataset experiments.

5.4.2.1 Delivery Ratio over Time

Table 5.14 and Figure 5.14 show the change in delivery ratio during the experiment times for Cambridge dataset.

Table 5.14: Delivery Ratio over Time (Cambridge dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	0.233	0.276	0.274	0.262	+12%	-5%	-4%
28800	0.127	0.150	0.156	0.150	+18%	0%	-4%
43200	0.091	0.108	0.114	0.108	+18%	0%	-6%
57600	0.070	0.084	0.087	0.082	+18%	-2%	-6%
72000	0.056	0.066	0.069	0.056	+1%	-15%	-18%
86400	0.048	0.057	0.058	0.056	+18%	-2%	-3%
100800	0.054	0.073	0.067	0.057	+4%	-23%	-15%
115200	0.068	0.106	0.093	0.082	+20%	-23%	-12%
129600	0.068	0.108	0.093	0.084	+23%	-22%	-10%
144000	0.062	0.099	0.089	0.077	+24%	-23%	-13%
158400	0.056	0.091	0.080	0.070	+24%	-24%	-13%
172800	0.052	0.081	0.074	0.065	+24%	-20%	-12%
187200	0.049	0.075	0.066	0.060	+23%	-20%	-8%
201600	0.056	0.092	0.080	0.075	+34%	-19%	-7%
216000	0.056	0.096	0.083	0.078	+40%	-19%	-6%
230400	0.058	0.098	0.087	0.081	+39%	-18%	-7%
244800	0.056	0.096	0.083	0.079	+41%	-18%	-5%
254150	0.057	0.096	0.083	0.077	+-36%	-20%	-8%

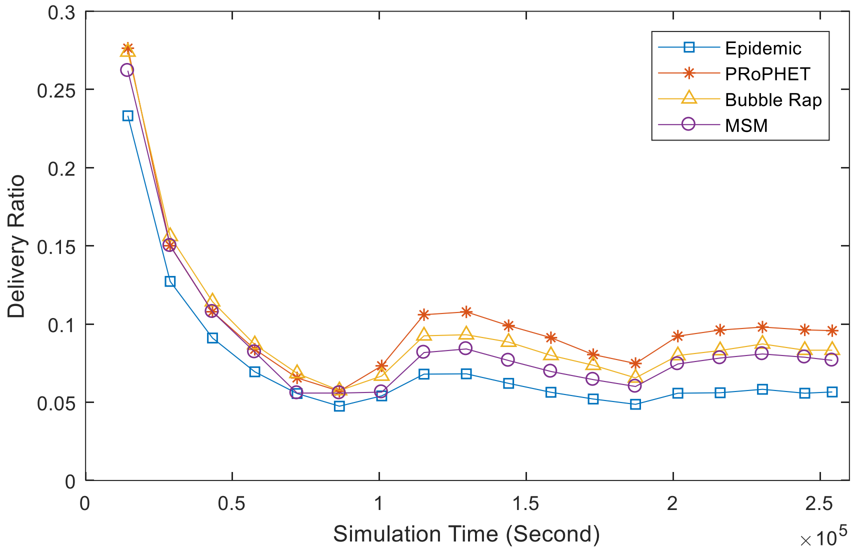


Figure 5.14: Delivery Ratio over Time (Cambridge dataset)

MSM protocol increases the delivery ratio compared with Epidemic, the percentage of the increase is, on average, along the experiment time is 23%. Comparing with PRoPHET and Bubble Rap protocols, MSM achieves very close but lower messages' deliver ratio on average 15% and 9% lower than PRoPHET and Bubble Rap respectively. Table 5.15 and Figure 5.15 depict the successful delivery ratio over time for INFOCOM05 dataset.

Table 5.15: Delivery Ratio over Time (INFOCOM05 dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	0.1746	0.1866	0.1938	0.201	+15%	+8%	+4%
28800	0.102	0.1044	0.1116	0.1176	+15%	+13%	+5%
43200	0.0758	0.0774	0.0822	0.0878	+16%	+13%	+7%
57600	0.1683	0.2246	0.1713	0.1725	+2%	-23%	+1%
72000	0.1873	0.2888	0.2328	0.2337	+25%	-19%	0%
86400	0.1895	0.2933	0.2279	0.2259	+19%	-23%	-1%
100800	0.189	0.2972	0.2362	0.239	+26%	-20%	+1%
115200	0.1675	0.266	0.2046	0.2127	+27%	-20%	+4%
129600	0.1499	0.2354	0.1888	0.1901	+27%	-19%	+1%
144000	0.1596	0.2368	0.186	0.1975	+24%	-17%	+6%
158400	0.1825	0.2679	0.2099	0.2271	+24%	-15%	+8%
172800	0.183	0.2707	0.2052	0.2345	+28%	-13%	+14%
187200	0.1716	0.2594	0.1939	0.219	+28%	-16%	+13%
201600	0.1624	0.2363	0.1844	0.2062	+27%	-13%	+12%
216000	0.153	0.2269	0.173	0.1939	+27%	-15%	+12%
230400	0.1719	0.251	0.1908	0.2189	+27%	-13%	+15%
244800	0.1742	0.261	0.1943	0.2246	+29%	-14%	+16%
254150	0.1711	0.2609	0.1878	0.221	+29%	-15%	+18%

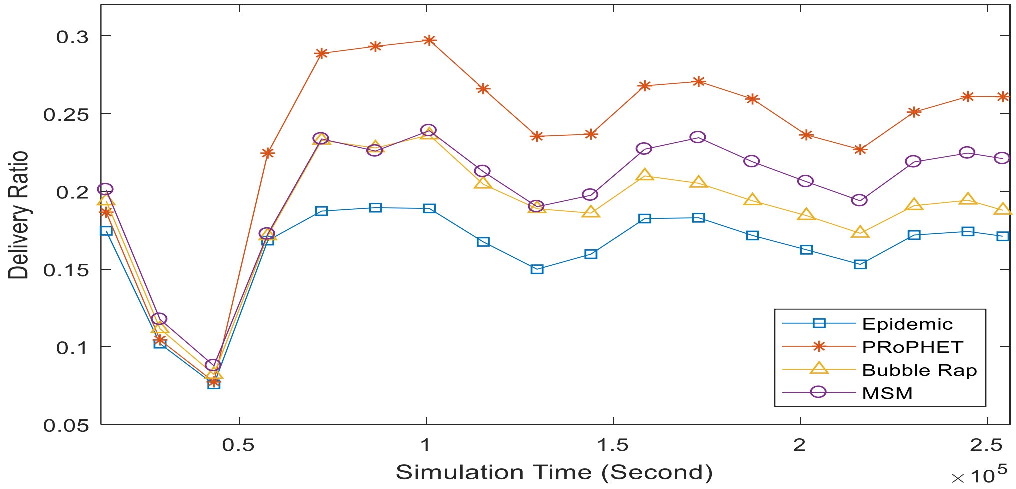


Figure 5.15: Delivery Ratio over Time (INFOCOM05 dataset)

As shown in Table 5.15 and Figure 5.15, at the beginning of the experiment (8 Hours), MSM has a close but slightly higher delivery ratio compared with Epidemic, PRoPHET and Bubble Rap. For the rest time of the experiment, MSM outperforms both Epidemic and Bubble Rap protocols, where it increases the delivery ratio with 25% and 8% on average respectively. Comparing with PRoPHET, MSM protocol has a lower delivery ratio, the decrease in the delivery ratio is 17%. Table 5.16 and Figure 5.16 show the experiment result for INFOCOM06 dataset.

Table 5.16: Delivery Ratio over Time (INFOCOM06 dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	0.11	0.24	0.28	0.40	+277%	+65%	+44%
28800	0.08	0.18	0.20	0.29	+255%	+60%	+45%
43200	0.06	0.14	0.16	0.22	+244%	+59%	+42%
57600	0.17	0.38	0.23	0.48	+177%	+25%	+107%
72000	0.17	0.35	0.22	0.47	+168%	+32%	+111%
86400	0.17	0.35	0.23	0.45	+161%	+28%	+93%
100800	0.15	0.31	0.20	0.40	+159%	+29%	+94%
115200	0.15	0.30	0.20	0.37	+144%	+24%	+87%
129600	0.16	0.30	0.20	0.36	+129%	+19%	+82%
144000	0.17	0.38	0.23	0.41	+136%	+8%	+78%

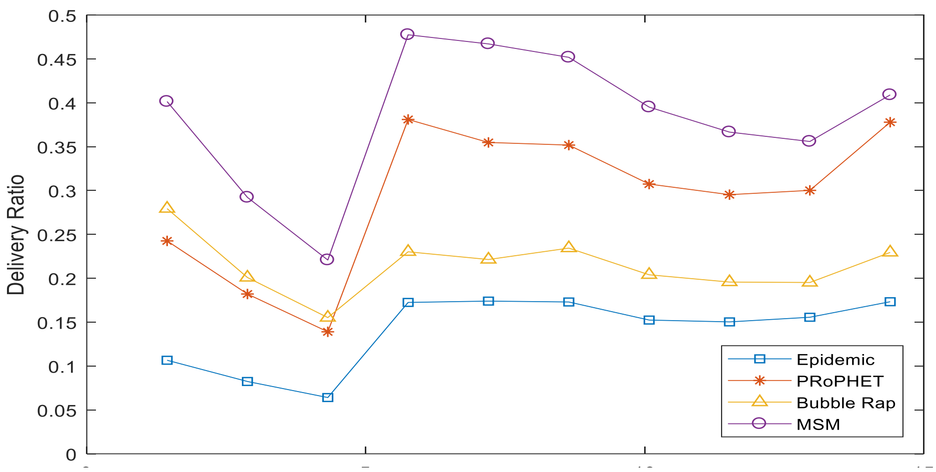


Figure 5.16: Delivery Ratio over Time (INFOCOM06 dataset)

For INFOCOM06 dataset, MSM outperforms all the other protocols along the experiment time. the increase is 185% over Epidemic, 35% over PRoPHET and 78% over Bubble Rap. This is because MSM exploits three social metrics to take the forwarding decision, so it forwards messages to nodes that are socially closer to the destination. In addition, considering the correlation among the different social metrics (similarity adjusts social activity and similarity and contact history adjust centrality) makes the forwarding decision more accurate. Therefore, the selected relays in MSM have a higher probability to encounter the destination and the delivered data amount will be higher. This results in increasing the delivery ratio in the network especially when the number of mobile nodes is high in the network (INFOCOM06 experiment).

5.4.2.2 Overhead Ratio over Time

This section studies the change in the overhead ratio against the experiment time. Table 5.17 and Figure 5.17 show the results for Cambridge dataset.

Table 5.17: Overhead Ratio over Time (Cambridge dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	730.94	482.77	47.08	21.92	-97%	-95%	-53%
28800	780.98	600.72	49.42	29.54	-96%	-95%	-40%
43200	730.91	559.44	47.47	27.38	-96%	-95%	-42%
57600	720.59	534.51	48.06	27.23	-96%	-95%	-43%
72000	720.59	545.96	48.78	27.23	-96%	-95%	-44%
86400	705.05	526.15	49.09	26.64	-96%	-95%	-46%
100800	548.08	372.53	41.27	23.39	-96%	-94%	-43%
115200	416.48	248.58	29.20	33.52	-92%	-87%	+15%
158400	386.30	218.58	26.04	35.94	-91%	-84%	+38%
172800	384.31	231.00	25.98	35.66	-91%	-85%	+37%
187200	382.20	229.53	26.78	35.33	-91%	-85%	+32%
201600	336.72	192.63	22.23	45.49	-86%	-76%	+105%
230400	323.38	193.53	20.01	67.38	-79%	-65%	+237%
244800	323.80	196.77	20.56	69.77	-78%	-65%	+239%
254150	309.44	189.41	19.53	68.93	-78%	-64%	+253%

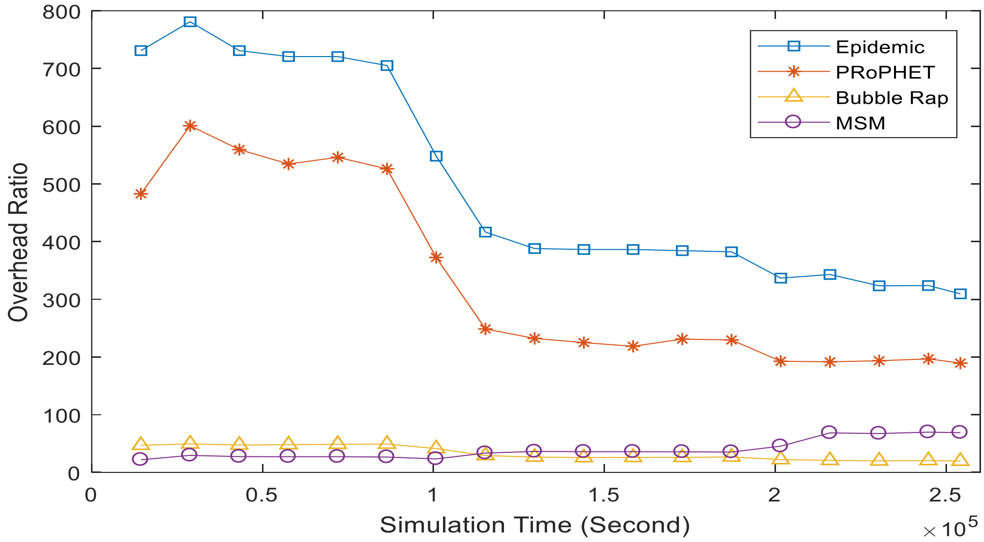


Figure 5.17: Overhead Ratio over Time (Cambridge dataset)

The results show that MSM protocol has a very low overhead ratio. Comparing with other protocols, MSM outperforms significantly both Epidemic and PRoPHET Protocols, it has, on average, 90% and 84% lower overhead ratio respectively. Regarding the social-based protocol i.e. Bubble Rap, MSM starts the experiment outperforming it until the time: 1day and 4h, then it has a higher overhead ratio for the rest of the experiment. Table 5.18 and Figure 5.18 show the evaluation results for INFOCOM05 dataset.

As can be seen, MSM protocol has a lower overhead ratio than Epidemic (on average, the reduction is 63%) and PRoPHET (on average, the reduction is 45%) along all the experiment time. Comparing with Bubble Rap, MSM starts the experiment with a higher overhead ratio and with the increase in experiment time; its performance becomes better until it outperforms Bubble Rap for the last seven periods of the experiment.

