Evaluation of Routing Protocols for Opportunistic Networks with Multiple-Criteria Decision-Making Methods

A Thesis

submitted to the designated

by the General Assembly of Special Composition

of the Department of Computer Science and Engineering

Examination Committee

by

Dimitrios-Georgios Akestoridis

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN COMPUTER SCIENCE

WITH SPECIALIZATION

IN COMPUTER SYSTEMS

February 2016

DEDICATION

I dedicate this thesis to Katerina for her love, support, and encouragement.

ACKNOWLEDGEMENTS

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Abstract

Dimitrios-Georgios Akestoridis, M.Sc. in Computer Science, Department of Computer Science and Engineering, University of Ioannina, Greece, February 2016.
Evaluation of Routing Protocols for Opportunistic Networks with Multiple-Criteria Decision-Making Methods.
Advisor: Evangelos Papapetrou, Assistant Professor.

The evaluation of routing protocols for opportunistic networks is a multidimensional problem. Several performance metrics are used for their evaluation, such as the number of packets that they delivered, their delivery delay, and the number of transmissions that they performed. These metrics are often highly correlated and they are usually conflicting. Furthermore, the characteristics of the underlying network affect the importance of each metric as well as the levels of correlation between metrics.

In this work, we first propose a set of normalized performance metrics that evaluate each routing protocol with respect to the optimal performance, tackling several shortcomings of the traditional performance metrics. We then formulate the evaluation of routing protocols for opportunistic networks as a Multiple-Criteria Decision-Making (MCDM) problem, where each routing protocol is an alternative and the performance metrics correspond to a set of criteria. We propose the VIC weighting method to determine the importance of each performance metric, by relying on its variability and the amount of dependence that it has in relation to the other performance metrics. The VIC method can be used for the assignment of objective weights in any MCDM problem. Finally, we develop an evaluation framework that ranks opportunistic routing protocols based on their performance.

We present detailed simulation results of well-known routing protocols in opportunistic networks of varying scale, which we rank according to the proposed framework. In conclusion, no algorithm was able to achieve the best performance in all or

most of the networks that we studied. This fact demonstrates the difficulty of routing in these networks.

Εκτεταμενη Περιληψη

Δημήτριος-Γεώργιος Ακεστορίδης, Μ.Δ.Ε. στην Πληροφορική, Τμήμα Μηχανικών Η/Υ και Πληροφορικής, Πανεπιστήμιο Ιωαννίνων, Φεβρουάριος 2016.
Αξιολόγηση Πρωτοκόλλων Δρομολόγησης για Οπορτουνιστικά Δίκτυα με Μεθόδους Λήψης Αποφάσεων Πολλαπλών Κριτηρίων.
Επιβλέπων: Ευάγγελος Παπαπέτρου, Επίκουρος Καθηγητής.

Η αξιολόγηση των πρωτοκόλλων δρομολόγησης για οπορτουνιστικά δίκτυα είναι ένα πολυδιάστατο πρόβλημα. Για την αξιολόγηση αυτή χρησιμοποιείται ένα σύνολο από μετρικές, καθεμία από τις οποίες αξιολογεί τον αλγόριθμο σε μία διαφορετική διάσταση. Για παράδειγμα, μπορούμε να αξιολογήσουμε την ικανότητα του αλγορίθμου να παραδίδει πακέτα, τον χρόνο που χρειάζεται, αλλά και το κόστος που δαπανά. Οι μετρικές αυτές συχνά παρουσιάζουν σημαντικό βαθμό συσχέτισης και συνήθως είναι αντικρουόμενες. Πολύ περισσότερο, τα χαρακτηριστικά του δικτύου στο οποίο πραγματοποιείται η αξιολόγηση επηρεάζουν τόσο τη σημαντικότητα της κάθε μετρικής, όσο και τα επίπεδα συσχέτισης των μετρικών μεταξύ τους.

Στην παρούσα εργασία, αρχικά προτείνουμε ένα σύνολο κανονικοποιημένων μετρικών επίδοσης, οι οποίες αξιολογούν το κάθε πρωτόκολλο δρομολόγησης σε σχέση με τη βέλτιστη επίδοση που μπορεί να επιτευχθεί. Η στρατηγική αυτή αντιμετωπίζει μία σειρά από μειονεκτήματα που συνοδεύουν τις παραδοσιακές μετρικές επίδοσης. Στη συνέχεια, διατυπώνουμε την αξιολόγηση των πρωτοκόλλων δρομολόγησης για οπορτουνιστικά δίκτυα ως ένα πρόβλημα λήψης αποφάσεων πολλαπλών κριτηρίων. Στη θεώρηση αυτή κάθε πρωτόκολλο δρομολόγησης είναι μία εναλλακτική λύση που αξιολογείται ως προς ένα σύνολο κριτηρίων, όπου το κάθε κριτήριο αντιστοιχεί σε μία μετρική επίδοσης. Προτείνουμε τη μέθοδο VIC για τον καθορισμό της σημαντικότητας της κάθε μετρικής. Η σημαντικότητα αυτή καθορίζεται από τη μεταβλητότητα της μετρικής και τον βαθμό εξάρτησής της από τις άλλες μετρικές. Η μέθοδος VIC μπορεί να χρησιμοποιηθεί για την ανάθεση αντικειμενικών βαρών σε

οποιοδήποτε πρόβλημα λήψης αποφάσεων πολλαπλών κριτηρίων. Τέλος, αναπτύσσουμε ένα πλαίσιο αξιολόγησης που έχει τη δυνατότητα κατάταξης της επίδοσης των οπορτουνιστικών πρωτοκόλλων δρομολόγησης.

Παρουσιάζουμε λεπτομερή αποτελέσματα προσομοιώσεων για ευρέως γνωστά πρωτόκολλα δρομολόγησης σε διαφορετικά οπορτουνιστικά δίκτυα, τα οποία κατατάσσουμε σύμφωνα με το προτεινόμενο πλαίσιο. Εν κατακλείδι, κανένας αλγόριθμος δεν κατάφερε να επιτύχει την καλύτερη επίδοση σε όλα ή στα περισσότερα δίκτυα που μελετήσαμε. Το γεγονός αυτό καταδεικνύει τη δυσκολία του προβλήματος της δρομολόγησης σε αυτά τα δίκτυα.

CHAPTER 1

INTRODUCTION

1.1 Opportunistic Networking

The increasing popularity of mobile devices with wireless communication capabilities enables the development of novel applications and services, where these devices can exchange messages in an ad hoc manner instead of relying exclusively on existing infrastructure [1, 2]. Whenever two devices are within communication range, i.e. whenever they are in *contact*, they have an opportunity to exchange data directly with each other [3]. An *opportunistic network* can be formed by a set of mobile devices that may serve as routers for others, enabling multi-hop communications in highly dynamic and sparse network topologies by exploiting such contacts [4]. Since these devices are often carried by people, opportunistic networks exhibit heterogeneous contact rates and unpredictable node mobility [5]. Furthermore, due to the frequent and long-lasting disconnections, routing protocols for opportunistic networks follow the *store-carry-and-forward* paradigm in order to achieve data delivery [6].

In Fig. 1.1 we show a series of snapshots from an opportunistic network in order to illustrate how routing protocols cope with intermittent connectivity to successfully deliver a message. Suppose that in the first snapshot, node S generates a message
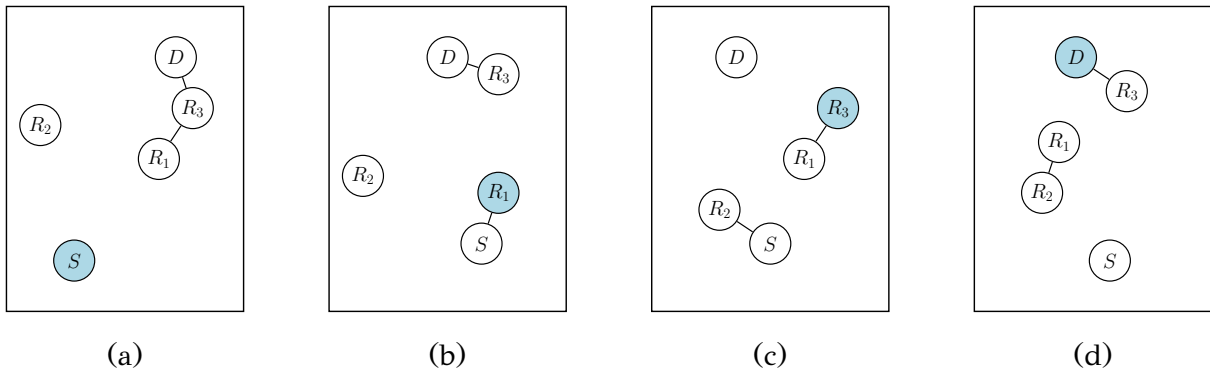
Figure 1.1: A series of snapshots from an opportunistic network for the illustration of the store-carry-and-forward paradigm.

destined for node D. Since there is not any node within its communication range, node S carries the message that it generated and waits for an opportunity to arise. In the second snapshot, node S comes in contact with node R_1. Then, based on the underlying routing protocol, node S decides to forward its message to node R_1. Similarly, in the third snapshot node R_1 forwards the message to node R_3, while in the fourth snapshot, node R_3 encounters node D and delivers the message that node S generated. By following the store-carry-and-forward paradigm, we were able to successfully transfer a message from the *source node S* to the *destination node D* through a series of *relay nodes*, even though there was no contemporary end-to-end path at any given time.

Most of the routing protocols that have been proposed for opportunistic networks make their routing decisions on a contact basis. Several approaches are used in order to determine whether a packet should be forwarded to an encountered node or not. Furthermore, some routing protocols maintain only a single copy of each packet in the network, while other routing protocols may replicate each packet either a limited or an unlimited number of times. The performance of each routing protocol is usually evaluated based on three metrics: (a) the number of packets that it was able to deliver, (b) the delivery delay of the delivered packets, and (c) the number of packet transmissions that it performed. However, these performance metrics are often highly correlated. For example, a routing protocol that aims to deliver many packets with low delivery delay is expected to have an increased number of transmissions. On the other hand, a routing protocol that performs less transmissions may delay or even fail the delivery of some packets. Thus, most routing protocols try to achieve a balance

between these conflicting performance metrics by utilizing the limited information that is available.

1.2 Scope of the Thesis

In this work, we formulate the evaluation of opportunistic routing protocols as a Multiple-Criteria Decision-Making (MCDM) problem. MCDM methods are often used for problems that require the evaluation of a set of alternatives in terms of a set of usually conflicting criteria. We can consider each routing protocol as an alternative and the performance metrics as a set of criteria. However, the traditional performance metrics have several shortcomings that make them not suitable to be considered as criteria of a MCDM problem. For example, a routing protocol that delivers only a small number of packets with low delivery delay may have a lower average delay than a routing protocol that delivered the same packets with equal delivery delay, but it also delivered other packets that required longer delays. Furthermore, the characteristics of the underlying network affect the amount of variation in the values of the performance metrics, as well as their levels of correlation, which should be taken into account to determine the importance of each performance metric. The main contributions of this thesis can be summarized as follows:

- We define a set of normalized performance metrics that evaluate the performance of each routing protocol with respect to the optimal performance.

- We propose a weighting method that relies on the variability and interdependences of criteria in order to determine their relative importance, which can be applied to any MCDM problem for the assignment of objective weights.

- We develop a framework for the evaluation of routing protocols for opportunistic networks, which utilizes MCDM methods in order to provide a ranking of the routing protocols.

- We analyze the performance of a wide range of opportunistic routing protocols on datasets of varying scale and structure, illustrating how different routing approaches perform under different network characteristics.

1.3 Overview of the Thesis

The rest of the thesis is organized as follows. In Chapter 2 we provide the background required for this thesis. In Chapter 3 we propose a framework for the evaluation of routing protocols for opportunistic networks. In Chapter 4 we evaluate the performance of several well-known routing protocol on four datasets with the proposed framework. Finally, in Chapter 5 we discuss the results of our research and summarize the basic conclusions.

CHAPTER 2

BACKGROUND

2.1 Routing in Opportunistic Networks

One of the main challenges in the design of opportunistic routing protocols is how to determine if a packet should be forwarded to an encountered node, with the two extremes being Epidemic Routing [7] and Direct Delivery [8]. According to the Epidemic Routing protocol, each node maintains a *summary vector* that describes the packets that it carries. Whenever two nodes meet they initiate an *anti-entropy session*, where they exchange their summary vectors and each node requests copies of the unknown packets that the other node carries. Therefore, Epidemic Routing forwards to every encountered node a replica of each packet that it does not carry, essentially flooding the network. On the other hand, Direct Delivery does not utilize any relay node, with the source node of a packet always waiting to encounter the destination node in order to deliver it. If there are no resource constraints, Epidemic Routing will deliver every packet that can be delivered with the minimum delivery delay and Direct Delivery will produce the least routing overhead. However, Epidemic Routing performs an excessive number of transmissions, while Direct Delivery often results in long delivery delays. Most of the routing protocols that have been proposed for

opportunistic networks try to achieve a balance between these two extremes.

Utility metrics are often used in order to determine how suitable an encountered node is to carry a certain packet. For example, between two encountered nodes, we can consider as the most suitable carrier of a packet to be the node that met its destination most recently [9]. A utility metric can be classified as either destination-independent or destination-dependent. For instance, the total number of contacts that a node had with every node in the network is a destination-independent utility metric, while the total number of contacts that a node had with a specific destination node is a destination-dependent utility metric [10]. Another destination-dependent utility metric, which is used by PRoPHET [11, 12, 13], relies on the history of previous encounters and the transitive property. More specifically, even though an encountered node may have never come in contact with the destination node, it can still be considered a suitable carrier if it frequently comes in contact with nodes that often encounter the destination node. Numerous utility metrics have been proposed in the literature to determine suitable carriers for a packet so that it will eventually reach its destination [14, 15].

Another challenge that arises in the design of an opportunistic routing protocol is whether it should follow a single-copy approach [16] or a multi-copy approach [17]. When a node forwards a packet to an encountered node, single-copy routing protocols will delete the packet from the previous carrier, thus each packet is unique in the network. On the contrary, multi-copy routing protocols do not delete the packet from the previous carrier, essentially replicating the original packet. By spreading multiple copies of a packet to multiple nodes in the network, multi-copy routing protocols are more likely to find a faster delivery path than single-copy routing protocols. Basically, Epidemic Routing is a multi-copy routing protocol that replicates a packet upon every encounter with a node that does not already carry a replica. By relying on a utility metric to determine when to replicate a packet to an encountered node, we can reduce the routing overhead of Epidemic Routing drastically. However, the routing overhead of a Compare and Replicate approach is significantly higher than that of a Compare and Forward approach, even though the latter approach may sometimes loop a packet among a set of nodes.

Several routing protocols have been proposed that bound the number of times that each packet can be replicated to a value L in order to reduce the routing overhead. When a source node generates a packet, it initially has L copies of that packet that

may eventually reach L distinct relay nodes. Spray and Wait [18] is a routing protocol that consists of two phases: the spray phase and the wait phase. In the spray phase, a fraction of the remaining copies are distributed upon contact. According to the binary spraying method, half of the remaining copies are handed over to every encountered node that does not have any copy of the packet. When a node is left with a single copy of a packet, it switches to the wait phase, where it waits to meet the destination in order to deliver it, just like Direct Delivery would do. Spray and Focus [19] was later proposed, which replaces the wait phase with a focus phase, where the nodes that are left with only one copy of a packet may forward it to an encountered node, just like a single-copy utility-based routing protocol would do. More specifically, in the spray phase it follows the binary spraying method, while in the focus phase it forwards the packet only if it encounters a node that encountered the destination more recently than the current carrier. Furthermore, Last-Seen-First (LSF) Spraying [20] is a utility-based spraying method that aims to distribute the L copies of a packet to a more useful set of relay nodes. According to this method, an encountered node will receive half of the remaining copies of a packet only if its last contact with its destination was more recent than that of the current carrier of the copies.

EBR [21] is another multi-copy routing protocol that limits the maximum number of replicas of each packet. However, EBR relies on a utility metric in order to determine how many replicas should be forwarded upon encounter. In particular, the utility value of each node corresponds to an exponentially weighted moving average of its number of encounters. So, when two nodes meet, the fraction of the remaining copies that the encountered node will receive depends on the utility values of the two nodes. Therefore, the encountered node will receive more replicas than a node with a significantly lower utility value would. Similarly, SimBetTS [22] relies on social network analysis metrics in order to determine when an encountered node should receive one or more replicas of a packet. More specifically, SimBetTS combines several destination-dependent utility metrics with a destination-independent utility metric to calculate an overall utility value. In the case that there is only one replica of a packet, SimBetTS operates as a single-copy routing protocol.

A different approach towards reducing the routing overhead of multi-copy routing protocols was introduced by Delegation Forwarding [23]. Unlike the simple Compare and Replicate approach, where each node replicates a packet when it encounters a node with a higher utility value, Delegation Forwarding takes into account the utility

values that each node has observed for a packet so far. The main idea is to create a small number of replicas only for the nodes with the highest utility values. More specifically, a node will replicate a packet only when it encounters another node whose utility value is greater than the highest utility value that has been observed for that packet so far. COORD [24] builds upon this concept to further reduce redundant replications. In particular, COORD enables the nodes to exchange their observations and coordinate their replication decisions. Finally, it should be noted that while most of the aforementioned multi-copy routing protocols must define the maximum number of replicas for each packet in the network, Delegation Forwarding and COORD only have to choose which utility metric should be used.

2.2 Performance Evaluation of Opportunistic Routing Protocols

While in traditional networks the routing objective may be easily expressed by a simple metric, in opportunistic networks it is more difficult to determine what the objective of a routing protocol should be [25]. A first approach to determine a routing objective for opportunistic networks could be the maximization of the number of packets that are successfully delivered. However, due to the unpredictable nature of opportunistic networks, a routing protocol may require an excessive number of additional transmissions in order to be able to deliver more packets. Another approach that would aim to minimize the routing overhead could result in a low fraction of successfully delivered packets as well as high delivery delays. It should also be noted that, while applications in opportunistic networks may be delay-tolerant, the minimization of end-to-end delay is often desired.

Traditionally, the most commonly used performance metrics for the evaluation of routing protocols in opportunistic networks are the following:

- *Delivery Ratio*: The total number of successfully delivered packets divided by the number of generated packets.

- *Average Delay*: The sum of all delivery delays divided by the number of delivered packets.

