Service Level Agreement-based adaptation management for Internet Service Provider (ISP) using Fuzzy Q-learning

Ahmad Kamal Bin Ramli

Submitted in accordance with the requirements for the degree of

Doctor of Philosophy

The University of Leeds
School of Computing

May 2018

Dedication

To my family and individuals who are consistently trust my capability

Declaration

The candidate confirms that the work submitted is his/her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to his work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Ramli, A. K., & Djemame, K. (2014, September). Autonomic management for convergent networks to support robustness of appliance technologies. In *Proceedings of the 7th International Conference on Security of Information and Networks* (p. 47). ACM. This paper is the candidate's own work. The paper was reviewed by the co-author Karim Djemame. Content of this paper is included throughout the thesis and mainly in chapter 1 and 2.

Ramli, A. K., & Djemame, K (2015). An Inter domain Adaptive Management architecture for Internet Service Providers (ISPs). *In Proceedings of the 31st UK Performance Engineering Workshop (UKPEW 2015)* (pp. 122-139). This paper is the candidate's own work. The paper was reviewed by the co-author Karim Djemame. Content of this paper is included throughout the thesis and mainly in Chapter 4 , Chapter 5 and Chapter 6.

Acknowledgements

The utmost thanks go to Allah (God) for making this thesis reached the end with the patients, good health and mentally cope with the intermittent situations.

To my supervisor, Dr Karim Djemame , thanks for the continuous support from the starter of this research till the last day of the submission. Your professional supervision, motivations and constructive criticism throughout this journey, does make me feel awake for the time where I am lost.

My family, whether at UK or back home in Malaysia really toasted my spirit to finish the final part of this research. My Mom (Tom Bt Omar) and my late father (Ramli bin Yusuf) thanks for your ultimate blessing and next goes to My Wife (Aisyah Bt Mat Jasin) and the lovely two energetic children (Abu Bakar and Nur Hannan). As a parent and both me and my spouse are PhD candidates, the emotional situations are repetitively present from the start till the end of this research.

Another thought goes to Dr Pooyan Jamshidi whom are dedicated and consistently updating me with the Fuzzy Q-Learning knowledge. To all my friends who included me in their whatsapp group either from primary school or secondary school, the continuous discussion alleviated my pressures and gave me faiths to be the person that known by them.

Special thanks to Nor Diana, PhD candidate at School of Computing who are marvellously generous enough printed this thesis to ensure the dateline are meets. Working remotely from my home country made me unaware of bank holidays and another extra day grants to print copy bureau before resuming their operation and the thesis submission dateline are slightly impossible to be achieve.

Finally, thanks to MARA as the funder with the solely financial provider to us even sometimes it is hard to convince other Malaysian friends that we are financially different compared to them. With the less appearances in the social activities, the chances to be left aside by the established group are likely high regardless of any reasons.

On the last note, against thanks to all the edutainment (education with entertainment) students who managed to travel within Europe countries during their studies. Their astonishing activities does affect our focus in progressing this research.

Abstract

Internet access is the vital catalyst for online users, and the number of mobile subscribers is predicted to grow from dramatically in the next few years. This huge demand is the main issue facing the Internet Service Providers (ISPs) who need to handle users' expectations along with their current resources. An adaptive mechanism within the ISPs architecture is a promising solution to handle such situation. A Service Level Agreement (SLA) is the legal catalyst to monitor any contract violation between end users and ISPs and is embedded within a Quality of Service (QoS) framework. It strengthens and advances the quality of control over the user's application and network resources and can be further stretched to fulfill the QoS terms through negotiation and re-negotiation. Moreover, the present literature does not focus on the combination of rule-based approaches and adaptation together to update the established learning repository. Therefore, this mainstream of this research in the context of SLAs is to fill in this gap by addressing the combination of rule-base uncertainties and iteration of the learning ability. The key to the proposed architecture is the utilization of self -* capabilities designed to have self-management over uncertainties and the provision of self-adaptive interactions.

Thus, the Monitor, Analyse, Plan, Execute and Knowledge Base (MAPE-K) approach is able to deal with this problem together with the integration of Fuzzy and Q-Learning algorithms. The proposed architecture is in the context of autonomic computing. An adaptation manager is the main proposed component to update admission control on the ISP current resources and the ability to manage SLAs. A general methodology type-2 fuzzy logic is applied to ensure the uncertainties and precise decision-making are well addressed in this research.

The proposed solution, demonstrating Q-Learning works adaptive with QoS parameters, e.g. Latency, Availability and Packet Loss. With the combination of fuzzy and Q-Learning, we demonstrate that the proposed adaptation manager is able to handle the uncertainties and learning abilities. Q-Learning is able to identify the initial state from various ISPs iterations and update them with appropriate actions, reflecting the reward configurations. The higher the iterations process the higher is the increase the learning ability, rewards and exploration probability. The research outcomes benefit the SLA framework by incorporating the information for SLA policies and Service Level Objectives (SLOs). Lastly, an important contribution is the ability to demonstrate that the MAPE-K approach is a contender for ISP SLA-based frameworks for QoS provision.

Table of Contents

Abbreviations

SLA	Service Level Agreement
QoS	Quality of Service
QoE	Quality of Experience
ISP	Internet Service Provider
ISPs	Internet Service Providers
FIS	Fuzzy Inference System
MPLS	Multi-Protocol Label Switching
BGP	Border Gateway Protocol
VOIP	Voice Over Internet Protocol
SQM	Service Quality Models
SQMM	Service Quality Meta Models
MAPE	Monitor , Analyze , Plan and Execute
MAPE-K	Monitor, Analyze, Plan, Execute and Knowledge Base
SDN	Software Defined Networking
IETF	Internet Engineering Task Force
Intserv	Integrated Services
Diffserv	Differentiated Services
IP-Based	Internet Protocol Based
SDLC	Software Development Life Cycle
RUP	Rational Unified Process
DOS	Denial of Service
DDOS	Double Denial of Service
FALA	Finite Action Learning Automata
CARLA	Continues Reinforcement Learning Automata
MACORD	Machine Learning-based silent data Corruption Detection Framework
HPC	High Performance Computing

List of Figures

List of Tables

Chapter 1
Introduction

In this chapter, we address the pilot information and the motivation in relation to the research. Fundamentally, the internet demands strings attached to the proper ISP management of their resources. Section 1.1 elaborates on the research context and is followed by Section 1.2 on the research motivation. The problem of interest is addressed in Section 1.3. The focus of this research is presented in Section 1.4 and the research methodology is highlighted in Section 1.5. Section 1.6 summarises the research contributions, and this is followed by the last section on how the entire thesis has been organised.

1.1 Research Context

This research considers QoS, Adaptive Architecture, SLA, ISP, Autonomic Computing and ISP architecture as the elements of the research context, applied in a computer network environment.

QoS is the set of service requirements to be fulfilled by the network providers in relation to delivering guaranteed services during network activities. In the recent world, half of the global population [1] are actively connected to the Internet and further initiatives have been made by Facebook, Motorola, Nokia, etc. [2] to capitalise the offline users with equal Internet connectivity through community service responsibility.

Social engineering software, Voice Over Internet Protocol (VOIP), Instant Messaging, online shopping, video streaming and robust innovations in communication devices are the major causes of why people heavily connect to the Internet and experience bandwidth issues.

One of the great benefits of QoS is administrative control over the application, as well as, the networks resources in the ISP's business model [3]. This can be further stretched out by leveraging into ensuring a permitted time in mission-critical applications, a better user experience and lastly, reducing any unwanted costs to do with using the resources efficiently. To secure the services accordingly, SLAs will be a companion to the given service [4].

The success rate of the Internet service depends enormously on the degree of satisfaction between providers and the customers with the measurement in the form of the satisfaction available within the QoS parameters. The major concern fields of this investigation will be the throughput, as well as other elements such as availability, security, response time, reaction time, and reliability [5]. Quality of Experience (QoE) is another argument whereby it is distinguished as the attributes that are based on subjective measurements. Some of these distinguished attributes are usability and reputation. This rating will be valued by the users and will be numerous in relation to the different attributes that belong to QoS.

The customer charges and service performance vary from one ISP to another because of the different rates, robust business model and inter-ISPs establishment fees. Yet, ISPs have the freedom to pick out and switch any of the associates who have provided them with good Internet quality or at least, best-effort services. An SLA Manager is the element that is available in the ISP architecture to accept or reject offers based on the correct information supplied by admission control. An SLA framework alongside monitoring QoS provision will be a major contribution towards the solution.

To ensure that this is in line with future generation networks, such as the Internet of Things, big data, real time applications and autonomous applications, IBM introduced autonomic computing [7]. The leading contribution of this to the network environment is the ability to perform self-network management systems [8]. It will mitigate the intervention of human experts in dealing with the management process, such as conformation, protection, healing and optimising the available resources.

These self-features will accommodate any command centre, which connects with the feedback control applications and monitors any violation of the agreed terms. In this instance, an SLA mechanism must be in place to tackle this issue.

The topics this research addresses are QoS, SLA, Autonomic Computing, ISP and Adaptive Architectures. Admission Control is the research element that resides within ISPs and plays a connecting role in relation to the adaptation manager.

1.2 Research Motivation

There are five motivations for this research.

I. Little research that is available and less focused on the highlighted research context

II. To help ISPs manage their resources and SLAs transparently between subscribers and tiers within an ISP.

III. Ensure the agreed SLAs are properly executed and any violations will be monitored accordingly with the adaptive policies and execution of penalties.

IV. The utilization of fuzzy systems and machine learning provide the adaptive and appropriate approaches between admission control and SLA management.

V. To produce an adaptive mechanism to address the highlighted problems in Table 1.1.

1.3 Problem of Interest

Research made by [3], identified three classified approaches to implement QoS systematically. These classified approaches are, Service Quality Models (SQM), Service Quality Meta Models (SQMM) and SLAs Meta Models. Although some progress has been noted, more research is needed for SLA management to manage the components between subscribers and providers. Admission control is the component that react to the request made by SLA manager to accept or reject any new SLA from provider to subscribers. In this situation, admission control resides within ISP architecture and communicate with SLA manager.

Admission controller process request related to utilization of the resources such as Voice over IP (VOIP) and Virtual Private Network [144]. The overwhelming numbers of SLAs affected the available resources and the adaptive framework to handle this is very vital to the ISP. Those important and critical components addressed in this research together with the tested algorithms.

To understand this situation, peeringDB [143], provides comprehensive information on how the connection is established between tiers in the ISP architecture. Details of the peeringDB are available in Appendix A.

1.4 Research Focus

This research understands the important of SLA within ISP, and it requires a systematic monitoring and feedback system for any violation (or near violation). A proper mechanism, such as reactive and proactive type, can be set in place to react with the situation. This approach is helpful in relation to the current admission control, because it should ensure that sufficient resources are available to fulfil current and future SLAs. An automated adaption that is based on the monitoring feedback is key and it can be realistic with the usage of MAPE-K [18].

Human interference will exist between analyses and planning to develop a knowledge foundation of the frequent decision-making. By causing this, the adaptive system, with an outstanding knowledge base, will be guided by a growing artificial intelligence which, in turn, learns from human behaviour. This research will extend the focus to positioning adaptive management architecture as the answer to the autonomic element. In this research, three QoS parameters were selected: latency, packet loss and availability.

1.4.1 Research Questions

There are **THREE** (3) inquiries that address the focus of this research:

I. Explain how to model and specify the QoS terms within an autonomic element to manage the establishment of ISP architecture? (**RQ1**)
II. Explain how to achieve the QoS provision of ISPs architecture using an autonomic computing approach? (**RQ2**)
III. What are the approaches used to autonomously self-configure and support QoS terms? (**RQ3**)

The overall idea of this research studies focus is as below:

Table 1.1. Comparison of QoS Research Contributions and Relation to the Provision. [76-84,32,96,101-102,108-112-115,123-127]

Activity	Current Research Problem	Proposed Solution	Future research activities	Benefit after completion of research activity
QoS provisions within ISP	No adaptive framework to monitor SLA agreements	Adaptive architecture as the autonomic element to handle the MAPE-K approach within ISP		• Transparent agreements and terms of the subscribers • Better network Management • System able to react adaptively to the available resources
QoS load balancing	The load balancing feature available for intra-domain		Inter-domain load balancing resource management	
QoS Services	Issues in the Integrated services and differentiated services.	Adaptive SLA mechanism to ensure customer satisfaction		Transparent SLA between users and providers. Users can have adaptive terms for the best effort and

				guaranteed services.
QoS performance	Issues with the uncertainty of network performance either in intra-networks or entire networks.		Bandwidth Management supported through usage-based module on a profiling basis	

There are four issues available in Table 1.1;

I. No adaptive framework to monitor SLA agreements
II. The load balancing feature available for intra-domain and not for inter-domain
III. Issues in the Integrated services and differentiated services
IV. Issues with the uncertainty of network performance either in intra-networks or inter-networks.

With the utilization of adaptive mechanism, this research addresses this issue to adaptively monitor SLA agreements, ensure enough resources available to cater for inter-domain and intra-domain. Besides that, two components within QoS, which are integrated services and differentiated services are able to run smoothly with ongoing monitoring components available in MAPE-K, and ensuring their execution make use of the correct amount of resources. On the last note, it really beneficial to the network performance to handle the uncertainty due to poor supervision of QoS parameters.

1.4.2 Research Objectives

The broad target of this research is to enable an adaptive framework for the ISPs to manage their resources. To understand their resources, SLA was applied as a (legal) QoS requirement to understand the engagement between ISP and their subscribers. Besides the uncertainties as the key issue in this research, another aim was to handle the learning ability of the suggested solution to work within the adaptive framework. The result of this research is beneficial, as the ISPs can monitor their SLAs and understand the need for any improvements in the resources usage. By understanding these, ISPs are able to cope with challenging business competition, and can be readily available for an active and proactive maintenance plan.

To meet this target, there are **FIVE** (5) objectives that have been established and identified, which include:

I. *Exploring the current research and issues related to adaptive framework, autonomous computing, QoS, SLA, ISP and Machine Learning.* This is here to help understand the current progress and how the remaining progress work can be established in this research. It provides information on the engagement of the connected domains in order for them to be unified, so they are able to be a solid tool for the execution of this study.

   Applied to **RQ1** and **RQ2.**

II. *Investigating the adaptive framework, SLA, and available case studies.* This is to understand the ability of the adaptive framework and match that is within the available information which is publicly available for ISP case studies on their performance and connectivity.

   Applied to **RQ1** and **RQ2.**

III. *Exploring the Telco, ISP, and admission control architecture together with the SLA Manager process.* This work contributes to the dynamic understanding of each component and how the SLA manager manages the SLA process.

   Applied to **RQ1, RQ2** and **RQ3.**

IV. *Investigating the fuzzy systems and Machine Learning algorithms to provide an adaptive mechanism*. This activity is used to understand the exact combination between the fuzzy system and machine learning. The ideal combination is able to handle the uncertainties and learning abilities during the iteration and provides dynamic adaptations.

   Applied to **RQ3.**

V. *Exploring simulation software to predict on the implementation of this research*. Simulation software is vital to this research because it provides the evidence for the mathematical algorithm execution, and for the discrete and network simulation software.

   Applied to **RQ3.**

1.5 Methodology

In the common computational research approach, there are three common methods which are; mathematical modelling, prototyping and simulation. Mathematical modelling is the combination of a sequence of equations, or a complete algorithm with symbols and operations. Prototyping is the development of an application to justify the scenario. This, in turn, helps the researcher to get the intended results. Lastly, the simulation is a tool to emulate the scenario and the configuration of the parameters to make it identical to the current research model. With the simulation, the findings must be carefully analysed to ensure that the proposed model and the simulation model produce relevant results to both.

Mathematic modelling and prototyping are the chosen methodologies used to drive this research. In the mathematical approach, the fuzzy logic technique with machine learning is the ideal match to handle the adaptation of the rule base approach. The combination of the rule base itself is translated into states and it is very versatile and crucial step in Reinforcement Learning.

A fuzzy system is the combination of multiple fuzzy controllers that represent an autonomic element in the autonomic computing environment. It is comprised of five major elements, such as:

i. **Monitor Module**
   a. Monitor the agreed SLA for any violations and provides feedback
ii. **Analyse Module**
   a. This is to analyse the data and to make necessary assessments to the available rules or policies
iii. **Planning Module**
   a. This is the phase in which to plan what to do, especially with the rules and policies.
iv. **Execute Module**
   a. This is the execution phase, and it has four fundamentals functions such as update knowledge, negotiate, terminate and adaptation.
v. **Knowledge Base Module**
   a. The last component is to have the learning ability within the looping framework.

The prototyping is the implementation of Fuzzy Q-Learning within the MATLAB environment. At this stage, the fuzzy q-learning algorithm was iteratively applied in MATLAB programming to ensure that the output was significant in relation to the intended research contributions.

1.6 Research Contributions

There are two major contributions of this thesis summarised in the following list:

1. **Introduce an adaptive architecture and adaptation manager for monitoring and responding to SLA terms within the ISP identify the current resources and limitations.**

   The proposed enhanced architecture is able to provide feedback system during the iterations. It reacts on the given SLA and updates the affected rules accordingly. The adaptation and learning abilities, of said defined policies, are demonstrated accordingly with the combination of QoS and Fuzzy Q-Learning parameters.
   This autonomic element can either placed as local or global variable depending on the requirements. In this research, there are other connected elements such as Admission Control, SLA Manager and Broker to automate the ISPs architectures.
   The solution helps admission control to update the status to SLA Manager either accepting or rejecting on any SLAs offered. The correct justification benefits the entire ISP architecture to prevent any unwanted situations such as penalties, poor performance and more than utilization on the resources.

2. **Implement the MAPE-K framework with fuzzy Q-learning to handle the adaptation and learning abilities.**

   The MAPE-K framework itself designed to support adaptation with the correct implementation. In this research the algorithm Fuzzy Q-Learning is applied, and the result demonstrated accordingly to the planned objectives. The combined algorithms able to demonstrate uncertainties and learning abilities to the whole adaptation design. These three elements, MAPE-K, Fuzzy and Q-Learning react positively to given requirements such as SLA, and it provides an effective feedback system to the architecture.

1.7 Report Structure

The remainder of this report is formed as follows:

- **Chapter 2** presents the resource management in ISPs, challenges and existing solutions; it covers the details of the research questions, contributions, architectures and relevant research progress made by other researchers. Further to that, the relationship between the research topics such as adaptive architectures, QoS, autonomic computing, Machine Learning and lastly, Fuzzy logic is explained.

- **Chapter 3** proposes the research architecture that covers the methodology that suits to the research advancement. In the beginning, it will cover the General Methodology with some of the data along the experimental system model. Further to that will be the assessment of the identified methodologies which are the mathematical approaches and prototyping. Each of these methods will be accompanied with needs, an evaluation and an early experiment.
- **Chapter 4** describes the application of Fuzzy Q-Learning with the experimental configuration, experimental results, experimental analysis and summary of the applications.
- **Chapter 5** includes the comparison, discussion and the overall assessment of the evaluation. It covers the limitations and a summary of the overall chapter.
- **Chapter 6** is the last discussion on the conclusion and future works.

Bibliography shows the list of references applied as the citations within this research proposal.

The appendix is included for any related matters tied to this proposal. This includes published papers, physical network design, logical network design, detail results, etc.

Chapter 2

Resource Management in ISPs: challenges and existing solutions

This chapter describes the current prominent research that is occurring and has occurred in the domain areas. The overall information about QoS and the sub-components related to this research have been described in Section 2.2, whereas Section 2.1 is the brief introduction of the overall related domains. Section 2.3 expresses the legal agreement researched between the agreed parties on QoS implementation and it was further extended into adaptive architecture, which was deliberated on in Section 2.4. In Section 2.5, the methods for the learning approaches have been discussed, from Machine Learning through to the Q-Learning approach. Lastly, for the chosen method, Fuzzy Systems and their use in solving uncertainties have been described in Section 2.6. In Section 2.7, the closest works related to this research have been discussed and later, the final section is the summary of the overall chapter.

2.1 Introduction.

The Internet has been fluctuating robustly within the last ten years. Especially with the introduction of appliances and gadgets. Creative people planned for the modern world. Small devices dynamically change the nature of people using communication via the Internet rather than conventional circuit connectivity. Skype’s current feature allows people to receive a real time translation when communication is engaged with two people with different and distinct native languages. Furthermore, the utmost competition between smart phone makers will rapidly transform peoples' behaviour in adjusting to the technological revolution.

To cater the increasing demand, QoS plays major part in guaranteeing that the services are according to the signed terms and conditions to deliver the complexity of the offered services in the subscribed availability, quality, flexibility, and security. This will then become difficult when dealing with several tiers of software, hardware, and bandwidth providers. Although there is the existence of Software Defined Networking (SDN), it does not resolve the entire connection, from the access router up to the backbone router, when coming from different ISPs providers.

New adaptive management should be present to ensure the ability to control diverse and rapidly growing technologies. This will be a challenge to the research community either from academic standpoint, or an industrial one.

With the various advancements of research have been in autonomic computing, since it was announced by IBM [23], several solutions towards the autonomic computing environment have been introduced, such as programming language [24], software-development life cycle [25-31], processing using event [32], profiling approach [33] and the formation of various academic and industrial [34] research groups.

2.2 QoS

QoS is the standard setup for measuring quality network performance from one connection to another, whether it is in a local or wide-area connection or not. QoS is built with five principles in mind that are: the integration principle, separation principle, transparency principle, asynchronous network management and lastly, the performance principle.

QoS specification is concerned with capturing the application's level quality of the service requirements and management policies. The QoS specification is generally different in each system layer and it is used to configure and maintain the QoS mechanism residents in each layer. For example, at the distributed system platform level, the QoS specification is primarily user-oriented rather than system-oriented. Lower level considerations such as tightness, the synchronisation of multiple related flows, the rate and burst size of flows, or the detail of thread scheduling should all be hidden at this level.

2.2.1 Qualities of Traffic

For every successful connection to the Internet or a network, there are three major activities; data, video and audio. Network guys will commonly call this a triple play where there is a combination of three core items. However, when we deal with a larger network, the performance will be a vital role to be sustained as before. In the early days of the Internet, users were granted with best-effort performance and with that agreement, network performance could be varied and there was no guarantee of reliability, delay, jitter, variation in delay and other performance characteristics.

This has been illustrated in Table 2.1. Due to that, a single bandwidth application will result in poor network performance, and no guarantees were given on the consistency of the Internet connection on an hourly or on demand basis. To overcome the uncertainty of this situation, QoS has been introduced globally to manage bottleneck issues in the computer network. It will ensure that quality is one of the core requirements, either for some applications or to provide different treatment for users with priority who will be treated differently than normal packets.

Table 2.1 QoS Components

Network Behaviours	Description
Bandwidth	Amount of traffic that is defined by the network environment
Latency	Delay in getting data from source to destination
Jitter	Difference pattern of latency issues
Reliability	Amount of percentage that will be dropped by the router due to data transaction issues

Urcoubetis [35] reported that sometimes the connectivity between tiers in terms of peering and misuse is among the strategies that are implemented by ISPs to insure their investment. Taking in these exercises, subscribers will proceed to gain greater network performance and better bandwidth connectivity. In a nutshell, this is the business model between the primary ISP and their collaborators to ensure that each of them will gain from the site. It is better known as the free-riding strategy and selective degradation strategy.

2.2.2 Applications

In the network environment, it is a mechanism to guarantee that the connectivity is delivered over the period of established association. There are two outstanding applications that reside in this connectivity, which are: connection-oriented and a connectionless application. Table 2.2 tabulates an example application running on the two associations.

Table 2.2. Sample Applications Running with QoS Categorization

No	TCP (Connection Oriented)	UDP (Connectionless)
1	Web	Tunnelling
2	SSH	VPN
3	FTP	Media Streaming
4	Telnet	Games
5	SMTP	Local Broadcast
6	IMAP / POP	

A survey has been performed over the implementation of QoS research on a distributed system platform, operating system, transport and multiple network layers [36]. With huge demands over distributed multimedia applications, it becomes a major issue and fewer researchers finding sufficient solutions in this field. In that, there are three core processes that are involved in these activities such as message passing services, remote invocation and stream services.

For operating systems, some major steps that are focused on, are the communication protocols [37] and scheduling [38] [39]. Nevertheless, the integration among the components from various operating systems is still in a grey area and it will be very beneficial if the results can be built to have one central component that quantifies the integrations.

Lastly, for the transport and network layers, the reasonable research has conversely been on the best-effort method [38, 43, 44, 45] to ensure that the delivery of data is less affected by time lag, jitter, error selection and relative precedence. In the effort of integrating the network layers [36], the recent research has contributed to the association of four parameters such as packet scheduler, classifier, admission controller and a reservation setup protocol.

2.2.3 Mechanisms

2.2.3.1 Over Provisioning

An inquiry produced by [40] has shown that, by using a provisioning centric QoS, control strategy has reduced by more than five times the signalling exchanges in their study. This outcome benefited from the application of over-provisioning mechanisms. This method allows for admitting multiple sessions without the intervention of any signalling.

