A Fuzzy Non-dominance Approach for Network Routing with Inaccurate Information

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A Fuzzy Non-dominance Approach for Network Routing with Inaccurate Information

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Dedicated to my wife and my parents...

ABSTRACT

Routing is one of the most essential functions in computer and telecommunications networks. As the network grows in size, complexity and mobility, it becomes more difficult to precisely determine the routing metrics due to networks' dynamic nature. As a result the information available for decision making of Quality of Service (QoS) routing is always inaccurate.

This thesis considers that network routing metrics are naturally uncertain due to the inaccurate information. A novel concept, fuzzy non-dominance multipath routing is developed for the network routing discovery and routing optimisation.

The fuzzy non-dominance multipath routing defines network routing problem in a fuzzy weight graph. The term fuzzy non-dominance routing used in this thesis is distinct from the conventional sense of fuzzy routing. Fuzzy non-dominance routing leads to the fuzzy Pareto-optimal multipath. A labelling setting algorithm is developed to find out the limited as well as full non-dominated set of routes for network packets forwarding. This approach provides an alternative way to deal with the network routing and multipath routing optimisation problem with less computational and management costs.

This thesis proposed a framework for adopting fuzzy non-dominance routing into conventional structure networks. The simulation results covered fuzzy non-dominance routing discovery by considering different network topologies, scales, fuzzy number designs and the grade of fuzziness. The thesis also addressed fuzzy non-dominance routing for general traffic-engineering. Compare to conventional Open Shortest Part First routing, fuzzy non-dominance routing allows the network to cope with at most 60 % more demand. In addition, the thesis also studied the fuzzy non-dominance routing for optimising network routing convergence, quality of service routing and its applications in Mobile ad-hoc networks.

Acknowledgements

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Abbreviations

4G	Fourth Generation (mobile network)
ADOV	Ad-hoc On-demand Distance Vector Routing
AS	Autonomous System
DSCP	DiffServ Code point
DSDV	Destination-Sequenced Distance-Vector
DSR	Dynamic Source Routing
ECN	Explicit Congestion Notification
EIGRP	Enhanced Interior Gateway Routing Protocol
FNDR	Fuzzy Non-dominance Routing
FSR	Fisheye State Routing
GSR	Global State Routing
ICMP	Internet Control Message Protocol
IP	Internet Protocol
IS-IS	Intermediate System to Intermediate System
LSA	Link-State Advertisement
MANET	Mobile Ad-hoc Networks
MPLS	Multi-protocol Label Switching
OSPF	Open Shortest Path First
QoE	Quality of Experience
QoS	Quality of Service
RFC	Request For Comment
RIP	Routing Information Protocol
RTT	Round Trip Time

TOS	Type of Service
VANET	Vehicular Ad Hoc Network
VoIP	Voice over IP
WRP	Wireless Routing Protocol

Symbols

iff	if and only if
$\in$	is an element of
$\notin$	is not an element of
$\forall$	for all
$\cup$	union
$\bigcap$	intersect
$\exists$	there exists
$\exists!$	there exists exactly one
$\blacksquare$	end of proof

Chapter 1

Introduction

1.1 Introduction

Routing is one of the most essential functions in computer and telecommunications networks. The most widely applied routing protocols choose one or more physically meaningful metric to determine the cost of possible routes for traffic forwarding. The most common used metrics include number of hops, bandwidth, delay, distance, throughout, and energy constraints.

However, as the network grows in size, complexity and mobility, it becomes more difficult to precisely determine the routing metrics due to the dynamic nature of networks. In a network with inaccurate metrics information due to rapid change (channel conditions, node mobility, traffic demand or dynamic topology), power constraints or administrative policies, routers may face several inaccurate and uncertain metrics when performing the routing calculation. Under such circumstance, it is difficult to evaluate the least cost for the packet delivery.

Numerous previous works modelled the inaccurate network traffic under probabilistic/stochastic sense [1]. However, the research works in this area used complex algorithms with a considerable amount of calculations, which limits their applicability.

In the real world, it is difficult to make a precise modelling due to the uncertainty nature of the information. Fuzzy Logic provides an alternative way to optimise the network routing with inaccurate metrics. It has been proved to manage the inaccurate, uncertain or vague network information and multiple QoS parameters with less computational cost [2][3]. However, additive network metrics are difficult to be processed with conventional fuzzy routing. In addition, it is difficult to integrate hop by hop routing discovery processes into the conventional fuzzy routing approach due to the fuzzy logic controller architecture. As a result, there applications are still limited.

In this work, a novel approach using the fuzzy weighted graph is applied to model and determine network routing and network QoS optimisation problems with inaccurate metrics information. Fuzzy graph and fuzzy shortest paths have been investigated in different research papers [4][5]. But few literatures applied it into the computer and telecommunications network routing and routing optimisations.

In this thesis, a novel fuzzy non-dominance routing (FNDR) is presented. The routing scheme leads to fuzzy non-dominance or Pareto-optimal multipath. In this work, a labelling setting algorithm is developed to find out k-best fuzzy non-dominance routes. FNDR achieves QoS support with inaccurate routing information by allowing routes to be selected according to their fuzzy rankings and the grade of fuzziness. In addition, this thesis discusses the potential application and how this work can be extended in the future.

1.2 Scope of the research

The goal of this research is to investigate and extend the use of fuzzy theory and fuzzy routing in the computer and telecommunications network. The thesis introduces the fuzzy non-dominance routing for the network multipath routing with inaccurate information.

Previous researches of fuzzy routing have shown limitations in dealing with additive routing metrics such as cost and delay. However, the conventional fuzzy routing has demonstrated its benefits that it could deal with network routing and routing optimisation problems with less computational cost. Therefore, this work concentrates on how to extend fuzzy theory into both conventional and emerging infrastructures network routing with less computational and management costs.

In the work reported in this thesis, the inaccurate information is modelled in a fuzzy weighted graph. This does not only introduce a fuzzy rule-based controller, but the additive link metrics of the entire network are naturally represented by fuzzy numbers. That means the conventional crisp weighted routing process is transformed into a fuzzy weighted network. The routing scheme leads to the fuzzy Pareto-optimal or non-dominated multipath, which can be used for the network optimisation.

This thesis presents algorithms and frameworks for the fuzzy non-dominance routing. The thesis examines how network topology, fuzzy number designs and the grade of fuzziness affect the fuzzy non-dominance routing discovery. And this work applies the fuzzy non-dominance routing to network optimisation processes in order to demonstrate network performance gains.

1.3 Research contributions

The primary contribution of this work is the development of a fuzzy non-dominance algorithm and the introduction of the concept for fuzzy non-dominated multipath routing into telecommunication networks. The fuzzy non-dominance routing is distinct from conventional fuzzy routing. The Fuzzy non-dominance routing provides an alternative way to deal with the uncertainty of the network routing information. The major contribution includes:

- This work extended the use of fuzzy theory in computer and telecommunications network routing, developing and using fuzzy non-dominance routing

(FNDR) to discover and maintain network routing with inaccurate information.

- A demonstration that FNDR can be used successfully for routing discovery in both conventional infrastructure and wireless ad-hoc networks.
- An approach that allows FNDR to manage the quality of service routing in the network by using non-dominance multipath and α-level cut.
- Using FNDR to optimise network convergence and network control overhead, and the work shows how vague routing information could be easily managed by administrators or a self-controlled network.

In addition, these contributions are backed up by the investigation into aspects such as fuzzy graph, fuzzy representation of inaccurate routing metrics, fuzzy arithmetics and ordering approaches, the appropriate definition of fuzzy non-dominance conditions in a fuzzy weighted graph, and the fuzzy-cost based multi-constrained QoS routing as well; these are tested on scenarios that include both conventional infrastructure networks and wireless ad-hoc networks.

1.4 Author's publications

1. Jing An, Paul Pangalos, A.H Aghvami, "Case-Based Reasoning for Network Routing Self-Configuration and Self-Optimisation", published by Wireless World Research Forum Meeting 27, 2011
2. Jing An, Paul Pangalos, A.H Aghvami, "Fuzzy Non-dominance multipath link-state routing framework for network routing management with inaccurate information", in Proceedings of the IEEE Global Communications Conference (GLOBECOM), MENS 2012
3. Jing An, Paul Pangalos, A.H Aghvami, "Novel Fuzzy Non-dominance Shortest Path Routing and Path Ordering for QoS Aware Routing", in Proceedings of the IEEE International Symposium on Personal, Indoor and Mobile

Radio Communications (PIMRC), London, United Kingdom, September 2013

4. Jing An, Paul Pangalos, A.H Aghvami, "Internet Routing in a Fuzzy Network", submitted to IET Journal of Networks, finished revision and submitted.

1.5 Organisation of this thesis

This thesis is organised as follows.

Chapter 2 gives the background of the research, including a brief summary of the network routing with a focus on state-of-the-art routing protocols. The network routing with inaccurate information is then explained as a background topic of this research. The fuzzy theory and fuzzy routing are then introduced, together with research works on state-of-the-art fuzzy routing applications and fuzzy routing optimisations. Lastly, the fuzzy graph theory (features, benefits and architecture) is explained together with previous works in finding fuzzy shortest paths.

Chapter 3 presents the first part of the novel work of this thesis. This chapter firstly gives some important preliminaries on extended fuzzy arithmetics principles which are behind the fuzzy non-dominance routing. Because the fuzzy arithmetics are still an open research topic, so one aspect of this work is the investigation of the choice of fuzzy operations and ordering approaches that measure the route preferences. In the following section, a number of informal descriptions of key issues for the fuzzy non-dominance routing are then given with a focus on the explanation of fuzzy non-dominance relation. A labelling setting algorithm was developed by this work in order to find out fuzzy non-dominance routes. The detailed mathematical explanations, algorithms and the framework for fuzzy non-dominance routing are given in the fourth section. This chapter also explains how the network simulators were designed and integrated into the overall simulation as well.

Chapter 4 presents route discovery results of fuzzy non-dominance routing. In this chapter, it is assumed that all the metrics in the entire network are inaccurate. The random fuzziness factors are applied to the entire network. The initial results demonstrate the non-dominance route searching processes step by step and then goes on to show how the approach can be applied for finding routes in the AT&T North America network. The initial results are then extended by examining the impact of network scales and different topologies. Following that, the design of fuzzy numbers, grade of fuzziness and α-level cut are tested and discussed. This Chapter also demonstrates that how k-best non-dominance routes could be used to improve the overall algorithm performance as well. .

In the chapter 4, it is assumed that the entire network's metrics are inaccurate. However, in the real application and network optimisation, the proper designs of the grade of fuzziness and fuzzy rankings are important for fuzzy non-dominance routing. The Chapter 5 demonstrates how fuzzy non-dominance routing could be applied to the network load-balancing, routing convergence and QoS route decision processes. The chapter gives guidance on fuzzy metrics designs and fuzzy ranking approaches. In addition, the chapter includes a scenario to demonstrate finding fuzzy non-dominance routes in the mobile environment. And the testing results demonstrate that with proper designs, non-dominance multipath routing could be applied to the network optimisation problems.

The thesis concludes in the Chapter 6 by giving the findings from this research together with an assessment to advise how the work could be extended.

The Appendix explains the operation of the OPNET network simulator.

Chapter 2

Background

2.1 Introduction

This chapter discusses the background state-of-the-art relevant to this thesis. It starts with an overview of the network routing with a focus on the routing with the inaccurate routing information. This chapter then focuses on fuzzy set theory and fuzzy routing. As mentioned in section 1.1, this thesis modelled network routing in a fuzzy weighted graph. The fuzzy graph itself is introduced in the section 2.5 and its applications to similar problems are discussed as well. However, this chapter is not intended to give an in-depth summary of the fuzzy theory in general or wider use of the conventional fuzzy routing.

2.2 Network routing

Routing is one of the most essential functions in computer and telecommunications networks. The basic function of the network routing is to discover and maintain possible routes to destinations for packets delivery. This section gives an overview of the network routing: state-of-the-art and open problems.

2.2.1 Routing in traditional infrastructure networks

In traditional infrastructure networks, routing protocols can be divided into two groups by their scales and applications: intra-domain routing protocols and inter-domain routing protocols. Inter-domain routing protocols like Border Gateway Protocol (BGP) is used to maintain routing table on the autonomous systems (AS) level. It is designed for exchanging routing and reachability information between AS domains such as between different Internet service providers (ISPs). This work focus on the intra-domain routing only. Conventional intra-domain routing protocols like Open Shortest Path First (OSPF) [6] and Intermediate System to Intermediate System (IS-IS) [7] are still widely used across traditional infrastructure networks. Although some QoS extensions [8] and Multi-protocol Label Switching (MPLS) have been developed and deployed in the network, in general, most intra-domain routing protocols perform two fundamental functions: constructing and maintaining of the routing table for packet delivery and exchanging routing information updates based on particular routing algorithms. In a traditional infrastructure network, routing protocols satisfy following fundamental requirements [9]:

- Passing, receiving reachability information to/from other routers.
- Determine optimal routing based on reachability information.
- A developed procedure for Reacting to, compensating for and advertising topology changes in the network.

From the view of algorithms, most intra-domain routing protocols can be classified into two types as follows:

- **Distance-Vector Routing Protocols** advertise route as a vector of distance and direction, where the distance is defined in terms of the metric and the direction is defined in terms of the next-hop router. Notable examples of Distance-Vector Routing Protocols are Routing Information Protocols (RIP) and Enhanced Interior Gateway Routing Protocol (EIGRP) for conventional infrastructures and Babel [10] for mobile ad-hoc routing.

- **Link-State Routing Protocols** exchange link state information (local metrics) across routing domain. Each node constructs a map of the connectivity of the network. Each node then independently calculates the best logical route from itself to every possible destinations in the network. Notable examples include conventional fixed infrastructure routing protocols like OSPF, IS-IS routing protocols and Optimised Link State Routing Protocol (OLSR) [11] for mobile ad-hoc networks.

There are several researches discussed routing optimisation in the conventional OSPF and IS-IS routing environment. B.Fortz and M.Thorup [12][13] discussed the optimisation of routing metrics for OSPF and IS-IS traffic engineering. Recent researches also discussed multi-plane routing extensions for QoS improvements [14][15]. However, conventional routing protocols are designed to use one or more administrative metric which is not flexible in dealing with rapid changes and inaccurate routing information. Frequent changes of routing information lead to route flapping, temporary routing loops and route unavailability.

The fuzzy non-dominance routing is built as a Link-State routing protocol.

2.2.2 Routing in mobile ad-hoc networks

Mobile ad-hoc is type of wireless ad-hoc network. Unlike traditional fixed, centralised and hierarchical network infrastructure model, in a mobile ad-hoc network (MANET), all nodes can be dynamically connected to each other and all nodes are free to move. Figure 2.1 gives an example of mobile ad-hoc network. There is no central node to determine the network layer logical topology and routing strategies. In such a dynamic environment, all devices are free to move and to discover their peers. They are both self-forming and self-healing. All devices in the network perform as routers. Because there is no fixed infrastructure required, mobile ad-hoc networks can be built fast and dynamically. MANET nodes could communicate directly without the help of the central base station, this reduces the congestion in the wireless network and saves the limited bandwidth resources.

However, finding routes in wireless ad hoc networks is much more complicated than it in traditional infrastructure networks: many additional factors are needed to be considered for routing protocols, such as the topology are changed dynamically and rapidly, how to minimise the routing overhead; moreover, in sensor networks, routes must be built under power constraints. This is in addition to finding the best routing path, a feature that is common with traditional infrastructure networks.

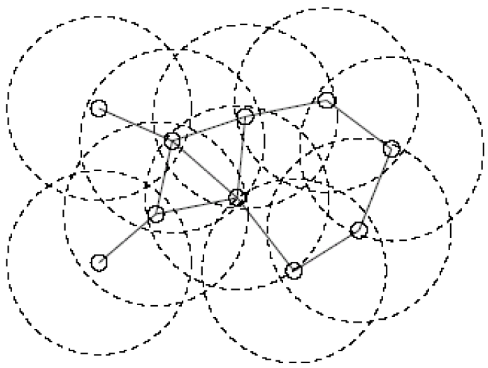


FIGURE 2.1: Mobile ad-hoc routing.

Generally, from the view of routing discovery, mobile ad-hoc routing protocols are divided into two groups, proactive protocols and reactive on-demand protocols.

- **Proactive protocols** are required to record all routes to the destinations so that the source node knows the route and the preferred route can be used immediately when a source node generates a packet to a destination. Any changes in the topology will be propagated across the network to notify each node for routing information updates. There are several notable examples of proactive routing protocols such as: global state routing (GSR) [16], destination-sequenced distance-vector (DSDV) routing [17], wireless routing protocol (WRP) [18], and fisheye state routing (FSR) [19].

- **reactive (on-demand) protocols** build routes only when a source node requires communication with a destination node; there are no predetermined routes in the network. If a source node wants to send a packet to a destination node, but there is no prospect route to the destination yet, the source node will initiate a route discovery process to build a communication route. After the route is established, a maintenance procedure will take place for the route continuance until the route breaks. Notable examples of proactive routing protocols are Dynamic Source Routing (DSR) [20] and ad-hoc on-demand distance vector routing (AODV) [21].

Proactive protocols are generally faster than on-demand protocols in routing decisions by get available routes immediately rather than waiting for route discovery processes. However, proactive protocols exchange and maintain routing information across the network with extra control overhead. Since on-demand protocols have less control overhead than proactive protocols, they normally require less bandwidth, although delays would take place during the new route discovery process for each destination.

Sensor network is a special case in the MANET. Sensor networks consist of tiny and cheap sensor nodes that are deployed in the area of interest. They are used for applications such as environmental monitoring, scientific observation and industrial sensing and it often uses an ad-hoc network structure to allow information to be collected from the sensors for analysis or to be transmitted back to some external points. The special feature of sensor networks is that the sensors are often limited in resources, especially power.

In this work, FNDR is generally considered as a proactive routing scheme. In the framework proposed in Section 3.4.4 FNDR collects routing information and stored in the routing database. Then it calculates routing table independently. However, it is possible to implement in the on-demand environment.

2.2.3 Quality of Service (QoS) and QoS routing

Quality of service refers to the ability of a network to provide a more reliable service to selected network traffic. Generally, a routing protocol with QoS features aims to achieve following objects [22]:

- Dynamic determination of feasible paths
- Optimisation of resource usage
- Graceful performance degradation

Differentiated Services (DiffServ) [23] is a simple and standard approach to achieve QoS marking in any IP networks. The main idea of DiffServ is to meet the different performance requirements of different users. As shown in Figure 2.2, the route with higher bandwidth is used to provide low-latency to critical network traffic such as Voice over IP (VoIP) or streaming while non-critical services such as web traffic and email services are subject to simple best-effort way.

As shown in Figure 2.3 the differentiated services classification is done by using a 6 bit DiffServ Code point (DSCP) field [24]. The DSCP field is part of the original type of service (ToS) field in the IPv4 header. The IETF redefined the meaning of the ToS field, splitting it into the 6-bit DSCP field and a 2- bit unused field which is later redefined in RFC 3168 [24] as Explicit Congestion Notification (ECN) field. In IPv6 header, DSCP and ECN are defined in the 8-bits Traffic Class field.

DiffServ is a distributed and stateless model. Each node does not need to keep state information. The marking and classifying is done at the boundaries between DiffServ domains.

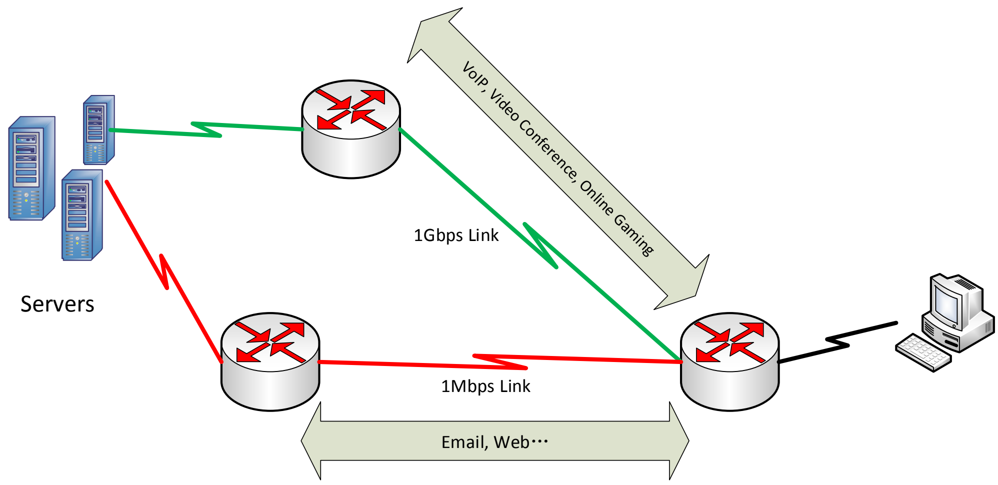


FIGURE 2.2: QoS routing.

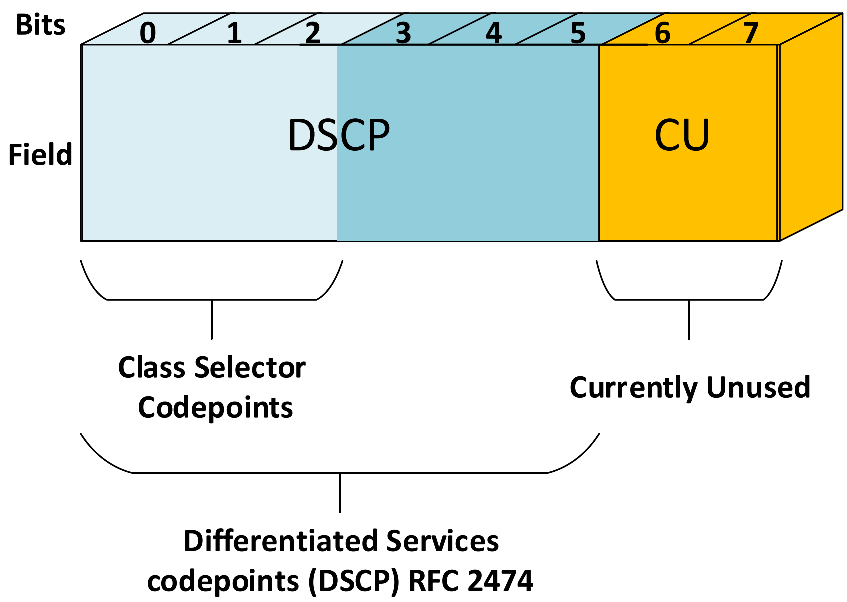


FIGURE 2.3: DiffServ field in IP packet.

In addition to packet marking at the network boundary, routers need to calculate an optimised QoS route for packet delivery. In order to calculate QoS route, several network parameters are often considered, such as distance, hops, error rates, packet loss, bandwidth, throughput, transmission delay and jitter. However, providing quality of service levels in a constantly changing environment is a challenge. The inherent stochastic nature of the communications quality of networks brings difficulties for calculating a single QoS route. In the real world, the information available for decision maker is always inaccurate [25][26]. Typically the inaccurate link state information is collected and adapted by a router as a result of network dynamics, channel quality variation, mobility, routing aggregation, out of date routing updates as well as any combination of above factors. The sources of inaccurate routing information are explained and discussed in the next section.

2.3 Routing with inaccurate information

Routing protocols rely on physically meaningfully metrics to make routing decisions. These metrics could be as simple as hop counts or distance. However, as networks grow in size and complexity, full knowledge of network parameters is typically unavailable. Particular in MANET, not only the QoS metrics, network topology is changing over the time as well. In this section, the resources of network inaccurate information and relevant studies are explained and discussed.

2.3.1 Inaccuracy due to measurement by average

The link condition changed rapidly due to the traffic demand variation, mobility and channel quality variation. Many parameters associated with QoS requirements are affected by temporal conditions, such as the network congestion.

Parameters advertised by a link such as delay might be based, for example, on average case or on worst-case behaviour. In either case, the advertised parameters are not accurate for routing decision.

Round Trip Time (RTT) is usually used by hosts to test end-to-end delay between source and destination. Figure 2.4 shows an example of Internet Control Message Protocol (ICMP) echo message on a Windows console. The average Round Trip Time (RTT) which used by devices for testing end-to-end delay is given by approximate boundary values and approximate average values only. Devices such as routers need to rely on average values to make routing decision. Even a single ECMP echo packet traverses multiple hops across networks but it is not designed to store timestamp of each nodes across its path. Therefore it can be used for measure round-trip-time but the out-bound and in-bound delay is not tested accurately. Commercialised protocols such as Cisco Service Assurance Agent (SAA) and Round Trip Time Monitor (RTTM) is using similar protocol as ICMP to monitoring average QoS metrics as well [27]. Other QoS relevant metrics such as jitter, throughput and packet loss rate are typically measured by average as well. Therefore, those metrics are always inaccurate for routing decision.

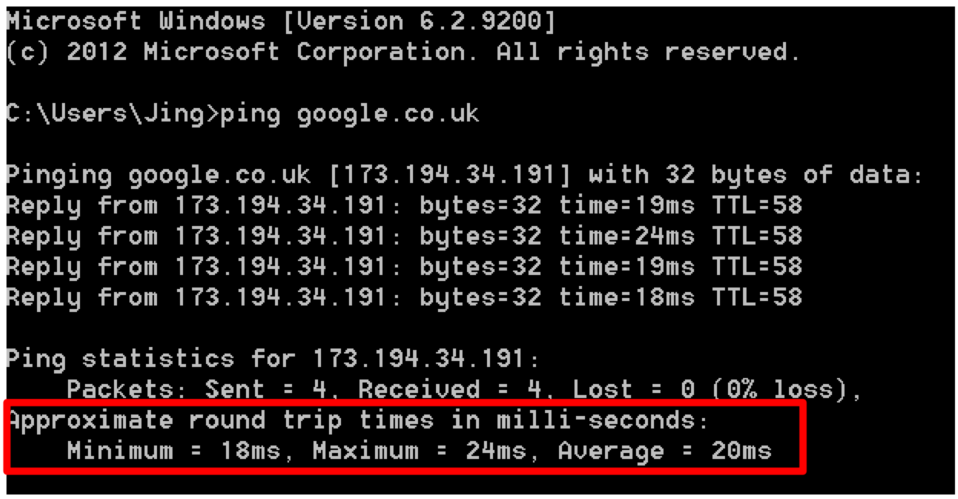


Figure 2.4: ICMP echo on a MS Windows console.

Technically, the inaccurate information can be eliminated by the rapidly advertising the current, updated, accurate conditions. Unfortunately, this is impractical when the network is highly dynamic and changes are frequent. Moreover, a synchronised routing table is a pre-condition for most of link-state routing protocols and table driven proactive MANET protocols. Frequent change of network metrics leads to route flapping, loops and route temporary unavailability. Thus, advertised routing metrics should be considered as by-default inaccurate information.

As a result, routers are unlikely to be able to make routing decisions with accurate QoS information.

2.3.2 Hidden information

It is quite normal that part of the network infrastructure between two ends are hidden from the public domain. Interconnected networks may include private networks and packets pass through different AS that hide some or all of their information. Networks are controlled by different administrative domain that routing information is not directly exchanged. One reason for this could be hiding network's internal proprietary mechanism.

Some stub networks received routing information only. The connection is maintained by static default route.

Nowadays, more and more companies deploy remote public cloud computing infrastructures such as Amazon EC2 and Google cloud platform. However, the cloud computing model brings even more uncertainty factors into the network routing. The routing, topology and QoS information are typically hided behind the cloud boundary. In scenario of Figure 2.5, the accurate QoS metrics in the ISP cloud, enterprise network and remote data centre are hidden from each other. In the case of the telecommuter, they access the network by using home routers or 4G mobile networks. It is impractical to obtain an accurate QoS metrics.

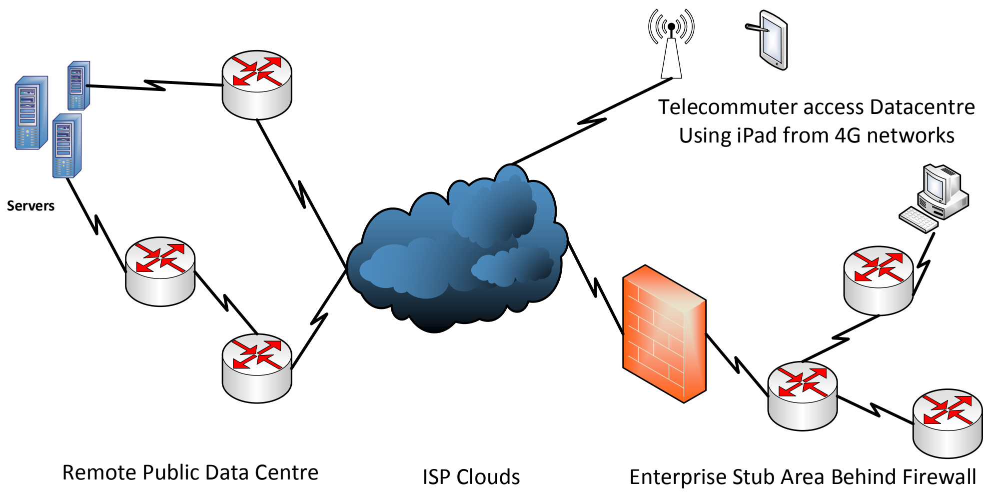


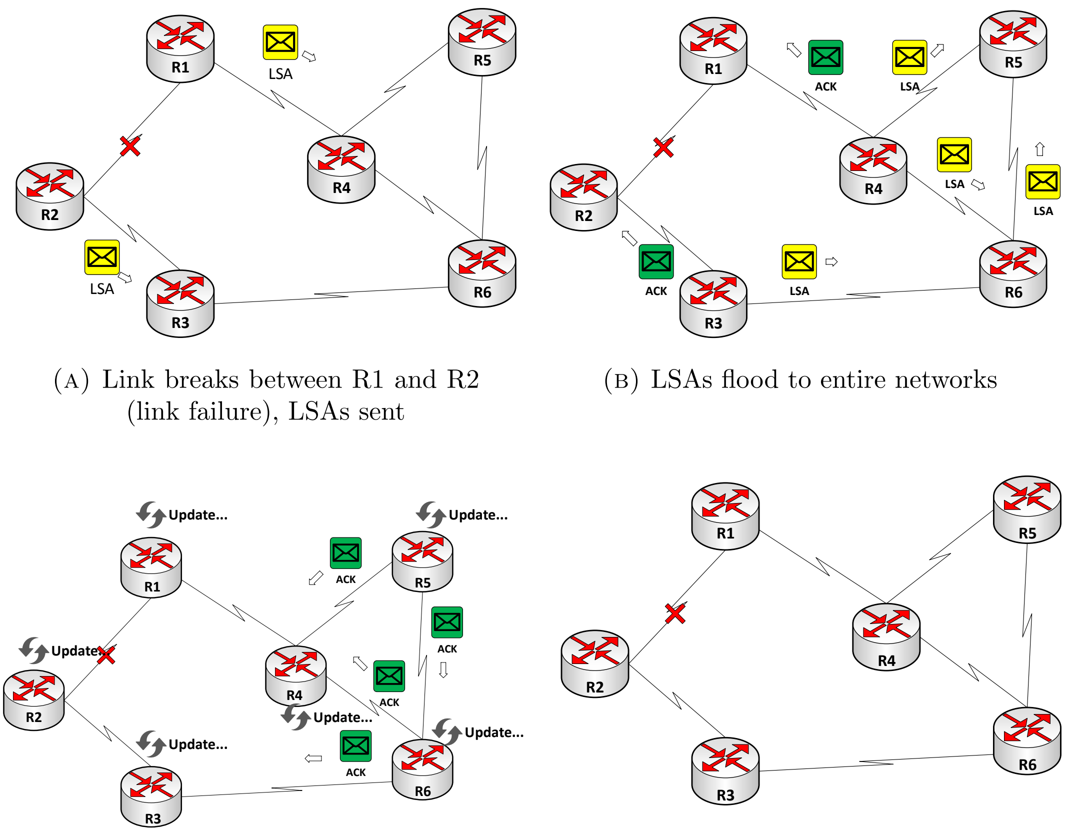
Figure 2.5: Hidden information between end user and data centre.