Table 5.18: Overhead Ratio over Time (INFOCOM05 dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	581.29	481.55	135.98	181.74	-69%	-62%	+34%
28800	579.99	501.28	130.12	208.21	-64%	-58%	+60%
43200	552.40	476.63	129.79	263.66	-52%	-45%	+103%
57600	295.52	200.23	84.93	143.85	-51%	-28%	+69%
72000	402.46	241.48	114.91	150.22	-63%	-38%	+31%
86400	383.60	224.75	120.35	150.42	-61%	-33%	+25%
100800	416.42	253.96	136.75	154.66	-63%	-39%	+13%
115200	415.51	249.93	138.41	155.81	-63%	-38%	+13%
129600	417.44	250.48	134.77	155.34	-63%	-38%	+15%
144000	379.99	246.42	130.18	142.58	-62%	-42%	+10%
158400	362.71	234.19	129.87	131.22	-64%	-44%	+1%
172800	371.69	242.42	138.96	128.52	-65%	-47%	-8%
187200	368.16	235.04	137.30	129.74	-65%	-45%	-6%
201600	363.28	243.90	135.38	128.16	-65%	-47%	-5%
216000	362.90	240.84	133.73	128.36	-65%	-47%	-4%
230400	334.97	224.16	126.74	113.47	-66%	-49%	-10%
244800	344.56	227.64	129.83	111.59	-68%	-51%	-14%
254150	349.60	227.06	131.87	112.32	-68%	-51%	-15%

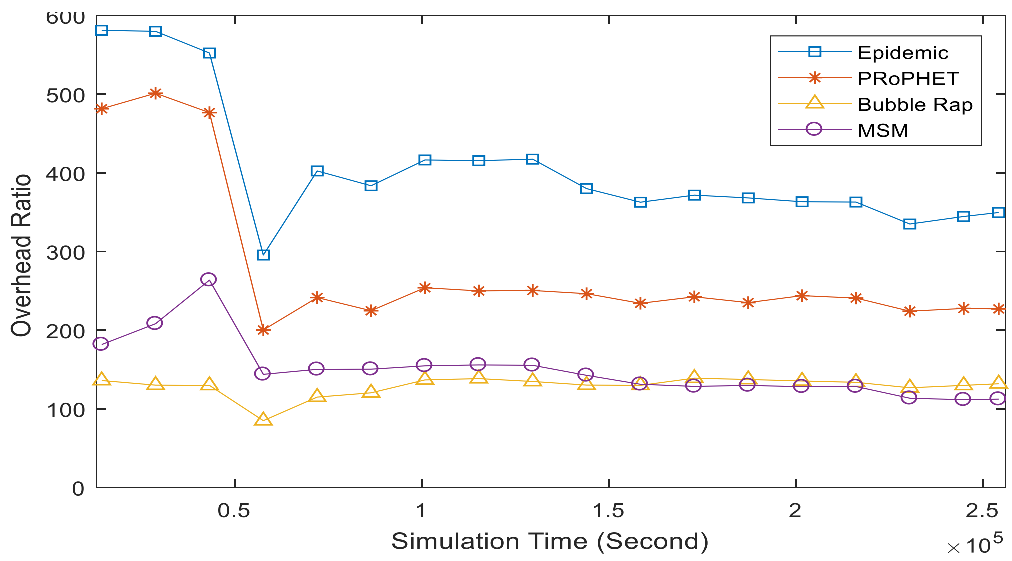


Figure 5.18: Overhead Ratio over Time (INFOCOM05 dataset)

For INFOCOM06 dataset, Table 5.19 and Figure 5.19 show the evaluation results.

Table 5.19: Overhead Ratio over Time (INFOCOM06 dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	530.8	287.44	109.6	20.62	-96%	-93%	-81%
28800	551.6	304.01	104.8	50.55	-91%	-83%	-52%
43200	511.3	277.69	94.94	67.05	-87%	-76%	-29%
57600	978.0	446.04	431.2	31.88	-97%	-93%	-93%
72000	1465.3	705.05	709.4	32.68	-98%	-95%	-95%
86400	1713.5	820.77	779.8	32.68	-98%	-96%	-96%
100800	1699.7	840.56	784.1	35.73	-98%	-96%	-95%
115200	1532.8	784.15	725.5	35.99	-98%	-95%	-95%
129600	1354.5	700.37	656.9	36.09	-97%	-95%	-95%
144000	1313.2	594.35	599.7	30.93	-98%	-95%	-95%

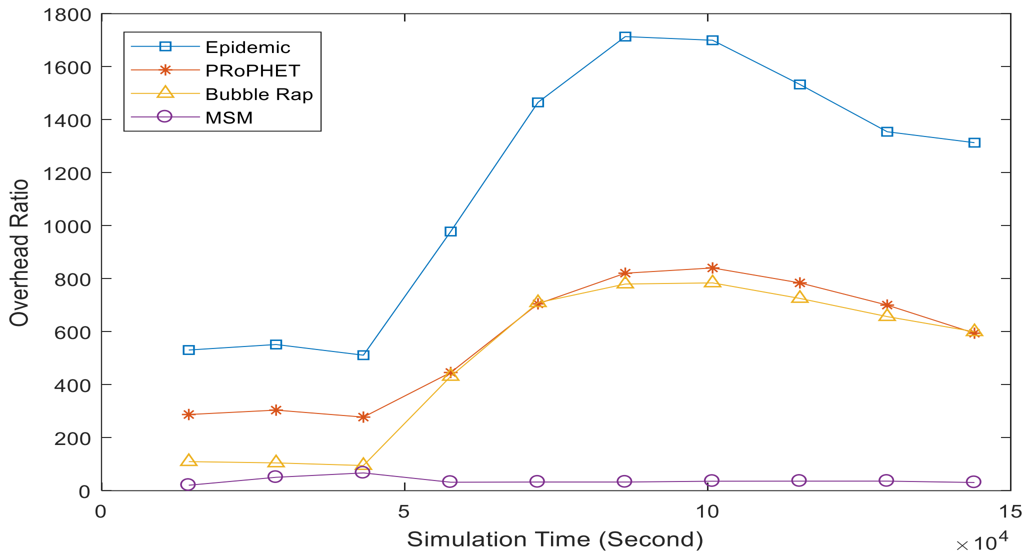


Figure 5.19: Overhead Ratio over Time (INFOCOM06 dataset)

MSM outperforms all other benchmark protocols and reduces the overhead ratio, 96% and 92% and 83% compared with Epidemic, PRoPHET and Bubble Rap respectively. This because MSM control the number of the message forwarding in the network by forwarding messages only to that nodes have close relation with the message destination.

Based on the results of the three experiments it is shown that MSM is able to significantly control the overhead in OMSN. The reason is that MSM applies strict rules to select the relay node where three social metrics are evaluated and used to make the forwarding decision. This decreases the number of forwardings in the network and hence decrease the delivery overhead in the network. MSM achieves a higher reduction in delivery overhead in INFOCOM06 experiment than INFOCOM05. This is because INFOCOM06 has a higher number of mobile nodes, so the exploiting of social information has more impact on the routing performance.

5.4.2.3 Average Latency over Time

This section studies the performance evaluation in term of average latency along the experiment time for MSM protocol and the other benchmark protocols. Table 5.20 and Figure 5.20 show the results for Cambridge dataset.

Table 5.20: Average Latency over Time (Cambridge dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	1799.6	1653.9	2128.1	2274	+26%	+38%	+7%
28800	2307.6	2360.0	2816.3	2942	+28%	+25%	+4%
43200	2817.8	2403.9	2968.7	3191	+13%	+33%	+7%
57600	2895.2	2354.0	2999.4	3306	+14%	+40%	+10%
72000	2895.2	2466.3	2950.3	3306	+14%	+34%	+12%
86400	3301.6	2957.9	3199.1	3643	+10%	+23%	+14%
100800	6347.1	7895.0	6162.5	5606	-12%	-29%	-9%
115200	9429.1	10889.2	9803.8	10099	+7%	-7%	+3%
129600	9414.2	11467.4	9943.2	10699	+14%	-7%	+8%
144000	9391.1	11341.1	10222.4	10656	+13%	-6%	+4%
158400	9391.1	11422.2	10137.7	10656	+13%	-7%	+5%
172800	9549.8	11693.8	10046.0	10843	+14%	-7%	+8%
187200	9595.1	11633.3	9880.1	10868	+13%	-7%	+10%
230400	10556.6	12650.1	11333.0	12170	+15%	-4%	+7%
244800	10669.6	12846.8	11327.0	12381	+16%	-4%	+9%
254150	10893.4	12864.5	11619.6	12414	+14%	-45%	+7%

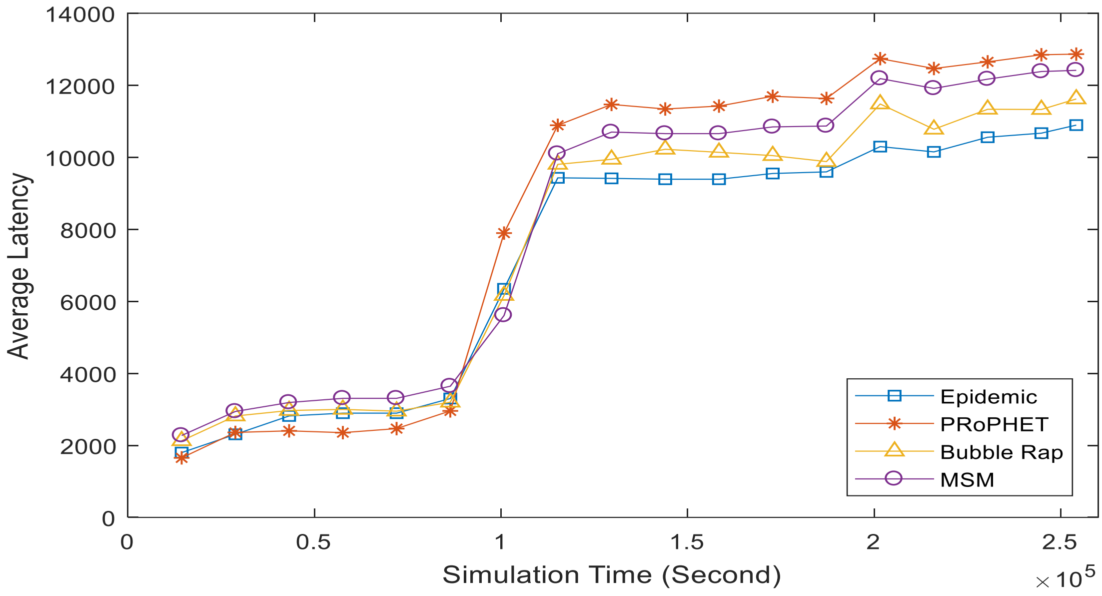


Figure 5.20: Average Latency over Time (Cambridge dataset)

The experimented protocols have a changed performance during the experiment time, this is up to the movement scenarios and the changing in the connectivity among mobile nodes and the message generation during the real dataset experiment. With the increase in the experiment time, new social relations are created, hence the amount of the information exchanged between mobile users in the network increases during the experiment and consequently the average latency for all delivered messages in OMSN increases.

It can be seen that MSM has close average latency to PRoPHET and Bubble Rap. Comparing with Epidemic, MSM protocol has higher end-to-end due to that it is a social-based forwarding protocol, so it is more conservative in forwarding the messages while Epidemic is flooding-based one. Table 5.21 and Figure 5.21 show the evaluation of average latency against experiment time for INCOCOM05 experiment.

Table 5.21: Average Latency over Time (INFOCOM05 dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	Epidemic	PRoPHET	Bubble Rap
14400	760.79	654.6	853.8	814.0	7%	24%	-5%
28800	1221.72	1094.0	1106.1	1166.2	-5%	7%	5%
43200	1123.38	821.9	1025.5	1246.7	11%	52%	22%
57600	9730.22	10926.8	8978.2	10068.6	3%	-8%	12%
72000	7916.25	10401.6	9891.8	8957.6	13%	-14%	-9%
86400	7994.67	10327.3	9404.2	8482.8	6%	-18%	-10%
100800	7615.97	9621.8	8937.1	7910.2	4%	-18%	-11%
115200	7659.49	9702.4	8852.2	8060.4	5%	-17%	-9%
129600	7605.08	9633.3	8898.8	8015.3	5%	-17%	-10%
144000	8851.71	10306.0	9247.0	9133.9	3%	-11%	-1%
158400	9416.71	10494.9	9818.7	9881.1	5%	-6%	1%
172800	9250.67	10494.6	9292.8	9559.4	3%	-9%	3%
187200	9207.48	10482.2	9498.2	9516.0	3%	-9%	0%
201600	9213.75	10126.4	9387.1	9526.9	3%	-6%	1%
216000	9171.14	10235.3	9339.5	9484.3	3%	-7%	2%
230400	10326.97	11211.3	9953.4	10355.5	0%	-8%	4%
244800	10268.52	11225.0	10202.0	10355.9	1%	-8%	2%
254150	10196.91	11208.9	9903.9	10331.5	1%	-8%	4%

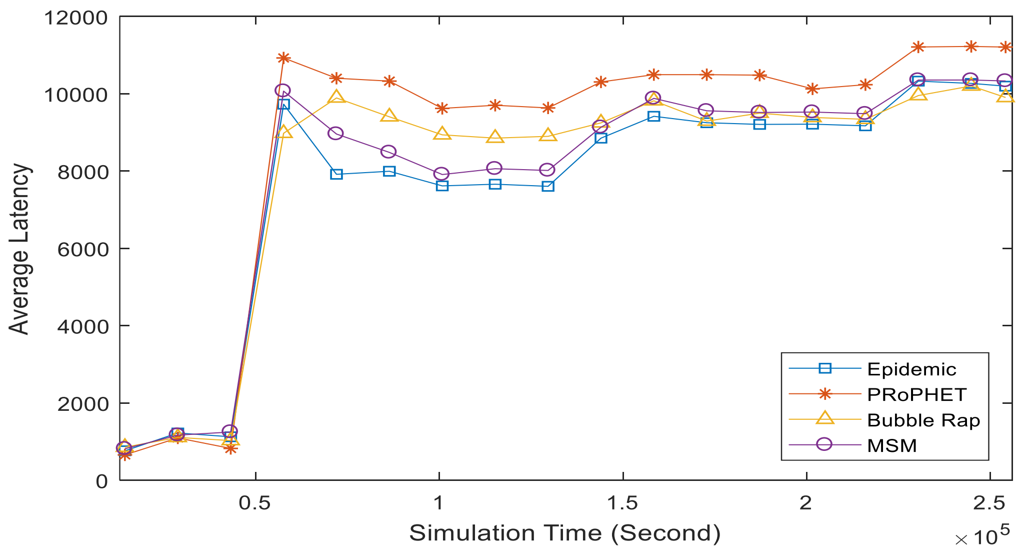


Figure 5.21: Average Latency over Time (INFOCOM05 dataset)

As can be seen, Epidemic protocol has the lowest end-to-end delay because it is a flooding-based forwarding protocol resulting in delivering the messages in a shorter time.