2.2.3.2 IP and Ethernet Efforts

The Internet Engineering Task Force (IETF) concluded that Integrated Services (Intserv) and Differentiated Services (Diffserv) are the most prominent models for QoS over the IP-Based network environment. The Intserv model integrates with available network resources for reservation and traffic control, to ensure that the proper mechanisms are in place for handling traffic flow with special privileges or normal use. The Diffserv model applies traffic control to support the various handling methods of aggregated traffic flows.

2.2.3.2.1 Integrated Services

The integrated services model is an extension [41] of two services. Guaranteed service and managed load service. Guaranteed service will cater for the applications that require a fixed delay bound. For the regulated load service, it will facilitate the applications that require reliable and enhanced best-effort service.

Beneath are the four elements that comprise integrated services.

Table 2.3. Elements Within Integrated Services

Component	Description
Signalling Protocol	Sets up the path and reserves the signalling
Admission Control Routine	Will decide whether the application can be permitted
Classifier	Perform Multi-Field classification and put packets in a specific queue based on the classification
Packet Scheduler	Schedule the packet to meet with QoS requirements

Three core issues with this approach are:

I. Processing overheads in the routers due to several flaws
II. High demand for the routers. All routers must be able to comply with the four elements.
III. Issues with bottleneck nodes due to Controlled load service and Resource Reservation Protocol (RSVP)

2.2.3.2.2 Differentiated Services

This mechanism was introduced due to difficulties in implementing integrated services and RSVP. To launch this mechanism, subscribers must be present with a valid SLA by and with the ISP. SLA can either be static or dynamic. A static SLA is able to be hashed out over a period of months, year or in the terms of service. However, for dynamic SLA, it will be present with an RSVP to request the service. With the existing parameters within SLA such as classification, policing, shaping and scheduling mechanism, better services can be provided to the guests. It can be compiled as such:

I. Premium Service
II. Assured Service
III. Olympic Service

Shaping operations is needed only at the boundary of the nets. This is the ultimate reason why ISPs prefer to apply this mechanism since their routers are placed on different boundaries and at different locations.

2.2.4 End to end quality service.

This service means quality transmission, and it is identical to the variants produced [41] by differentiated providers, such as premium service, guaranteed service and Olympic service. As an example, the guaranteed service is the inverse service that is provided by integrated services, which is commonly known as the best effort.

2.2.4.1 Autonomous System

It is the mechanism that is able to ensure the stability of an application that connected via Internet packets. In this example, it can be synced with the premium service and the guaranteed service provided by differentiated services.

2.2.4.2 Non-Autonomous System

In this method, the instance can be the Olympic service [41], whereby it has three tiers of service such as Gold, Silver and Bronze. The QoS will be diminished due to the subscription level and the eligibility of the current tiers that are connected over cyberspace.

2.2.4.3 Resource Reservation Protocol

2.2.4.3.1 RSVP - TE (Traffic Engineering)

Resource allocation mainly runs [46, 47] at the ISP level because they will ensure that their resources, such as boundary routers, are able to handle incoming packets from another ISP. For the static SLA, reservation can be configured according to the terms and unused resources such as bandwidth that can be deviated to other activities.

2.2.4.3.2 MPLS

It is a combination of Multi-Protocol Label Switching and historically having been developed by Cisco. It is different from other protocols since it able to pick up any other label of application to run it smoothly in one pipeline or tunnel. Having this solution, it provides faster packet classification and forwarding [48, 49].

2.3 SLA

SLA was introduced back in the 1980s by telecommunication companies. By giving an SLA, the telecommunication providers can spell out their commitment to the customer either it as a best-effort connection or guaranteed connection. Normally, the customer will trust the ISP commitment by saying that their services can do almost everything before the establishment of any agreement.

Figure 2.1. SLAs Life Cycle

The subscription can either be broadband or a leased line depending upon the needs of the user. Other issues are to do with the IPv4 running out, and some countries have established IPv6 as their pillar. Lots of Internet activities such as Cloud computing and other services have a SLA as a must between subscribers and the providers to ensure that the services are according to their promises. Table 2.4 updates the reader on the research made between SLA and QoS.

Table 2.4 SLAs versus QoS

Reference	Author(s)	Comments
[50]	Srecko Krile Dragan Perakovic	Research made on how to effectively manage resources for Diffservs MPLS-based network
[51]	Byeongsik Kim Heesung Chae Taehman Han	This paper using Diffserv as the main reference for QoS and bandwidth broker to engage in their research. The difference is to understand the inter-domain protocol such as IPv4 and Ipv6
[52]	Mohamed Hamze Nader Mbarek Oliver Togni	Research made to establish better service for NaaS and IaaS. Self-establishing that proposes SLA between brokerage to ensure service runs well, especially multimedia elements Will be done by Autonomic cloud managers The result most likely focusing on multimedia elements such as videoconferencing applications. Next research will be run on a large scale or enterprise network. At the moment, it is based on the simulation and small-scale design.
[53]	Jose Simao Luis Veiga	To schedule cloud isolation and execution units. Allows providers to transfer resources to VM Relevant to private clouds Helps provider in overcommitted environments The outcome is able to help the provider lower down prices and maintain the packages as well as the software and appliances
[54]	Lise Rodier David Auger Johanne Cohen Helia Pouyllau	Trying to understand past SLAs from NSPs and how it reflects user performance without their knowledge User will be connected to three ISPs and from there, the analysis will be done. The result shows that NSPs behave as reward distribution machines.
[55]	Duo Liu Ukarsh Kanabar Chung Horng Lung	Introduction of concept in mitigating the violation of SLA from provider to end user. VM manager being used to organise the efficiency of each domain under its supervision To identify the utilisation of each domain by adopting this method

		The model is not suitable as an enterprise solution
[56]	Jeroen Famacy Steven Latre Tim Wauters Filip De Turck	Trying to maximise the performance of multimedia through; - SLAs - QoS Contracts - Negotiation with content provider - Capture the delivered QoS resource reservation cost - The idea most likely will utilise the proxy concepts from end user to the destination over the net
[57]	Adel El Atawy Tahgrid Samak	Trying to understand the difference at every intermediate hop using diffserv configuration. Suitable for MPLS VPN or any private network connection. Appropriate to locate any misuse of the SLA agreement.

Starting in 2011, we can see the parallel contributions made by researchers and industrial players to identify possibilities to address this situation. IT Companies such as Cisco, Juniper, NEC, Samsung, Frost and Sullivan kept the momentum up to connect the research with present and future research activities. In this situation, CISCO played a major role in the ISP company to ensure that there was motivation within that circle by analysing usage-based pricing and non-usage-based pricing in various countries such as Canada, United States, United Kingdom, Asian, etc.

Juniper, on the other hand, gave the owner or enterprise users the ability to ease into the management of network activities by focusing deeply on a solution called “Software Determine Networking”. By having this solution, the users were able to totally control the network activities regardless of the brand's equipment that they had within their network setup.

Considerable research has been made on SLA and Bandwidth Management. However, until now, there have been no significant efforts made to develop a novel and prudent architecture as proposed by this research. An efficient routing algorithm has been introduced regularly and continuously, as well allow for a better Internet tariff both paid and pay per use.

2.4 Adaptive Architecture

The concept consists of the iterative process to ensure the sequential flow from one to another when improvising. Basically, in learning, there are two routes; cognitive and adaptive learning. Cognitive is known to be a static method and the user or the learner should enhance their own capabilities without any intelligent interference from the application or system that they are using at the moment.

Adaptive will understand the user's capabilities and will afterwards assist him/her in areas that he should improve. The system itself is capable of recording and tracking his progress individually and next it can identify the most relevant way to improve his or her counting skills. In the computer network, this method is used to understand the current workloads that are coming from various sources and it will mitigate and normalise this into the available resources.

2.4.1 Learning Technique

Artificial intelligence is the discipline that used an appropriate machine learning method to capture human intelligence and later translate to machine codes. To some extent, into the same ability within a computer. It can be improved, in the logical sense, by creating an application with artificial intelligence elements, such as neural networks, fuzzy logic, a decision support system, knowledge base, etc [62]. However, this method still requires human intervention in understanding their right and false alarms before it can really confirm the attended situation.

Supervised, semi-supervised, non-supervised and reinforcement learning are the methods available in Machine Learning to teach agent with human behaviour and gradually increases their learning ability.

This discussion available at Section 2.6.

2.4.2 Dynamic Network Reconfiguration

The proposed autonomic computing can manage the framework and free the system administrator from routine tasks in the networking environment. Moving towards IBM in self-management embraces four elements.

A. *Self-Configuration*

In conventional computing, this is done by corporate data centres that have multiple vendors and platforms. Installing, configuring, and integrating systems is time consuming and error prone. However, in autonomic computing, the automated configuration of components and systems follows high level policies. The rest of the system components adjust automatically and seamlessly.

B. *Self-Optimisation*

This feature ensures that the components and systems continually seek opportunities to improve their own performance and efficiency. This is difficult in current computing where systems have hundreds of manually set, non-linear tuning parameters and their number increases with each release.

C. *Self-Healing*

Having this opportunity, autonomic computing can automatically detect, diagnose and repair localised software and hardware problems. This is problematic in conventional approaches due to problem determination. In large, complex systems that can take a team of programmer’s weeks.

D. *Self-Protection*

In current practise, the detection of and recovery from attacks and cascading failures is manual. Placing this feature will ensure that the system automatically defends itself against malicious attacks or cascading failures. It uses early warnings to anticipate and prevent system-wide failures.

Schroeder [67] introduced Autonet, to forecast the possibility of handling huge high-speed data transactions in a next-generation approach. However, in the same year, J.M. Garcia and J. Duato investigated [68] dynamic reconfiguration and focused on transparent processing between one network node to another. The novelty of that research was to ensure that the flow of data runs smoothly and is less affected by parallel applications within the network. In contrast, the approach was limited to one aspect of self-configuring, and it is not an inclusive model.

Autonomic Management as mentioned earlier become another element within autonomic networking that plays major role in perfecting the whole four concepts of self-process. It was stated in the IBM blueprint paper v7 [23] that there is another side of factors that crucially exist in implementation, namely:

1. Autonomic manager
2. Knowledge source
3. Touchpoint
4. Manual manager
5. Enterprise service bus

Figure 2.2 illustrates the concept of an autonomic manager and the links with the adaptive process.

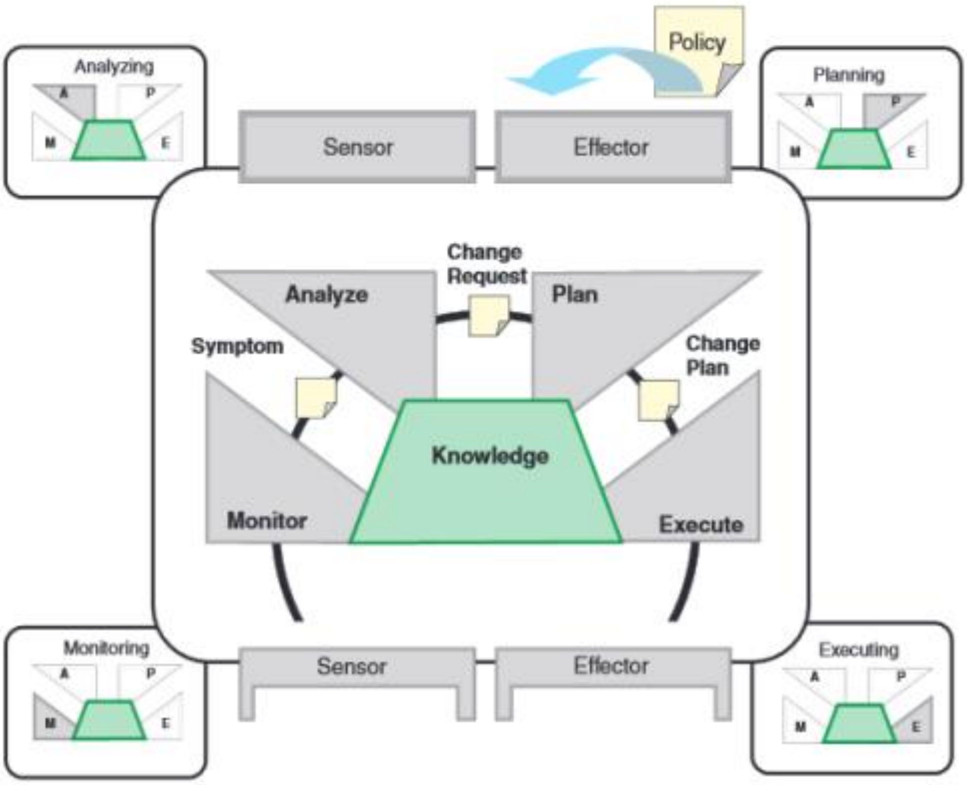


Figure 2.2: Functional details of the autonomic manager. [23]

Several researchers have presented significant work on autonomic management from various aspects. The vast knowledge base has been injected into research to justify the flexibility of taxonomy and semantic searching capabilities that can drive the autonomic management forward into better decision-making [69]. The outcome was very positive, whereby self-management was capable to understand the content of a predefined knowledge base. To extend the capabilities of autonomic management to intra-domain capabilities, research in [19] was successful in implementing an algorithm in a test bed environment.

Subsequent research, [70] was conducted using a virtual network and trying to understand the failure node using their own algorithm for the betterment of management issues related to autonomic management. It was very pleasant to know the outcome of the research, which stated that the algorithm was able to recover the failure nodes and managed the virtual environment with less technical interference from human intervention.

Self-routing ability has been extensively reviewed by adopting an Extensible Open Router Platform with a Great Plains Environment for Network Innovation [71]. Within this research study, the virtual environment and wired topology has been tested for routing issues. The results confirmed that the virtual network fully worked and was able to route equally efficiently in wired topology. The test bed of the research was done by a team [72] of various researchers coming from reputable universities. The Great Plains Environment for Network Innovation (GENI) allows experimenters to obtain computer resources from locations around the United States, to connect to computing resources using Layer 2 networks in topologies best suited to their experiments, to install custom software or even custom operating systems, to control how the network switches in their experiment's traffic flows, to run their own Layer 3 and above protocols by installing protocol software and by providing flow controllers for the switches. It is well suited for exploring networks at scale, thereby promoting innovation in network science, security, services and applications.

On the other side, Gamer and their team [73] have investigated security in self-healing capacities over autonomic computing. According to their research, it was proven that self-healing algorithms can overcome malicious attacks ranging from and including viruses, worms, DOS and DDOS. Having this result is a great start to informing of security over autonomic management. Added contributions can be further made to secure the network from unwanted outbreaks.

2.4.3 Adaptive Management

Two main contributions that are significant in the scope of this paper are self-management with the ability to support SLAs and managing resources using autonomic management.

In the Self-Adaptive literature, research conducted by [96] focused on adaptive pricing strategies with the assumption of healthy competition between domain operators to get as much inter-domain traffic profit as possible. The competition was based on the available route connections, prices, agents and the network load. The later research by [108] expressed the adaptation framework with the integration of Fuzzy Q-Learning to handle the varied workload performance from cloud providers.

The learning methods were able to produce the learning rate of each performance. However, the number of inputs was limited to two inputs and the iterations numbers were on a small scale. The same research has been enhanced with back to back comparison with Q-Learning and Sarsa to understand each capacity in relation to handling the workload.

Besides Fuzzy Q-learning, Finite Action Learning Automata (FALA) and Continues Reinforcement Learning Automata (CARLA) have been applied by [96] in his research. The objectives were to demonstrate that Interdomain model routing, as an eternal flow on a certain link, has a cost for the ISP owner. Interdomain links are shared among domains and their prices are equal to the routing costs. They provide virtual link prices to generate income. The pricing model with the appropriate costs and utilities has been introduced as the outcome of his work.

In the fuzzy system, the research made by [97-98] demonstrates the benefit of the adaptation of the available services together with SLA. The adaptation also helps to maximise profits in service level management [99], deals with the negotiation [97] and lastly, the adaptation is based on QoS requirements [100].

The following fact sheet in Table 2.5 will conclude and highlight some of the other research that is generally relevant to research areas. The detailed comparison on the closest research available is in Table 2.6.

Table 2.5. Comparison of Closest Research Reviews – Autonomic Management

Ref	ISPs Architectures	Autonomic Management Properties (Self-Configuration, Self-Optimisation, Self-Healing and Self-Protection)	Human Intervention in the framework
[76]	Using Web Server Environment	Carrying out of an autonomic manager in predicting the next sequence or actions based on previous behaviour. The autonomic manager will choose one or more appropriate actions of anticipation.	Each element will deliver its own associated policies that will help the autonomic manager to decide on the following course of action. Human Intervention = **Unsupervised**
[77]	No	Using autonomic elements called SelfLet. It can communicate from one component to another to work within the complex infrastructure. The model can understand the specifying behaviour, abilities and goals of each component. It will direct them to the autonomic manager that is able to understand the entirety of the components.	It works on the Model called SelfLet. Human Intervention = **Unsupervised.**
[78]	No	Autonomic Management approaches to identify the preferred uses of existing policies or learn new policies.	Applying a Reinforcement Learning Model to accommodate the alterations. Human Intervention: **Unsupervised**
[79]	Future Internet Networks, such as wireless network issues	Using a cognition cycle to adapt the adaptive network management. Cognitive network managers can interpret the previous events in the circle and this works for betterment in the hereafter.	Using a Cognitive Cycle Process Human Intervention: **Unsupervised.**

[80]	ISPs (Tiered Infrastructure)	No elements of adaptive management. Using an Autonomous System within the ISP to understand the routing table sizes and churn rates.	Connect ISPs using inter-domain concepts to grow worldwide as a topology. Human Intervention: **Unsupervised**
[81]	Cloud Computing Environment	Using Hierarchical Autonomic (HA) – SLAs. Within this approach, each SLA is expected to have its own control mechanism to increase SLA validity without compromising the response time. Using autonomic features to show the self-management SLA.	Using SLAs attributes to connect one SLA and another. Human Intervention: **Unsupervised**
[82]	Cloud Networking Environments	Using autonomic management features to establish NaaS and IaaS services. The architecture ensures the self-establishment between cloud managers.	Using SLA as the medium between the Cloud Service Provider and Cloud Service User. Human Intervention: **Unsupervised**
[83]	Cloud Networking Environments	A novel policy-based adaptive approach to solve the issues of contract between provider and customer. It will then provide a contract template embedded with the policy to adapt to the changes of service provision and the participant's requirements.	Using SLA to ensure satisfaction between both parties. Human Intervention: **Unsupervised**
[84]	Cloud Computing Environments	Presented with self-manageable architecture to ensure less violations in the contract of SLA between providers and subscribers. The research was based on the SLA-based service virtualisation that provides an easy process in its execution.	Using SLAs to ensure satisfaction between both sides. Human Intervention: **Semi Supervised**
[32]	Intra Network	The interaction uses events as the skeleton between one autonomic element to another. Events allow one to precisely monitor the	Using Algorithm skeletons as the feature for self-configuration and self-optimisation.

		status of the execution of the algorithm skeletons.	Human Intervention: **Unsupervised**
This Research	To provide a solution for ISPs Architecture.	System will fully utilise the autonomic management features to ensure that it is able to adapt to the changes and available resources. With that approach, SLAs will be the mainstream contract or template that is transparent between the providers and their partners, which will have be back to the subcarriers and subscribers.	To present robust autonomic management with the ability to be semi-supervised from the initial start. The system will further mitigate the process with an unsupervised approach using the MAPE-K framework.

Table 2.6: Comparison of Closest Research Reviews – SLA

	Research Features				
Reference	**Research Problems**	**Contributions**	**What they do not do**	**How Can I Improve**	**My Contributions**
[96]	There is no tool to the ISPs to gain the optimal link prices.	a) Introduce a selective exploration rule, Learning Automata (LA) for stationary and non-stationary environment for ISPs. b) Using a formal method to calculate the inter-domain routing within ISPs with two scenario. c) Two pricing models available; utility model and cost model.	Full MAPE-K Framework and an evaluation of the agreement between ISPs. It is very crucial to identify any metrics which cannot be fulfilled throughout the SLA.	Incorporate the inter-domain services between ISPs and bind them with SLA. A further framework should be exhibited to ensure the signed SLA will be actively monitored on the agreed terms. Any violations will be subject to the agreement for both parties.	An inter-domain architecture with the present of MAPE-K framework to ensure that the SLA terms actively monitor for any violations.
[101]	To have a renegotiation	Using two approaches; a) Bargaining-based negotiation	The solution is for one	To have a dynamic Service	To ensure that the renegotiati

	approach within a cloud based system to ensure the flexibility and scalability.	b) Offer generation-based negotiation Ability to generate multiple offer SLA parameters within one round during negotiation	cycle and not through the MAPE-K framework, whereby the SLA Manager will act as the autonomic element to supervise the running agreements.	Level Objective (SLO) that is adaptive to the agreements during renegotiation. This will then avoid any violations.	on will have all of the possible inputs from other providers and the enhancement of the SLO will be thoroughly monitored.
[102]	To have a renegotiation protocol with multi round capabilities. It can cater for network environment such as message lost, delayed, duplicated and reordered.	A clear definitions of the protocol has been established. There are three main contributions under protocol specification ; such as a) Protocol Messages (RenegotiationQuoteRequest, RengotiationQuote , Renegotiation Offer, RenegotiatioOfferAck, RenegotiationAccept, RenegotiationReject, RenegotiationNotPossible) b) Protocol Behaviours i) Customer Behaviour ii) Resource Provider Behaviour c) Handling Inconsistencies	This protocol, although it is a thorough process, does not apply in any of the case studies, especially in the MAPE-K framework.	To evaluate the proposed protocol with the MAPE-K framework. This exercise can prove the consistency of the framework with the running research activities.	The MAPE-K framework will have a thorough renegotiation protocol to ensure the stability of the entire process.

2.5 Machine Learning

This section describes the current research into machine learning, which is widely known as one of the divisions of artificial intelligence. OptCon [103] is the research focused on adaptable SLA-Aware, where the use of the machine learning technique to automate the choice of subscriber-centric consistency settings under a user-specified latency and staleness threshold which was agreed to in the SLA. Decision tree learning and the Bayesian approach was applied in OptCon and it contains two phases, which are Labelling and Training.

Machine-learning-based silent data Corruption Detection Framework (MACORD) [104] was exercised using a supervised learning method. There were 11 High Performance Computing (HPC) applications that were evaluated from various domains and the list has been scaled down to 5 due to the nature of this research. The 11 applications are K-Nearest-neighbour(K-NN), Decision Tree (DT), Linear Regression (LM), Support Vector Machines (SVR), Ada Boost Regressor (AB), Gaussian Process Regression (GP), Stochastic Gradient Boosting (SGB), Random Forest (RF), Extremely Randomized Trees (ET), Bagging (BR) and Symbolic Regression (SYM). From the observations, K-NN, DT, LM, SVM and AB were selected due to the significantly lower training cost compared to the other algorithms. It was governed by an online spatial learning algorithm to manage the most five detector algorithms.

Josep Li [105] introduced an adaptive framework for the autonomic scheduling of tasks and web services in the cloud environments, optimising and penalty violation in SLA. He used a combination of linear functions, decision trees within a linear regression model and a feature selection process. The main contribution is that the developed model able to find optimal solutions according to the presented policies.

Swayam [106] is a fully distributed autoscaling framework that exploits the production of Machine Learning to deliver the dual challenge of resource efficiency and SLA compliance. An assessment was made of the 15 popular services that hosted machine learning as a platform for specific SLA terms. The model itself is governed with request rate prediction, backend resource estimation model, distributed autoscaling protocol, and lastly, load balancing.

In the series of research studies on Markov Decision Process (MDP), Reinforcement Learning, Q-Learning, Sarsa has been thoroughly reviewed by [109] in his research. Although Q-learning and Sarsa are the most famous off policy and on policy methods, the extension of fuzzy helps the algorithm to integrate with uncertainties in the rules. In his works, the implementation was Fuzzy Q-Learning, which was originally introduced by [107].

Table 2.7 tabulates the other research studies conducted and has identified the key contributions.

Table 2.7. Comparison of Closest Research Reviews – Machine Learning

	Q-Learning	**Sarsa**	**Deep Learning**	**Neural Network**
Adaptive	Yes [115] [114] [127]	Yes [127]	Yes	Yes [112]
Integration with Fuzzy	Yes [123] [110] [128][107]	Yes [129]	Not Available	Not Available
Optimisation	Yes [124] [125] [126] [127]	Yes [124] [125] [126] [127]	Yes	Yes
External Knowledge (connect with admission control)	Yes	Yes	Not Available	Not Available
Policies (Feedback, Rewards, Penalties, QoS)	Yes [off policy] [111] [113] [15]	Yes [on policy] [111] [15]	Not Specific	Not Specific
SLA	Yes	Yes	Not Available	Yes [112]
Fuzzy	Yes [108]	Yes [109]	Not Specific	Not Specific

A considerable amount of literature has been published specifically on the collaboration of fuzzy with other algorithms. The idea is to prove the ability of the other algorithms to work with the uncertainties feature that is the ultimate ability rendered in fuzzy. Consistent research by [108-110] suggests the establishment of Fuzzy with the Q-Learning and Sarsa algorithms.