Therefore, due to hidden network information, QoS metrics can be only calculated based on parameters supplied by networks, or by prior experience.

2.3.3 Out of date routing information

Link-state routing protocols maintain the connectivity and routing table by exchange hello messages and link-state advertisements (LSAs). However, due to the control overhead and route convergence constraints, LSAs are triggered by timeout counters or by events such as link failures only. Therefore, the routing databases in the link-state routers are always inaccurate. Figure. 2.6 gives an example of routing reconvergence process when network state changes due to a node failure. When the link between router 1 and router 2 breaks (see Figure 2.6a) , R1 and R2 send LSAs to its neighbours. Network becomes unavailable due unsynchronised routing table. The LSAs are passed by hop-by-hop manner and flood to entire network. The entire network is unavailable until the routing information databases of each router in the network are synchronised again (in Figure 2.6d).

OSPF is a notable example of updating LSAs by both timeout and event triggers. The default timeout trigger for OSPF routing information is 30 minutes. The



(A) Link breaks between R1 and R2 (link failure), LSAs sent

(B) LSAs flood to entire networks

(C) Routers sent ACK and updates routing information database

(D) Convergence process finish

FIGURE 2.6: Example of OSPF routing update processes.

typical convergence speed for OSPF is about 10 second. This is not anywhere near the desired time interval for accurate routing information updates. During the convergence processes, the routing is disabled. As a result, frequent updates cause unaccepted control overhead and routing flapping.

As routers always make route decisions with out-of-date routing information. The QoS relevant metrics are always inaccurate.

2.3.4 Node mobility

Node mobility is considered to contribute to uncertainty by changing the network topology. A synchronised routing table is pre-condition of link-State and Table-driven proactive routing protocols. Therefore, it is particularly difficult for traditional infrastructure routing protocols to response frequent topology changes.

However, node mobility could be studied by mobility models. The mobility model is designed to describe the movement pattern of mobile users, and how their location, velocity and acceleration change over time. There are several types of mobility models. However, they can be summarised as few groups (see Figure. 2.7):

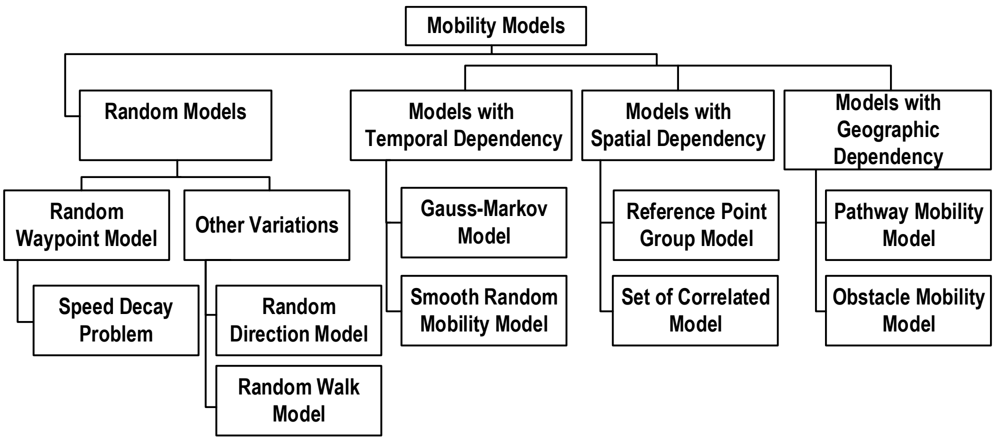


Figure 2.7: Mobility models

- **Random-based mobility model**: Random mobility models are simple and memoryless. In random-based mobility models, the mobile nodes move randomly and freely without restrictions. To be more specific, the destination, speed and direction are all chosen randomly and independently of other nodes. Notable examples include Random Waypoint Model [28] proposed by Broch et al and Random Walk Model [29]

- **Temporal Dependency model**: In temporal dependency model, the current state of the nodes depends on its previous state. Because nodes are constrained by physical laws of acceleration and velocity. Thus, these states for a single node at different time slot are correlated. Gauss-Markov Mobility Model proposed by Liang and Haas [30] is an example of temporal dependency.

- **Spatial Dependency model**: In the spatial dependency model, the movement of nodes is influenced by other neighbouring nodes. This is particularly important for some situation such as collaborations.
- **Geographic restriction model**: Geographic restriction model is especially important for modelling vehicular ad hoc network (VANET). In the geographic restriction model, the nodes is restricted to be moved on certain pathway or areas. Pathway Mobility Model [31] and Obstacle Mobility Model [32] are notable examples of the geographic restriction model.

In this work, the Random-based mobility is considered to be the major impact to the network uncertainty. However, other models are considered in some cases as well.

2.3.5 Pervious researches

Numerous previous researches had been studied in this area. Most of researches assumed that the uncertainty can be expressed through probabilistic models. The uncertainty QoS metrics were studied by [25][26][33][34]. The [35] and [36] studied the uncertainty in wireless networks. However, the research work in this area used complex algorithms with a considerable amount of calculation, which limits their applicability.

Fuzzy set is an alternative way of modelling the uncertainty. The overview of fuzzy routing is given by next section. Fuzzy QoS representation was first introduced by W. Arnold et al [37]. Their work concentrated on using rule-based fuzzy logic to handle and evaluate linguistic link performance. They have shown that fuzzy representation of link metrics provides flexibility and easy-management features for network routing. More previous works about fuzzy routing and its applications will be introduced in section 2.4.

2.4 Fuzzy routing

Most of traditional tools for formal modelling, reasoning and computing are *crisp*, *deterministic* and *precise* in character. Precision assumes that parameters of a model represent exactly either the perception of the phenomenon modelled or the features of the real system that has been exactly modelled.

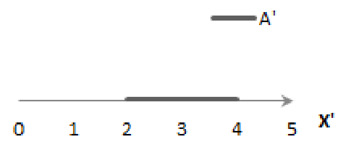
However, in the real world, it is difficult to make a precise modelling due to the nature of information. This applies even to many terms people used in their day to day life, such as Tom is 'tall', a girl is 'beautiful'. Because different people may have different benchmark to these simple terms. As the last section discussed, in a computer network, the QoS relevant metrics are by nature uncertain and inaccurate as well. For example, the degree of mobility in a MANET can be 'high'.

The fuzzy set theory has been suggested by Lotfi. A. Zadeh as a mathematical framework to describe the vagueness, inaccuracy and uncertainty. It has been introduced as a powerful tool to model network routing problems. FNDR uses fuzzy sets and fuzzy number to describe network QoS metrics.

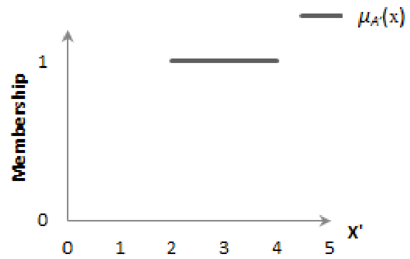
In this section, the fundamentals of fuzzy set theory and the principle of fuzzy routing are introduced. The researches in the relevant areas are discussed as well.

2.4.1 The fuzzy set theory and the fuzzy logic

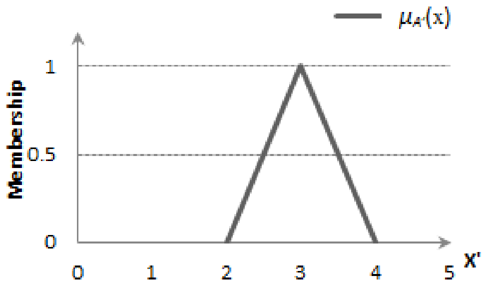
Fuzzy set theory was introduced by Zadeh in 1965 [38]. It is an extension of the classical set theory. In the classical set theory, the membership of elements in a



(A) Crisp set A'



(B) Crisp set A' with membership function $\mu_{A'}(x)$



(C) Fuzzy set A'

FIGURE 2.8: Fuzzy sets and fuzzy number

set is assessed in binary terms according to a bivalent condition — an element either belongs to or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval $[0, 1]$. In the rest of the thesis, classic sets are called *crisp sets* to distinguish them from fuzzy sets. Fuzzy set theory provides a mathematical way to model information that is vague, imprecise or uncertain [39]. A fuzzy set is defined as follows.

X is a *universal* set of objects with object x belonging to X. For a given subset A belonging to X, there is a membership function (or characteristic function) $\mu_A(x)$ to examine if x belongs to A or not. The membership function $\mu_A(x)$ is represented as:

$$\mu_A(x) = \begin{cases} 1 & \text{iff } x \in A \\ 0 & \text{iff } x \notin A \end{cases} \tag{2.1}$$

Here $\mu_A(x) \to \{0, 1\}$ is called a valuation set. If the valuation set is defined on an interval between $[0, 1]$, then A is called a fuzzy set. In this fuzzy set, the object x does not strictly belong to or not belong to set A. By the introduction of the interval valuation set, the membership function can be used to represent how much an object x belongs to the set A. The more $\mu_A(x)$ closes to 1, the more the object x belongs to the set A. This is called the grade of membership. The grade of membership is used to describe vague or inaccurate information.

Figure 2.8 gives an example of how a crisp set can be transformed into a fuzzy set. X' is a *continuous universal* set contains all values between 2 and 4. According to the description above, all values between 2 and 4 belongs to this crisp set. The membership function of this crisp set $\mu_{A'}(x)$ where $\mu_{A'}(x) \to \{0, 1\}$ which is defined as

$$\mu_{A'}(x) = \begin{cases} 1 & \text{iff } 2 \leq x \leq 4 \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

As shown in Figure. 2.8a and Figure.2.8b, A' is a crisp set: Consider the membership function $\mu_{A'}(x)$, each value x has either 0 or 1 degree of membership. It means that all values of x between 2 to 4 belong to set A'. This set does not reflect how much the value belongs to the set A' .To transform A' to a fuzzy set, another membership function (See Figure. 2.8c) is defined. It allows value to be partially belonged to the set.

As an example of fuzzy sets, in Fig.2.9, the meanings of the expressions cold, warm and hot are represented by functions mapping a temperature scale. The temperature at the black vertical line has three "truth values"—one for each of these three functions. Since the hot functions point to zero, this temperature can be interpreted as "not hot". The warm function (pointing at grade 0.7) can be described as "quite warm" and the cold function (pointing at 0.3) is "a little bit cold".

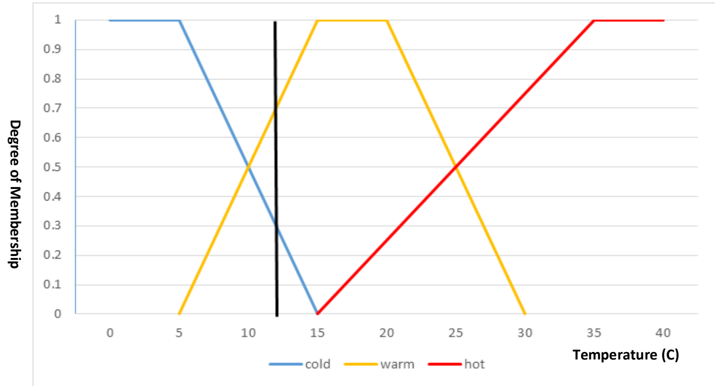


FIGURE 2.9: Fuzzy representation of temperature

The fuzzy set and fuzzy logic have been widely applied to many research areas such as electrical and civil engineering [40], computer sciences [40], medical researches [41] and the social sciences researches [42]. Fuzzy logic has been used in numerous real-life applications as well, such as facial pattern recognition [43], industrial automation [42] and the intelligent transportation systems [44]. The advantages and benefits that offered by fuzzy sets and fuzzy logic includes:

- A simple approach to dealing with linguistic information and human sense.
- Fuzzy logic can handle problems with imprecise and incomplete data, and it can model nonlinear functions of arbitrary complexity.
- Assistant for approximate reasoning in decision making in the absence of complete and precise information

One more thing needs to be discussed is, if the term *fuzziness* is as same as the *randomness* in probability theory? Fuzzy set is not the probability, although they have some similarities. Fuzzy logic and probability address different forms of uncertainty. A 0.5 degree of membership does not mean 50% probability. A fuzzy membership function is not a probability density function. The probability theory assumes that everything is well studied in the model. A *priori* or a *posteriori* frequency is required. Fuzzy set theory, however naturally accepts the imprecision and vagueness of the information. Another immediately apparent difference is that the sum of probabilities of a finite universal set must be equal to 1, while there is no such requirement for membership degrees. However, a fuzzy set cannot replace the probability model. The term fuzziness is considered as an alternative to randomness for describing uncertainty. Fuzzy sets actually provide an alternative way to measure the inaccurate nature of the information. More information about fuzzy sets, probability and fuzzy membership functions and probability density functions can be found in the [39][45] and [46].

In the next section, the generalised fuzzy control system which currently used by most fuzzy routing algorithms is explained.

2.4.2 Fuzzy control system

Fuzzy control system is used as a core approach for conventional fuzzy routing and other fuzzy systems. The basic idea behind the fuzzy logic control is to incorporate the expert experience of a human operator in the design of a controller in controlling a process whose input-output relationship is described by a collection of fuzzy control rules (e.g. IF-THEN rules) involving linguistic variables.

A Fuzzy control system is a system that is defined as the nonlinear mapping of an input data set to a scalar output data. A fuzzy control system involves four main sections: *fuzzification*, *rules*, *inference engine*, and *defuzzification*. A generalised fuzzy controlled system is shown in the Fig. 2.10. Firstly, a crisp set of input data is received and then converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms, and membership functions. The conversion process of crisp numbers into fuzzy numbers is called fuzzification. After that, an inference is made by applying fuzzy rules to the input data. Finally, the fuzzy output is mapped to a crisp output by the membership functions again. This process is called defuzzification.

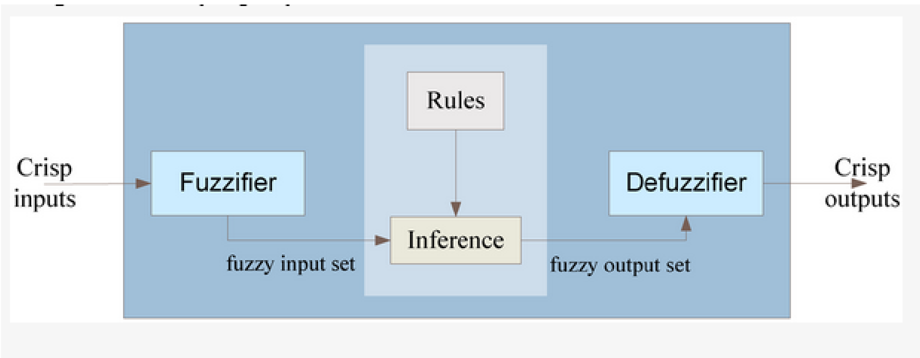
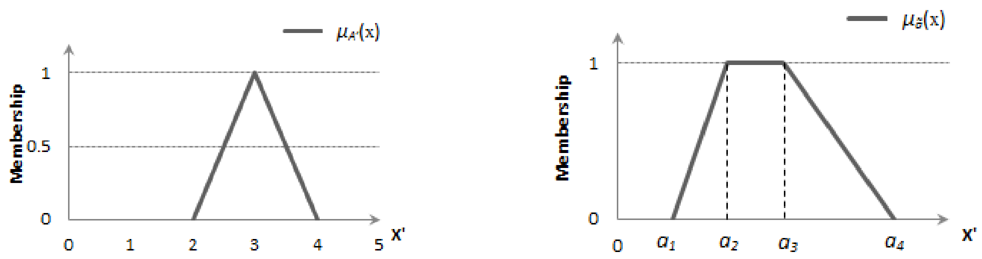


FIGURE 2.10: Generalised fuzzy control system

The general fuzzy control system is designed by following procedure:

1. Initialisation of the linguistic variables and terms, identify controller inputs and outputs as the fuzzy variables
2. Create the fuzzy membership functions
3. Create the fuzzy rule base
4. Design of the fuzzification processes which convert crisp input data into fuzzy values based on fuzzy membership functions
5. Evaluate the rules in the rule base
6. Choose defuzzification strategy, covert the output data to non-fuzzy value again
7. Test and tune the adjustable parameters

The linguistic variables are typically used as input and output variables for fuzzy systems. These variables are words or sentences of a natural language, instead of numerical values. The membership functions are used to quantify the linguistic



(A) triangular fuzzy number (B) trapezoidal fuzzy number

FIGURE 2.11: Example of triangular fuzzy number and trapezoidal fuzzy number

terms. The common types of the membership functions are triangular, trapezoidal, and Gaussian shapes. The triangular and trapezoidal fuzzy numbers are used for FNDR for their simplicity. An example of triangular fuzzy number and trapezoidal fuzzy number is shown in Fig. 2.11:

In a typical fuzzy control system. A simple IF-THEN statement with a condition and a conclusion constructs a fuzzy rule. As an example, some simple fuzzy rules for an air conditioning system are listed below. In this system, the fuzzy engine compares the room temperature and humidity periodically, and predict the apparent air temperature in the human sense:

- IF the TEMPERATURE is hot, and the HUMIDITY is high, THEN apparent air temperature is VERY HOT.
- IF the TEMPERATURE is hot, and the HUMIDITY is low, THEN apparent air temperature is HOT
- IF the TEMPERATURE is warm, and the HUMIDITY is high, THEN apparent air temperature is HOT.
- IF the TEMPERATURE is warm, and the HUMIDITY is low, THEN apparent air temperature is NOT HOT.

In this system, the crisp temperature and the humidity are firstly fuzzificated into fuzzy number, then fuzzy rules are applied to decide the output. The output can be defuzzificated further.

Most conventional fuzzy routing systems are fuzzy control system. It is explained in the next section.

2.4.3 Fuzzy routing

The term *fuzzy routing* used in this section means conventional fuzzy control routing or fuzzy logic based routing. This approach is an extension to the fuzzy control system. The term fuzzy routing was introduced by W. Arnold et al [37]. Their work concentrated on using rule-based fuzzy logic to handle and evaluate linguistic network QoS performance. They have shown that fuzzy representation of link metrics provides flexibility and easy-management features for routing metrics.

The general idea of fuzzy routing is to use fuzzy numbers and fuzzy logic to represent QoS metrics in the network. From one aspect, fuzzy logic aided technique is incorporated into the routing algorithm for mitigating the influence of imprecise routing information. On the other hand, fuzzy theory is a simple way for dealing with multiple constrained QoS information.

The work by Zuo et al. [47] is a good example of introducing the fuzzy control system for Dynamic Source routing (DSR) protocol in MANET. They introduced the fuzzy control system into DSR protocol in order improve the route reliability in the mobility environment. In their design, they used normalised number of hops and route lifetimes as fuzzy input, aiming to identifying the right balance between them. The route lifetime reflects the grade of route stability. The longer the route lifetime, the higher the route stability. At the same time, the fewer hops the route has, the less likely that the route breaks, hence the higher the route stability becomes. (See Fig. 2.12).

No.	*NumHops*	*RouteLifetime*	*RouteStability*
1	Short	Short	Medium
2	Short	Medium	High
3	Short	Long	High
4	Medium	Short	Low
5	Medium	Medium	Medium
6	Medium	Long	High
7	Long	Short	Low
8	Long	Medium	Medium
9	Long	Long	High

FIGURE 2.12: Fuzzy rules design in Zuo et al 's work

The routing algorithm was quite simple and clear. This is quite similar to a fuzzy control system in section 2.3. The classic "IF-THEN" rule is chosen as the inference rule:

- IF Number of Hops is Short, AND Route Life time is Short, THEN route Stability is Medium
- IF Number of Hops is Medium, AND Route Life time is Short, THEN route Stability is Low
- IF Number of Hops is Long, AND Route Life time is Short, THEN route Stability is Low

Their results showed that, by introducing fuzzy control system, the network throughput is improved and route break events due to mobility are minimised.

Like other fuzzy control systems, most of fuzzy routing designs rely on expert knowledge. The general design process is similar to the fuzzy control system as well (See Fig.2.13).

There are numerous works about fuzzy routing and fuzzy QoS routing. S. Pithani and A.S Sethi's [48] proposed a fuzzy set delay representation for network

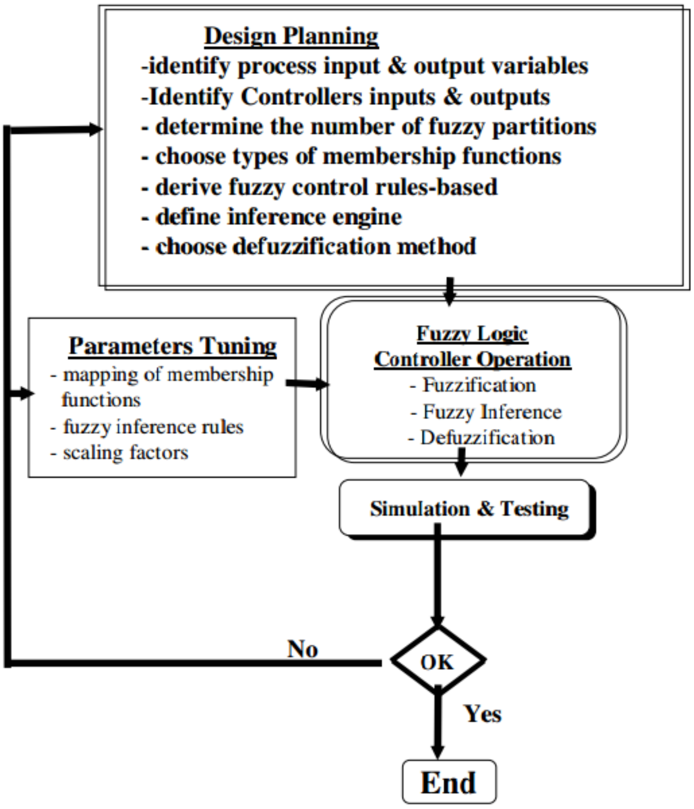


FIGURE 2.13: Generalised fuzzy routing design

routing algorithms. They applied fuzzy numbers for representing the uncertainty of network delays. E. Aboelela and C. Douligeris [49] proposed a fuzzy metric approach for Quality-of-Service routing in B-ISDN. Their results showed an improvement in network performance with little computational effort. Furthermore, Liu and Kao [50] demonstrated an example of applying fuzzy weighted link QoS metric for multimedia transmission associated with RSVP. J A. Khan and H M. Alnuweiri [51] propose a fuzzy constraint-based routing algorithm for MPLS traffic engineering. C. Wu etc. [52] introduced fuzzy theory to VANET. Combining with reinforcement learning technique, they introduced a flexible, portable, and practicable Fuzzy ADOV solution for routing in VANET. In addition, fuzzy logic has been reported in enhancing lifetime of wireless sensor network [53] and sensor network link quality estimation [54]. Other related works can be found in [2][3][4][5][55][56][57][58] and [59].

However, there are a few studies adapting additive metrics into fuzzy routing. In this work, the metrics representation approach is used for FNDR as well. However, FNDR does not use fuzzy rules for its decision making. The fuzzy weighted graph is introduced into FNDR for its routing selection process. The Fuzzy weighted graph is briefly explained in the next section.

2.5 Fuzzy weighted graph

In this section, the fuzzy weighted graph and fuzzy shortest path are introduced.

It is quite well known that graphs are simply models of relations. A graph is a convenient way of representing information involving relationship between objects. The objects are represented by vertices and relations by edges. However, in a network with inaccurate information, when there is vagueness in the description of the objects or in its relationships or in both, it is natural to introduce fuzzy weighted graph.

In a computer and telecommunications network, any packet-switched network can be modelled as a directed weighted graph. In this graph, vertices (nodes) are routers and edges represent wireless channel, cables and links. Network routing problem equivalents to finding the shortest path in the graph associated to the network. The Dijkstra's algorithm and the Bellman-Ford's algorithm are two well-known algorithms which are widely applied by routing algorithms to finding the shortest or least cost route. However, if the topology or the graph is dynamic or the costs of the links are fuzzificated, the definition of the shortest path becomes uncertain as well. Therefore the problem becomes finding the fuzzy shortest path for packet delivery.

In this thesis, the term *crisp graph* is used to describe conventional graph where the costs of the edges are crisp numbers. A fuzzy weighted graph means that the vertices or edges/arcs of the graph are fuzzy weighed. Fig. 2.14 shows a directed graph with 4 vertices and 4 arcs. If this graph is a crisp graph with its arcs costs

$a = 1, b = 2, c = 2, d = 3$. It would be very simple to find out that the shortest path from node A to D is A-B-D.

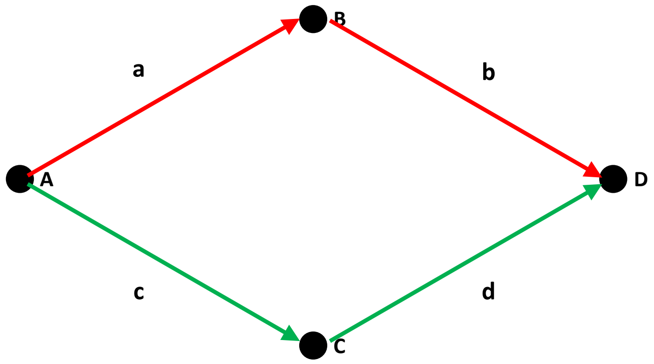


FIGURE 2.14: A graph with 4 vertices and 4 arcs

However, if the arcs costs are fuzzy numbers. As Fig. 2.15 shown, four arcs are fuzzy membership functions other than crisp numbers. The fuzzy shortest path cannot be easily identified. It is noticeable that the crisp graph can be actually considered as a special case of a fuzzy graph with its vertices and edges have fuzzy memberships of 1. When a, b, c and d have fuzzy memberships of 1, they have crisp cost.

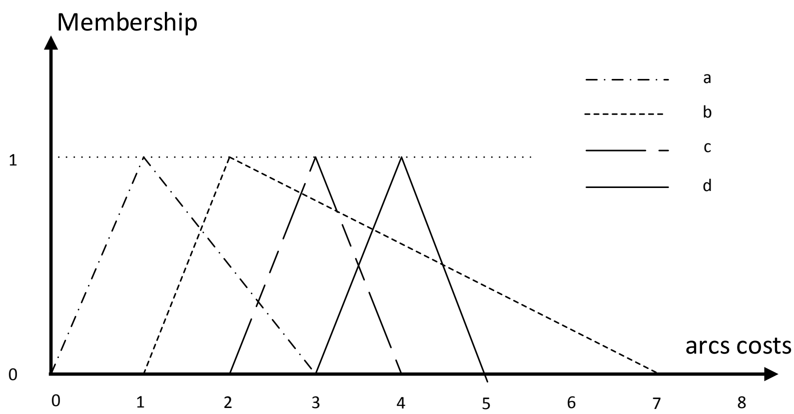


FIGURE 2.15: Fuzzy membership function for 4 arcs in Fig. 2.14

There are many mathematical models of fuzzy shortest path problems concentrate on graphs with fuzzy weighted arcs. The fuzzy shortest path problem was first introduced and analysed by Dubois and Prade [60]. Floyd's and Ford's algorithm was adapted to find the fuzzy shortest path. However, their work didn't guarantee the existence of a fuzzy shortest path. Klein [61] then proposed a dynamic programming based algorithm to solve the fuzzy shortest path problem. However, their solution can lead to dominated paths which are not Pareto optimal. The Soper introduced an order relation between fuzzy numbers based on the concept of "fuzzy min" proposed by Dubois and Prade [62]. M Ghatee and S.M Hashemi [63] have successfully introduced a fuzzy method by using the minimal cost multi-commodity flow problem to handle imprecise travel cost and inexact supply-demand. Other related works can be found in [4][5][64][55][65] and [66]. However, few works addressed the applications of fuzzy graphs for fuzzy routing and fuzzy routing problem in computer and telecommunications networks.

In this thesis, the fuzzy non-dominance multipaths are explored as a solution for computer and telecommunications routing and QoS routing. It is explained and discussed in detail in the next chapter.

2.6 Summary

In this chapter, some essential principles of network routing have been briefly reviewed. Then the sources of inaccurate routing information were explained and discussed. The researches on relevant topic were reviewed as well.

Fuzzy set theory, fuzzy control system and fuzzy routing approach with a focus on advantage of fuzzy QoS metric representation were discussed in more detail as these are the main topics of this research. The fuzzy weighted graph was also introduced as this is the fundamental theory for introducing FNDR in the next chapter.

In the next chapter, the principles of applying fuzzy weighted graph into network routing are explained in detail together with the implementations. In the subsequent chapters the results of FNDR routing and QoS optimizations are presented and discussed.

Chapter 3

Fuzzy Non-dominance Approach for Network Routing

3.1 Introduction

In the previous chapter, the network routing state-of-the-art, the origin of inaccurate routing information, fuzzy sets and the conventional fuzzy routing issues were identified. In this chapter, the design and algorithms of the fuzzy non-dominance routing are explained in detail.

In the next section, related terminologies of fuzzy theory and arithmetics are introduced. As some fuzzy arithmetics approaches are still open research topics [67], different explanations and operations were given by various literatures. Therefore, relevant approaches are reviewed with remarks and explanations.

In the section 3.3 , a number of informal descriptions of key issues for the fuzzy non-dominance routing are given with cases. This is the first novel part of this work.

In the section 3.4, the fuzzy non-dominance routing is formally introduced. This section gives the mathematical descriptions to the fuzzy shortest path problem and defines the fuzzy non-dominance conditions which is one of the core concepts to FNDR. Then the k-th fuzzy non-dominance routing algorithm is introduced with explanations and remarks. This section discusses some important issues for the improvement of the time complexity performance of this algorithm as well. Then the section move onto the fuzzy non-dominance routing framework in order to adapt FNDR to state-of-the-art network infrastructures.