MSM and Bubble Rap, which are social based routing schemes, have similar performance in terms of average latency and they outperform PRoPHET Protocol. For INFOCOM06, evaluation results are shown in Table 5.22 and Figure 5.22.

Table 5.22: Average Latency over Time (INFOCOM06 dataset)

Experiment Time (Seconds)	**Epidemic**	**PRoPHET**	**Bubble Rap**	**MSM**	**Epidemic**	**PRoPHET**	**Bubble Rap**
14400	989.76	804.2	611.4	1576.9	+59%	+96%	+158%
28800	2928.65	2679.5	2493.3	3138.20	+7%	+17%	+26%
43200	3319.54	4300.1	3638.2	4284.85	+29%	+1%	+18%
57600	8213.38	10335.1	7846.0	10864.3	+32%	+5%	+38%
72000	6987.14	9351.4	7861.2	10375.7	+48%	+11%	+32%
86400	6439.84	8963.8	10455.2	10082.5	+57%	+12%	-4%
100800	6550.31	8951.0	10471.4	10116.5	+54%	+13%	-3%
115200	7179.51	9462.2	11899.1	10344.9	+44%	+9%	-13%
129600	7638.50	10135.5	12900.2	10756.6	+41%	+6%	-17%
144000	8122.76	11491.6	15568.0	11714.2	+44%	+2%	-25%

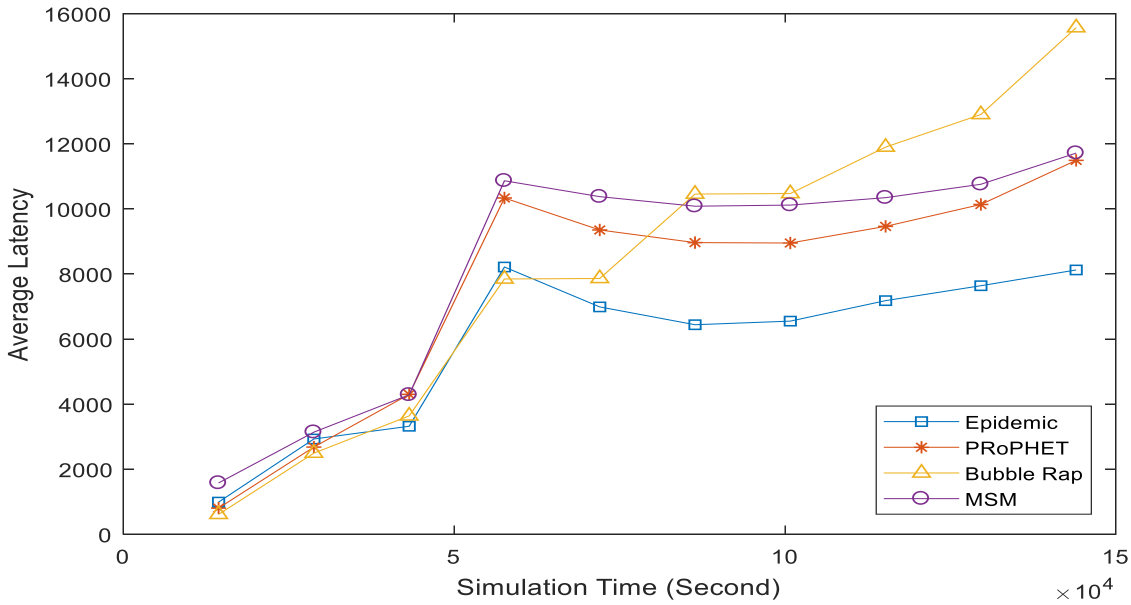


Figure 5.22: Average Latency over Time (INFOCOM06 dataset)

Also in this experiment, Epidemic outperforms the other protocols because it is flooding-based routing protocol. MSM has almost a similar and slightly higher end-to-end delay compared with PRoPHET. Comparing with Bubble Rap, it starts with higher latency until approximately half of the experiment time (86400 minutes), then it becomes more efficient than Bubble Rap with a lower average latency.

Based on the experimental results for Cambridge, INFOCOM05 and INFOCOM06 datasets, it can be said that Epidemic has the best achievement regarding average latency over time and this is because, as mentioned before, it is a flooding-based protocol. However, in INFOCOM05 experiment, MSM has, on average, lower average latency compared with Bubble Rap and PRoPHET Protocols and has very close achievement compared to Epidemic. In INFOCOM06 experiment, MSM almost has similar average latency compared to PRoPHET and it outperforms Bubble Rap at the end of the experiment.

5.4.2.4 Average Hop Count over Time

The average hop count is evaluated in this section along the experiment time. Table 5.23 and Figure 5.23 record the performance evaluation for the experienced routing protocols: MSM, Epidemic, PRoPHET and Bubble Rap through the simulation time.

Table 5.23: Average Hop Count over Time (Cambridge dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	8.97	3.21	2.62	1.72	-81%	-46%	-34%
28800	9.30	3.34	2.55	1.73	-81%	-48%	-32%
43200	8.94	3.09	2.45	1.67	-81%	-46%	-32%
57600	8.81	3.11	2.48	1.66	-81%	-46%	-33%
72000	8.81	2.80	2.47	1.66	-81%	-40%	-33%
86400	8.61	3.12	2.47	1.65	-81%	-47%	-33%
100800	7.05	2.80	2.26	1.57	-78%	-44%	-30%
115200	6.13	2.19	2.18	1.65	-73%	-25%	-24%
129600	6.09	2.24	2.15	1.66	-73%	-26%	-23%
144000	6.03	2.22	2.16	1.65	-73%	-26%	-24%
158400	6.03	2.20	2.13	1.65	-73%	-25%	-23%

Table 5.23 continued

172800	5.99	2.15	2.15	1.64	-73%	-23%	-23%
187200	5.94	2.12	2.17	1.64	-72%	-23%	-25%
201600	5.50	2.09	2.09	1.69	-69%	-19%	-20%
216000	5.32	2.08	2.06	1.70	-68%	-18%	-17%
230400	5.17	2.09	2.02	1.71	-67%	-18%	-15%
244800	5.15	2.10	2.05	1.71	-67%	-18%	-17%
254150	4.98	2.17	2.06	1.70	-66%	-225	-17%

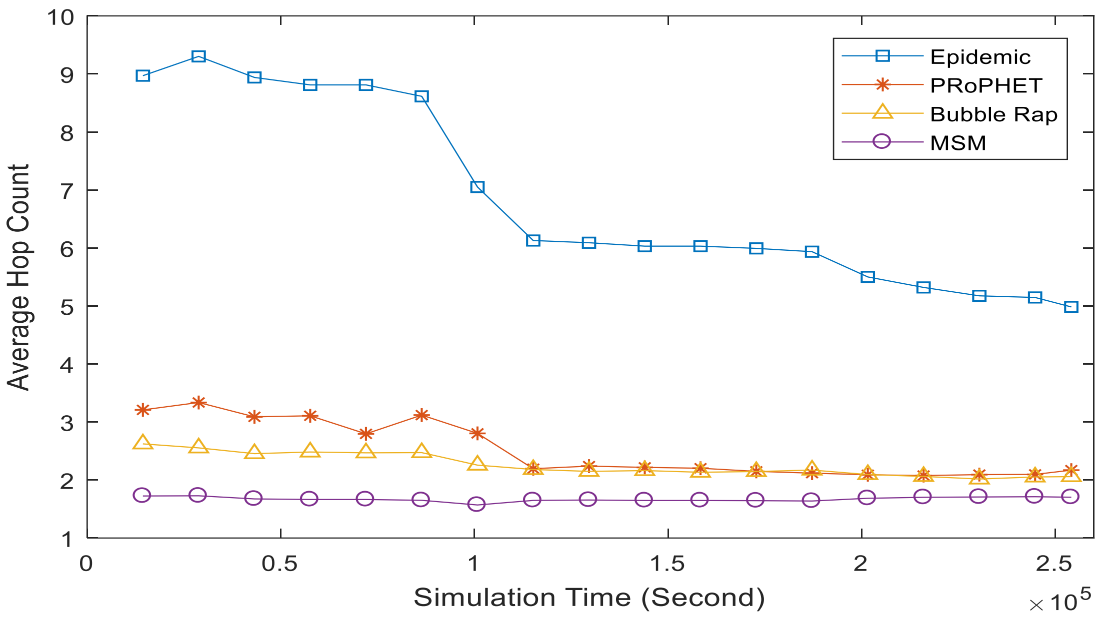


Figure 5.23: Average Hop Count over Time (Cambridge dataset)

Based on the achieved results. MSM protocol outperforms all other routing schemes and achieves the lowest average hop count. It decreases the average hop count, on average, with 74%, 31%, and 25% compared with Epidemic, PRoPHET, and Bubble Rap respectively.

Table 5.24 and Figure 5.24 show the experimental results average hop count with the change in experiment time for INFOCOM05 dataset.

Table 5.24: Average Hop Count over Time (INFOCOM05 dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	4.32	2.67	2.30	1.90	-56%	-29%	-17%
28800	4.24	2.56	2.14	1.81	-57%	-30%	-16%
43200	3.92	2.38	2.04	1.75	-55%	-26%	-14%
57600	5.98	3.53	2.37	1.87	-69%	-47%	-21%
72000	6.36	3.75	2.52	2.05	-68%	-46%	-19%
86400	6.39	3.98	2.67	2.06	-68%	-48%	-23%
100800	6.64	3.86	2.63	2.11	-68%	-45%	-20%
115200	6.61	3.96	2.54	2.11	-68%	-47%	-17%
129600	6.57	4.02	2.55	2.10	-68%	-48%	-17%
144000	6.46	3.96	2.52	2.07	-68%	-48%	-18%
158400	6.88	3.96	2.47	2.09	-70%	-47%	-15%
172800	7.53	4.17	2.50	2.10	-72%	-50%	-16%
187200	7.44	4.27	2.47	2.10	-72%	-51%	-15%
201600	7.35	4.15	2.47	2.09	-72%	-50%	-16%
216000	7.29	4.07	2.39	2.08	-71%	-49%	-13%
230400	7.56	4.17	2.41	2.04	-73%	-51%	-15%
244800	7.80	4.21	2.41	2.05	-74%	-51%	-15%
254150	7.79	4.21	2.40	2.05	-74%	-51%	-155

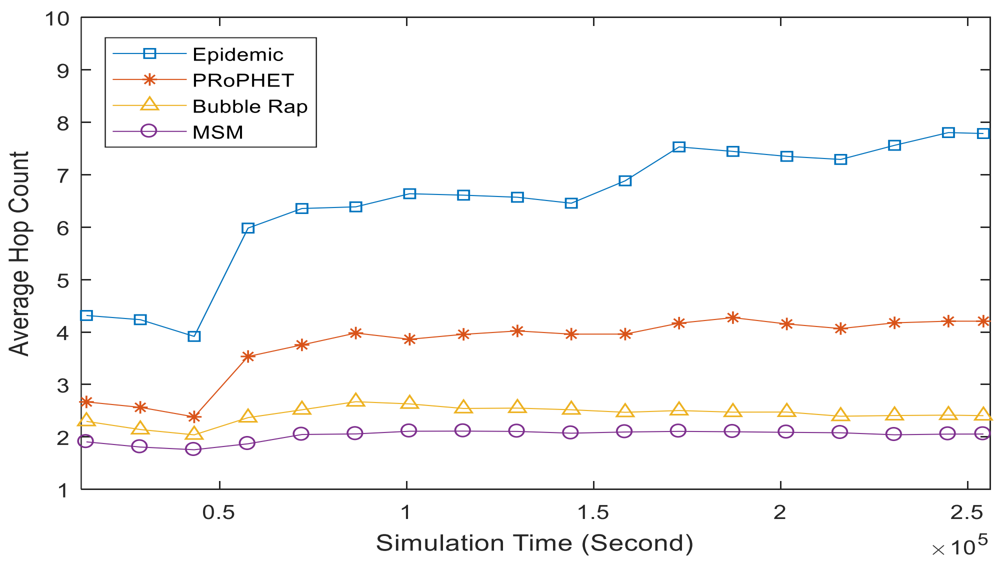


Figure 5.24: Average Hop Count over Time (INFOCOM05 dataset)

For INFOCOM05 experiment, MSM protocol has the superiority achievement over all other routing schemes. On average, it reduces the average hop count by 68%, 58% and 17% compared with Epidemic, PRoPHET and Bubble Rab respectively.

Similar results can be seen for INFOCOM06 experiment, Table 5.25 and Figure 5.25 show that MSM has lower hops count compared with Epidemic, PRoPHET and Bubble Rap, where the average decrement is 82%, 53%, and 41% respectively.