Both methods are derived from reinforcement learning. The main issues with Q-Learning and Sarsa are the exploitation and exploration approach. In Sarsa, the method is more open to exploitation and if they able to reach the goal, most likely the numbers of steps taken will be less compared to Q-Learning. It will be risky due to not all of the steps being explored. In the Q-learning path, the method is mainly exploration and the learning is consistent from one iteration to another.

In [109], they addressed the ability of fuzzy to handle uncertainties and q-learning to handle the learning ability. It covers the MAPE-K framework adaptation used to monitor SLA implementation in Microsoft Azure and Amazon.

2.6 Closest Related Work

The closest research conducted by [108-110], he established SLA violation, reward configurations, MAPE-K framework and Fuzzy Q-Learning in cloud environments. The overall works of his research is to formulate adaptation environment in handling multiple cloud providers executions. Such as Google and Amazon.

Although the numbers of research done increasing in domains of SLA and Admission Control [132], the focus are not present in providing adaptive information about availability and limitation of resources to continue serving the subscribers. Vranc et.al [96] explored the utilization of Learning Automata with dynamic adaptation framework and the framework differentiating from the framework of MAPE-K. In his research, the data input for monitoring process are manually created, and the iteration does not developed ability to make decision which are present in MAPE-K.

On the recent research made by [109], he added Fuzzy Sarsa as another algorithms to evaluate the generated results from Fuzzy Q-Learning application. Although both algorithms belong to Reinforcement Learning, Fuzzy Sarsa focused on the exponential rather than exploration. Exploration is important parameter in this research to evaluate the smooth learning process from one state to another in Q-Learning values.

The framework itself contains dynamic elements which are Monitor, Analyse, Plan, Execute and Learning (Knowledge Base). This framework is related to autonomic computing and it is often referred to by its self -* properties, such as self-configuring, self-optimising, self-healing and self-protecting [119]. Typical self-adaptive architecture consists of two major components; adaptable software and adaptation manager.

Adaptable Software: Application logic is implemented in adaptable software and requires sensors and effectors for the adaptation.

Adaptation Manager: The adaptation manager utilises the monitoring, detecting, deciding and acting of the sub-process in order to control the reaction of adaptable software.

The goal of reinforcement learning is to develop agents that learn, interact and adapt in complex environments, based on feedback in the form of rewards. Recent self-adaptive systems contain decision-making processes that maximize policy-based and goal-based results [119].

We incorporated three major domains, SLA, Machine Learning and Adaptive Framework to fulfil this thesis. SLA agreement and ISP performance data captured from public case study [139-140] and later applied as the input for the iterations. The purpose of this research are different from [108-110] , we addressed the SLA management within ISP using dynamic data input , QoS and Q-values parameters in addition to the complexity of the rules and policies.

2.7 Summary

The overall summary of this chapter is that the related domains to this research have been established by their recent research outcomes. The outputs are very much related to progress in the areas of adaptive architecture, framework, QoS, SLA and lastly, the combination of machine learning and fuzzy. An adaptive framework is the key to handling the blueprint of this algorithm and it sets the boundaries of this research.

Nevertheless, since the application of MAPE-K framework, SLA and Machine Learning can be applied in different research areas such as monitoring cloud performance, SLA renegotiations, brokering and admission control, there is a research opportunity to discover the same combinations in the ISP environment in order to handle their agreement and resources. With a good adaptive approach, ISPs are able to perform the following efficiently:

- Identify service objectives (performance, availability, responsiveness)
- Determine the right system configuration to be used for each customer.
- Monitor agreed–upon services.
- If monitoring indicates a possible violation of objectives, it can react to the situation
- Issue SLA reports
- Issue appropriate credits/feedback.

Chapter 3
Fuzzy Q-Learning Architecture

In this section, we have proposed architecture to support the adaptation activities. The architecture has been identified and designed with the important components in line with the requirements. We streamlined the QoS, ISP, SLA admission control to the architecture definition. Section 3.1 explains the general methodology involved and that is followed by Section 3.2 on the methods of the research. Section 3.3 elaborates on the assumptions and constraints of the chosen tools and the methodology for the implementation of the architecture. Section 3.4 highlights the architecture and was followed by Section 3.5 on the Early Experiment using Opnet Simulation and Section 3.6 on another experiment using the Fuzzy Rule Base approach. Then we extended the autonomic architecture with the reinforcement learning method to support the overall proposal. This is important to show the relationship between the different architectures and how we have plotted for a holistic design.

3.1 General Methodology

Methodology is a way to achieve the proposed contributions in a very systematic approach. In the computing science domain, commonly there are three approaches, which are mathematical modelling, simulation and direct experiment. Each of these results compliments the others in justifying the final verdict of the research outcome.

On top of said methodologies, it is very appropriate for this research to be in line with the MAPE-K approach, which has been designed and globally tested by the International Business Machine (IBM) in the autonomic computing environment. By getting this right in the first instance, it will ensure that the simulation and direct experiment is significant and appropriate to the available architecture. It matches the need for the enterprise environment to work well with targeted autonomic computing architectures.

As for the mathematical model, the chosen approach is a combination of Fuzzy and Q-Learning algorithms to adapt to the uncertainties and learning abilities. The Fuzzy Q-Learning itself was established in 1994 by [107] and has been creatively renovated with enhanced features [130] to support the different research areas.

3.2 Method of Research

With an understanding of the experimental system model, especially on the connection of different contexts, this can then be used to conclude the research proposal in this report. There are a number of approaches that can be used to overcome the findings. The results can either be along the lines of mathematical modelling, network simulation or lastly, by direct experimentation.

In the following chapter, this research further elaborated on the availability of each method to carry out this proposal and how it can unify the involved elements.

3.2.1 Mathematical Modelling

Computer science research is formulated with mathematics via logic, data analysis, and the experimental findings. The focus points of computer science are also connected with socially significant research into software and information networks. The main process in mathematical algorithms is the computational ability to sort the unstructured algorithm into an automated and presentable solution. The iteration process within the mathematical model will be introduced to understand the problems and to adapt. In most ways, it can be simplified.

Handling uncertainties and adaptation involves a lot of equations and this can be formulated in a systematic mathematical approach using the machine learning approach. The term 'machine learning' is quoted as below. "***We say that a machine learns with respect to a particular task: T, performance metric P, and type of experience E, if the system reliably improves its performance P at task T, following experience E. Depending on how we specify T, P, and E, the learning task might also be called by names such as mining, autonomous discovery, database updating, programming by example, etc.*** ". [142]

Machine Learning is a division from Artificial Intelligence, and it is parallel to the following:

- Deduction, Reasoning and Problem Solving
- Knowledge Representation
- Planning
- Perception: Computer Vision
- Robotics: Motion and Manipulation
- Natural Language Processing
- Social Intelligence.

The three machine learning sub divisions are supervised, unsupervised and reinforcement learning. Each of the divisions runs using different methods and produce different learning capabilities. Q-Learning is about the policy method underneath temporal different learning, and it is below reinforcement learning. The character of a policy is the target policy equal to behavioural policy, and about using a model free method for learning.

Q-Learning is a competitive learning program in which agents act optimally using policies to reach the target [131]. A Q-function is a technique used to map action-state pairs to predictive reinforcement. Although the method is attractive, due to online policies, it is model free and contains the identification of the best operator at any time. It is slow and requires extension to accelerate the learning. To overcome said issues, fuzzy q-learning was introduced by [107] with the immediate extension of the basic q-learning method and the combination of the fuzzy inference system.

Both are able to blend uncertainties and learning abilities, which is a major contribution for adaptation.

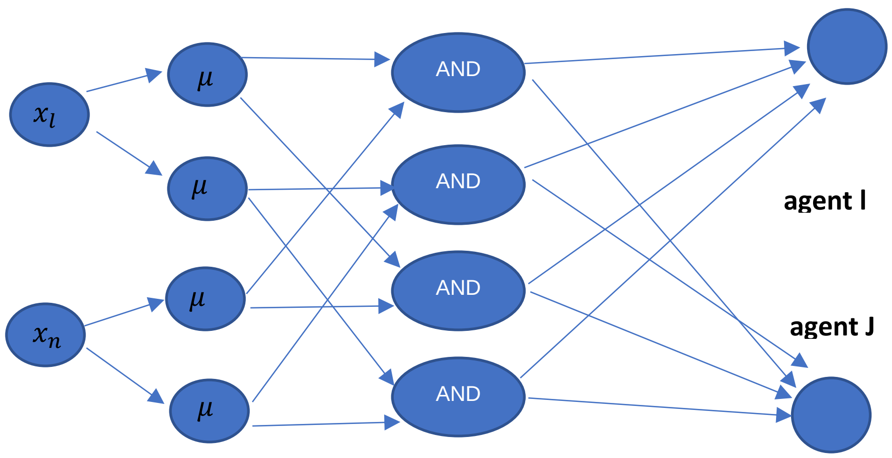


Figure 3.1 Fuzzy Q-Learning Architecture [107]

In Figure 3.1, the rule base is equivalent to the action when it computes the possible outcomes from all of the listed combinations.

3.2.2. Simulation

Simulation is another method that can be practically used to gather prominent results with the proper findings activities. It is applicable in the computer network by using a few prominent simulation software, either on open source networks or proprietary-based. A network simulator is a technique of implementing a network on the computer. Every component within the simulation will carry out their own behaviours and profiles and can be connected with embedded formulas or by capturing and playing back observations from a production network.

In this research study, there are two applications - MATLAB and OPNET academic edition - which have been purposely applied to run the experimental simulation. The utilisation of each software is tailored to the early experiment and final experiment. The idea in the early experiment to ensuring the environment of autonomic computing can be simulated. Later, it can be extended to a narrower research context, whereas in this research, it is the SLA management within ISP.

The two software in detail have been explained below:

1) OPNET Academic Edition

The network simulator allows for the researchers to gather the data and findings in a very cost-effective way rather than having real equipment. In relation to the research method, this is known as a real direct experiment. It is particularly useful to test new networking protocols or to change the existing protocols in a controlled and reproducible environment. Network design can be robust, and the users have various options to integrate such as different topologies, devices, products, enterprise or local networks.

The network simulators are of different types which can be compared based on:

1. Simple design in a complex environment
2. Specifying the number of nodes from the main route to the tiers
3. Able to adapt with various protocols
4. Good Graphical User Interface (GUI) in commanding the design
5. Any form of advanced mode such as command line, scripts, etc

There are different network simulators with different features that have been tabulated in Table 3.1.

Table 3.1 Network Simulators Review

Brand	Freeware / Commercial	Enterprise Solution	Features	Versioning
NS2	Free	It is a discrete event simulator that provides support for the simulation of TCP, routing, and multicast protocols over wired and wireless Networks.	Ns2 code comprises of OTCL and C++. OTCL is an interpreter used to execute the commands. NS2 follows two levels of hierarchy Namely C++ Hierarchy and the interpreted OTcL,	Continue to NS3
NS3	Free	It is an extension from NS2. The new modules of ns3 can handle multiple interfaces or nodes correctly, and	Simulators are written in C++ and Python. They are able to extend to the following features: a. Initialisation and	

		the use of IP addressing, more alignment with Internet protocols and more detailed 802.11 models .	termination of ns3 objects b. Definition of Network Topology c. Transport protocols and applications in ns3 d. Scheduling events in ns3 e. Tracing events in ns3	
OPNET	Commercial , Free for Academic Version	Developed at the Massachusetts Institute of Technology (MIT) and since 1987, it has become commercial software. It provides a comprehensive development environment supporting the modelling of communication networks and distributed Systems.	OPNET supports four simulation technologies such as 1. DISCREET EVENT SIMULATOR 2. FLOW ANALYSIS 3. ACE QUICK PREDICT 4. HYBRID SIMULATION	Bought over by Riverbed. Now the software known as Riverbed Modeler. Ver 18.0 Academic Edition (IT GURU) Ver 17.5
NetSiM	Academic	Discrete event simulator, object-oriented and simulation to support simulation of voice and data communication. Developed by Cisco to understand the running packets and designing a complex network.	Netsim is a stochastic discrete event simulator which allows for the simulation of various networks Including Wireless sensor networks, wirelesses LAN, WiMAX, TCP, IP networks.	Netsim Ver 10.
OMNeT++	For Academic	OMNeT++ is a discrete event simulation environment. Its primary	Has the following components ; Simulation kernel library	4.5

		application area is the simulation of communication networks, but because of its generic and flexible architecture, it is successfully used in other areas like the simulation of complex IT systems, queuing networks or hardware architectures	compiler for the NED topology description language, OMNeT++ IDE based on the Eclipse platform GUI for simulation execution, links into simulation executable (Tkenv) command-line user interface for simulation execution (Cmdenv) utilities (makefile creation tool, etc.) documentation, sample simulations.	

In addition to the top five, there are other network simulators available:

a. Spnp
b. Sense
c. Query Cycle
d. Maise
e. Neurogrid
f. Tossim
g. GloMoSim
h. INSANE

With the comparison of the top and average network simulation software completed, the OPNET Modeller was chosen as the network simulator due to the following criteria:

a. OPNET has the highest development version and is heavily applied in ISP environments.
b. NetSim was developed by CISCO and really works with other CISCO simulation software such as BOSON, which is a routing emulator, whereas OPNET contains repositories of unusual brands and the software itself does not belong to any network competitors.
c. Although NS3 is capable of executing in an enterprise environment, it stills requires a lot of code interventions due to having fewer graphical abilities compared to OPNET.

d. OPNET is competent at connecting with distinct existing data that was extracted from a real ISP environment and using that to improve core network performance.
e. OPNET and Wireshark are able to link with their own API to connect and understand the collected data for data gathering.

2) MATLAB

This software was developed by Cleve Moler, Jack Little and Steve Bangert with an initial code named ‘Matrix Laboratory ‘[145]. It later grew and has become accepted globally as one of the utmost tools for mathematical simulation software. At present, MATLAB is accompanied by a robust set of features and a toolbox within the original product family or as an extension by third party companies. Among the features related to this research are:

- Math, Statistics, and Optimisation
    - Optimisation Toolbox
- Control Systems
    - Fuzzy Logic Toolbox

With the utilisation of the fuzzy logic toolbox, it helps the translation of the fuzzy rule base into established fuzzy systems, such as Mamdani and Sugeno. It later can perform specific membership functions, create fuzzy rules, evaluate and visualise fuzzy systems, import and export and lastly, construct custom fuzzy systems.

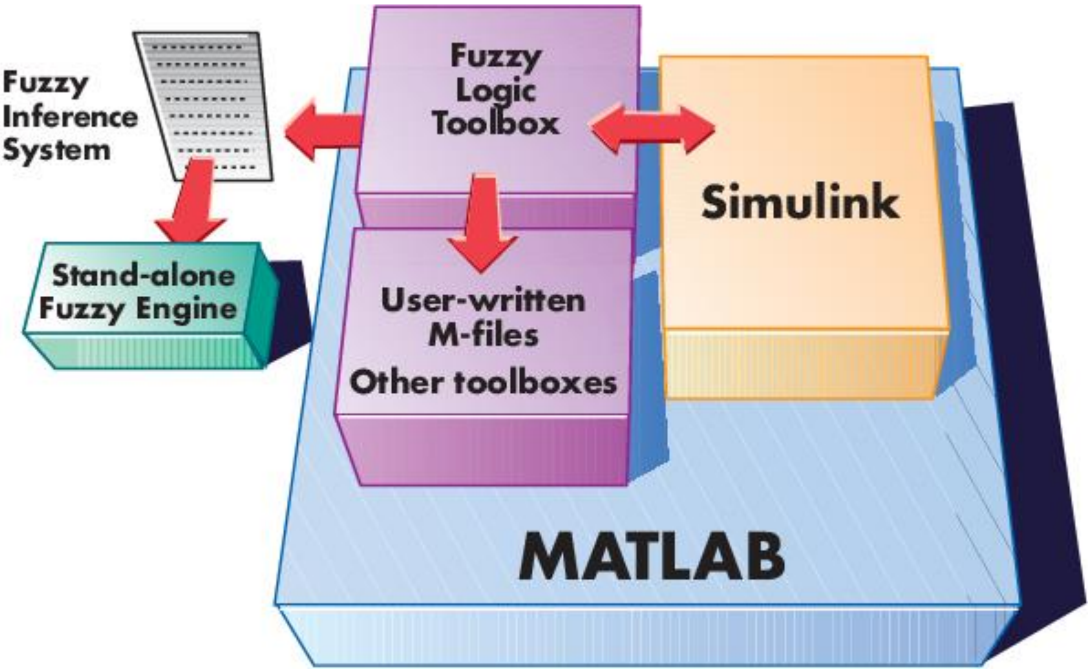


Figure 3.2 Fuzzy Logic Toolbox within MATLAB

The fuzzy inference system is among the key functions within the fuzzy toolbox as illustrated in Figure 3.2. It formulates the crafted input into fuzzy logic output. This is called the mapping process and is very useful for decision-making and understanding the pattern of the defined rules.

The toolbox covers from early fuzzification up to the end of the defuzzification process. The steps involved include fuzzily inputs, applying the fuzzy operator, applying the implication method, aggregating all outputs and lastly, defuzzifying.

3.2.3 Direct experiments

Direct experiments resulted in more prominent data and findings as well as analysis. However, in this research, the utilisation of direct experiments refers to the public case studies for SLA and ISP performance. Both case studies contributed significantly to formulating the categorisation of SLA in the real ISP environment and the actual ISP performance.

3.3 Assumptions and Constraints

In this proposed research, there are three methodologies that are likely to be relevant, which are **mathematical formula, simulation and direct experiments.** Following are the assumptions and constraints that are available in this proposal:

a) To ensure that the collected data for simulation is identical to the ISP architecture and environments.

b) To further examine the connectivity of the various mathematical models to create a seamlessly autonomic computing environment with multiple autonomic elements plugged in layers of the ISPs.

c) OPNET Modeller ver. 17.5 is the enterprise version that has been globally applied in ISP simulation. Nevertheless, Academic version applied in the early research, and it was limited with the numbers of days it was available together with the limitations in place to do with the functionalities of the number of nodes that could either be in the stations or network devices.

d) MATLAB is a great piece of mathematical simulation software and it is embedded within the fuzzy and optimisation toolbox which is significant to this research. However, the analysis of the produced result is a major proposition for improvement in the software.

3.4 High level architecture Adaptation Manager

The adaptation control can be classified into three core areas, such as approach, adaptation decision criteria and the degree of decentralisation. Figure 3.3 portrays the information about thorough self-adaptation taxonomy.

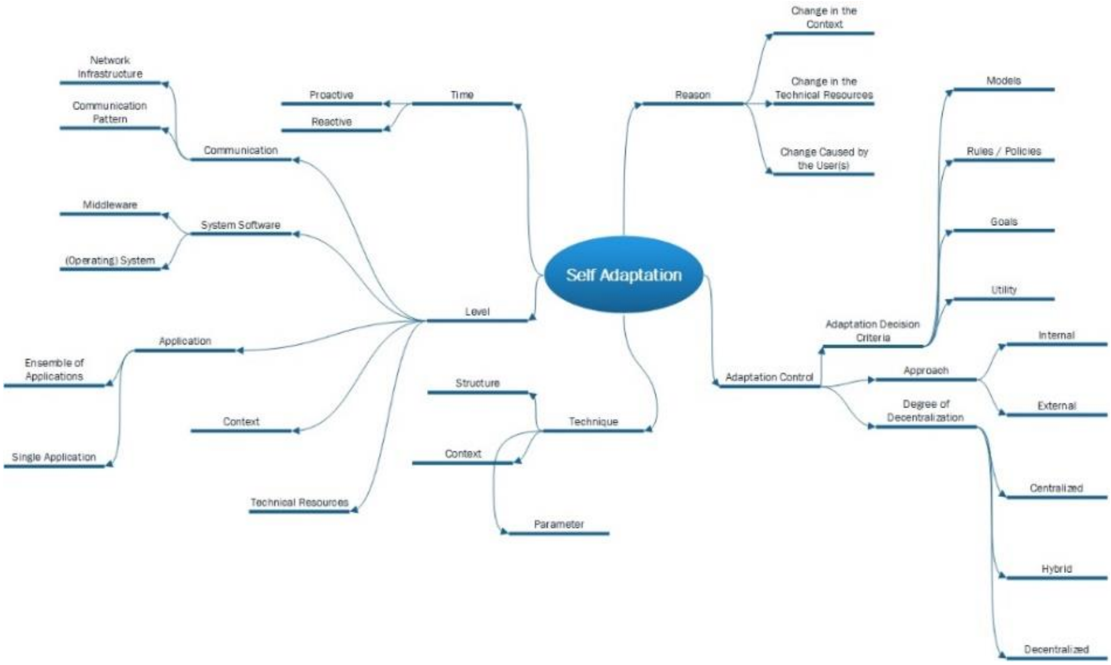


Figure 3.3 Self-Adaptation taxonomy

The key central question related to the adaptation time is how long it can adapt to the situation. It is related to the input from the user perspective, to evaluate and justify the adaptation with regards to all of the arguments that are connected to the situation. This approach can be realistic with the usage of MAPE-K.

Research will extend the focus on the establishing autonomic elements that will be contained within the adaptive management architecture. The elements will be the policy exchanges between the local and global autonomic managers, whereby the overall management will be controlled by the enterprise adaptive architecture.

3.4.1 Proposed Architecture

SLA is to be appraised by the Local Autonomic Manager within the same tier on the cost saving, effective routing that concludes the latency issue. It will further be accessed by the enterprise autonomic manager for the results and governance of the autonomic computing within high level architecture as in Figure 3.4. Autonomic element interacts autonomously among them to exchange information, negotiations and perform agreed executions. It works similarly like an autonomous agent in the autonomic computing environment. Local autonomic manager is the handler for each autonomic element under their environment.

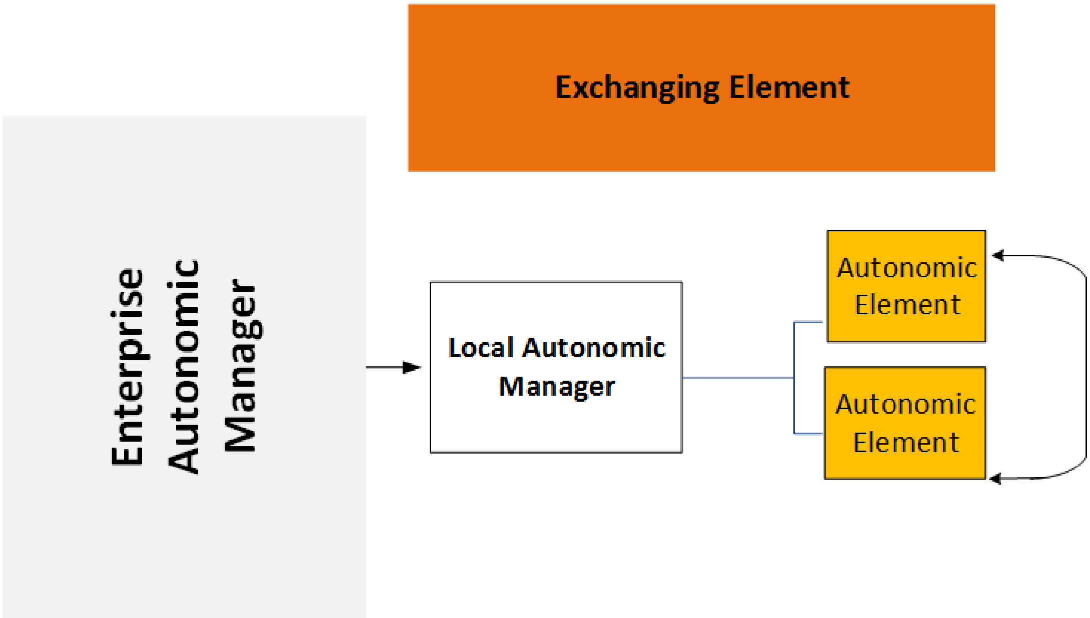


Figure 3.4 High Level Design of the proposed architecture

Further connection between the local autonomic manager and the enterprise autonomic manager over the autonomic computing main architecture is addressed in Figure 3.5.