- *Overhead Ratio*: The total number of packet transmissions normalized to the

number of generated packets.[1]

Another performance metric which is often omitted from the evaluation results of some studies, even though it can provide valuable information for the performance of a routing protocol, is the *Average Number of Hops* [26]. Similar performance metrics have also been widely used for the evaluation of routing protocols in mobile ad hoc networks (MANETs) [27, 28]. All of the above performance metrics should be taken into account for the performance analysis of routing protocols. Furthermore, the characteristics of the underlying network should also be taken into consideration, such as its connectivity patterns and node mobility [14].

2.3 Multiple-Criteria Decision-Making

Since the evaluation of opportunistic routing protocols is a multidimensional problem, we could formulate it as a Multiple-Criteria Decision-Making (MCDM) problem. Each routing protocol could be considered as an alternative and the performance metrics could correspond to a set of criteria. In this section we review some concepts that are necessary for the development of our framework for the evaluation of opportunistic routing protocols.

2.3.1 Basic Concepts

Suppose that we have a multiple-criteria evaluation problem with n alternatives that have been evaluated using m criteria. This can be easily expressed in a *decision matrix* of the following format:

$$
\mathbf{X} = \begin{array}{c} \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \vdots \\ \mathbf{a}_n \end{array} \begin{array}{c} \mathbf{c}_1 \quad\; \mathbf{c}_2 \quad\; \cdots \quad\; \mathbf{c}_m \\ \left(\begin{array}{cccc} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{array} \right) \end{array}, \tag{2.1}
$$

where $x_{i,j}$ corresponds to the performance value of the alternative $\mathbf{a}_i$ with respect to the criterion $\mathbf{c}_j$ for $i = 1, \ldots, n$ and $j = 1, \ldots, m$. We refer to the criteria that have a

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[1]In some studies, the routing overhead may be quantified by the number of transmissions per delivered packet.

positive impact as *benefit criteria*, such as a quality index, which we aim to maximize. On the other hand, we aim to minimize criteria that have a negative impact, such as a damage index, which we refer to as *cost criteria*. However, it is necessary to normalize the decision matrix in order to eliminate any units of measurement, since the criteria could be expressed in different measurement units. Here we present some of the most common normalization methods:

$$z_{i,j} = \begin{cases} \dfrac{x_{i,j}}{x_j^{max}}, & i = 1, \ldots, n, \quad j \in J_b, \\[3mm] \dfrac{x_j^{min}}{x_{i,j}}, & i = 1, \ldots, n, \quad j \in J_c, \end{cases} \tag{2.2}$$

$$z_{i,j} = \frac{x_{i,j}}{\sum\limits_{k=1}^{n} x_{k,j}}, \quad i = 1, \ldots, n, \quad j = 1, \ldots, m, \tag{2.3}$$

$$z_{i,j} = \begin{cases} \dfrac{x_{i,j} - x_j^{min}}{x_j^{max} - x_j^{min}}, & i = 1, \ldots, n, \quad j \in J_b, \\[3mm] \dfrac{x_j^{max} - x_{i,j}}{x_j^{max} - x_j^{min}}, & i = 1, \ldots, n, \quad j \in J_c, \end{cases} \tag{2.4}$$

$$z_{i,j} = \frac{x_{i,j}}{\sqrt{\sum\limits_{k=1}^{n} x_{k,j}^2}}, \quad i = 1, \ldots, n, \quad j = 1, \ldots, m, \tag{2.5}$$

where $x_j^{max} = \max\{ x_{i,j} \mid i = 1, \ldots, n \}$ and $x_j^{min} = \min\{ x_{i,j} \mid i = 1, \ldots, n \}$, while J_b and J_c are the index sets of the benefit and cost criteria respectively. After selecting a normalization method, we can construct the *normalized decision matrix* as follows:

$$\mathbf{Z} = \begin{array}{c} \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \vdots \\ \mathbf{a}_n \end{array} \begin{array}{c} \mathbf{c}_1 \quad\; \mathbf{c}_2 \quad \cdots \quad \mathbf{c}_m \\ \begin{pmatrix} z_{1,1} & z_{1,2} & \cdots & z_{1,m} \\ z_{2,1} & z_{2,2} & \cdots & z_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n,1} & z_{n,2} & \cdots & z_{n,m} \end{pmatrix} \end{array}. \tag{2.6}$$

Furthermore, in order to be able to have criteria of different importance, we introduce a *weight vector* $\mathbf{w} = (w_1\ w_2\ \ldots\ w_m)$, where $\sum_{j=1}^{m} w_j = 1$ and $w_j \geq 0$ for $j = 1, \ldots, m$. Thus, w_j corresponds to the relative importance of the jth criterion. In Section 2.3.2 we review decision-making methods that produce a ranking of the alternatives, while in Section 2.3.3 we review weighting methods that assign values to the weight vector.

2.3.2 Decision-Making Methods

Given a decision matrix and a weight vector, several decision-making methods have been proposed in order to provide an overall score of each alternative [29, 30]. In this section we briefly review some of the most commonly used decision-making methods. The simplest and probably the most widely used method is the Simple Additive Weighting (SAW), which is also known as the Weighted Sum Model (WSM) [31]. According to the SAW method, the overall score of each alternative $\mathbf{a}_i$ is determined by the following formula:

$$SAW(\mathbf{a}_i) = \sum_{j=1}^{m} w_j z_{i,j}, \quad i = 1, \ldots, n. \tag{2.7}$$

It should be noted that this method is applicable only when all the performance values are expressed in the same measurement unit. Another similar decision-making method is the Multiplicative Exponential Weighting (MEW), which is also known as the Weighted Product Model (WPM) [32, 33]. Their main difference is that instead of addition, MEW relies on multiplication. More specifically, the overall score of each alternative $\mathbf{a}_i$ with the MEW method is given by:

$$MEW(\mathbf{a}_i) = \prod_{j=1}^{m} (z_{i,j})^{w_j}, \quad i = 1, \ldots, n. \tag{2.8}$$

If we assume that all the criteria are benefit criteria, then the best alternative is the one that yields the highest overall score.

A different approach is followed by the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [34, 35]. The basic idea of this method is that the best alternative is the closest to the positive ideal solution and the farthest to the negative ideal solution. After normalizing the performance values, it constructs a *weighted normalized decision matrix* as follows:

$$\mathbf{T} = \begin{array}{c} \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \vdots \\ \mathbf{a}_n \end{array} \begin{array}{cccc} \mathbf{c}_1 & \mathbf{c}_2 & \cdots & \mathbf{c}_m \\ \begin{pmatrix} t_{1,1} & t_{1,2} & \cdots & t_{1,m} \\ t_{2,1} & t_{2,2} & \cdots & t_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n,1} & t_{n,2} & \cdots & t_{n,m} \end{pmatrix} \end{array}, \tag{2.9}$$

where $t_{i,j} = w_j z_{i,j}$ for $i = 1, \ldots, n$ and $j = 1, \ldots, m$. The positive ideal solution $\mathbf{a}^+ = \begin{pmatrix} t_1^+ & t_2^+ & \ldots & t_m^+ \end{pmatrix}$ consists of the maximum values of all the benefit criteria and the

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minimum values of all the cost criteria, where

$$
t_j^+ = \begin{cases} \max\{\, t_{i,j} \mid i = 1, \ldots, n \,\}, & j \in J_b, \\[2ex] \min\{\, t_{i,j} \mid i = 1, \ldots, n \,\}, & j \in J_c. \end{cases} \tag{2.10}
$$

Similarly, the negative ideal solution $\mathbf{a}^- = \left(t_1^- \ t_2^- \ \ldots \ t_m^- \right)$ consists of the minimum values of all the benefit criteria and the maximum values of all the cost criteria, where

$$
t_j^- = \begin{cases} \min\{\, t_{i,j} \mid i = 1, \ldots, n \,\}, & j \in J_b, \\[2ex] \max\{\, t_{i,j} \mid i = 1, \ldots, n \,\}, & j \in J_c. \end{cases} \tag{2.11}
$$

Then, it calculates the Euclidean distance between the alternative $\mathbf{a}_i$ and the positive ideal solution $\mathbf{a}^+$ as

$$
d_i^+ = \sqrt{\sum_{j=1}^{m} \left(t_j^+ - t_{i,j} \right)^2}, \quad i = 1, \ldots, n \tag{2.12}
$$

and the Euclidean distance between the alternative $\mathbf{a}_i$ and the negative ideal solution $\mathbf{a}^-$ as

$$
d_i^- = \sqrt{\sum_{j=1}^{m} \left(t_{i,j} - t_j^- \right)^2}, \quad i = 1, \ldots, n. \tag{2.13}
$$

Finally, it determines the relative closeness of each alternative $\mathbf{a}_i$ as its overall score as follows:

$$
TOPSIS\left(\mathbf{a}_i \right) = \frac{d_i^-}{d_i^- + d_i^+}, \quad i = 1, \ldots, n. \tag{2.14}
$$

Therefore, the alternative with the highest overall score is considered the best alternative, because it has the shortest Euclidean distance from the positive ideal solution and the longest Euclidean distance from the negative ideal solution.

A modified version of TOPSIS has also been proposed, which we refer to as mTOPSIS [36]. Instead of calculating the Euclidean distances of each alternative from the positive ideal solution and the negative ideal solution of the weighted normalized matrix, mTOPSIS uses the weighted Euclidean distances of each alternative from the positive ideal solution and the negative ideal solution of the normalized matrix. After transforming any cost criteria into benefit criteria, mTOPSIS calculates the following weighted Euclidean distances:

$$
d_i^{max} = \sqrt{\sum_{j=1}^{m} w_j \left(z_j^{max} - z_{i,j} \right)^2}, \quad i = 1, \ldots, n, \tag{2.15}
$$

$$d_i^{min} = \sqrt{\sum_{j=1}^{m} w_j \left(z_{i,j} - z_j^{min} \right)^2}, \quad i = 1, \ldots, n, \qquad (2.16)$$

where $z_j^{max} = \max\{ z_{i,j} \mid i = 1, \ldots, n \}$ and $z_j^{min} = \min\{ z_{i,j} \mid i = 1, \ldots, n \}$. Then, the overall score of each alternative $\mathbf{a}_i$ is given by:

$$mTOPSIS\left(\mathbf{a}_i\right) = \frac{d_i^{min}}{d_i^{min} + d_i^{max}}, \quad i = 1, \ldots, n. \qquad (2.17)$$

2.3.3 Weighting Methods

Numerous weighting methods have been proposed in order to determine the importance of each criterion. These methods can be broadly classified into three categories: subjective, objective, and integrated. Subjective weighting methods rely on the decision maker to determine the importance of each criterion [37, 38, 39, 40, 41, 42], while objective weighting methods determine the importance of each criterion based on the available information in the decision matrix [43, 36]. Integrated weighting methods combine subjective and objective information to determine the importance of each criterion [44, 45, 46, 47, 48], which are usually used when the objective weights are not consistent with the subjective preferences of the decision maker. In this work, we focus on objective weighting methods in order to provide an unbiased evaluation of routing protocols on datasets with vastly different characteristics.

The most simplistic approach, which is usually used when the decision maker cannot assign subjective weights reliably, is to assume that all the criteria are equally important. This approach is known as the Mean Weights (MW) method [43], which determines the relative importance of each criterion as

$$w_j = \frac{1}{m}, \quad j = 1, \ldots, m, \qquad (2.18)$$

i.e. it depends only on the total number of criteria m. However, if there is little variation in the performance values of a criterion, even if the decision maker considers it as an important criterion, it has little use in differentiating the alternatives [49]. For example, when we want to evaluate a set of routing protocols, we usually consider the fraction of successfully delivered packets as an important performance metric. However, if all the routing protocols deliver about the same number of packets, then this criterion has little influence on the overall evaluation of the routing protocols. In such cases the focus is shifted towards other performance metrics, such as the

number of transmissions that each routing protocol performed, where they do not have similar performance values.

If we view the criteria as information sources, then their importance can be perceived as their contrast intensity [50], which can be quantified by a measure of entropy or the standard deviation. In order to use the Entropy Measure (EM) method [36], the decision matrix must be normalized using Eq. (2.3). According to this method, the amount of information emitted from each criterion $\mathbf{c}_j$ is measured by e_j, which is defined as follows:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} z_{i,j} \ln(z_{i,j}), \quad j = 1, \ldots, m. \tag{2.19}$$

Then, the weight of each criterion is given by normalizing its degree of divergence, according to the following formula:

$$w_j = \frac{1 - e_j}{\sum\limits_{k=1}^{m}(1 - e_k)}, \quad j = 1, \ldots, m. \tag{2.20}$$

Similarly, the Standard Deviation (SD) method [43] determines the relative importance of each criterion through the following equations:

$$\sigma_j = \sqrt{\frac{1}{n} \sum_{i=1}^{n}(z_{i,j} - \mu_j)^2}, \quad j = 1, \ldots, m, \tag{2.21}$$

$$w_j = \frac{\sigma_j}{\sum\limits_{k=1}^{m} \sigma_k}, \quad j = 1, \ldots, m, \tag{2.22}$$

where μ_j is the arithmetic mean of the criterion $\mathbf{c}_j$ for $j = 1, \ldots, m$.

The notion of conflict among criteria was first taken into consideration for the determination of objective weights by the CRITIC method [43], which is an abbreviation for "CRiteria Importance Through Intercriteria Correlation". The CRITIC method relies on the standard deviation to quantify the contrast intensity of each criterion, as seen in Eq. (2.21), and a symmetric matrix of linear correlation coefficients

$$\rho_{j,k} = \frac{\sum\limits_{i=1}^{n}(z_{i,j} - \mu_j)(z_{i,k} - \mu_k)}{\sqrt{\sum\limits_{i=1}^{n}(z_{i,j} - \mu_j)^2 \sum\limits_{i=1}^{n}(z_{i,k} - \mu_k)^2}}, \quad j = 1, \ldots, m, \quad k = 1, \ldots, m, \tag{2.23}$$

in order to measure the conflicting character of the criteria. The linear correlation coefficient, also known as the Pearson product-moment correlation coefficient, is used

to measure the strength of linear correlations between two random variables, which ranges between -1 and 1. When the Pearson correlation is equal to -1 it indicates a perfect negative linear correlation, while when it is equal to 1 it indicates a perfect positive linear correlation. In the case that the Pearson correlation is equal to 0, it implies that there is no linear correlation between the two random variables. The CRITIC method measures the conflict that each criterion has with the rest criteria and combines it with its standard deviation in order to determine its importance according to the following formula:

$$f_j = \sigma_j \sum_{k=1}^{m} \left(1 - \rho_{j,k}\right), \quad j = 1, \ldots, m. \tag{2.24}$$

Therefore, according to the CRITIC method, the importance of each criterion depends on the amount of variation in its performance values and the amount of discordance that it has with the other criteria. Finally, the objectives weights are derived by the following normalization:

$$w_j = \frac{f_j}{\sum_{k=1}^{m} f_k}, \quad j = 1, \ldots, m. \tag{2.25}$$

CHAPTER 3

A FRAMEWORK FOR THE EVALUATION OF OPPORTUNISTIC ROUTING PROTOCOLS

3.1   Performance Metrics as Evaluation Criteria

The proposed framework evaluates a set of routing protocols for opportunistic networks by considering each routing protocol as an alternative and each performance metric as a criterion of a Multiple-Criteria Decision-Making (MCDM) problem. However, the traditional performance metrics that are used for the evaluation of routing protocols in opportunistic networks have several shortcomings that make them not suitable to be considered as evaluation criteria for a MCDM problem. In Section 3.1.1 we outline these shortcomings, while in Section 3.1.2 we describe the proposed performance metrics that we use for the construction of decision matrices.

3.1.1   Traditional Performance Metrics

The traditional performance metric with the most significant shortcomings is the average delay. For example, the comparison of the average delay between two routing

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Table 3.1: Average values of the traditional performance metrics for a subset of routing protocols on the Dartmouth dataset.

	DR	AD	OR	ANH
Epidemic	0.9780	27.30	560.44	10.13
Direct	0.0430	54.75	0.04	1.00
CnF.PRoPHET	0.5521	78.11	8.51	9.50
CnR.PRoPHET	0.9518	41.20	120.34	6.43
DF.PRoPHET	0.8234	59.64	14.73	5.02
COORD.PRoPHET	0.7819	61.83	10.81	4.87

protocols can be misleading if they do not deliver the exact same packets. In such a case, the average delay of a routing protocol with low delivery ratio will be derived from a smaller sample of packets than a routing protocol with higher delivery ratio. Worse still, if the latter protocol delivered with equal delay every packet that the former protocol did, it will have a higher average delay if it also delivered some additional packets that required longer delays. Obviously, the performance of the latter protocol is better, since it did not deliver any packet with higher delay than the former protocol.

Even if two protocols delivered the same number of packets, the comparison of average delays could still be unfair if they delivered packets of different source-destination pairs. For example, two protocols could deliver two different packets with exactly the same delay, but the first protocol may have delivered its packet with optimal delay, while the packet of the second protocol could have been delivered with less delay. This implies different levels of "difficulty", since some destination nodes can be reached more easily than others. This also affects the traditional overhead ratio performance metric. In addition, for the evaluation of routing overhead, we do not consider how each protocol utilized its transmissions. Two protocols could perform the same number of transmissions for a packet, with the first protocol delivering it with the optimal number of forwards and the second protocol failing to deliver it.

In Table 3.1 we provide the average values of the traditional performance metrics for a subset of routing protocols that we study in Section 4.2.4. More specifically, we show the average values of the *Delivery Ratio (DR)*, the *Average Delay (AD)* in hours, the *Overhead Ratio (OR)*, and the *Average Number of Hops (ANH)*. As expected, Epidemic

Routing has by far the highest average value for the overhead ratio metric, while Direct Delivery has the lowest average value for the delivery ratio metric. Observe that Direct Delivery has a better performance value for the average delay metric than Delegation Forwarding and COORD with the PRoPHET utility metric. However, both algorithms delivered every packet that Direct Delivery was able to deliver with less or at least equal delivery delay. This is because with Delegation Forwarding and COORD, the source node will always have a replica of its packet. Therefore, Delegation Forwarding and COORD will deliver every packet that can be delivered directly, either with the same delivery delay as Direct Delivery or with less delivery delay by utilizing a set of relay nodes. In Appendix A we provide the average values and 95% confidence intervals of the traditional performance metrics for more routing protocols and on more datasets, which are derived from the simulation setup that we describe in Section 4.1.