Table 5.25: Average Hop Count over Time (INFOCOM06 dataset)

Experiment Time (Seconds)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
14400	4.83	3.05	2.83	1.57	-67%	-48%	-44%
28800	7.23	3.08	2.69	1.66	-77%	-46%	-38%
43200	7.38	3.20	2.76	1.72	-77%	-46%	-38%
57600	9.69	3.55	2.62	1.58	-84%	-56%	-40%
72000	10.86	3.63	2.73	1.60	-85%	-56%	-41%
86400	11.36	3.77	2.86	1.61	-86%	-57%	-44%
100800	11.95	3.74	2.83	1.61	-87%	-57%	-43%
115200	12.03	3.75	2.87	1.64	-86%	-56%	-43%
129600	11.75	3.69	2.88	1.69	-86%	-54%	-41%
144000	11.34	3.78	2.90	1.70	-85%	-55%	-41%

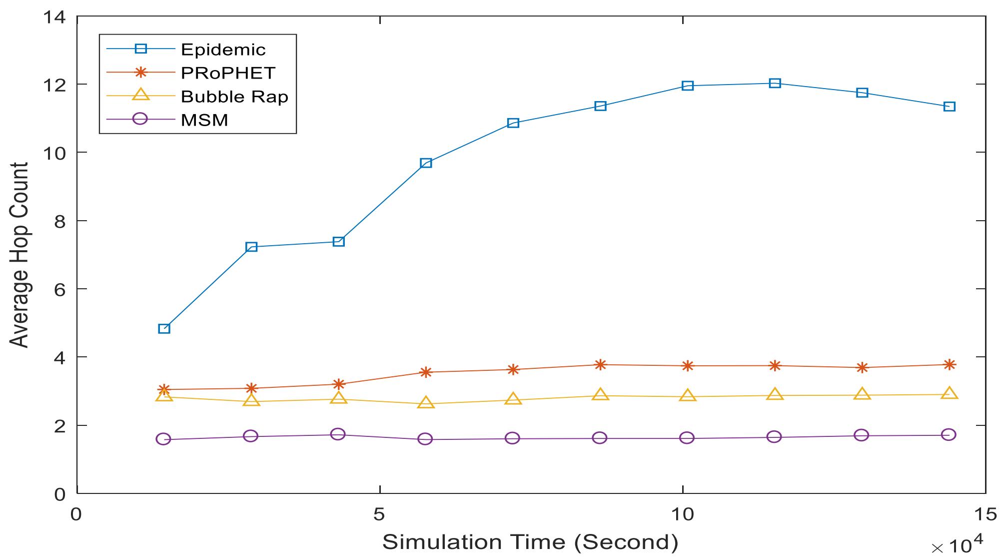


Figure 5.25: Average Hop Count over Time (INFOCOM06 dataset)

Exploiting three social metrics and considering the mutual impacts among them enables MSM to decrease the number of forwardings in the network. As selecting the next forwarder in MSM is based on the strength of the social relationship with the destination, a lower number of mobile nodes will contribute to the forwarding process. Therefore, the overall hops required to deliver the message is decreased in the MSN network, which in its turn results in preserving network and nodes resources.

5.4.3 Performance Evaluation for Different TTL

Message's TTL has high impact on data dissemination in OMSN network. Low TTL values may lead to dropping messages before delivering, and on another hand, high TTL values can cause congestion in the mobile nodes.

This section investigates the impact of TTL value on the routing efficiency of MSM and its benchmarks schemes by changing TTL from low value (10 Minutes) to high value (1.6 Days). This is applied for the three datasets: Cambridge, INFOCOM05, and INFOCOM06 and then evaluate the different performance metrics.

5.4.3.1 Delivery Ratio vs. TTL

Table 5.26 and Figure 5.26 present the evaluation results of the delivery ratio metric against different TTL values for Cambridge dataset.

Table 5.26: Delivery Ratio vs. TTL (Cambridge dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	0.04	0.04	0.03	0.02	-45%	-38%	-20%
30	0.06	0.06	0.04	0.04	-37%	-36%	-14%
60	0.08	0.07	0.06	0.05	-33%	-26%	-11%
240	0.07	0.10	0.09	0.09	+28%	-15%	+3%
480	0.08	0.13	0.10	0.11	+35%	-18%	+7%
960	0.10	0.16	0.12	0.13	+36%	-19%	+13%
1200	0.09	0.16	0.12	0.13	+39%	-20%	+11%
1440	0.09	0.16	0.12	0.13	+38%	-19%	+11%
1680)	0.09	0.16	0.12	0.13	+39%	-19%	+13%
1920	0.09	0.16	0.12	0.13	+40%	-19%	+13%
2160	0.09	0.16	0.12	0.13	+39%	-19%	+13%
2400	0.10	0.16	0.12	0.13	+36%	-18%	+11%

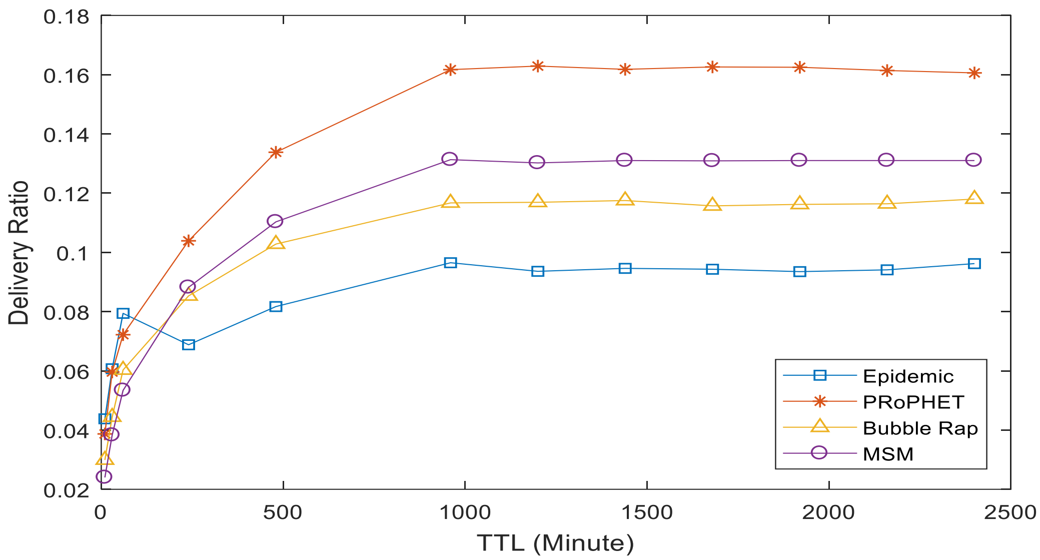


Figure 5.26: Delivery Ratio vs. TTL (Cambridge dataset)

All the experimented protocols achieve a low delivery ratio for low TTL values (10, 30, 60 minutes) due to the high message dropping rate, and Epidemic protocol is affected more than other protocols where it performs better than the other protocols for these scenarios. This is because it is a flooding-based protocol so the high rate of replications decreases the negative impact of messages' dropping due to TTL expiration. With the increase in TTL Epidemic becomes worse than the other protocols because of the congestion and buffers' overflow due to carrying messages for a longer time in nodes' buffers.

It can be seen from the results that MSM protocol has the lowest delivery ratio for these values compared with other protocols because it is stricter in selecting the next relay node. However, increasing TTL value (4 Hours and higher) enables MSM to outperform both Epidemic and Bubble Rap routing protocols because messages can be carried for a long time without being dropped until MSM selects the appropriate relay node based on the exploited social metrics. The increase in the delivery ratio is, on average, 37% and 11% over Epidemic and Bubble Rap respectively. Comparing with PRoPHET Protocol, MSM achieves lower delivery for all TTL values. MSM has, on average, 33% and 19% achievement lower than PRoPHET does for low and high TTL values respectively. Similar results can be seen in Table 5.27 and Figure 5.27 for INFOCOM05 experiment.

Table 5.27: Delivery Ratio vs. TTL (INFOCOM05 dataset)

TTL Minutes	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	0.09	0.08	0.06	0.04	-51%	-43%	-24%
30	0.15	0.13	0.10	0.08	-42%	-36%	-17%
60	0.16	0.17	0.15	0.13	-22%	-25%	-13%
240	0.17	0.22	0.18	0.19	+18%	-13%	+10%
480	0.17	0.25	0.18	0.21	+25%	-14%	+16%
960	0.17	0.27	0.20	0.24	+39%	-13%	+20%
1200	0.18	0.27	0.20	0.24	+30%	-11%	+20%
1440	0.17	0.27	0.19	0.23	+34%	-13%	+21%
1680	0.18	0.27	0.19	0.23	+30%	-13%	+22%
1920	0.17	0.26	0.19	0.24	+39%	-9%	+23%
2160	0.16	0.26	0.19	0.23	+42%	-11%	+24%
2400	0.18	0.26	0.19	0.24	+33%	-11%	+23%

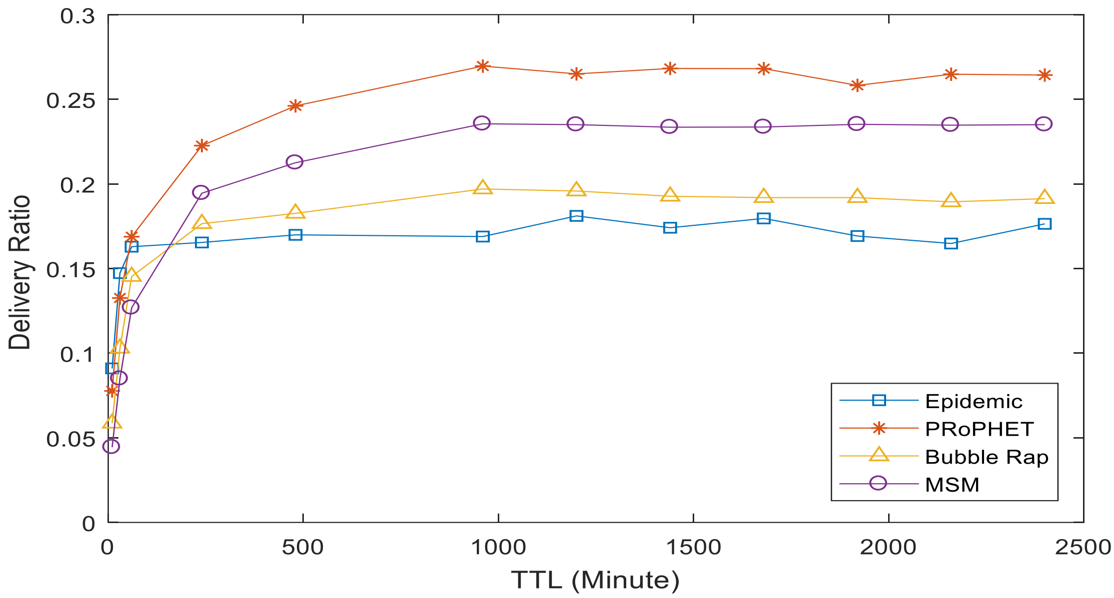


Figure 5.27: Delivery Ratio vs. TTL (INFOCOM05 dataset)

Also in this experiment, MSM protocol has lower delivery ratio compared with other protocols for low TTL values, while its performance becomes better when increasing TTL value (4 Hours and higher). For low TTL values (10, 30, 60 Minutes), the percentage differences are 39%, 35%, and 18% lower than Epidemic, PRoPHET and Bubble Rap respectively. For higher TTL values, MSM achieves, on average, 32% and 20% delivery ratio higher than Epidemic and Bubble Rap respectively, while still has a lower value compared with PRoPHET with an average decrement of 12%.

As it has been shown for Cambridge and INFOCOM05 experiments, in the scenarios of very low TTL values (10, 30 and 60 Minutes), MSM has the lowest delivery ratio compared with Epidemic, PRoPHET and Bubble Rap. This is because MSM restricts the selection of the next relay according to the evaluation of the social metric and the social tie with the destination. Therefore, a low number of messages will be delivered and the other will be dropped due to TTL expiration. This results in a very low number of delivered messages and hence low delivery ratio. However, increasing TTL value gives messages more time to be buffered before being dropped, this gives the opportunity to encounter other intermediate nodes that fulfill the MSM conditions to select the relay node and forward the messages. Consequently, MSM achieves better delivery ratio. The evaluation results of INFOCOM06 experiment are shown in Table 5.28 and Figure 5.28.

Table 5.28: Delivery Ratio vs. TTL (INFOCOM06 dataset)

TTL Minutes	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	0.20	0.18	0.12	0.07	-65%	-61%	-43%
30	0.27	0.24	0.19	0.12	-56%	-51%	-38%
60	0.26	0.26	0.22	0.17	-36%	-36%	-23%
240	0.19	0.32	0.24	0.30	+58%	-7%	+23%
480	0.17	0.37	0.25	0.38	+120%	+3%	+52%
960	0.15	0.36	0.25	0.43	+178%	+19%	+70%
1200	0.14	0.35	0.24	0.42	+196%	+23%	+74%
1440	0.15	0.34	0.24	0.42	+188%	+22%	+74%
1680	0.14	0.33	0.23	0.41	+185%	+23%	+75%
1920	0.14	0.33	0.23	0.41	+202%	+23%	+74%
2160	0.14	0.33	0.23	0.40	+181%	+24%	+76%
2400	0.13	0.32	0.23	0.40	+202%	+27%	+76%

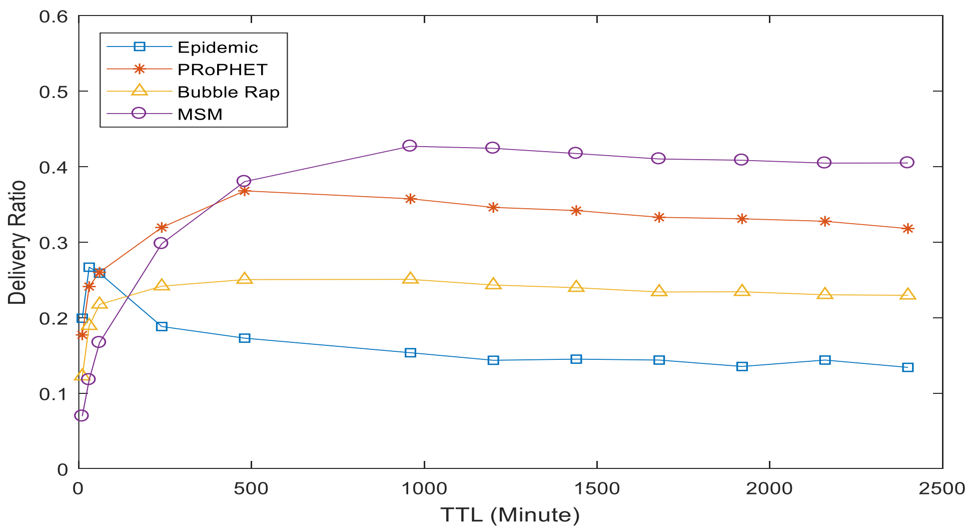


Figure 5.28: Delivery Ratio vs. TTL (INFOCOM06 dataset)

Although MSM protocol has a lower delivery ratio when TTL value is low (less than 8 Hours), it achieves better delivery ratio and outperforms all other protocols when TTL is higher than 8 Hours. MSM protocol increases the delivery ratio, on average, with 181%, 21% and 72% compared with Epidemic, PRoPHET and Bubble Rap respectively. This is because the number of mobile nodes in INFOCOM06 dataset is higher than Cambridge and INFOCOM05 datasets, so exploiting the social relations to enhance routing performance has a higher impact.