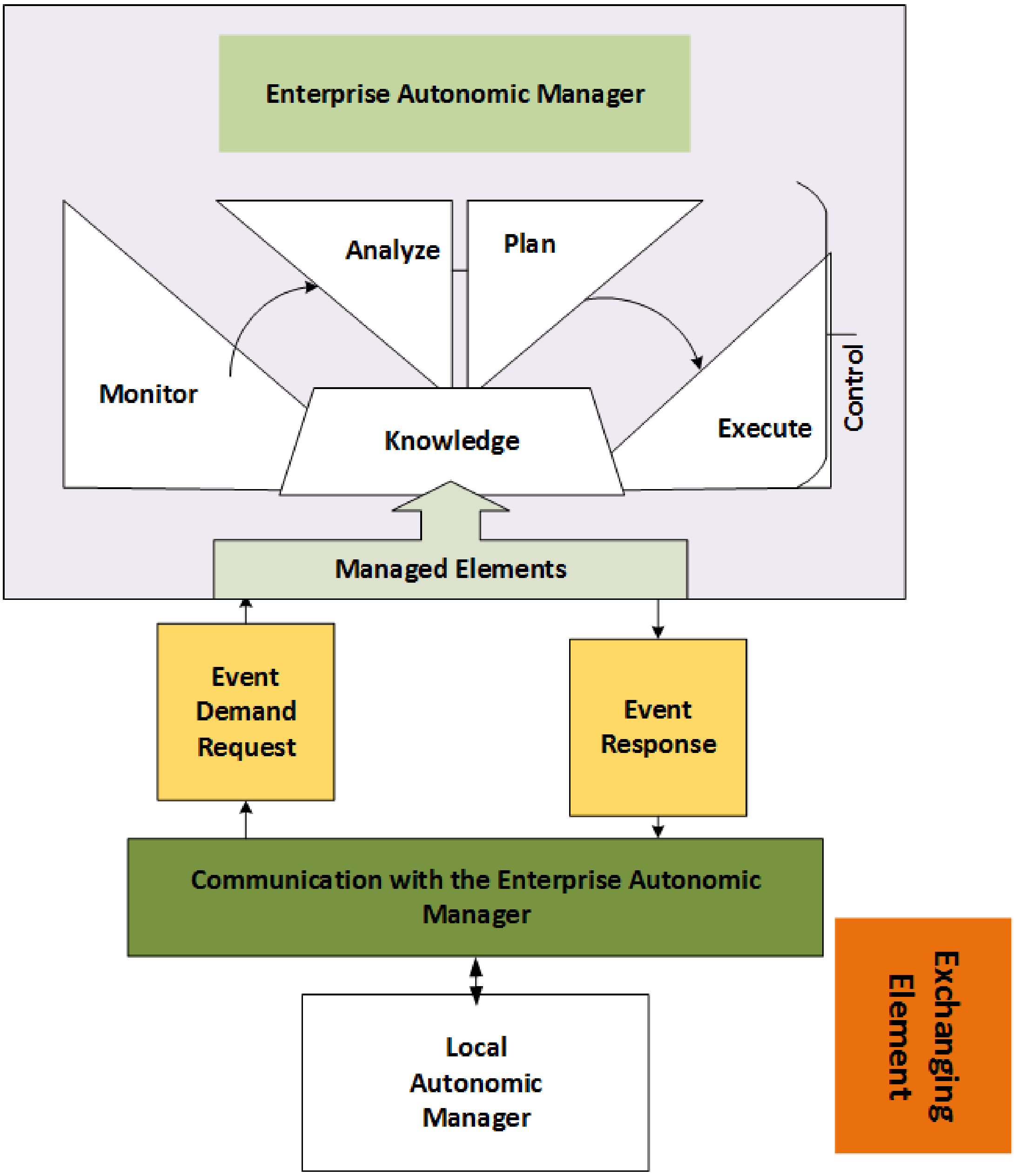


Figure 3.5 Adaptive autonomic computing between Local Autonomic Manager and Enterprise Autonomic Manager

The enterprise autonomic manager and the local autonomic manager consist of the same MAPE-K model design for autonomic computing. With abilities to minimise human intervention by providing suitable managed elements via touch point, it will then develop betterment of the knowledge base which runs recursively in the iteration procedure.

Within this architecture, MAPE-K will evaluate the exchanging elements either from the local and enterprise process and to provide the accepted system response. The system will have four core functions, which are monitor, analyse, plan and execute to ensure that the environments are running smoothly and are intelligently updated with every new alert.

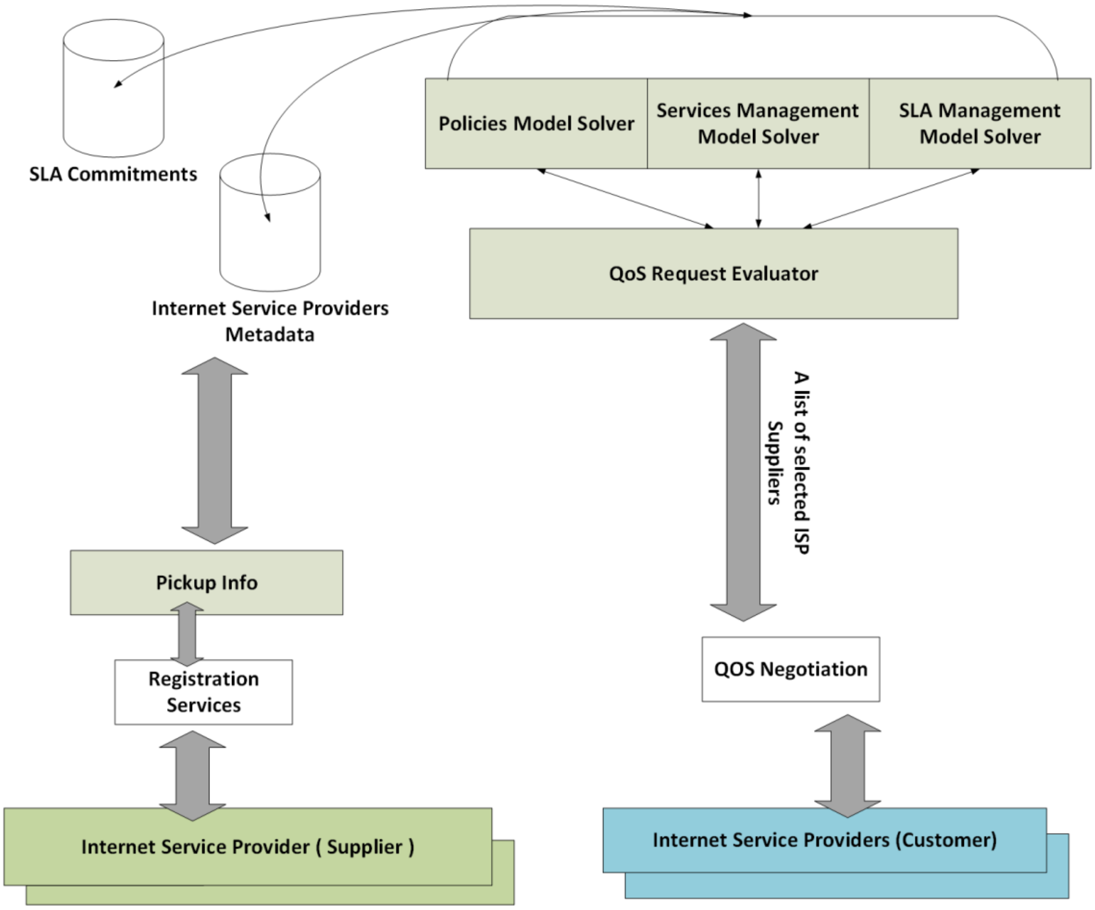


Figure 3.6 Framework of SLA between ISPs

Figure 3.6 contains two more sub-elements, which are vital to this operation. The User Profile model solver inherits three main databases such as the user profile metadata, SLA commitments and ISP Metadata. The first one is the trailing of the user profile from one broker to another and lastly, the negotiation of terms and services with another ISP.

All the information related to ISPs performance stored in the Internet Service Providers Metadata and comparison of the SLA commitments. Subscribers able to review the performance of ISP and how they commit in the produced SLA. Having this information, it helps subscribers to evaluate SLA given by ISP and understand the current assessment of ISP. This framework able to list numbers of ISPs according to the selection criteria.

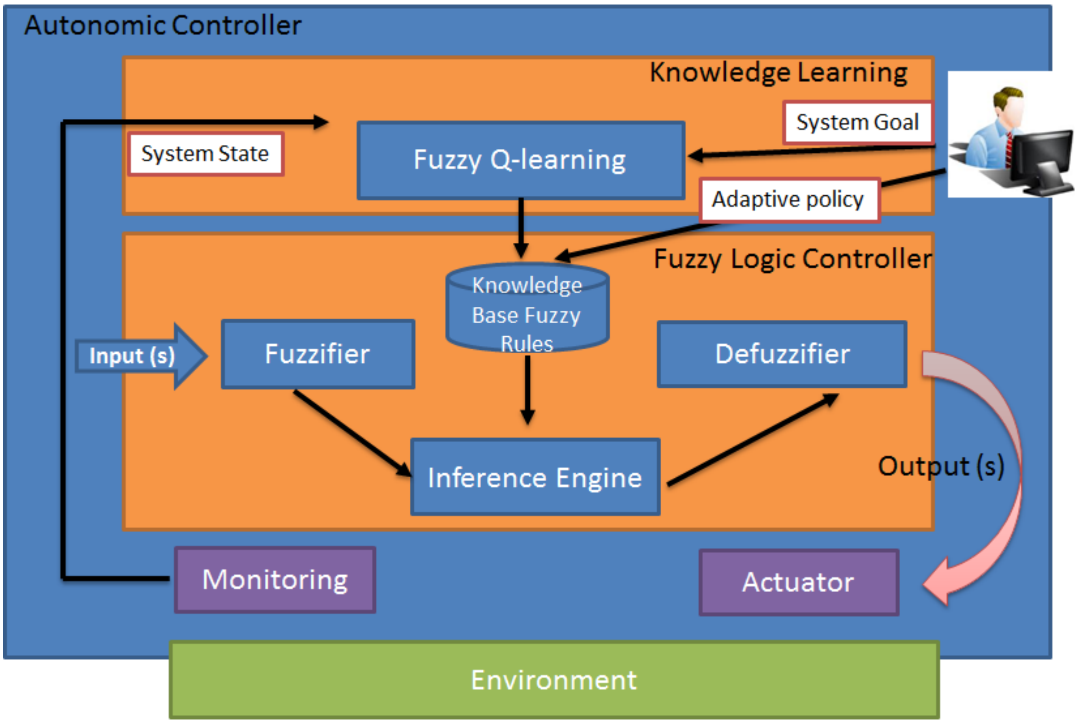


Figure 3.7 Proposed Fuzzy Q-Learning Architecture

The information portrays in Figure 3.7 are the setup of fuzzy q-learning environment. It contains two main layers. Fuzzy and Knowledge Learning. Knowledge learning is where the fuzzy q-learning interacts with input from fuzzy and translated that to system state. System goal is where the learning completed for one episode and later return the value through adaptive policy to knowledge base within fuzzy layer.

As for the Fuzzy logic layer, it handles input and translated into rule base and evaluate with the running adaptive policies. The rule base is configured to be adaptive with the working environment and the value of each rule reflected accordingly.

In a nutshell, Figure 3.7 explains the executions of MAPE-K framework with the utilization of Fuzzy and Q-Learning.

The further discussion available at Section 4.2.1.4.

The proposed architecture in Figure 3.7 is the extension from Figure 3.8.

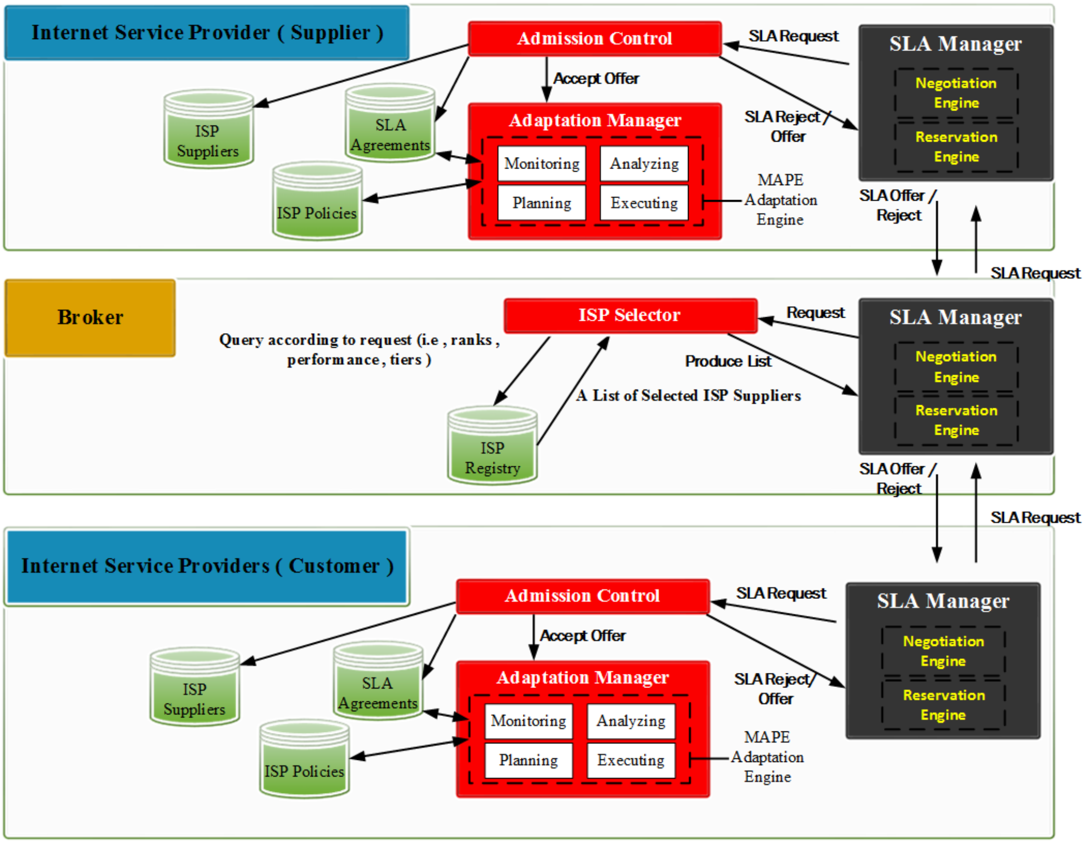


Figure 3.8 The proposed high-level architecture – Adaptation Manager

Figure 3.8 explains the adaptation manager elements within existing ISPs architecture. Adaptation manages resides in each ISP and it connected with admission control. In the normal routines, admission control give feedback to SLA manager either to accept or reject SLA request. Accepting SLA will consume more ISP resources and rejecting SLA affects the daily business operation. It reduces the amount of money coming from customer.

With the introduction of adaptation manager, it contains the MAPE-K framework to perform four major activities. Monitoring, analysing, planning and executing. This is iteration process and every result stored in the database and it helps adaptation manager to refine better executions and information accordingly.

In the final architecture, the autonomic controller, which is part of the autonomic elements, compliments the overall autonomic computing environment.

3.5 Early Experiment – Opnet Simulation

The Opnet Academic Modeller ver. 17.5 was the simulation tool for the network simulation due to its capabilities in handling enterprise network environments and the maturity of the product itself.

3.5.1 Objectives of the experiments

There are four main objectives which have been identified for this assessment to ensure that the chosen network simulator is able to be simulated in the enterprise network environment with various protocols. For instance:

i. To prove that the BGP environment has a better throughput performance compared to non-BGP.
ii. To justify that the outcomes of Ethernet delay between two scenarios is in line with this proposal.
iii. To ensure that the application response time is able to record using the simulation software and that it produces the intended result for BGP configuration.
iv. To ensure that every user profile within this network simulation is embedded with all of the proper configurations.

3.5.2 Setup

In this experiment, there are two scenarios. One with a Border Gateway Protocol (GBP) and another one with a GBP environment. Border Gateway Protocol was chosen as the protocol to justify the autonomous concept which is available in the autonomous system as it is uniquely available for each server. Later, it can be connected within the same autonomous system number to create a group of neighbourhoods or with different neighbour routers. The following tables tabulate the scenario information.

Table 3.2 Scenario Parameters for the Simulation Exercises

No	Description	Quantity
1	ISPs	2 (Non BGP) and 3 for BGP
2	Country within ISP	One Country with two regions
3	Logical Subnet	Two Subnets
4	Router	2 (for Non BGP) and 10 for BGP
5	Number of Nodes	One group of workstations for both subnets. Three servers located within one of the logical subnets.
6	Cloud Connection	Using Cloud32. It is worldwide internet connection connected via PPP DS3. It is also known as T3 line and the signal transmission is up to 45 Mb per seconds.

Table 3.3 Personal Computer Parameters

Windows Edition	Windows 8.1 Single Language
Processor	Intel ® Core ™ i5-4200M CPU @ 2.50 GHZ 2.50 GHZ
Installed Memory (RAM)	8 GB
System Type	64 Bits Operating System , x64 based processor
Disk Drives	1 Terabyte
Display Adapters	Nvidia GeForce GT 740M
Network Interface Card	Qualcomm Atheros AR8161 PCI-E Gigabit Ethernet Controller
Wireless Interface Card	Qualcomm Atheros AR956x Wireless Network Adaptor

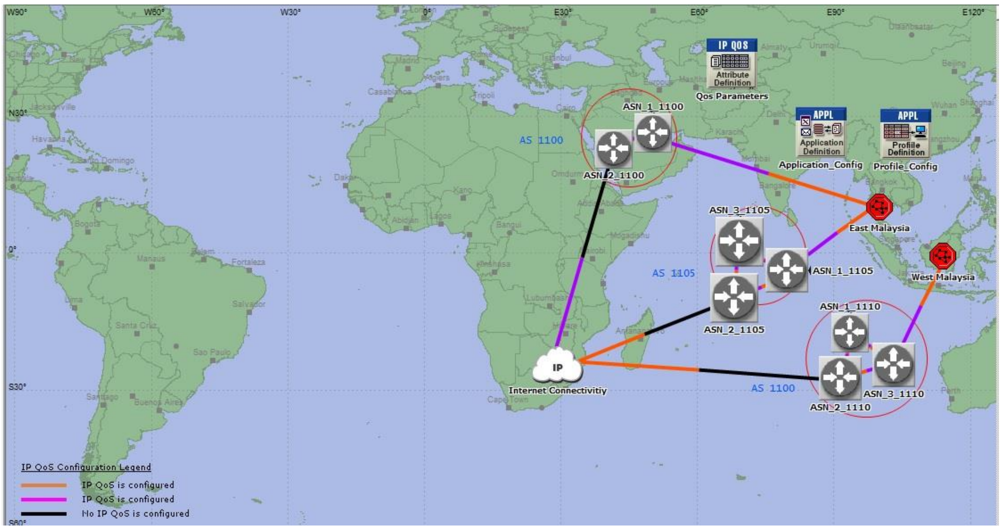


Figure 3.9 Opnet Academic Modeller BGP Environment Design

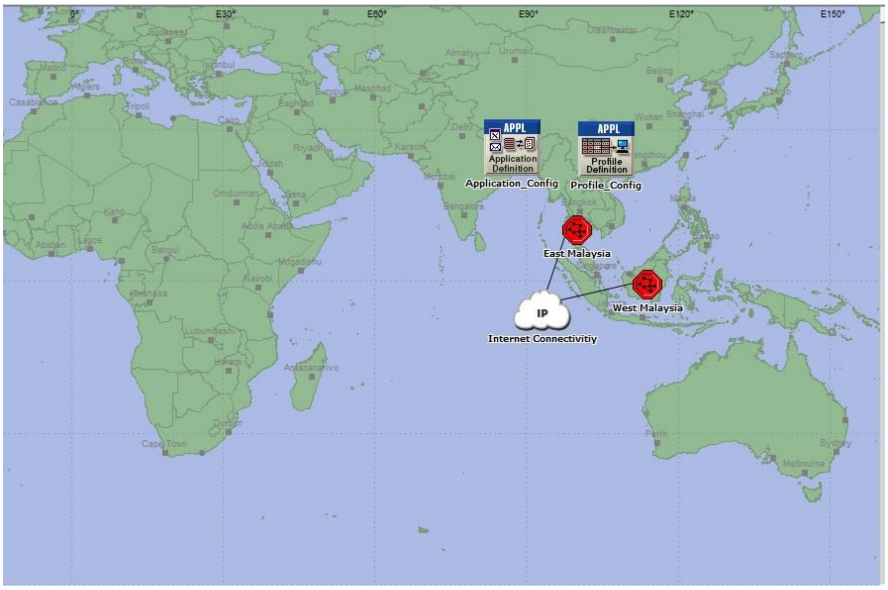


Figure 3.10 Opnet Academic Modeller Non BGP Environment Design

3.5.3 Results

The evaluation will be based on three outcomes from the finding, which are throughput, delay and response time respectively. Below are the criteria for the assessment:

i) Throughput

As for this section, it will have two logical subnets from each region as in Figure 3.9 and Figure 3.10. Each of these will be an individual scenario. In the scenario without BGP, the output will be very straightforward because it will measure from one region to another region through one ISP. Whereas for the next scenario, the environment will be in BGP mode and connection from one region to the internet connection will be based on the dedicated autonomous system and neighbourhood concept.

All of the assessments will be for the outgoing packets rather than the incoming packets. The outgoing packets will ensure that the connectivity from one point to another from the different routers will be carefully measured to produce the designated finding.

a) Results from the simulation software

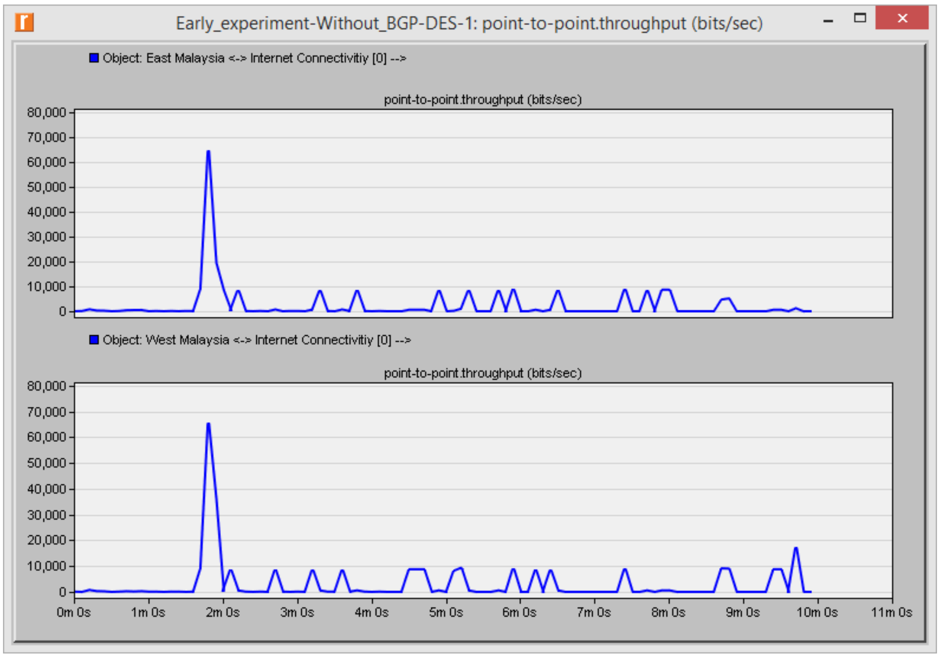


Figure 3.11 Point to point throughput – East and West Malaysia

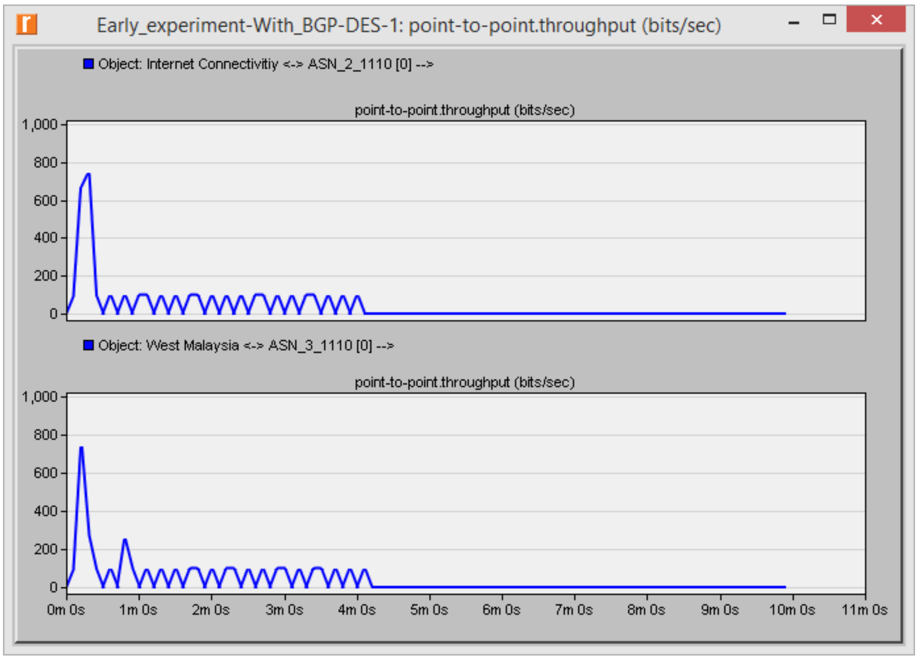


Figure 3.12 Point to point throughput – West Malaysia using BGP

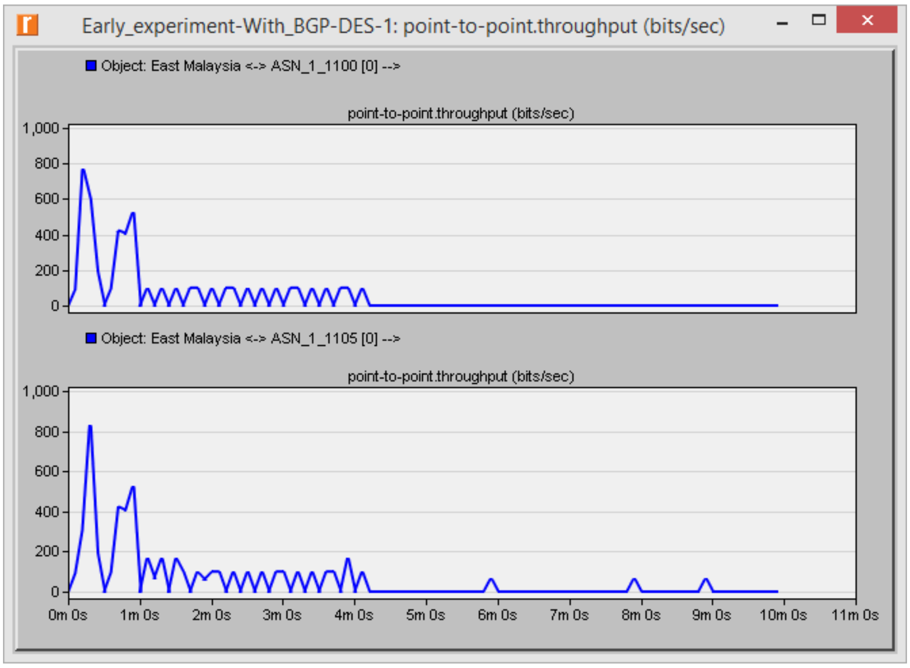


Figure 3.13 Point to point throughput – West Malaysia using multiple BGP – (A)

