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Advanced Topology Analysis in Three Wireless Community Networks

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Introduction

Wireless networking is changing the world. Not many years ago, the idea of accessing the Internet with a mobile phone seemed crazy; nowadays, children grow surrounded by technology and are used to expect this sort of information ubiquity.

Cellular networks are usually not very performing with regard to speed and offer a limited amount of traffic at prices that are quite high. Still, they are not the only way to connect in mobility: municipalities and commercial activities are building public Wi-Fi networks for their citizens or customers, usually for free.

Laws that regulate wireless communications also evolved in recent years, loosening the initial restrictions imposed on radio transmissions over public areas. Another step further was allowing network owners to open up their networks to other people without bureaucratic hurdles and worries of being prosecuted for traffic generated by other users.

Wireless Community Networks fit in this diversified scenario as an alternative approach, which leverages existing technology to build networks in ways that were not foreseen. They push the Wi-Fi standard to the limit of its efficiency, especially in terms of range. They exist thanks to the volunteer actions of their members, and they grow with the community (most of the time, community is first and the network follows).

They represent a challenge and an ideal place for experiments for a network scientist, because they have features which are not found in any other network. The hacker culture that permeates most community network project means that information on the networks is readily available or easily obtained by just asking.

The development of tailored network protocols for mesh networks, a category of which Wireless Community Networks are part, is an active research field. Traditional routing protocols have been shown to be poor suited to these environments, for a variety of reasons.

Another topic which gathers much interest is measuring the performances of these networks. Their decentralised nature makes it difficult to analyse the behaviour of traffic: just knowing its volume is a challenge, since in theory every node should be monitored to acquire this information.

A reason that made it really interesting to examine Wireless Community Networks is that they seem a credible approach toward a communication infrastructure which is really a common good. An infrastructure owned by the citizens and operated without central authorities seems a more than reasonable approach, especially now that, according to the news, the era of mass Internet surveillance has officially begun.

This thesis aims to analyse three big Wireless Community Networks, with a focus on their topological features, their robustness and their efficiency in propagating message. To do so, their behaviour is simulated and compared to theoretical models. Chapter 1 provides an introduction to the topic of Wireless Community Networks, while chapter 2 gives a survey of the mathematical methodologies used to analyse networks and introduces the two random network models which are subsequently compared to real networks in their behaviour. Chapter 3 then explains the most important features of OLSR, a popular routing protocol in Wireless Community Networks.

Chapter 4 describes the three analysed networks, explaining their differences in terms of history, community approach, internal organisation and, most importantly, high level topological features.

Chapter 5 and chapter 6 present the two metrics analysed in the networks and in the random models. The former analyses the robustness of the networks in different failure and attack scenarios. There has been interest in literature to the behaviour of many real world networks, which are quite robust to random failure but collapse quickly in the case of a targeted attack. This analysis extends this considerations also to the three Wireless Community Networks.

Chapter 6, on the other hand, examines the networks in a dynamic scenario through a simulation of the exchange of routing information between nodes. Wireless links are notoriously unreliable and the loss of packets negatively impacts the diffusion of information on the topology. Nodes which do not receive this information often enough may suffer from the choice of suboptimal routes or even ignore the existence of other nodes. This analysis shows the impact of link loss on routing information in the three networks, simulating three routing protocols with different signalling methodologies.

1 Wireless Community Networks

The term "Wireless Community Network" (WCN) is used in literature to indicate various kinds of networks. The most common usage refers to wireless mesh networks operated by a community of citizens, as opposed to those controlled by a single entity (corporations or governments). Other authors also use the term for the public hotspot networks run by municipalities, or more generally for networks that provide wireless connection to the public. In this document the term is used with the first meaning, only for networks which are run – not merely accessible – by the community.

History

The appearance of the first Wireless Community Network can be dated to the late 1990s-early 2000s, when the IEEE 802.11 protocol (Wi-Fi) was first introduced.

They started as experiments by radio enthusiasts who wanted to explore the potential of this new technology, pushing it to the limit: Wi-Fi was designed as a protocol for local communication, but it was shown that, with the right equipment, it can perform well also on long distance links. The experimentation was made easier by the unlicensed spectrum of frequencies in which Wi-Fi operates.

With Wi-Fi gaining popularity and wireless enabled devices becoming mainstream, the cost of Wi-Fi equipment decreased and so did the barrier to participate in WCNs. At the same time, wireless protocols evolved and improved. For instance, 802.11a operates in the less crowded 5GHz band, allowing more separation between the used frequencies and thus, less interference.

In addition, a key factor to the diffusion on WCNs was the scarce availability of broadband connections in certain areas. In such cases, networks were not an experiment any more, but were used to provide services where commercial initiatives were lacking.

Today, the WCN scenario has changed: in some places they are still used to mitigate the digital divide, elsewhere they work as experimental test beds or are more focused on the social/political aspect of being an autonomous network owned and run by citizens. In the latter, the focus is on the services provided inside the network rather than on Internet access, which in some cases is not even available.

Some WCNs have grown to the point of having an Autonomous System (AS) number assigned and being able to peer with other networks at Internet eXchange Points (IXPs).

WCNs usually have a cultural background of Open Source enthusiasts and hackers[1] in general. Some of them are run by a formal associations, other by informal groups of citizens, but in every case node owners know each other and there is a sense of community. More experienced participants share their technical knowledge (and their time), making it possible for new members to enter the network with minimum effort.

Because of their spontaneous nature, it is difficult to determine precisely the number of active WCNs as there is no central registry to look at. However, there is a Wikipedia page [1] which, albeit incomplete, lists 262 WCNs at the time of writing. The dimensions of such networks vary from just a handful of nodes to nearly 25,000 as in Guifi[2], which is widely regarded as the world's largest WCN.

Technology

Figure 1.1: Antennas of a WCN node

[1] as in "curious", not as in "criminal"
[2] http://guifi.net

WCNs were born together with the IEEE 802.11 protocol family and continue to use it for various reasons, such as hardware availability and low cost, unlicensed frequency spectrum operation and the constant improvement of subsequent versions. Other solutions for the physical layer are sometimes used – for example proprietary protocols, maybe operating in licensed frequencies, or even methods not based on radio[3] – but they are an uncommon last resort when Wi-Fi can not work (due to interference or other reasons).

A node of a WCN is a router connected with one or more radio interfaces. There is not a standard for the construction of a node, but over time every community has gathered some best practices and guidelines based on experience and trial-and-error. The equipment used varies from consumer Wi-Fi routers (such as the very popular Linksys WRT54GL) with home-made antennas, to professional and more expensive equipment dedicated to long-range Wi-Fi links (Figure 1.1). Smaller nodes, especially if they are close enough, may use a single omnidirectional antenna to connect to different nodes. Usually, however, directive antennas with a limited beam width are used, to reduce interference leveraging different channels, avoid receiving noise from all directions and achieve an higher gain (Figure 1.2). Some nodes use both kinds of antennas, directive for backbone links and omnidirectional to provides an hotspot access.

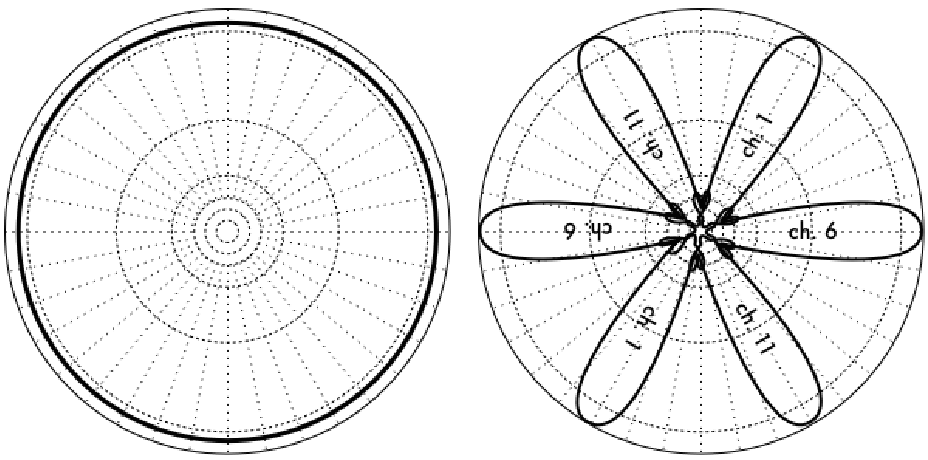


Figure 1.2: The difference between an omnidirectional and multiple directive antennas.

[3]Ronja, http://ronja.twibright.com/

Mesh networks

A mesh network is a type of network in which every node relays information to other nodes. The advantage of using a mesh, rather than a hierarchic structure, is that mesh networks can automatically configure and adapt to changes, without the need for manual intervention.

Mesh networks also benefit from having redundant paths and being able to adapt in case of failure of some links.

Mesh networks are usually wireless, since wired connections tend to be more permanent and reliable, and when cables are laid usually configuring the network is the smallest issue.

Wireless mesh networks have a large number of applications. They are used in sensor networks, which employ small embedded devices that communicate with each other to relay data to an observation point. The “One Laptop Per Child” project, which developed laptops to give to students in third-world countries, equipped them with mesh networking capabilities to enable sharing without a network infrastructure.