Regarding the delivery ratio, it can be concluded based on the results shown on previous tables and figures, all routing protocols have a low delivery ratio in low TTL values scenarios due to the high dropping ratio of messages because of expired TTL. Increasing TTL causes rising up the delivery ratio until reach a plateau where increasing TTL values decrease slightly the delivery ratio. MSM protocol has better performance compared with the other protocols when messages have high TTL values and there is a high number of mobile nodes in OMSN network because in such scenarios utilizing social information will be more effective.

5.4.3.2 Overhead Ratio vs. TTL

This section studies the impact of varying TTL values on the overhead ratio. For the three real datasets, the performance of MSM protocol is evaluated and compared with Epidemic, PRoPHET and Bubble Rap protocols. Table 5.29 and Figure 5.29 show the experimental results of Cambridge dataset.

Table 5.29: Overhead Ratio vs. TTL (Cambridge dataset)

TTL Minutes	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	33.26	16.55	11.69	8.25	-75%	-50%	-29%
30	32.50	19.19	11.18	8.89	-73%	-54%	-20%
60	35.97	108.19	11.09	9.62	-73%	-91%	-13%
240	537.38	332.98	69.54	120.1	-78%	-64%	+73%
480	464.03	285.22	79.14	143.9	-69%	-50%	+82%
960	399.34	244.65	81.78	133.6	-67%	-45%	+63%
1200	406.03	240.40	82.25	134.8	-67%	-44%	+64%
1440	403.65	243.76	82.07	133.9	-67%	-45%	+63%
1680	404.22	242.46	82.03	134.3	-67%	-45%	+64%
1920	407.60	241.99	83.38	134.2	-67%	-45%	+61%
2160	405.78	243.50	83.21	134.2	-67%	-45%	+61%
2400	400.27	244.56	81.60	134.2	-66%	-45%	+64%

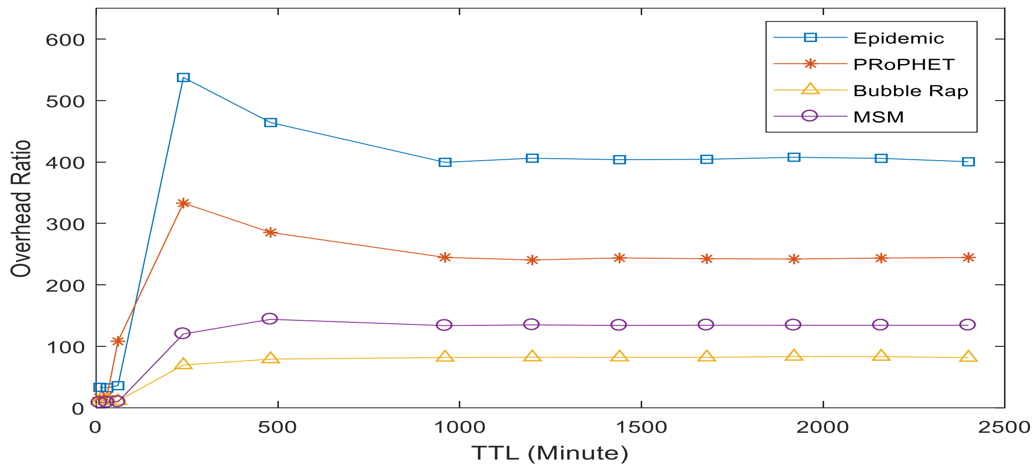


Figure 5.29: Overhead Ratio vs. TTL (Cambridge dataset)

As can be observed, for low TTL value (10, 30, 60 Minutes), MSM protocol achieves the lowest overhead ratio, it decreases the overhead ratio with 74%, 65%, and 21% compared with Epidemic, PRoPHET and Bubble Rap respectively. For higher TTL values, 4 Hours and above, MSM protocol outperforms both Epidemic and PRoPHET with an average decrement of 55% and 49% in overhead ratio respectively. Comparing with Bubble Rap, MSM protocol accomplishes a higher overhead ratio with an average increase of 78%, this is because it is more strictly in selecting the relay nodes, which results in a low number of delivered messages and hence higher overall overhead ratio in the network. Table 5.30 and Figure 5.30 show the evaluation results of INFOCOM05 experiment.

Table 5.30: Overhead Ratio vs. TTL (INFOCOM05 dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	36.26	21.12	15.21	12.0	-67%	-43%	-21%
30	53.55	28.20	16.44	13.4	-75%	-52%	-19%
60	213.25	130.96	32.39	23.5	-89%	-82%	-27%
240	341.26	224.94	107.1	81.0	-76%	-64%	-24%
480	351.52	231.04	132.1	106.5	-70%	-54%	-19%
960	369.02	229.00	137.5	127.1	-66%	-44%	-7%
1200	344.99	236.60	140.3	130.0	-62%	-45%	-7%
1440	357.01	237.01	144.2	131.0	-63%	-45%	-9%
1680	352.87	238.7	144.1	132.0	-63%	-45%	-8%
1920	375.55	246.8	144.1	130.0	-65%	-47%	-10%
2160	380.26	239.08	146.6	130.8	-66%	-45%	-11%
2400	364.03	241.1	145.7	130.3	-64%	-46%	-11%

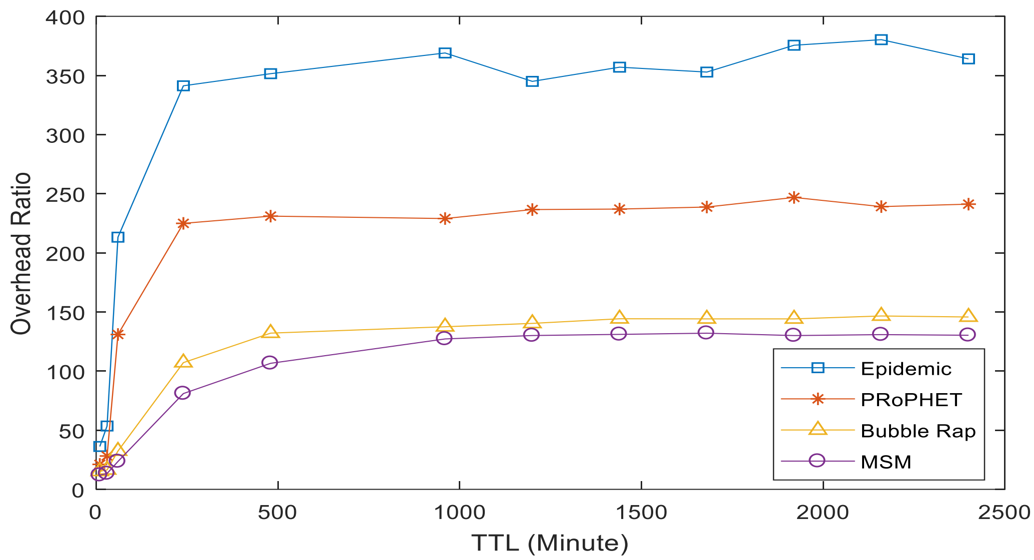


Figure 5.30: Overhead Ratio vs. TTL (INFOCOM05 dataset)

It is clear from the results that MSM protocol outperforms all other routing protocols. MSM reduces the overhead ratio with 69%, 51%, and 14% compared with Epidemic, PRoPHET and Bubble Rap respectively. Similar results achieved for INFOCOM06 experiments, Table 5.31 and Figure 5.31 show the results of this experiment.

Table 5.31: Overhead Ratio vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	73.5	52.4	26.45	5.08	-93%	-90%	-81%
30	105.0	74.0	28.19	7.09	-93%	-90%	-75%
60	764.1	624.8	108.8	8.38	-99%	-99%	-92%
240	1214.3	641.6	450.2	18.06	-99%	-97%	-96%
480	1312.7	598.3	552.9	28.03	-98%	-95%	-95%
960	1378.5	608.1	585.1	40.57	-97%	-93%	-93%
1200	1373.2	588.09	586.8	43.04	-97%	-93%	-93%
1440	1309.7	578.08	579.5	45.17	-97%	-92%	-92%
1680	1309.9	593.67	596.9	50.38	-96%	-92%	-92%
1920	1391.2	598.38	596.4	50.47	-96%	-92%	-92%
2160	1310.4	603.96	608.1	52.00	-96%	-91%	-91%
2400	1392.0	609.93	599.7	52.03	-96%	-91%	-91%

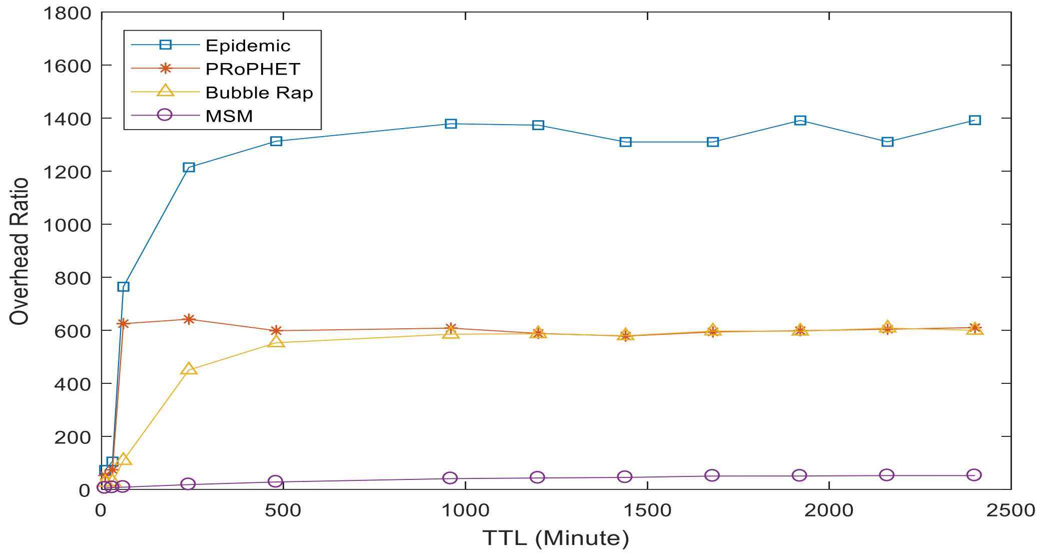


Figure 5.31: Overhead Ratio vs. TTL (INFOCOM06 dataset)

Also in INFOCOM06 experiment, MSM protocol has superiority over the other protocols, but the reduction in the overhead ratio is higher than INFOCOM05 experiment.

Comparing with Epidemic, PRoPHET and Bubble Rap MSM has a much lower overhead ratio; the average reduction is 96%, 93%, and 90% respectively.

The experimental results of the three datasets show that MSM decreases overhead ratio significantly in OMSN network for all TTL values. It reduces the overhead in the network by applying a strict relay selection strategy, where social activity, similarity and similarity metrics are exploited to select the next message's forwarder. The objective of this forwarding method of MSM is to reduce the number of forwardings in the network and also forward messages to nodes that are more socially closer to the destination and therefore have a higher probability to deliver the messages.

5.4.3.3 Average Latency vs. TTL

This section evaluates the performance of MSM protocol in term of average latency against other protocols i.e. Epidemic, PRoPHET and Bubble Rap for different TTL values. The TTL value is varied between low (10 minutes) and high (2400 minutes) to study the impact of TTL on the average latency for all routing protocols. Table 5.32 and Figure 5.32 show the experiment results for Cambridge dataset.

Table 5.32: Average Latency vs. TTL (Cambridge dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	71	84.7	77.3	97.6	+37%	+15%	+26%
30	378	455.2	422.9	496.0	+31%	+9%	+17%
60	926	996.2	1028.9	1116.0	+20%	+12%	+8%
240	4339	4917.4	4364.7	4889.7	+13%	-1%	+12%
480	8939	10298.8	9279.0	9773.4	+9%	-5%	+5%
960	16689	17507.5	15976.4	15848.7	-5%	-9%	-1%
1200	16968.	17708.8	16557.6	16035.8	-5%	-9%	-3%
1440	17524	17890.8	16586.5	16122.5	-8%	-10%	-3%
1680	17562	17929.2	16441.2	16094.3	-8%	-10%	-2%
1920	17571	17753.1	16532.4	16131.8	-8%	-9%	-2%
2160	17450	17786.4	16598.5	16131.8	-8%	-9%	-3%
2400	17708	17821.8	16655.9	16131.8	-9%	-9%	-3%

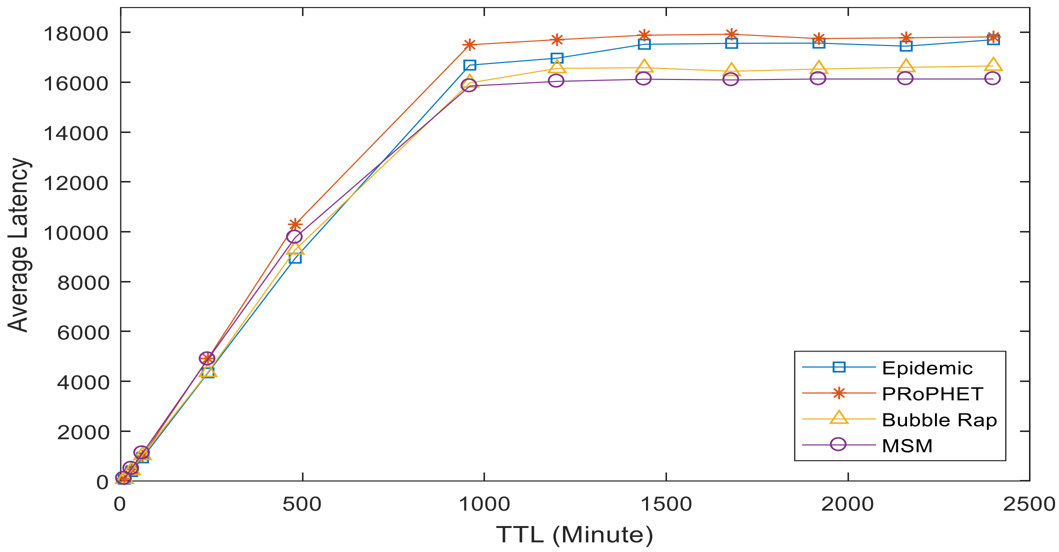


Figure 5.32: Average Latency vs. TTL (Cambridge dataset)

It can be noted that average latency increases with the increase in TTL value for all the routing protocols until it reaches a plateau. The reason is that increasing TTL value enables messages to live more, hence more messages will be delivered before dropping due to TTL expiration. The messages that take a longer time to be delivered will not be dropped and consequently, the average end-to-end delay for all the delivered messages will be higher.