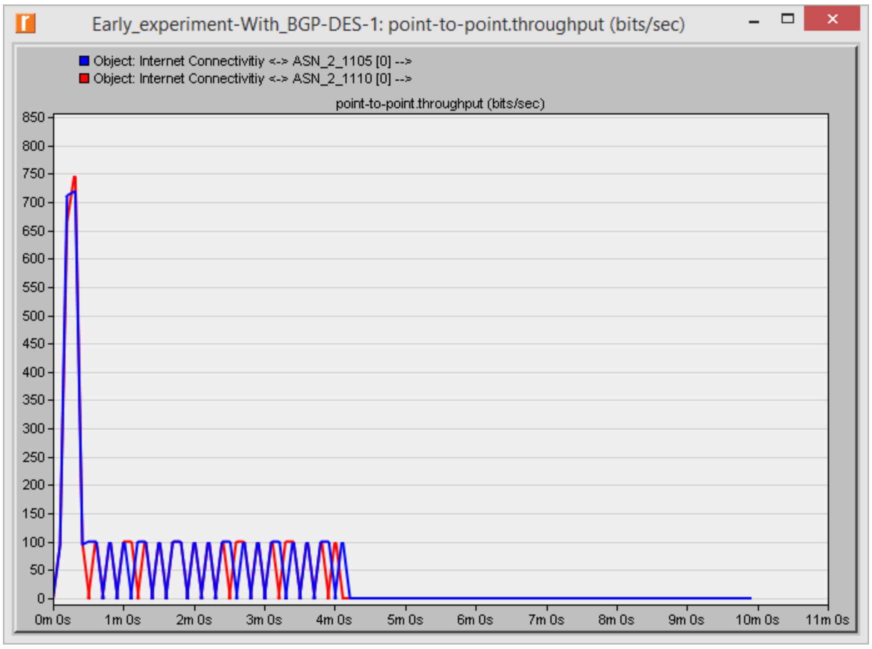


Figure 3.14 Point to point throughput – West Malaysia using multiple BGP – (B)

As for the outcomes, Figures 3.11-3.14 displayed the results according to the different situations. In Figure 3.11, the outcome is based on normal network connectivity using a non-BGP environment from one region to another, whereas for Figure 3.12, it was in a BGP environment with a dedicated autonomous number from one router to another. Figure 3.13 and Figure 3.14 are the results of a connection from one region with multiple BGP within multiple BGP neighbourhoods.

The results generated from Figure are measured by the quantum of 10 minutes for the x axis, and the y-axis is the number of bits per second. In Figure 22, it took a duration of two minutes before the performance reached 62,000 bits per second. The number of packets and this graph are much different within the BGP environment presented by Figure 3.13-3.14, whereas the increments for the bits per second rocketed by 0.5 minute.

In this early feedback, we can conclude that by using a non-BGP environment, the throughput will be efficient at the beginning of the simulation and after 4 minutes of simulation, whereas when using BGP, the network performance is better as seen in Figures 3.13 and 3.14.

ii) Response Time (Application)

Upload response time and download response time will be the indicator for this simulation to measure performance of both scenarios. It will simulate one email server with two groups of workstations from different regions running email activities. Each of the activities has been profiled using an application profile feature within the Opnet application.

a) Results from the simulation software

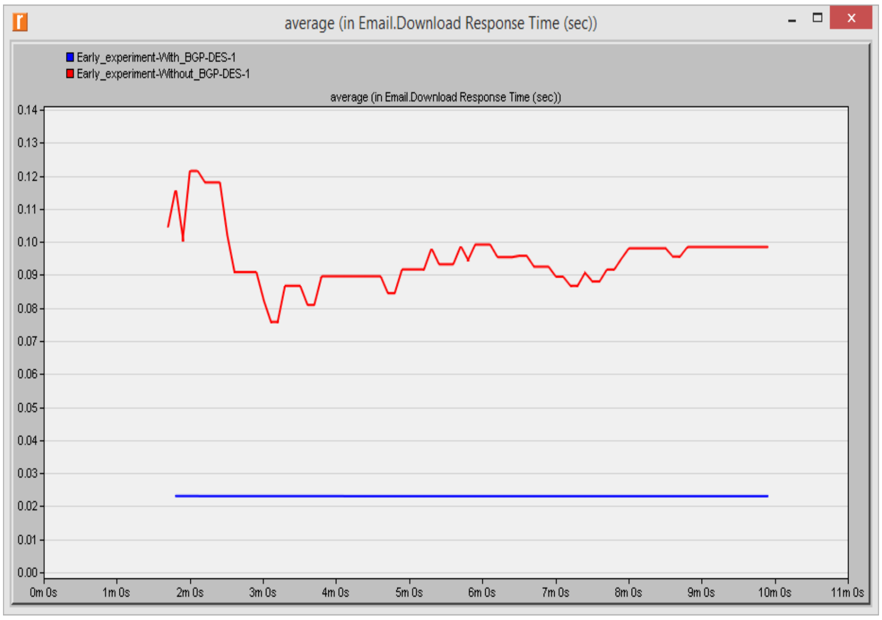


Figure 3.15 Average Response Time for Email Downloads

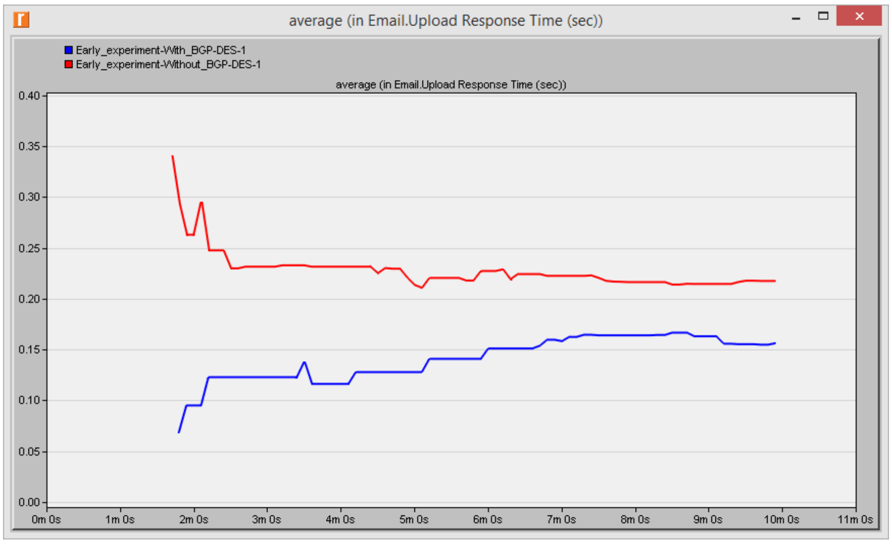


Figure 3.16 Average Response Time for Email Uploads

In Figure 3.15, we can see that the performance of the average response time for the BGP environment is constantly at 0.024 seconds from the beginning of the 2 minute simulation until the end of the simulation time. This situation is different without being in the BGP environment and the results are inconsistent from one duration to another with high processing loads.

On another note, the average of the upload response time for email activities in Figure 3.16 was slightly inverse from one to the other between BGP and without BGP. The performance of BGP was better at the beginning of 0.07 seconds until the end of the simulation with 0.15 seconds.

Having this result is a justification that, in the BGP environment, the application is able to run within the autonomous environment that is able to share the load from one point to another within the neighbourhood.

iii) Delay (Application)

The last indicator for this simulation will measure the connectivity from one Ethernet point to another while connecting different types of application over the networks. In this moment, there are three targeted applications which are email, streaming and http activities.

a) Result from Simulation software

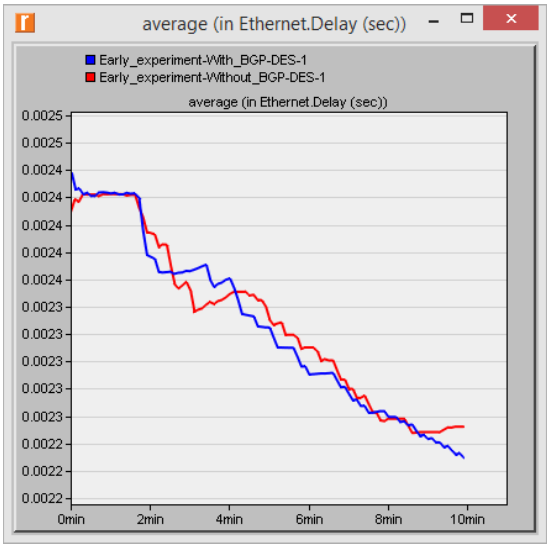


Figure 3.17 Ethernet Delay

Figure 3.17 displays the evaluation of the Ethernet delay while running all of the applications and services for BGP and without BGP environments. Although the performance is identical from one to another in this figure, in many circumstances, BGP wins and reduces until the end of the simulation. The lowest scored for BGP was below 0.0022 seconds at the last simulation time.

3.5.4 Summary of the result

To conclude on the findings in the early experiment, the early results really lean towards the autonomic computing approach. There is significant evidence that the presented tools can be excessively applied to the research activities on the following years. The Opnet Academic Modeller has lots of simulation variants available to analyse the findings and in the next phase, it should be incorporated with custom code or a framework to really adapt to the full blonde autonomic computing proposal within this proposal.

Along with that, the results will be better if the evidence can be mathematically proven using an algorithm or formula that is in line with autonomic computing. At this moment, binomial heaps, Bayesian networks and reinforcement learning are among the growing options for this proposal. The following figure will be the outcome of the current and continuous research within this proposal to enhance the current ISP architecture.

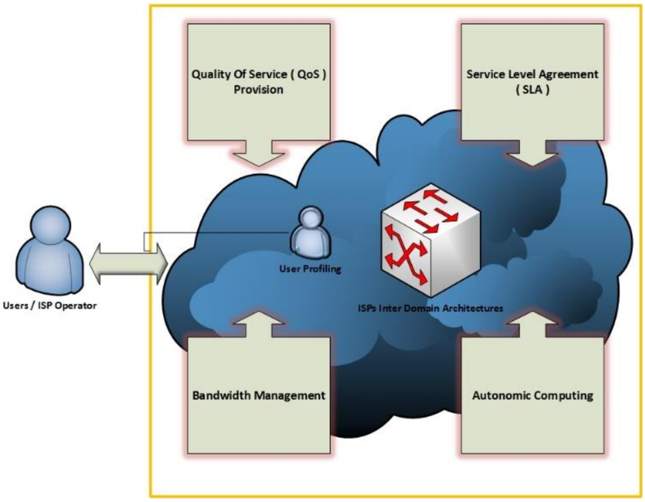


Figure 3.18 Illustration of Completed Proposal

3.6 Early Experiment – Fuzzy Rule base approach

This research focuses on the inter-domain of ISP and the current broker architecture. The broker in this research can run as a virtual provider. Table 3.4 tabulates the information of the high-level design and components. The whole blueprint is inspired by the self-healing properties which are the features of autonomic computing.

- *Self-Configuration*

Initiative following the negotiation process between the application and the service provider.

- *Self-Optimisation*

A compromise between maximising the use of resources and maintaining an acceptable level of service.

- *Self-Healing*

Concerned with outright QoS violations or QoS degradations.

- *Self-Protection*

Linked to policing and monitoring.

- *Self-Awareness*

Application and middleware can perform adaptations depending on the changing environment.

Table 3.4 Components in the ISPs and Middleman

Architecture	ISP	Middleman / Virtual Provider
	Telecommunications and Management Network • Business Management • Service Management • Network Management • Element Management	Self-Adaptive Autonomic Broker • Monitoring • Feedback • Adaptive • Decision • Renegotiation • Engagement and Monitoring of the Violation

<table>
<tr><td></td><td>Policies
Identify Problem Spots
Create Policies
Deploy Policies
Monitor
Verify</td><td></td></tr>
<tr><td></td><td>SLA
Service Level Management
Minor Variations
Discrete Requirements
Projects
Temporary
Specific SLAs
End User Agreement
Policies
Authorization Request
Authorization Decision
Role Mapper Content Extractor</td><td></td></tr>
</table>

Figure 3.19 and Figure 3.20 explain the establishment of a Self-Adaptive autonomic broker with four major components, in addition to renegotiation and monitoring of the violation. ISPs and Virtual Provider are the actors that play their role in this architecture. A record of the existing agreement will be verified to ensure that the violation will be subject to the agreed penalties.

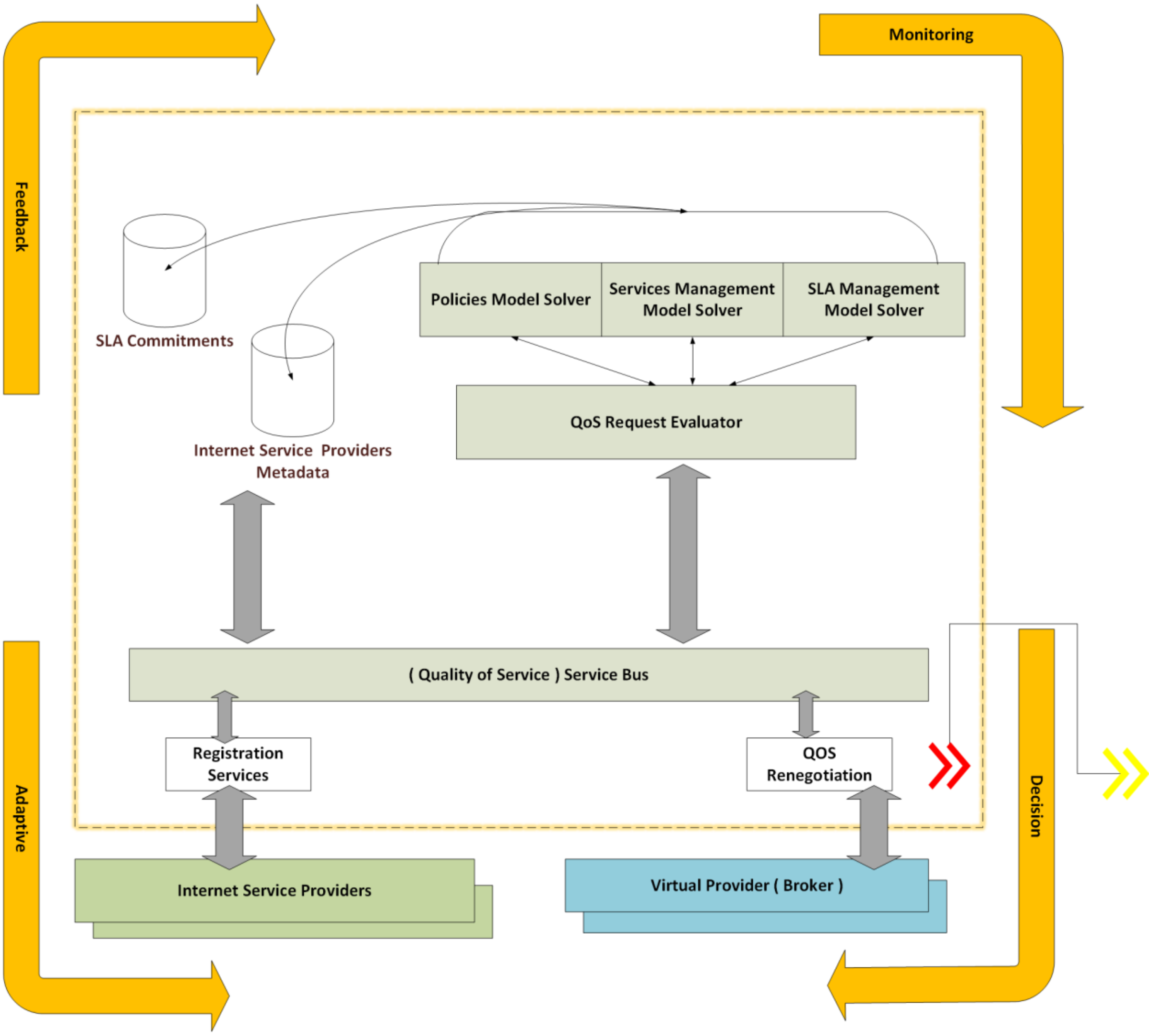


Figure 3.19 Self Adaptive Brokerage Architecture

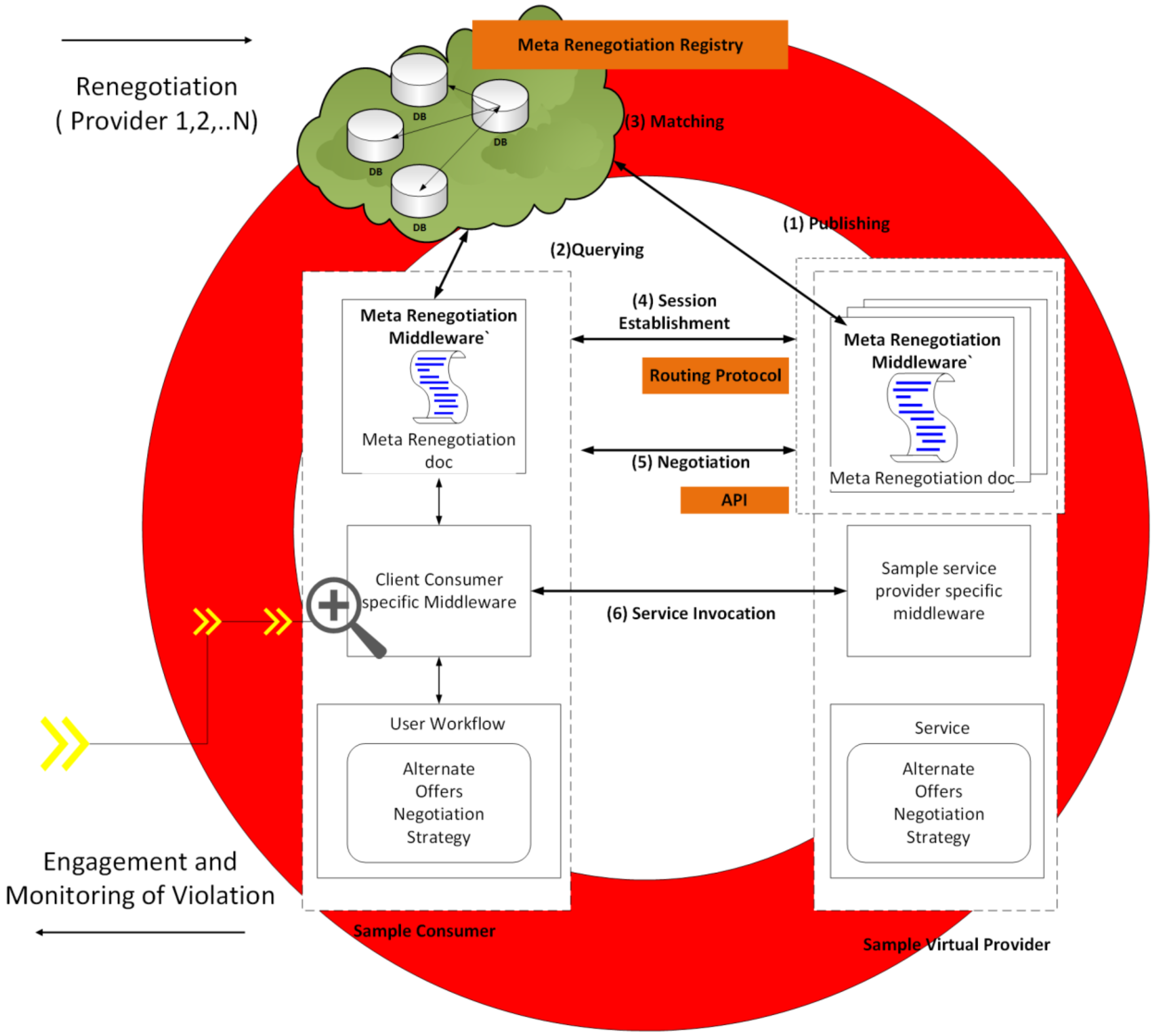


Figure 3.20 Details of the renegotiation process within the self-adaptive brokerage architecture

3.6.1 MAPE-K Architecture

The architecture is based on the MAPE-K approach. It has two layers; goal management and adaptation model. This is the thorough architecture available in the abstract model. Figure 3.21 explains the four components that form goal management, all stored in the goal model repository. The policy approach is the main connector for the two layers. In this research, there are two scenarios which tally to the architecture.

The first scenario is available in Figure 3.22, where each ISP has MAPE-K and a middleman runs as the temporary negotiator before the establishment of the agreement. After engagement, ISP must play their own role to ensure that the relevant penalty will be applied to any violation of the signed agreement. Whereas in Figure 3.23, it illustrates a second scenario within a fully MAPE-K environment.

In this scenario, the virtual provider has the MAPE-K framework interact within the environment and the monitoring will be executed until the end of the agreement.

Three simple adaptation rules have been applied for both scenarios:

1. Suitable adaptation rule has been learned
2. The environment has changed the approach of the goal
3. Another rule is applicable

The parameters during the adaptation of these rules with the MAPE-K architecture are the control data and functional components.