3.1.2 Proposed Performance Metrics

Since opportunistic networks are characterized by heterogeneous contact rates and unpredictable node mobility, the aforementioned issues are often encountered during the evaluation of opportunistic routing protocols. To address these issues, we argue that the performance of each opportunistic routing protocol should be normalized with respect to the optimal performance. In order to achieve this, we need two versions of an algorithm that we call *Optimal Routing*. The first version, which we refer to as OPT_D, delivers every packet that can be delivered with the minimum delivery delay. The second version, which we refer to as OPT_F, delivers every packet that can be delivered with the minimum number of forwards. In other words, OPT_D will select the fastest delivery path with the minimum number of hops, while OPT_F will select the shortest delivery path with the minimum delivery delay. Note that both OPT_D and OPT_F are actually non-realistic algorithms. However, they are useful for providing performance limits.

The first performance metric that we propose is the *Normalized Delivery Ratio (NDR)*, which is defined as the total number of successfully delivered packets normalized to the maximum number of packets that could have been delivered. Both versions of Optimal Routing deliver every packet that can be delivered, which we refer to as deliverable packets. Thus, the normalized delivery ratio of a routing protocol

RP is given by:

$$NDR\left(RP\right) = \frac{\left|Delivered\left(RP\right)\right|}{\left|Deliverable\right|} .$$ (3.1)

This performance metric is particularly useful for scenarios where a large proportion of the generated packets cannot be delivered even by Optimal Routing. In such cases, it is not reasonable to assume that a routing protocol performed poorly. Instead, the normalized delivery ratio of a routing protocol will be equal to 1 only if it delivered the same packets with Optimal Routing.

For the evaluation of delivery delay, we compare the end-to-end delay that a routing protocol achieved for a packet with the end-to-end delay that OPT_D achieved for the same packet. OPT_D always achieves the minimum possible end-to-end delay for each packet. Thus, the end-to-end delay that OPT_D achieved for a packet divided by the end-to-end delay that any routing protocol achieved for the same packet will always be between 0 and 1. This ratio will be equal to 1 only if the evaluated routing protocol delivered the packet as fast as OPT_D did, while in every other case it will be less than 1. Hence, we define the *Normalized Delivery Delay (NDD)* of a routing protocol *RP* as follows:

$$NDD\left(RP\right) = \frac{\displaystyle\sum_{i \in Delivered(RP)} \frac{Delay_i\left(OPT_D\right)}{Delay_i\left(RP\right)}}{\left|Deliverable\right|} .$$ (3.2)

Observe that, while the traditional average delay metric divides the sum of all delivery delays by the number of packets that the routing protocol delivered, the proposed normalized delivery delay metric divides a sum of ratios by the number of deliverable packets. In other words, with the proposed performance metric, each routing protocol is evaluated based on how fast it was able to deliver each packet that could have been delivered with respect to its optimal delivery delay. Note that the normalized delivery delay decreases and moves away from the optimal performance value, which is equal to 1, for each deliverable packet that the evaluated routing protocol fails to deliver. This feature tackles the problem of the traditional average delay metric, where a routing protocol that delivers only a small number of packets with low delay has an overall low average delay.

Similarly, for the evaluation of routing overhead, we compare the number of forwards that a routing protocol performed with the number of forwards that OPT_F would have performed. However, we are also interested in evaluating the number of forwards that a routing protocol did for the packets that could not be delivered

even by Optimal Routing. Since a realistic routing protocol does not know if a packet is deliverable or not, it will try to deliver every generated packet. Therefore, if we assume that a generated packet has an initial routing overhead equal to 1, regardless of the number of times that it will be forwarded, we can define the *Normalized Routing Overhead (NRO)* of a routing protocol *RP* according to the following formula:

$$NRO\left(RP\right) = \frac{\displaystyle\sum_{i \in Delivered(RP)} \frac{1 + Forwards_i\left(OPT_F\right)}{1 + Forwards_i\left(RP\right)} + \sum_{i \notin Delivered(RP)} \frac{1}{1 + Forwards_i\left(RP\right)}}{\left|Generated\right|} .$$
(3.3)

Notice that we use two sums for two different types of ratios. The first sum of ratios evaluates the routing protocol based on its resource efficiency compared to OPT_F for the packets that it delivered. The second sum of ratios evaluates the routing protocol based on the number of transmissions that it performed for the packets that it was unable to deliver. The reason why we do not handle differently packets that could have been delivered, but the evaluated routing protocol failed to deliver, is because the performance of OPT_F cannot be considered as its limit. Since the evaluated routing protocol was unable to find a delivery path for such packets, it could perform less transmissions than OPT_F that delivered these packets. If a routing protocol did not perform any transmission for an undelivered packet, it is considered as optimal performance in terms of routing overhead. Therefore, the normalized routing overhead of a routing protocol that delivered its packets with the optimal number of transmissions and did not perform any redundant transmissions for the rest packets will be equal to 1.

Observe that the proposed performance metrics are all bounded between 0 and 1, with 1 indicating optimal performance. Furthermore, their values are monotonically increasing, which means that a higher value indicates a better performance. Therefore, the proposed performance metrics can be used as benefit criteria in order to evaluate a set of routing protocols as a multiple-criteria evaluation problem.

In Table 3.2 we provide the average values of the proposed performance metrics for the same simulation scenario that we showed in Table 3.1. As we can see, Epidemic Routing achieves the optimal performance value for the normalized delivery ratio and the normalized delivery delay metrics, but its performance value for the normalized routing overhead is close to 0 because of its excessive number of transmissions. On the other hand, Direct Delivery achieves the optimal performance value for the nor-

Table 3.2: Average values of the proposed performance metrics for a subset of routing protocols on the Dartmouth dataset.

	NDR	NDD	NRO
Epidemic	1.0000	1.0000	0.0170
Direct	0.0439	0.0200	1.0000
CnF.PRoPHET	0.5645	0.2378	0.2889
CnR.PRoPHET	0.9732	0.7069	0.0909
DF.PRoPHET	0.8419	0.4618	0.3040
COORD.PRoPHET	0.7994	0.4287	0.3349

malized routing overhead, but its performance values for the other metrics are very low compared to the other algorithms. Notice that with the proposed performance metrics, Delegation Forwarding and COORD achieve better performance values for the normalized delivery delay metric than Direct Delivery, as we would expect. In addition, Delegation Forwarding and COORD also achieve better performance values for the normalized routing overhead metric than the single-copy Compare and Forward approach. Even though Compare and Forward performed less transmissions than the other two algorithms in total, it was also unable to deliver a significant fraction of the deliverable packets, which implies that many of these transmissions were not used for the delivery of packets. In Section 4.2 we evaluate the performance of more routing protocols and on more datasets based on these metrics, while in Appendix A we provide the average values and 95% confidence intervals of each simulation scenario in detail.

3.2   Variability and Interdependencies of Criteria

After constructing a decision matrix with the proposed performance metrics as evaluation criteria, we must determine the relative importance of each criterion. Like most weighting methods that have been proposed, we also consider the amount of variation in the performance values of a criterion as an indicator of its importance. However, since the variability of a criterion examines its importance in isolation from the other criteria, several weighting methods have been proposed that also utilize the correlation among criteria. For example, the CRITIC weighting method [43] cal-

culates the standard deviation of each criterion and then it increases its importance according to the amount of conflict that it has with the other criteria, based on their linear correlation coefficients. While we believe that this method is heading in the right direction, there are several pitfalls associated with it. In Section 3.2.1 we describe a weighting method that avoids these pitfalls, while in Section 3.2.2 we provide numerical examples and discuss the weight vectors of different weighting methods.

3.2.1   Description of the VIC weighting method

We propose the VIC weighting method, which utilizes the variability and interdependencies of criteria in order to determine their relative importance. Our motivation is as follows:

- We argue that the importance of each criterion should be characterized by the amount of *independence* that it has in relation to the other criteria. In other words, a highly independent criterion should be more important than a highly dependent criterion, regardless of whether it is positively or negatively correlated.

- If the Pearson correlation between two random variables is equal to 0, this only implies that there is no *linear* association between the two random variables, which means that there may be a *non-linear* association. In order to be able to determine when two random variables are independent, another measure of dependence must be used.

- We argue that the importance of a totally independent criterion should be determined solely by its variability. On the other hand, the importance of a dependent criterion should be determined by a fraction of its variability, according to the amount of dependence that it has in relation to the other criteria. In other words, we should *reduce* the importance of highly dependent criteria instead of increasing the importance of highly independent criteria.

Hence, the VIC weighting method calculates the importance of each criterion as

$$g_j = \frac{\sigma_j}{\sum\limits_{k=1}^{m} \mathcal{R}_{j,k}}, \quad j = 1, \ldots, m, \tag{3.4}$$

where σ_j is the standard deviation of the criterion $\mathbf{c}_j$ and $\mathcal{R}_{j,k}$ is the distance correlation (dCor) [51, 52] between the criteria $\mathbf{c}_j$ and $\mathbf{c}_k$ for $j = 1, \ldots, m$ and $k = 1, \ldots, m$.

The objective weight of each criterion is then given by:

$$w_j = \frac{g_j}{\sum\limits_{k=1}^{m} g_k}, \quad j = 1, \ldots, m.$$ (3.5)

The main reason we selected the distance correlation as the measure of dependence for the VIC method is because it is equal to 0 if and only if the two random variables are independent. Furthermore, while the Pearson correlation ranges from -1 to 1, the distance correlation ranges from 0 to 1 instead. Therefore, according to Eq. (3.4), the importance of a totally independent criterion corresponds to its standard deviation. This is because its distance correlation coefficient will be equal to 0 with every other criterion, except with itself which it will always be equal to 1. Therefore, the denominator of the fraction in Eq. (3.4) will be equal to 1 for every totally independent criterion. In every other case it will be greater than 1, with the maximum possible value being the number of criteria m.

3.2.2 Numerical Examples

In this section we present some numerical examples in order to examine the weights that different objective weighting methods produce in various scenarios. More specifically, we present the weight vectors obtained by the Mean Weights (MW) method, the Standard Deviation (SD) method, the CRITIC method with linear correlation coefficients as it was originally proposed [43], a modified version of CRITIC with distance correlation coefficients (CRITIC.dCor), and the proposed Variability and Interdependencies of Criteria (VIC) method.

Table 3.3 depicts a decision matrix with seven alternatives and three highly dependent criteria. Their standard deviations, linear correlation coefficients, and distance correlation coefficients are provided in Table 3.4, based on which each weighting method determines the importance of the criteria. Since the standard deviations of all three criteria are equal in this example, the SD method considers every criterion as equally important, just like the MW method always does. The CRITIC method considers the third criterion as the most important, because it has a perfect negative linear correlation with the second criterion and a strong negative linear correlation with the first criterion. However, if we view a perfect negative linear correlation between two criteria as a perfect trade-off, their importance should be reduced equally since as we try to select an alternative with a higher performance value in one criterion it results

Table 3.3: A trivial example that illustrates how different weighting methods determine the weights of highly dependent criteria.

Alternatives	Criteria		
	$\mathbf{c}_1$	$\mathbf{c}_2$	$\mathbf{c}_3$
$\mathbf{a}_1$	0	0	1
$\mathbf{a}_2$	0.1	0.2	0.8
$\mathbf{a}_3$	0.2	0.4	0.6
$\mathbf{a}_4$	0.3	0.7	0.3
$\mathbf{a}_5$	0.6	0.8	0.2
$\mathbf{a}_6$	0.8	0.9	0.1
$\mathbf{a}_7$	1	1	0
Method	Weights		
	w_1	w_2	w_3
MW	0.3333	0.3333	0.3333
SD	0.3333	0.3333	0.3333
CRITIC	0.2500	0.2586	0.4914
CRITIC.dCor	0.5000	0.2500	0.2500
VIC	0.3382	0.3309	0.3309

Table 3.4: Standard deviations and correlation coefficients of the example in Table 3.3.

Criteria	σ_j	$\rho_{j,k}$			$\mathcal{R}_{j,k}$		
		$\mathbf{c}_1$	$\mathbf{c}_2$	$\mathbf{c}_3$	$\mathbf{c}_1$	$\mathbf{c}_2$	$\mathbf{c}_3$
$\mathbf{c}_1$	0.3493	1	0.9314	-0.9314	1	0.9369	0.9369
$\mathbf{c}_2$	0.3493	0.9314	1	-1	0.9369	1	1
$\mathbf{c}_3$	0.3493	-0.9314	-1	1	0.9369	1	1

in a reduction in the other criterion. Similarly, the importance of two criteria that have a perfect positive linear correlation should also be reduced equally since as we try to select an alternative with a higher performance value in one criterion it also results in a higher performance in the other criterion. Thus, the weakly correlated criteria should be considered as the most important, since their performance values depend the least from the performance values of the other criteria. In this example, if we use the CRITIC method with distance correlation instead of linear correlation it

Table 3.5: A trivial example that illustrates how different weighting methods determine the weights of criteria with non-linear associations.

Alternatives	Criteria		
	c_1	c_2	c_3
a_1	0	0	0
a_2	0	0	1
a_3	0.2	0.5	0
a_4	0.2	0.5	1
a_5	0.4	1	0
a_6	0.4	1	1
a_7	0.6	1	0
a_8	0.6	1	1
a_9	0.8	0.5	0
a_{10}	0.8	0.5	1
a_{11}	1	0	0
a_{12}	1	0	1
Method	Weights		
	w_1	w_2	w_3
MW	0.3333	0.3333	0.3333
SD	0.2733	0.3266	0.4001
CRITIC	0.2733	0.3266	0.4001
CRITIC.dCor	0.2397	0.2865	0.4738
VIC	0.2263	0.2705	0.5031

results in an exaggeration of the importance of the first criterion, because its importance was increased twice as much compared to the other two criteria. By reducing the importance of each criterion according to their amount of dependence that it has in relation to the other criteria, the proposed VIC weighting method derives objective weights that reflect the aforementioned rationale. Since the criteria are highly dependent with each other in this scenario, their weights should be almost equal, with the first criterion having a slightly higher weight because it is the least dependent criterion.

Observe that similar weights would have been obtained for the previous example

Table 3.6: Standard deviations and correlation coefficients of the example in Table 3.5.

Criteria	σ_j	$\rho_{j,k}$			$\mathcal{R}_{j,k}$		
		$\mathbf{c}_1$	$\mathbf{c}_2$	$\mathbf{c}_3$	$\mathbf{c}_1$	$\mathbf{c}_2$	$\mathbf{c}_3$
$\mathbf{c}_1$	0.3416	1	0	0	1	0.5186	0
$\mathbf{c}_2$	0.4082	0	1	0	0.5186	1	0
$\mathbf{c}_3$	0.5000	0	0	1	0	0	1

if we used the *strength* of the linear associations, i.e. the absolute values of the linear correlation coefficients, instead of the distance correlation coefficients. If we followed this approach however, we would not be able to distinguish when two criteria have a non-linear association and when they are independent, like the scenario in Table 3.5. In this example, the first criterion has a non-linear association with the second criterion, while the third criterion is totally independent. As we can see in Table 3.6, the linear correlation coefficient is equal to 0 in both cases, while the distance correlation coefficient is equal to 0 only in the latter case. As a result, the weights derived from the CRITIC method are identical to the weights derived from the SD method. On the other hand, the VIC method assigns a significantly higher weight to the third criterion because it has the highest amount of variation in its performance values and it is also independent from the other two criteria. In Section 4.2 we examine the associations of the proposed performance metrics on several datasets and we provide the weight vector that each method produces.

3.3   Selection of a Decision-Making Method

After calculating the normalized performance metrics that were proposed in Section 3.1.2 for each routing protocol that we want to evaluate, we can construct a decision matrix where each routing protocol corresponds to an alternative and each performance metric corresponds to a benefit criterion. Then, we can obtain a weight vector that depicts the relative importance of each criterion using the VIC weighting method that we described in Section 3.2.1. Therefore, provided the aforementioned decision matrix and weight vector, we can now use a decision-making method in order to produce a ranking of routing protocols. However, a decision-making paradox is reached in the process of selecting the best decision-making method, since that

Table 3.7: A trivial example that illustrates how different decision-making methods handle trade-offs between criteria.

Alternatives	Criteria		SAW score	MEW score	mTOPSIS score
	c_1	c_2			
a_1	0	1	0.5000	0	0.5000
a_2	0.25	0.75	0.5000	0.4330	0.5000
a_3	0.5	0.5	0.5000	0.5000	0.5000
a_4	0.75	0.25	0.5000	0.4330	0.5000
a_5	1	0	0.5000	0	0.5000

would require the best decision-making method [53].

In the context of the evaluation of routing protocols for opportunistic networks, we recommend the use of the MEW method [32, 33], mainly because of the way that it handles trade-offs between criteria. Suppose that we have a decision matrix with two conflicting criteria that are equally important, like the one depicted in Table 3.7. As we can see, the SAW method [31] and the modified version of the TOPSIS method [36] rank all the alternatives equally. On the contrary, the MEW method considers the third alternative as the best alternative, which achieves an average score in both criteria, followed by the second and fourth alternatives. Since most opportunistic routing protocols search for a middle ground between the extreme routing overhead of Epidemic Routing [7] and the unsatisfactory delivery delays of Direct Delivery [8], the MEW method seems the most suitable for their evaluation. This is because routing protocols with a low performance value in at least one criterion will also have an overall low MEW score.

In Table 3.8 we provide the overall score of the subset of routing protocols that we examined in Table 3.2 with three different decision-making methods. However, the weight vector was derived from the full set of routing protocols that we analyze in Section 4.2.4. More specifically, the normalized routing overhead is the most important metric in this scenario, with its weight value being equal to 0.4275. The normalized delivery ratio metric follows with a weight value equal to 0.3337, while the normalized delivery delay metric is the least importance in this scenario with a weight value equal to 0.2387. Even though Epidemic Routing performs by far the most packet transmissions, the SAW method and the mTOPSIS method consider it

Table 3.8: Evaluation of a subset of routing protocols on the Dartmouth dataset, with different decision-making methods and the VIC weight vector of the full set of routing protocols.

	SAW score	MEW score	mTOPSIS score
Epidemic	0.5797	0.1752	0.5321
Direct	0.4470	0.1384	0.4679
CnF.PRoPHET	0.3687	0.3449	0.3609
CnR.PRoPHET	0.5324	0.3272	0.5094
DF.PRoPHET	0.5212	0.4719	0.5042
COORD.PRoPHET	0.5123	0.4749	0.4969

as the best alternative, followed by the multi-copy Compare and Replicate approach. This is because their high performance values for the normalized delivery ratio and normalized delivery delay metrics overshadow their very low performance value for the normalized routing overhead metric. In addition, SAW and mTOPSIS assign a higher overall score to Direct Delivery than the single-copy Compare and Forward approach, because Direct Delivery achieves the optimal performance value for the most importance metric in this scenario. This is clearly unreasonable, since Direct Delivery has by far the worst performance in terms of the other two metrics. On the hand, the MEW method assigns low overall scores to Epidemic Routing and Direct Delivery because they perform poorly for at least one metric. Furthermore, COORD and Delegation Forwarding are ranked the highest by the MEW method, since they achieve reasonable performance values for every metric. In Section 4.2 we provide the ranking of the full set of routing protocols using the MEW decision-making method and the VIC weighting method on datasets with vastly different characteristics, while we also discuss the rankings that other decision-making and weighting methods produce.