The section 3.5 explains and validates the network simulation platform. This work setup simulations on both Matlab and OPNET simulation platform. The simulation processes on both platforms are explained. And the chapter concluded in the section 3.6.

3.2 Fuzzy arithmetic operations

In the chapter 2, some essential background of fuzzy sets and fuzzy theory were reviewed. In this section, the detailed fuzzy arithmetics are introduced and explained. Relevant approaches and operations are given in this section with remarks.

3.2.1 Preliminaries

The formal definition of a *fuzzy set* is defined as follows:

X is a *universal* set of objects with object x belonging to X. For a given subset A belonging to X, there exists a membership function $\mu_A(x)$ to examine if x belongs to A or not. The membership function $\mu_A(x)$ is represented as:

$$\mu_A(x) = \begin{cases} 1 & \text{iff } x \in A \\ 0 & \text{iff } x \notin A \end{cases} \tag{3.1}$$

Here $\mu_A(x) \rightarrow \{0, 1\}$ is called a *valuation set*. In Zadeh's fuzzy set definition, if the valuation set is allowed to be the real interval $[0, 1]$, then A is called a fuzzy set. The membership function $\mu_A(x)$ is the *grade of membership* of x in A. The closer the value of $\mu_A(x)$ is to 1, the more the object x belongs to A. A fuzzy set A can be fully described in a pair, which contains objects x and its membership function $\mu_A(x)$,

$$A = \{x,\ \mu_A(x) \mid x \in X\} \tag{3.2}$$

The equality of two fuzzy sets depends on their membership functions. Two fuzzy sets A and B are said to be equal if and only if:

$$\forall x \in X,\ \mu_A(x) = \mu_B(x) \tag{3.3}$$

It denoted as $A = B$.

The *Support* of a fuzzy set A is a crisp set that contains all elements of X that have a non-zero membership grade in A. It can be represented by

$$supA = \{x \in X \mid \mu_A(x) > 0\} \tag{3.4}$$

The classical union and intersection of two fuzzy sets A and B can be extended by following formulas as proposed by Zadeh:

$$\forall x \in X,\ \ \mu_{A \cup B} = max(\ \mu_A,\ \mu_B\ ) \tag{3.5}$$

$$\forall x \in X,\ \ \mu_{A \cap B} = min(\ \mu_A,\ \mu_B\ ) \tag{3.6}$$

There are other intersection operations suggested by different literatures. However, in this work, the Zadeh's operations are applied for its usefulness and simplicity.

The *core* of fuzzy set A is the set

$$\forall x \in X,\ \ \mu_A(x) = 1 \tag{3.7}$$

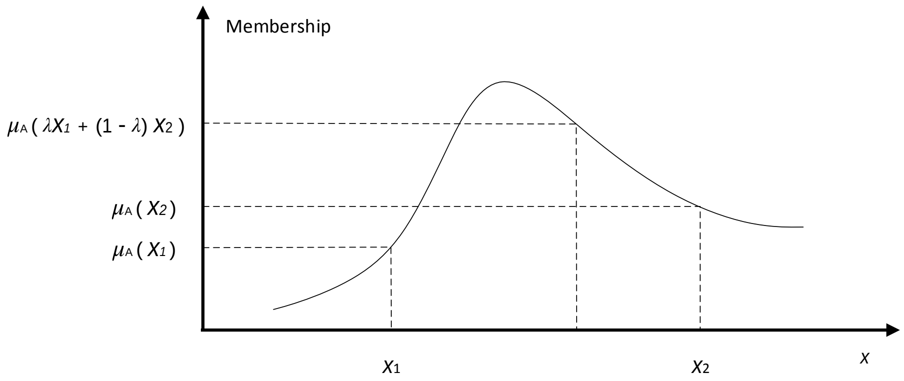
The α-cut (or α-level fuzzy set) is an important definition in fuzzy sets. It shows the membership values that are greater than a threshold $\alpha \in (0, 1]$. The α-cut is all points x in *universal* set X such that, $\mu_A(x) \geq \alpha$, which is denoted by

$$A_\alpha = \{x \in X,\ \ \mu_A(x) \geq \alpha\} \tag{3.8}$$

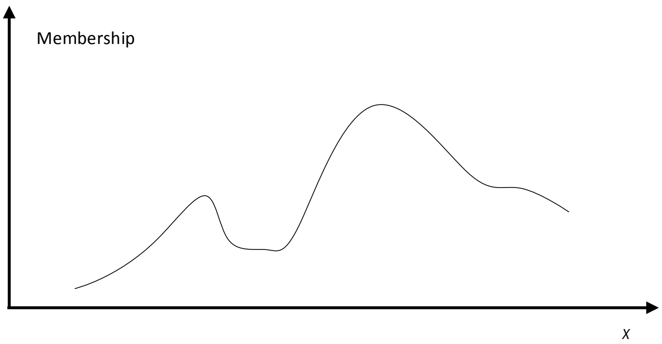
The strong α-cut is defined as

$$A_{\alpha'} = \{x \in X, \mu_A(x) > \alpha\} \tag{3.9}$$

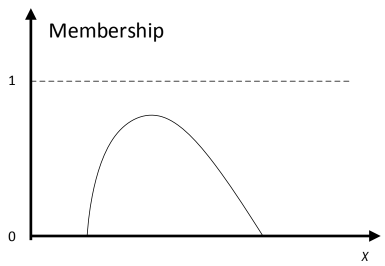
The following union and intersection properties are held for α-cut:



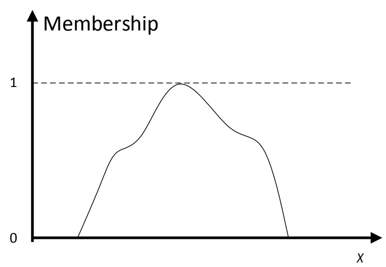
(A) Convex fuzzy set



(B) Non-convex fuzzy set



(C) Non-normalised fuzzy set



(D) Normalised fuzzy set

FIGURE 3.1: Convex and normalised fuzzy sets

$$(A \cup B)_\alpha = A_\alpha \cup B_\alpha \tag{3.10}$$

$$(A \cap B)_\alpha = A_\alpha \cap B_\alpha \tag{3.11}$$

The fuzzy numbers used for FNDR are convex and normalised fuzzy sets. The normalised fuzzy (Fig. 3.1d) set is defined as

$$\exists x_0 \in X,\ \mu_A(x_0) = 1. \tag{3.12}$$

The notion of convexity can be generalised to fuzzy sets as Figure 3.1 shown. The formal definition was given by Zadeh. A fuzzy set A is *convex* if and only if its α-cuts are convex. It can be expressed as A is convex if:

$$\begin{aligned} \mu_A\left(\lambda x_1 + (1-\lambda)\, x_2\right) \geq min\left(\mu_A(x_1)\mu_A(x_2)\right), \\ \forall x_1, x_2 \in X, \forall \lambda \in [0,1] \end{aligned} \tag{3.13}$$

Where μ_A represents fuzzy membership function, λ is a constant. There is a remark that if fuzzy sets A and B are convex, their intersection $A \cap B$ is a convex fuzzy set as well.

3.2.2 Fuzzy numbers

The *fuzzy numbers* are used to express inaccurate network's metrics in this thesis. There is more than one definition of fuzzy numbers. In this work, an extended version is adopted. The formal definition of fuzzy number is based on convex and normalised fuzzy set.

Definition 1. A *fuzzy number* is a convex normalised fuzzy set A of the real line **R** such that

1. $\exists!$ a set X $[x_a, x_b] \in \mathbf{R}$, $\mu_A(X) = 1$
2. μ_A is piecewise continuous

LR-type fuzzy number is an important type of fuzzy numbers which is widely applied for its significance. The LR represents left and right spreading function of fuzzy numbers. An LR-type fuzzy number in Figure 3.2 can be denoted as $\tilde{a} = (a_1, a_2, a_3, a_4)_{LR}$ where

$$\mu_{\tilde{a}}(x) = \begin{cases} L(\frac{x-a_1}{a_2-a_1}), & a_1 \leq x \leq a_2, \\ 1, & a_2 \leq x \leq a_3, \\ R(\frac{a_4-x}{a_4-a_3}), & a_3 \leq x \leq a_4, \\ 0 & otherwise \end{cases} \tag{3.14}$$

where L and R are two non-decreasing membership functions such that $R(0) = L(0) = 0$, and $R(1) = L(1) = 1$. $a_2 - a_1$ and $a_4 - a_3$ are left and right side spreading. L and R are left and right spreading reference function.

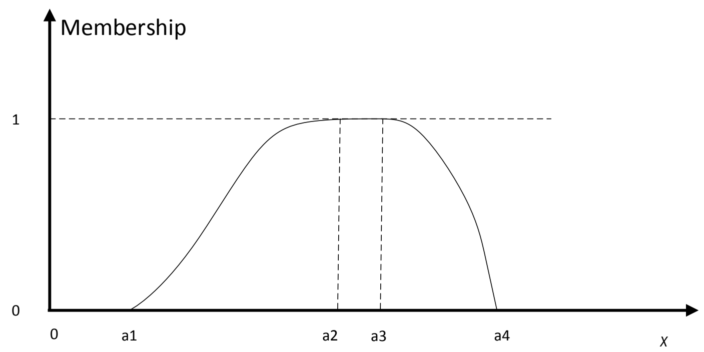
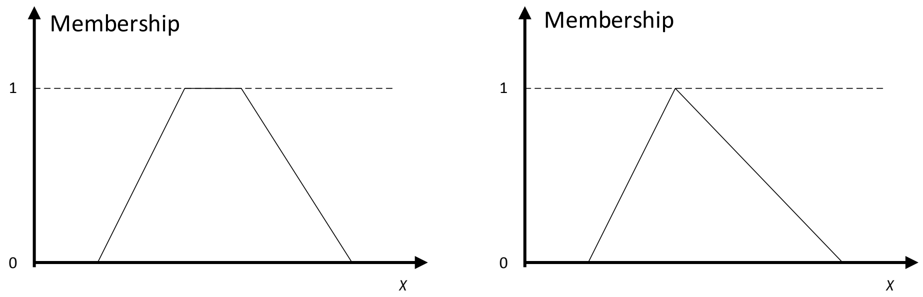


FIGURE 3.2: An LR type fuzzy number

The triangular and trapezoidal LR-type fuzzy numbers (See Figure 3.3) are two important cases among other LR-type fuzzy numbers. They have been validated in numerous literatures for its effectiveness and simplicity. They are applied in this work for their special arithmetic properties which will be addressed in the Section 3.2.3.

The membership function of LR-type trapezoidal can be simplified as



(A) Trapezoidal fuzzy number (B) Triangular fuzzy number

FIGURE 3.3: Trapezoidal and triangular LR-type fuzzy numbers

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-a_1}{a_2-a_1}, & a_1 \leq x \leq a_2, \\ 1, & a_2 \leq x \leq a_3, \\ \frac{a_4-x}{a_4-a_3}, & a_3 \leq x \leq a_4, \end{cases} \tag{3.15}$$

When $a_2 = a_3$, the trapezoidal fuzzy number can be transformed into a triangular fuzzy number.

The trapezoidal and triangular fuzzy numbers are benefiting from their special properties in fuzzy arithmetics and rankings. The fuzzy arithmetics and rankings are explained in the following section.

3.2.3 Fuzzy arithmetics

The fundamental arithmetics operations for crisp numbers need to be revised for fuzzy numbers.

The fuzzy sum $\tilde{\gamma}$ of two fuzzy numbers $\alpha = (a_1, a_2, a_3, a_4)_{LR}$ and $\beta = (b_1, b_2, b_3, b_4)_{LR}$ is defined as

$$\mu_{\tilde{\gamma}}(z) = sup_{z=x+y} min \left\{ \mu_{\tilde{\alpha}}(x), \mu_{\tilde{\beta}}(y) \right\} \tag{3.16}$$

Where $sup_{z=x+y}$ is the least upper bound of $x \in \mu_{\tilde{\alpha}}$ and $y \in \mu_{\tilde{\beta}}$. In this work, the symbol $\oplus$ is used for fuzzy sum. For trapezoidal and triangular LR-type fuzzy numbers, the fuzzy sum can be simplified as

$$\tilde{\gamma} = \tilde{\alpha} \oplus \tilde{\beta} = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4)_{LR} \tag{3.17}$$

In addition, the union relation is important to this work as well. However, the union of two fuzzy numbers is not necessary to be a fuzzy number. As shown in Fig 3.4, the union of two fuzzy numbers can be a non-convex fuzzy set. Therefore, this work defined the interval union to deal with this problem.

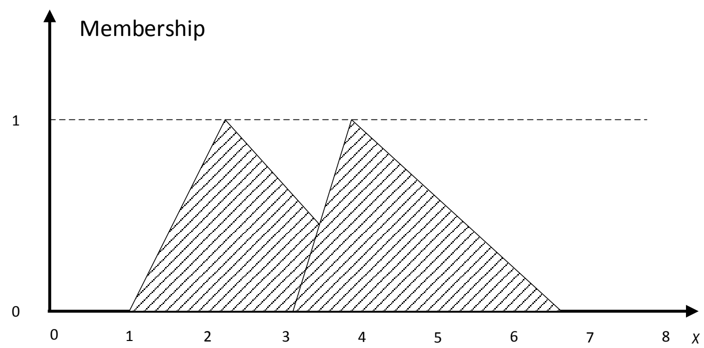


Figure 3.4: Non-convex fuzzy union

For trapezoidal LR-type fuzzy numbers, the interval union $\cup_{ivl}$ of two fuzzy numbers $\alpha = (a_1, a_2, a_3, a_4)_{LR}$ and $\beta = (b_1, b_2, b_3, b_4)_{LR}$ is defined as

$$\tilde{\gamma} = \tilde{\alpha} \cup_{ivl} \tilde{\beta} = (min(a_1, b_1), min(a_2, b_2), max(a_3, b_3), max(a_4, b_4)) \tag{3.18}$$

The interval union of two triangular fuzzy numbers $\alpha = (a_l, a_m, a_r)_{LR}$ and $\beta = (b_l, b_m, b_r)_{LR}$ is defined as:

$$\tilde{\gamma} = \tilde{\alpha} \cup_{ivl} \tilde{\beta} = (min(a_l, b_l), min(a_m, b_m), max(a_m, b_m), max(a_r, b_r)) \quad (3.19)$$

The interval union of two triangular fuzzy numbers is a trapezoidal fuzzy number.

3.2.4 Fuzzy ordering

To compare the preference of multiple fuzzy routes, it is important to define an ordering approach between two fuzzy numbers. However, the total ordering relation for crisp numbers cannot be adopted for fuzzy numbers directly. Therefore, the partial ordering relation is proposed.

The *lexicographical order* $\prec_{lex}$ between two fuzzy numbers is defined as:

Definition 2. Let $\breve{x} = (\breve{m}_l, \breve{a}, \breve{b}, \breve{m}_r)$ and $\tilde{y} = (\tilde{m}_l, \tilde{a}, \tilde{b}, \tilde{m}_r)$ be two L-R type fuzzy numbers. $\breve{x} \prec_{lex} \tilde{y}$ if any of following cases hold:

1. $\breve{m}_l < \tilde{m}_l$.
2. $\breve{m}_l = \tilde{m}_l$, $\breve{a} < \tilde{a}$.
3. $\breve{m}_l = \tilde{m}_l$, $\breve{a} = \tilde{a}$,$\breve{b} < \tilde{b}$.
4. $\breve{m}_l = \tilde{m}_l$, $\breve{a} = \tilde{a}$,$\breve{b} = \tilde{b}$ and $\breve{m}_r < \tilde{m}_r$.

The graded mean integration representation approach by and Deng [5] and Chou et al. [68] is considered to be used for fuzzy ranking as well. The definition of graded mean integration representation of a fuzzy number A (See Figure 3.5)is defined as

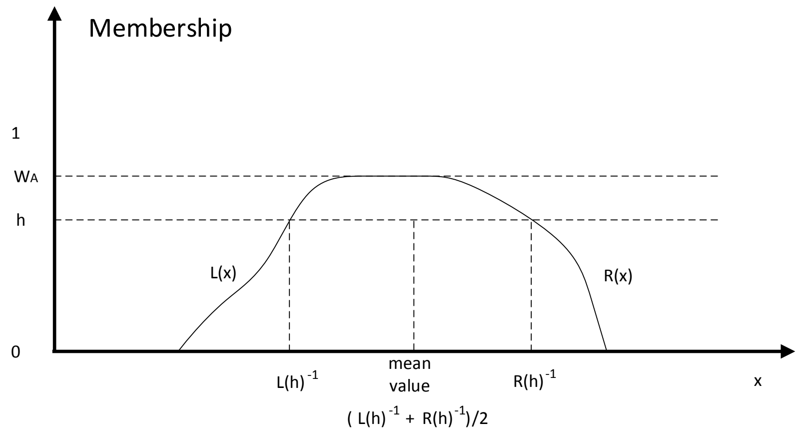


FIGURE 3.5: Fuzzy graded mean integration

Definition 3. Let L^{-1} and R^{-1} be the inverse function of the function L and R, respectively; then the graded mean at h-level is $h(L_h^{-1} + R_h^{-1})/2$ as Figure 3.5 . Then the graded mean integration representation of A is

$$P(A) = \frac{\int_0^{wA}(h(L_h^{-1} + R_h^{-1})/2)dh}{\int_0^{wA} hdh} \tag{3.20}$$

For triangular and trapezoidal fuzzy numbers, the graded mean integration have been proven where the graded mean integration for a trapezoidal fuzzy number (a, b, c, d) is:

$$P(A) = \frac{1}{6}(a + 2b + 2c + d) \tag{3.21}$$

This equation can be easily adapted for a triangular fuzzy number by setting $b = c$.

Other lexicographical or partial ordering methods can also be applied with a decision maker's preference. This may include, but not limited to weighted sum, maximum components and the fuzzy probability.

In the next section, the general ideas of fuzzy non-dominance routing are explained.

3.3 General idea of FNDR

In this section, a number of informal descriptions of key issues for the fuzzy non-dominance routing are given with a focus on discussion of the non-dominance relation.

3.3.1 Use of case

In this section, a simple network (See Figure 3.6) with 4 routers and 5 links is used to explain the fuzzy non-dominance routing problem. Packets are sent from Router 1 to 4. The fuzzy cost and associated α-level cut of each link are shown in the Fig. 3.6 as well. There are three potential routes from source router 1 to destination router 4 which are denoted as $p_{\alpha 1}$,$p_{\alpha 2}$ and $p_{\alpha 3}$, where $p_{\alpha 1} = \{1,(1,2),2,(2,4),4\}$ with α-cut $= 0$ and its cost $\tilde{c}_1 = \tilde{c}_{\alpha 1} = (25,32,36,50)$, $p_{\alpha 2} = \{1,(1,4),4\}$ with α-cut $= 0.2$ and it cost $\tilde{c}_2 = (5,30,30,80)$ and its cost with α-cut $\tilde{c}_{\alpha 2} = (10,30,30,70)$, $p_{\alpha 3} = \{1,(1,3),3,(3,4),4\}$ with cost α-cut $= 0$ and $\tilde{c}_3 = \tilde{c}_{\alpha 3} = (60,70,75,87)$.

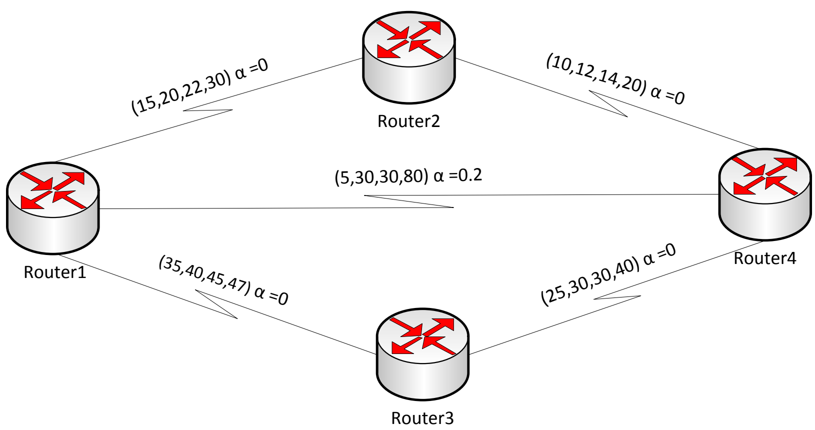


FIGURE 3.6: A network with 4 routers and fuzzy link costs

3.3.2 Non-dominated metrics

The terminology *fuzzy non-dominance routing* in this work is distinct from the term *fuzzy routing*. Conventional fuzzy routing aims to use fuzzy sets and fuzzy logic to represent inaccurate and uncertainty network metrics. Those metrics are non-additive fuzzy linguistic terms. However, the key idea of fuzzy non-dominance routing in this work is to use fuzzy weighted metrics to represent the uncertain and dynamic nature of the network routing. And non-dominated routes can be used for multipath routing and load balancing.

The relation between non-dominated paths is also known as Pareto-optimal. The physical meaning of fuzzy route a is not dominated by fuzzy route b is that path a is not worse than path b meanwhile b is not worse than a. The formal mathematical explanation will be presented in the next section.

Consider an example based on the use case of this section. As shown in the Figure 3.6, three routes have different fuzzy cost from the source Router 1 to the destination Router 4. The mean value of $\tilde{c}_\alpha$ with the α-cut $= 1$ is a crisp cost which can used by classic shortest path routing algorithms. Under such scenario, the route p_2 in the Figure 3.6 with the least cost 30 is always preferred.

However, as discussed in the previous chapter, the network metrics are always inaccurate and uncertain. If routing costs become inaccurate fuzzy metrics as shown in the Fig. 3.6, ranking route preferences based on the single crisp cost becomes impracticable. Comparing two fuzzy route cost $\tilde{c}_{\alpha 2}$ and $\tilde{c}_{\alpha 1}$, the worst case of $\tilde{c}_{\alpha 2}$ is 80 which is much greater than 50 in $\tilde{c}_{\alpha 1}$, though its best case 10 is smaller than $\tilde{c}_{\alpha 1}$ which is 25. Under such circumstances, where the cost of route a is not completely worse than route b meanwhile route b is not completely worse than path a as well. It is called in this work that route a is not dominated by route b and route b is not dominated by route a. Two routes are non-dominated routes.

In this case, two paths $p_{\alpha 1}$ and $p_{\alpha 2}$ are non-dominated to each other. And $p_{\alpha 3}$ is dominated by the other two routes. In the fuzzy non-dominance routing, the link metrics are additive fuzzy numbers, which are assigned by considering any uncertainty issues of one or multiple physically meaningful dynamic link QoS metrics. In this work, fuzzy non-dominance routing are used to optimise the network utilisation by applying non-dominance multipath for load balancing.

For instance, in a rate based-service model network as [26] , the link load is the only key metric to optimise network performance. A congested route and a free route do not have to be of equal cost as the classic shortest path routing for load balancing. A higher usage link experiences a higher grade of uncertainty due to its dynamic nature. Under such circumstances, two or more routes are not dominating each other. Thus, the network achieves the non-dominance multipath condition.

3.3.3 α-cut route control

α-cut route control plays an important role in the fuzzy non-dominance routing. From one aspect, α-cut can be used to control the total numbers of routes that can be searched by FNDR in order to improve the computational overhead. In the other hand, α-cut is used to control the grade of fuzziness of routing metrics. The term normalized α-cut fuzzy number is defined later in this work to covert a fuzzy number with α-cut to a normalised fuzzy number.

In the real practices, α-cut is a simple way to manage and optimise QoS metrics of the network. For example, one of the problems caused by equal-cost multipath routing optimization in the conventional infrastructure network is that it is difficult for network administrators to maintain the link weight. Any incorrect setting may cause convergence failures. Fuzzy non-dominance routing maintains routing cost by configuring the level of the α-cut. A higher level α-cut stands for a lower grade of uncertainty. The α-cut tends to move towards 0 until it leads a full support to the fuzzy number when more inaccurate or uncertainty factors are faced.

Consider the case where p_2 is a high-speed link and p_1 is a low bandwidth redundant standby load balancing route. During off peak hours, the network administrator requires the faster route to be used in order to enhance the network performance. However, the best route is likely to be congested during the peak hours. In a conventional infrastructure network, it is necessary to reset the link metrics for equal-cost multipath routing. However, in FNDR, the process is much easier that by simply setting α-level cut to 0, the path $p_{\alpha 1}$ now is not dominated by $p_{\alpha 2}$. Therefore, both routes are used for multipath routing.

3.3.4 Mobility

The fuzzy non-dominance routing can be adapted to handling a network with mobility nodes and dynamic topology as well. Similar to conventional fuzzy routing, the grade of fuzziness is used to describe the dynamic of nodes. Instead of fuzzy logic controller, the different fuzzy ranking approaches can be used to compare the reliability of routes. For example, in a mobile environment, the route with less fuzziness is preferred for higher availability.

3.4 Fuzzy non-dominance routing

3.4.1 Shortest paths in a fuzzy graph

Consider a directed network $G = (N, A)$. It consists of a finite set of nodes $N = \{1, \ldots, n\}$ and a set of directed ordered pairs of arc $A = (i, j) \subseteq N \times N$. where $i, j \in N$ and $i \neq j$. There is a positive cost c_{ij} associated with each arc $(i, j) \in A$. In a telecommunications or computer network, for example, the cost could represents bandwidth, delay or link weight, which can be used for routing calculations. A route p_{sd} is defined in G from source node $s \in N$ to a destination node $d \in N$. p_{sd} can be denoted as a sequence of nodes and arcs $p_{sd} = \{i_0 = s, (i_0, i_1), i_1, \ldots, i_{l-1}, (i_{l-1}, il), i_l = d\}$.

In a fuzzy network, instead of the crisp cost c_{ij}, the arcs' cost is represented by a positive LR-type fuzzy number $\tilde{c_{ij}} = (m_l, a, b, m_r)_{LR}$. where m_l and m_r are left and right direction spreading. Each arc also has a α-level cut α_{ij} which is defined on an interval $[0, 1]$ associated with it. In this work, the α-level cut cost of arc i, j is denoted as $c_{\alpha ij} = \alpha_{ij}\tilde{c}_{ij}$. The total cost among a fuzzy route p on graph is defined as $\sum_{i,j \in p} \alpha_{ij}\tilde{c}_{ij} = \sum_{i,j \in p} \alpha_{ij}(m_l, a, b, m_r)_{LRij}$

The fuzzy shortest path problem can be formulated following a linear programming formulation. This formulation is an extended version of the classical shortest path problem:

$$\min \tilde{z}(x) = \sum_{(i,j) \in A} \tilde{c}_{ij} x_{ij} \tag{3.22}$$

$$s.t. \sum_j x_{ij} - \sum_j x_{ji} \tag{3.23}$$

$$= \begin{cases} 1 & \text{if} \quad i = s \\ 0 & \text{if} \quad i \neq s \text{ and } i \neq d \\ -1 & \text{if} \quad i = d \end{cases} \tag{3.24}$$

where, in the objective function, the $\tilde{c}_{ij}$ is the fuzzy link cost. The $\sum$ represents the fuzzy addition $\oplus$ between elements. The main issue is that the objective function of this problem is fuzzificated. The fuzzy ordering between two fuzzy numbers is not well defined, therefore the minimum value for a fuzzy function cannot be easily identified. Thus the LR-type trapezoidal fuzzy number is introduced to defuzzificate the objective function, and to transform this problem into a multi-objective shortest path problem.

Existing solutions to this formulation apply methods to transform the fuzzy cost $\tilde{c}_{ij}$ into a crisp number. Therefore this formulation can be solved as a classic shortest path problem either by introducing fuzzy probability theory or by fuzzy ranking method such as graded mean integration. However, the existing solutions did not support the multipath routing for load balancing in a telecommunications network, therefore their uses are limited.

This work introduces fuzzy non-dominance condition to solve the problem. In the next section, the fuzzy non-dominance conditions are explained and discussed in details.

3.4.2 Fuzzy non-dominance conditions

A definition of non-dominance condition for computer networks QoS was introduced in [69]. However, this work defined a fuzzy non-dominance relation for LR-type trapezoidal fuzzy numbers. In this work, the LR-type trapezoidal fuzzy number $\tilde{c}_{ij}$, where $\tilde{c}_{ij} = (m_l, a, b, m_r)$, is applied in order to transform this problem into a multi-objective shortest path problem. By using LR-type trapezoidal fuzzy number, the problem can be reformulated as following multi-objective programming functions:

$$\begin{cases} \min \quad z_1(x) = \sum_{i,j \in A} m_{lij} x_{ij} \\ \min \quad z_2(x) = \sum_{i,j \in A} a_{ij} x_{ij} \\ \min \quad z_3(x) = \sum_{i,j \in A} b_{ij} x_{ij} \\ \min \quad z_4(x) = \sum_{i,j \in A} m_{rij} x_{ij} \end{cases} \tag{3.25}$$

A feasible solution can be obtained that would meet these requirements: An improvement to one objective $z_k(x)$ can only occur with the degrading of at least one another objective $z_g(x)$, where $g \neq k$.

Definition 4. A feasible solution $\tilde{x} \in X$ is called non-dominance if for all $\check{x} \in X$, $Z(\tilde{x}) = (z_1(\tilde{x}), z_2(\tilde{x}), z_3(\tilde{x}), z_4(\tilde{x})) \leq (z_1(\check{x}), z_2(\check{x}), z_3(\check{x}), z_4(\check{x}))$. Then $Z(\tilde{x})$ is called *non-dominated* by $Z(\check{x})$or *Pareto efficient*.

Therefore, the problem is to find all non-dominated routes.

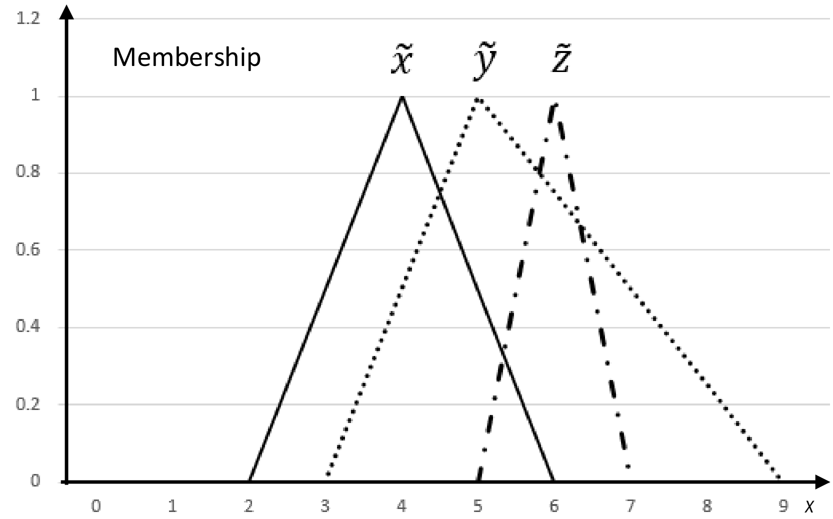


FIGURE 3.7: Fuzzy non-dominance condition

This work defines the non-dominance relation between two LR-type trapezoidal fuzzy number $\prec_{dom}$ as

Definition 5. Let $\check{x} = (\check{m}_l, \check{a}, \check{b}, \check{m}_r)$ and $\tilde{y} = (\tilde{m}_l, \tilde{a}, \tilde{b}, \tilde{m}_r)$ be two L-R type fuzzy numbers. $\check{x} \ <_{dom} \tilde{y}$ if $\check{m}_l < \tilde{m}_l$, $\check{a} < \tilde{a}$, $\check{b} < \tilde{b}$ and $\check{m}_r < \tilde{m}_r$. A fuzzy number $\tilde{y}$ is weak dominated by $\check{x}$ if $\check{m}_l < \tilde{m}_l$ and $\check{m}_r < \tilde{m}_r$.