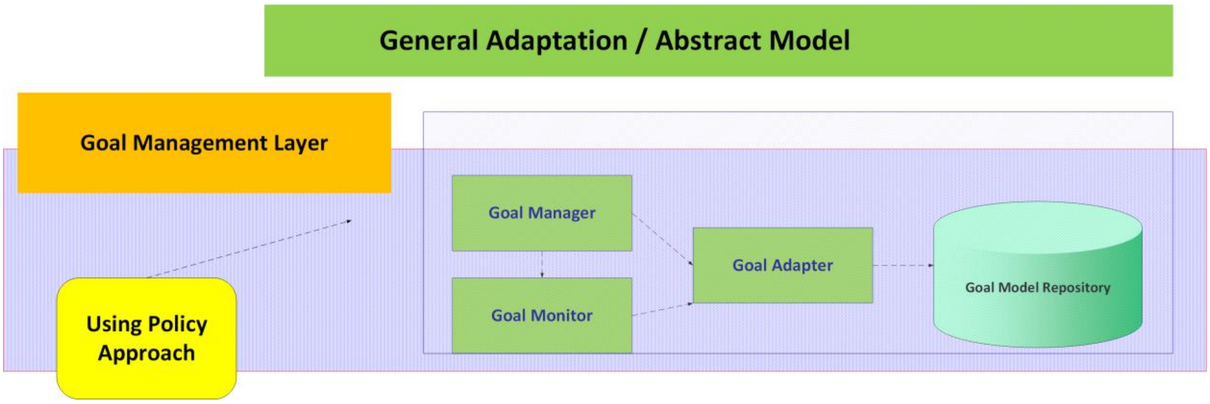


Figure 3.21 Abstract Model

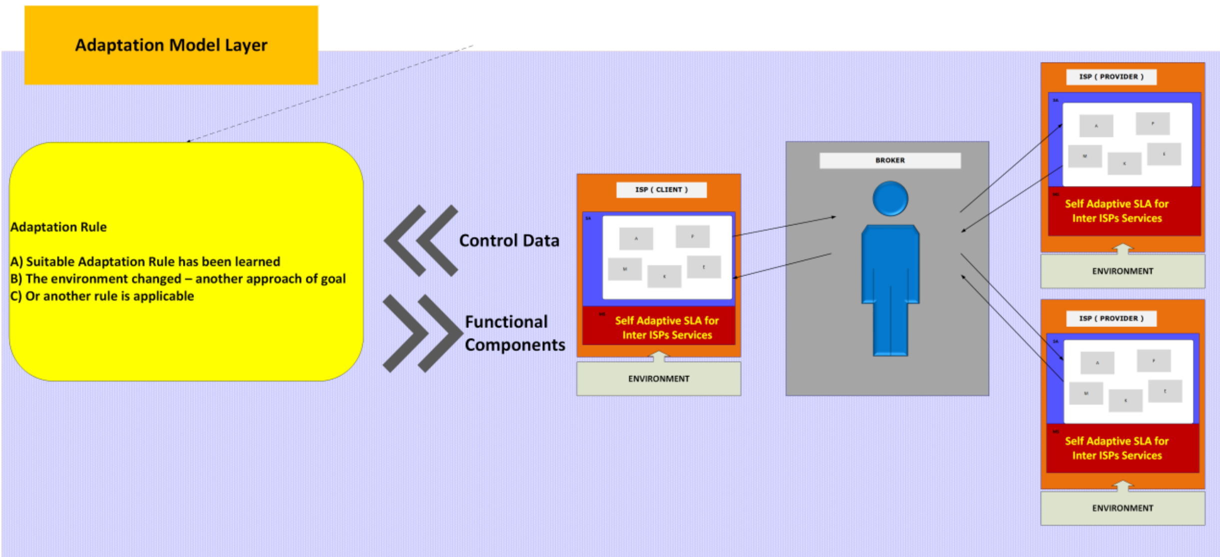


Figure 3.22 Adaptation Model Layer for First Scenario

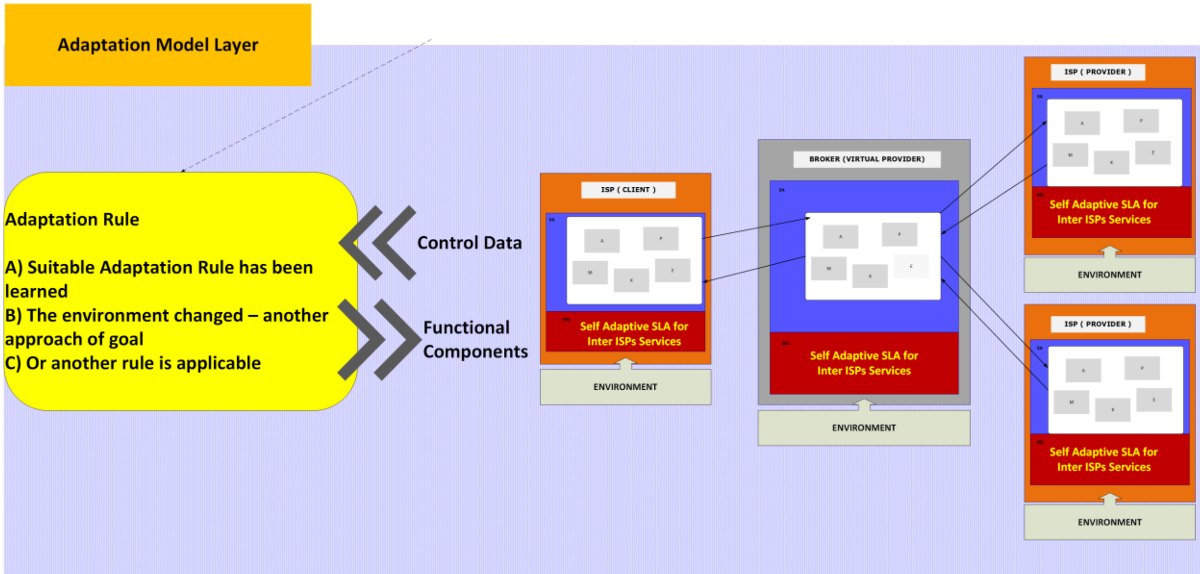


Figure 3.23 Adaptation Model Layer for the Second Scenario

3.6.2 Results

In this assessment, the significant integration between the ISP and their associate business partners will be demonstrated using the early implementation of MAPE-K. This exercise is relevant to the first scenario of the research proposal and the motivation is to have fundamental knowledge of MAPE-K integration between current brokerage approaches.

The framework is based on the MAPE-K approach, invented by IBM. It has five core elements such as monitor, analyse, planning, execute and knowledge base. Each of these elements has its own function and it contributes to a fully autonomic computing environment. In a nutshell, MAPE-K can be considered as an autonomic element. It has an autonomic manager globally and locally to manage that.

SLA and ISP policies are the main contributions towards this approach. SLA is the set of agreements that are signed between parties once the terms are finalised. This agreement will be the ultimate measurement to ensure the deliverables are as agreed and the mechanism to monitor the violations over the running of the SLA will be an added value.

The ISP, on the other hand, is a company that is making business through internet connectivity through normal or corporate subscribers. In order to sustain their business model, an ISP should have a good business partner with another ISP. With that, it can ensure a productive delivery of their services globally. Since each ISP has its own limitations, such as financial and technical resources, SLA will address the itemised terms during the business engagement. This situation can be addressed with an adaptive approach that is hugely applied in the autonomic computing.

3.6.3 Objectives

There are four main objectives as to how significant this exercise is to the research activities.

i. To prove that the MAPE-K framework can be applied within ISP using the fuzzy logic approach.
ii. To prove that the MAPE-K framework is able to pick up the inputs and tally with the potential results.
iii. To prove that the fundamentals of the MAPE-K framework can exist within a middleman or broker.
iv. To exhibit a fundamental result that is able to cope with the next scenario of fully autonomic computing between ISPs and the virtual provider which acts as the ISP.

3.6.4 Experimental Design

The framework can be adapted into a fuzzy system approach with the following components:

a) Inputs

Table 3.5 Fuzzy Membership Function Inputs

Performance	Throughput	Below Satisfactory , Average , Satisfactory , Exceed	
	Uptime	Below Satisfactory , Average , Satisfactory , Exceed	
	Packet Loss	Low , Average , Critical	
	Latency	Low , Medium , High	
	Jitter	High Quality , Acceptable , Poor	
	Grade of Service	Routine , Intermittent , Critical	
	Response Time	Low, Medium , High	
Fault Repair	Target Response Time	System Failure	
		Major Faults	
		Minor Faults	
		Other	
	SLA Clearance Time	System Failure	
		Major Faults	
		Minor Faults	
		Other	

b) Rules

Table 3.6 Fuzzy Membership Function Rules

Increase Bandwidth	Low , Medium , High
Change Package	Platinum , Gold , Silver , Bronze
Service Performance	Low , Medium , High

MATLAB was the chosen software with embedded fuzzy logic to execute this exercise. The inputs were available in two categories; performance and fault repair. This is a normal practise applied in the SLAs given by ISP to their subscribers. In the performance, there were seven major inputs and the warm-up experiment will focus on the three core inputs which have a strong comparison potential between them. The chosen inputs were packet loss, latency, and jitter.

In the preliminary research progress, to demonstrate fuzzy logic's ability to handle rules and uncertainty, increased bandwidth was used to meet this purpose. The other rules will proceed gradually within the research progress.

Table 3.7 Fuzzy logic Rules

Rule		Jitter	Logic Operator	Packet Loss	Logic Operator	Latency	Logic Operator	Increase Bandwidth
1	IF	Poor	AND	Critical	AND	High	Then	High
2	IF	Poor	OR	Critical	OR	High	Then	High
3	IF	Poor	OR	Average	OR	High	Then	High
4	IF	Acceptable	OR	Critical	OR	High	Then	High
5	IF	Acceptable	OR	Average	OR	High	Then	High
6	IF	Acceptable	AND	Critical	AND	High	Then	High
7	IF	Acceptable	AND	Average	AND	Medium	Then	Medium
8	IF	Acceptable	OR	Average	OR	High	Then	Medium
9	IF	Acceptable	OR	Critical	OR	Low	Then	Medium
10	IF	Acceptable	AND	Critical	AND	Low	Then	Medium
11	IF	High Quality	AND	Low	AND	Medium	Then	Low
12	IF	High Quality	AND	Low	AND	Low	Then	Low
13	IF	High Quality	OR	Average	OR	High	Then	Low
14	IF	High Quality	OR	Critical	OR	High	Then	Low
15	IF	High Quality	OR	Critical	OR	Medium	Then	Low
16	IF	High Quality	OR	Low	Or	Medium	Then	Low
17	IF	High Quality	OR	Average	OR	Low	Then	Low

The assumption is made through normal practise which is available in the SLA between ISPs. Below are the membership functions that are available in the Matlab tables.

Table 3.8 Packet Loss Membership Function

Membership Function	Packet Loss	
	Mean	
Low MF	0	Low MF
Average MF	50	Average MF
Critical MF	100	Critical MF

Table 3.9 Latency Membership Function

Membership Function	Latency	
	Mean	
Low MF	0	Low MF
Medium MF	50	Medium MF
High MF	100	High MF

Table 3.10 Jitter Membership Function

Membership Function	Jitter	
	Mean	
HighQuality MF	0	HighQuality MF
Acceptable MF	35	Acceptable MF
Poor MF	60	Poor MF

3.6.5 Experimental Result

The early results driven from Table 3.5 have produced the expected outcome for increase bandwidth. The results can be read below:

a) *Packet Loss vs Jitter*

In this scenario, increased bandwidth is not urgent if jitter is high quality and packet loss is low. However, the state of urgency increases when jitter is poor and packet loss is critical. Figure 3.24 shows the outcome of the results.

b) *Latency vs Packet Loss*

Figure 3.25 illustrates the scenario between packet loss and latency. In this situation, an increase in bandwidth is not necessary when latency is low and packet loss is low. However, the graph increases gradually when both latency and packet loss reach average performance. Lastly, increasing bandwidth reaches the peak demand when there is a logical combination of average and peak performance for both latency and packet loss.

Although the resulted output is identical to pyramid shapes, it shows the consistency of the combination of the rules on the defined QoS parameters.

c) *Latency vs Jitter*

In Figure 3.26, the result is static between latency and jitter. This result is expected because the two factors are interrelated in network performance.

.

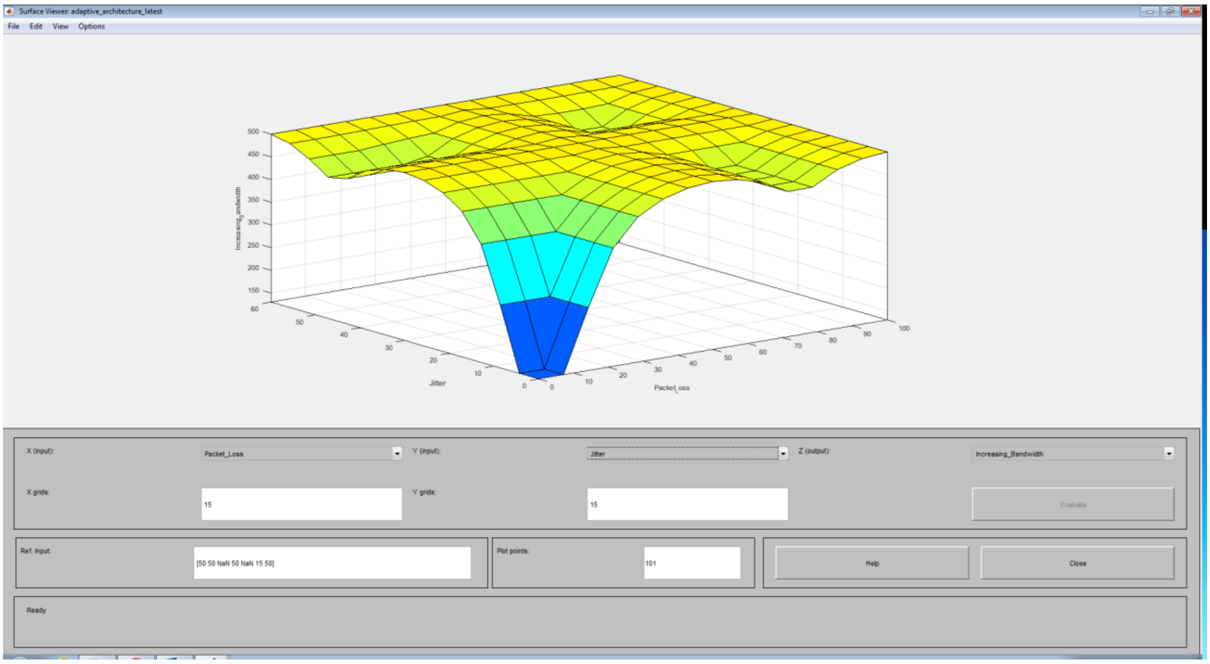


Figure 3.24 Packet Loss vs Jitter

Figure 3.24 illustrates the combination of Packet Loss versus Jitter and the urgency of high bandwidth. As per the illustration, the higher values of the Packet Loss and Jitter, it reflects the demand of high bandwidth.

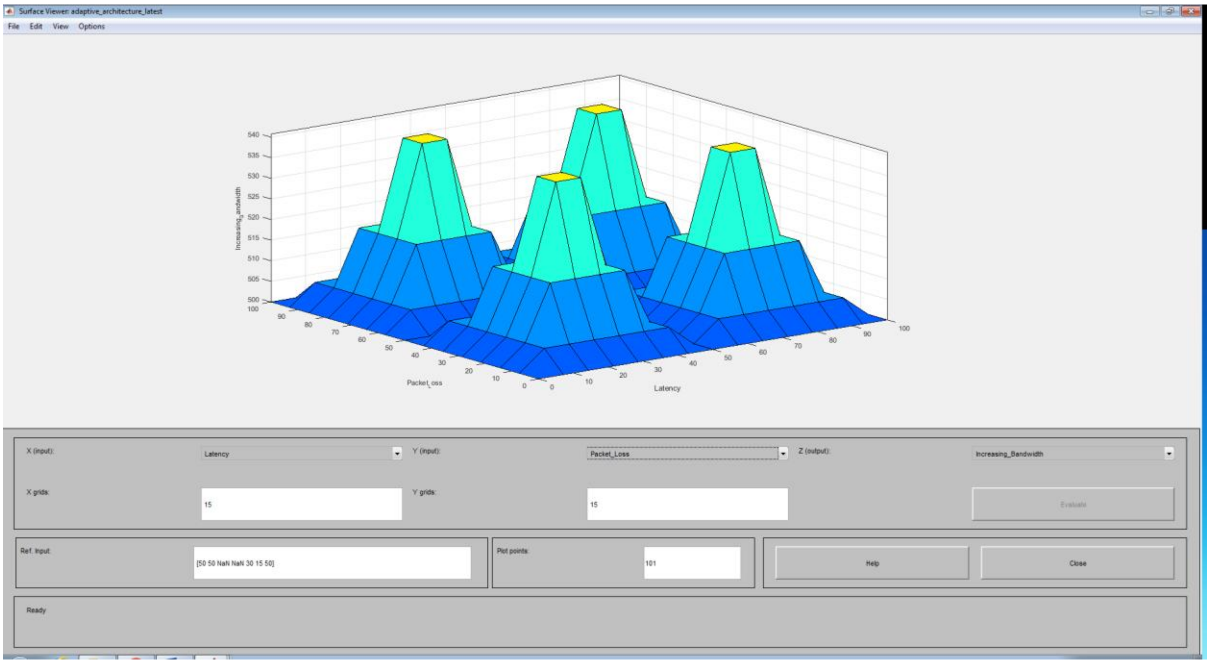


Figure 3.25 Latency vs Packet Loss

In Figure 3.25, two QoS parameters; Latency and Packet Loss are shown. The output demonstrates that high bandwidth is only applicable if the combination of both parameters are at Medium and gradually increase.

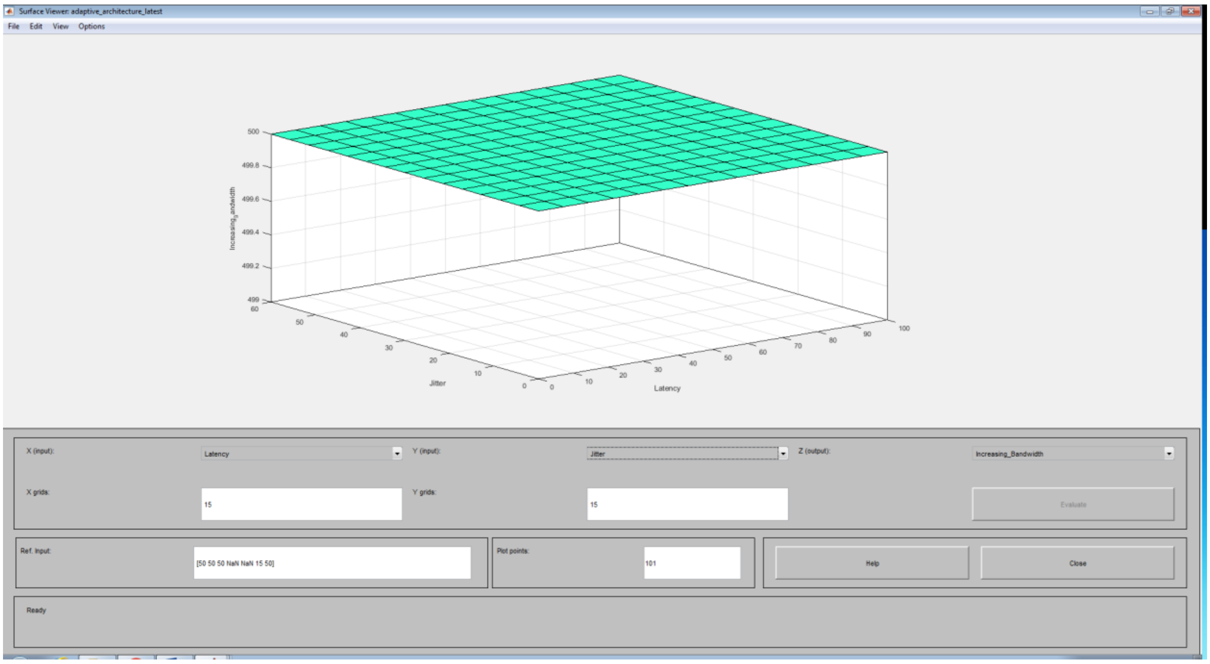


Figure 3.26 Latency vs Jitter

Figure 3.26 illustrates the combination of Latency versus Jitter (with no Low or Medium combination, only High is presented). It shows that both parameters are identical in the QoS measurement.

3.7 Summary

In this section, the chosen architecture is supported by the series of methodologies. The elements of the domains have been identified and the connections with the research are present in the first two early experiments. The initial results suggest that the architecture is in line with the research objectives and is able to meet the research questions addressed in the previous chapter.

Chapter 4
Application of Fuzzy Q-Learning

In this chapter, the author has identified the elements that are derived from the experiment with Fuzzy Q-Learning. Fuzzy Q-Learning is the combination of Fuzzy and Q-Learning in order to address the need for adaptation as well as uncertainties and learning ability. Section 4.1 highlights the motivation of this experiment, followed with the proposed solution in Section 4.2. The execution applied is in Section 4.3, followed by Section 4.4 for the Evaluation and Section 4.5 on the summary.

4.1 Motivation

As illustrated in Figure 4.1, the MAPE-K framework is the ideal solution for ISP to handle SLAs due to the self-management features. Admission control is made up of the authorised components used in [132] to justify whether the SLA Manager is able to accept or reject new SLA requests. The utmost prerogative is to provide admission control with the actual conditions of ISP to satisfy its QoS commitments. In this research, the adaptation manager is a vital contribution to adapt and provide feedback to the requested components.

With all of the motivation factors, it is crystal clear that a prudent and robust solution is needed to overcome the issues. Since being introduced by Pierre Yves Glorennec and Lionel Jouffe [133], Fuzzy Q-Learning is made up of the algorithms that manage two elements which are uncertainties and adaptive process.

Below is the core motivation for using Fuzzy Q-Learning as the solution.

- *SLA*

  A general SLA framework in Figure 2.1 consists of two main motivations in association with this proposal. They are Service Level Objectives (SLOs) and Service Goals. SLOs are the key objectives within the entire SLA agreement, such as the measurement of availability, response time and latency. This factor is available in the QoS and is chosen as the input for fuzzy rule base approach. Each of the inputs and outputs are later developed as a matrix for Q-Learning. The service goals are to achieve a Service Level Guarantee (SLG) which is promised in the event of breakdown or service failure.

- *MAPE-K Framework*
  An adaptation engine, also known as a managing system, is the ability to extend the current features with good feedback, robustness and performance. To achieve this, the MAPE-K framework is proven and widely used for the translation of architecture-based self-adaptation with known and established components. The flows work by monitoring the inputs in the gathered environment and updating the information with the Analyse component. The process continues with Planning and Execute. Figure 4.1 portrays this process and details are available in the following chapter.
- *Uncertainties, Adaptation and Learning*
  The motivation for the framework is to handle three major issues. Uncertainties, adaptation and learning rate. Although fuzzy itself is able to handle uncertainties and adaptation [107], it is unable to prove the learning ability in isolation from the combined rules. On the other hand, machine learning is divided into three major groups. Supervised, unsupervised and reinforcement learning. Reinforcement learning, also known as semi-supervised, is able to provide critical algorithms [134-137]. The function is for it to act as an artificial teacher. Within reinforcement learning, SARSA and Q-Learning famously are known for on policy and off policy learners. Although there is a combination of Sarsa and Q-Learning by [138], it unable to demonstrate the combination of another logic approach, which is where fuzzy comes in. Therefore, this is clear motivation to show that the chosen frameworks are able to handle the issues presented.

4.2 Proposed Solution

4.2.1 MAPE-K Framework

According to [146], a framework is a basic structure that is underlying a system concept text. Therefore, in this research, the MAPE-K is established with self-properties and it is able to interact with the assigned components iteratively within the loops. The framework is illustrated in Figure 4.1.

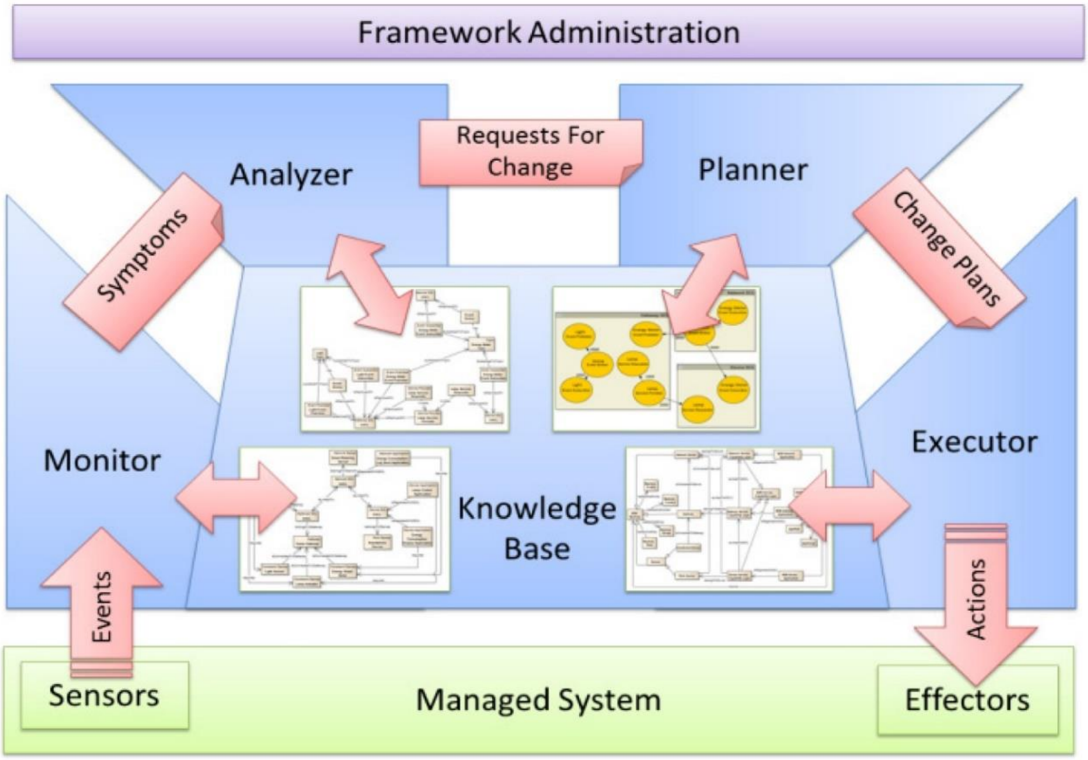


Figure 4.1. MAPE-K Framework [1]

The architecture is based on the MAPE-K approach, and it has two layers. Goal management in Figure 3.21, and adaptation model in Figure 3.22-3.23. On top of the layers is the abstract model. The policy approach is the main connector for the two layers. In this research, each ISP has MAPE-K and must play their own role to ensure that the relevant actions will be applied to any violation of the signed agreement.