Routing is one of the biggest challenges in wireless mesh networks. Due to the nature of wireless links, traditional routing protocols thought for wired networks perform poorly when applied to them. In recent years, many new routing protocols have been proposed to address this issue and today there is a competition with no clear winner. The two most widely known routing protocols for wireless mesh and ad-hoc networks are OLSR and B.A.T.M.A.N. The former, which is used in the three WCNs analysed in this work, will be the subject of chapter 3.

2 Network topology and graphs

Some mathematical instruments are required to do any kind of description or analysis of the topology of a network, or to explain the functioning of a routing protocol.

One mathematical structure which is used to describe networks is the *graph*. A *simple, undirected graph* is an ordered pair $G = (V, E)$, where elements of V are the *nodes* (also called *vertices*) of the graph, while $E \subseteq \binom{V}{2}$ is the set of the *edges* of the graph. As a convention, in the rest of this thesis, nodes will be denoted with v_i, $i \in \mathbb{N}$, without meaning any particular ordering of the nodes. Also, for convenience, an edge $\{v_i, v_j\}$ will be denoted e_{ij}.

An edge e_{ij} is said to be *incident* to the vertices v_i and v_j; equivalently, v_i and v_j are incident to e_{ij}. Two vertices incident to the same edge are said *adjacent*.

The graph is said simple since there are no loops (i.e. $\{u, u\} \notin E$) and each pair of vertices is connected by at most one edge. The above mentioned graph is also said undirected. On the other hand, a *directed graph* is a pair $D = (V, A)$ where $A = \{(u, v) \text{ st. } u, v \in V,\ u \neq v\}$. The notation (a, b) means an ordered pair, in contrast to edges of an undirected graph which are unordered. The elements of A are usually called *arcs*.

For the purposes of describing networks, graphs are considered to be *finite*, so V and E are finite sets. Many well known finite graph properties do not hold in the infinite case.

A *weighted graph* is a graph in which every edge has an associated label *weight*, usually a real number. It is useful to define a function $w : E \to \mathbb{R}$ which associates weights to edges; in the case of unweighted graphs, it can be assumed $w : e \mapsto 1\, \forall e \in E$.

To model networks as graphs, each node of the network is represented by a node in the graph and a link between two nodes is represented by an edge between those nodes. If there are unidirectional link, a directed graph is used. In the routing protocol used by the networks analysed here, only bidirectional links are used, and the quality of a link is measured on the round-trip, so it is symmetrical. Given so, from now on "graph" will be used for simple, undirected graphs.

Terminology

This section introduces the terminology that will be used throughout the thesis when referring to graph properties.

Order and size

The *order* of a graph is the number of its nodes, $|V|$. The *size* of a graph is the number of its edges, $|E|$.

Degree

The *degree* k_v of a vertex v is the number of edges incident to that vertex. A vertex of degree 0 is an *isolated vertex*. A vertex of degree 1 is a *leaf*.

The *total degree* of a graph is $\sum_{v \in V} k_v$.

The *degree sequence* of a graph is the list of degrees in non-increasing order.

The *degree distribution* of a graph is a function $p_k : \mathbb{N} \to [0, 1]$ such that

$$p_k(n) = \frac{|\{v \in V \text{ st. } k_v = n\}|}{|V|}$$

The degree distribution is a discrete probability distribution since $\sum_k p_k = 1$.

Subgraphs

The set E of the edges of graph G can also be seen as a relationship between the vertices of the graph. This means that given a subset of the vertices, $V' \subseteq V$, the restriction $E \restriction_{V'}$ can be defined. As a set, $E \restriction_{V'} := \{\{v_i, v_j\} \in E \text{ st. } v_i, v_j \in V'\}$

A *subgraph* $G' = (V', E')$ of G is a graph such that $V' \subseteq V$ and $E' \subseteq E \restriction_{V'}$.

Walks, paths

A *walk* is a sequence of vertices $P = (v_0, v_1, \ldots, v_n) \in V \times V \times \ldots \times V$ such that $\{v_i, v_{i+1}\} \in E$, $0 \leq i < n$. A walk is *closed* if $v_0 = v_n$, *open* otherwise. The *length* of the walk is n. The *weight* of the walk is $w_P = \sum_{i=0}^{n-1} w(\{v_i, v_{i+1}\})$. In unweighted graphs, $w_P = n$.

A *path* is a walk with no repeated vertices. A *cycle* is a closed walk with no repeated vertices, except obviously the starting one which is repeated once at the end.

Given a graph with no negative-weight cycles, a *geodesic path*, also called *shortest path*, between v_0 and v_n is a walk $P = (v_0, v_1, \ldots, v_n)$ such that $\nexists P' = (u_0, u_1, \ldots, u_m)$ with $u_0 = v_0$, $u_m = v_n$ st. $w_{P'} < w_P$.
In a graph with negative-weight cycles, the geodesic path is not defined, since it is possible to have walks with $w_P = -\infty$.
The length of a geodesic path (which is the length of all of them) from u to v is called *geodesic distance* of u and v, indicated with d_{uv}

Neighbours

Each vertex adjacent to v is also called a *neighbour* of v. The set of the neighbours of v is called *neighbourhood* of v.

The concept of neighbourhood may be extended to vertices at any distance. For example, the *2-hop neighbourhood* of v is the set of vertices u such that there is a walk from v to u with length 2. Similarly, the *strict 2-hop neighbourhood* of v is the set of vertices which are in the 2-hop neighbourhood, excluding v itself and its direct neighbours.

Connectivity

A graph is called *connected* if, for each pair $\{u, v\}$ of nodes, there is a path between u and v.

A *connected component* of G is a maximally connected subgraph of G.

Centrality

In network science there is substantial interest in the concept of the centrality of a vertex (or an edge) in a graph. The idea behind this metric is to determine the most "important" components of a network. The meaning of "important" varies depending on the context: in social networks importance is usually defined by the influence of a node, measured by the size of it neighbourhood. In communication networks, the most important nodes are those who participates to most communications, either by forming circuits or by relaying packets. These are just two examples of different notions of importance that require different ways to be measured. The following paragraphs present the centrality metrics relevant to this thesis.

Degree centrality (C_D)

The degree of a vertex is the simplest possible measure of centrality and it is the only one that is only based on local properties. This is an advantage from the computational point of view, but it also implies that degree centrality is the least significant centrality metric. Nonetheless, depending on the graph, it can approximate quite well the behaviour of other metrics.

$$C_D(v) = k_v \tag{2.1}$$

Betweenness centrality (C_B)

Betweenness centrality of vertex v is defined as the fraction of shortest paths between any two vertices that pass through v. Formally, define $\sigma(s,t)$ the number of shortest paths from s to t and $\sigma(s,t|v)$ the number of those paths that pass through v. If $s = t$, $\sigma(s,t) = 1$. There is not a consensus in literature if a path "passes through" its endpoint; in this case, it is assumed not: $\sigma(s,t|s) = \sigma(s,t|t) = 0$. The betweenness centrality is

$$C_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{2.2}$$

betweenness centrality is especially useful in the study of communication networks because information usually travels through the shortest path, so C_B helps estimating how much traffic a node will see, in a way other centrality measures do not consider. For example, in the classic Barbell graph – two complete graphs connected by a path – vertices on the path have a very small degree but since every path between the two complete graphs passes through them they have high betweenness. This reflects the big control they have over the communications between other nodes.

Edge betweenness centrality (C_E)

The concept of betweenness centrality can also be easily extended to edges, with a similar notation.

$$C_E(e) = \sum_{s,t \in V} \frac{\sigma(s,t|e)}{\sigma(s,t)} \tag{2.3}$$

Closeness centrality (C_C)

Closeness centrality is also based on shortest paths, but has a different approach and a different meaning. It is based on the mean distance between v and the other vertices. If d_{vu} is the geodesic distance between v and u, the *mean geodesic distance* of v, averaged over all vertices is

$$\mathcal{L}_v = \frac{1}{n} \sum_u d_{vu} \tag{2.4}$$

Since usually centrality metrics have high values for more central nodes, closeness centrality is usually defined as the inverse of the mean distance $\mathcal{L}_v$.

$$C_C(v) = \frac{1}{\mathcal{L}_v} = \frac{n}{\sum_u d_{vu}} \tag{2.5}$$

Closeness centrality, despite being often used in network studies, has shortcomings. For example, the above definition is only valid if the graph is connected, since d_{vu} is defined to be infinite if there is no path from v to u. In graphs with more than one connected components, C_C would then be zero for every vertex. The usual solution is to compute the closeness centrality for each connected component separately: this works, but since distances are usually smaller in small components, vertices in those components tend to have higher closeness centrality, which may be undesirable.

Another issue with closeness centrality is that its values are often cramped in a small range from lowest to highest. In most networks distances tend to be small, typically increasing with the logarithm of the size n of the graph. So, the lower and upper bound for $\mathcal{L}_v$ are, respectively, 1 and $\log n$. Similarly, the range for C_C is limited.

Random graph models

A random graph is a graph generated by a random process. The reason for using random graph models in network analysis is that they can produce graphs with known degree distributions, which can be used to prove mathematically or otherwise analyse empirically their structural and dynamical properties.

Erdős-Rényi random graph

The random graph model originally proposed by Erdős and Rényi is also called $G(n, M)$ model, since it consists in the uniform random selection of a graph from the set of all graphs with n nodes and M edges.