Following this definition, the non-dominance relation check of LR-type trapezoidal fuzzy number can be significantly simplified. As shown in the Figure 3.7, $\tilde{x}$, $\tilde{y}$ and $\tilde{z}$ are three triangular LR-type fuzzy numbers where $\tilde{x} = (2, 4, 6)$, $\tilde{y} = (3, 5, 9)$ and $\tilde{z} = (5, 6, 7)$. According to Definition 5, $\tilde{y}$ and $\tilde{z}$ are dominated by $\tilde{x}$, $\tilde{y}$ and $\tilde{z}$ are not dominated to each other.

A labelling setting algorithm by setting *temporary and permanent labels* on each nodes has been developed to this problem in order to finding the fuzzy non-dominance paths. The algorithm is then revised and applied to solve this problem by searching the limited number of labels on each node in order to improve the time complexity.

3.4.3 Route searching

The computation of the full set of routes for this problem is difficult due to numbers of non-dominance routes. It is clear that, in the worst case, the number of non-dominated fuzzy paths grows exponentially with the network size. In order to find out fuzzy non-dominance routes from node s to all destinations with lexicographically or other non-decreasing order in an acceptable time complexity. The temporary labels for each node are set to a limited number of k. In this work, it is called fuzzy k-nondominance paths.

Definitions and lemmas are introduced first.

Property 1. For two L-R type fuzzy numbers $\tilde{x}$ and $\tilde{y}$, if $\tilde{x} \leq_{dom} \tilde{y}$, then $\tilde{x} \preceq_{lex} \tilde{y}$ and $\tilde{y} \succeq_{lex} \tilde{x}$ hold.

Property 2. For two L-R type fuzzy numbers $\tilde{x}$ and $\tilde{y}$, if $\tilde{x} \leq_{lex} \tilde{y}$, then $\tilde{x}$ is not dominated by $\tilde{y}$

These properties are clearly derived from the Definition 2 and Definition 3. In addition, these properties can be easily applied to other ordering methods such as graded mean integration.

In order to get k non-dominated fuzzy path, following Lemma is needed to be applied as well.

Lemma 3.1. *A path p_{st} from node s to t is a non-dominated path only if every sub-path $p_{si} \in p_{st}$ from node s to an any intermediate node i is also a non-dominated path.*

The above lemma has been proved based on Bellman's principle of optimality [70].

The algorithm is a fuzziness version of label setting algorithms which is a multi-objective generalisation of Dijkstra's algorithm. An extended label contains LR-type fuzzy cost $\tilde{c}$ and a vector (u, k) which directs to kth label of the previous node u. The label provides a recursive backtrack of the paths. This work defines a permanent label set P which contains a non-dominated fuzzy sub-path and a set of temporary label T which contains the candidate temporary fuzzy sub-path for the next iterations. This work also defined a set B which contains all the nodes that have not reached a permanent label limit. Besides a count number is applied in the algorithm to limit the maximum number of temporary and permanent labels being associated with each node. The permanent labels are chosen based on lexicographical or other non-decreasing order in each iteration. A non-dominance check is applied on each iteration with the arriving of every new temporary label.

Before giving the next lemma, the concept of deviation of non-dominated fuzzy paths is firstly defined

Definition 6. Let p_{st} be the non-dominated fuzzy path from s to t and i is an intermediate node on $p_{st}, i \in p_{st}$. If there is a neighbour node j of i, $j \notin p_{st}$ which makes $p'_{st} = p_{si} \cup p_{ij} \cup p_{jt}$ not dominated by p_{st}, then p'_{st} is called a forward deviation non-dominated path of p_{st} on node i. If there is a neighbour node j' which makes $p'_{st} = p_{sj'} \cup p_{j'i} \cup p_{it}$ is not dominated by p_{st}, then p'_{st} is called a backward non-dominated deviation path of p_{st} on node i.

In order to find a limited number of non-dominated fuzzy paths, limited number of subpaths or temporary labels should be found on each node. The following lemma will be used. The lemma is based on the assumption that all backward deviation paths of node i is non-dominated on p_{it}

Lemma 3.2. *If all backward deviation paths of node i are non-dominated on* p_{it}*, the number of non-dominated fuzzy sub-paths* $p_{si} \in p_{st}$ *need to be searched on each intermediate node i in order to get lexicographical ordered of non-dominated fuzzy paths from s to t is equal or less than k.*

Proof. Let $P_{st} = \{p_{st}^1, p_{st}^2 \ldots p_{st}^n\}$ be a set of all non-dominated paths from s to t, where $p_{st}^1 \leq_{lex} p_{st}^2 \leq_{lex} \ldots \leq_{lex} p_{st}^n$. Let P_k be a subset of P_{st} which contains k ($k \in [1, n-1]$)paths from s to t. Let i be an intermediate node, which contains m ($m \geq k+1$)non-dominated intermediate sub-paths of P_{st}, where $p_{si}^k <_{lex} p_{si}^{k+1}$. Let p'_{it} be the lexicographically smallest non-dominated path from i to t. $p_{st}^k \leq_{lex} p_{si}^k \cup p\prime_{it} \leq_{lex} p_{si}^{k+1} \cup p'_{it}$. The number of non-dominated paths need to be searched on node i is equal to or less than k times. □

The lemma is based on the assumption that backward deviation paths are non-dominated on p_{it}. Based on the above lemma the algorithm searches a maximum of k non-dominated sub-paths (temporary or permanent labels) by lexicograph-ical non-decreasing order on each node. The following lemma guarantees that the paths from s to t are non-dominated by searching only k permanent label on each node.

Lemma 3.3. *The lexicographical smallest non-dominated path p_{st} is searched first when permanence label is searched by lexicographical non-decreasing order.*

Proof. Considering two paths p_{st} and p'_{st} which are non-dominated to each other, where $p_{st} \prec_{lex} p'_{st}$. If p'_{st} is first added as permanent label, then $p'_{st} \prec_{lex} p_{st}$. □

Corollary 3.4. *The first path found from s to t is the lexicographically smallest non-dominated fuzzy path even if only one permanent label is allowed on each node.*

Proof. The proof of corollary is clearly following lemma 2 and Dijkstra's algorithm. When only single label is allowed on each node, the algorithm becomes lexicographical ordered version of Dijkstra's algorithm. Therefore lexicographical smallest non-dominated path could be found.

□

Corollary 3.5. *All the paths from s to t are non-dominated even only k permanent labels are allowed on each node.*

Proof. Assume that p_{st} is lexicographically the smallest fuzzy path founded. According to lemma 2 and Corollary 1, there is no path p'_{st} which makes $p'_{st} \leq_{lex} p_{st}$. Consider the property 2, p_{st} is not dominated by any other p'_{st}. On the other side, any path which is dominated by p_{st} is removed from the result. □

The pseudo-code of fuzzy multipath algorithm is presented in Algorithm 1.

The pseudo-code of fuzzy non-dominance routing algorithm is presented in Algorithm 1.

Algorithm 1 Fuzzy multipath

set path search limitation $LIMIT$
for each v in V **do**
    set fuzzy cost to ∞, set label counter to 0
    set permanent label set to $\emptyset$
end for
Set temporary label set to $\emptyset$
set a pointer $(n,k)_{v,i} = (-1,-1)$ with fuzzy cost $\tilde{c} = (0,0,0,0)$ direct to the root node.
put root pointer to temporary set
while *temporary set* is not empty **do**
    find the temporary label $(n,k)_{v,i}$ with the smallest fuzzy cost according our rules
    remove the label from temporary set and put it to permanent set in v. Add 1 to label counter
    if the set of *permanent set* of v reach $LIMIT$ **then**
        Deactivate node v
    end if
    for each active neighbour v' of v **do**
        Generate a temporary label $(n',k')_{v',i'} = (v,i)v', i'+1$ with fuzzy cost $\tilde{c} + \tilde{c'}$
        Check the dominance relation through all label of v'
        Put the new label into *temporary set* if it is not dominated by current labels of v'
        Deactive any labels of v' which is dominated by $(n',k')_{v',i'}$ and remove them from *temporary set*
    end for
end while
if exist count(v) <LIMIT **then** ▷ this is not compulsory
    RE-SEARCH(DT)
end if

The lines 1-8 are initialisations. In line 9-11, the lexicographical smallest label is chosen. This label will be deleted from the temporary label set and added to a permanent set. Meanwhile the corresponding label counter is accumulated. In line 12-14, if a label counter reaches a pre-decided limit, the corresponding node u will be deactivated and all associated temporary labels will be deactivated. This means the label associated to u would not be selected again and the node u will be not considered as successor anymore. The deactivated labels are temporarily stored in a set for re-search. In the following 5 lines, each neighbour node v' of node v is selected. After the fuzzy cost calculation, the non-dominated new label is added to the temporary set and any label in temporary set, which is dominated by new label, will be deactivated.

The time complexity is largely depends on the total number of temporary labels and the non-dominance checks. The use of path search limitation $LIMIT$ is to bound the convergence time for the network. The dominance check procedure is presented in Algorithm 2. If we require all nodes with non-dominated temporary label to have a minimum of k paths then the re-search procedure will be taken across remaining temporary label sets.

The proof of Algorithm 1 is following Lemma1 and Lemma2 and Lemma3 and corollary 3.4 and 3.5. Here are some remarks on the algorithm: firstly, when the path $LIMIT$ $k = 1$, the algorithm becomes a partially ordered Dijkstra's algorithm, and a lexicographical smallest fuzzy path is found; secondly, the re-search procedure is not essential in order to improve the paths search speed. When $LIMIT$ is set to k, it does not guarantee to find k paths for each node. Finally, when k to is set to a larger value or without a boundary limit, the full non-dominated fuzzy path sets can be found.

There are several improvements can be made on 2. Firstly, the temporary label set can be initially sorted and inserted by non-decreasing order. Then $testLabel$ is not necessary to be compared with existing labels which are greater than $testLabel$. And only labels greater than test label can dominant $testLabel$. In

Algorithm 2 Dominance check procedure

procedure DOMINANCECHECK($testLabel, allLabels$)
    for each $sublabel$ in $allLabels$ **do**
        if $testLabel \succ_{dom} sublabel$ **then**
            $allLabels \leftarrow allLabels \setminus testLabel$
            break
        end if
        if $sublabel \succ_{dom} testLabel$ **then**
            $allLabels \leftarrow allLabels \setminus sublabel$
        end if
    end for
    return $allLabels$
end procedure

addition, the maximum temporary labels for each nodes can be set to k as well to limited the time complexity.

3.4.4 Routing framework

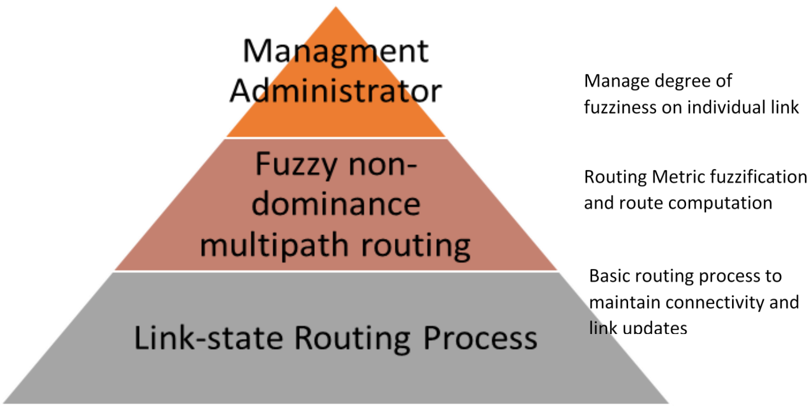


FIGURE 3.8: Fuzzy non-dominance routing framework

The fuzzy non-dominance routing scheme could be implemented independently or based on existing protocols. As Figure 3.8 shown, the structure of fuzzy non-dominance routing is divided into 3 layers. In compatible mode, a conventional protocol could be used to maintain the connectivity and link-state database. A lower layer crisp metric is then mapped into a fuzzy number in the fuzzy routing layer. The control overhead is minimised as only metric variation exceed the maximum fuzziness needs to be advertised.

The upper level of routing framework is management administrator (MA). The main role of the MA is to define range of inaccuracy and fuzziness of neighbour links, to determine the maximum routes for load balancing and QoS constraints. Two MA modes are defined in the framework, includes the centralised management administrator (CMA) and the distributed management administrator (DMA). Under the CMA mode, network traffic, link-state metrics and parameters are collected by single administrative node (a router or centralised server) which providing centralised routing optimisation. The administrator node determines the spreading factor and α-cut of each link, and floods control messages to all other routers in the same area. In distributed management administrator mode, routers in the network assess its local fuzzification factor by predetermined rules, and exchange fuzzification factor with other routers in the same area.

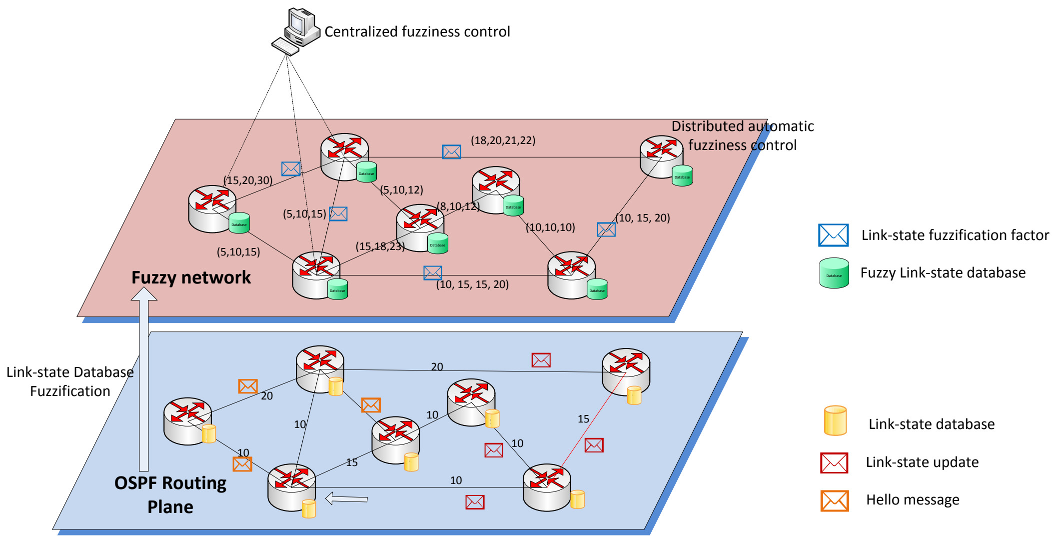


Figure 3.9: Fuzzy non-dominance routing framework: an example on conventional infrastructure network

3.5 System design for simulation

In this section, system model and assumptions for simulations are introduced.

3.5.1 System model and assumptions

The fuzzy non-dominance routing scheme is examined under a rate-based service model in [71]. Under the assumption, the end-to-end delay bound $d(p)$ that the network can guarantee on an n-hop path p is the following form

$$d(p) = \frac{\sigma}{r} + \frac{\Sigma_{l \in p} c_l}{r} + \Sigma_{l \in p} d_l \tag{3.26}$$

Where σ is the size of the flow burst, c_l is a fixed quantity at link l, typically the maximum packet length for the flow, d_l is a static delay value, typically the link propagation delay, and r is the minimal rate that can be guaranteed to the flow at each link along the path. In this work, it is assumed that weighted fair queueing scheduling is used by router [72]. As a result $c_l = c$ can be applied which is the flow's maximum packet size. Thus, for an n-hop path p, the above equation is give by:

$$d(p) = \frac{\alpha_n}{r} + \Sigma_{l \in p} d_l \tag{3.27}$$

where $\alpha_n = \sigma + cn$, n is the number of hops from source to destination.

The major benefit of the rate-based model is that, under such circumstance the available bandwidth is considered as main parameter to guarantee the network end-to-end delay.

3.5.2 Fuzzy numbers

Trapezoidal and triangular fuzzy numbers are used for FNDR metrics. This work defines following types of fuzzy numbers.

The unit random trapezoidal fuzzy number is give by:

$$\begin{aligned} m_l &= c * rand(0,1) \\ a &= 1c + c * rand(0,1) \\ b &= 2c + c * rand(0,1) \\ m_r &= 3c + c * rand(0,1) \end{aligned} \tag{3.28}$$

Where $rand(0,1)$ is a random number between $(0,1)$. c is a constant. This function is used to generate completely randomised trapezoidal fuzzy numbers.

The triangular fuzzy number with spreading factor is give by

$$\begin{aligned} m_l &= a * (1 - C(0,1) * r) \\ a &= b = cost \\ m_r &= b * (1 + C(0,1) * r) \end{aligned} \tag{3.29}$$

where the cost is the initial crisp cost of the link. r is the spreading factor in the interval $[0,1]$. A larger value of r represents a greater grade of fuzziness. The $C(0,1)$ is a constant or uniform distributed random value in the interval $[0,1]$.

The trapezoidal fuzzy number with random spreading factor is given by

$$\begin{aligned}
m_l &= a - cost * r_s * C(0,1) \\
a &= cost * (1 - r_f * C(0,1)) \\
b &= cost * (1 + r_f * C(0,1)) \\
m_r &= b + cost * r_s * C(0,1)
\end{aligned} \tag{3.30}$$

Where $m_l > 0$. r_s and r_f is LR and flat spreading factor in the interval $[0, 1]$. A larger value of r_s represents a greater grade of fuzziness on the left and right spreading. A larger value of r_f represents greater grade of fuzziness on the centre value. The $C(0, 1)$ is a constant or uniform distributed random value in the interval $[0, 1]$.

3.5.3 Topology models

The network topologies used by this work are generated according to the Doar-Leslie's graph model. This model is an extension version of Waxman's random graph model. Compare to Waxman's Model, Doar-Leslie's model allows graph generator to generate network with the desired node degree. This is important for this work to test the route discovery function of FNDR within different level of link-density.

In the original Waxman's model, the probability of an edge from u to v is given by

$$P(u, v) = \alpha * e^{-d/\beta L} \tag{3.31}$$

Where L is the maximum distance between two nodes, and α and β are two parameters in the interval $(0, 1]$. A larger value of α leads to higher link densities, meanwhile small values of β increase the density of short links relative to longer ones. [73]. In the Doar-Leslie's graph model, a factor $k\epsilon/n$ is applied. Where the ϵ is the desired average node degree, n is the number of nodes and k is a constant. The Doar-Leslie's model is given by:

$$P(u,v) = \frac{k\epsilon}{n}\alpha * e^{-d/\beta L} \tag{3.32}$$

In order to generate graphs with preferred degree, the graphs used by works are generated by following algorithm.

Algorithm 3 Topology generation

```
generation nodes positions
input desired average node degree ε;
initialize average degree degree = 0;
initialize constant k = 0.5;
while degree ≤ ε do
    for each nodes peer do
        Calculate the edge probability by P(u,v) = (kε/n) α * e^(−d/βL);
    end for
    calculate degree;
    k = k + 0.1;
end while
return Graph
```

The constant k is increased by 0.1 for each iteration until graph reach desired average degree. An example of generated graph with 100 node and average degree of 4 is shown in the Fig.3.10

3.5.4 Simulation platforms

The Matlab and OPNET Modeler are used together for the simulations. The Matlab is used for initial routing discovery algorithm as it is a powerful tool for graph and matrix operations. The project then partially migrated to OPNET

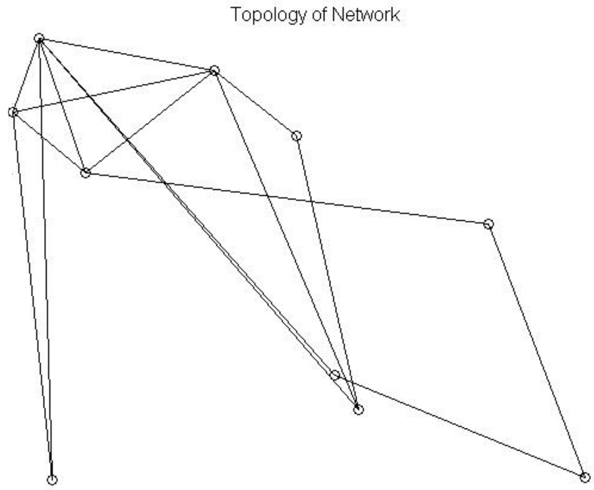


Figure 3.10: Example random topology

Modeler to benefit from its built-in QoS and Cisco Routing API. The OPNET Modeler is used to simulate OSPF QoS and routing convergence process.

A time-driven network simulator based on Matlab is developed for simulation process. The general processes of Matlab simulator is shown in the Figure 3.11

A simulation based on OPNET Moderler 14.5 is also implemented. The simulation process and models designs are in the Appendix.

3.6 Summary

This chapter introduced main ideas and algorithms of fuzzy non-dominance routing. The important fuzzy arithmetics approaches were reviewed with remarks. The novel principles, ideas, and the algorithms of FNDR were given in the third and the fourth section. The chapter introduced system design and simulation platform as well.

In the next chapter, results of fuzzy non-dominance routing in route finding are presented and discussed.

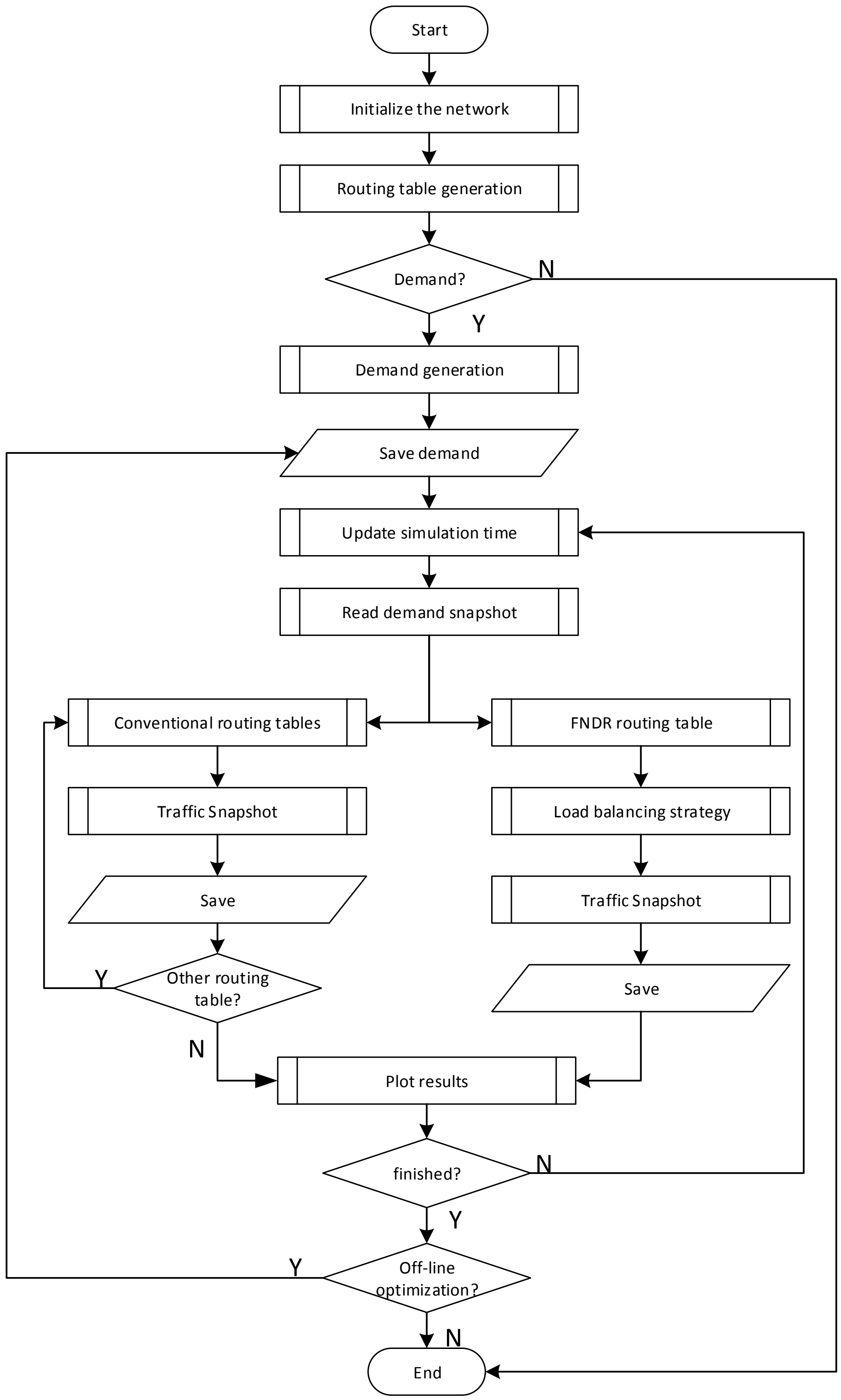


Figure 3.11: Flowchart of the Matlab simulation

Chapter 4

Fuzzy Non-dominance Routing Discovery

4.1 Introduction

In this chapter, the approaches described in the Chapter 3 are implemented and compared against previous works. This chapter aims to explore and discuss the most fundamental route finding results of fuzzy non-dominance routing. The initial results are extended by considering network topology and scales, fuzzy number designs, the grade of fuzziness and different α-cut levels. The testing covers the time-complexity performance of the k non-dominance algorithms as well.

In this chapter, it is assumed that all the metrics in the network are inaccurate. The random grade of fuzziness is applied to the entire network. In the real practice and the network optimisation, it is not necessary to apply fuzzy number into entire networks as it leads to exceptional high volume of non-dominance routes and computational overhead. However, this chapter aims to explore and discuss the non-dominance route finding and the impact of the topologies and fuzzy number designs on routes finding outcomes. Therefore, random fuzzy metrics are applied to networks.

Three real networks AT&T, Sprint North America core network and EU Géant core network are used in this Chapter to examine the performance of the FNDR. These network are with different topologies and average degrees. The Sprint North America core network and EU Géant network are generated with the real geographical information.

4.2 Initial results

The basic route searching is demonstrated by a simple network with 6 nodes and 8 directed arcs (See Fig. 4.1). This simple scenario is used to demonstrate the routing algorithm. In this scenario, the fuzzy metrics are randomised and the lexicographical ordering is applied for demonstrating. The label limitation k is set to unlimited. This means all non-dominated routes will find by router. The initial results demonstrate the route searching from the source node 1 step by step.

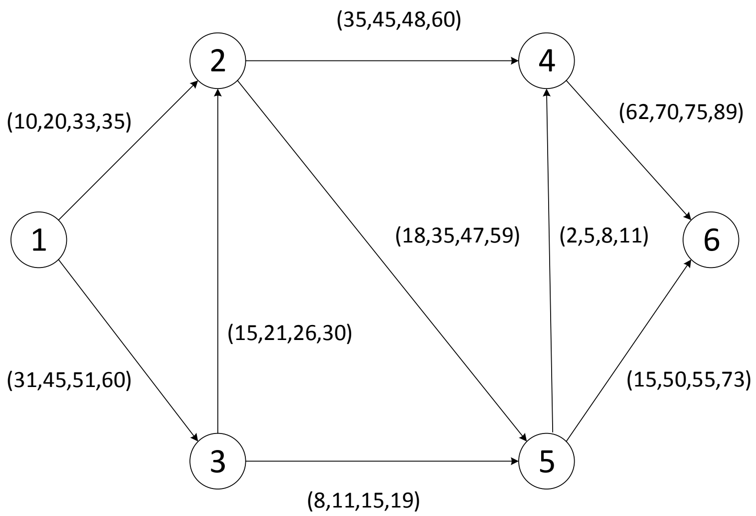


FIGURE 4.1: Initial result network topology

TABLE 4.1: Initial result on lexicographical ordering

label	node 1	node 2
1	$[(0,0,0,0)(-,-)]^{p1}$	$[(10,20,33,35)(1,1)]^{p2}$
2		$[(46,66,77,90)(3,1)]^{d}$
label	node 3	node 4
1	$[(31,45,51,60)(1,1)]^{p5}$	$[(45,65,81,95)(2,1)]^{d}$
2		$[(30,60,88,105)(5,1)]^{p4}$
3		$[(41,61,74,90)(5,2)]^{p7}$
label	node 5	node 6
1	$[(28,55,80,84)(2,1)]^{p3}$	$[(43,105,135,167)(5,1)]^{p8}$
2	$[(39,56,66,79),(3,1)]^{p6}$	$[(92,130,163,194),(4,2)]^{d}$
3		$[(54,106,121,152),(5,2)]^{p9}$
4		$[(103,131,149,179),(4,3)]^{d}$

From the initial step, the fuzzy cost $[(0,0,0,0)]$ with a temporary label (-, -) is assigned to the source node 1. This label is then marked as permanent label. In the next step, node 2 and 3 are assigned new temporary labels with costs and labels $[(10,20,33,35)(1,1)]$ and $[(31,45,51,60)(1,1)]$ respectively.

In the next step, the first label of the node 2 is set to permanent as it is the lexicographically smallest temporary label in the poll. From the node 2, two new temporary labels on the node 4 (first) and the node 5 (first) are set. Then the first label of the node 5 becomes lexicographically smallest temporary label and marked as a permanent label. Two labels on the node 4 and 6 with cost $[(30,60,88,105)(5,1)]$ and $[(43,105,135,167)(5,1)]$ are then being set from node 5 respectively. In the following dominance check, the first label of the node 4 is dominated by the second one. The label is marked as dominated label. Then the iteration continued until the pool of temporary labels becomes empty. Finally, two routes from node 1 to node 6 $p1 = 1 \longrightarrow 2 \longrightarrow 5 \longrightarrow 6$ and $p2 = 1 \longrightarrow 3 \longrightarrow 5 \longrightarrow 6$ are founded. The rest labels are dominated by these two labels.

The performance of the proposed fuzzy non-dominance routing scheme is initially tested on the AT&T north American network with 25 nodes and 52 arcs. The initial testing is to examine the route searching of FNDR.