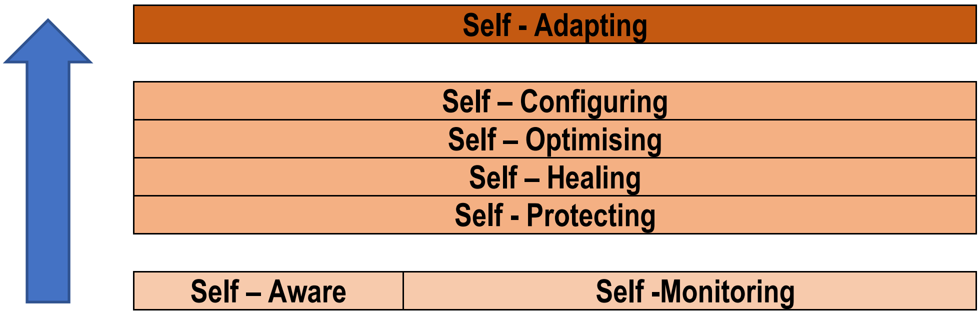


Figure 4.2. Three Level Self * Hierarchy [2]

Illustration of the framework and the three levels of self * features have been presented in Figure 4.1 and Figure 4.2. As per the information, it is clearly tabulated that self-adapting is the highest component supported by the other self-features.

Three simple adaptation rules have been applied as below:

- Suitable adaptation rules have been learned
- The environment has changed, there is another approach to the goal
- Another rule is applicable

The adaptation controller applied in MAPE-K comes with the following sequences.

- Monitor the QoS inputs (Latency, Workload and Response Time)
- Analyse the input from the data file and distinguish the rule base violations. This is like a SLA document.
- Plan the possible corrective action to react, such as update in the state to reach the possible learn rate, rewards and explorations.
- Execute the rule base.
- Update the recent executions, and use possible actions. The contributions of knowledge at this point enhance the knowledge base of the main framework.

4.2.1.1 Fuzzy Logic Control

Fuzzy logic in a nutshell is the translation of crisp values into logical ones using linguistics information. This is in contrast with the classical control strategy, whereby the point to point control has been established with range to point or range to range control. The linguistic variables in this case are the QoS inputs and the output as a rule base itself.

The common implementation of a fuzzy type 1 logic system has been illustrated in Figure 4.3 and the approach for this research done using type 2 fuzzy logic is available in Figure 4.4. The main advantages of using type 2 fuzzy logic systems are due to third dimension giving more degrees of freedom in handling uncertainties compared to type 1, and the ability to perform complex crisp outputs for mathematical expression. Therefore, in this research, this has the best adaptation capability.

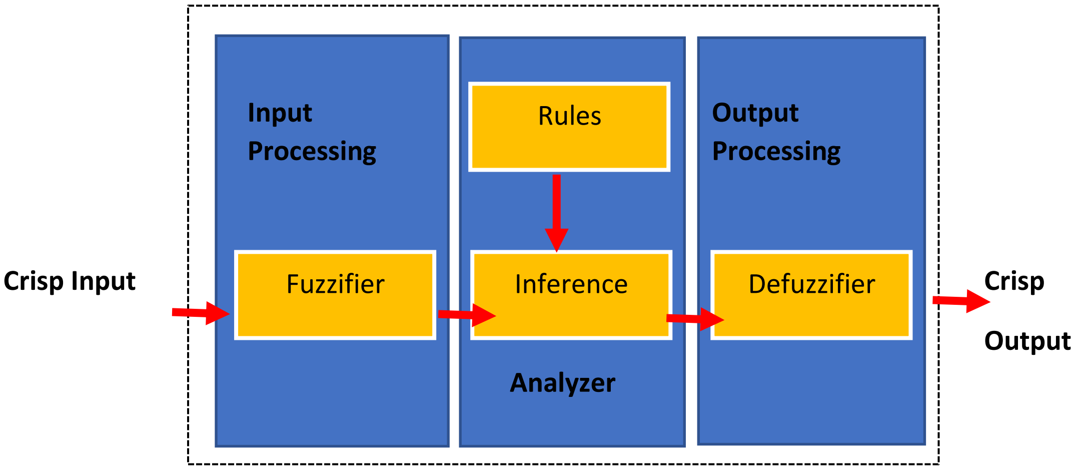


Figure 4.3. Type-1 fuzzy logic system

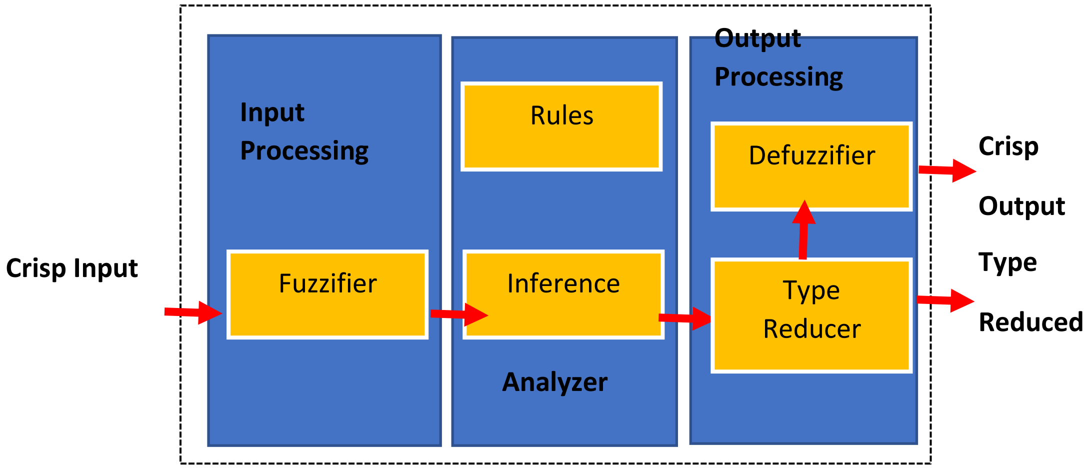


Figure 4.4: Type-2 fuzzy logic system

The complexity of type-2 fuzzy logic system definitions has been well addressed and executed by the application of MATLAB Release R2015a. The implementation in the early experiment was done using the Mamdani Fuzzy Inference System, but later continued with Sugeno FIS.

The proof of concept model is based on three QoS parameters, which have been segmented into two inputs per session due to the current configuration of the available prototype [110]. The outputs have been defined as nine possible learning rates.

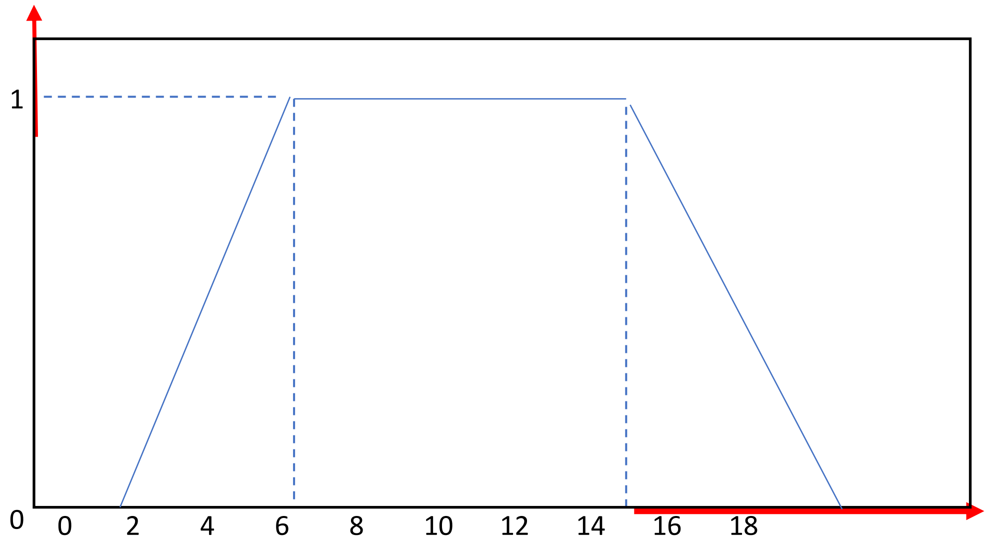


Figure 4.5. Type-1 Trapezoidal Fuzzy Set

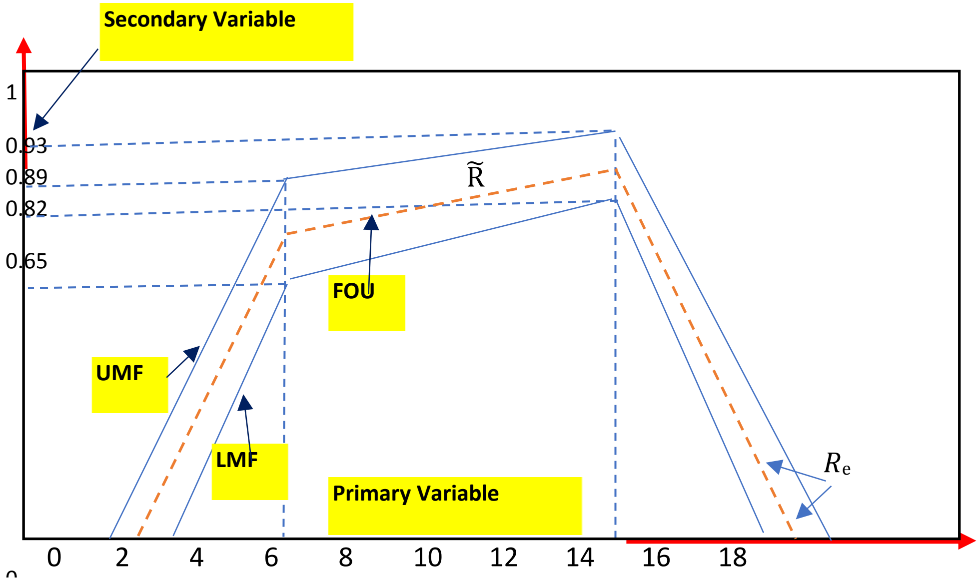


Figure 4.6. Interval Type-2 Fuzzy Set

Figure 4.5 and Figure 4.6 are the reflection of type-1 fuzzy and type-2 fuzzy. Both were introduced by Zadeh to handle linguistic expression. Type-1 fuzzy can take values from the interval [0,1] and for type-2 fuzzy, it can have a precise interval value between 0 and 1, such as [0.65,0.82,0.89,0.93].

Below are the standard definitions of the type-2 fuzzy set we derived from [149], [150], [151], and enhanced in [148].

Definition 1. Three-Dimensional Membership Function (MF) and described as T2 Fuzzy Set (FS).

$$\widetilde{R} = \{((x,u), \mu_{\widetilde{R}}(x,u)) | \forall x \in X, \forall \mu \in Jx, \mu_{\widetilde{R}}(x,u) \leq 1\} \quad (1)$$

Definition 2: Interval type-2 fuzzy set (IT2 FS)

$$\mu_{\widetilde{R}}(x,u) = 1, \widetilde{R} \quad (2)$$

Definition 3: Footprint of uncertainty (FOU)

$$FOU(\tilde{R}) = \cup_{xeX} J_x = \{(x,u) | \forall x \in X, \forall u \in J_x\} \quad (3)$$

Definition 4: Upper Membership Function (UMF)

$$\bar{\mu}_{\widetilde{R}}(x) \quad (4)$$

Definition 5: Lower Membership Function (LMF)

$$\underline{\mu}_{\widetilde{R}}(x) \quad (5)$$

Definition 6: Embedded Fuzzy

$$R_e \quad (6)$$

In this approach, the above definitions have been revised and this research has understood the importance of this. However, since we used a case study [139-140], the groups and values have been fixed as per Table 4.1 and Table 4.2. The elements of QoS are as listed below:

Latency = La

Packet Loss = PL

Availability =Av

Table 4.1: QoS group labels for negative performance

Service Element	Measures	Penalty
Latency	500 ms ≤La< 750 ms	5%
	750 ms ≤La< 1 s	10%
	1 s ≤La< 5 s	20%
	5 s ≤La	100%
Availability	95% < Av ≤ 98%	5%
	90% < Av ≤ 95%	10%
	80% < Av ≤ 90%	15%
	Av ≤ 80%	100%
Packet loss	2% ≤ PL < 4%	5%
	4% ≤ PL < 8%	10%
	8% ≤ PL < 20%	15%
	20% ≤ PL	100%

Table 4.2: QoS group labels for positive performance

Inputs	Minimum	Mean	Maximum
Latency	499 ms	249	0s
Availability	99 %	99.5%	100%
Packet Loss	1 %	0.5 %	0 %

The linguistic rules used were Sugeno which is type2 fuzzy logic due to it being computationally efficient and good for mathematical analysis. It was also recommended for adaptation when compared to Mamdani. The output of Sugeno in this case has been defuzzification with the centre of weight approach. The sequence of the defuzzification process equations start from Definition 7 up to Definition 12.

Definition 7: Singleton

$$\mu_{\tilde{\mathrm{R}}} = \begin{cases} 1 & x = u_{\mathrm{i}} \\ 0 & otherwise \end{cases} \tag{7}$$

Definition 8: Centroid

$$C_{\tilde{\mathrm{R}}} = \cup_{\forall R_{\mathrm{e}}} c(R_{\mathrm{e}}) = [c_{\mathrm{l}}(\tilde{R}), C_{\mathrm{r}}(\tilde{R})] \tag{8}$$

Definition 9: Centre of set type reduction

$$Ycos = \bigcup_{\substack{f^{\iota}\epsilon F^{\iota} \\ y^{\iota}\epsilon C_{\tilde{G}\iota}}} \frac{\sum_{\iota=1}^{N} f^{\iota} x\, y^{\iota}}{\sum_{\iota=1}^{N} f^{\iota}} = [y_{\iota}, y_{r}] \qquad (9)$$

Definition 10: Response from rule base

$$R\iota: IF\ x_1\ is\ F_1^{\iota}\ and\ \ldots.\ and\ x_p\ is\ F_p^{\iota},\ then\ y\ is\ y^{(t_u^{\iota})} \qquad (10)$$

Definition 11: Representation as interval-based on the firing rules.

$$R^{\iota}: IF\ \left(the\ latency\ (x_1) is\ \tilde{F}_{i1}, AND\ the\ availability\ (x2) is\ \tilde{G}_{i2}\right),$$

$$THEN\ \left(\frac{add}{remove}\ C_{avg}^{\iota}\ instances \qquad (11)\right.$$

Definition 12: Centre of Weighted Average

$$C_{avg}^{\iota} = \frac{\sum_{u=1}^{N_{\iota}} w_u^{\iota}\, x\, C}{\sum_{u=1}^{N_{\iota}} w_u^{\iota}} \qquad (12)$$

Table 4.3-4.5 illustrates the values of the centre of the weighted average. The values later update in MATLAB for the rule base approach in Figure 4.7.

In Figure 4.16, the latency and availability are x_1=5 x_2=85 respectively and the final defuzzification value is 0.5. This calculation was applied automatically using MATLAB.

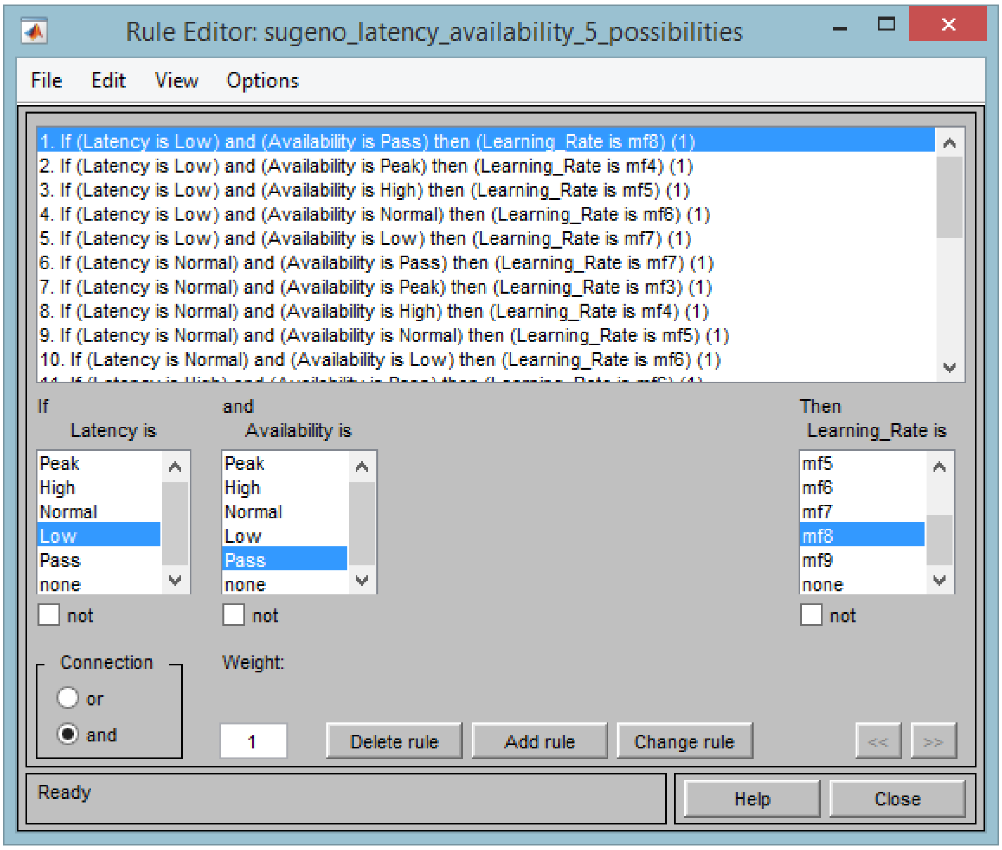


Figure 4.7: Rule base conditions

With the development of the fuzzy controller, it controlled execution using three simple steps:

i. *Fuzzification of Inputs*
It accepts three QoS inputs, which are Latency, Availability and Packet Loss. The crisp data is translated into fuzzy values using membership functions.

ii. *Fuzzy Reasoning*
At this stage, the engine will understand the condition and matches with the available rule-base and suggests fuzzy actions.

iii. *Defuzzification*
This phase translates the fuzzy values into crisp mode, and stimulates the adaptation function within the fuzzy q-learning algorithms.

4.2.1.2 Q-Learning

Like any other Reinforcement Learning technique, Q-Learning uses rewards to learn and to make decisions on several policies. This is a fall under off-policy method where the target policy is not equal to the behavioural policy.

In Q-Learning, it is derived from Markov Decision Process (MDP) and consists of three inputs. State, action and reward. Every state will have a different score depending on the steps taken toward the final policy and continuing with the learning update.

Figure 4.8 illustrates how reinforcement learning applied the mentioned parameters.

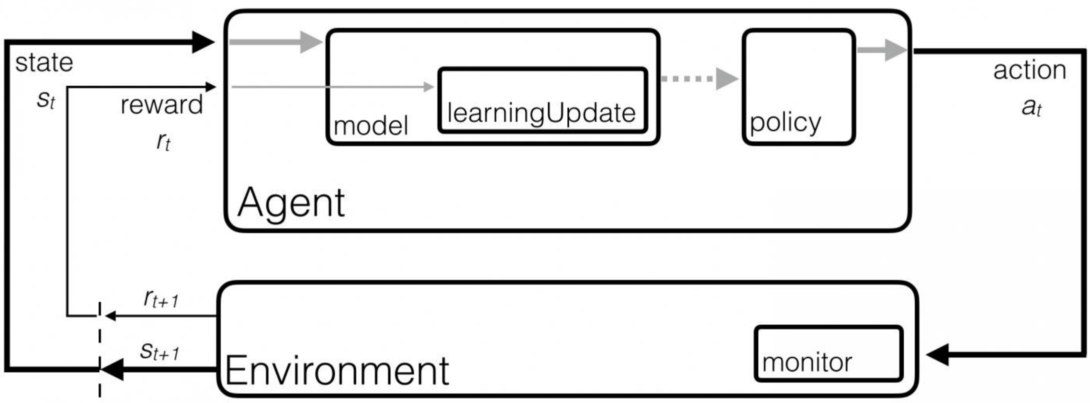


Figure 4.8. Q-Learning Framework [141]

The algorithm will have an iteration process. This is known as an episode to ensure that it will optimise with the alpha and gamma values:

a) γ = *Gamma* value in the range of 0 and 1. The lowest value will instruct Q-Learning to find the instance reward and ignore the total score of the accumulated reward.

b) α = Alpha value identical to gamma, which is a range between 0 and 1. In normal circumstances, the value is set low to optimise the algorithm, such as 0.2.

Definition 13: Q-Learning Update

. $Q(s_t, a_t) \longleftarrow Q(s_t, a_t) + a[r_{t+1} + \gamma_a^{max} Q(s_{t+1}, a) - Q(s_t, a_t)]$

Q-Learning Algorithm [131]

Initialize Q_0 (s, a) to random values
Choose a starting point s_0
While the policy is not good enough
Choose at according to values $Qt\ (st,.)$
$at = f(Qt(st,.))$
Obtain in return: $st + 1\ (s')$ and rt
Update using Definition 13
End While

4.2.1.3 Fuzzy Q-Learning

This is the algorithm based on Q-Learning and the limitations of fuzzy, introduced by [131] and iteratively enhanced by [133], [130] and [134]. The constraint of fuzzy [147], is that it must be heavier that 'W', where in his case the 'W' refers to Weight. On the other hand, Fuzzy Q-Learning actions are able to process fuzzy constraints and proceed with the optimal policy. This feature is not available for the actions in Q-learning introduced by [131].

Fuzzy Q-Learning Algorithm – Basic [107]

Observe the state x
For each rule, choose the actual consequence using some EEP
Compute the global consequence a(x) and its corresponding Q-value Q(x,a)
Apply the action a(x). Let y be the new state
Receive the reinforcement r
Update the q-values using Definition 13.

Enhanced Fuzzy Q-Learning Algorithm [4-9]

Require: $\gamma, \eta, \in$

1) Initialize q-values
   $q[i, j] = 0{,}1 < i, 1 < j < J$
2) select an action for each fired rule:
   $a^i = argmax_k q[i, k] with\ probability\ 1{-}\in$
   $a_i = random\ \{a_k, k = 1{,}2, \dots, J\} with\ probability\ \in$
3) Calculate the control action by the fuzzy controller:
   $a = \sum_{i=1}^{N} \mu_i\ (\chi) x\ a_i$, where $\alpha_i(s) is\ the\ firing\ level\ of\ the\ rule\ i$
4) Approximate the Q function from the current q-values and the firing level of the rules:
   $Q(s(t), a) = \sum_{i=1}^{N} \alpha(s)\ \ X\ q[i, a_i]$, where $Q(s(t), a)$ is the value of the Q function for the state current state $s(t)$ in iteration t and the action a.
5) Take action a and let system goes to the next state $s(t+1)$.

6) Observe the reinforcement signal, $r(t+1)$ and compute the value for the new state: $V(s(t+1)) = \sum_{i=1}^{N} \alpha_i \left(s(t+1)\right).max_k(q|i, q_k])$.
7) Calculate the error signal:
$\Delta Q = r(t+1) + \gamma x\, V_t(s(t+1)) - Q(s(t), a)$, where γ is the discount factor
8) Update q-values:
$q[i, a_i] = q[i, a_i] + \eta.\Delta Q.\alpha_i(s(t))$, where η is the learning rate
9) Repeat the process for the new state until it converges

4.2.1.4 Architecture

The proposed architecture is available in Figure 3.7 and the components are mapped into a MAPE-K model in Figure 4.10. This architecture is the enhanced version of [108-110] with the introduction of an adaptive policy.

4.2.1.5 Algorithm

This section presents an approach which provides the overall algorithm of this research. The algorithm itself is segmented into phases and produces the results for further analysis.

Implementation of the Complete Algorithm

Phase One.

1. Acceptance of the three QoS parameters (Latency, Availability and Packet loss).

Phase Two

1. Execution of QoS parameters from case study [139] (Pass, Low, Normal, High, Peak) to centre of weighted approach.
   - Use scores for each performance
   - Use reward for Q-Learning algorithm
   - Populate the values for next phase

Phase Three

1. Application of fuzzy Sugeno for membership functions and rule base

Phase Four

i. Comparison of three QoS parameters
   a. Execution of QoS pair
      i. Require: Latency, Availability (QoS)
         1. 1st Set
            a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Small =0.1)
            b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
         2. 2nd Set
            a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Medium =0.5)

b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].

3. 3rd Set
    a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Large =1.0)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
4. 4th Set
    a. Require: Epsilon (Large =1.0), Lambda (Large =1.0) and Alpha (Small =0.1)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
5. 5th Set
    a. Require: Epsilon (Large =1.0), Lambda (Large =1.0) and Alpha (Medium =0.5)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
6. 6th Set
    a. Require: Epsilon (Large =1.0), Lambda (Large = 1.0) and Alpha (Large =1.0)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].

ii. Require: Packet Loss, Availability (QoS)

1. 1st Set
    a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Small =0.1)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
2. 2nd Set
    a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Medium =0.5)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
3. 3rd Set
    a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Large =1.0)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
4. 4th Set

a. Require: Epsilon (Large =1.0), Lambda (Large =1.0) and Alpha (Small =0.1)
b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].

5. 5th Set
   a. Require: Epsilon (Large =1.0), Lambda (Large =1.0) and Alpha (Medium =0.5)
   b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
6. 6th Set
   a. Require: Epsilon (Large =1.0), Lambda (Large = 1.0) and Alpha (Large =1.0)
   b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].

iii. Require: Packet Loss, Latency (QoS)
1. 1st Set
   a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Small =0.1)
   b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
2. 2nd Set
   a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Medium =0.5)
   b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
3. 3rd Set
   a. Require: Epsilon (Small =0.1), Lambda (Small =0.1) and Alpha (Large =1.0)
   b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
4. 4th Set
   a. Require: Epsilon (Large =1.0), Lambda (Large =1.0) and Alpha (Small =0.1)
   b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].
5. 5th Set
   a. Require: Epsilon (Large =1.0), Lambda (Large =1.0) and Alpha (Medium =0.5)
   b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].