Chapter 4

Case Studies

4.1   Simulation Setup

We selected four datasets of varying scale to evaluate the performance of routing protocols for opportunistic networks according to the proposed framework. More specifically, the datasets that we selected are the following: Reality Mining [54, 55], INFOCOM 2005 [56, 57], Lyon [58, 59, 60], and Dartmouth [61, 62, 63]. The Lyon dataset was downloaded from the website of the SocioPatterns collaboration[1], while the rest datasets were downloaded from the website of the CRAWDAD archive[2]. In Table 4.1 we summarize the characteristics of each dataset. As we can see, the datasets that we studied differ significantly in terms of the number of participants, while their durations vary from a few days to several months. Additionally, the scanning interval and the communication range also varies between the datasets that we studied.

We have developed an event-driven simulator that is capable of processing contact traces, called Adyton [64], where we have implemented several routing protocols that have been proposed for opportunistic networks. Furthermore, we have also implemented the two versions of the Optimal Routing algorithm that are required for the

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[1]http://www.sociopatterns.org/

[2]http://crawdad.org/

Table 4.1: Characteristics of the datasets.

	Reality Mining	INFOCOM 2005	Lyon	Dartmouth
Number of Nodes	97	41	242	738
Duration (days)	283	3	2	14
Granularity (seconds)	300	120	20	1
Network Interface	Bluetooth	Bluetooth	RFID	Wi-Fi

calculation of the proposed normalized performance metrics. The routing protocols that we simulated on each of the aforementioned datasets are the following:

- Epidemic Routing (Epidemic) [7].

- Direct Delivery (Direct) [8].

- Compare and Forward (CnF) [16].

- Compare and Replicate (CnR) [17].

- Delegation Forwarding (DF) [23].

- COORD [24].

- Spray and Wait (SnW) [18].

- LSF-Spray and Wait (LSF-SnW) [20].

- Spray and Focus (SnF) [19].

- SimBetTS [22].

- EBR [21].

For the routing protocols that require a maximum number of replicas L (i.e. Spray and Wait, LSF-Spray and Wait, Spray and Focus, SimBetTS, and EBR), we assigned four distinct values: $L = 2$, $L = 4$, $L = 8$, and $L = 16$. For the routing protocols that require a utility metric (i.e. Compare and Forward, Compare and Replicate, Delegation Forwarding, and COORD), we used one destination-independent and three destination-dependent utility metrics. In particular, we used the Last Time Seen (LTS) [9], the Destination Encounters (DestEnc) [10], the Encounters (Enc) [10], and the delivery predictabilities of the latest version of PRoPHET with the default

parameter settings [13]. The VACCINE anti-packet scheme [65] was used for the multi-copy routing protocols, which erases redundant replicas of a packet after its successful delivery.

For each simulation, we generated 1000 packets of fixed size with a random pair of source and destination nodes. However, because some users did not participate for the entire duration of the respective dataset, each node can be the source or the destination only for packets that were generated during its presence in the network. Like most evaluation studies of opportunistic routing protocols in the literature, we assumed that there are no resource constraints during our simulations. To avoid statistical bias, the results were collected after a warm-up period and before a cool-down period, each of which lasted as much as 20% of the total simulation time, so that the network would be in its steady state. We simulated 25 repetitions of each scenario in order to calculate the average values and 95% confidence intervals of the traditional and the proposed performance metrics.

4.2   Simulation Results

In the following sections, we evaluate the performance of a wide range of opportunistic routing protocols on four datasets. More specifically, we first present scatter plots of the normalized performance values in order to illustrate their variability and their levels of correlation on each dataset. Then, we construct a decision matrix with the normalized performance values of the evaluated routing protocols and we discuss the rankings that decision-making methods produce with different weighting methods. Finally, we provide the ranking of the routing protocols with the MEW decision-making method and the VIC weighting method, according to the proposed framework. Detailed simulation results on each dataset and for each routing protocol can be found in Appendix A.

4.2.1   Performance Evaluation on the Reality Mining dataset

The Reality Mining dataset [54, 55] consists of contacts between students and faculty members at the MIT. It is one of the most widely used datasets, mainly because of its large number of participants and long duration. Fig. 4.1 depicts the associations between the normalized performance values that the evaluated routing protocols
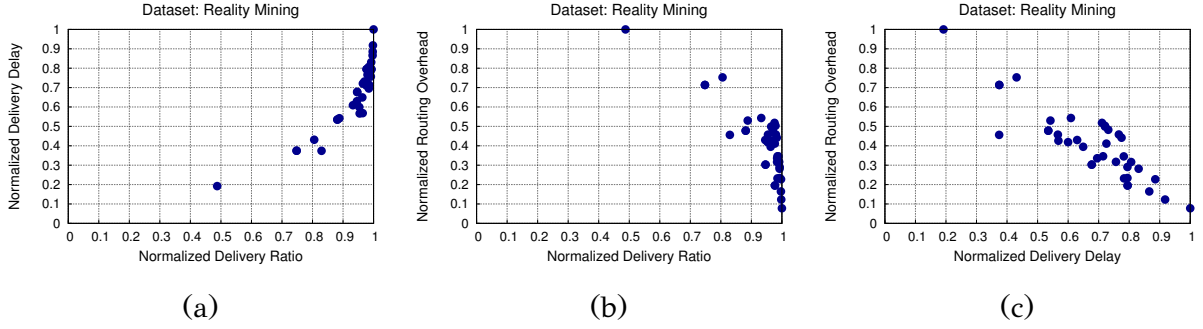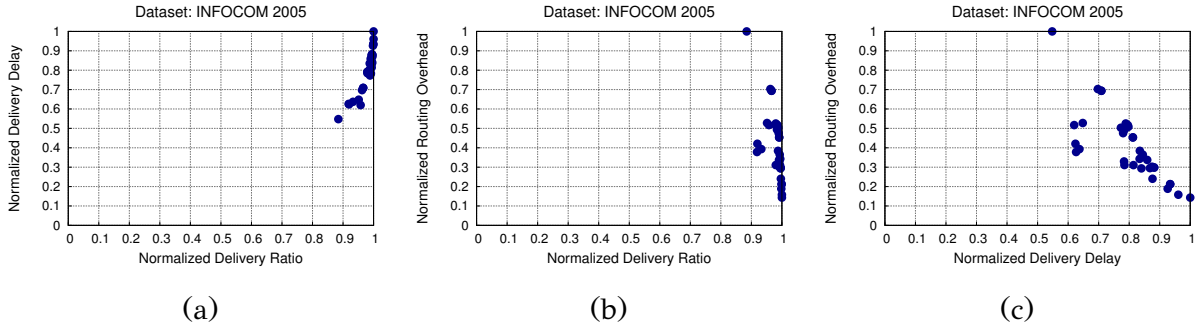
Figure 4.1: Scatter plots of the normalized performance metrics on the Reality Mining dataset.

Table 4.2: Relative importance of each performance metric on the Reality Mining dataset according to different weighting methods.

	MW	SD	CRITIC	CRITIC.dCor	VIC
NDR	0.3333	0.2193	0.1598	0.1997	0.2168
NDD	0.3333	0.3737	0.2790	0.3118	0.3660
NRO	0.3333	0.4070	0.5612	0.4885	0.4172

achieved. As we can see in Fig. 4.1a, the lowest normalized delivery ratio that a routing protocol achieved on this dataset is almost equal to 0.5, which corresponds to the performance of Direct Delivery. This indicates that almost half of the deliverable packets could be delivered directly, i.e. with the least possible routing overhead. However, as we would expect, Direct Delivery also achieves the lowest value for the normalized delivery delay performance metric. The rest of the routing protocols are able to deliver a lot more packets than Direct Delivery, but that comes at the cost of a significant reduction of their performance in terms of routing overhead. However, observe in Fig. 4.1b that most protocols deliver about the same number of packets but with significantly different routing overhead. Furthermore, the conflict between the normalized delivery delay and normalized routing overhead is evident in Fig. 4.1c.

We then constructed a decision matrix with the proposed performance metrics as the set of criteria and the routing protocols as the set of alternatives. In Table 4.2 we provide the calculated weight vectors from different weighting methods. All the weighting methods, except for the MW method, consider the normalized routing overhead as the most important performance metric in this scenario, followed by the normalized delivery delay. CRITIC assigns by far the highest weight value to
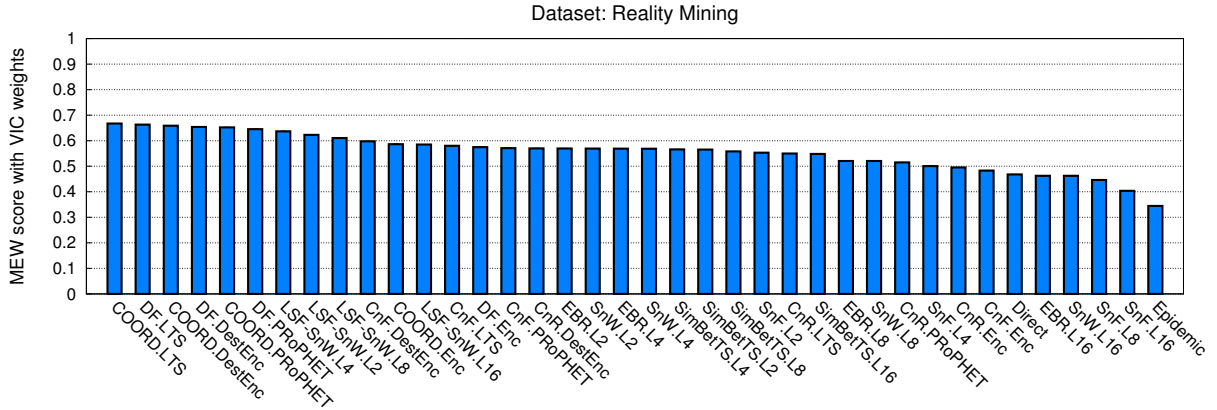
Figure 4.2: Ranking of the routing protocols by the MEW method with VIC weights on the Reality Mining dataset.

the normalized routing overhead, because of its strongly conflicting character. If we used the MEW method with the weight vector of the CRITIC method, LSF-Spray and Wait with $L = 2$ would have the highest overall score, even though it delivers significantly less packets than almost every other routing protocol and with a lot higher delivery delays. However, by overestimating the importance of the normalized routing overhead, the fact that LSF-Spray and Wait with $L = 2$ has the second-best performance value for that criterion is enough to rank him the highest, followed by COORD with the LTS utility metric. Similarly, the mTOPSIS method with CRITIC weights would also assign the highest score to LSF-Spray and Wait with $L = 2$, followed by Direct Delivery. Worse still, if we used the CRITIC weights with the SAW method, which is their suggested decision-making method, the highest SAW score corresponds to the Direct Delivery protocol. On the contrary, the weight vector of the proposed VIC method is close to that of the SD method, since all the performance criteria are highly dependent. If we use the weight vector of the VIC method, all three decision-making methods rank COORD with the LTS utility metric the highest, followed by Delegation Forwarding with the LTS utility metric.

In Fig. 4.2 we provide the MEW score of each routing protocol, in descending order, with the weight vector of the VIC method. As we can see, COORD and Delegation Forwarding with the destination-dependent utility metrics are ranked the highest on the Reality Mining dataset. The use of the destination-independent utility increased the routing overhead of both algorithms, without achieving a higher delivery ratio or lower delivery delays, which results in a lower overall score. LSF-Spray and Wait with $L = 4$ is ranked next, which has a better performance value in terms of normal-
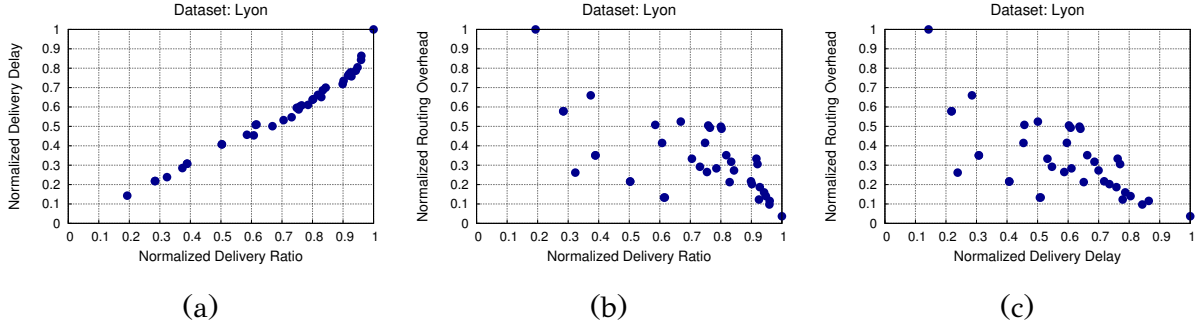
Figure 4.3: Scatter plots of the normalized performance metrics on the INFOCOM 2005 dataset.

Table 4.3: Relative importance of each performance metric on the INFOCOM 2005 dataset according to different weighting methods.

	MW	SD	CRITIC	CRITIC.dCor	VIC
NDR	0.3333	0.0866	0.0554	0.0760	0.0844
NDD	0.3333	0.3413	0.2342	0.2253	0.3197
NRO	0.3333	0.5721	0.7104	0.6987	0.5959

ized routing overhead than any version of COORD and Delegation Forwarding, but it also have noticeably worse performance values in terms of the other two performance metrics. Notice that Direct Delivery has a really low overall score, as we would expect, which would be among the highest ranked routing protocols if we used the weight vector of the CRITIC method instead of the VIC method.

4.2.2 Performance Evaluation on the INFOCOM 2005 dataset

The INFOCOM 2005 dataset [56, 57] is another commonly used dataset for the performance evaluation of opportunistic routing protocols. During the INFOCOM Student Workshop in 2005, 41 devices were distributed to attendees that recording their contacts. It is clear from Fig. 4.3 that this dataset is not challenging in terms of delivering a certain number of packets. Even Direct Delivery was able to deliver more than 85% of the generated packets and almost 90% of the deliverable packets. Not only that, but it also achieves a much higher performance value for the normalized delivery delay metric than it usually achieves on other datasets. This results in a smaller range of the values for the performance metrics. However, we can still observe
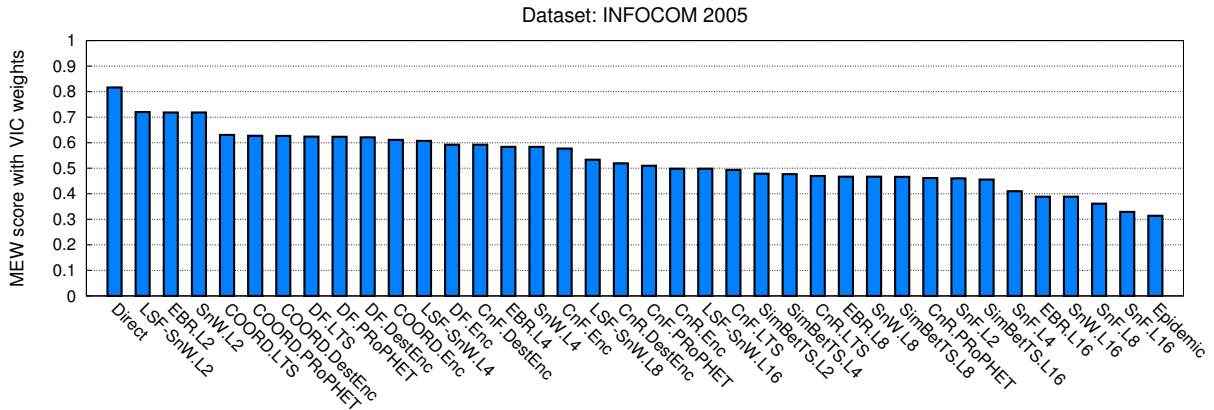
Figure 4.4: Ranking of the routing protocols by the MEW method with VIC weights on the INFOCOM 2005 dataset.

some variation in the performance values of the normalized routing overhead and the normalized delivery delay.

It is obvious that, in this scenario, the most important performance metric is the normalized routing overhead. We would therefore expect all the weighting methods, except for MW of course, to assign a high weight value to the normalized routing overhead and a low weight value to the normalized delivery ratio. As we can see in Table 4.3, CRITIC assigns the highest weight value to the normalized routing overhead and the lowest weight value to the normalized delivery ratio. However, it seems that CRITIC underestimates the relative importance of the normalized delivery delay. Nevertheless, regardless of the weighting method, all the decision-making methods consider Direct Delivery as the best alternative.

Direct Delivery achieves by far the highest overall MEW score with the VIC weighting method, as we can see in Fig. 4.4. This should not come as a surprise, given that Direct Delivery performs optimally in terms of the normalized routing overhead metric, which is the most important metric in this scenario, and that it also achieves reasonable performance values for the other two performance metrics. We can also observe that the next three routing protocols in the ranking order share some characteristics. They all perform limited replication, with only two replicas, and once a node is left with only one replica of a packet it will wait to meet its destination node in order to deliver it. Since the normalized routing overhead is the most important metric in this scenario, these protocols are next in the ranking order due to their very small number of transmissions. Furthermore, every version of COORD is ranked higher than the corresponding version of Delegation Forwarding, since it performs

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Figure 4.5: Scatter plots of the normalized performance metrics on the Lyon dataset.

Table 4.4: Relative importance of each performance metric on the Lyon dataset according to different weighting methods.

	MW	SD	CRITIC	CRITIC.dCor	VIC
NDR	0.3333	0.3628	0.2761	0.2885	0.3441
NDD	0.3333	0.3301	0.2564	0.2465	0.3097
NRO	0.3333	0.3071	0.4676	0.4650	0.3462

less transmissions without a noticeable decrease in the other performance metrics. Finally, as we would expect, Epidemic Routing has the lowest overall score.

4.2.3 Performance Evaluation on the Lyon dataset

The Lyon dataset [58, 59, 60] consists of close-range contacts between 232 children and 10 teachers over the course of two school days in a primary school in Lyon, France. The fact that these students were from 10 different classes should offer a challenge for most routing protocols.[3] Indeed, as we can see in Fig. 4.5, Direct Delivery was only able to deliver about 20% of the deliverable packets. The large variability of the normalized delivery ratio metric is evident, as well as its high correlation with the normalized delivery delay metric. On the contrary, the normalized routing overhead is less dependent from the other two metrics. Routing protocols with similar performance values for the normalized routing overhead metric may have very different performance values for the other performance metrics.