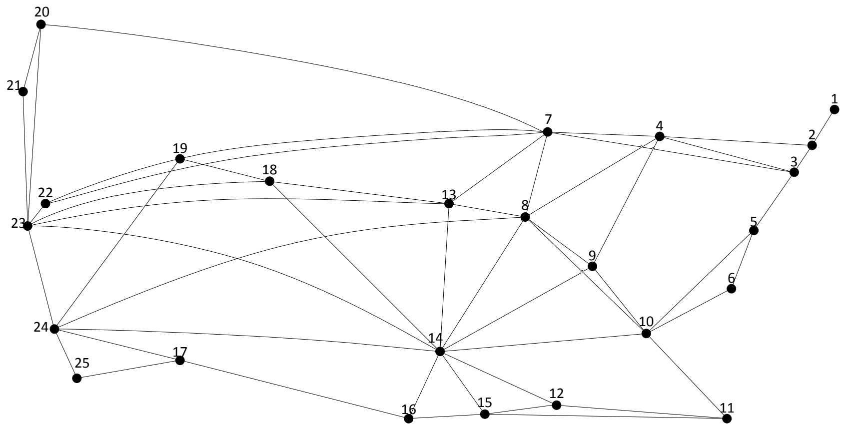


FIGURE 4.2: AT&T American network, 25 nodes with 52 arcs

During the test, all links between each node are assumed to have the same bandwidth. Trapezoidal fuzzy metrics are applied. The link metrics $(m_l, a, b, m_r)_{LR}$ are generated following standard unit trapezoidal fuzzy number with the constant $c = 50$:

$$\begin{aligned} m_l &= 50 * rand(0,1) \\ a &= 50 + 50 * rand(0,1) \\ b &= 100 + 50 * rand(0,1) \\ m_r &= 150 + 50 * rand(0,1) \end{aligned} \tag{4.1}$$

The α-cut of each link is set to 0. There is no limitation on the maximum labels k on each node. Besides, each link has a unit OSPF cost of 100 for comparison. The result of a single test of route searching outcome between node 1-23 is shown in the table 4.2. This table gives specific non-dominated routes and their associated cost. For example, the route 1 from node 1-23 has a fuzzy cost of (121,495, 791, 1062). The path of this route is 1 — 2 — 3 — 4 — 8 — 13 — 23.

TABLE 4.2: Result of path finding on the AT&T North American network

No.	Path cost from node 1 to 23	Non-dominated Paths
1	(121,495,791,1062)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 4 \longrightarrow 8 \longrightarrow 13 \longrightarrow 23$
2	(131,484,885,1217)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 5 \longrightarrow 10 \longrightarrow 14 \longrightarrow 18 \longrightarrow 23$
3	(133,441,801,1086)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 4 \longrightarrow 8 \longrightarrow 14 \longrightarrow 23$
4	(140,394,759,1105)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 5 \longrightarrow 10 \longrightarrow 14 \longrightarrow 23$
5	(141,418,666,888)	$1 \longrightarrow 2 \longrightarrow 4 \longrightarrow 8 \longrightarrow 13 \longrightarrow 23$
6	(146,364,656,831)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 7 \longrightarrow 22 \longrightarrow 23$
7	(161,386,629,877)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 7 \longrightarrow 20 \longrightarrow 23$
8	(166,371,664,810)	$1 \longrightarrow 2 \longrightarrow 4 \longrightarrow 7 \longrightarrow 22 \longrightarrow 23$
9	(173,386,639,853)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 7 \longrightarrow 13 \longrightarrow 23$
10	(181,394,638,858)	$1 \longrightarrow 2 \longrightarrow 4 \longrightarrow 7 \longrightarrow 20 \longrightarrow 23$
11	(191,473,744,996)	$1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 7 \longrightarrow 20 \longrightarrow 21 \longrightarrow 23$
12	(192,394,648,834)	$1 \longrightarrow 2 \longrightarrow 4 \longrightarrow 7 \longrightarrow 13 \longrightarrow 23$
OSPF	(—-,—-,—-,—-)	$1 \longrightarrow 2 \longrightarrow 4 \longrightarrow 8 \longrightarrow 24 \longrightarrow 23$

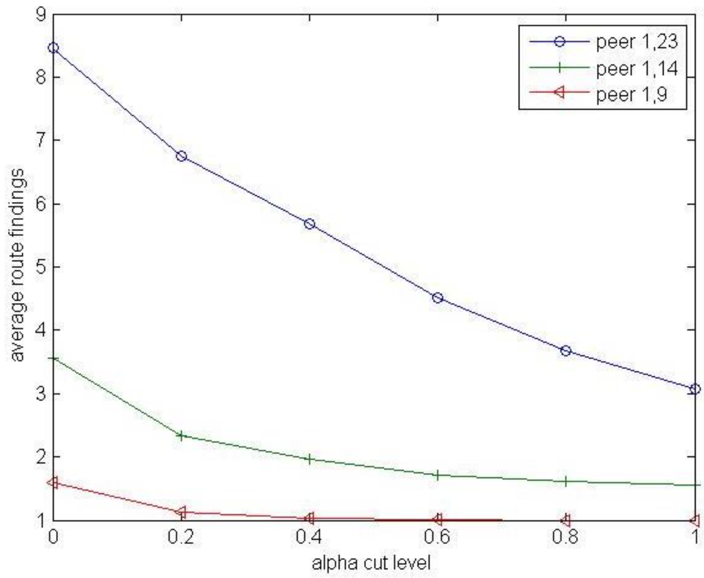


Figure 4.3: Result of path finding with different α-cut levels

The link metrics is this test are randomised generated. In a single test there are 12 routes in total that found between nodes 1-23. All these routes are non-dominated between each other. If the cost is associated with physically meaningful link metrics like bandwidth and delay, the non-dominated multipath can be used for load balancing of the network traffic.

The effect of α-cut on fuzzy route searching is also considered. 6 levels of α cut on each link are tested in the initial scenario. From 0 to 1, a link associated with lower α-cut has a higher grade of fuzziness. Three peers with different distance are selected. Simulation is running 1000 times to obtain the mean non-dominance routes on each peer by a given link α-level cut value. Figure 4.3 shows that the number of non-dominated routes decreased with the growing of α-cut levels. The higher level α-cut leads to a higher grade of fuzziness. More non-dominated routes are founded when link metrics have a smaller α-cut. The result shows that α-cut designs have a significant impact on the total number of routes. The number of total routes also depends on the distance between the peers. Two nodes separated by long distance tend to have more non-dominated routes between them. In large scale networks, the set of non-dominated routes between two long distance peers can be very large. Therefore, it is necessary to limit the maximum number of temporary and permanent labels on the each node.

In the next section, FNDR is tested on different network topologies and scales.

4.3 Test on different network topology and scales

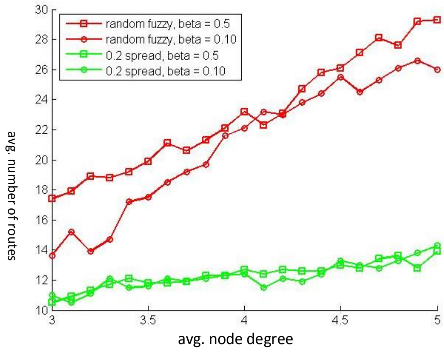
In the previous section, some initial testing results were introduced. In this section, FNDR is tested within different network topologies and scales. The Doar-Leslie's model is used to generate network with different scales and average node degrees. The average node degree shows the link-density of a network. For given bi-direction graph $G = (V, E)$, the average node degree can be calculated by

$$\sum_{(v)\in V} deg(v) = 2|E|/V \tag{4.2}$$

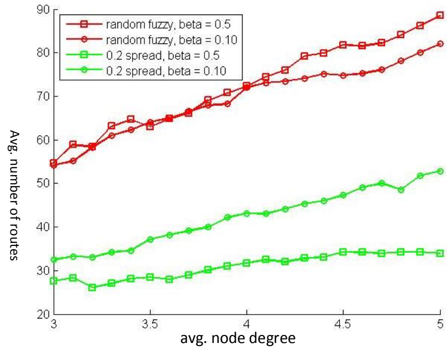
Where V is the number of vertices, E is the number of edges.

The Dora-Leslie's model was introduced in Chapter 3.5.3. The density of the connection is increased with the network degrees and the value of β determines the ratio of short and long connections. According to [74], the value of α is set to 0.1 initially. The β is set to 0.1 and 0.5 respectively in each test in order to examine the result with different topologies.

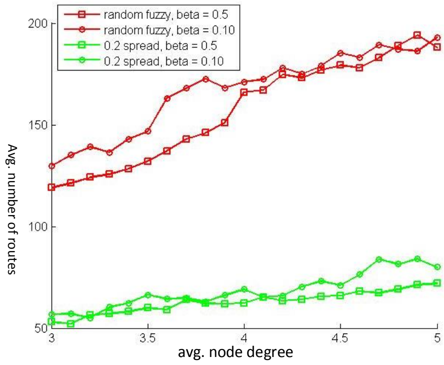
In this experiment, 4 different scenarios with 10, 25, 50 and 100 nodes are tested in order to examine the total number of non-dominance routes (permanent labels) in different network scales. The location of the nodes is randomly distributed across the network. 5 random topology seeds are generated for each test and each topology are tested for 10 times in order to get an average number of permanent



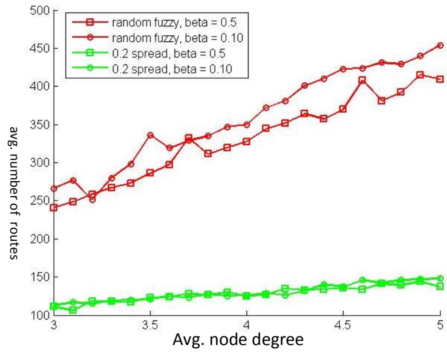
(A) random network with 10 nodes



(B) random network with 25 nodes



(C) random network with 50 nodes



(D) random network with 100 nodes

FIGURE 4.4: Total numbers of permanent labels for each node

labels. The standard triangular fuzzy number and triangular fuzzy number with a spreading factor of 0.2 are used for comparison. The distance between nodes are used as the *cost* value of fuzzy numbers. The results are shown in the fig 4.4

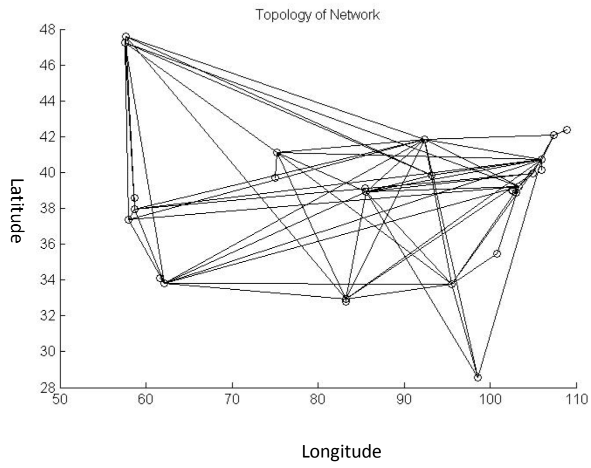
The result shows that the total number of permanent labels has increased with the growth of the network link density (average node degree). The higher network degrees introduce a higher degree of redundancy into the network. However, the ratio of short and long edges does not have a significant impact on the average numbers of permanent labels that found by each node. Compare to the triangular fuzzy number with 0.2 spreading factor, the permanent label outcomes of the standard triangular fuzzy numbers have a greater rate of growth.

The Doar-Leslie's model focus only on the link generation. The physical location of nodes in the previous test is randomly distributed across the network. However, in the real practice, network designers are usually constrained on node locations. For example, the node location of any major ISP is guided by economic conditions (e.g. major cities) and policy decisions (e.g. coverage requirements) and plays a dominant role in the resulting network topology. Therefore, two real ISP core networks are introduced. The above results can be compared with these two real networks: the Sprint North America network and the EU Géant Network (See. Fig.4.5). These two networks cover major cities in the North American and Europe. The nodes and links are generated according to their real geographic locations and logical topologies. In these test, the distance between nodes are chosen as the link cost.

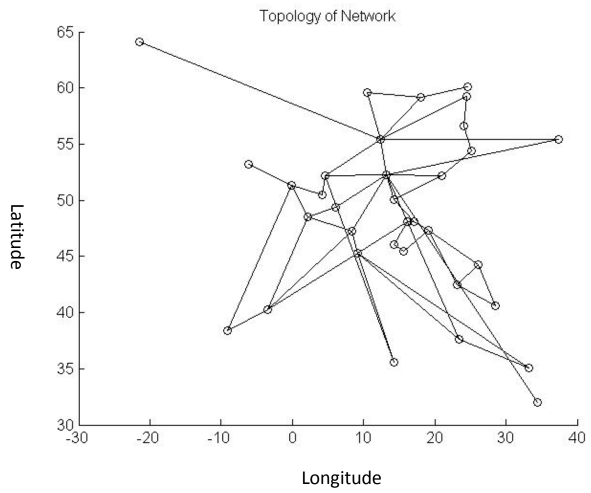
The Sprint Core network has 27 nodes and 68 links. The average node degree is 5.04. The EU Géant Core network consists of 34 nodes with 51 links. The average node degree is 3. The Sprint core network shows a higher link density than EU Géant core network. However, the tests demonstrate similar results to the random networks by Doar-Leslie's model.

The test is repeated with 20 random seeds on each topology to get average values. The Sprint core network had an average of 95 and 54 permanent labels found with the unit fuzzy and 0.2 spreading scheme respectively. The Géant network has 67.4 and 38.8 permanent labels found with the unit random fuzzy and 0.2 spreading scheme respectively. The results match to the random network with 25 nodes closely.

Overall results show that the total number of permanent labels increased with the growth of the link density and network scales. The degree of redundancy results a higher grade of fuzziness. However, the ratio of short and long links does not have a significant impact on the result. The next section will examine the impact of the grade of fuzziness on route findings.



(A) US Sprint Core Network



(B) EU Geant Core Network

Figure 4.5: Sprint and Geant core network

4.4 Test on fuzzy metrics designs

The last section discussed how network scales and topologies affected the results of FNDR route findings. This section focus on the design of the fuzzy number metrics. The section explores and discusses how FNDR route finding outcomes could be affected by different fuzzy number designs. Tests focus on the total number of the permanent labels firstly, then move on to the number of peer to peer routes. The results are compared with unit equal-cost multipath routing.

Table 4.3: Testing results on US Sprint and EU Geant Network

	Sprint Core Network	EU Geant core network
num. of nodes	27	34
num. of edges	68	51
avg. degree	5.04	3
unit random		
avg. P labels	95	67.4
maximum P labels	114	48
minimum P labels	82	83
0.2 spreading		
avg. P labels	54	38.8
maximum P labels	69	35
minimum P labels	44	43

4.4.1 Permanent labels results

The number of permanent labels is the number of the total routes (entire routing table) of a single node to all nodes across the entire network. This section discusses how the grade of fuzziness affects the total number of permanent labels finding by FNDR.

The Doar-Leslie's model is used to generate random network. The value of the β is set to 0.4 to generate relative larger sets of redundant routes. 50 nodes are randomly distributed across the network. As typical networks have an average degree from 3 – 10, two scenarios with average degree of 4 and 8 are generated to be tested. 5 random topology seeds are tested for 10 times each to get the average number of permanent labels.

The trapezoidal fuzzy number with random spreading factor is used.

$$
\begin{aligned}
m_l &= a - cost * r_s * rand(0,1) \\
a &= cost * (1 - r_f * rand(0,1)) \\
b &= cost * (1 + r_f * rand(0,1)) \\
m_r &= b + cost * r_s * rand(0,1)
\end{aligned}
\tag{4.3}
$$

where $m_l > 0$. r_s and r_f is spreading factor in the interval $[0,1]$. A larger value of r_s represents a greater grade of fuzziness on the left and right spreading of trapezoidal fuzzy numbers. A larger value of r_f represents greater grade of fuzziness on the core centre value where the fuzzy number's grade of fuzziness is 1. When $r_f = 0$, the fuzzy number becomes a triangular fuzzy number. The $rand(0,1)$ is a uniform distributed random value in the interval $[0,1]$. The distance between nodes are used as the cost.

The results are shown in the following figures.

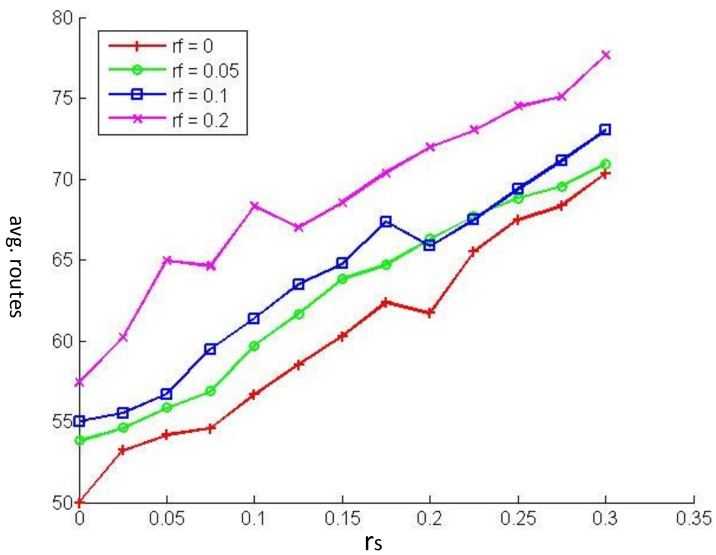


FIGURE 4.6: Test on grade of fuzziness: 50 nodes, avg. degree = 4

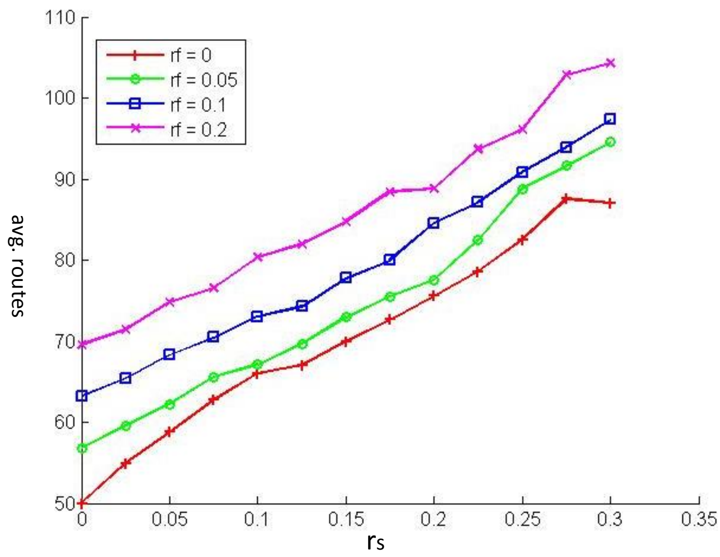


Figure 4.7: Test on grade of fuzziness: 50 nodes, avg. degree = 8

The result in fig. 4.6 and fig. 4.7 shown that the total number of permanent labels is increased with the growth of the grade of fuzziness. A larger value of spreading factor r_s and r_f leads to greater grade of fuzziness. Compare to the triangular fuzzy number where $r_f = 0$, the trapezoidal fuzzy number with $r_f = 0.2$ has on average 20 more routes found. The random network result could be compared to the testing result in the Sprint core network.

The results in fig.4.8 show the average number of total routes found over 5 random cost seeds. The figure gives both average value and the maximum and the minimum boundary values. Compare to the random network generated by Doar-Leslie's model, it gives a similar trend. Although the bars showing the variation are fairly large, considering the individual results that go to make up the average (See Figure 4.9), it can be seen that in each case the trend of permanent labels growth obtained through FNDR is similar; however, the larger grade of fuzziness causes a higher degree of randomness.

Because of this, during the fuzzy metrics design, the higher grade of fuzziness should be applied carefully to the network in order to achieve performance gains. The higher grade of fuzziness leads to a large routing table. It is necessary

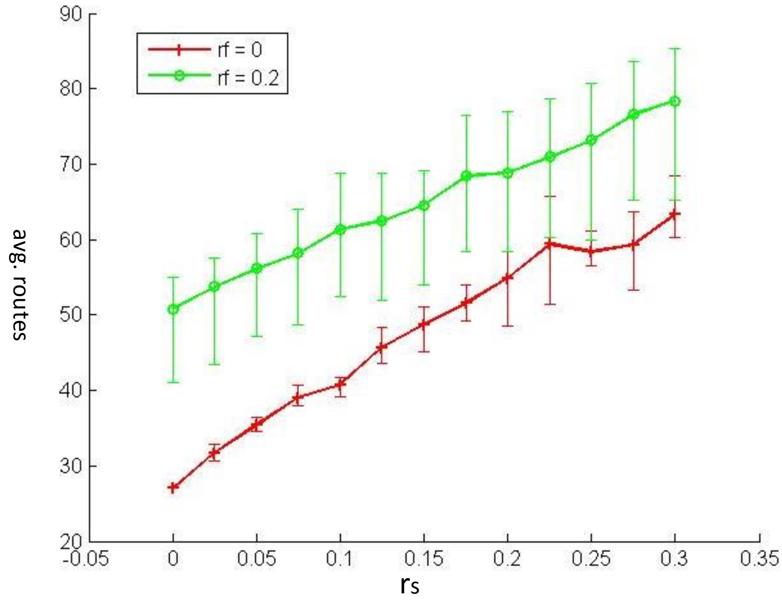
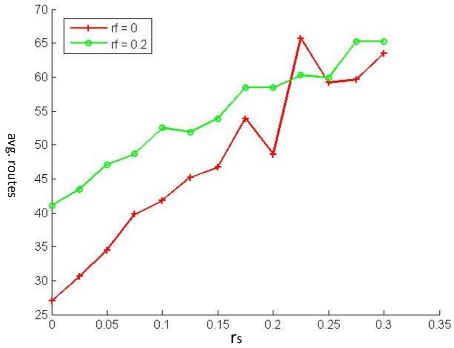


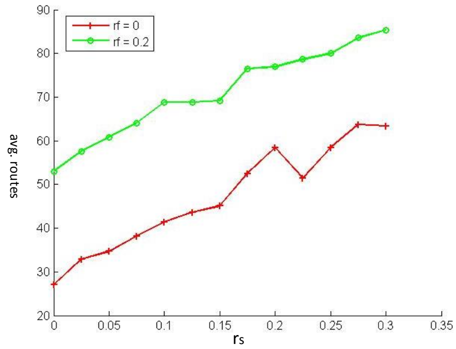
FIGURE 4.8: Test on grade of fuzziness: Sprint Core Network

to limit the maximum grade of fuzziness of metrics in order to manage and optimise the network performance. The details of the applying α-level cut and k non-dominance routes are discussed in the 4.5 and 4.6.

The number of permanent labels gives only the total number of routes from a node to all nodes across the network. The next section examines the number of the total routes between the peers.



(A)



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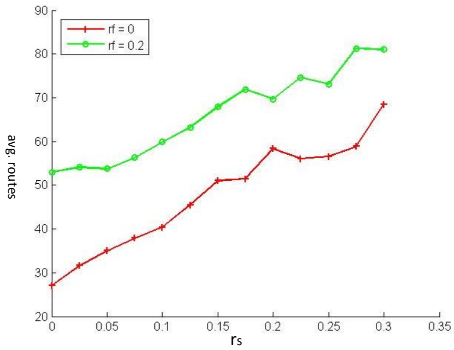

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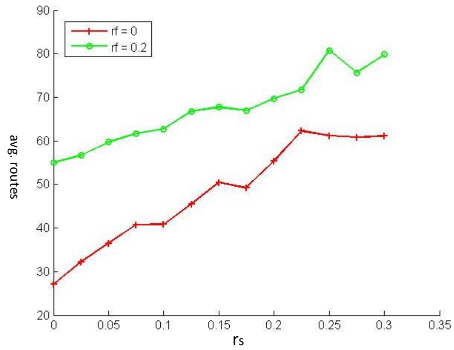
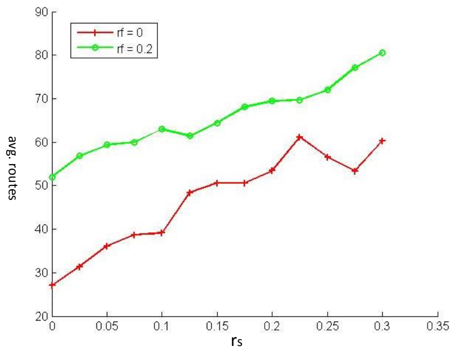


(D)



(E)

FIGURE 4.9: The result making up the result in Fig.4.8

4.4.2 The number of routes between the peers

This section examines the how grade of fuzziness of fuzzy number designs affect the number of routes between the peers. The Sprint North America core network is used for this test. The results are compared with the equal cost multipath routing. For each network, node 1, and the largest numbered node and a middle node (i.e., node 27, node 13 for the Sprint Core Network), are considered to be the source node and the destination node, respectively.

50 random seeds are applied to each test in order to generate the average results. Two levels of r_f are selected for the test. The results are shown in the fig.4.10 and fig.4.11. The table 4.4 and the table 4.5 give the complete test results.

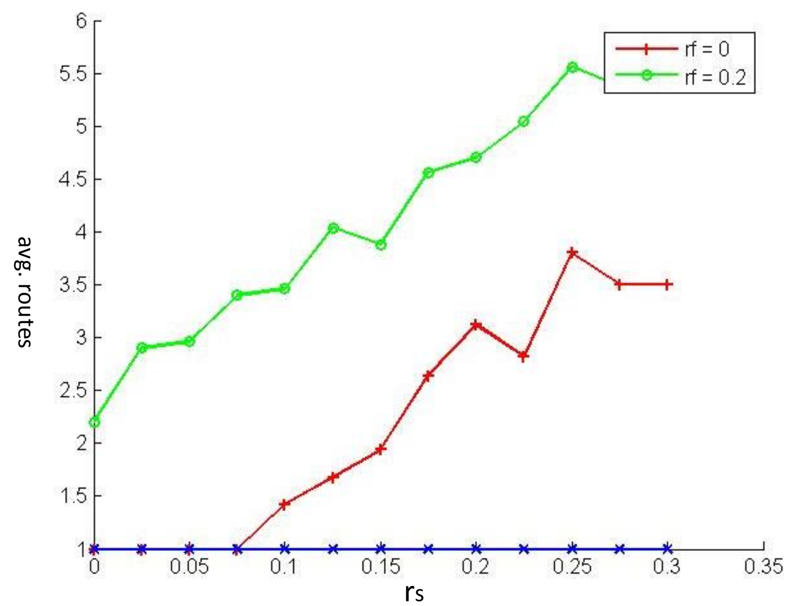


FIGURE 4.10: Test on grade of fuzziness: Sprint core network peer 1-27

The fig.4.10 result shows that the number of routes between peers are increased with the growth of the grade of fuzziness. The table 4.4 gives the complete results. The number of routes between peer 1 and 27 is increased with the growth of the r_s and r_f.

TABLE 4.4: Test on grade of fuzziness: Sprint core network peer 1-27

r_f \ r_s	0	0.05	0.1	0.15	0.2	0.25	0.3
0	1.00	1.00	1.42	1.94	3.12	3.80	3.50
0.05	1.00	1.04	1.62	2.58	3.14	3.50	3.26
0.1	1.20	1.38	1.81	2.58	3.40	4.04	3.84
0.15	1.80	1.90	2.44	3.18	4.00	4.40	4.74
0.2	2.20	2.96	3.46	3.88	4.70	5.56	5.72
equal cost	1.00	1.00	1.00	1.00	1.00	1.00	1.00

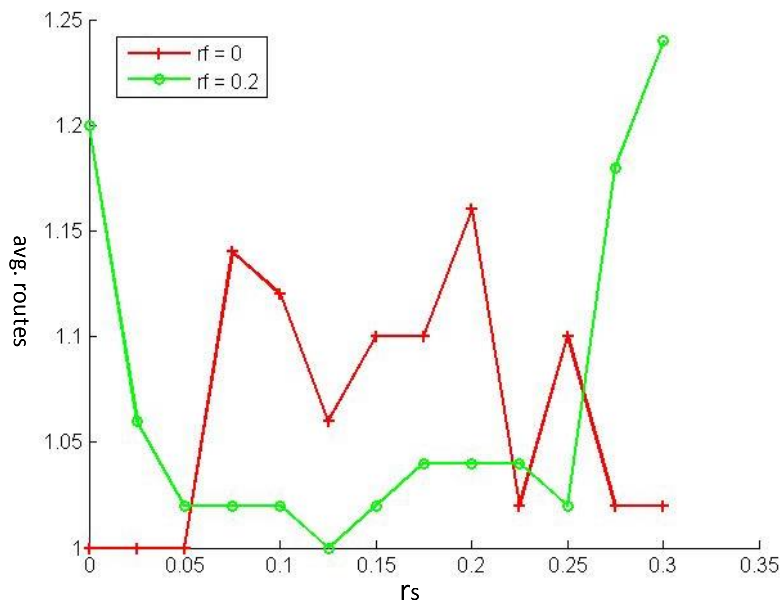


FIGURE 4.11: Test on grade of fuzziness: Sprint core network peer 1-13

However, in the middle point (as shown in the fig. 4.11 and table 4.5), peer routes do not give the similar trend as the end peers 1-27. The unit equal-cost multipath gives 3 routes between nodes 1 and 13. But actually all of these 3 routes have higher distances than non-dominance routes (see table 4.6). Actually the peer 1 and 13 has few redundant routes with similar costs. This is the reason leads to result in the fig. 4.11.

Generally, the greater grade of fuzziness in fuzzy number designs leads to more routes to be founded between peers. However, it relies on the redundant routes

TABLE 4.5: Testing results on US Sprint network: peer 1-13

	r_s						
r_f	0	0.05	0.1	0.15	0.2	0.25	0.3
0	1.00	1.00	1.12	1.10	1.16	1.10	1.02
0.05	1.20	1.06	1.12	1.06	1.10	1.08	1.06
0.1	1.00	1.12	1.12	1.16	1.08	1.04	1.10
0.15	1.00	1.16	1.10	1.02	1.10	1.08	1.08
0.2	1.00	1.00	1.00	1.02	1.02	1.10	1.14
equal cost	3.00	3.00	3.00	3.00	3.00	3.00	3.00

TABLE 4.6: Compare the route costs of peer 1 and 13

	route	cost
unit equal cost		
1	1 – 14 – 13	3614
2	1 – 15 – 13	3446
3	1 – 10 –13	3390
fuzzy non-dominance		
1	1 – 2 – 8 – 13	(1744,2360,2644,2927)

with similar cost as well.

In order to apply fuzzy metrics to the network optimisation, α-cut is introduced as a tool to manage the grade of fuzziness of the individual link. The next section discusses the effect of applying α-cut into FNDR.

4.5 Applying α-cut

α-cut is used as a tool to manage the grade of fuzziness of the fuzzy metrics. This test examines how α-cut levels affect the route searching results.

It is suggested to apply different level of α-cut to the individual link in order to optimise the network performance. However, in this test the same α-cut level is applied to the entire network. Both total permanent labels and number of routes between peers are examined.