The model used here is a variation first introduced by [2], called the $G(n, p)$ model. The algorithm starts form a graph with n nodes and no edges. Then, for each unordered pair of nodes $\{i, j\}.i \neq j$, the edge ij is added with probability p.

The $G(n, p)$ models has some interesting properties which are not obvious at a first look. For example, the number of edges is not known as in the $G(n, M)$ models, but the expected number of edges can be determined to be $\binom{n}{2}p$. Another important aspect is connectedness: with a large enough n, for $p > \frac{(1+\epsilon)\ln n}{n}$ the graph will almost surely be connected, while for $p < \frac{(1-\epsilon)\ln n}{n}$ it will almost surely have isolated vertices.

Finally, the degree distribution has the form

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k} \tag{2.6}$$

Barabási-Albert graph

A scale free network is a network whose degree distribution follows a power law of the form

$$p_k = Ck^{-\alpha} \tag{2.7}$$

A method for generating graphs with a power law degree distribution, using a preferential attachment mechanism, was devised by A. L. Barabási and R. Albert in [3]. Given a target number n of nodes and a parameter m which controls the density of the network, the algorithm starts from a graph with m nodes and no edges. Then other nodes are added and from each new node m edges are created. The probability of an existing node to be chosen as the destination of a new link is proportional to its degree – this is the meaning of preferential attachment. The procedure continues until there are n nodes in the graph, meaning the final graph will contain $(n-m)m$ edges.

3 Survey of the OLSR protocol

Optimized Link State Routing (OLSR) is a proactive routing protocol standardized by the IETF in RFC 3626 [4] and designed to have a better performance on wireless mesh and ad-hoc networks than traditional protocols for wired networks.

In link state routing protocols, each node is supposed to know the entire topology of the network in order to calculate the routes. This means that each time the topology changes, the new information must be propagated to every node. This is traditionally done by flooding link-state advertisement packet through the network.

In the case of traditional networks with wired links, this method is acceptable since the topology seldom changes. In WCN (and wireless networks in general), however, links change their cost quite often and may also disappear temporarily. Flooding in this situation imposes a big effort on the network and may degrade the performance consistently.

OLSR addresses this concern with an optimized flooding mechanism which significantly reduces the overhead by using only selected nodes, called multipoint relays (MPRs), to broadcast link-state advertisements, as seen in Figure 3.1. The next sections outline the details of this mechanism and of OLSR in general.

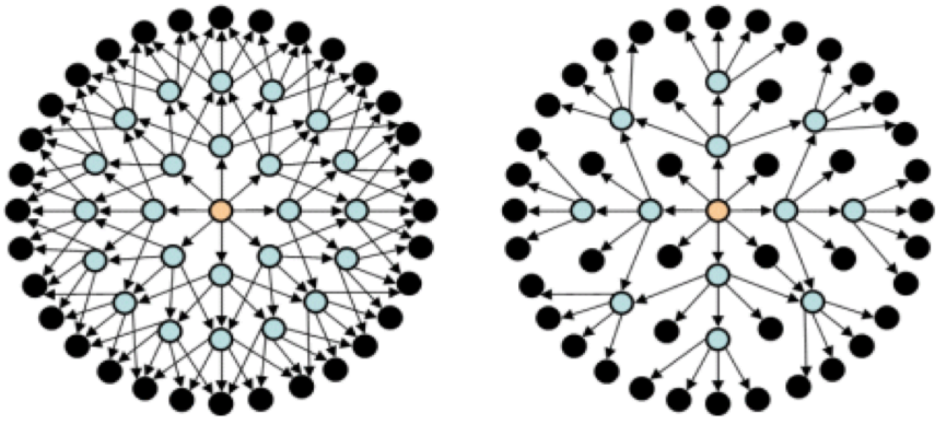


Figure 3.1: Flooding vs. MPR forwarding

Generic packet format

OLSR uses different types of messages in its specification. In order to take advantage of the maximal frame size provided by the network, one or more messages are encapsulated in a packet which has the same format for all types of messages (see Figure 3.2). This facilitates the extensibility of the protocol and allows the transmission of different kinds of information in a single packet.

Each message is flooded through the network with a TTL. The transmission to neighbours is just a special case of flooding with TTL=1. Duplication is eliminated locally, since each node records the originator address and sequence number of all the messages it processes.

```
 0                   1                   2                   3
 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0 1
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|         Packet Length         |    Packet Sequence Number     |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|  Message Type |     Vtime     |         Message Size          |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                      Originator Address                       |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|  Time To Live |   Hop Count   |    Message Sequence Number    |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                                                               |
:                            MESSAGE                            :
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|  Message Type |     Vtime     |         Message Size          |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                      Originator Address                       |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|  Time To Live |   Hop Count   |    Message Sequence Number    |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                                                               |
:                            MESSAGE                            :
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
:                                                               :
               (etc.)
```

Figure 3.2: Fields of a generic OLSR packet

Link sensing and neighbour discovery

Link sensing and neighbour discovery are achieved in OLSR with the use of `HELLO` messages, which are transmitted by each node to its neighbours and contain the addresses of the neighbours it knows. Of course, the first `HELLO` messages are empty and only serve the purpose of link sensing. After each node populates its neighbour set, it includes this information in its `HELLO` messages, along with some information on the links and the neighbours (e.g. if the links are verified to be symmetric). This allows all nodes to gather the necessary knowledge of their 2-hop neighbourhood. Only bidirectional links are considered by OLSR as valid.

`HELLO` messages are generated and transmitted at a regular interval (`HELLO_INTERVAL`). Lost links are also advertised for some time (with a link type of `LOST_LINK`).

MPR selection and signalling

Using the information from the `HELLO` messages, each node can select a set of its neighbours such that every node in its 2-hop neighbourhood is at 1 hop from the set. Formally, call $N_1(v)$ the neighbourhood, $N_2(v)$ the strict 2-hop neighbourhood, select $\mathrm{MPR}(v) \subseteq N_1(v)$ such that

$$\forall u \in N_2(v)\, \exists s \in \mathrm{MPR}(v) \text{ st. } u \in N_1(s)$$

This requirement essentially means that each node in the strict 2-hop neighbourhood can be reached through a MPR. Once a node has selected its MPRs, it needs to signal its choice to the neighbours. `HELLO` messages are used also for this purpose: the selected MPRs are advertised with a neighbour type of `MPR_NEIGH`.

As a notational convention, $v \to u \Leftrightarrow u \in \mathrm{MPR}(v)$.

Message forwarding

Observing the `HELLO` messages it receives, node v populates and maintains an `MPR Selector Set`. This is the set

$$\mathrm{MSS}(v) \coloneqq \{u \in V \text{ st. } u \to v\}$$

Node v then need to retransmit only the messages it receives by nodes in $\mathrm{MSS}(v)$.

When v receives a message (except for `HELLO` messages, which are never forwarded), it checks if the time-to-live has reached zero or if the message was already processed (by examining the duplicate set). If the message passes this preliminary checks, it is forwarded only if it was received from a selector.

The primary goal of using MPRs is reducing the number of duplicate message retransmissions while ensuring that each node receives the required information. The selection of MPR nodes influences the capacity of reaching this goal. The OLSR specification suggests that the size of the MPR set should be minimized. However, it leaves freedom to the implementer or the network administrator to override the default heuristic in order to achieve, for instance, more redundancy.

Topology control

The link-state information is propagated throughout the network with `Topology Control` messages (`TC`). This messages are generated only by the MPRs and propagated following the above described rules. Each `TC` message contains the identification of the node who generated the message and a list of the addresses of its neighbours, but not all neighbours are necessarily included.

The OLSR specification requires that the nodes in the `MPR Selector Set` of a node be in the `TC` messages it generates. To add redundancy, each node can advertise, in addition, the neighbours selected by it as MPRs, or even all of its neighbours. The added redundancy comes at the cost of longer `TC` messages, which may be more susceptible to congestion.

The links between an MPR and the neighbours that it does not advertise in `TC` messages effectively disappear from the topology which is known to other nodes. Thus, nodes in OLSR have only a partial knowledge of the network and can calculate routes with this incomplete information.

Link quality

OLSR implements a mechanism to avoid using “bad” links (links which are usually too weak but may let `HELLO` messages pass from time to time). Since `HELLO` messages are transmitted at a regular interval, each node knows how many of them to expect from each neighbour over a period of time. Comparing this with the number of received messages it computes a measure of the Link Quality (LQ). This metric was originally only used to decide if a link was reliable enough to use. New versions of OLSR have put more importance on link quality.

It is common in WCNs to use the ETX metric to express link quality. ETX stands for Expected Transmission Count and was proposed in [5]. It indicates the expected number of transmissions (including retransmissions) required to successfully deliver a packet.

In OLSR, ETX is derived directly from LQ. `HELLO` messages contain the calculated values, so each node has for every link two measures: its own (LQ) and its neighbour’s (NLQ). Since each unicast packet transmission requires an acknowledgement, the estimated probability of success is $\mathrm{LQ} \cdot \mathrm{NLQ}$. ETX is calculated as

$$\mathrm{ETX} = \frac{1}{\mathrm{LQ} \cdot \mathrm{NLQ}} \tag{3.1}$$

The measure of ETX in OLSR is surely an approximation because it does not describe the behaviour of real data packets. Only relatively small broadcast packets are taken into account and this may introduce a bias since bigger packets have more probability to be involved in collisions. In addition, no regard is given to the possibility of getting a link quality measure from the radio layer.