Table 4.4 provides the weight vectors that different methods determined, which

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[3]A visualization of their contacts during the first school day is available at https://vimeo.com/31490438.
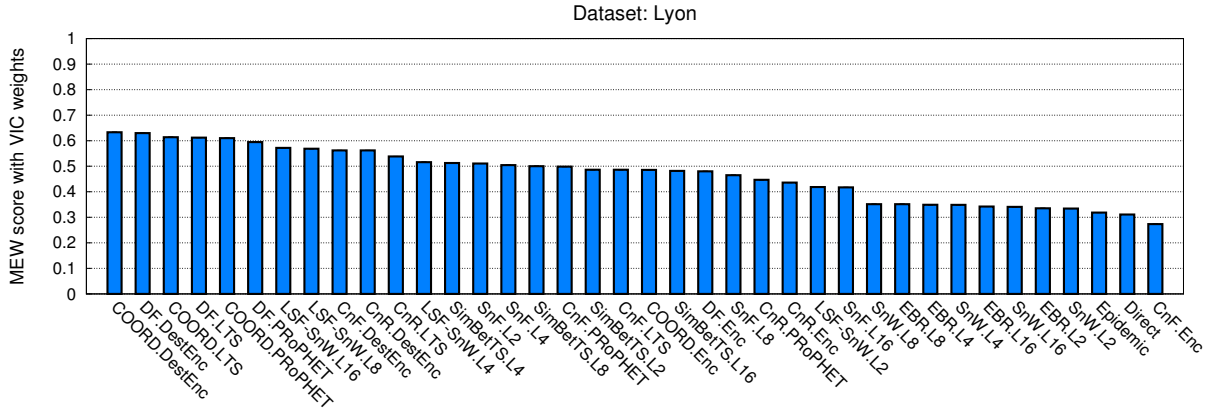
Figure 4.6: Ranking of the routing protocols by the MEW method with VIC weights on the Lyon dataset.

assign noticeably different weight values, in contrast to the previous datasets. The SD method considers the normalized delivery ratio metric as the most important criterion, followed the normalized delivery delay metric. This is because the SD method does not take into account the interdependences of the criteria. CRITIC increases the importance of the normalized routing overhead, which has the least variation in its values, because it still comes in conflict with the other two criteria. Similar weights are derived from the modified CRITIC method that relies on the distance correlation coefficients of the criteria instead of their linear correlation coefficients. A different assignment of weights is given by the VIC method, which considers the normalized delivery ratio and normalized routing overhead as almost equally important metrics. This is because the normalized delivery ratio metric has the highest amount of variation, but it also has a very strong correlation with the normalized delivery delay metric. On the other hand, the normalized routing overhead metric has the lowest amount of variation, but it is also has a moderate correlation with the other criteria.

The ranking of the routing protocols with the MEW decision-making method and the VIC weighting method is given in Fig. 4.6. Similarly to the simulation results on the Reality Mining dataset, COORD and Delegation Forward with destination-dependent utility metrics are ranked the highest. However, on the Lyon dataset, both algorithms were able to deliver noticeably more packets with the utility metric that depends on the number encounters with the destination instead of the last time that they saw the destination. Observe that the versions of LSF-Spray and Wait with the highest limit of replicas are ranked next, implying that another version with an even higher value of L may perform better. Furthermore, notice that Direct Delivery and

Epidemic Routing have significantly lower MEW scores than the other routing protocols. The reason they have so low MEW scores is because both routing protocols perform poorly in terms of at least one performance metric. If we used SAW or mTOPSIS to calculate their overall scores, Epidemic Routing would be ranked a lot higher. In particular, with the SAW decision-making and the weight vector of VIC, Epidemic Routing would be considered the second-best alternative, after COORD with the PRoPHET utility metric. Worse still, if we used the weight vector of the CRITIC method, even Direct Delivery would be among the highest-ranked alternatives. The ranking that the MEW method with VIC weights provided seems to be the most reasonable, where only Compare and Forward based on the total number of encounters has a lower score than Epidemic Routing and Direct Delivery, because it performs poorly in all three performance metrics.

4.2.4   Performance Evaluation on the Dartmouth dataset

The Dartmouth dataset [61, 62, 63] contains associations of wireless cards with access points at the Dartmouth College campus. We can construct a large-scale opportunistic network if we treat each wireless card as a node and assume that two nodes are in contact when they are associated with the same access point at the same time. The approximated contacts that we extracted are between 738 nodes from February 8, 2004 to February 21, 2004. From the datasets that we studied, this was the most challenging for the routing protocols as it is evident from Fig. 4.7. Less than 5% of the deliverable packets could be delivered directly. Even the algorithms that were able to deliver more packets, they achieved that with significantly higher delivery delays compared to the optimal performance. Note that Epidemic Routing delivered every deliverable packet with the optimal end-to-end delay by performing about 560 transmissions for each generated packet.

Notice that there is a set of algorithms with similar performance values for the normalized routing overhead metric and the normalized delivery ratio metric. These algorithms relied on destination-dependent utility metrics that required direct contacts with the destination node in order to increase their utility values. However, due to the large-scale of this dataset, utility metrics such as the number of encounters with the destination node rarely considered an encountered node as suitable to carry a packet. As a result, these algorithms performed a very small number of transmissions
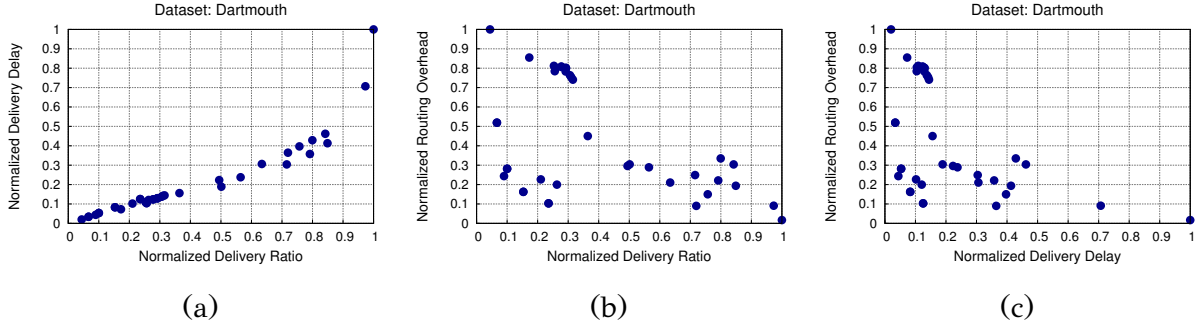
Figure 4.7: Scatter plots of the normalized performance metrics on the Dartmouth dataset.

Table 4.5: Relative importance of each performance metric on the Dartmouth dataset according to different weighting methods.

	MW	SD	CRITIC	CRITIC.dCor	VIC
NDR	0.3333	0.3616	0.2692	0.2689	0.3337
NDD	0.3333	0.2578	0.1936	0.1951	0.2387
NRO	0.3333	0.3806	0.5372	0.5360	0.4275

and were unable to deliver a large proportion of the deliverable packets. Interestingly enough, the algorithms that relied on the transitive property of the PRoPHET utility metric performed much better. In particular, the second-highest performance values for the normalized delivery ratio metric and the normalized delivery delay metric were achieved by the Compare and Replicate approach with PRoPHET as its utility metric. However, even though this algorithm achieved these performance values with significantly less routing overhead compared to Epidemic Routing, about 120 transmissions for each generated packet, other replication strategies performed a lot less transmissions. For example, COORD with the PRoPHET utility metric performed about 11 transmissions for each generated packet and delivered about 80% of the deliverable packets.

As we can see in Table 4.5, all the weighting methods consider the normalized routing overhead metric as the most important, except for the MW weighting method of course. This should be expected, since it has the highest amount of variation and the least amount of dependence from the other criteria. However, CRITIC once again overestimates the relative importance of the normalized routing overhead metric. If we used the SAW or the mTOPSIS method with CRITIC weights, Direct Deliv-
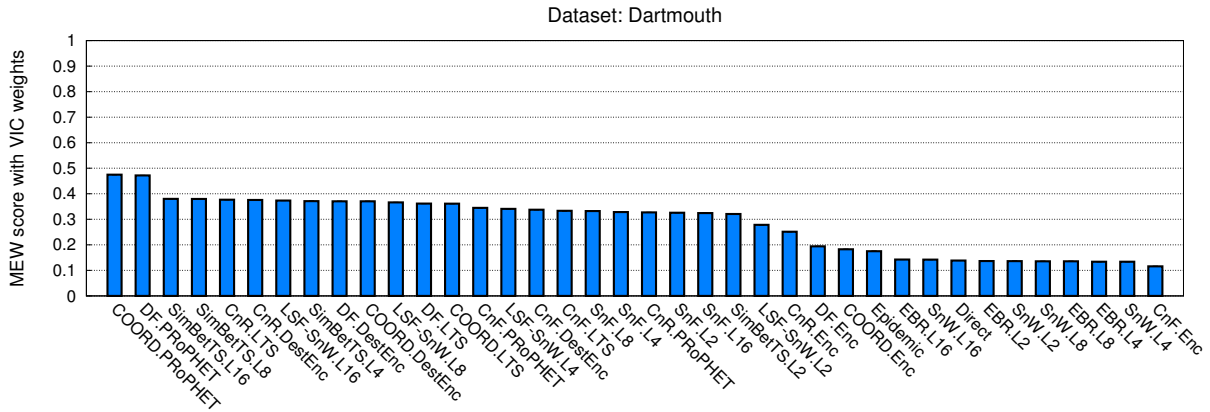
Figure 4.8: Ranking of the routing protocols by the MEW method with VIC weights on the Dartmouth dataset.

ery would be ranked the highest, which is clearly unreasonable. Even if we used the MEW method with CRITIC weights, the set of algorithms that we observed to have a high performance value for the normalized routing overhead metrics, but low performance values for the other two metrics, would be among the highest-ranked algorithms. In Fig. 4.8 we show the MEW score of each routing protocol with the weight vector of the VIC method. As we can see, COORD and Delegation Forwarding with the PRoPHET utility metric have noticeably higher MEW scores than the other algorithms. This is because both algorithms had among the highest performance values for the normalized delivery ratio and normalized delivery delay metrics, while performing a very small number of transmissions compared to every other algorithm that was able to deliver a certain number of packets. SimBetTS with $L = 16$ and $L = 8$ is next in the ranking order, which was able to deliver more packets than COORD and Delegation Forwarding, but it also had lower performance values for the normalized delivery delay and the normalized routing overhead metrics. Recall that SimBetTS does not rely on the transitive property of a utility metric, but instead it combines several destination-dependent utility metrics with a destination-independent utility metric. However, this approach resulted in many redundant transmissions, especially in networks of smaller scale as we showed in the previous datasets. It should be noted that, if we used the SAW or the mTOPSIS method with VIC weights, Epidemic Routing would be ranked the highest. This is because it achieved the optimal performance values for two criteria with high relative importance, overshadowing its very poor performance value for the third criterion, even though it is the most important performance metric in this scenario. On the other hand, as we can see in Fig. 4.8, the

MEW method assigns a low overall score to the Epidemic Routing protocol because of its very poor performance in the most important criterion. Thus, the ranking of the routing protocols that was provided by the MEW method with VIC weights seems to be the most reasonable.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

5.1 Discussion

There are some factors that should be taken into consideration in order to apply the proposed framework. First of all, the decision matrix should contain performance values of a representative set of routing protocols. Even if we are interested in the performance comparison of only a small number of routing protocols, the performance values of algorithms such as Epidemic Routing and Direct Delivery should be included. This is because such algorithms provide useful information for the underlying network, which is then used to calculate the standard deviation and the distance correlation coefficients of each performance metric. For the same reason, the set of alternatives in the decision matrix should consist of only realistic algorithms, since non-realistic algorithms would affect the relative importance of the criteria that are then used for the evaluation of feasible solutions. Notice that in our analysis, the two versions of Optimal Routing were only used for the normalization of the performance metrics and they were not included in any decision matrix as alternatives. Furthermore, while in this work we used three normalized performance metrics as our criteria for the evaluation of the routing protocols, more criteria could be introduced in the evaluation process. For example, a fairness index could be considered as

another criterion. Additionally, the proposed method for the assignment of objective weights could easily be combined with subjective information in order to determine the importance of each criterion. This approach could be useful for scenarios with specific routing objectives.

5.2   Conclusions

Several conclusions can be drawn from the performance analysis that we conducted with the proposed framework. First of all, no algorithm was able to achieve the best performance on all or most of the datasets that we studied. In the small-scale opportunistic network, Direct Delivery and replication strategies with a small maximum number of replicas were ranked the highest. In opportunistic networks of larger scale, utility-based replication strategies were considered as the best alternatives. In particular, the replication strategies of Delegation Forwarding and COORD were often ranked the highest. Yet, there was not even a utility metric that performed better than the others on every dataset that we studied. More specifically, in the large-scale opportunistic network, the transitive property of the destination-dependent utility metric that is used by PRoPHET was crucial for the performance of the utility-based routing protocols. However, in opportunistic networks of smaller scale, this approach often resulted in a noticeable increase in the number of transmissions compared to other utility metrics. Our case studies demonstrate the difficulty of routing in opportunistic networks.

Bibliography

[1] M. Conti and S. Giordano, "Mobile ad hoc networking: Milestones, challenges, and new research directions," *IEEE Communications Magazine*, vol. 52, no. 1, pp. 85–96, 2014.

[2] V. F. Mota, F. D. Cunha, D. F. Macedo, J. M. Nogueira, and A. A. Loureiro, "Protocols, mobility models and tools in opportunistic networks: A survey," *Computer Communications*, vol. 48, pp. 5–19, 2014.

[3] K. Fall, "A delay-tolerant network architecture for challenged internets," in *Proceedings of the 2003 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications (SIGCOMM)*, pp. 27–34, 2003.

[4] L. Pelusi, A. Passarella, and M. Conti, "Opportunistic networking: Data forwarding in disconnected mobile ad hoc networks," *IEEE Communications Magazine*, vol. 44, no. 11, pp. 134–141, 2006.

[5] P. Hui, J. Crowcroft, and E. Yoneki, "BUBBLE rap: Social-based forwarding in delay-tolerant networks," *IEEE Transactions on Mobile Computing*, vol. 10, no. 11, pp. 1576–1589, 2011.

[6] Z. Zhang, "Routing in intermittently connected mobile ad hoc networks and delay tolerant networks: Overview and challenges," *IEEE Communications Surveys & Tutorials*, vol. 8, no. 1, pp. 24–37, 2006.

[7] A. Vahdat and D. Becker, "Epidemic routing for partially connected ad hoc networks," Tech. Rep. CS-2000-06, Duke University, 2000.

[8] M. Grossglauser and D. N. C. Tse, "Mobility increases the capacity of ad hoc wireless networks," *IEEE/ACM Transactions on Networking*, vol. 10, no. 4, pp. 477–486, 2002.

[9] H. Dubois-Ferriere, M. Grossglauser, and M. Vetterli, "Age matters: Efficient route discovery in mobile ad hoc networks using encounter ages," in *Proceedings of the 4th ACM International Symposium on Mobile Ad Hoc Networking & Computing (MobiHoc)*, pp. 257–266, 2003.

[10] V. Erramilli, A. Chaintreau, M. Crovella, and C. Diot, "Diversity of forwarding paths in pocket switched networks," in *Proceedings of the 7th ACM SIGCOMM Conference on Internet Measurement (IMC)*, pp. 161–174, 2007.

[11] A. Lindgren, A. Doria, and O. Schelén, "Probabilistic routing in intermittently connected networks," in *Service Assurance with Partial and Intermittent Resources*, vol. 3126 of *Lecture Notes in Computer Science*, pp. 239–254, Springer Berlin Heidelberg, 2004.

[12] S. Grasic, E. Davies, A. Lindgren, and A. Doria, "The evolution of a dtn routing protocol - PRoPHETv2," in *Proceedings of the 6th ACM Workshop on Challenged Networks (CHANTS)*, pp. 27–30, 2011.

[13] A. Lindgren, A. Doria, E. Davies, and S. Grasic, "Probabilistic routing protocol for intermittently connected networks," RFC 6693, Internet Research Task Force (IRTF), 2012.

[14] T. Spyropoulos, R. N. B. Rais, T. Turletti, K. Obraczka, and A. Vasilakos, "Routing for disruption tolerant networks: taxonomy and design," *Wireless Networks*, vol. 16, no. 8, pp. 2349–2370, 2010.

[15] Y. Zhu, B. Xu, X. Shi, and Y. Wang, "A survey of social-based routing in delay tolerant networks: Positive and negative social effects," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 1, pp. 387–401, 2013.

[16] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Efficient routing in intermittently connected mobile networks: The single-copy case," *IEEE/ACM Transactions on Networking*, vol. 16, no. 1, pp. 63–76, 2008.

[17] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Efficient routing in intermittently connected mobile networks: The multiple-copy case," *IEEE/ACM Transactions on Networking*, vol. 16, no. 1, pp. 77–90, 2008.

[18] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Spray and wait: An efficient routing scheme for intermittently connected mobile networks," in *Proceedings of the 2005 ACM SIGCOMM Workshop on Delay-tolerant Networking (WDTN)*, pp. 252–259, 2005.

[19] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Spray and focus: Efficient mobility-assisted routing for heterogeneous and correlated mobility," in *Proceedings of the 5th Annual IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom)*, pp. 79–85, 2007.

[20] T. Spyropoulos, T. Turletti, and K. Obraczka, "Routing in delay-tolerant networks comprising heterogeneous node populations," *IEEE Transactions on Mobile Computing*, vol. 8, no. 8, pp. 1132–1147, 2009.

[21] S. C. Nelson, M. Bakht, and R. Kravets, "Encounter-based routing in DTNs," in *Proceedings of the 28th IEEE International Conference on Computer Communications (INFOCOM)*, pp. 846–854, 2009.

[22] E. M. Daly and M. Haahr, "Social network analysis for information flow in disconnected delay-tolerant manets," *IEEE Transactions on Mobile Computing*, vol. 8, no. 5, pp. 606–621, 2009.

[23] V. Erramilli, M. Crovella, A. Chaintreau, and C. Diot, "Delegation forwarding," in *Proceedings of the 9th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, pp. 251–260, 2008.

[24] N. Papanikos and E. Papapetrou, "Coordinating replication decisions in multi-copy routing for opportunistic networks," in *Proceedings of the 10th IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, pp. 8–13, 2014.