The Sprint North America core network and EU Géant network are used in this section for testing. The trapezoidal fuzzy number with random core-spreading factor $r_f = 0.1$ and LR-spreading factors $r_s = 0.1$ and 0.3 are tested. 500 random seeds are applied to each topology to get the average value. The different α-cut levels in the interval $[0, 1]$ are applied to the test.

The fig. 4.12 and fig.4.13 give the results in the Sprint core network.

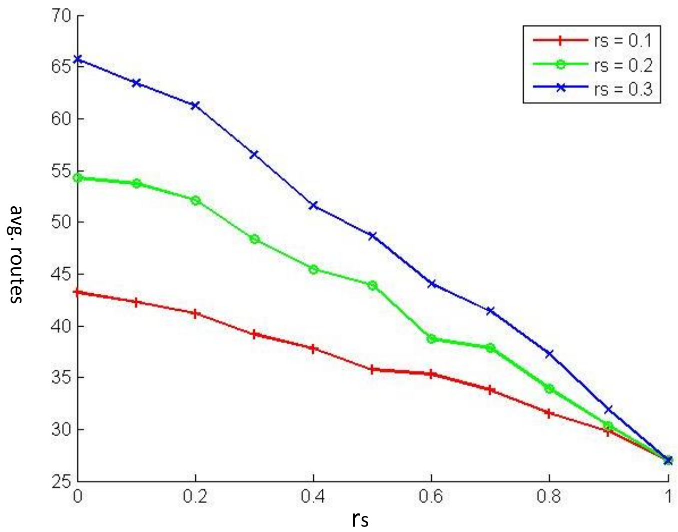


FIGURE 4.12: Test on α-cut levels: Total permanent labels of Sprint core network

The number of total permanent labels is decreased linearly with the decay of the α-cut levels. The total permanent labels decreased from 65.7 to 54.3 and 43.2 to 27 respectively. The grade of fuzziness decreased with decay of the α-cut levels. When α-cut $= 1$, triangular fuzzy metric is transformed in to the crisp number and its cost equals to the core of the fuzzy set which is a crisp cost in this scenario. As a result FNDR performs like a conventional shortest path algorithm. The peers route between node 1 and 27 is subject to decay as well. The result can be compared with the EU Géant core network which has a smaller average degree than Sprint core network.

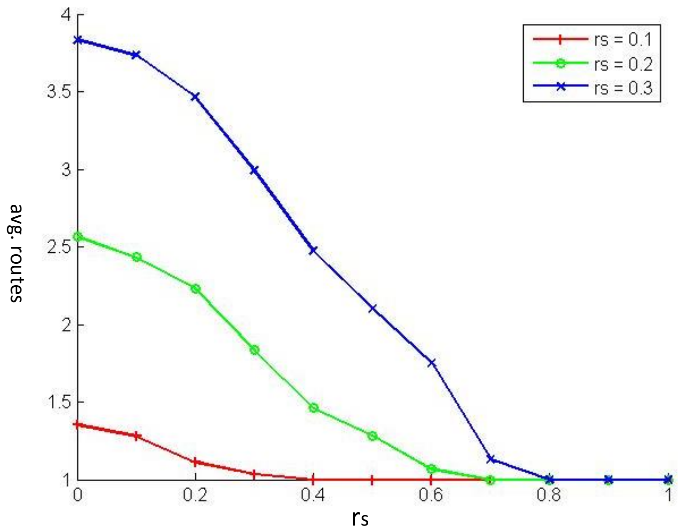


FIGURE 4.13: Test on α-cut levels: Average number of routes between peer 1 -27 of Sprint core network

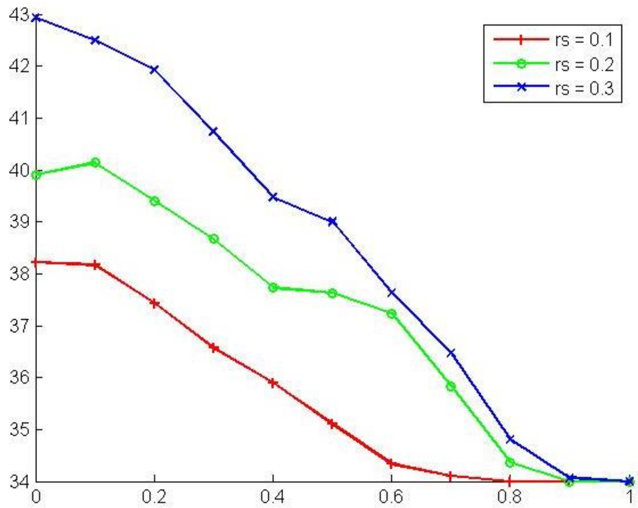


FIGURE 4.14: Test on α-cut levels: Total permanent labels of Géant core network

The results (See Figure 4.14 and Figure 4.15) of Géant core network show a similar trend to the Sprint core network. However, Géant core network has a smaller average degree than Sprint core network. Due to its poor redundancy, the results show a greater randomness. However, this is cause by using random

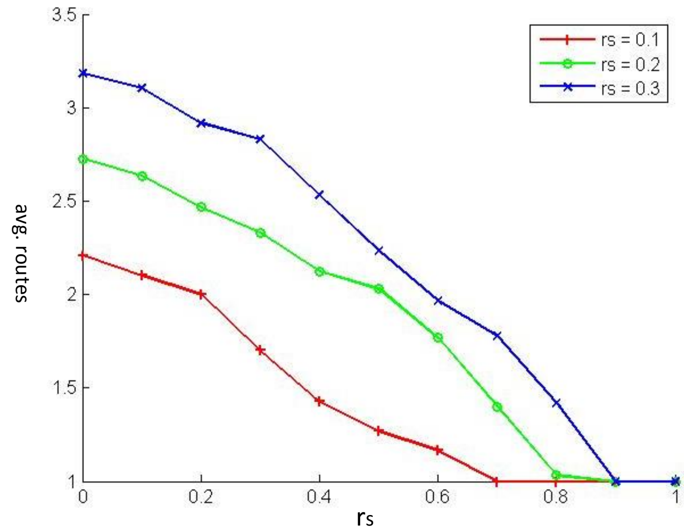


FIGURE 4.15: Test on α-cut levels: Average number of routes between peer 1 -27 of Géant core network

seeds and random fuzzy metrics. With proper design, the randomness can be eliminated.

4.6 Algorithm performance

The k non-dominance routing is tested in this section in order to evaluate the algorithm performance. This test will firstly focus on the running time optimisation. In the second part, the route searching results are examined.

4.6.1 Running time optimisation

The performance of the algorithm depends on the total numbers of the temporary labels that founded by each node. From one aspect, without a label limitation k, algorithm needs to examine every non-dominated temporary labels in the queue. In each iteration, with each arrival of a new temporary label, a dominance check process across all temporary and permanent labels is compulsory to make sure dominated labels can be deleted.

In the first test, the impact of node degree is considered. Random topologies with 20, 50, 100 and 150 nodes with node degree of 4 −10 are tested in order to get normalised running time. The larger set of nodes is leading to complex topology that takes longer running times. The standard unit trapezoidal fuzzy number with the constant $c = 50$ is applied to the test. For each scenario, 5 topology are tested for 10 times each in order to get the average running time. Three k levels $k = 1$, $k = 3$ and $k = unlimited$ are tested. The normalised running time is given by:

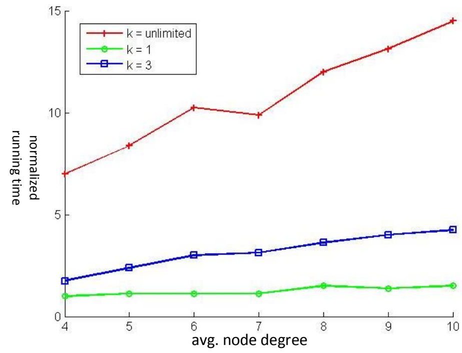
$$CPUtime(x)/(CPUtime(degree = 4, k = 1))$$

The results are shown in the fig. 4.16

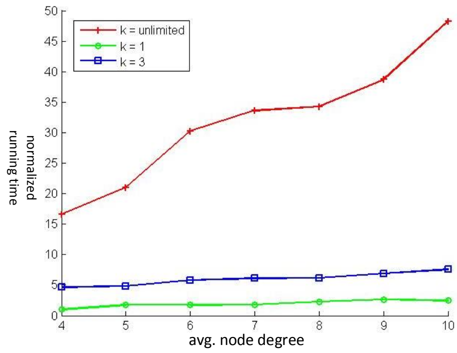
The average running time are increased with the growth of the average node degrees. However, by applying label limitation k into the algorithm, the time complexity performance are significantly improved. The Figure 4.17 and Figure 4.18 give the results of time performance according to the network scales.

When applying FNDR to large scale networks, the running time growth exponentially with the scales of the network. Figure 4.19 gives the normalised running time when the total number of nodes equals to 150. The normalised running time is growing with the increment of the label limitation k. It is noticeable that the normalised time performance of the k non-dominance routing has at the most 25 times better than the result with $k = unlimited$ (see Figure 4.19).

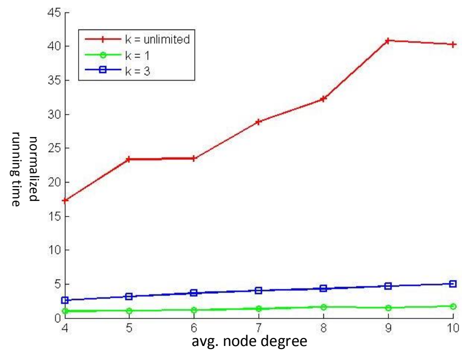
By applying k equals to 10, the maximum number of permanent labels could be founded and applied for each destination are 10. However, in the above scenario, the algorithm still performs on average 2.5 times faster than results that without label limitation k. Therefore it is suggested that k should be applied to large scale network for better performance.



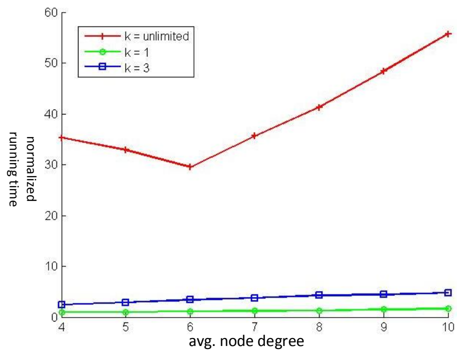
(A) node = 20



(B) node = 50



(C) node = 100



(D) node = 150

FIGURE 4.16: Normalised running time by applying k into algorithm

4.6.2 α-cut running time optimisation

The α-cut level could affects the FNDR running performance by limiting the grade of fuzziness of link metrics. α-cut levels optimise time performance by reduce the grade of fuzziness across the network. Random topologies with 25, 50, 100 and 150 nodes with node degree of 6 are tested. This is to validate α-cut running time optimisation in different network scales in order to get normalised running time. The normalised running time is given by

$$runningtime(\alpha(x))/runningtime(\alpha(1.0))$$

The results are shown in the fig. 4.20

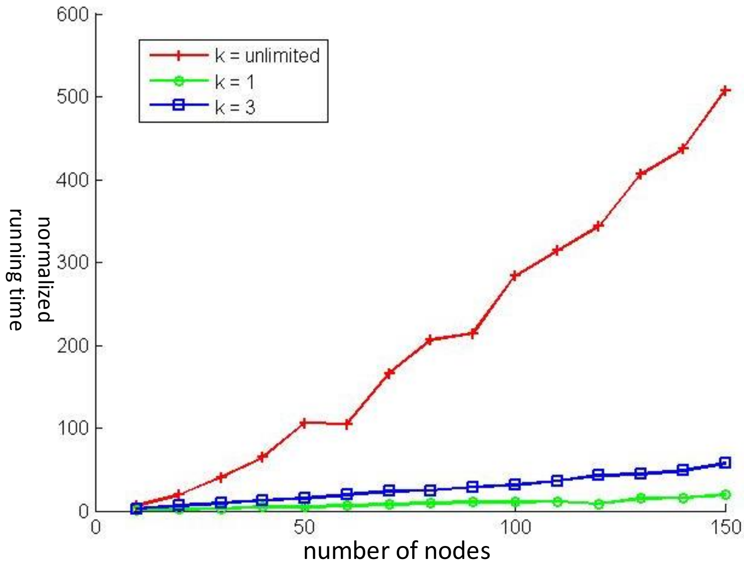


Figure 4.17: Results of time performance, average node degree = 4

When α-cut levels equal to 1, the triangular fuzzy numbers are transformed into crisp numbers. Therefore the algorithm performs as well as typical shortest path algorithm. The average running time are decreased with the growth of the α-cut levels. However, α-cut level is designed to control the grade of fuzziness of the network. Therefore it is not intended to used as a tool to optimise running times.

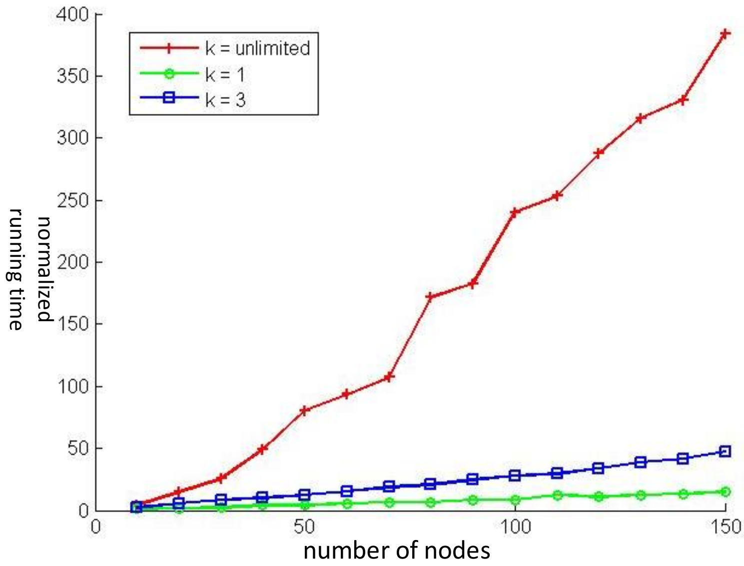


FIGURE 4.18: Results of time performance, average node degree = 8

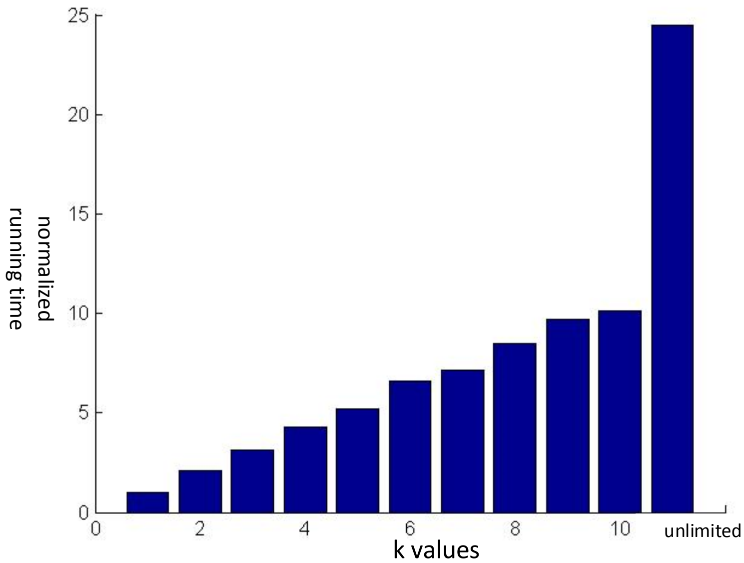
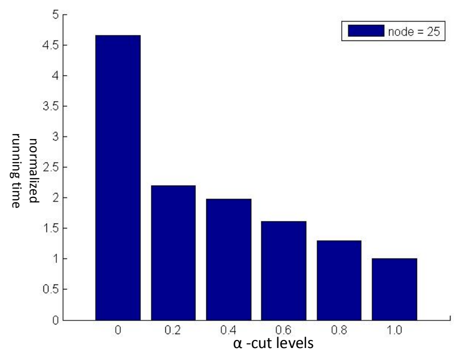
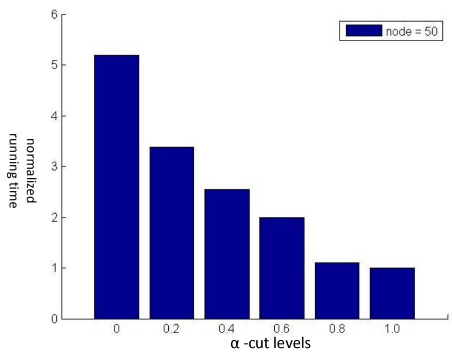


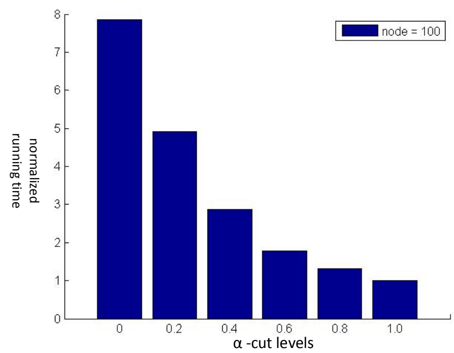
FIGURE 4.19: Normalised running time increased with k, node = 150



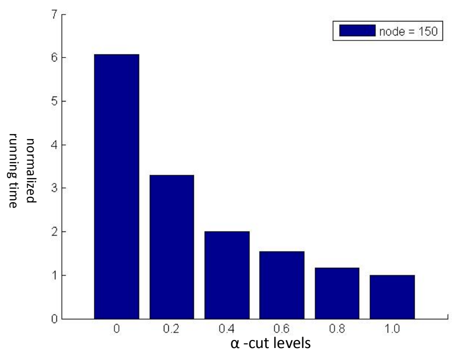
(A) node = 25



(B) node = 50



(C) node = 100



(D) node = 150

FIGURE 4.20: Normalised running time by applying different α-cut levels into algorithm

4.7 Summary

This chapter has considered the fundamental routing searching results for the fuzzy non-dominance routing. While the performance shows FNDR could applied to multipath routing with inaccurate link metrics. However in this chapter the random fuzzy metrics are applied to entire networks in order to demonstrate routes finding. The key points demonstrated includes:

- The FNDR is not to sensitive to the the ratio of long and short links, however the permanent labels (available routes for destinations) are increased with the growth of the network scale, link density and the grade of fuzziness.
- The total number of routes depends on the grade of fuzziness of each link.
- Care needs be taken on how to deal with fuzzy number designs for real applications.
- Algorithm achieves a significant performance gain by applying label limitation k.

However, the number of non-dominance routes relies on the density of the links. There are relatively few routes can be found with networks with lower link density. In order to apply FNDR to real network applications and optimisations, the fuzzy metric designs and routing table rankings are very important. Like other fuzzy system. the expert knowledge and past experiences can be import into fuzzy non-dominance routing in order to improve the network performance.

The next chapter considers exactly how FNDR could be applied to deal with the network optimisation.

Chapter 5

Fuzzy Non-dominance Routing Optimization

5.1 Introduction

In the chapter 4, it is assumed that the entire network metrics are inaccurate. The testing results showed how fuzzy non-dominance routing could be affected by network topology, fuzzy number designs and other factors. The conventional fuzzy routing relies on the expertise knowledge in order to design the fuzzy controller for network optimisation. The similar optimisation process can be applied to fuzzy non-dominance routing, particular for fuzzy number designs. However, the FNDR focus on the control of the grade of fuzziness for individual links in order to improve the network performance.

The next two sections apply FNDR for network traffic engineering problems. The FNDR could get benefits from applying multiple non-dominated paths for load balancing in order to improve network capacity. This chapter also tests how fuzzy non-dominance routing could optimise network convergence and QoS routing. The Chapter discusses how FNDR could be applied to the mobile ad-hoc network in order to improve the QoS as well.

5.2 Mobile access networks optimisation

In the initial test, a real application scenario of using fuzzy non-dominance routing for the traffic engineering in a conventional infrastructure network is demonstrated. A mobile access network with partial-meshed topology is used in this section to demonstrate FNDR network optimisation. The mobile access network is defined within a single AS domain which is matched the application of FNDR. The practical designing of access network is typically following the Cisco's cisco hierarchical model [75]. It is widely applied in the real network design therefore it is chosen for the project to use as initial test scenario. The network topology is shown in the fig.5.1.

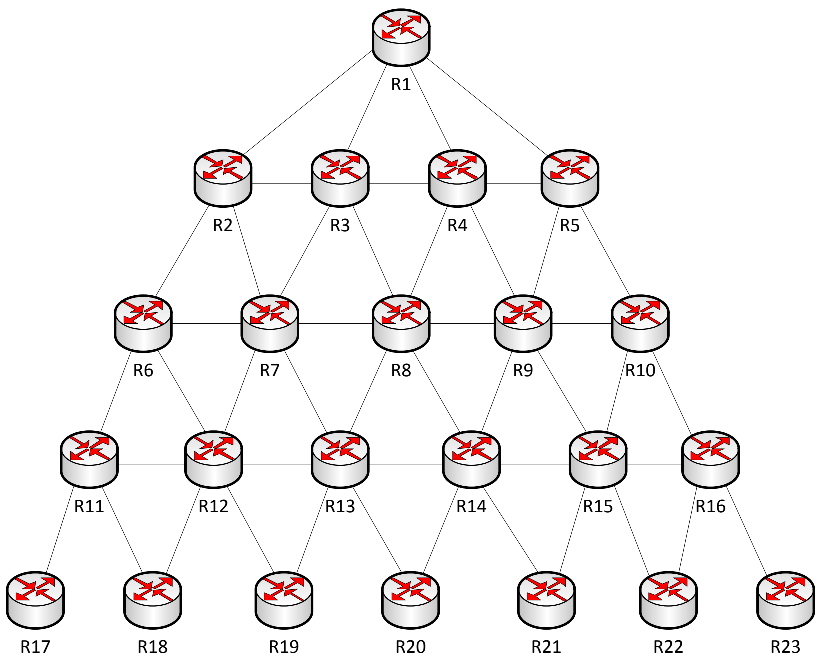


FIGURE 5.1: A partial meshed mobile access network with 23 routers

The mobile access network used by project contains 23 routers in total. The designing of the network is following Cisco's code of practise [75]. The network design contains three levels. Routers 17-23 are access routers with lower bandwidth. They are border gateway routes and provide access service only. Between

Routers 11-16 and Routers 2-5 is distribution layer. This layer provides redundant links for QoS routing. Between router 1 i and Router 2-5 is core layer for this access network. Network traffic is migrated in this layer so it should provide higher-speed connections. Traffic is sent and received between router 1 and routers 17-23. According to design, three classes of link bandwidth are applied to the network. In the core lever, links between router 1 and routers 2-5 have 100 M bps bandwidth. The links between routers 11-16 and 17-23 have a bandwidth of 50 Mbps. All other links have a bandwidth of 70 Mbps. The simulation traffic is generated based on daily basis, containing web traffic, video and voice.

The fuzzy cost of each link follows Cisco's reversed OSPF scheme with up to spreading factor of 50. The α-cut levels of each link are pre-determined off-line. The links which tend to be congested under OSPF routing protocol have α-cut level of 1. All other links remain 0 α-level cut. The congestion threshold is set to 75% utilisation of link. This is following Cisco's default congestion management scheme [76]. Cisco suggested a default congestion awareness threshold to be set as 75% utilisation at network interface. The network should leave 25% interface bandwidth for its management overhead.

The labels limitation $k = 1, k = 2, k = 3$ and unlimited are tested. The results are then compared with OSPF scheme. Multiple non-dominated paths are used for load balancing with the traffic equally shared among these routes.

Table 5.1 shows that the fuzzy non-dominance routing results a better link utilisation performance against OSPF. The average available link bandwidth is increased when more permanent labels are applied to each node. The network is severely congested when label limitation k is set to 1. This is caused by only a single route being applied to each destination. The traffic distribution is balanced due to the multipath routing which is applied across the non-dominated routes.

The daily max utilisation in the Figure 5.2 is the peak link utilisation across all links in a single simulation day. The daily max utilisation of FNDR shows a

TABLE 5.1: Result of bandwidth utilisation on selected congestion links

Link No.	**Max**	**Bandwidth**	**Utilisation**			**Gain**	**Compare**	**With**	**OSPF**
	OSPF	Fuzzy							
		k = 1	k = 2	k = 3	k Unlimited	k = 1	k = 2	k = 3	k Unlimited
1-2	107.18	144.06	105.49	92.77	58.87	-36.88	1.69	14.41	48.31
1-3	73.9	0	20.84	27.78	68.7	—	53.06	46.12	5.20
1-4	0	0	21.90	41.73.	72.13	—	21.90	41.73	72.13
1-5	78.26	114.57	111.46	97.90	60.70	-36.30	-33.20	-19.63	17.56
3-7	105.57	0	0	0	27.48	—	—	—	78.08
5-10	111.81	163.67	106.93	73.29	52.88	-51.86	4.88	40.52	58.92
6-11	111.05	111.05	83.99	56.00	51.83	—	27.06	55.06	59.22
8-14	105.57	0	0	0	28.24	—	—	—	77.32
10-16	111.81	111.81	87.19	58.13	54.02	—	24.62	53.68	57.78
11-18	75.76	75.76	37.88	25.25	18.94	—	37.88	50.51	56.82
14-20	75.19	0	37.59	25.06	37.59	—	37.59	50.13	37.59
14-21	72.60	0	36.30	24.20	41.49	—	36.30	48.40	31.12
15-22	80.74	80.74	40.37	26.91	20.19	—	40.37	53.83	60.56
Daily Max	111.81	163.67	111.46	97.90	75.55	-51.86	0.35	13.91	36.26
Daily Mean	60.53	64.09	37.78	31.89	30.21	-3.56	22.75	28.64	30.32

result of 0.35%, 13.91% to 36.26% gain against OSPF when 2, 3 and unlimited permanent labels are allowed on each node respectively. The mean utilisation utilisation in the Figure 5.2 is average link utilisation across all link of the network in a single simulation day. The mean utilisation of all links has 22.75% to 30.32% gain across all links.

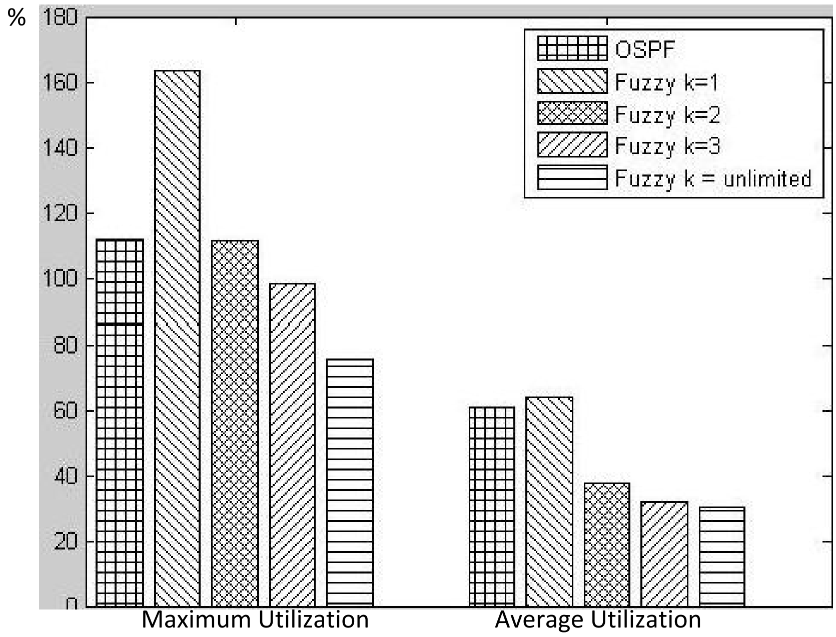
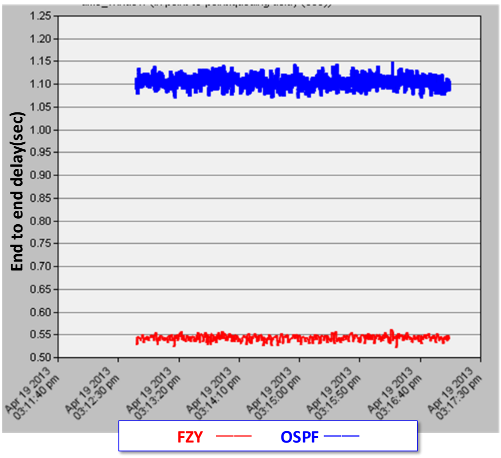


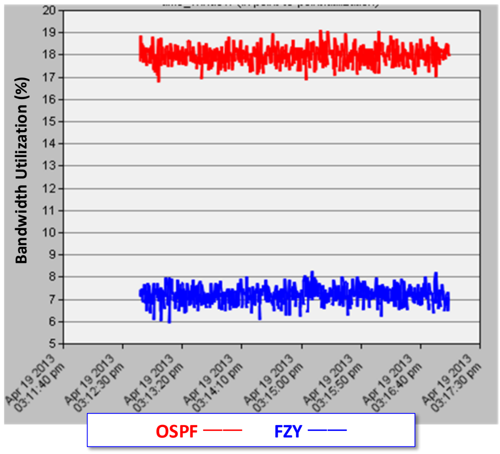
FIGURE 5.2: Maximum and mean link load

In order to obtain the fuzzy shortest path routing in the real network the administrator needs to consider assigning the fuzzy cost/weight for each link. This can be a fuzzy number, or it can be derived by a physical meaningful additive metrics such as distance, inverse-bandwidth or delay. The α-level cut needs to be determined to control the path selection. This can be completed off-line. Alternatively, α-level cut can be determined on-line by setting a threshold on each link.

A QoS enhancement case of fuzzy non-dominance routing is also given. A partial meshed mobile access network with 30 nodes is generated in this case. The network has a single gateway. The traffic flow is sent from all nodes to the gateway. The maximum connections between each node are limited to 5. The maximum bandwidth between nodes are set to 30 Mbps, 50 Mbps or 100 Mbps.



(A) end to end delay



(B) average bandwidth utilization through the path

FIGURE 5.3: Partial meshed network with 30 nodes, QoS enhancement

The figure 5.3 shows the performance of fuzzy non-dominance routing against open shortest path routing(OSPF). In Fig.5.3a, the fuzzy non-dominance path half the packet flow end-to-end delay from the source to the gateway. The average end-to-end delay is decreased from 1.1 sec to 0.5 sec. In Fig.5.3b, the chosen path average bandwidth utilisation has a 10% reducing, which decreased from 18% to 8%. The fuzzy non-dominance routing shows a better QoS performance against shortest path routing in the testing scenario.

The initial results shows a mobile access network optimisation case with FNDR. However, the mobile access network has the feature that traffic is always sent to/from multiple access nodes to the gateway. The FNDR can get benefits from such features by applying multiple routes for load balancing. In the next section, the thesis discusses the cases of applying FNDR for general traffic engineering.