Use of LQ in MPR selection

The heuristic proposed in the RFC to compute the MPR set of a node gives no importance to link quality. This means that a node could choose as an MPR a neighbour with a weak connection. Since MPRs advertise the route to their selectors, this weak link may end up being used in place of a better one, because the latter is not shared with an MPR.

To address this issue, it has been proposed to use an algorithm for selecting MPRs that accounts for link quality. Unfortunately, the rapidly changing nature of link quality causes instability in the MPR set. This in turn causes MPRs to generate `TC` messages more often, leading to an increase in signalling, the exact opposite of the reason why MPR were introduced in the first place.

To avoid this effect, but still ensure that good links are not discarded for weak ones, the implementation of OLSR used by the analysed WCNs forces each node to be an MPR [6]. Every node has thereby the complete knowledge of the network topology.

4 The networks

The three WCNs which are analysed in the theses are Ninux (in Italy), FunkFeuer Wien and FunkFeuer Graz (in Austria). The study considers 50 snapshots of the networks taken in January 2014. The exact timings of the snapshots are described in Table 4.1.

The snapshots were obtained by the interpolation of the OLSR topology exported directly by the routing daemons on the nodes (since each node has the complete knowledge of the topology) and information published (or otherwise provided) by the communities.

Some supernodes with several antennas make each of them run OLSR as an independent node, connecting them to a switch. These cases have been considered a single node for the purpose of this analysis, since they represent devices in a single location, run by a single person and connected to a single power source. Moreover, this type of configuration is being replaced by a more efficient one, which uses a single router running OLSR. The separate devices are then configured as simple 802.11 Access Points/clients and connected to the router using separate VLANs.

The analysis of the three networks has been performed with computer simulations, using software written during my internship with Prof. Renato Antonio Lo Cigno and Dott. Leonardo Maccari of the Advanced Networking Laboratory of DISI.

The software, the test cases and the raw result data are available on a public git repository at https://github.com/mpitt/bsc_thesis.

	Ninux	FFWien	FFGraz
date	20/01/14	13/01/14	13/01/14
snapshot interval	5 min	5 min	10 min
timespan	4h 10min	4h 10min	8h 20min

Table 4.1: Details of the data collection

The simulations make use of NetworkX[1], a Python library for graph manipulation that incorporates many algorithms and random graph generators.

Ninux

Ninux[2] is the largest Italian WCN. It was started in 2001 in Rome and now consists of about 250 active nodes, located in different "Ninux islands" all over Italy. The name "Ninux" originally was a tribute to the project founder, Nino, but now the project members usually take it with the meaning "Neighbourhood Internet, Network Under eXperiment". The logo of the group is shown in Figure 4.1.

Ninux is managed in an informal way: every member is the owner and responsible of its node (or nodes), but there is no formal association. This is a deliberate choice of the Ninux community, motivated by the excessive bureaucratic effort it would require. Moreover, all associations must have a president responsible for the activities of the association itself, and Ninux members prefer the responsibility to be decentralised (as the network is).

The different islands use a variety of protocols and have different topologies:

- in Pisa, Sicily and Friuli there are three mesh networks, with routing based on B.A.T.M.A.N.
- in Rome, the biggest Ninux island (Figure 4.2) uses a backbone with point-to-point links combined with some mesh areas, employing OLSR for all the routing
- in recent years other networks have been created in Florence, Viterbo, Catanzaro, Cosenza and Reggio Calabria, all based on OLSR

The islands are connected together by tunnels using a variety of protocols.

[1] http://networkx.github.io
[2] http://wiki.ninux.org/

Figure 4.1: The Ninux logo

Ninux is an Autonomous System (AS# 197835)[3] and it is a member of the NaMeX[4] Internet Exchange Point.

In this work, the biggest Ninux island has been analysed (since it is the biggest OLSR routing domain), which is Rome's network. It consists of 132 nodes connected by 154 links (average degree of 2.333).

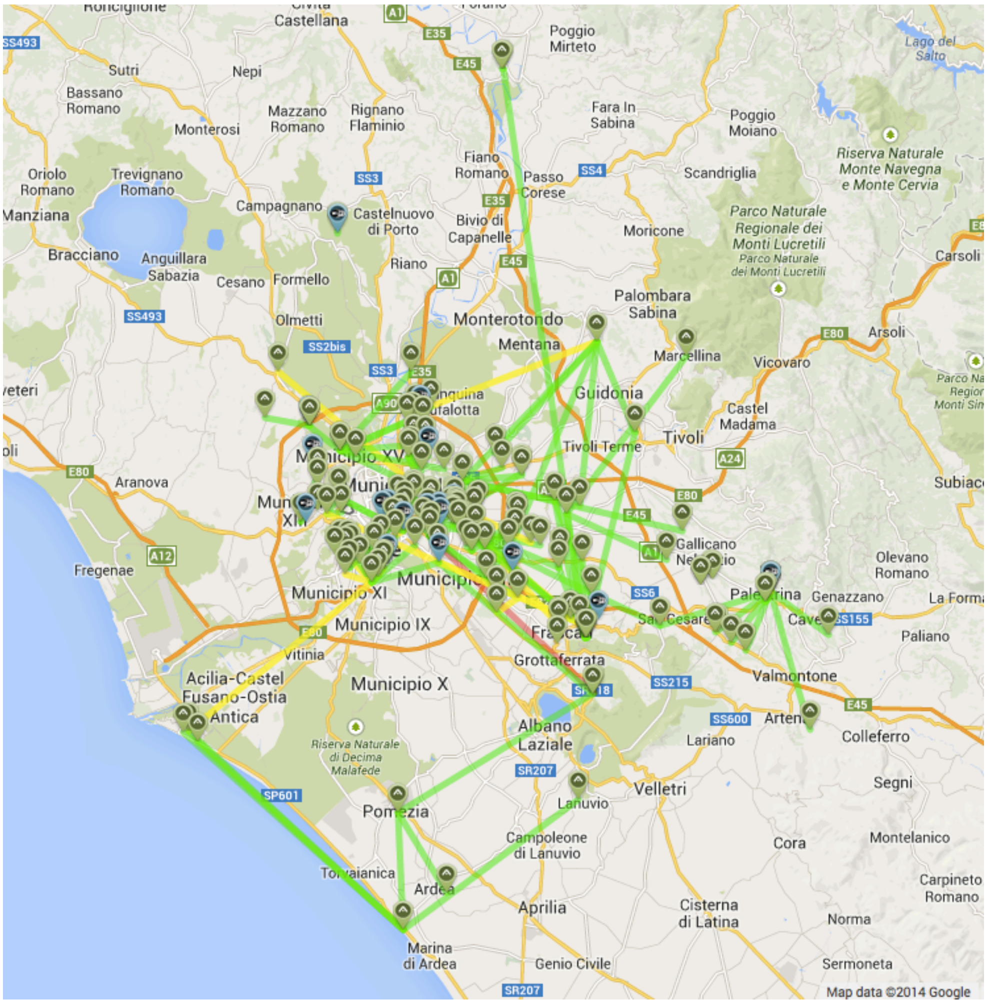


Figure 4.2: Map of the Rome Ninux island

[3] https://apps.db.ripe.net/search/query.html?searchtext=AS197835&object_type=aut-num#resultsAnchor

[4] http://www.namex.it/en/who/members

FunkFeuer: Wien

FunkFeuer[5] is a project that comprises networks in different places of Austria (Vienna, Graz, parts of Weinviertel and Bad Ischl). The literal meaning of "funkfeuer" in German is "radio beacon". FunkFeuer is also a registered association in Austria, differently from Ninux.

The origins of FunkFeuer are in the experiments of an Austrian ISP based in Vienna, Silver Server, which, during the 1990s, explored the commercial viability of wireless radio data links. After a test phase, Silver Server ultimately decided that the technology was not ready to be used commercially; however, the infrastructure was already in place and it was handed off to two associations, Team Teichenberg and Public Voice Lab. With direction from Franz Xaver and Roland Jankowski, they further expanded the network, bringing the node count to 15, but failed to create easy end-user access.

The network was ultimately decentralised, giving the opportunity to the citizens to buy the hardware of the nodes. The advent of cheap GNU/Linux based embedded Wi-Fi products promoted the growth of the network and an association was founded to have a more structured organisation and address the issues of decentralisation. The existence of a formal association also enables to request sponsoring from local administrations.

FunkFeuer Wien (FFWien)[6] is the biggest of FunkFeuer networks, covering 1/3 of the city. The active node in the analysed snapshots were 237, with 433 links (an average degree of 3.654).

FunkFeuer: Graz

FunkFeuer Graz (FFGraz)[7] is the "smaller sister" of the FFWien network, situated in the homonymous city. It was founded after FFWien by Othmar Gsenger, Erwin Nindl and Roland Jankowski and has its own association to apply for local sponsoring. It consists of 144 nodes and 199 edges, with an average degree of 2.764 (see the map on Figure 4.3).