[25] S. Jain, K. Fall, and R. Patra, "Routing in a delay tolerant network," in *Proceedings of the 2004 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications (SIGCOMM)*, pp. 145–158, 2004.

[26] S. Grasic and A. Lindgren, "An analysis of evaluation practices for DTN routing protocols," in *Proceedings of the 7th ACM International Workshop on Challenged Networks (CHANTS)*, pp. 57–64, 2012.

[27] J. Broch, D. A. Maltz, D. B. Johnson, Y.-C. Hu, and J. Jetcheva, "A performance comparison of multi-hop wireless ad hoc network routing protocols," in *Proceedings of the 4th Annual ACM/IEEE International Conference on Mobile Computing and Networking (MobiCom)*, pp. 85–97, 1998.

[28] C. E. Perkins, E. M. Royer, S. R. Das, and M. K. Marina, "Performance comparison of two on-demand routing protocols for ad hoc networks," *IEEE Personal Communications*, vol. 8, no. 1, pp. 16–28, 2001.

[29] S. H. Zanakis, A. Solomon, N. Wishart, and S. Dublish, "Multi-attribute decision making: A simulation comparison of select methods," *European Journal of Operational Research*, vol. 107, no. 3, pp. 507–529, 1998.

[30] E. Triantaphyllou, B. Shu, S. N. Sanchez, and T. Ray, "Multi-criteria decision making: An operations research approach," in *Encyclopedia of Electrical and Electronics Engineering*, vol. 15, pp. 175–186, John Wiley & Sons, New York, 1998.

[31] P. C. Fishburn, "Additive utilities with incomplete product sets: Application to priorities and assignments," *Operations Research*, vol. 15, no. 3, pp. 537–542, 1967.

[32] P. W. Bridgman, *Dimensional Analysis*. Yale University Press, 1922.

[33] D. W. Miller and M. K. Starr, *Executive Decisions and Operations Research*. Prentice-Hall, Inc., 1969.

[34] C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making*, vol. 186 of *Lecture Notes in Economics and Mathematical Systems*. Springer-Verlag Berlin Heidelberg, 1981.

[35] C.-L. Hwang, Y.-J. Lai, and T.-Y. Liu, "A new approach for multiple objective decision making," *Computers & Operations Research*, vol. 20, no. 8, pp. 889–899, 1993.

[36] H. Deng, C.-H. Yeh, and R. J. Willis, "Inter-company comparison using modified TOPSIS with objective weights," *Computers & Operations Research*, vol. 27, no. 10, pp. 963–973, 2000.

[37] D. von Winterfeldt and W. Edwards, *Decision Analysis and Behavioral Research*. Cambridge University Press, 1986.

[38] W. Edwards, "How to use multiattribute utility measurement for social decisionmaking," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 7, no. 5, pp. 326–340, 1977.

[39] W. Edwards and F. H. Barron, "SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement," *Organizational Behavior and Human Decision Processes*, vol. 60, no. 3, pp. 306–325, 1994.

[40] T. L. Saaty, "A scaling method for priorities in hierarchical structures," *Journal of Mathematical Psychology*, vol. 15, no. 3, pp. 234–281, 1977.

[41] T. L. Saaty, "How to make a decision: The analytic hierarchy process," *European Journal of Operational Research*, vol. 48, no. 1, pp. 9–26, 1990.

[42] K. O. Cogger and P. L. Yu, "Eigenweight vectors and least-distance approximation for revealed preference in pairwise weight ratios," *Journal of Optimization Theory and Applications*, vol. 46, no. 4, pp. 483–491, 1985.

[43] D. Diakoulaki, G. Mavrotas, and L. Papayannakis, "Determining objective weights in multiple criteria problems: The CRITIC method," *Computers & Operations Research*, vol. 22, no. 7, pp. 763–770, 1995.

[44] J. Ma, Z.-P. Fan, and L.-H. Huang, "A subjective and objective integrated approach to determine attribute weights," *European Journal of Operational Research*, vol. 112, no. 2, pp. 397–404, 1999.

[45] X. Xu, "A note on the subjective and objective integrated approach to determine attribute weights," *European Journal of Operational Research*, vol. 156, no. 2, pp. 530–532, 2004.

[46] Y.-M. Wang and Y. Luo, "Integration of correlations with standard deviations for determining attribute weights in multiple attribute decision making," *Mathematical and Computer Modelling*, vol. 51, no. 1–2, pp. 1–12, 2010.

[47] A. Jahan, F. Mustapha, S. M. Sapuan, M. Y. Ismail, and M. Bahraminasab, "A framework for weighting of criteria in ranking stage of material selection process," *The International Journal of Advanced Manufacturing Technology*, vol. 58, no. 1, pp. 411–420, 2012.

[48] M. Alemi-Ardakani, A. S. Milani, S. Yannacopoulos, and G. Shokouhi, "On the effect of subjective, objective and combinative weighting in multiple criteria decision making: A case study on impact optimization of composites," *Expert Systems with Applications*, vol. 46, pp. 426–438, 2016.

[49] M. F. Shipley, A. de Korvin, and R. Obid, "A decision making model for multi-attribute problems incorporating uncertainty and bias measures," *Computers & Operations Research*, vol. 18, no. 4, pp. 335–342, 1991.

[50] M. Zeleny, *Multiple Criteria Decision Making*. McGraw-Hill, New York, 1982.

[51] G. J. Székely, M. L. Rizzo, and N. K. Bakirov, "Measuring and testing dependence by correlation of distances," *The Annals of Statistics*, vol. 35, no. 6, pp. 2769–2794, 2007.

[52] G. J. Székely and M. L. Rizzo, "Brownian distance covariance," *The Annals of Applied Statistics*, vol. 3, no. 4, pp. 1236–1265, 2009.

[53] E. Triantaphyllou and S. H. Mann, "An examination of the effectiveness of multi-dimensional decision-making methods: A decision-making paradox," *Decision Support Systems*, vol. 5, no. 3, pp. 303–312, 1989.

[54] N. Eagle and A. S. Pentland, "Reality mining: sensing complex social systems," *Personal and Ubiquitous Computing*, vol. 10, no. 4, pp. 255–268, 2006.

[55] N. Eagle and A. S. Pentland, "CRAWDAD dataset mit/reality (v. 2005-07-01)." [Online]. Available: `http://crawdad.org/mit/reality/20050701`.

[56] P. Hui, A. Chaintreau, J. Scott, R. Gass, J. Crowcroft, and C. Diot, "Pocket switched networks and human mobility in conference environments," in *Proceedings of the 2005 ACM SIGCOMM Workshop on Delay-tolerant Networking (WDTN)*, pp. 244–251, 2005.

[57] J. Scott, R. Gass, J. Crowcroft, P. Hui, C. Diot, and A. Chaintreau, "CRAWDAD dataset cambridge/haggle (v. 2009-05-29)." [Online]. Available: `http://crawdad.org/cambridge/haggle/20090529`.

[58] J. Stehlé, N. Voirin, A. Barrat, C. Cattuto, L. Isella, J.-F. Pinton, M. Quaggiotto, W. Van den Broeck, C. Régis, B. Lina, and P. Vanhems, "High-resolution mea-

surements of face-to-face contact patterns in a primary school," *PLoS ONE*, vol. 6, p. e23176, 2011.

[59] V. Gemmetto, A. Barrat, and C. Cattuto, "Mitigation of infectious disease at school: targeted class closure vs school closure," *BMC Infectious Diseases*, vol. 14, no. 1, pp. 1–10, 2014.

[60] SocioPatterns, "Primary school temporal network data." [Online]. Available: `http://www.sociopatterns.org/datasets/primary-school-temporal-network-data/`.

[61] D. Kotz and K. Essien, "Analysis of a campus-wide wireless network," *Wireless Networks*, vol. 11, no. 1, pp. 115–133, 2005.

[62] T. Henderson, D. Kotz, and I. Abyzov, "The changing usage of a mature campus-wide wireless network," *Computer Networks*, vol. 52, no. 14, pp. 2690–2712, 2008.

[63] D. Kotz, T. Henderson, I. Abyzov, and J. Yeo, "CRAWDAD dataset dartmouth/campus (v. 2009-09-09)." [Online]. Available: `http://crawdad.org/dartmouth/campus/20090909`.

[64] N. Papanikos, D.-G. Akestoridis, and E. Papapetrou, "Adyton: A network simulator for opportunistic networks." [Online]. Available: `https://github.com/npapanik/Adyton`.

[65] Z. J. Haas and T. Small, "A new networking model for biological applications of ad hoc sensor networks," *IEEE/ACM Transactions on Networking*, vol. 14, no. 1, pp. 27–40, 2006.

APPENDIX A

DETAILED SIMULATION RESULTS

A.1   Performance Evaluation on the Reality Mining dataset

Figure A.1: Delivery Ratio of each routing protocol on the Reality Mining dataset.
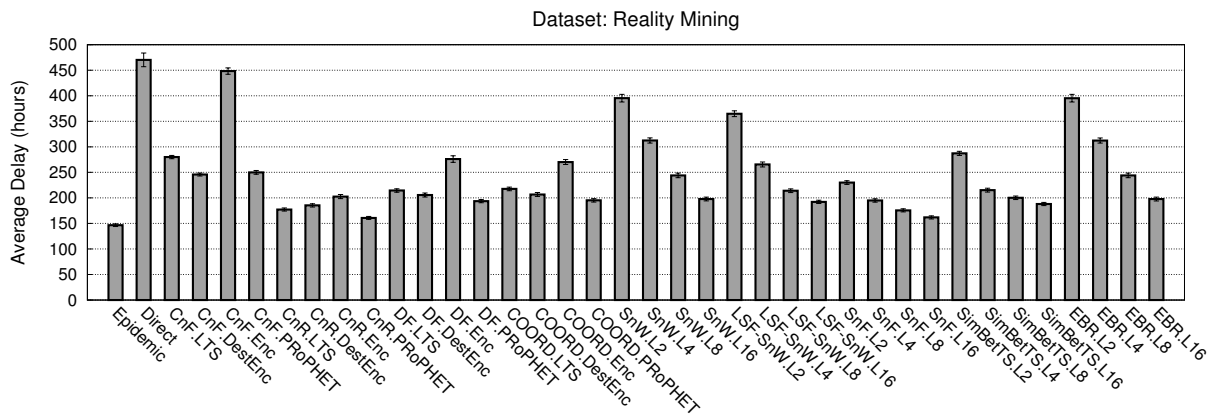
Figure A.2: Average Delay of each routing protocol on the Reality Mining dataset.
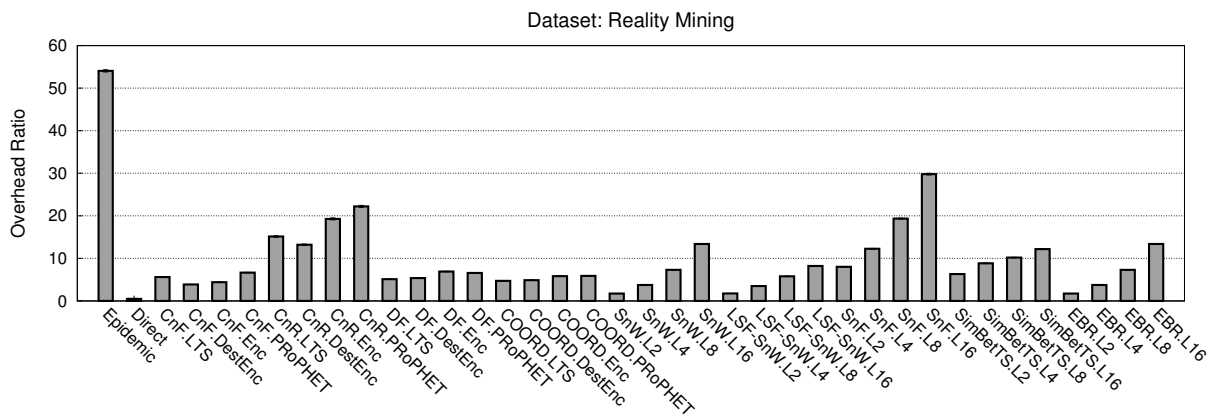
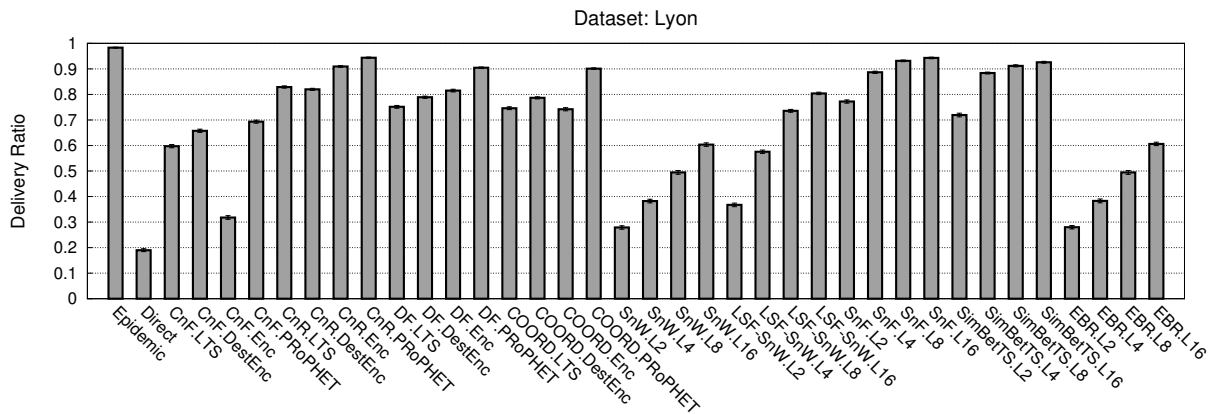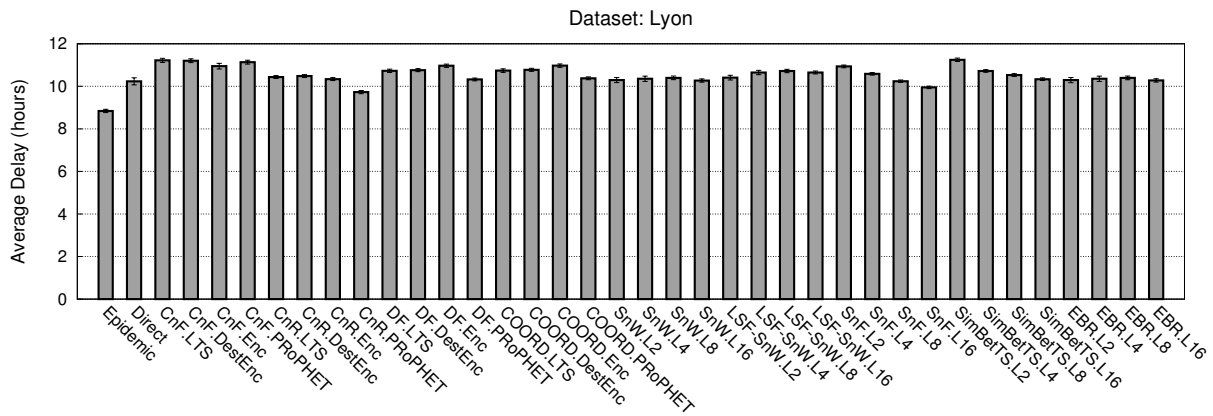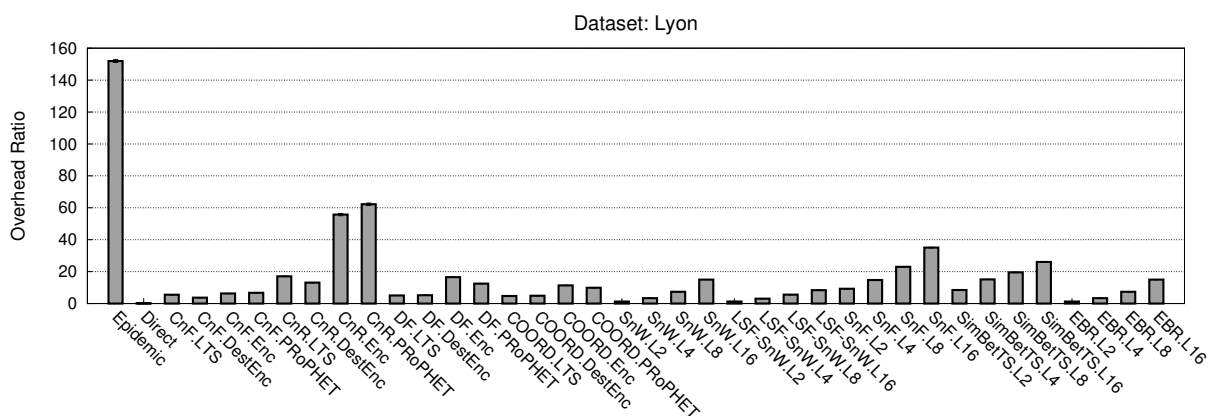Figure A.3: Overhead Ratio of each routing protocol on the Reality Mining dataset.
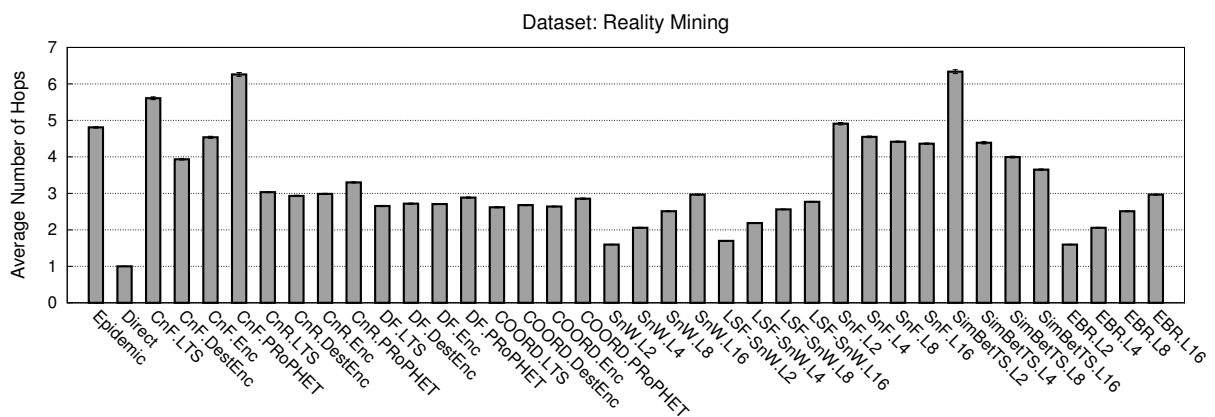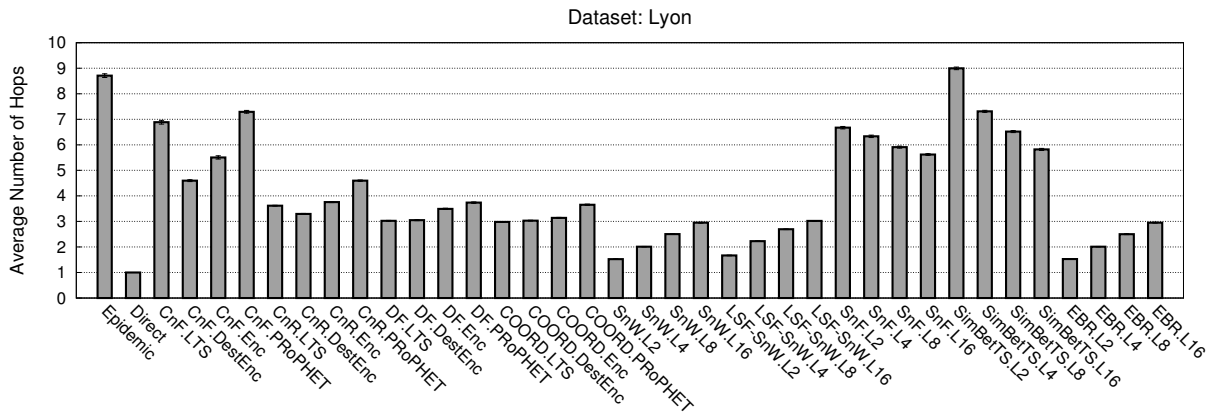