5.3 FNDR for general traffic engineering

In the last test, a special case of mobile access network is considered in the testing. In such networks, the traffic is sent from multiple access routers to a single gateway. This test aims to examine applying FNDR to general traffic engineering. The test shows that with simple fuzzy metrics design, the FNDR network utilisation outperforms conventional infrastructure networks. The sprint North America core network and EU Géant network are used for testing. However, the connections between peers are partially regenerated in order to get avoid of stub area. The location of the nodes remains at the same position, but the Sprint and Géant network are regenerated with an average node degree of 6 and 5 respectively. The links are divided into three groups according to the Euclidean distance between any pairs of nodes. The peers with $Euclideandistance < 500$ are generated with a bandwidth of 200 Mbps. The peers with $500 \geq Euclideandistance < 2000$ have a bandwidth of 500 Mbps. The peers with $Euclideandistance \geq 2000$ have a bandwidth of 1000 Mbps. The unit traffic demand (kbps) between peers are generated according to following scheme:

$$\alpha * \exp(-\delta(x, y)/2\Delta)$$

where α is a random value in the interval of $(0, 1)$. $\delta(x, y)$ is the Euclidean distance between the node x and y. Δ is the largest Euclidean distance between peers. The demand function implies that close peers have relatively more demand than long distance peers. The designs of fuzzy numbers following Cisco's Invcap Schemes. The metric designs are given as follows:

$$linkweight = linkbandwidth(Mbps)/1000Mbps$$

The cost of each link is calculated following B.Fortz's [12] Method:

$$\Phi = \sum_{a \in A} \Phi(l(a)) \tag{5.1}$$

$$\phi_a^{'}(x) = \begin{cases} 1 & \text{for} \quad 0 \leq x/c(a) < 1/3 \\ 3 & \text{for} \quad 1/3 \leq x/c(a) < 2/3 \\ 10 & \text{for} \quad 2/3 \leq c(a) < 9/10 \\ 70 & \text{for} \quad 9/10 \leq x/c(a) < 1 \\ 500 & \text{for} \quad 1 \leq x/c(a) < 11/10 \\ 5000 & \text{for} \quad 10/11 \leq x/c(a) < \infty \end{cases} \tag{5.2}$$

Where $a \in A$ is the links of networks. $l(a)$ is the sum over all demand of the amount of flow for that demand which is sent over link a. The cost function Φ is the cost of all arcs. The results are normalised following:

$$\Phi_{Uncap} = \sum_{(s,t) \in N \times N} (D(s,t) \cdot dist_1(s,t)) \Phi_{Nor} = \Phi / \Phi_{Uncap}$$

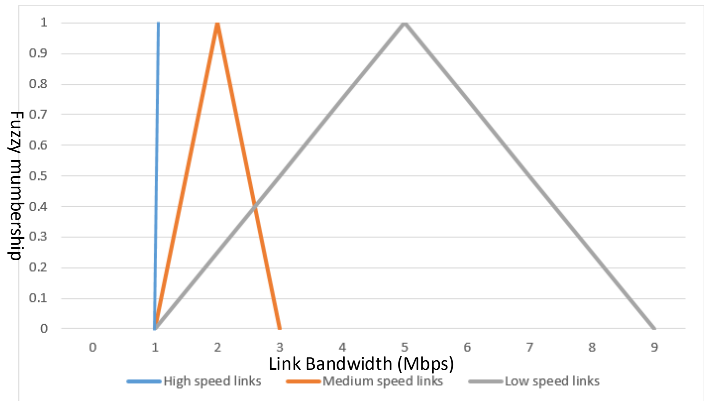


FIGURE 5.4: Fuzzy metric design for section 5.3

In the test, the α-cut levels for all links are set to 0 by default. The fuzzy metrics are designed according to the Invcap schemes (See Fig. 5.4).

According to this design, the high speed link (1000 Mbps) has a crisp link metric 1. It means the high speed links are always preferred during route calculation. The medium speed (500 Mbps) and low speed links (200 Mbps) have metrics [1, 2, 2, 3] and [1,5,5,9] respectively. When high speed links are congested, these links can be used for load balancing by applying α-cut levels to 0. The 50% traffic is sent to shortest path and rest are evenly distributed in the load balancing paths.

The results are compared against Random OSPF, Unit OSPF and Invcap OSPF. The results are shown in the Figure 5.5 – 5.10

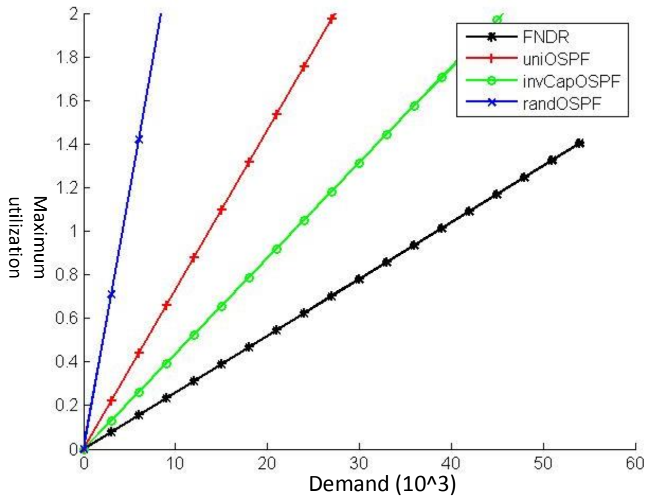


Figure 5.5: The regenerated Sprint network with average degree of 6: maximum utilisation

Figure 5.7 and Figure 5.8 compare the maximum link utilisation across all link by using FNDR, uniOSPF, inverseCap OSPF and Random OSPF in regenerated Sprint and Géant network. The results show that the maximum utilisation is increased with the growing demand. In the tests, the shortest path scheme with random metrics and unit metrics (RandOSPF and unitOSPF) have the worst maximum utilisation. The costs of these two schemes are increasing rapidly which means these two scheme lead to network congestion at lower demand. The result shows that compare to rest of widely applied network routing schemes, FNDR could cope with more demand without congesting a link.

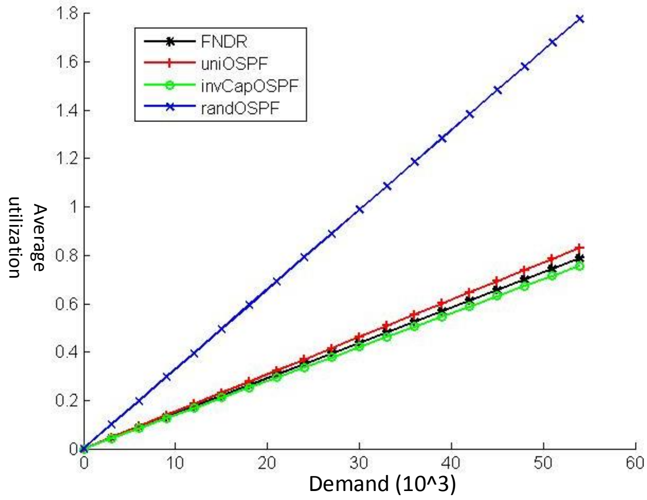


FIGURE 5.6: The regenerated Sprint network with average degree of 6: mean utilisation

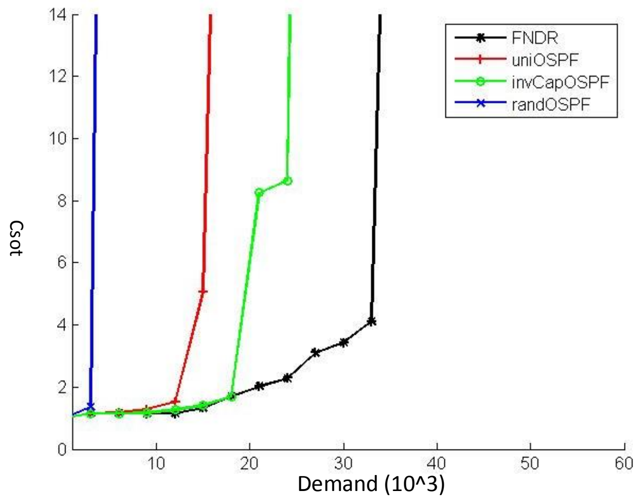


FIGURE 5.7: The regenerated Sprint network with average degree of 6: normalised cost

The Figure 5.6 and Figure 5.9 compare the maximum link utilisation. The mean utilisation of random OSPF increased rapidly with the growth of the demand. This is due to network link resources are not used in a proper way. Under such schemes, some link has been congested while others remain unused. The InvcapOSPF, UnitOSPF and FNDR have similar mean utilisation. However, FNDR based on Invcap cost settings performs better than other schemes in the

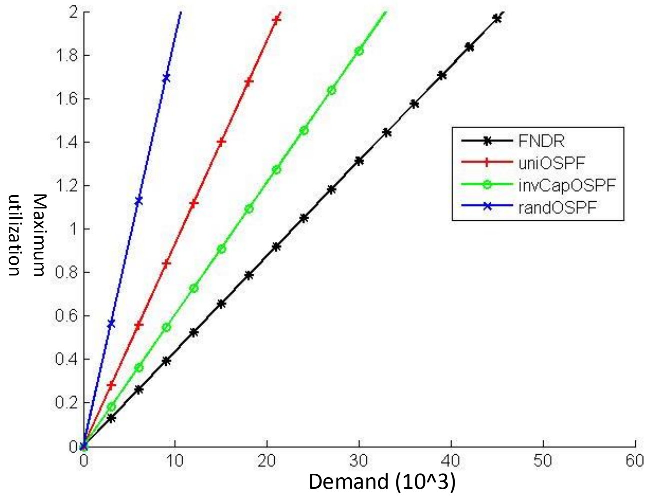


FIGURE 5.8: The regenerated Géant network with average degree of 5: maximum utilisation

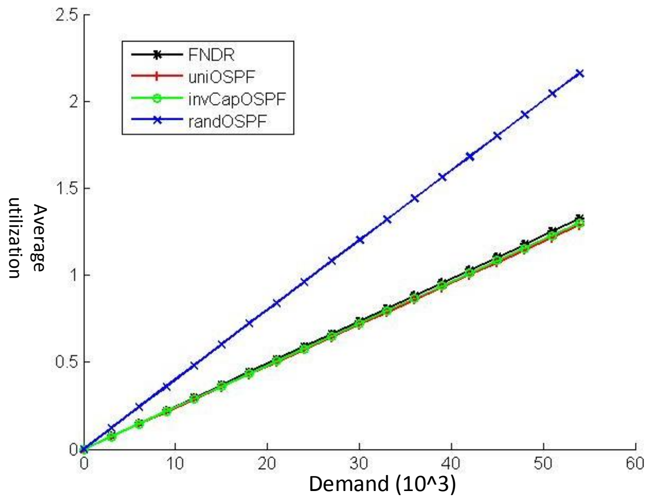


FIGURE 5.9: The regenerated Géant network with average degree of 5: mean utilisation

maximum utilisation and the costs.

The FNDR also shows a better capacity of lower the network cost when coping with higher demand (See Fig. 5.7 and Fig. 5.10). In both Sprint and Géant network, the cost of random OSPF are increased rapidly. In the Sprint North America core network, The FNDR allows the network to cope 40% more demand.

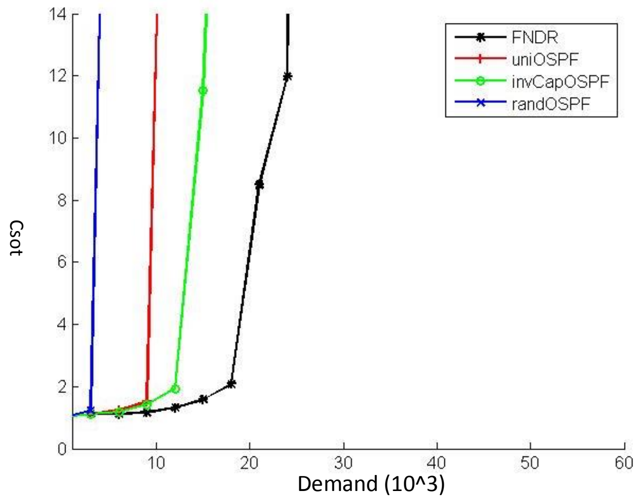


Figure 5.10: The regenerated Géant network with average degree of 5: cost

And in the Géant network, FNDR increased network capacity by almost 60% compared to Invcap OSPF Solution.

However, the FNDR remains simple metrics design based on Invcap OSPF. In conclusion, the results indicate that with FNDR, a network could get benefits from fuzzy non-dominance multipath routing and to cope with more demand. And the metrics settings are still relatively simple.

However, as discussed in the previous section, the non-dominated paths relies on the link density. In a network with a lower average node degree, the FNDR is not necessary to outperform other routing scheme.

The next scenario tests FNDR within a random generated graph with lower node degrees. In this test a random generated graph with 20 nodes with average node degree of 2.6 is applied. As Figure 5.11 – 5.13 shown, the FNDR brings limited capacity gains in the random network. In this scenario, the link density is much lower than previous scenarios. As fewer redundant routes available, FNDR does not give a significant gains than Invcap or unit OSPF schemes.

The next section examines how FNDR could optimise network quality of service in networks with inaccurate or uncertain information.

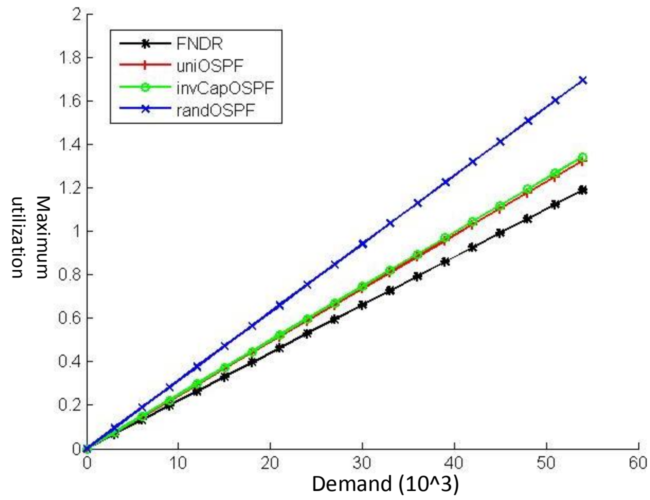


FIGURE 5.11: Random network with 20 nodes and avg. degree 2.5: maximum utilisation

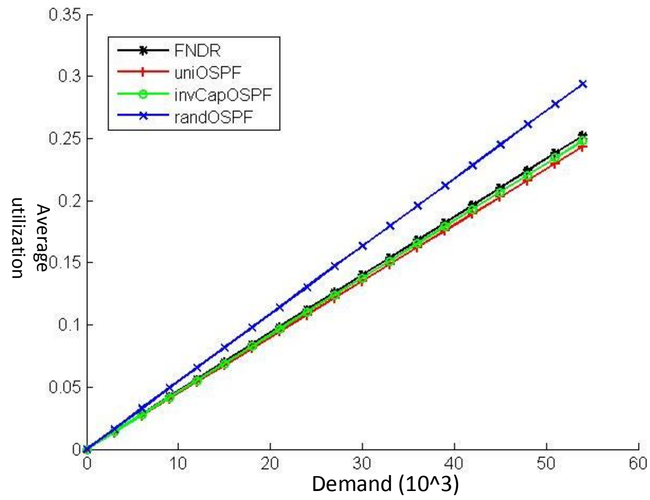


FIGURE 5.12: Random network with 20 nodes and avg. degree 2.5: mean utilisation

5.4 FNDR for quality of service with inaccurate information

The advantage of fuzzy non-dominance routing is that FNDR could manages additive fuzzy metrics. The conventional routing protocols use crisp routing

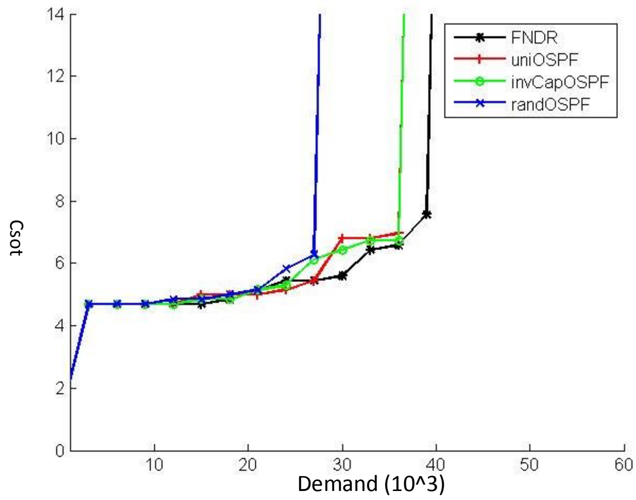


FIGURE 5.13: Random network with 20 nodes and avg. degree 2.5: cost

metrics which are insufficient to represent uncertain or inaccurate routing information. The fuzzy controller routing provides a simple way of dealing with uncertainty, however it has limitation in processing additive routing information. The fuzzy non-dominance routing could get benefits from applying fuzzy metrics into networks to tackle this problem. This section demonstrates how fuzzy non-dominance routing could be applied to the network to optimise network reconvergence time meanwhile it gives some initial guidance on applying FNDR for QoS routing.

5.4.1 FNDR for optimising network convergence

This section introduces FNDR for optimising network routing convergence. In a conventional infrastructure network, the link metrics are crisp values. When link condition changes, particularly for proactive table driven routing protocols, it is necessary for router to re-advertises the new metrics across entire network domains. Then each router needs to re-calculate the routing table according to the new settings. This process is called routing convergence. The routing convergence causes temporary network unavailable and routing failure that may affect Quality of Service.

The fuzzy non-dominance routing could get benefits from multiple non-dominated routes that a temporary link condition change would not trigger re-convergence process. The router could use other non-dominated routes for traffic forwarding unless there is no alternative route available in the routing table.

This test is based on OPNET Modeler. And the Sprint North America core network is used for this test. FNDR is introduced into the network in order to reduce network re-convergence time. Meanwhile, the route with higher bandwidth should be always preferred for improving overall QoS performance. The design of fuzzy metrics aims to achieve two features: firstly, the network with higher bandwidth should be used with higher priority; secondary, the fuzzy metrics could reflect the grade of link uncertainty in order to find out non-dominance routes.

During the test, the service levels of links are divided into three groups randomly. The first group has a very high availability rate of 99.999%. The second group has an availability rate of 99.995%. The rest links have an availability rate of 99.99%. The bandwidth is assigned according to the Euclidean distance between any pairs of nodes. The peers with $Euclideandistance < 1000$ are generated with a bandwidth of 200 Mbps. The peers with $Euclideandistance \geq 2000$ has bandwidth 1000 Mbps. The simulator has been running for 30 days and only re-convergence events are captured.

The figure 5.14 gives the result of the test. The red cross indicates FNDR experienced a route re-convergence event. The blue cross indicates OSPF routing process experienced a routing re-convergence event at that moment. When router cannot find a back-up entry for a destination due to link-failure, it triggered a routing re-convergence event. The process of routing re-convergence was discussed in the section 2.3.3.

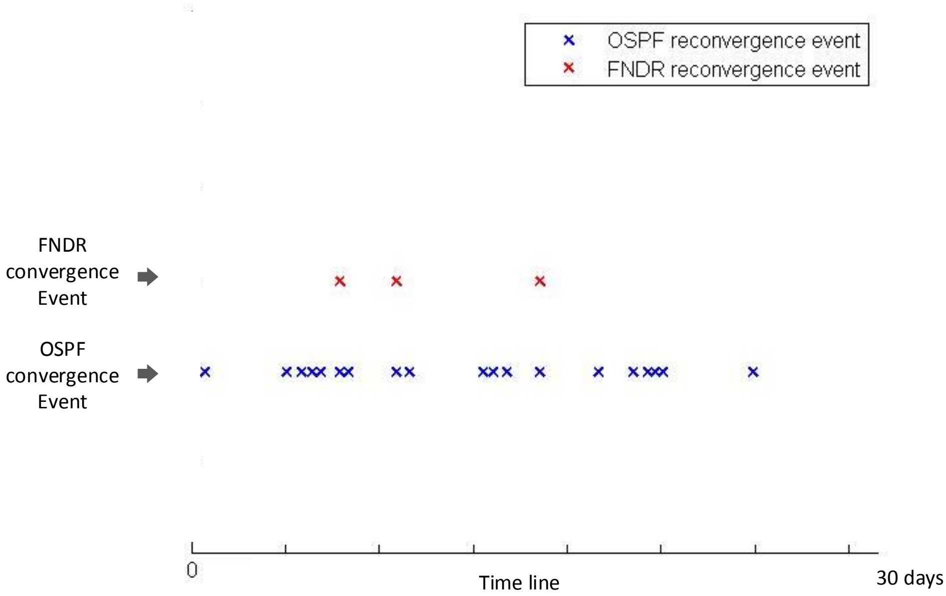


Figure 5.14: The re-convergence events of OSPF and FNDR

The result has shown that, compare to OSPF's 19 times routing re-convergence, FNDR only proceeds re-convergence for 3 times during simulation time. The network will get benefits from less control overhead and routing failure time due to fewer re-convergence events.

5.4.2 Optimising network with different fuzzy rankings

As discussed in previous sections, the QoS metrics for network routing are always inaccurate. Under certain circumstance, the link conditions are estimated based on predictions. This section uses an example to demonstrate how fuzzy rankings could be applied to networks for QoS routing.

In this case, the Sprint North America Network is used for testing. The random delay in millisecond is generated for each link. The delay is bound between 5 ms to 20 ms. The triangular fuzzy metric is designs as (best delay, estimated delay, worst delay). The table 5.2 gives the detailed routes from node 1 to node 27.

Table 5.2: Sprint Network with random delay, non-dominance routes between 1-27

No.	Route	Left	Core	Right
1	1–14–26–27	43.0622	55.0148	74.2241
2	1–10–23–26–27	43.0416	58.1682	79.3240
3	1–25–25–26–27	48.1235	60.9022	68.9985

In the test, there are three non-dominated routes founded from node 1–27. There fuzzy cost are (43.0622, 55.0148,74.2241), (43.0416, 58.1682, 79.3240) and (48.1235, 60.9022, 68.9985) respectively. The three fuzzy cost can be compared in following figure (Fig. 5.15).

All of these three routes are not dominate each other. It means any of these three routes are at least not worse then each other. However, it is possible to rank these three routes with different preference for QoS routing by their least delay, the possible delay, and the worst delay.

For example, the best delay of read route is 48.1235 ms and the most possible delay of this route is 60.9985 which are greater than rest two routes. If a router only considers best or most possible delay, this route should be evicted. However, this route has minimum grade of uncertainty and the best possible worst delay. Therefore, the routes should be used for providing QoS routing for critical service.

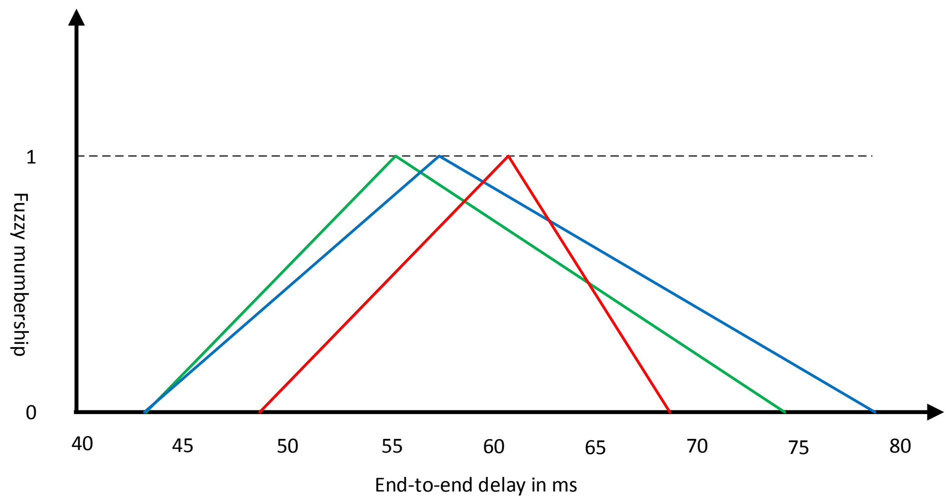


FIGURE 5.15: Compare of the delay for three routes between 1–27

The blue route has minimum best possible delay, however it gets the worst case for it grade of uncertainty. Therefore the routes is best to be used for best effort traffic forwarding. And both green and red routes can be used for load balancing.

In addition, it is possible to manage the non-dominance routes by applying α-cut into the fuzzy routes. If the network administrator is confident with possible delay, they could set α-cut level to 1, then only the green route is used for traffic forwarding in such case.

In the next section, the fuzzy non-dominance routing for mobile ad-hoc network will be discussed.

5.5 FNDR for Mobile ad-hoc network(MANET)

Unlike traditional fixed, centralised and hierarchical network infrastructure model, in a mobile ad-hoc network (MANET), all nodes can be dynamically connected to each other and all nodes are free to move. Node mobility is considered to contribute to uncertainty by constantly changing the network topology. A synchronised routing table is pre-condition of link-State and Table-driven proactive routing protocols. Therefore, it is particularly difficult for traditional infrastructure routing protocols to response frequent topology changes.

The mobility always brings uncertainty and inaccurate node states. The frequent topology changes can be managed by reactive routing approaches, however it leads to increased control overhead as well. Fuzzy controlling routing has been applied to MANET in order to model the uncertain node states. As an extension to the conventional fuzzy routing, this section discusses and examines how fuzzy non-dominance routing could potentially contribute to manage node mobility in MANET. The section gives some initial research on how fuzzy metrics could be designed and how multiple routes could be found in a MANET.

This section will focus on random-based mobility model. Under such model, nodes have maximised grade of fuzziness.

5.5.1 FNDR for random-based mobility model: connectivity

Random mobility models are simple and memoryless. In random-based mobility models, the mobile nodes move randomly and freely without any restrictions. The Random-based mobility model is applied by numerous literatures for modelling mobile ad-hoc networks. In this work, the Random Waypoint Model is applied.

The following assumption is applied in this work: each node is assigned an independent maximum speed. Each node begins by pausing for 1 second. The node then selects a random destination in the simulation area and a random speed between 0 and its maximum speed. The node moves to this destination and again pauses for 1 second before selecting another random location and speed. The Euclidean distance is the only metric to measure the costs between nodes. In the future, the costs can be selected according to other metrics, however this work applied Euclidean distance for simplicity. Peer of nodes loss direct connection if their distance is greater than 10.

Following above assumptions. In traditional fuzzy routing protocols, the fuzzy logics are typically assigned according to the distance, hops, and speed of nodes. For example, the fuzzy logic can be designed according to node speed as slow, medium and fast. And the distance between two nodes can be designed as close, medium and far. The fuzzy logic controller could be designed according to fuzzy logic combinations.

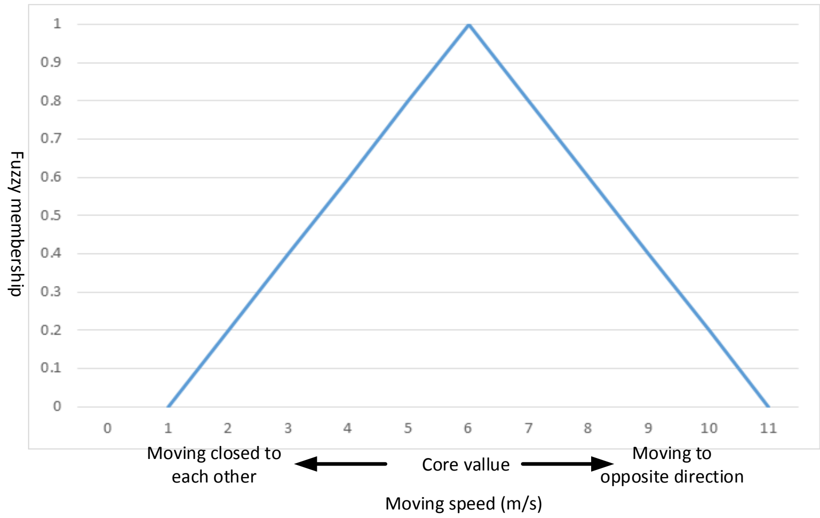


FIGURE 5.16: The fuzzy metrics design for MANET

In fuzzy non-dominance routing metrics design, where the initial distance between two nodes can be used for the core of fuzzy metrics. The left spreading and right spreading is the minimum and maximum distance possible for any two nodes according to their speed respectively.

For example, if two nodes, node A and node B, have an initial distance of 6, node A is moving at a maximum speed of 4 and node B is currently moving at a maximum speed of 1, then the fuzzy metric can be designed as a triangular fuzzy number cost = [1,6,11] (as shown in the fig. 5.16). Under such design, the core of the fuzzy number represents the current state of the nodes. The node's moving speeding contributes to the grade of fuzziness. The faster the node move, the grater grade of fuzziness applied to the metric.

The maximum number of permanent labels will be firstly examined.

In the initial test, The default area is 50 by 50. Nodes are not moved. The number of nodes is increased from 20 to 100. The simulator runs for 50 times to get average permanent label numbers from node 1 to all connected nodes from node 1. The result is compared with shortest path routing.

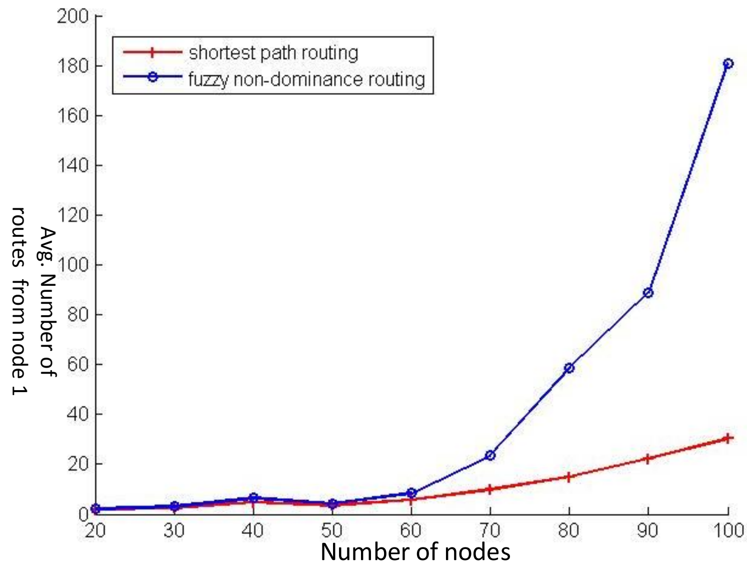


FIGURE 5.17: Initial routing discovery result for wireless network

The figure 5.17 shows the result. The average number of permanent labels in the figure is the number of routes that start from node 1 to all direct or indirect connected nodes. In this scenario, nodes are not necessary to be connected due to the distance limitation which means the graph is not necessary to be strongly connected. Therefore, the number of routes is less than the number of nodes. The set of routes that found by fuzzy non-dominance routing is obviously greater than shortest path scheme. However, it should be noticed that without label limitation k, the number of permanent labels are increased exponentially with the growth of the number of nodes. This brings extra computational overhead. Therefore, the proper limitation k and α-cut are suggested to be set. The Fig. 5.18 and Fig. 5.19 give the results with different label limitation k and α-cut applied to routing the discovery process.