[5] http://www.funkfeuer.at/
[6] http://www.funkfeuer.at/Vienna.206.0.html?&L=1
[7] http://graz.funkfeuer.at/

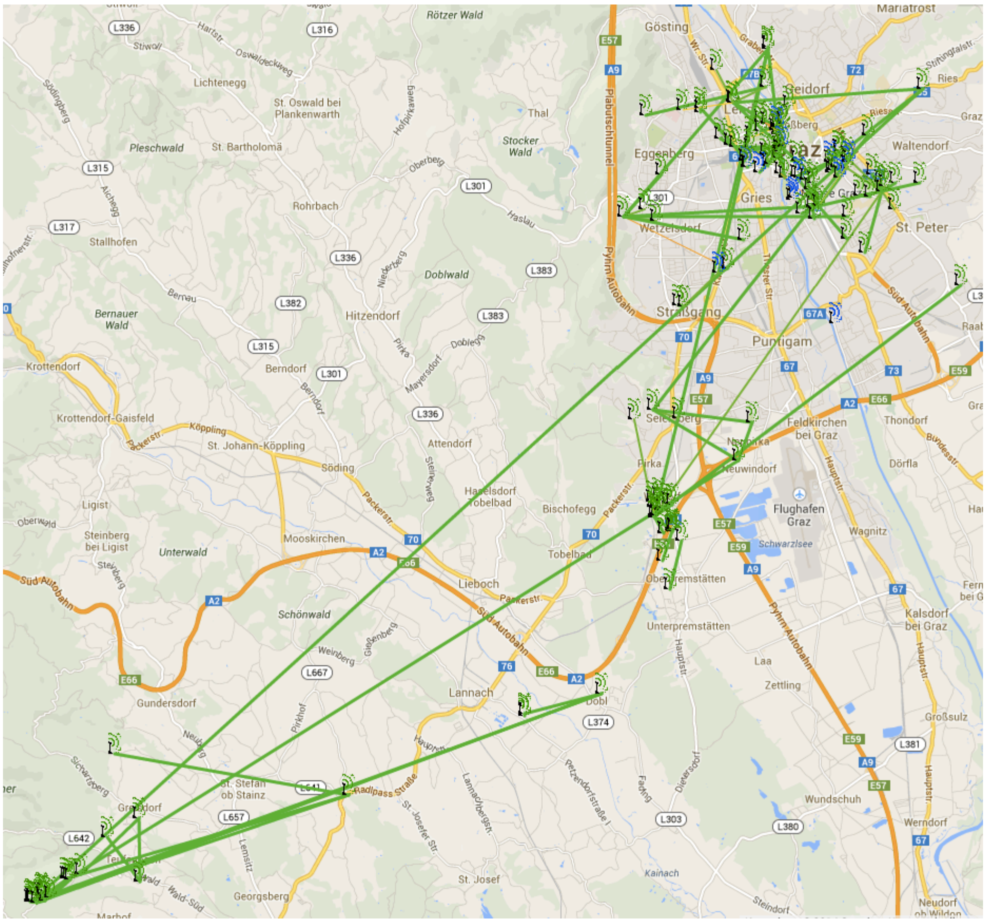
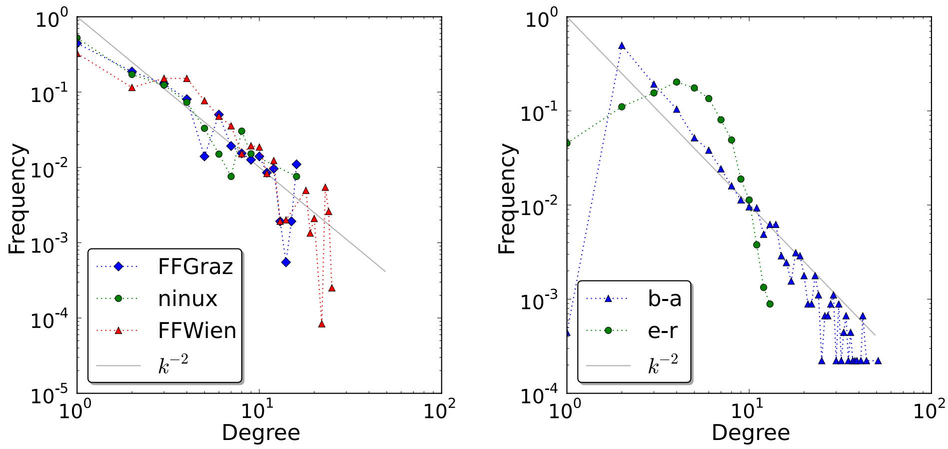


Figure 4.3: Map of the FunkFeuer Graz network

Comparison



(a) Ninux, FFWien and FFGraz (b) Random models

Figure 4.4: Degree distribution of the three WCNs, compared with the Erdős-Rényi and Barabási-Albert models

As Figure 4.4a shows, the degree distributions of the three WCNs roughly follow a power law k^{-2}, as does the random Barabási-Albert model (Figure 4.4b). One objective of this analysis is to understand if the model can be used to predict other properties of the real networks.

As can be seen in Figure 4.5, the three networks have a quite different distribution of link quality (the metric shown in the graph is $1 - \frac{1}{\mathrm{ETX}}$, which is also used for the signalling analysis in chapter 5). FunkFeuer Graz has by far the highest average weight, while Ninux seems to have the best links.

	Ninux	FFWien	FFGraz
Nodes	132	237	144
Links	154	433	199
Average degree	2.333	3.654	2.764
Density	0.018	0.015	0.019
Leaf nodes	69.02 (52%)	77.96 (33%)	64.72 (0,45%)

Table 4.2: High level features of the three WCNs

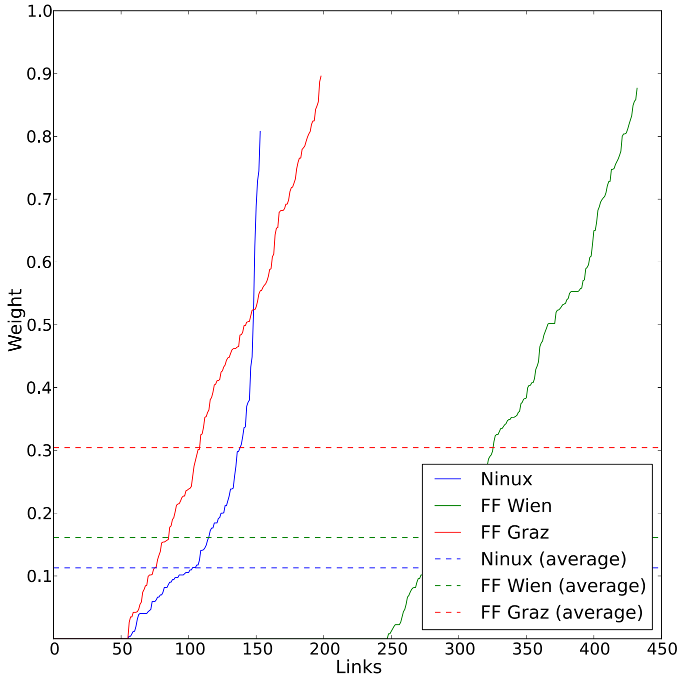


Figure 4.5: Links of the three WCNs, ranked by probability to lose packets

5 Robustness analysis

The first metric analysed is the robustness of the network. The chosen methodology is a variation of the percolation process described in Chapter 16 of [7].

Percolation

Percolation is the process of removing nodes (*site percolation*) or edges (*bond percolation*) and observing the properties of the remaining graph. More specifically, by examining the connected components of the graph, the degree of functionality of the underlying system after removing nodes (or edges) can be evaluated. The removal of nodes simulates a variety of real-world situations – from hardware failures in communication networks to vaccinated people in the spread of a disease. Removing edges addresses other cases, also interesting in real-world systems. In the following paragraphs, only site percolation is considered, but the remarks are also valid, with the necessary adaptations, for bond percolation.

It is not trivial, at a first look, how it should be decided if the network "functions" after removing nodes. Nonetheless, there is a simple answer to this issue that gives very significant results: the order of the largest connected components. Removing a node from a network obviously removes the node itself from any connected component, but also affects potentially other nodes, which received information through the removed node.

If enough nodes are removed, the network will become disconnected, but usually there will be a large connected component containing most of the surviving nodes and some smaller ones with just a few nodes. It can be affirmed that in such a situation, at least part of the network is still working as intended. Removing even more nodes, however, leads to a point where the largest component does not contain a significant fraction of the nodes – it becomes indistinguishable from the smaller ones. This is the point in which the network loses its function.

To formally define a robustness metric, name the connected components of a graph, ordered non-increasingly by the number of their nodes, $C_0, \ldots, C_m$.

$|C_0|$ is then the order (number of nodes) of the largest connected component. The robustness metric is defined as

$$S = \frac{|C_0|}{|V|} \tag{5.1}$$

Removal order

Nodes and links in a network are not all equal. As seen in Chapter 3, different centrality metrics give different measures of the importance of a node in a network. When considering robustness, it is interesting to study which nodes have the biggest impact when removed and how much difference there is between more and less impacting nodes.

The classical approach to percolation is to remove nodes randomly in an uniform way. Also popular is the removal of the nodes with highest degree first. Other methods, such as ordering by centrality, have also been explored. Comparing these different methods gives not only useful information on how the metrics predict the impact of the removal of a node, but also on the behaviour of the examined networks. Some networks, for example, behave more or less the same regardless of the order of removal. Others show a dramatically different response. Scale-free networks are the typical example of a network that is highly robust to random failures, but collapses quickly if the nodes with the highest degree are removed.