MSM protocol has higher average latency for low TTL values (10, 30, 60 and 240 Minutes) compared with other protocols, this is due to that MSM is more conservative in selecting the relay nodes and messages will be dropped quickly as a result of expired TTL value. However, with increasing TTL value (480 Minutes and higher), MSM achieves lower average latency and outperforms other protocols because the social based forwarding protocol will be more effective with higher TTL. Similar results almost can be seen for INFOCOM05 experiment, the results are depicted in Table 5.33 and Figure 5.33.

Table 5.33: Average Latency vs. TTL (INFOCOM05 dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	156.2	164.4	159.2	170.2	+9%	+4%	+7%
30	542.9	566.2	566.8	625.9	+15%	+11%	+10%
60	1248.7	1259.2	1271.1	1308.8	+5%	+4%	+3%
240	4279.3	4905.8	4334.1	4721.1	+10%	-4%	+9%
480	8084.2	9091.4	7995.3	8368.4	+4%	-8%	+5%
960	13340	15972	14443	14830	+11%	-7%	+3%
1200	15968	16510	15021	15253	-4%	-8%	+2%
1440	14790.	16973	14758	15177	3%	-11%	+3%
1680	16157	17071	14564	15120	-6%	-11%	+4%
1920	15614	16674	14614	15189	-3%	-9%	+4%
2160	15723	17019	14880	15217	-3%	-11%	+2%
2400	16883	16763	14869	15220	-10%	-9%	+2%

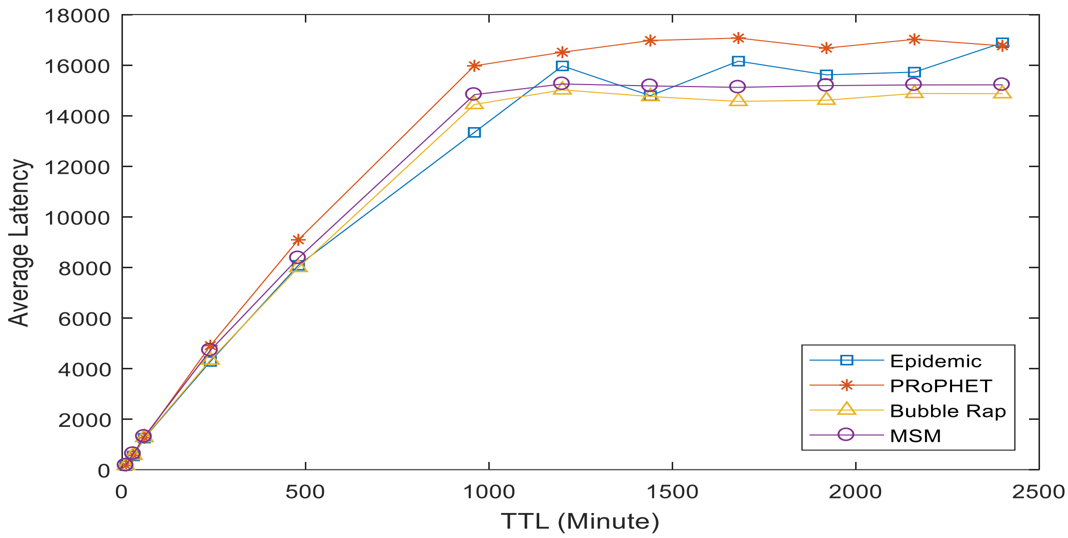


Figure 5.33: Average Latency vs. TTL (INFOCOM05 dataset)

Similar to Cambridge dataset, MSM protocol has higher latency in INFOCOM05 experiment for low TTL value (10, 30, 60, 240 Minutes) scenarios. On average, the average latency is 25%, 9% and 16 higher than Epidemic, PRoPHET and Bubble Rap respectively. For higher TTL value (480 minutes and higher) the performance of MSM is very close to other protocols. On average, it is 4% lower than Epidemic and 10% lower than PRoPHET and 3% higher than Bubble Rap. Table 5.34 and Figure 5.34 show the experimental results for INFOCOM06 dataset.

Table 5.34: Average Latency vs. TTL (INFOCOM06 dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	87	112	141	183	+109%	+63%	+29%
30	370	390	466	563	+52%	+44%	+21%
60	1078	1012	981	1177	+9%	+16%	+20%
240	4127	4723	4556	4740	+15%	+1%	+4%
480	6908	9413	8437	9651	+40%	+3%	+14%
960	9957	14602	14167	16063	+61%	+10%	+13%
1200	9690	16028	15235	17363	+79%	+8%	+14%
1440	9534	16816	15991	17405	+83%	+3%	+9%
1680	11330	17134	1582	17657	+56%	+3%	+12%
1920	9774	17146	15787	17952	+84%	+5%	+14%
2160	10043	17364	15486	17977	+79%	+4%	+16%
2400	9255	16835	15568	17926	+94%	+6%	+15%

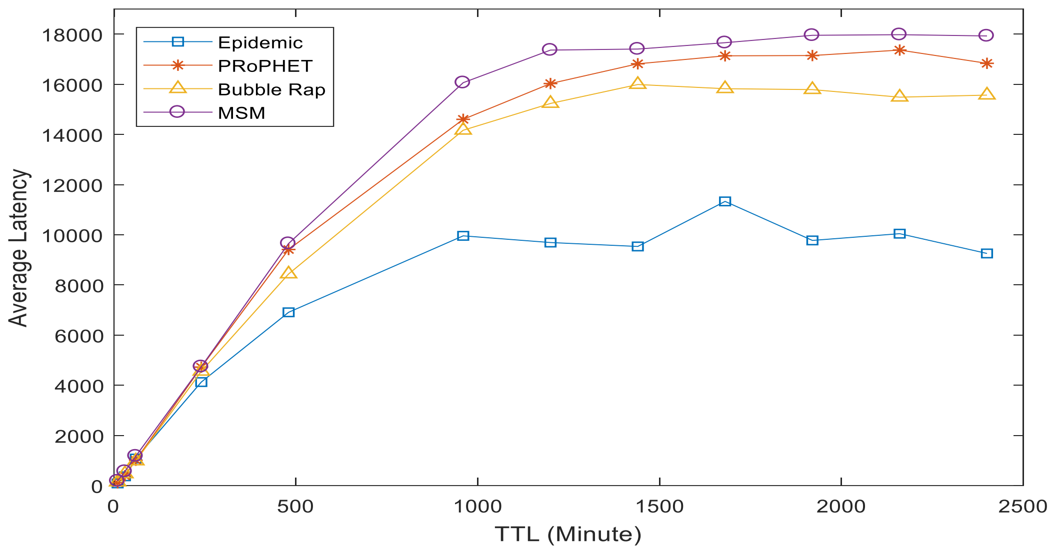


Figure 5.34: Average Latency vs. TTL (INFOCOM06 dataset)

MSM protocol has higher average latency compared with other protocols. That is because MSM forwards messages only to the nodes that have a very strong social relationship with the destination this causes a delay in forwarding the messages and hence the overall end-to-end delay in the network will be higher.

5.4.3.4 Average Hop Count vs. TTL

Average hop count is an important metric to evaluate the routing efficiency in the mobile social network. Delivering messages with lower hop counts is a key goal for routing protocols to conserve the resources in the opportunistic MSN network.

This section shows the evaluation of the performance of MSM protocol in term of average hop counts against different values of the message's TTL. The investigations is applied for the three datasets: Cambridge, INFOCOM05 and INFOCOM06. Table 5.35 and Figure 5.35 show the evaluation results of Cambridge dataset.

Table 5.35: Average Hop Count vs. TTL (Cambridge dataset)

TTL (Minutes)	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	2.63	2.23	1.87	1.58	-40%	-29%	-15%
30	2.81	2.50	1.96	1.78	-37%	-29%	-9%
60	2.84	2.63	2.01	1.85	-35%	-30%	-8%
240	7.50	3.08	2.12	1.94	-74%	-37%	-9%
480	7.38	2.93	2.12	1.92	-74%	-34%	-9%
960	6.65	2.90	2.13	1.95	-71%	-33%	-8%
1200	6.92	2.87	2.16	1.94	-72%	-32%	-10%
1440	6.92	2.90	2.14	1.94	-72%	-33%	-9%
1680	7.13	2.91	2.14	1.95	-73%	-33%	-9%
1920	7.01	2.91	2.13	1.95	-72%	-33%	-9%
2160	6.71	2.95	2.16	1.95	-71%	-34%	-10%
2400	6.68	2.91	2.15	1.95	-71%	-33%	-9%

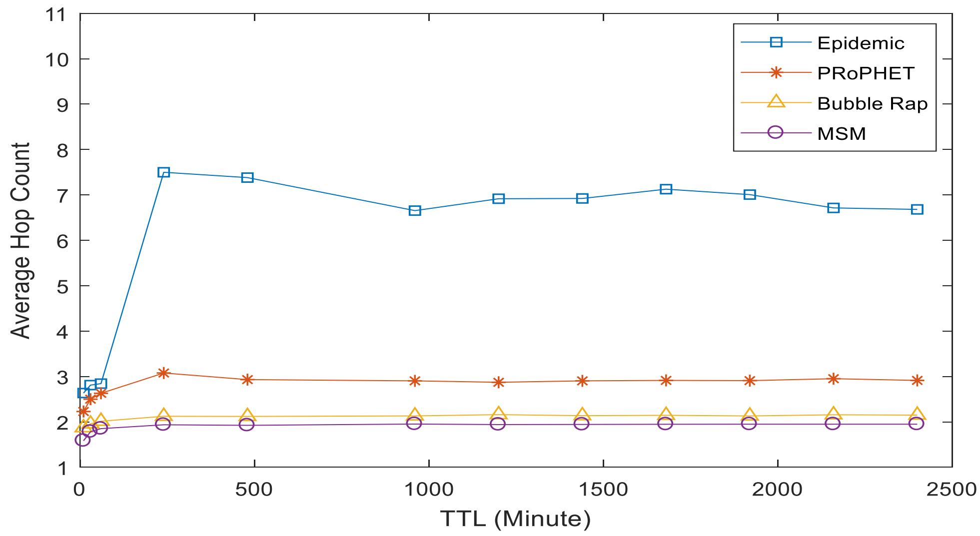


Figure 5.35: Average Hop Count vs. TTL (Cambridge dataset)

It is clear that MSM protocol has the lowest average hop count compared with the other protocols. It reduces the average hop count, on average, with 63%, 33% and 10%, compared with Epidemic, PRoPHET and Bubble Rap respectively.

Also for INFOCOM05 dataset, Table 5.36 and Figure 5.36 show the results, MSM has the superiority over the other protocols.

Table 5.36: Average Hop Count vs. TTL (INFOCOM05 dataset)

TTL Minutes	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	3.20	2.48	1.81	1.52	-52%	-39%	-16%
30	3.49	2.86	2.05	1.73	-50%	-39%	-16%
60	4.67	3.31	2.24	1.86	-60%	-44%	-17%
240	6.93	3.74	2.40	2.05	-70%	-45%	-14%
480	7.45	4.04	2.44	2.04	-73%	-49%	-16%
960	8.97	4.10	2.48	2.07	-77%	-50%	-17%
1200	9.37	4.16	2.44	2.04	-78%	-51%	-16%
1440	9.36	4.19	2.43	2.06	-78%	-51%	-15%
1680	9.71	4.30	2.43	2.05	-79%	-52%	-16%
1920	9.21	4.10	2.42	2.05	-78%	-50%	-15%
2160	8.76	4.29	2.42	2.04	-77%	-52%	-15%
2400	9.63	4.04	2.41	2.05	-79%	-49%	-15%

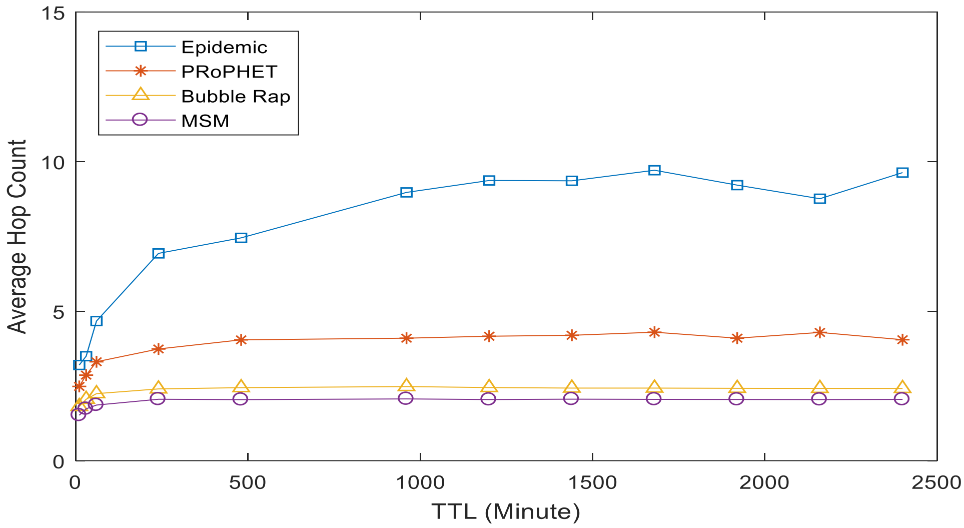


Figure 5.36: Average Hop Count vs. TTL (INFOCOM05 dataset)

The reduction that MSM achieved in average hop count is 71%, 48% and 16% compared with Epidemic, PRoPHET and Bubble Rap respectively. Table 5.37 and Figure 5.37 show that MSM protocol also outperforms other protocols for INFOCOM06 experiment.