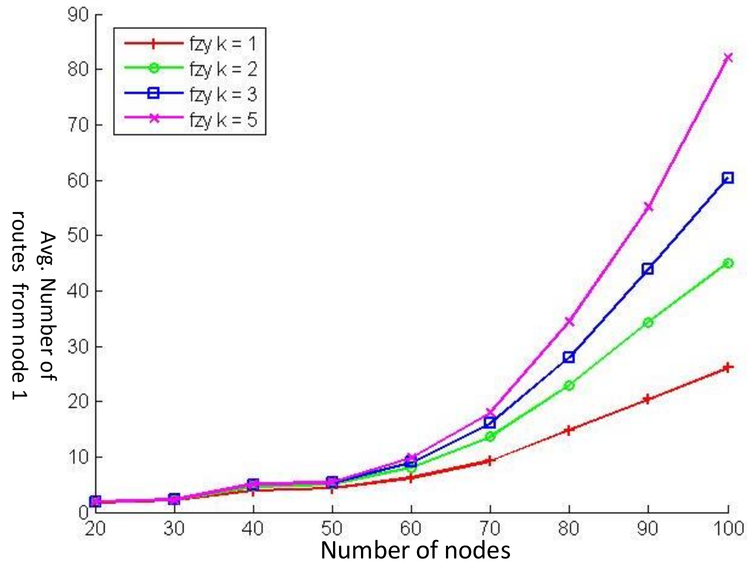


FIGURE 5.18: Optimizing initial result by applying different levels of k

The result shows network could still get benefits from fuzzy non-dominance multipath by applying k and α-cut. Meanwhile, as discussed in the previous Chapter, the computational overhead could be significantly improved. An election process like OLSR could potentially reduce the computational overhead further, however it will not be discussed in this work.

The next section will discuss moving nodes in random-based mobility model.

5.5.2 FNDR for random-based mobility model: moving and routing convergence

The last section discussed connectivity issues of finding non-dominance routes in the random-based mobility model network. The biggest challenge is that the random-based mobility brings higher grade of uncertainty. In this section, the random waypoint model is applied in order to simulate node mobility.

In this test, 20 nodes are generated in a 30 by 30 area. The maximum node speed is set to 0 - 5. The test examines the route finding result for peer 1 - 20.

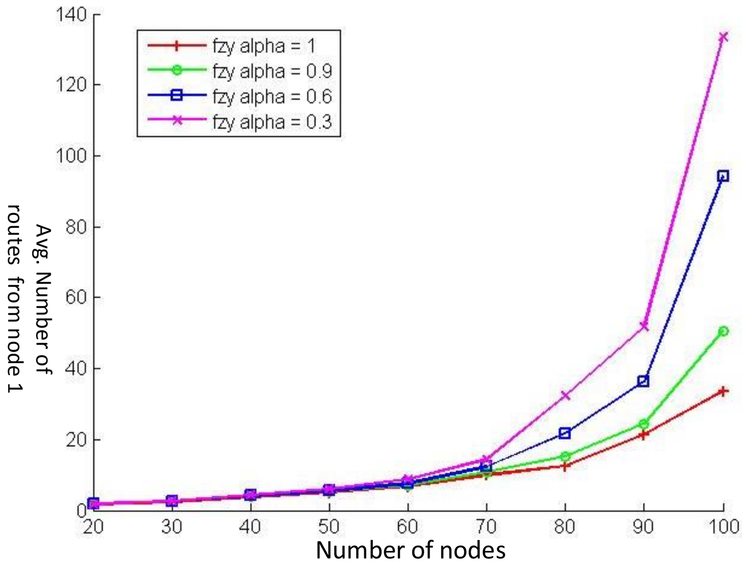


Figure 5.19: Optimizing initial result by applying different α-cut levels

The result is compared with shortest path algorithm. The result is shown in the table 5.3 and 5.4.

At the beginning of the simulation, 6 routes are found by FNDR. These 6 routes are all non-dominated multipath. It means these routes have similar conditions due to uncertain and inaccurate node mobility. These fuzzy routes, particularly the disjoint routes can be used for load-balancing to improve the network performance. Meanwhile, it provides redundancy that those disjoint alternative routes can be used for traffic forwarding without routing re-convergence when routes lost connectivity due to node mobility. In this scenario, the current shortest path is 1–4–20 and the route cost is 17.0967.

The simulation is then run for 5 second. After 5 seconds, the previous shortest path 1–4–20 has been broken. However, two fuzzy non-dominance routes survives from topology changing. The path 1–6–20 becomes the new shortest path.

There are two ways that a MANET could get benefits from fuzzy non-dominated multipath. From one side, the router could use disjoint routes for traffic forwarding in order to improve the network capacity such like 5.3. In the table

Table 5.3: Random result of route discovery node 1 - 20

No.	Route	Left	Core	Right	Live
1	1–13–4–20	3.9689	17.2700	30.9942	Y
2	1–13–6–20	3.3190	18.4882	36.0205	Y
3	1–13–6–7–20	2.6047	21.6063	43.0112	Y
4	1–6–20	3.9158	17.7445	31.5733	Y
5	1–6–7–20	3.2015	20.8627	38.5639	Y
6	1–4–20	7.0761	17.0967	27.1172	Y
s	1–4–20	17.0967			

Table 5.4: Random result of route discovery node 1 - 20, after 5 seconds

No.	Route	Left	Core	Right	Live
1	1–13–4–20	3.9689	17.2700	30.9942	N
2	1–13–6–20	3.3190	18.4882	36.0205	Y
3	1–13–6–7–20	2.6047	21.6063	43.0112	N
4	1–6–20	3.9158	17.7445	31.5733	Y
5	1–6–7–20	3.2015	20.8627	38.5639	N
6	1–4–20	7.0761	17.0967	27.1172	Y
s	1–6–20	18.2756			

5.3, there are 6 routes found between peers 1 and 20. The route 1–4–20 and 1–6–20 are completely disjoint routes. Those routes could be used for traffic engineering for load balancing which results a QoS improvement. In addition, the fuzzy non-dominance multipath could be applied into MANET to reduce the control overhead. The non-dominance routes could be applied to improve the routes lifetime between two ends by using multiple non-dominance path for traffic forwarding without re-convergence until all the connections are broken.

The figure 5.20 shows the routes lifetime of fuzzy non-dominance multipath against the shortest path. In this test, 20 nodes are generated in a 30 by 30 area. The test runs 1000 times to get average values. The test examines the routes lifetime between node 1 and 20. It is obvious that the route lifetime of shortest path is decreasing with the growth of the maximum moving speed. The

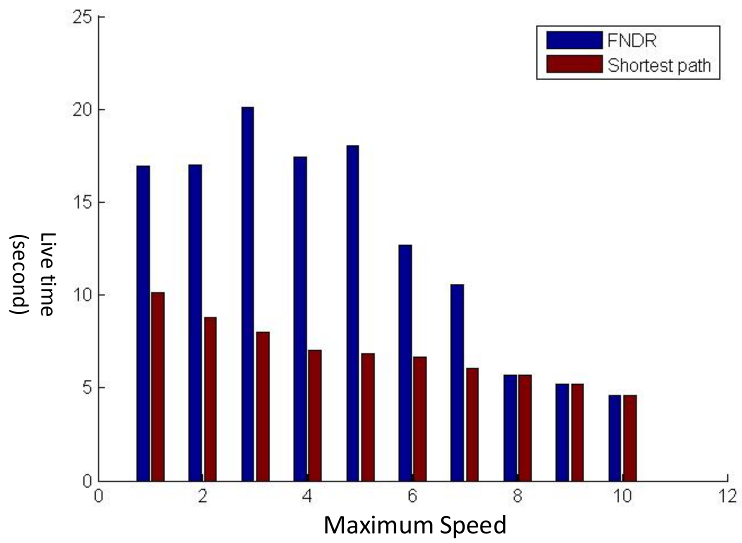


Figure 5.20: Route average live time between peer 1 - 20

fuzzy non-dominance multipath could get benefits from multiple non-dominance routes that the routes lifetime outperforms shortest path routing when node moving speeding is between 1–7. The routes lifetime is slightly increased when node moving speeding is between 3–5. This is due to higher grade of uncertainty leads to more non-dominated routes. When the node maximum moving speed is greater than 7, the FNDR cannot outperforms shortest path due to a very high degree of mobility.

It is possible to apply FNDR for other mobility models. For example, the geographic restriction model which is especially important for modelling vehicular ad hoc network (VANET). In the geographic restriction model, the nodes is restricted to be moved on certain pathway or areas. Compared to random mobility model, the grade of uncertainty in the geographic restriction model is limited. However, it is not possible to apply fuzzy metrics design in the random waypoint model into VANET directly. The design of fuzzy metrics could be followed relative speed, acceleration, signal strength and other metrics. Like conventional fuzzy routing, the design of fuzzy metrics needs to be changed case by case to adapt different types of networks. The design of fuzzy metrics for specific types of mobile ad-hoc network is beyond this work, however it can be extended for further researches.

5.6 Summary

In this section, the fuzzy non-dominance routing for network routing optimisation is examined.

In the initial test, fuzzy non-dominance routing is used to optimise a mobile access network. Similar to the initial test, FNDR is then applied to general traffic engineering. The results demonstrate that by applying multiple non-dominated paths, FNDR could bring improvement on network capacity. However, it should be noticed that as Chapter 4 discussed, the number of alternative routes depends on the link density and grade of fuzziness. When the link density is very low, FNDR could not find out enough non-dominated path for traffic forwarding.

The Chapter also studies the application of FNDR for optimising network convergence, quality of service routing and FNDR for Mobile ad-hoc networks. The conclusion is that fuzzy non-dominance routing has potential to optimise network with less computational and control overhead. It provides an alternative way of dealing with multipath routing and QoS Routing. However, the selection and the relation between non-dominance routes, the fuzzy metrics designs need to be studied further to receive better results.

Chapter 6

Conclusions and Further Works

6.1 Conclusion

This thesis proposes a fuzzy non-dominance approach for network routing with inaccurate information. The primary contribution of this work is the development of the fuzzy non-dominance algorithm and the introduction of the concept of fuzzy non-dominated multipath routing into telecommunication networks. The fuzzy non-dominance routing is distinct from conventional fuzzy routing. The Fuzzy non-dominance routing provides an alternative way to deal with the uncertainty of the network routing information.

The work examines the features of fuzzy non-dominance routing. The work examines how network topology, and how fuzzy number designs, α-cut levels could affect FNDR route finding. This work also gives label limitation k to improve the algorithm performance. Then the work demonstrates how fuzzy non-dominance routing could be applied to the network load-balancing, routing convergence and QoS route decision processes. In addition, the work includes a scenario to demonstrate finding fuzzy non-dominance routes in the MANET environment. The testing results demonstrate that with proper designs, non-dominance multipath routing could be applied to the network optimisation problems.

However, in a large scale network, the number of temporary labels and non-dominance routes could grow exponentially that increasing the computational overhead. The problem can be tackled by applying α-cuts or label limitation k. The α-cut improve the performance by reducing the grade of fuzziness. The label limitation k could improve the performance by searching a limited number of temporary and permanent labels as a result the running time can be bounded.

The number of non-dominance routes is affected by link density as well. In a network with relative lower node degrees, FNDR could not find non-dominated routes for load balancing. Under such circumstance, FNDR could not provide significant network performance gains.

The conclusion is that fuzzy non-dominance routing has potential to optimise network with less computational and control overhead. Overall, the network could get benefits from the non-dominated fuzzy multipath and achieves performance improvements. It provides an alternative way of dealing with multipath routing and QoS Routing. However, the selection and the relation between non-dominance routes, the fuzzy metrics designs need to be studied further to receive better results.

6.2 Further works

One direction would be researches of fuzzy set theory itself that further works could investigate applying type-2 fuzzy numbers into fuzzy non-dominance routing so that more uncertainty can be handled. The research could focus on the design of type-2 fuzzy metrics. Yuste, A.J. [77] addressed type-2 fuzzy logic for optimising MANET, however their work did not gives detailed results. Therefore more works can be done in this area.

Another direction would be researches on the optimisation of α-cut levels for individual link. As discussed in Chapter 4, α-cut is used as a tool to manage the grade of fuzziness of fuzzy metrics. Further researches could concentrate on the mathematical formulation of α-cut optimisation for network traffic engineering in order to improve the network capacity.

Further researches could also focus on fuzzy non-dominance routing for mobile ad-hoc network. As discussed in the Chapter 5, this work could be extended by investigating the application of FNDR for particular types of MANET.

In addition, it is worth to investigate the application of fuzzy non-dominance routing in the areas such as sensor networks which constrained resources are applied to the network.

Another direction of further work would be applying machine learning approaches such as Case-Based Reasoning to investigate how FNDR could assist network routing self-configuration and self-optimisation. Fuzzy set could benefits from expert knowledge as a result machine learning based expert system could help FNDR to learn and manage network uncertainty.

Appendix A

Appendix OPNET Simulation Designs

A.1 Introduction

As part of this work, an OPNET simulation was built for demonstration and testing. The simulator is following proposed fuzzy non-dominance routing framework in the Chapter 3.4.4. The centralised mode is applied to the simulator.

The commercial discrete-event simulator OPNET 14.5 was used to setup the simulation. In this section, node models and other major process models are introduced.

A.2 Node model

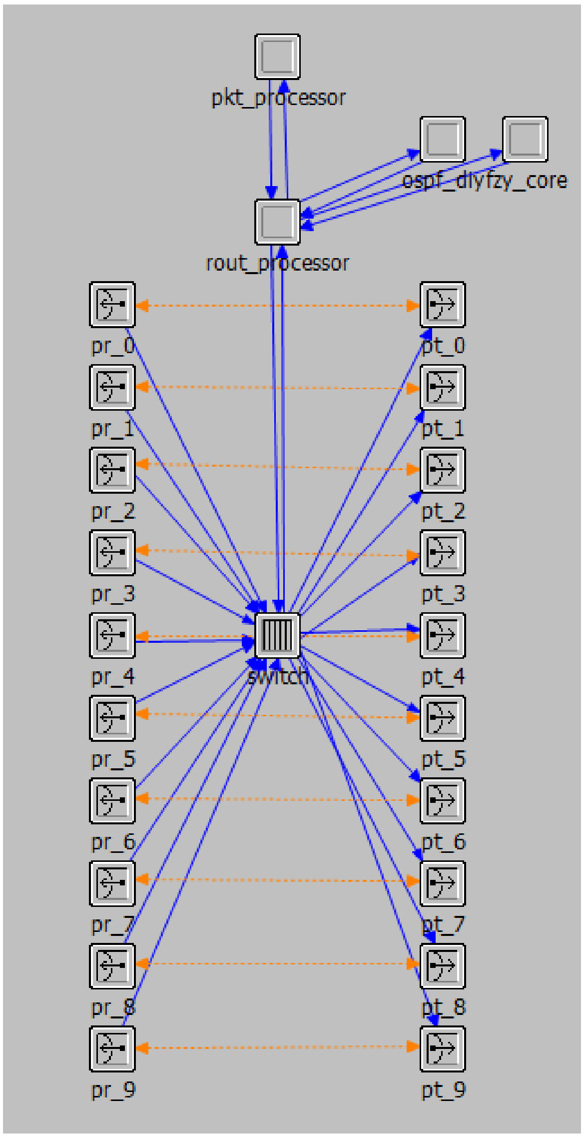


FIGURE A.1: Node model for routers

As shown in Fig. A.1, the FNDR router node model is built according to the OSI layer stack. The major processes focus on the network layer.

The modules in the node model are described below:

pkt_processor: pkt_processor is a traffic generator/receiver and packet processor. pkt_processor generates packets with specific size and inter-arrival time. The packets are then sent to the lower layer. The pkt_processor also receives packets from lower layer when node performs as the destination.

rout_processor: rout_processor performs routing functions. It works on the network layer to decide the destination of the received packets.

ospf_diy: ospf_diy is a simplified OSPF protocol for routing table calculation. It maintains connectivity by broadcast hello packets as well.

fzy_core: fzy_core is responsible to build the fuzzy non-dominance routing table according to the configurations.

switch: switch receives and processes packets from receivers. It contains queues and buffers to send packets to upper layers at a specific rate. It also receives packets from the upper layer and sends packets to the transmitter.

pr and pt: These modulus are receivers and transmitters.

A.3 Process model

The key process models are introduced in this section. The process models are represented by finite state machine (FSM), and it is created with icons that represent states and lines that represent transitions between states.

1. pkt_processor:

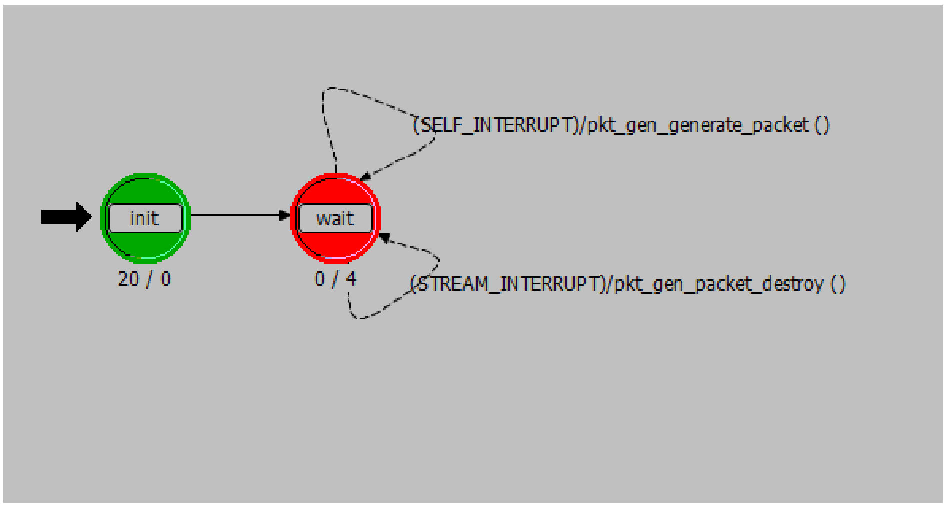


FIGURE A.2: Process model: pkt_processor

The pkt_processor is a simple packet generator and receiver. As a packet generator, It generates packet at pre-determined rate and size. It writes ICI information such as destination, time_stamp and time to live into the packet as well. Then the packet is sent to the lower layer for routing processes.

When it acts as a receiver, pkt_processor calculates packet delay, arrival rates and then destroys packets.

2. rout_processor:

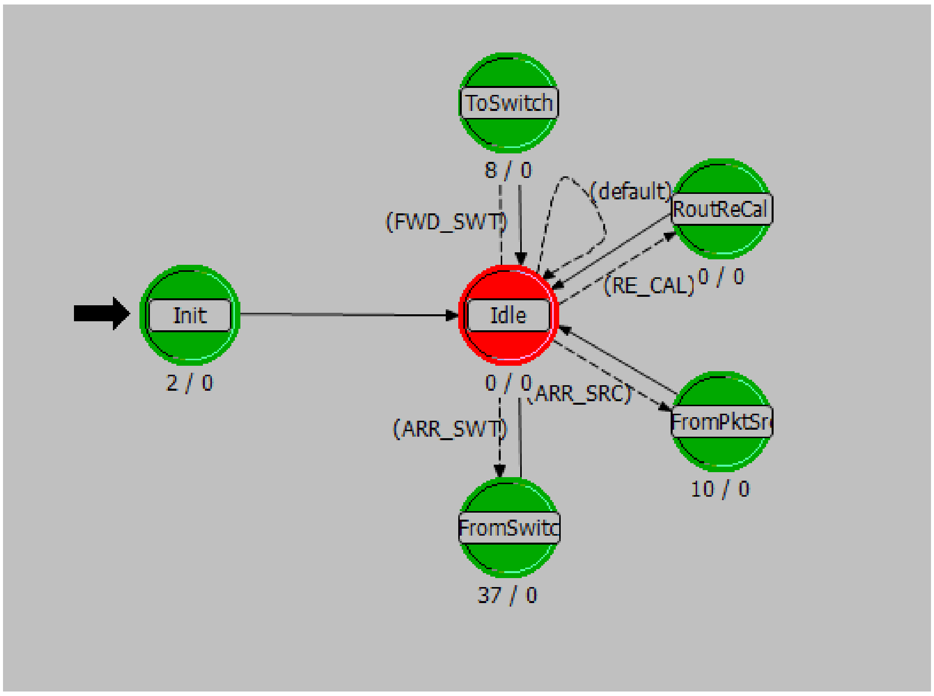


FIGURE A.3: Process model: rout_processor

The rout_processor performs routing decision functions.

init state: This state starts the initialisation of the process. Routing configurations are initialised here (routing protocols, metrics, network topologies etc.). Once the initialisation is completed, the process transits to the *idle* state.

FromSwitch state: This state monitors and receives interrupt from the *switch* for packets arriving. The state lookups the routing table and load balancing strategy and it decides next hop for the packet.

ToSwitch state: This state rewrites the network layer routing information of packets and sends them back to *switch*.

FromPktSrc state: This state receives and sends packets to upper layers. For packets from the upper layer, the state writes the routing information according to their destination and then sends packets to the switch. For packets to upper layer, the state removes routing information and sends then to the *pkt_processor* for further processes.

RoutReCal state: This state receives link condition change interrupt RE_CAL. It receives updated routing metrics and recalculates the routing table. It also records the convergence events.

3. ospf_diy:

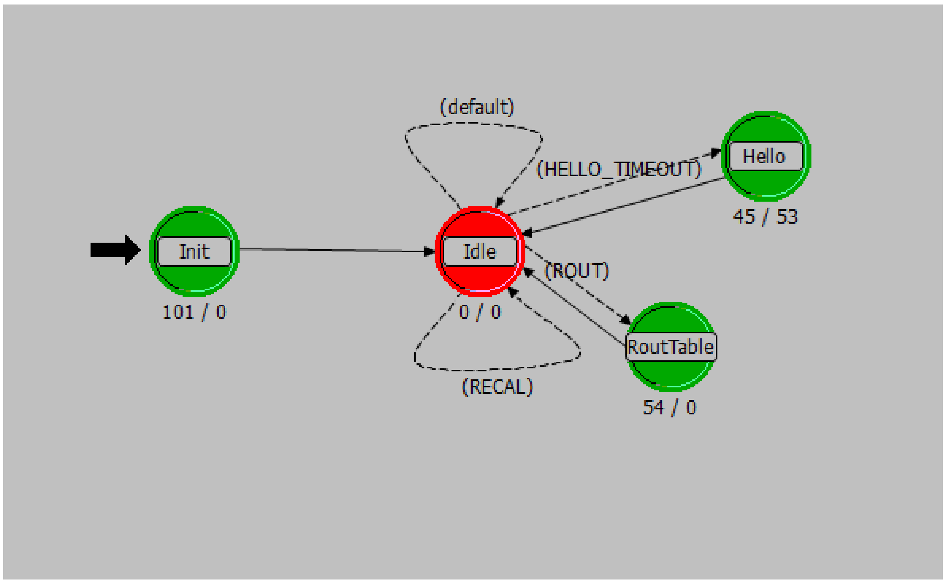


FIGURE A.4: Process model: ospf_diy

ospf_diy is a simplified OSPF protocol for routing table calculation. It maintains connectivity by broadcast hello packets as well.

init state: This state starts the initialisation of the process. Routing information such as metrics, hello intervals are initialised in this state. Once the initialisation completed, the process transits to the *idle* state.

Hello state: This state broadcasts HELLO messages in every HELLO INTERVAL time to advertise its presence to directly corrected neighbours. The state receives HELLO messages and monitors the neighbourhood connectivity as well.

Rout state: This state receives interrupt from the rout_processor and calculates the routing table according to the shortest path algorithm.

4. fzy_core:

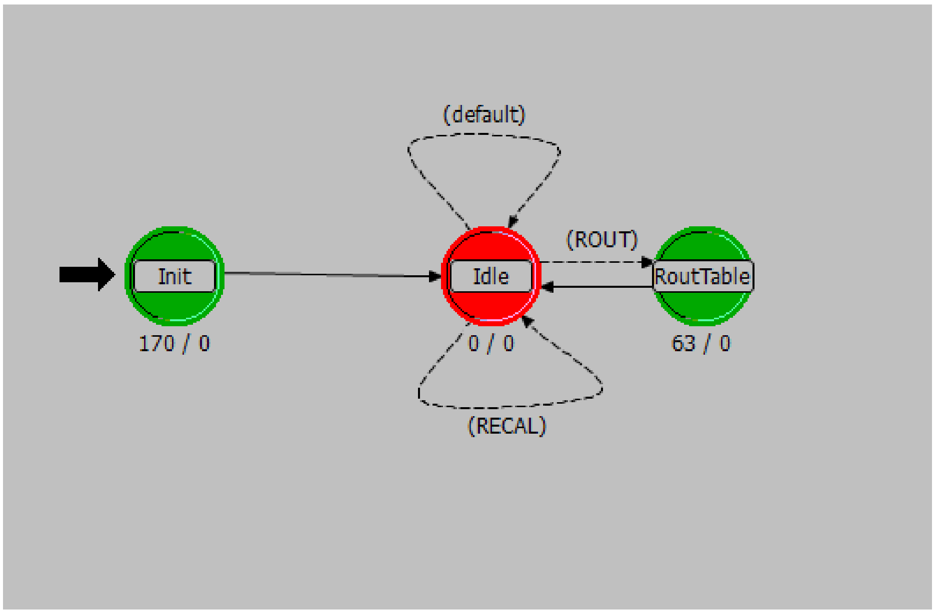


FIGURE A.5: Process model: fzy_core

fzy_core is responsible to build the fuzzy non-dominance routing table according to the configurations.

init state: This state starts the initialisation of the process. Routing information such as fuzzification factors, α-cut levels and labels limitation k are initialised. Once the initialisation completed, the process transits to the *idle* state.

Rout state: This state receives interrupt from rout_processor and calculates the routing table according to the fuzzy non-dominance multipath algorithm.

5. switch:

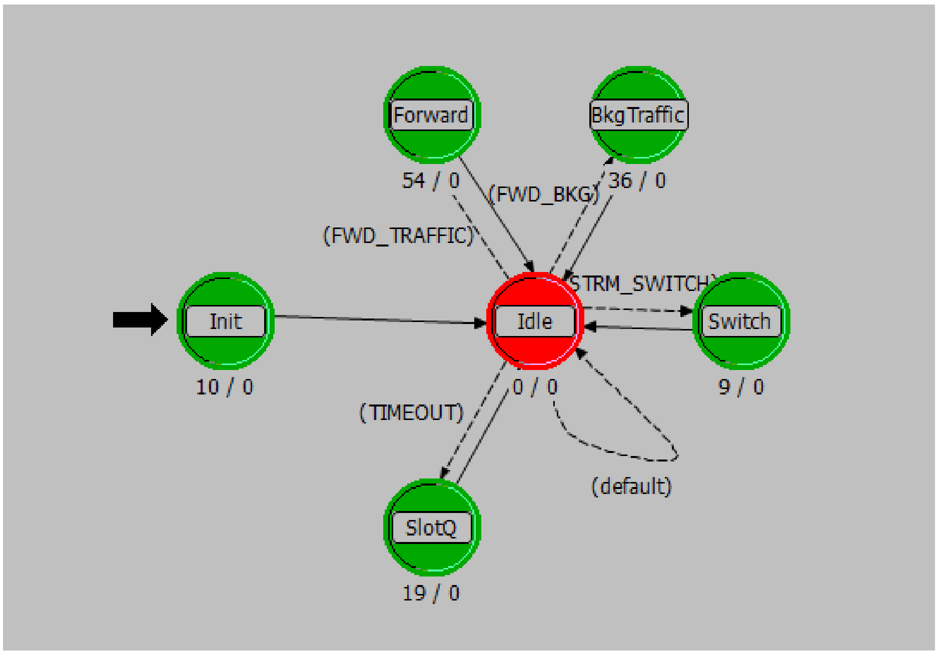


Figure A.6: Process model: switch

The switch is queue process that receives and processes packets from receivers. It contains queues and buffers to send packet to upper layers at a specific rate. It also receives packets from upper layers and sends packets to the transmitter.

Init state: This state starts the initialisation of the process.

SlotQ state: This state uses TIMEOUT value to decide the processing rate. For each TIMEOUT interval, a packet is pushed into the SlotQ and being forward-eded to the upper layer.

Switch state: Switch state receives and buffers the arriving packets from lower layers.

Forward state: Forward state receives interrupt from rout_processor and forwards the frame into right transmitter.

BkgTraffic state: BkgTrafic state is a special state that forwards background traffic to its neighbour.

6. config:

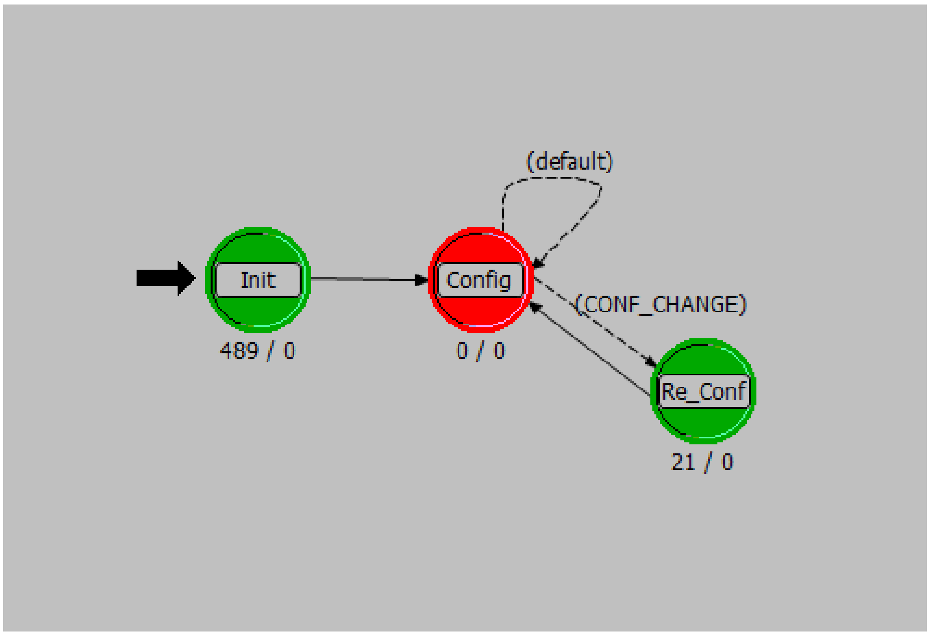


Figure A.7: Process model: config

The config is an extra process model that works in the centralised mode as a server. It determines metrics for routing protocols

init state: This state starts the initialisation of the process. All routing related information are initialised at this state. These information include routing protocols, metrics, FNDR metrics for individual links and load balancing strategies.

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