Changing the removal order has also another level of significance when studying real-world networks. There are various situations in which nodes have different probabilities of failing: for example, malicious attacks often try to target the nodes that would cause the most damage.

All of the above considerations are also valid for links, but the metrics differ: there is nothing corresponding to the degree, but there is betweenness centrality.

This analysis covers:

- random removal of nodes
- removal of nodes by degree
- removal of nodes by betweenness centrality
- removal of nodes by closeness centrality
- random removal of links
- removal of links by betweenness centrality

Comparing different networks

The objective of doing a robustness analysis on WCNs, apart from determining their resilience to failure, is also understanding if the presently used random models are useful in describing their behaviour.

One feature of networks that highly influences their robustness is the density of links with respect to nodes. Intuition suggests that a network with more links should be more robust of a less dense one with the same number of nodes. This is in fact confirmed.

Keeping this in mind, any robustness comparison between two networks is significant if the networks have comparable densities. It is of no use comparing a 100-node network with 200 edges to one with 2000.

To express the density of a graph, the average degree may be used. Recall the three WCNs which are the subject of this analysis have average degrees 2.333, 3.654 and 2.764. Since they are to be compared to graphs generated by random models, care must be taken to generate graphs with an average degree not too distant from those.

The average degree of random graphs can be predicted easily, given the parameters:

- for the Erdős-Rényi $G(n, p)$ model, the expected average degree is

$$\langle k \rangle = \frac{2\binom{n}{2}p}{n} = (n-1)p \tag{5.2}$$

- for the Barabási-Albert preferential attachment model the exact average degree is known

$$\langle k \rangle = \frac{2(n-m)m}{n} = 2m\left(1 - \frac{m}{n}\right) \tag{5.3}$$

Unfortunately, while the p parameter of the $G(n, p)$ model is a real number and can be adjusted at will, the preferential attachment models requires a natural number m. This means that only some values of average degree can be achieved, as outlined in table 5.1.

m	1	2	3	4	5	6
$\langle k \rangle$	1.99	3.96	5.91	7.84	9.75	11.64

Table 5.1: Average degrees for a 200-node graph with the Barabási-Albert model

Methodology

The analysis was performed on 50 snapshots of the topology of the three WCNs, as well as 30 graphs for each of the random models.

The algorithm simply removes nodes (or links) one by one and checks the size of the largest connected component. In the case of random removal, the test was repeated 30 times for each graph, with a different random sequence every time.

The test considered the removal of at most 40% of the nodes (or links). Other values have been tried, but this was determined to be sufficient to observe the expected behaviour. Highest values just increased the simulation time without adding useful information.

The results were averaged over the graphs of the same kind and expressed in terms of fraction of removed nodes, rather than number of nodes, in order to compare them in the same graph.

Results

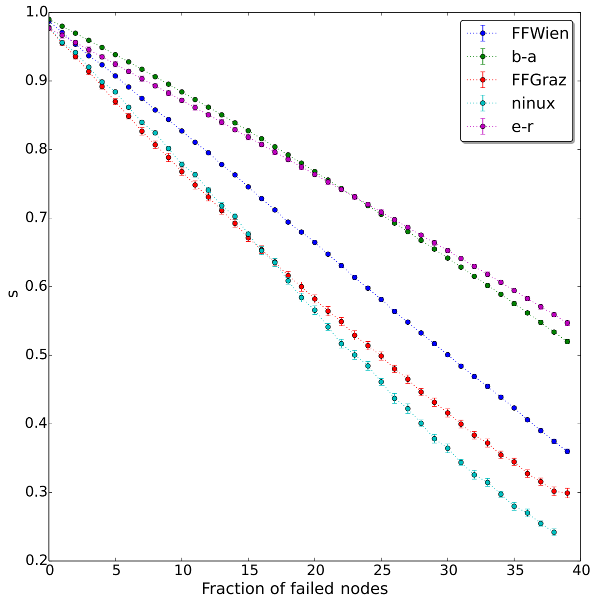


Figure 5.1: Random removal of nodes

As shown in the figures, there is a evident difference between the behaviour of the three WCNs (which is similar) and the behaviour of the random graphs.

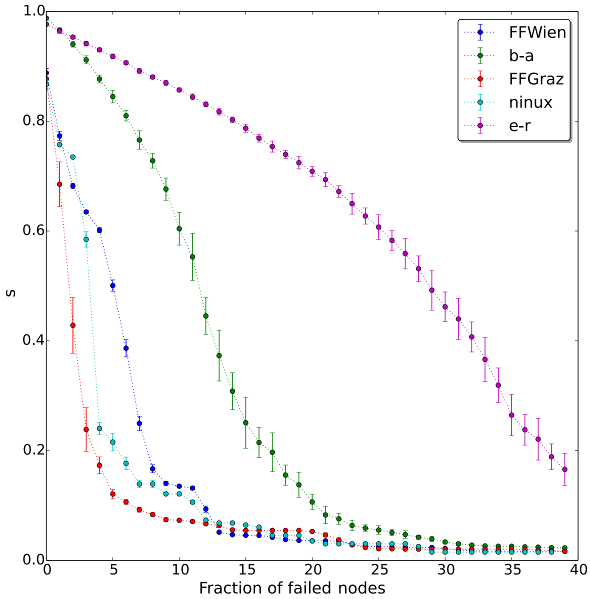


Figure 5.2: Removal of nodes by degree

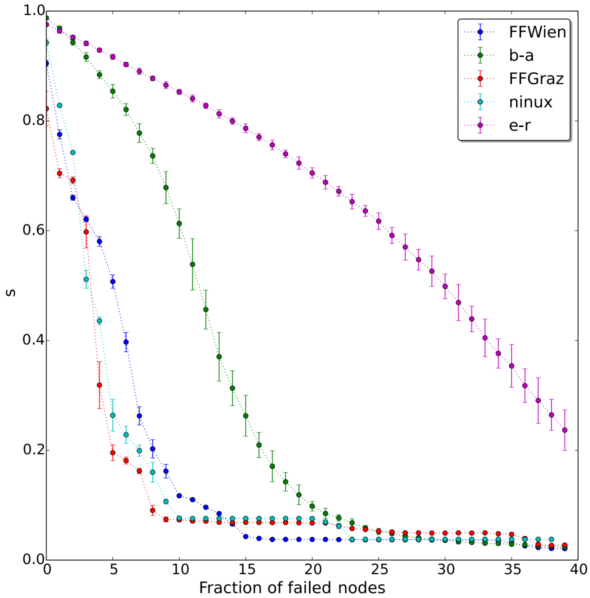


Figure 5.3: Removal on nodes by betweenness centrality

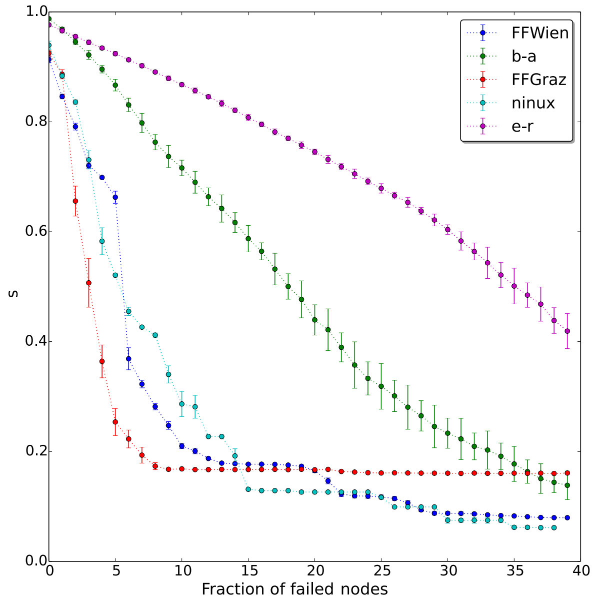


Figure 5.4: Removal of nodes by closeness centrality

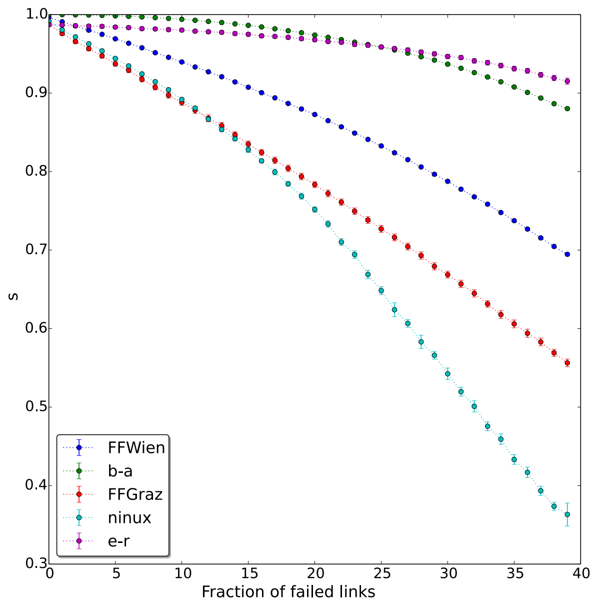


Figure 5.5: Random removal of links

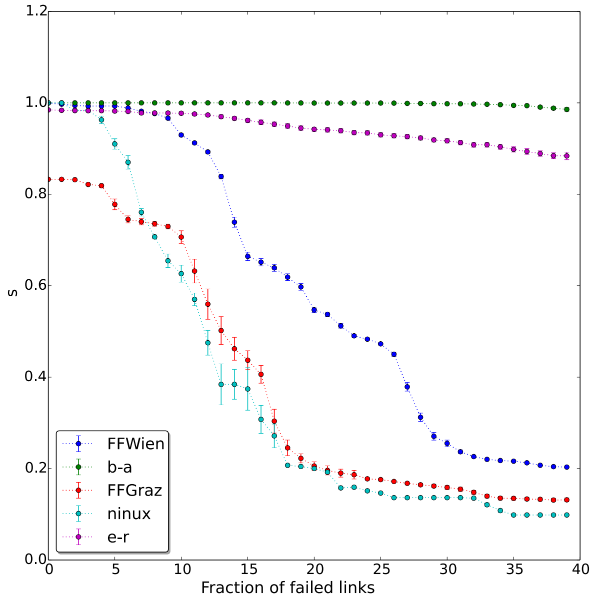


Figure 5.6: Removal of links by betweenness centrality

The WCNs are more fragile in all tests, but while the difference in the random removal case (Figure 5.1) may be explained by the lower density, in all of the ordered removal cases they consistently fail after just 10% of nodes are removed.