Table 5.37: Average Hop Count vs. TTL (INFOCOM06 dataset)

TTL Minutes	Epidemic	PRoPHET	Bubble Rap	MSM	MSM vs. Epidemic	MSM vs. PRoPHET	MSM vs. Bubble Rap
10	4.04	3.48	2.54	1.30	-68%	-63%	-49%
30	4.27	3.65	2.64	1.45	-66%	-60%	-45%
60	5.64	4.29	2.72	1.58	-72%	-63%	-42%
240	8.58	3.60	2.73	1.69	-80%	-53%	-38%
480	10.50	3.79	2.76	1.71	-84%	-55%	-38%
960	11.75	4.10	2.85	1.69	-86%	-59%	-41%
1200	12.49	4.15	2.94	1.68	-87%	-59%	-43%
1440	13.25	4.20	2.91	1.68	-87%	-60%	-43%
1680	12.73	4.29	2.94	1.67	-87%	-61%	-43%
1920	12.18	4.26	2.92	1.67	-86%	-61%	-43%
2160	12.66	4.38	2.92	1.66	-87%	-62%	-43%
2400	12.15	4.21	2.90	1.66	-86%	-61%	-43%

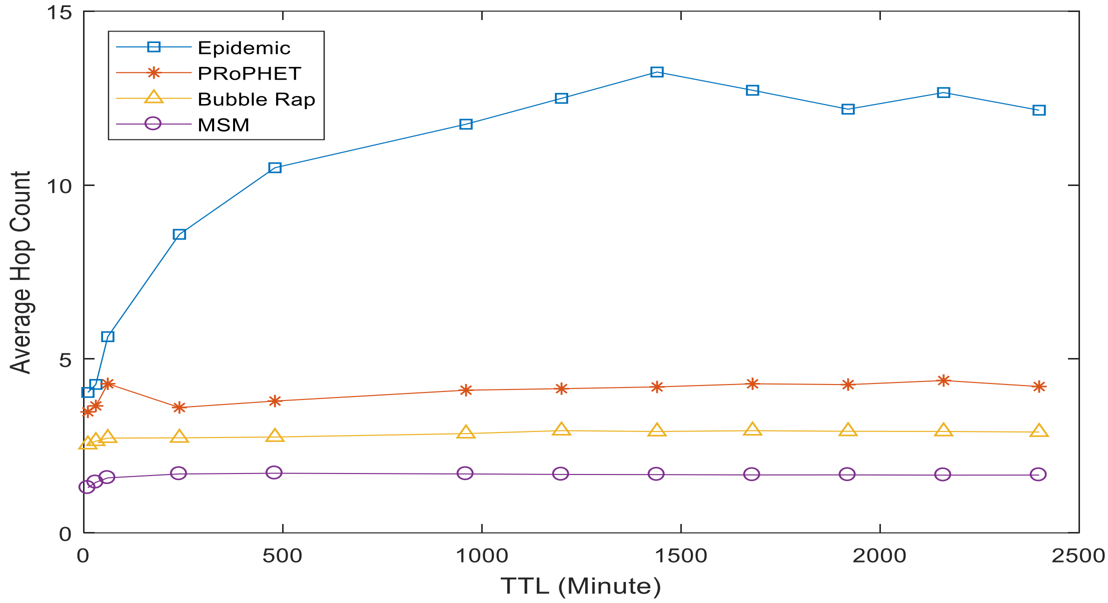


Figure 5.37: Average Hop Count vs. TTL (INFOCOM06 dataset)

MSM protocol reduces the average hop count with 81%, 60% and 42%, on average, compared with Epidemic, PRoPHET and Bubble Rap respectively.

Based on the results obtained for the three datasets, it can be concluded that the social based forwarding strategy of MSM is very efficient in decreasing the number of forwardings required to deliver a message in MSN network. This is because MSM decreases the number of nodes participating in messages forwarding by selecting as a relay only node which has better social relation with destination based on the three social metrics i.e. activity, similarity, and centrality. Consequently, MSM has a lower overhead for network and node compared with other protocols; Epidemic, PRoPHET and Bubble Rap.

5.5 Conclusion

This chapter investigates exploiting multiple social metrics in order to enhance routing in the OMSN. The exploited social metrics are degree centrality, social similarity, and social activeness. These social metrics, which reflect the social properties and behavior of mobile users in OMSN, are utilized with considering their mutual impacts and the interrelation among them. A new social-based forwarding protocol called the Multiple-Social Metrics routing protocol (MSM) was proposed with the main objective of reducing the overhead in the OMSN network.

The performance of the proposed protocol is evaluated for three real datasets: Cambridge (university campus environment), INFOCOMM05 and INFOCOMM06 (Conference environment). These datasets have a different social environment and a different number of mobile nodes. In addition, the performance evaluation conducted using three impacting different factors on routing efficiency: experiment time, buffer size and TTL value

Based on the evaluation results, MSM has the superiority over three benchmarks: Epidemic (Flooding-based routing protocol), PRoPHET (Probability-based routing protocol) and Bubble Rap (Social-based routing protocol) in terms of overhead ratio and average hop counts. MSM reduces the overhead ratio significantly, for high buffer size scenarios the decrease is on average 74%, 66%, 57% compared with Epidemic, PRoPHET, and Bubble Rap respectively. Furthermore, the enhancement becomes higher with the increase in the number of nodes in the network, in the INFOCOMM06 experiment the reduction is on average 95%, 93%, and 90% compared with Epidemic, PRoPHET, and Bubble Rap respectively. Regarding average hop counts, MSM achieves the lowest number of hops to deliver the messages in OMSN; it has 64%, 41%, and 15% lower than Epidemic, PRoPHET, and Bubble Rap respectively. In addition, the reduction becomes higher with the higher TTL scenarios where it reaches 81%, 60%, and 42% compared with Epidemic, PRoPHET, and Bubble Rap respectively. MSM has competitive achievements regarding delivery ratio and average latency. In conclusion, exploiting multiple social metrics with considering the interrelations among them results in efficient routing protocol in term of preserving network and nodes resources because it decreases the average hop count and the overhead significantly.

CHAPTER 6

PERFORMANCE EVALUATION OF EPSOC, SOR, AND MSM

6.1 Introduction

The objective of this chapter is to give further insight into the differences between the proposed protocols and to suggest suitable scenarios for application. Therefore, an evaluation of the three proposed protocols i.e. Epidemic-based Social-based protocol (EpSoc), Routing based on Ranked social features protocol (SOR) and Multiple Social-based Metrics protocol (MSM) will be conducted. The evaluation of EpSoc, SOR, MSM will be in terms of delivery ratio, overhead ratio, average latency, and average hop count against buffer size and TTL.

As aforementioned in chapter1, the main objective of this thesis is to exploit social features to enhance the efficiency of data dissemination in the Opportunistic Mobile Social Network (OMSN). Therefore, the proposed three protocols focus on reducing the delivery cost by decreasing both overhead ratio and average hop count and not to affect negatively the delivery ratio and the average latency in the network.

The proposed protocols outperform other routing protocols i.e. Epidemic, ProPHET, and Bubble Rap in terms of overhead ratio and average hop count, and also achieved competitive performance in terms of delivery ratio and average latency. However, the following section intend to compare the proposed protocols with each other to show the main advantages for each of them and to suggest the appropriate applying scenarios.

6.2 EpSoc, SOR and MSM Performance Evaluation

The proposed protocols have different achievements and advantages based on the applied forwarding strategy. Firstly, in EpSoc protocol, social information integrated with Epidemic forwarding strategy; so EpSoc is an enhanced social-based version of Epidemic. Combining centrality social metric with Epidemic forwarding strategy resulted in a significant decrement in the average latency and overhead ratio.

Secondly, in SOR, the regularity in the social activities of people during daily life is exploited to rank the social characteristics. Furthermore, the relative importance of the ranked social features is utilized for forwarding messages. The results show a significant increase in the delivery ratio with a competitive decrease in the overhead ratio and average hop count.

Lastly, in MSM protocol, three social metrics and the mutual correlation among them are exploited to make the forwarding decision. So, MSM deploys a very strict selection policy of relay nodes. The result is a signification decrease in the overhead ratio and average hop count. Table 6.1 summarizes the main advantages of the proposed protocols and Figure 6.1, Figure 6.2, Figure 6.3 and Figure 6.4 show the achievement comparison of the three proposed protocols in terms of delivery ratio, overhead ratio, average latency, and average hop count.

Table 6.1: Main Advantages of the Proposed Protocols

Protocol	Main Advantages
EpSoc	Low average latency Low overhead ratio
SOR	High delivery ratio
MSM	Low overhead ratio Low average hop count

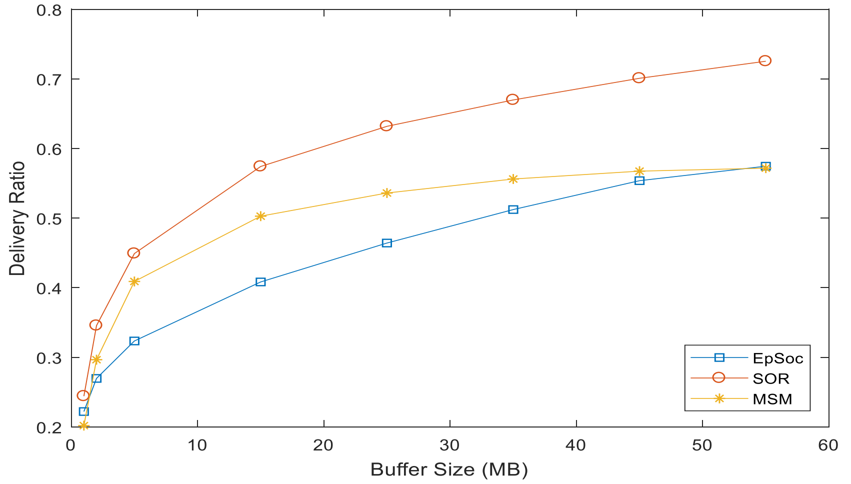


Figure 6.1: Delivery Ratio vs. Buffer Size

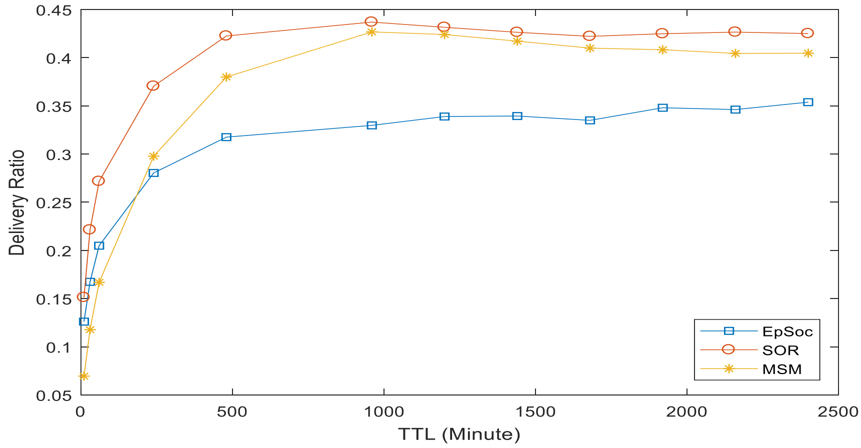


Figure 6.2: Delivery Ratio vs. TTL

Figure 6.1 shows that SOR achieves the highest delivery ratio as compared with MSM and EpSoc. This is because it considers the regularity in social activity and the relative importance of social characteristics when forwarding the messages. This yields increasing the number of the social-based candidate relays and hence increasing the delivered messages. On the other hand, MSM and EpSoc has lower delivery ratio because MSM deploys very strict forwarding selection policy, and EpSoc controls socially the Epidemic replications in the network. EpSoc has a lower delivery ratio than MSM because social information is used only to control the replications of Epidemic whereas MSM exploits the social metrics in the forwarding decision which provide better delivery ratio.

Figure 6.3 and Figure 6.4 show the performance evaluation in terms of overhead ratio.

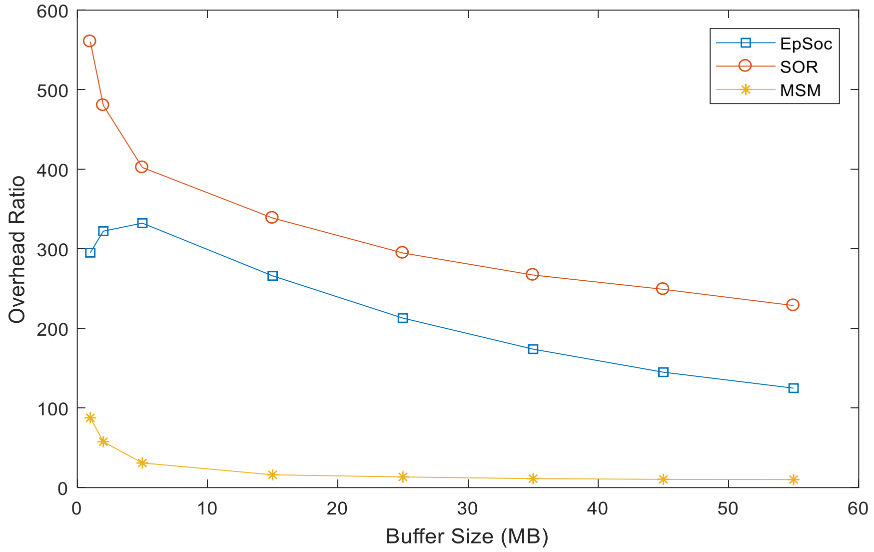


Figure 6.3: Overhead Ratio vs. Buffer Size

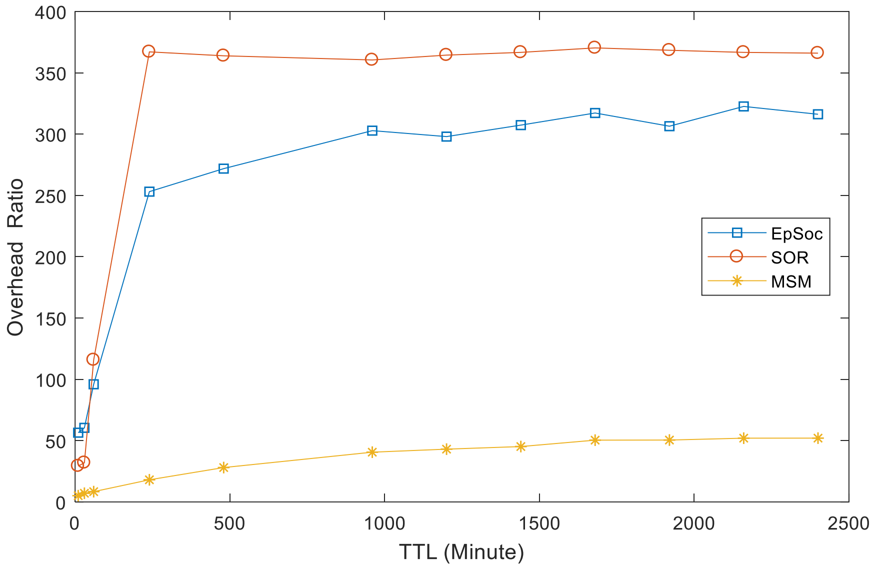


Figure 6.4: Overhead Ratio vs. TTL

It is clear that MSM has superiority over SOR and EpSoc regarding overhead ratio. It can be noticed also that EpSoc outperforms SOR. This is because both MSM and EpSoc deploy a control mechanism when routing the messages in the network. MSM uses a strict forwarding strategy and EpSoc decree TTL value and block resent messages. This results in a low number of messages forwarding in OMSN. Average latency achievement is shown in Figure 6.5 and Figure 6.6.