Figure A.4: Average Number of Hops of each routing protocol on the Reality Mining dataset.
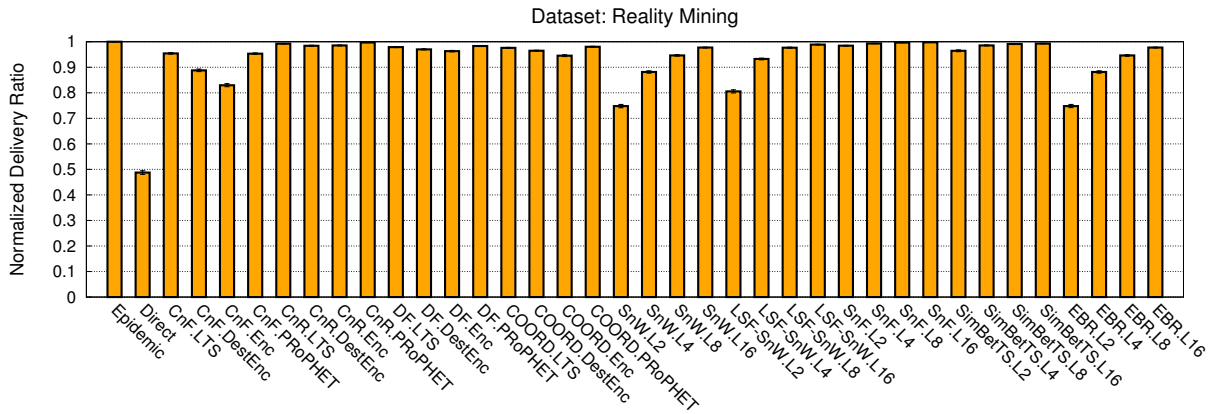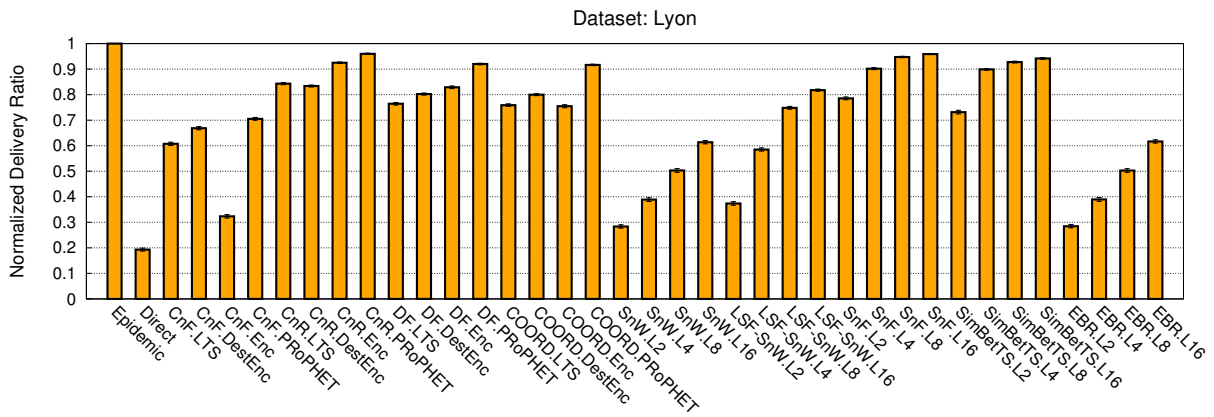
Figure A.5: Normalized Delivery Ratio of each routing protocol on the Reality Mining dataset.
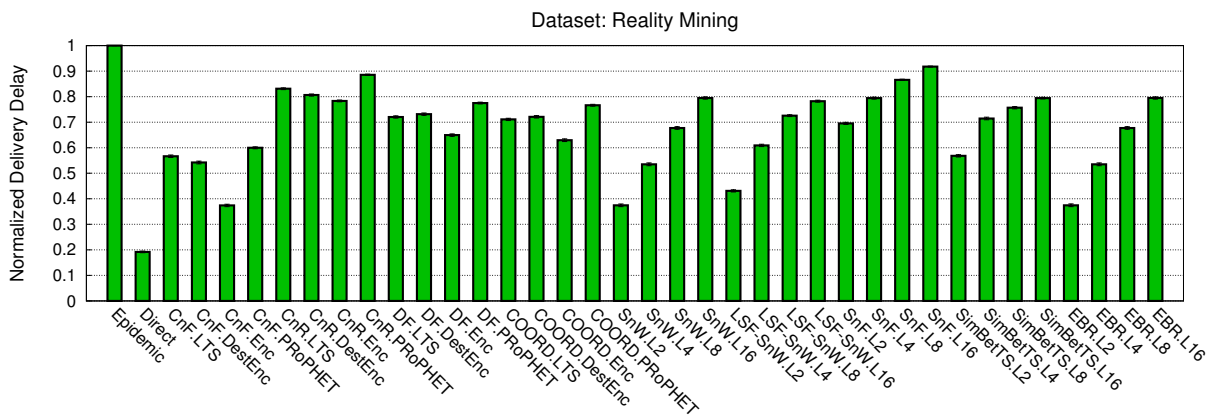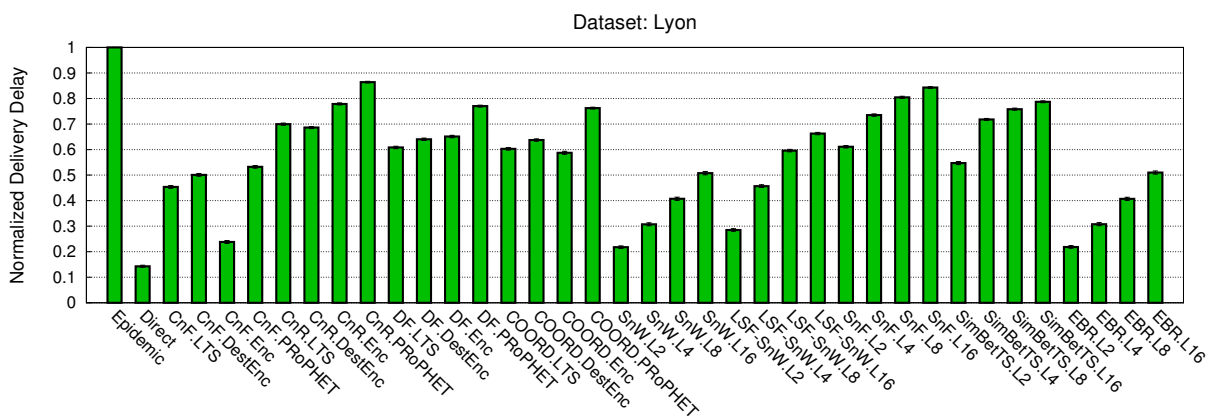

Figure A.6: Normalized Delivery Delay of each routing protocol on the Reality Mining dataset.
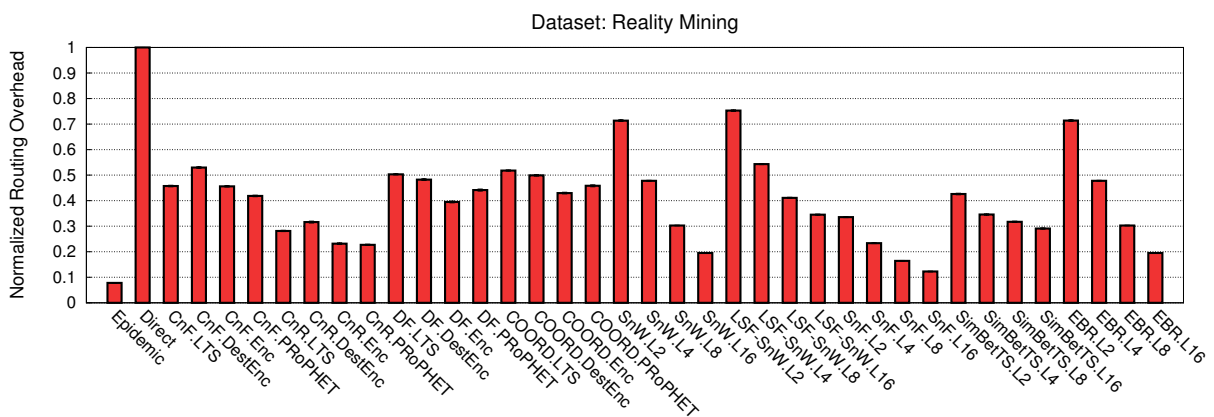
Figure A.7: Normalized Routing Overhead of each routing protocol on the Reality Mining dataset.

A.2 Performance Evaluation on the INFOCOM 2005 dataset
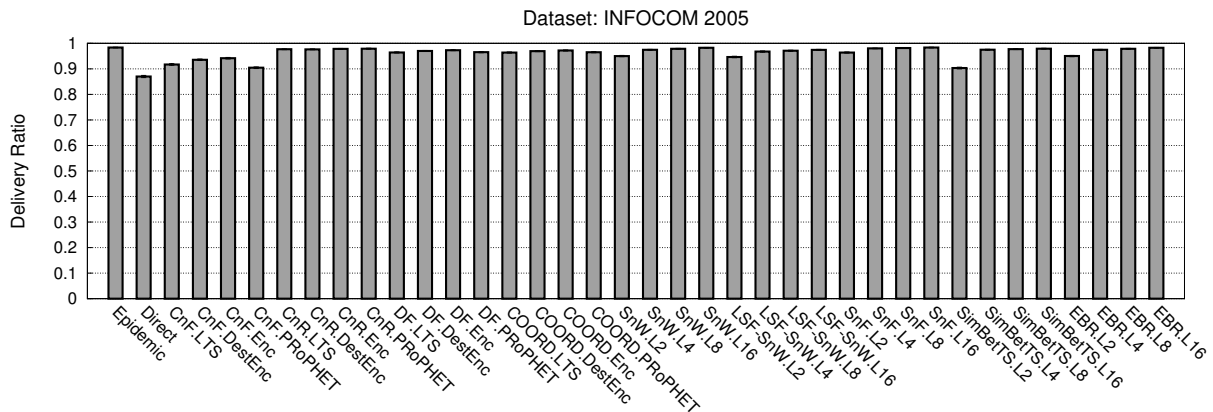
Figure A.8: Delivery Ratio of each routing protocol on the INFOCOM 2005 dataset.
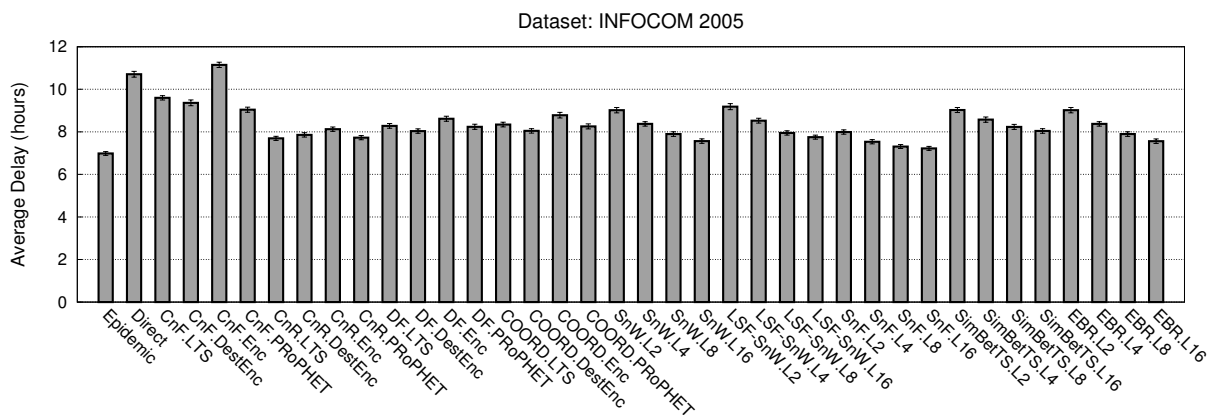
Figure A.9: Average Delay of each routing protocol on the INFOCOM 2005 dataset.
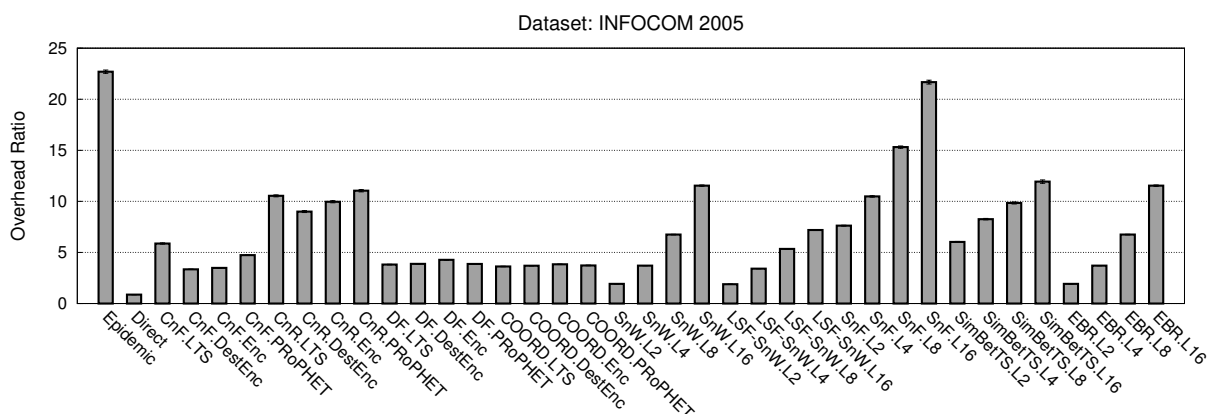
Figure A.10: Overhead Ratio of each routing protocol on the INFOCOM 2005 dataset.
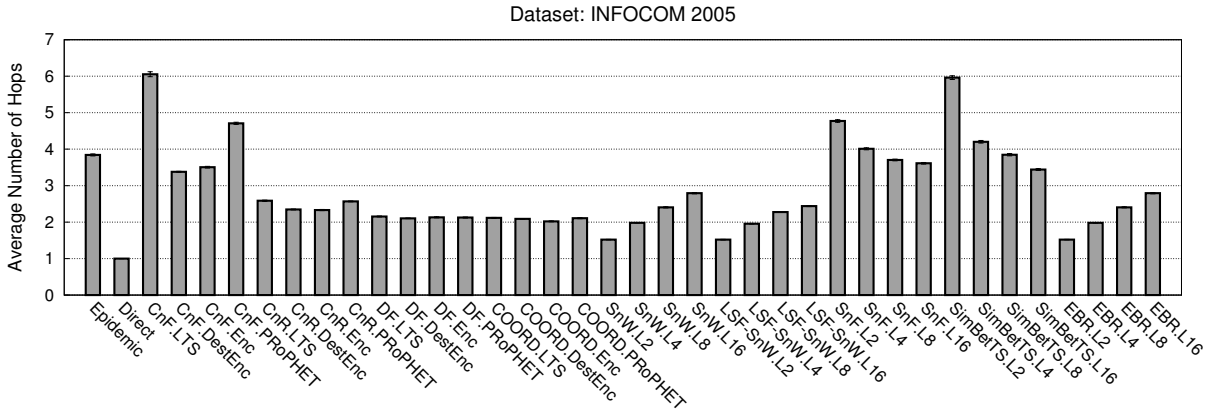
Figure A.11: Average Number of Hops of each routing protocol on the INFOCOM 2005 dataset.
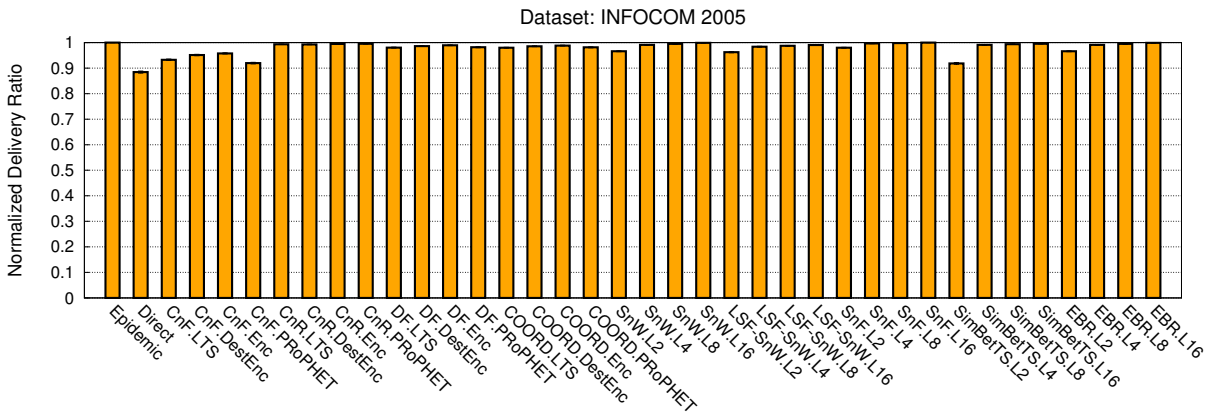
Figure A.12: Normalized Delivery Ratio of each routing protocol on the INFOCOM 2005 dataset.
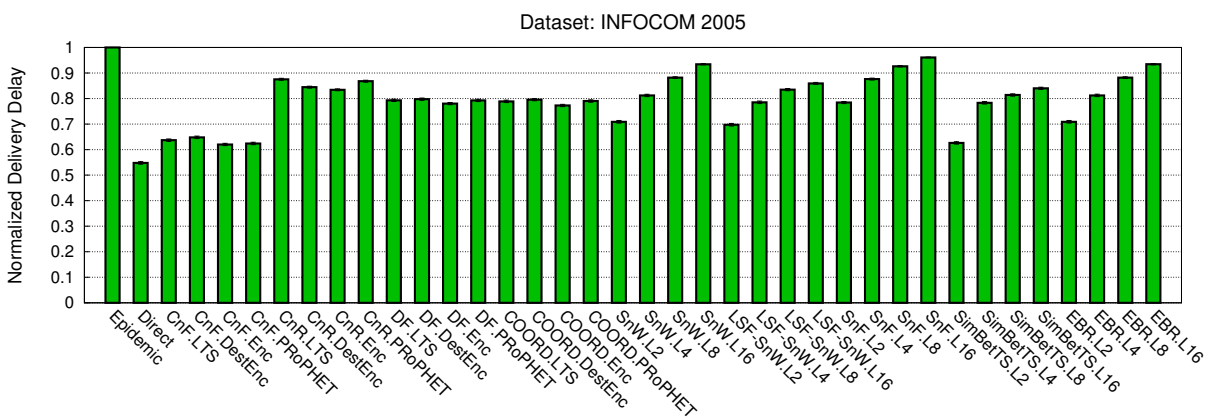
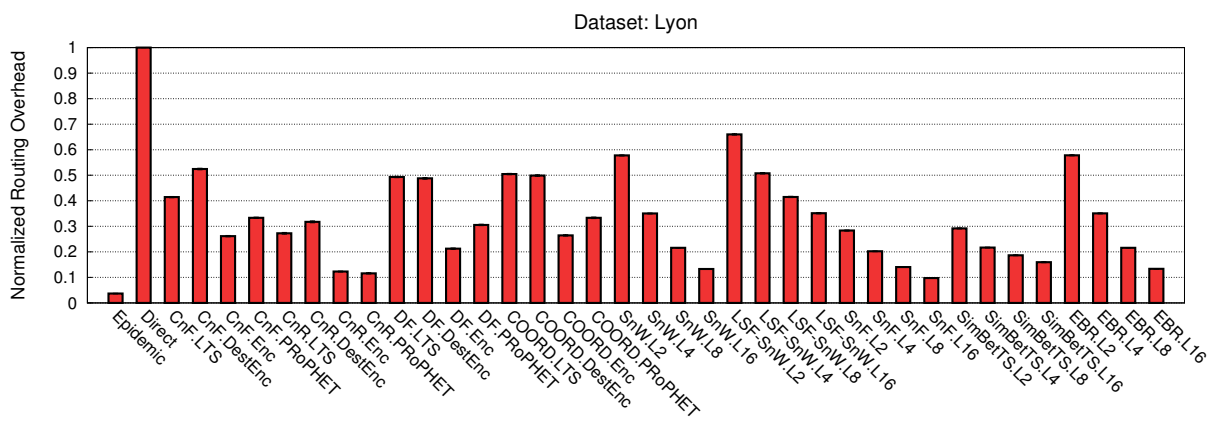Figure A.13: Normalized Delivery Delay of each routing protocol on the INFOCOM 2005 dataset.
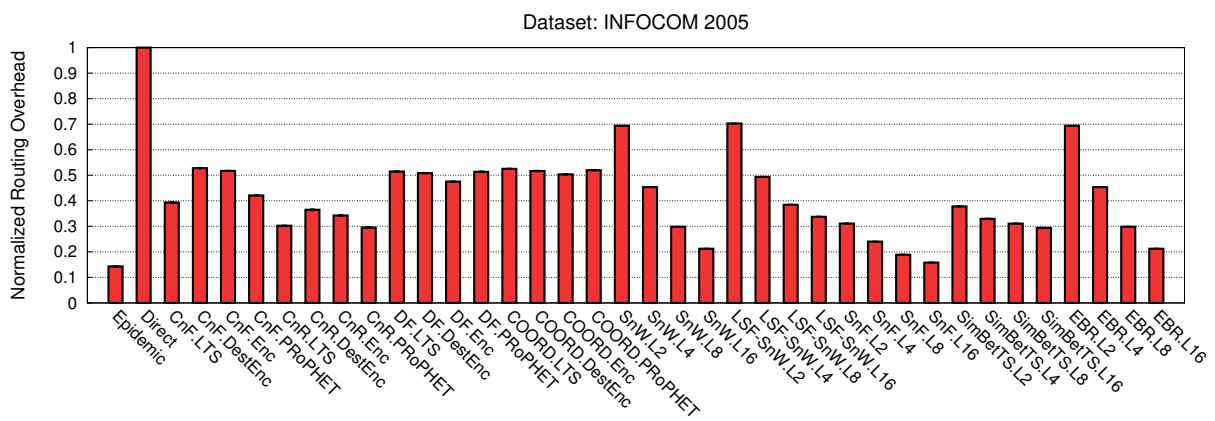
Figure A.14: Normalized Routing Overhead of each routing protocol on the INFOCOM 2005 dataset.