The scale-free random networks is, as expected, less robust than the Erdős-Rényi model in the removal of nodes by degree (Figure 5.2), and has the same proceeding with removal by betweenness centrality (Figure 5.3). On the other hand, removing nodes by closeness centrality (Figure 5.4) shows a quite less marked difference between the two models.

WCNs, on the contrary, behave the same in all the scenarios in which nodes are removed by the centrality metrics, independently from the specific metric used (Figure 5.2, 5.3, 5.4). This suggest that, in those networks, the central nodes are the same for all the metrics. This also means that the topology of WCNs, despite the big similarity of the degree distribution, is different from the preferential attachment model. Moreover, this difference seems to go in the direction of less robustness.

The removal of links (Figure 5.5 and 5.6) also shows a similar picture. None of the random models approximates well the behaviour of the WCNs, which quickly fail after a small fraction of links has been removed. Here a peculiar behaviour appears in FFGraz: in this network, there are some nicely connected areas that are geographically distant between themselves, so there are some long links that provide connection between those clusters. These long links are apparently (and intuitively) the ones with the highest centrality, so the first to be removed.

The inadequacy of the preferential attachment model to predict the robustness of WCNs deserves some considerations. Despite the degree distributions following in both cases a power law, the robustness metrics behave quite differently, so it is worth considering what are the features of real world networks the model does not account for.

Firstly, one thing that can be noticed is that the preferential attachment model builds a graph with no leaves. With $m = 2$, which is the parameter used in this analysis, the graph at step zero is two vertices without links, at step 1 it is a path of length 2, at step 2 it is either a square or a triangle with a leaf. In either case, since each new node is added with 2 links, the final graph will contain at most 1 leaf, in contrast with WCNs where leaves are a large part of the nodes.

A second observation is that the nodes with highest degree in WCNs are usually those installed in good locations (for instance on a hill or another elevated spot). This is because Wi-Fi links require a line of sight. When a new node is added it usually starts as a leaf and does not choose its neighbour(s) based on their degree, instead it is forced to choose a node it can see. So, the growth of a WCN does not follow the preferential attachment rule, even if the resulting degree distribution seems similar.

To sum up, WCNs demonstrate to be quite robust to random failures but they are really vulnerable to targeted attacks to their most important components. This is in part expected by the knowledge about random network models, but the WCNs are even less robust than the models would predict.

6 Message propagation analysis

The importance of signalling

The robustness of a network is based on a static analysis of the connectivity of the network graph when removing nodes or links. A communication network, however, is a dynamic system where information needs to move between nodes. Moreover, the decentralised nature of computer networks means that the complete topology of the network is not necessarily the topology used to transmit information, depending on the routing protocol used for the network.

Given this, in order to understand the behaviour of a communication network it is necessary to study the behaviour of its routing protocol with different underlying topologies. The phase analysed here is that of topology discovery, where link-state advertisements are exchanged and each node receives information on the existence of the other nodes in the network and a route to reach them.

In traditional link-state routing protocols, link-state advertisement messages are usually flooded through the network with a simple duplicate detection mechanism to avoid broadcast storms.

OLSR uses a more sophisticated technique to reduce the overhead of routing. This of course comes at a cost in redundancy, since if a `TC` message is lost, it is not received through other routes. OLSR also has `HELLO` messages, which are only exchanged with neighbours and enable `TC` messages, which are only generated by MPRs, to contain information about all the neighbours of the node which generates them.

The implementation of OLSR used in WCNs differs from the specification and forgoes optimization by forcing each node to be an MPR.

Simulation algorithm

The goal of this analysis is to understand how efficiently routing information is propagated in WCNs, and what would change if different topology discovery strategies were used.

To do so, the algorithm simulates the sending of a single link-state advertisement message for each node and the forwarding of these messages throughout the network, taking into account the forwarding policy and, most importantly, the potential loss of packets on links. The results, after a large number of runs of this algorithm, are an average of the fraction of nodes each node v knows and of the fraction of nodes who have received information on v.

The signalling on an unreliable network (a network in which packets are lost) is simulated with an algorithm similar to a Breadth-First Search (BFS) on a graph, with an important variation: while the BFS always proceeds with the neighbours of a node, messages may fail propagating on some links.

The network is represented by a weighted graph $G = (V, E)$, where link weights correspond to the probability of losing a packet on that link $(1 - \frac{1}{\mathrm{ETX}})$. For each node v, a message consisting in a set $V' \subseteq V$ is generated. A queue Q is also initialised, initially containing the links to the neighbours of v as ordered pairs (v, v_i). The algorithm pops a link off the queue, checks its weight and compares it with a random number (between 0 and 1). Only if the weight is smaller, the links from v_i to its neighbours are added to Q. When Q is empty, the simulation ends.

Whenever a link (v, v_i) is popped from Q, v_i is added to D, the set of visited nodes which is used to ensure that duplicate messages are not processed a second time.

In the OLSR scenario, when (v, v_i) is popped of the queue, the algorithm also checks if $v_i \in \mathrm{MPR}(v)$. If this is not the case, the neighbours of v_i are not added to Q.

In order to explain the algorithm as clearly as possible, the pseudocode version is reported in Algorithm 1. R is a $|V| \times |V|$ matrix initialised with 0s, w is the weight function defined in chapter 2.

The functions "originators", "message" and "forward" differ based on the variant of signalling:

- L-S: originators(G) returns V, message(G, v) returns v and forward always returns True.
- WCN: originators(G) returns V, message(G, v) returns neighbours(G, v) and forward always returns True.

- OLSR: originators(G) returns MPR(v_0) $\cup \ldots \cup$ MPR($v_{|V|}$), message (G, v) returns neighbours(G, v) and forward(G, v, v_i) returns True if $v_i \in$ MPR(v), False otherwise.

Algorithm 1 Algorithm for the link-state advertisement propagation

```
Require: G, R
  for all v ∈ originators(G) do
    V' ← message(G, v)
    D ← Set()
    Q ← Queue()
    for all v_i ∈ neighbours(G, v) do
      Q.append((v, v_i))
    end for
    while not empty(Q) do
      Q.pop((v, v_i))
      n ← random(0, 1)
      if n ≥ w(v, v_i) and v_i ∉ D then
        D.add(v_i)
        for all v_j ∈ V' do
          R[j][i] ← 1
        end for
        if forward(G, v, v_i) then
          for all v_j ∈ neighbours(G, v_i) do
            Q.append(v_i, v_j)
          end for
        end if
      end if
    end while
  end for
  return R
```

Since this is a probabilistic simulation, the algorithm was run 1000 times and the results were averaged. Each run x returns a matrix $R(x)$. The metrics described above are then calculated as follows.

$$T_i(x) = \sum_{j=1}^{|V|} R(x)_{ij},\ x \in [1..1000] \tag{6.1}$$

$$T'_i(x) = \sum_{j=1}^{|V|} R(x)_{ji},\ x \in [1..1000] \tag{6.2}$$

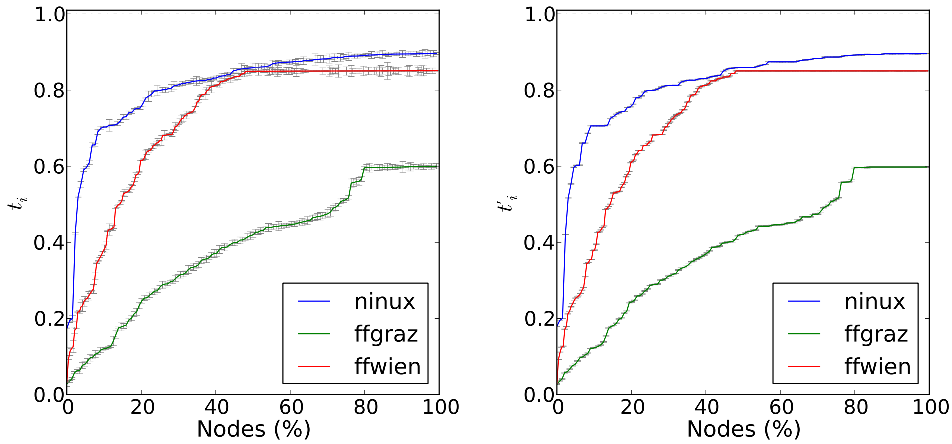
The averages over all runs of these metrics estimate respectively the expected number of nodes that receive information about v_i and the expected number of nodes that v_i receives information about. These are then normalised with respect to $|V|$, obtaining

$$t_i = \frac{1}{|V|}\left(\frac{1}{1000}\sum_{x=1}^{1000} T_i(x)\right) \tag{6.3}$$

$$t'_i = \frac{1}{|V|}\left(\frac{1}{1000}\sum_{x=1}^{1000} T'_i(x)\right) \tag{6.4}$$

These quantities were chosen in order to understand the efficiency of different signalling methods in networks, considering the real efficiency of their links.