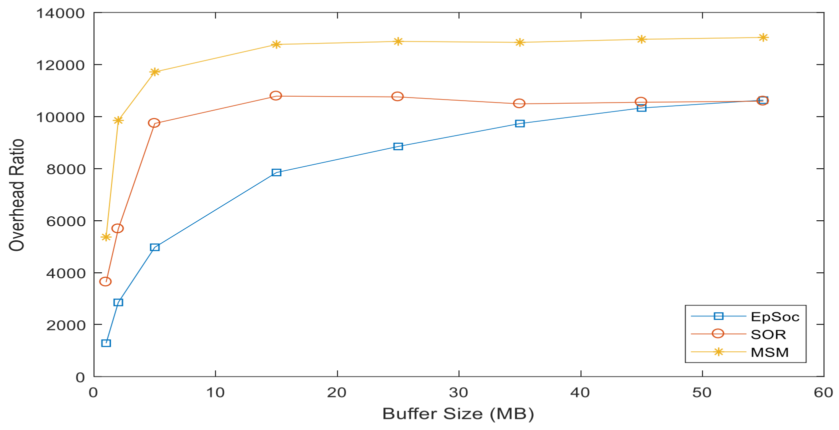


Figure 6.5: Average Latency vs. Buffer Size

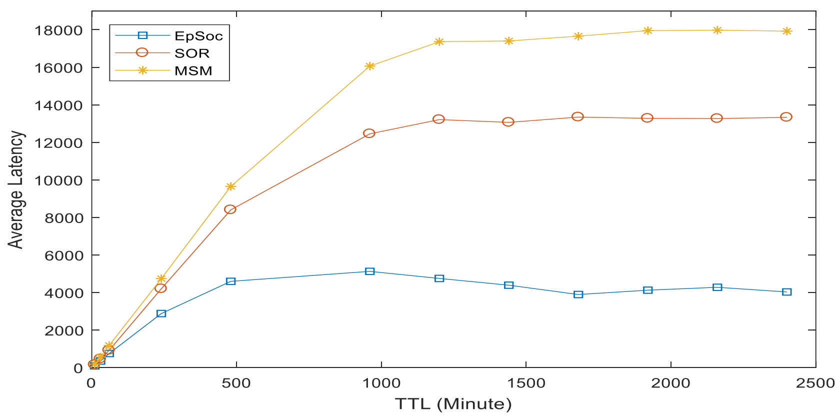


Figure 6.6: Average Latency vs. TTL

Regarding average latency depicted in Figure 6.5 and Figure 6.6, EpSoc achieves the lowest value because it is an Epidemic-based protocol, flooding the network with the replicas decrease the end-to-end time to deliver the messages. On the contrary, MSM and SOR are more conservative in selecting the next forwarder because they apply social-based strategies, therefore messages will be stored for a longer time and hence the overall latency will be higher. Finally, the average hop count metric evaluation is presented in Figure 6.7 and Figure 6.8.

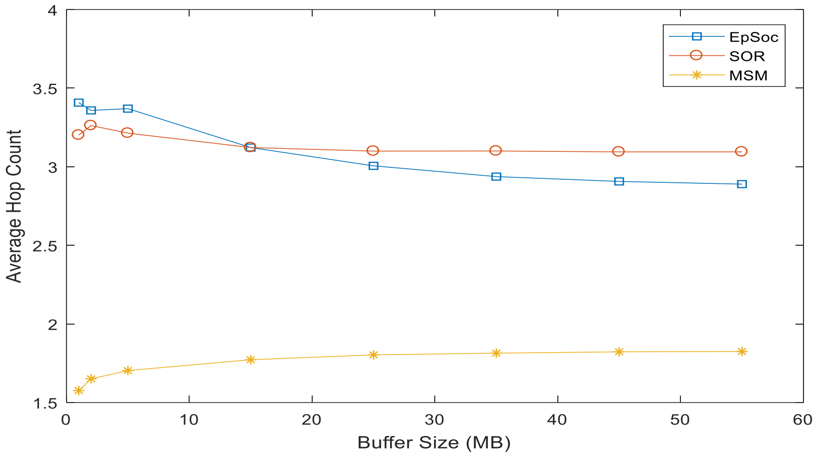


Figure 6.7: Average Hop Count vs. Buffer Size

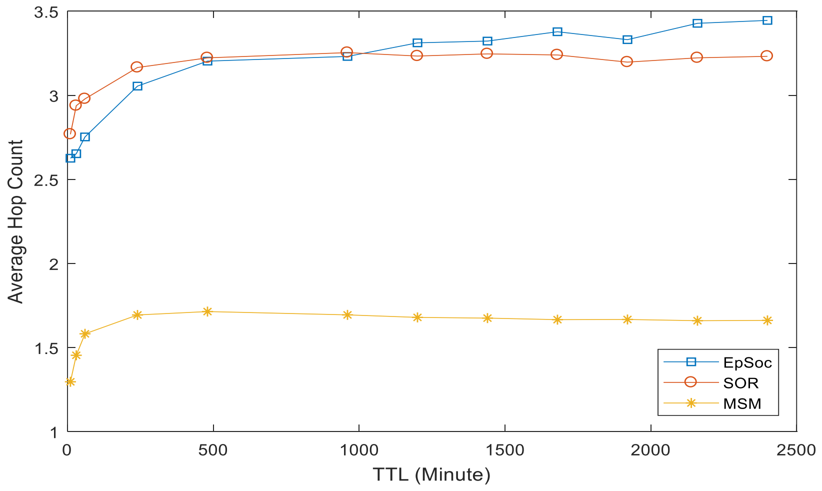


Figure 6.8: Average Hop Count vs. TTL

Figure 6.4 shows that MSM outperforms both SOR and EpSoc in terms of average hop count. This is because its forwarding decision is very strict which decreases the number of the intermediate nodes that are involved in delivering the messages.

Based on the results, EpSoc as a hybrid routing approach (Epidemic and social-based) is a simple protocol (low computation cost) because of the flooding-based forwarding strategy. In addition, because of its superiority in terms of low latency, this makes it an efficient routing protocol for opportunistic networking scenarios that concern about delivering messages quick and about node resources.

SOR considers the regularity of people social activity and exploits the similarity metric for the ranked social characteristics. This enables it to deliver more messages in the network, and as aforementioned, it outperforms both EpSoc and MSM in terms of delivery ratio. However, to achieve this objective, two conditions must be satisfied; first, the availability of users' social characteristics in their profiles because SOR utilizes these social characteristics in the ranking algorithm. Second, the social contacts and interaction activities have to be maintained and updated for each time period in the day. Consequently, SOR achieves a high delivery ratio but incurs storage and computing cost. This enables SOR to be applied in networking scenarios with high capable nodes and requires a high delivery ratio.

MSM has the lowest values overhead ratio and average hop count because it applies a strict social-based strategy to forward the messages. This enables it to be applied in constrained resource scenarios. However, the cost is increasing the average latency in the network.

Table 6.2 shows the suggested scenarios to apply the proposed protocols.

Table 6.2: Suggested Application Scenarios

Protocol	Scenarios to apply for
EpSoc	Constrained node resources and low delivery time requirements
SOR	High capable nodes and high delivery ratio requirements
MSM	Very low constrained node resources with tolerance in delivery time

CHAPTER 7

CONCLUSION

The main aim of this thesis is to investigate how social features can be exploited to improve the efficiency of messages routing in OMSN. To achieve this, the objectives of this study is to investigate the social features and its impact on the routing performance, to propose new social-based routing protocols to control the overhead, and to evaluate the performance of the proposed protocols. Therefore, the work in this thesis is subdivided as follows:

- Integrate social features with Epidemic routing protocol.
- Utilize the user profile as a social information source and consider the regularity of human social activities during the day periods.
- Exploit multiple social features and use their interconnection to produce an efficient forwarding strategy.

These issues are investigated thoroughly in the chapters of this thesis. This chapter summarizes the work in this study. It includes the following sections: the contributions of each chapter, the recommendations based on this study, and the proposed future works.

7.1 Thesis Contributions

This study focuses mainly on developing social-based efficient forwarding protocols to improve the routing process in OMSN. Overhead ratio, delivery ratio, average latency, and average hop counts are the key performance indicators used in this study for performance evaluation. The key objective of this study is to decrease the overhead ratio and achieve a rival performance compared to the determined benchmarks according to the other metrics.

The main contributions of this thesis are:

- Develop an efficient social-based Epidemic-based routing protocol (EpSoc) by integrating degree centrality in Epidemic protocol. Based on the experiment results, it is proven that EpSoc outperformed Epidemic protocol for all the KPIs. Also, EpSoc decreased the overhead ratio and the average latency compared to Bubble Rap protocol. The main concept of EpSoc was to utilize the user's social popularity to shorten the life of the replicas that are forwarded to nodes have higher activity than the current carrier.
- The second social-based proposed protocol: Social aware routing based on Ranked social features (SOR) considered three important interrelated issues; the routine of human activities during day lives, the social characteristics in the user profile, and the intercontact history.

  SOR employs a ranking algorithm to determine the relative importance of the social characteristics during the different day periods. The results of the simulation experiments showed that SOR successfully decreased the overhead ratio and increase the delivery ratio while achieving good performance in terms of average latency and average hop counts. SOR employs strict policy in forwarding the messages in the network, where the next relay is chosen based on the similarity with the social feature of the destination which has the highest importance in each time period.

  For more enhancement, the EpSoc strategy to control the overhead is integrated with SOR. The results showed a higher reduction in the overhead ratio in OMSN with slightly negative impact on the other performance metrics.

- The last forwarding protocol developed in this thesis: Multiple Social Metrics based routing protocol (MSM) exploits three social features; social activity, social similarity, and degree centrality. This protocol is called MSM. The main concept of MSM is to utilize the interconnection and the mutual effects of the social features to enhance the efficiency of the forwarding decision in OMSN. The experiment results showed a great reduction in the overhead with good delivery ratio and average latency.

  Also, for more reduction in the overhead ratio, EpSoc overhead controlling strategy is integrated with MSM. The integration contributed extra decrease in overhead ratio while maintaining good routing performance regarding the other KPIs.

7.2 Recommendations

In this thesis, three social-based forwarding protocols are proposed; EpSoc which was described in Chapter 3, SOR was presented in Chapter 4, and MSM was explained in Chapter 5. Based on the lessons learned from these works, the following recommendations are provided:

- Social features should be selected carefully when it is integrated with other protocols for performance enhancement in OMSN. The routing methodology of the protocol plays a key role in determining the suitable social feature to be utilized. In this study, degree centrality feature was exploited because it can control efficiently the impact of the high redundancy in Epidemic protocol.
- Social-based approaches incur high average latency. This is because of the selective approach it employs to form the forwarding decision depending on the social information. So, it is important to define the main goal of the exploitation of the

social information. Exploiting social features is efficient to decrease the ratio of the overhead or to increase the delivery ratio.

- From the routing perspective in OMSN, it is more efficient to combine social information with other effective factors such as contact history, buffer management. this is because the efficiency of exploiting the social features is affected by the other factors significantly. In this thesis, a high reduction was achieved in the overhead ratio when the EpSoc strategy of shortening life messages is integrated.
- Social features have mutual impacts that can be exploited for performance improvement in OMSN. So, defining the interconnections between the social features carefully, and studying the impacts of the other factors like contact history is a critical issue for developing efficient routing protocols in OMSN.

7.3 Future Work

The proposed protocols in this thesis provide efficient ways to exploit social features for routing improvement in OMSN especially in controlling the overhead cost. However, several future works can be carried out based on this work for further enhancement.

The suggestions for the future works are:

- Since this research focuses on the pure mobile social network where all the nodes in the network are mobile devices, the next potential research is to study the hybrid networking scenarios where the network has both stationary nodes and mobile nodes. Stationary nodes can be exploited for gathering various type of information such as the social characteristics, the previous contacts, and the messages statics. These big gathered data can be processed and analyzed to extract valuable information for messages' routing in the network.

- Social Internet of Things (SIoT) has risen up in the field of the internet of things (IOT), where social information exploited to enhance information sharing and open the door for new applications and services (Roopa et al., 2019). Furthermore, machines will establish relations among themselves similar to what humans do. Consequently, these machines will have the ability to make decisions without human intervention and will serve humans by exchanging information through the social relationships they had created previously. So, this work can be extended to consider the social relationships of both humans and devices to improve routing in OMSN.

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APPENDIX

International Peer-reviewed Journals

1. **Lenando, H.**, & Alrfaay, M. (2018). EpSoc: Social-Based Epidemic-Based Routing Protocol in Opportunistic Mobile Social Network. *Mobile Information Systems, 2018*(6462826), 1-8. https://doi.org/10.1155/2018/6462826
2. **Lenando, H.**, Alrfaay, M., & Chikha, H. Ben. (2019). Multiple Social Metrics Based Routing Protocol in Opportunistic Mobile Social Networks. *Advances in Science Technology and Engineering Systems Journal*, *4*(2). 176-182. https://doi.org/10.25046/aj040223

International Refereed Conferences

1. **Alrfaay, M.**, Lenando, H., & Ben Chikha, H. (2019). ProphSoc: Probability-based Social-based routing Scheme in Mobile Social Network (MSN). *2019 International Conference on Computer and Information Sciences*, Sakaka, Saudi Arabia. https://doi.org/10.1109/iccisci.2019.8716396