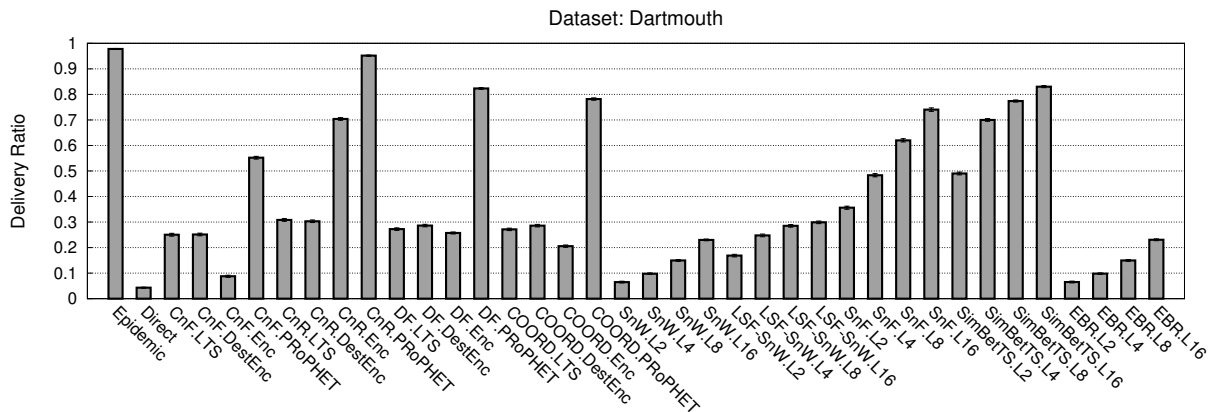## A.3 Performance Evaluation on the Lyon dataset

Figure A.15: Delivery Ratio of each routing protocol on the Lyon dataset.
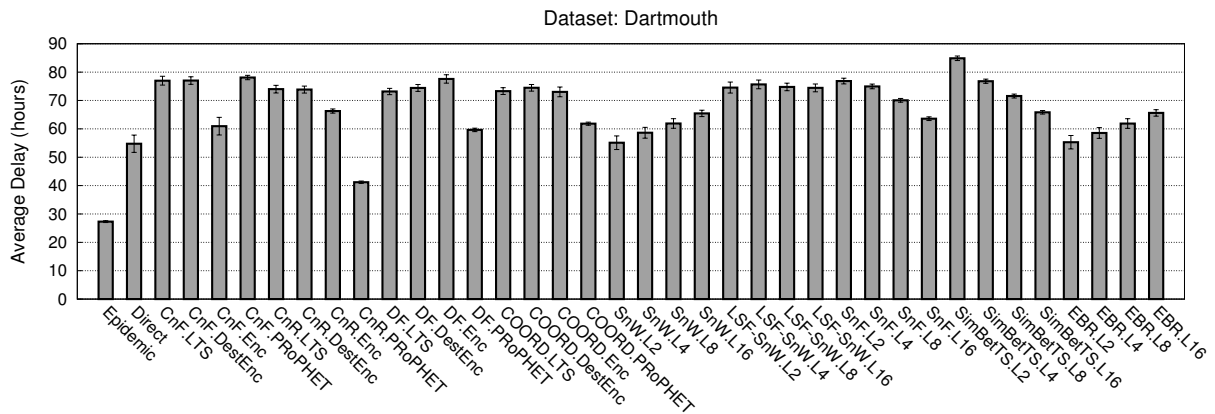

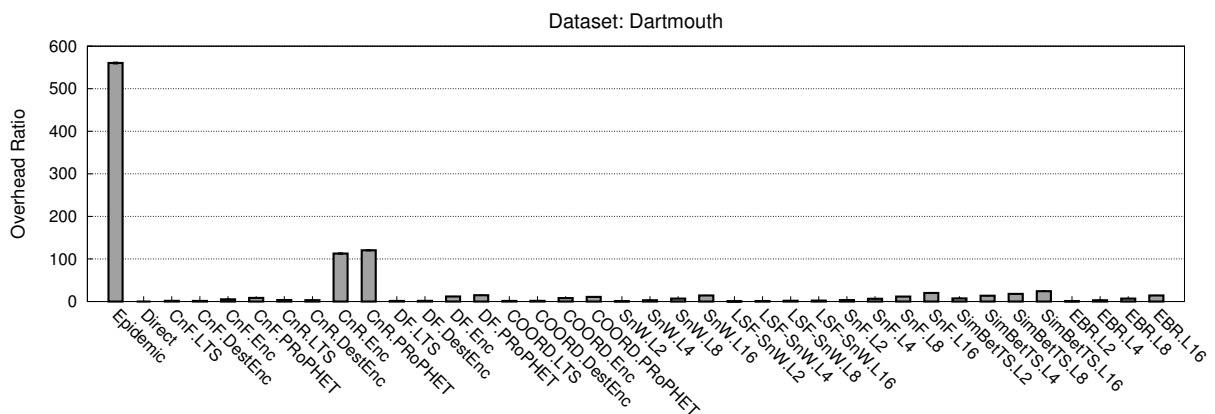Figure A.16: Average Delay of each routing protocol on the Lyon dataset.

Figure A.17: Overhead Ratio of each routing protocol on the Lyon dataset.

Figure A.18: Average Number of Hops of each routing protocol on the Lyon dataset.

Figure A.19: Normalized Delivery Ratio of each routing protocol on the Lyon dataset.

Figure A.20: Normalized Delivery Delay of each routing protocol on the Lyon dataset.

Figure A.21: Normalized Routing Overhead of each routing protocol on the Lyon dataset.

A.4 Performance Evaluation on the Dartmouth dataset

Figure A.22: Delivery Ratio of each routing protocol on the Dartmouth dataset.

Figure A.23: Average Delay of each routing protocol on the Dartmouth dataset.

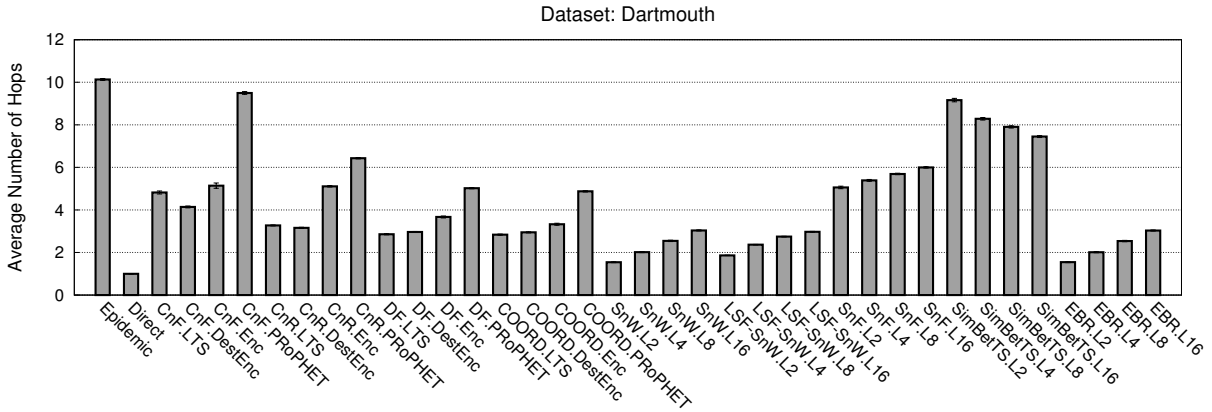Figure A.24: Overhead Ratio of each routing protocol on the Dartmouth dataset.

Figure A.25: Average Number of Hops of each routing protocol on the Dartmouth dataset.
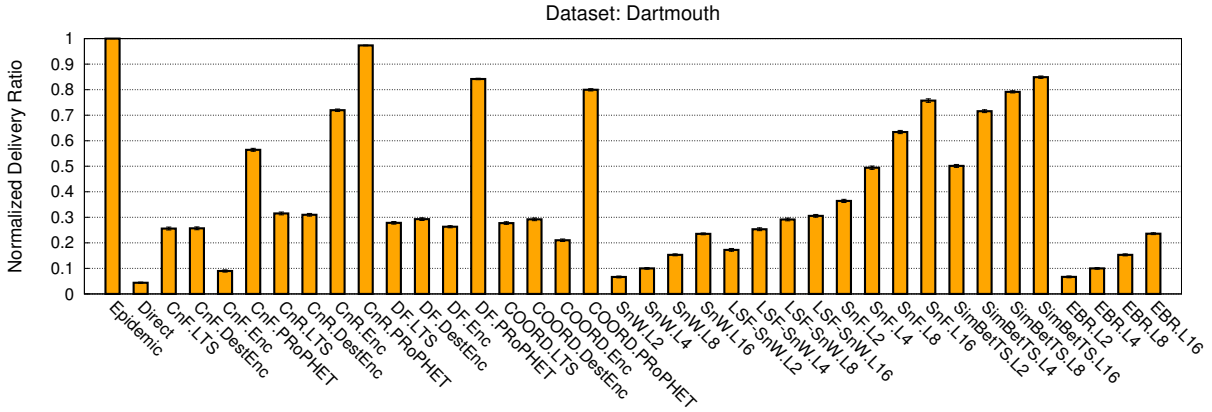

Figure A.26: Normalized Delivery Ratio of each routing protocol on the Dartmouth dataset.
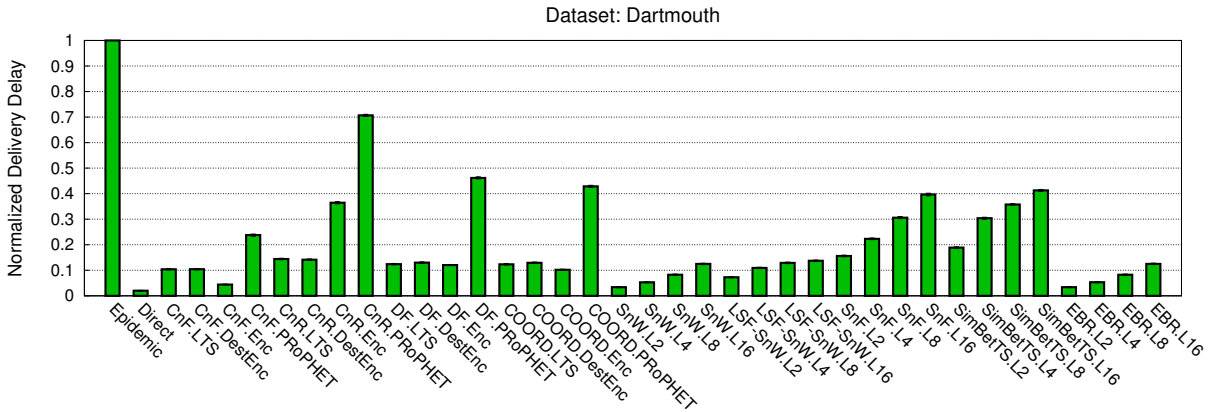

Figure A.27: Normalized Delivery Delay of each routing protocol on the Dartmouth dataset.
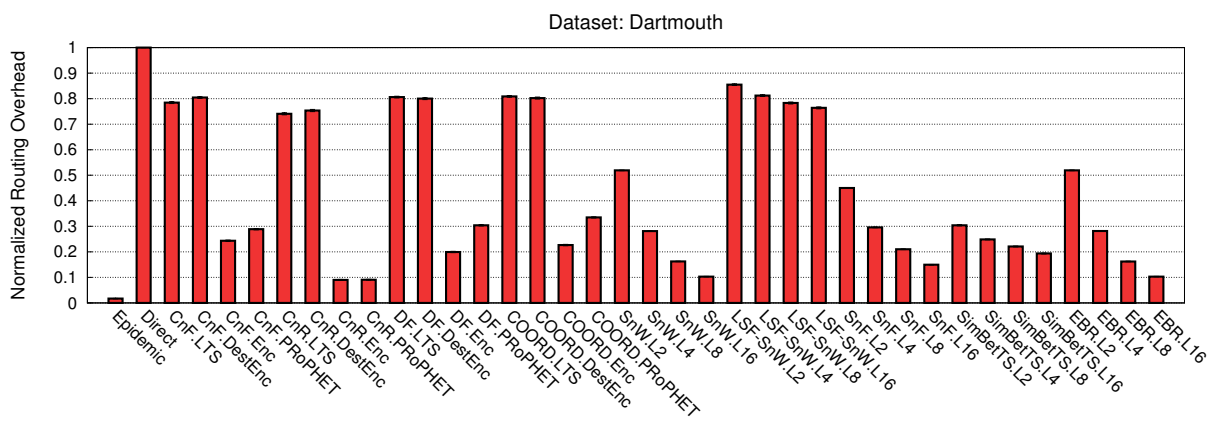
Figure A.28: Normalized Routing Overhead of each routing protocol on the Dartmouth dataset.

SHORT BIOGRAPHY

Dimitrios-Georgios Akestoridis was born in Athens, Greece in 1991. Currently, he is a Graduate Student in the Department of Computer Science and Engineering of the University of Ioannina, from which he received his B.Sc. degree in 2013. He is an IEEE and ACM student member since 2014, as well as a member of the Networks Research Group of the University of Ioannina since 2012. His research interests include Opportunistic Networks, Mobile Data Offloading, Network Security, and Social Network Analysis.