Results

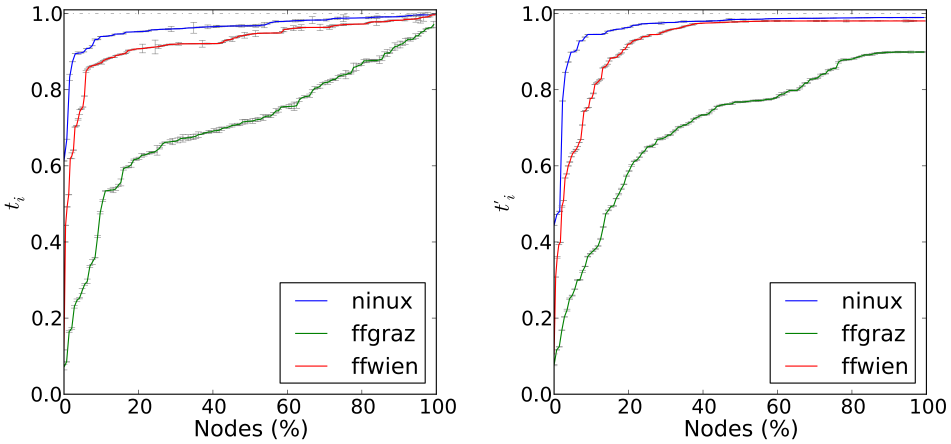


(a) Normalised nodes ranked by t_i (b) Normalised nodes ranked by t'_i

Figure 6.1: L-S scenario

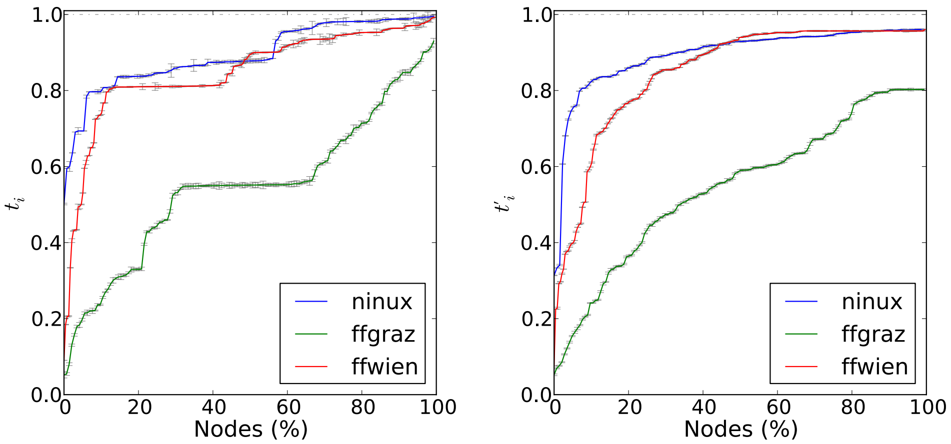
Figure 6.1, 6.2 and 6.3 show a ranking of nodes ordered by the calculated metrics (t_i and t'_i). The nodes are normalised to 100 in order to allow and easy comparison between the three networks even if they have different sizes.

As expected, FunkFeuer Graz is the network that shows the poorest performance, due to the bad quality of its links and its peculiar topology. Ninux and FunkFeuer Wien have similar results, with the former responding a bit better.



(a) Normalised nodes ranked by t_i (b) Normalised nodes ranked by t'_i

Figure 6.2: WCN scenario



(a) Normalised nodes ranked by t_i (b) Normalised nodes ranked by t'_i

Figure 6.3: OLSR scenario

Figure 6.1 shows that nodes have a big difficulty reaching the entire network with their messages, with no one, even in the best case, exceeding 0.9. Figure 6.2 shows a slightly better situation, suggesting the importance of transmitting information about neighbours. The addition of MPR forwarding logic (Figure 6.3) is predictably worse than the WCN scenario, since redundancy is removed both by the non-use of some links and by some nodes not generating messages. Nonetheless, this mode of propagation works substantially better than the L-S case, because again information about the neighbourhood is transmitted with each message.

By adding content to the messages, signalling becomes more effective and less traffic is needed to propagate the required information. Moreover, in OLSR the discovery of neighbours through `HELLO` messages can happen at an higher ratio than the propagation of `TC` messages, since they are not flooded. This introduces a sort of hierarchy: local topology is refreshed more often in order to propagate more information rich messages to the rest of the network.

A hierarchic approach is precisely what the Open Source implementation of OLSR uses to ensure that topology information is up to date without suffocating the network with overhead. The implementers decided to take advantage of the TTL field in OLSR message and send `TC` messages with TTL values different from the default of 255 (the maximum). By sending `TC` messages with small (1, 2, 3) TTL values often, the local topology is updated more frequently without imposing much overhead of the network [8].

The efficiency of topology information propagation is key to the performance of a network, at least as much as keeping the routing protocol overhead low. This analysis considered the propagation of a single message per node, on a static topology where link costs do not change. In reality, a link-state protocol is based on the synchronisation of information between the different nodes. Outdated information may cause routing loops that completely destroy the throughput.

In this simulation, the ETX metric has been used to decide the probability of losing packets. It should be noted that ETX is designed to work in the case of unicast packet transmission, taking into account also the retransmission due to losing the acknowledgement (as seen in chapter 3). The results of this analysis may be worse than expected also because of this feature of ETX.

7 Conclusions

The first analysis reported in this thesis is the robustness metric. Different possible real-world scenarios have been simulated, by the usage of different policies in the removal of nodes and links from the networks. Random removal was used to simulate independent failures of nodes or links, while removal of nodes and links with the highest centrality metrics was a possible interpretation of an attack scenario in which the most important nodes are maliciously targeted.

The analysis has shown the behaviour of three WCNs and compared it, in the different analysed scenarios, to the properties of synthetic networks generated with two random graph models (Erdős-Rényi and Bararbási-Albert) that have a known degree distribution (respectively Poisson and power law).

The fragility of the WCNs has been highlighted, which is partly due to their small density and partly to their peculiar structure. WCN show the same behaviour in attack scenarios regardless of the centrality metric used in the simulation. This suggests that, in the three analysed networks, all the metrics are equivalent in their results.

The Barabási-Albert model, which was expected to give results similar to those of the WCNs due to its similar degree distribution, had instead shown some remarkable differences. First of all, in the removal by degree and betweenness centrality, it remained consistently more robust than the WCNs, despite a similar density. Secondly, when removing nodes by closeness and links by betweenness centrality it performed more similarly to the Erdős-Rényi model than to the WCNs.

This findings suggest that the preferential attachment growth model used by that random graph generator is not really suited for modelling WCNs. This may be because it does not produce leaves, which are a consistent part of a WCN; another explanation is that different factors guide the growth of a WCN, other than the degree of existing nodes.

Subsequently, an analysis of the diffusion of topology information in WCNs has been performed. Since they use a link-state routing protocol, the correct propagation of the knowledge about the topology is central in order to avoid the different nodes having unsynchronised routing tables. Such a situation may lead to potentially catastrophic effects on the whole network, like the creation of routing loops.

The two metrics reported by this analysis are: a ranking of nodes by the expected fraction of other nodes they receive information from; and a ranking by the expected number of nodes which receive information from them.

The most evident result is that loss of messages in WCNs is really common on long paths. In WCNs links are highly heterogeneous, there are really good one as well as really bad ones. Unfortunately, a single really bad link in a path is enough to jeopardize all the communications that pass through that path.

However, the day-to-day experience shows that the WCNs have a static enough topology that they can bear the loss of some packets with routing information without suffering major problems.

Another, more subtle result, obtained by comparing different strategies of flooding and different kind of link-state advertisement messages, is that networks benefit from a more frequent diffusion of information on local (nearby) nodes with respect to information on distant nodes. This produces a beneficial effect because, with the same frequency of distant node updates, if each nodes propagates information on its neighbours the distribution is more efficient.

Moreover, since each node can only choose the next hop, the complete and exact knowledge of the route when doing long distance routing is in most cases unnecessary and reducing the rate of far reaching topology updates may produce more advantages than damage.

Some authors, for instance the implementers of the OLSR daemon and of the B.A.T.M.A.N. routing protocol, suggested that link-state routing protocols, which presume that each node must have the possibility to calculate every route, are ill suited to wireless mesh networks, where the topology is rapidly changing.

Research is ongoing in the field of mesh network routing protocols, and there is not yet a winner. In the meantime, WCNs all over the world continue running with a variety of routing protocols and configurations, despite their weaknesses and shortcomings. If the situation today appears good for WCNs, it is also clear that there are large opportunities of technological improvement.

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