6. 6th Set
    a. Require: Epsilon (Large =1.0), Lambda (Large = 1.0) and Alpha (Large =1.0)
    b. Repeat the process with the input files for 500 until it converges. Use enhanced fuzzy q-learning algorithm [108].

Phase Five

1. Analysis of the results.

4.2.1.6 Model

In reinforcement learning, there are two models; model-based and model free. As we understand it, there are three components under machine learning; supervised, unsupervised and reinforcement. The model-based method illustrated in Figure 4.11 is well-known for planning and model free is meant for exploitation.

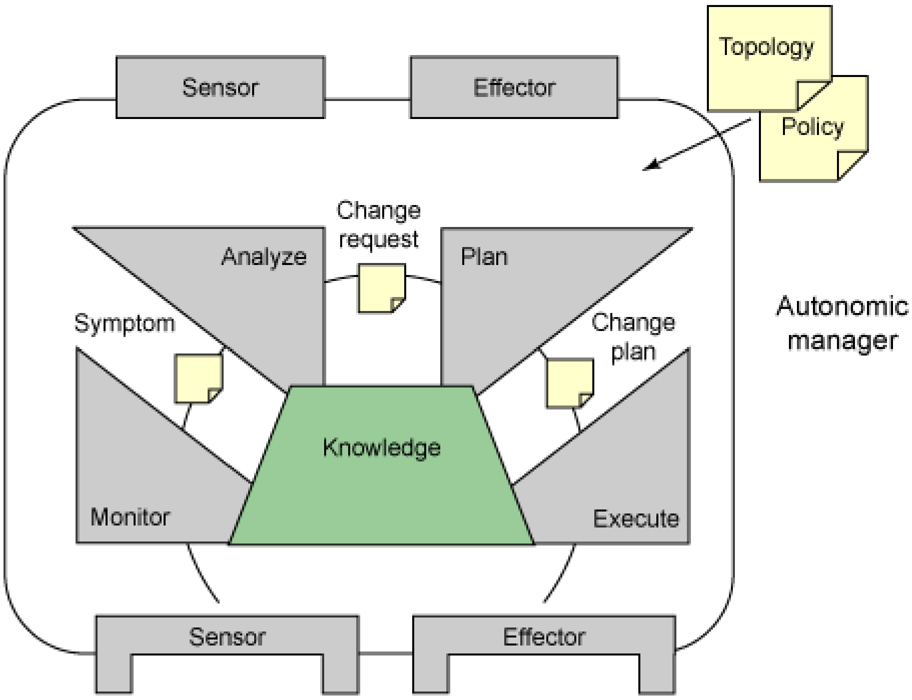


Figure 4.10: MAPE-K Model

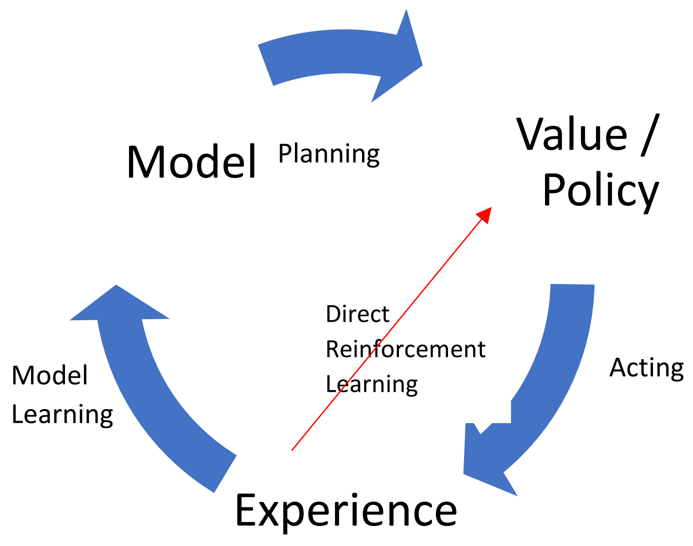


Figure 4.11. Model-Based Method

In this phase, the chosen model answered this research question;

Research Question (RQ)1.

How to model and specify QoS terms within an autonomic element to manage the establishment of ISP architecture?

In this phase, the MAPE-K framework was selected to be the adaptive framework to be integrated with fuzzy logic together with the completed architecture.

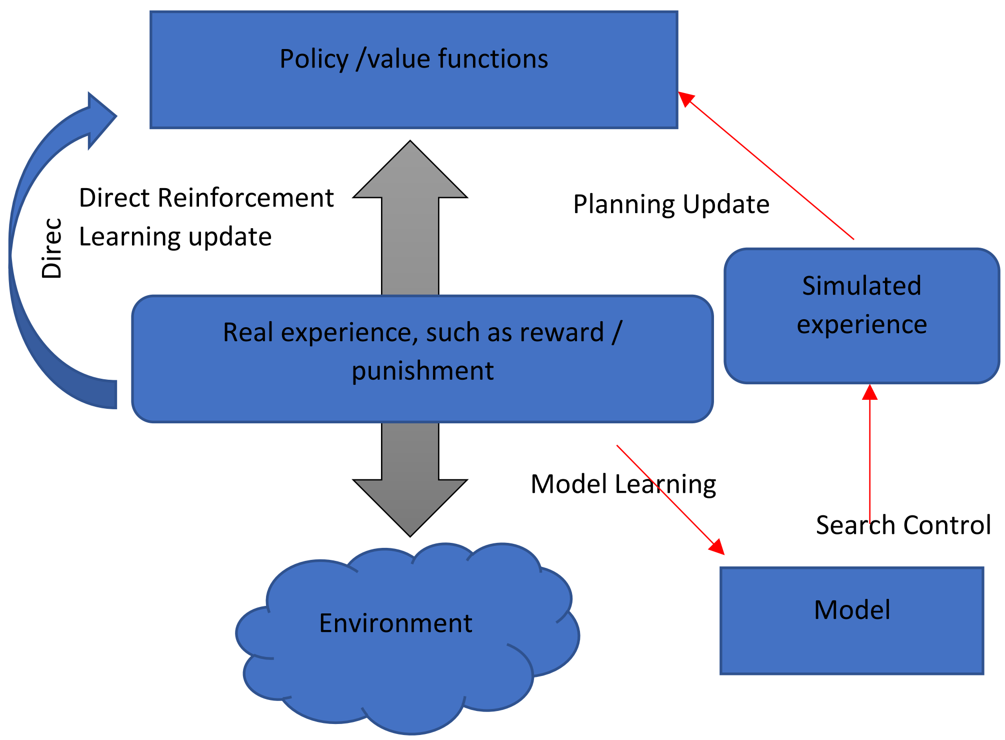


Figure 4.12. Model Free Method

As illustrated in Figure 4.12, the model free method is very suitable for this approach. The model interacts with the rewards and punishments based on the movement of the state. Every state has a different reward system and policy towards the end goals. The reinforcement learning agent is the forwarder that updates the real experience of the policy or value functions.

The movement of the reinforcement learning agent can be understood by three common Q-Learning attributes which are derived from Markov Decision Process (MDP), namely State, Action and Reward. Once the agent moves from one state to another, it gains different rewards and end up with an update from the policy in relation to choosing an appropriate action.

4.3 Implementation

As for the execution of this experiment, the application of well-established prototyping, mathematical modelling and MATLAB Release R2015a was successfully applied throughout the whole process.

There are four main objectives, which have been established for this assessment to ensure that the results address the highlighted research questions in the previous chapters. The goals are:

v. To demonstrate that the MAPE-K framework able to work in the adaptive environment together with defined autonomic elements.
vi. To apply and combine Fuzzy Q-Learning and a model free-based method to work efficiently on the proposed algorithm.
vii. To evaluate the updating rules which are associated with the algorithm.
viii. To provide the stability of the MAPE-K framework in dealing with the iteration.
ix. To prove that the elements of uncertainties, adaptation and learning abilities are present and established in the proposed algorithm.

4.3.1 Experimental Configuration

In this approach, there are three scenarios of QoS comparison which are:

I. Latency versus Availability
II. Packet Loss versus Availability
III. Packet Loss vs Latency.

In the each of the comparisons, the number of iterations was fixed to 500 and a total of 125 rule base combinations were identified to cater for all possible ranges of the selected QoS parameters. The details of the 125 rule base combinations are available in Appendix B.

Table 4.3. Rule base declaration in Fuzzy Toolbox (Excerpt)

Rule	QoS Parameters			Scores group on the service Performance					Weighted Total using centre of weighted average method
	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	2	1	**2.00**
2	Low	Pass	Normal	0	0	1	1	1	**1.50**
3	Low	Pass	High	0	1	0	1	1	**1.00**
4	Low	Pass	Peak	1	0	0	1	1	**0.50**
5	Low	Pass	Pass	0	0	0	1	2	**2.50**
6	Low	Peak	Low	1	0	0	2	0	**0.00**
7	Low	Peak	Normal	1	0	1	1	0	**-0.50**
8	Low	Peak	High	1	1	0	1	0	**-1.00**

Table 4.4. Latency vs Availability Combination (Excerpt)

Rule	QoS Parameters			Scores group on the service Performance					Weighted Total using centre of weighted average method
	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	1	1	**1.50**
2	Low	Pass	Normal	0	0	0	1	1	**1.50**
3	Low	Pass	High	0	0	0	1	1	**1.50**
4	Low	Pass	Peak	1	0	0	1	1	**0.50**
5	Low	Pass	Pass	0	0	0	1	1	**1.50**
6	Low	Peak	Low	1	0	0	1	0	**-0.50**
7	Low	Peak	Normal	1	0	1	1	0	**-0.50**
8	Low	Peak	High	1	0	0	1	0	**-0.50**
9	Low	Peak	Peak	1	0	0	1	0	**-0.50**
10	Low	Peak	Pass	1	0	0	1	0	**-0.50**

Table 4.5. Latency vs Packet Loss (Excerpt)

Rule	QoS Parameters			Scores group on the service Performance					Weighted Total using centre of weighted average method
	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	2	0	**1.00**
2	Low	Pass	Normal	0	0	1	1	0	**0.50**
3	Low	Pass	High	0	1	0	1	0	**0.00**
4	Low	Pass	Peak	1	0	0	1	0	**-0.50**
5	Low	Pass	Pass	0	0	0	1	1	**1.50**
6	Low	Peak	Low	0	0	0	2	0	**1.00**
7	Low	Peak	Normal	0	0	1	1	0	**0.50**
8	Low	Peak	High	0	1	0	1	0	**0.00**
9	Low	Peak	Peak	1	0	0	1	0	**-0.50**
10	Low	Peak	Pass	0	0	0	1	1	**1.50**

Table 4.6. Packet Loss vs Availability

Rule	QoS Parameters			Scores group on the service Performance					Weighted Total using centre of weighted average method
	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	1	1	**1.50**
2	Low	Pass	Normal	0	0	1	0	1	**1.00**
3	Low	Pass	High	0	1	0	0	1	**0.50**
4	Low	Pass	Peak	1	0	0	0	1	**0.00**
5	Low	Pass	Pass	0	0	0	0	2	**2.00**
6	Low	Peak	Low	1	0	0	1	0	**-0.50**
7	Low	Peak	Normal	1	0	1	0	0	**-1.00**
8	Low	Peak	High	1	1	0	0	0	**-1.50**
9	Low	Peak	Peak	2	0	0	0	0	**-2.00**
10	Low	Peak	Pass	1	0	0	0	1	**0.00**

The next phase is the purification of 125 rule base into five groups which are Low, Normal, High, Peak and Pass. The total of the 25 rules base represents the composition of the overall rules that have been identified and match with the values calculated with the centre of the weighted average (Equation) and the information as per Tables 4.4-4.6. The details of the rule base transformation to the state values are available in Appendix C.

Table 4.7. Rule base in the State values (Latency versus Availability)

Latency	Availability	Rules sequence in Matlab	Values according to Rules
Low	Pass	1	Mf8
Low	Peak	2	Mf4
Low	High	3	Mf5
Low	Normal	4	Mf6
Low	Low	5	Mf7
Normal	Pass	6	Mf7
Normal	Peak	7	Mf3
Normal	High	8	Mf4
Normal	Normal	9	Mf5
Normal	Low	10	Mf6
High	Pass	11	Mf6
High	Peak	12	Mf2
High	High	13	Mf3
High	Normal	14	Mf4
High	Low	15	Mf5
Peak	Pass	16	Mf5
Peak	Peak	17	Mf1
Peak	High	18	Mf2
Peak	Normal	19	Mf3
Peak	Low	20	Mf4
Pass	Pass	21	Mf9
Pass	Peak	22	Mf5
Pass	High	23	Mf6
Pass	Normal	24	Mf7
Pass	Low	25	Mf8

Table 4.8. Membership function values – Centre of weighted average (Latency versus Availability)

Membership Function	Values
Mf1	-2
Mf2	-1.5
Mf3	-1
Mf4	-0.5
Mf5	0
Mf6	0.5
Mf7	1
Mf8	1.5
Mf9	2

In Figure 4.13-4.15, we applied the Sugeno approach using fuzzy toolbox to handle the type-2 fuzzy values which are available in MATLAB. This is the first part of the fuzzy approach up to the inclusion of defuzzification values, which were later combined in Q-Learning.

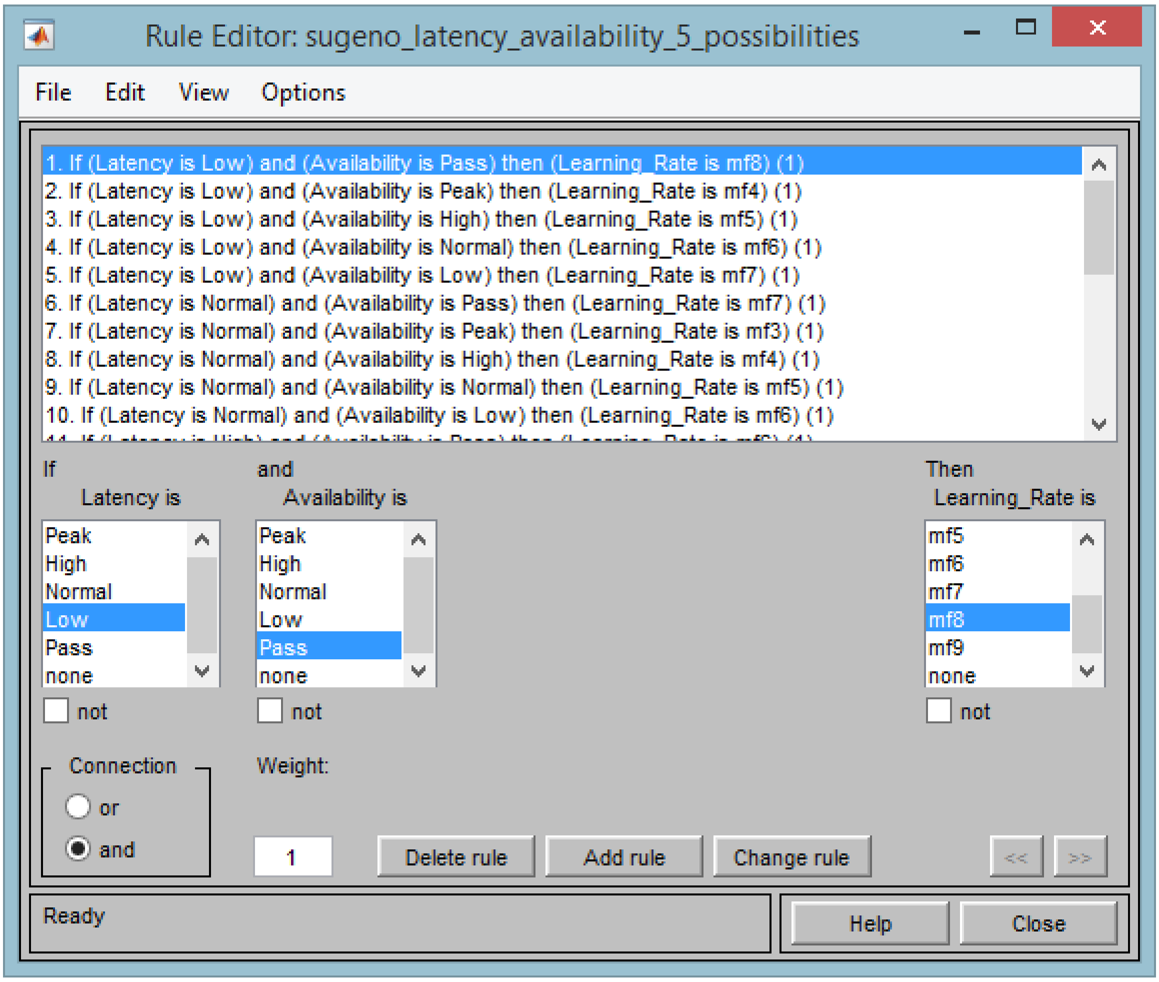


Figure 4.13. Latency vs Availability

Figure 4.13 illustrates the interface of rule editor using Sugeno approach. It has rules and the conditions interface. This information entered according to the defined rules in the rule base exercise. It caters for two QoS perimeters, latency and availability.

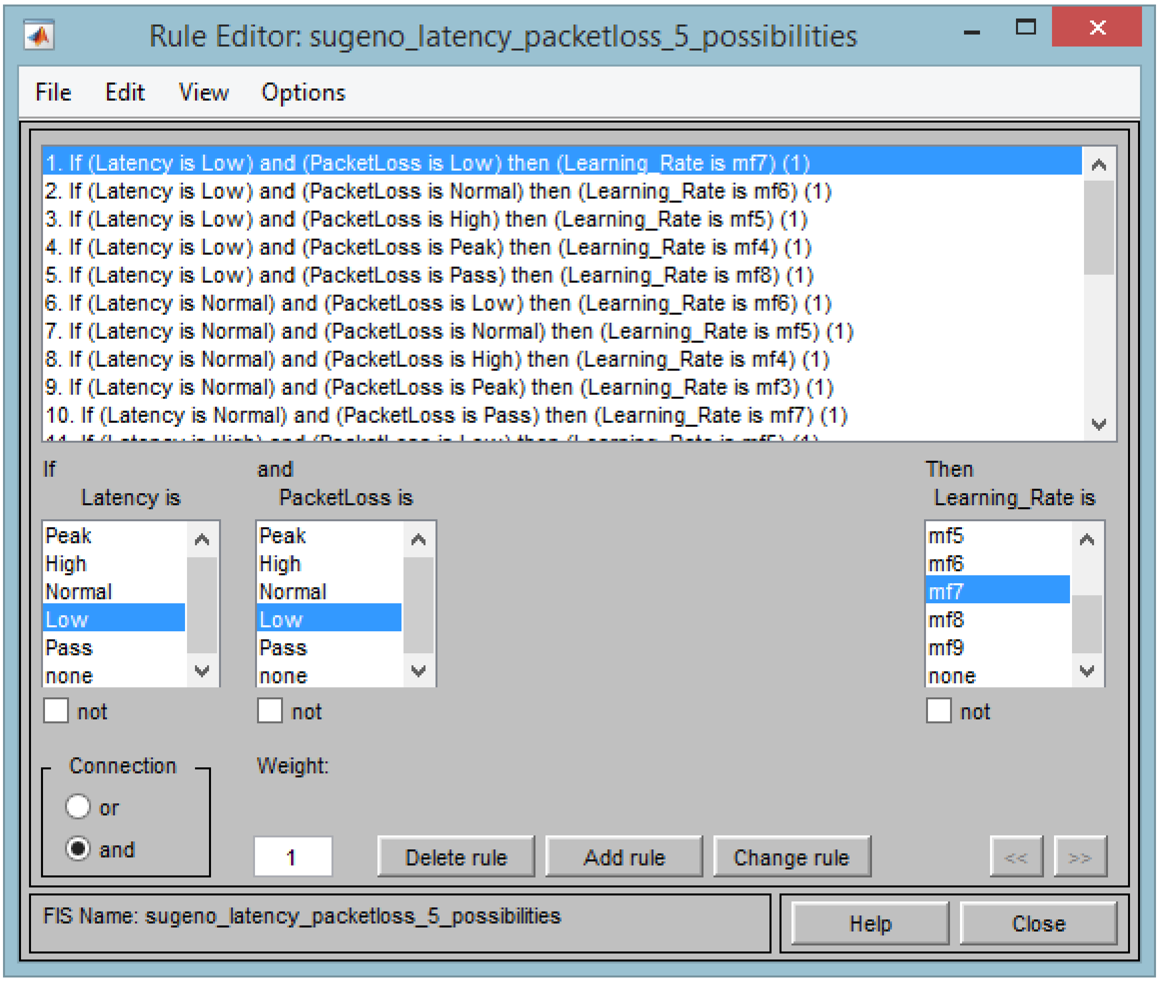


Figure 4.14. Latency vs Packet Loss

Figure 4.14 shows the interface of rule editor using Sugeno approach. It has rules and the conditions interface. This information entered according to the defined rules in the rule base exercise. Latency and packet loss are the two QoS parameters that executed in this figure.

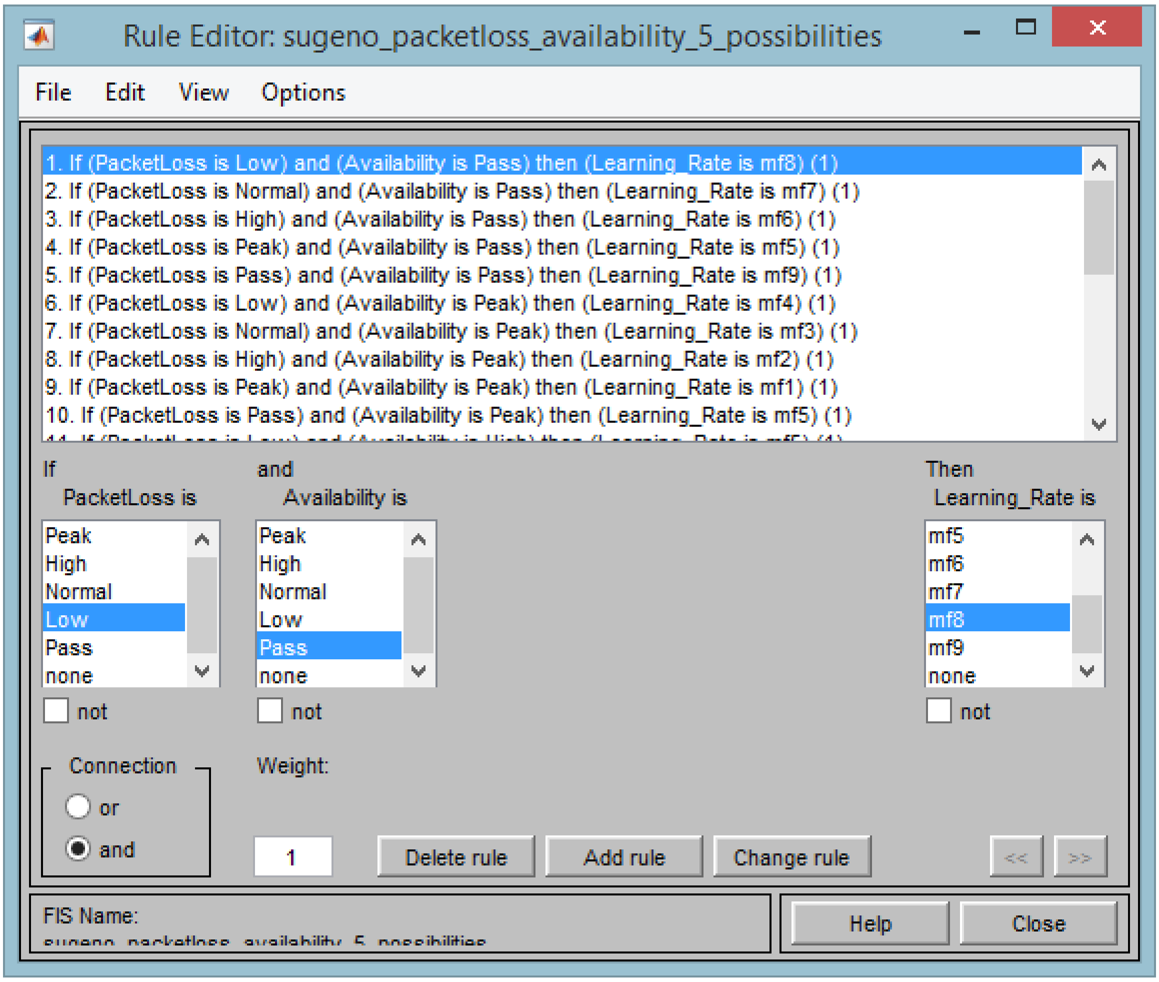


Figure 4.15. Packet Loss vs Availability

The reward approach was applied with positive and negative values. The justification of each value was identified accordingly to the grouping of the QoS parameters. Tables 4.9-4.12 tabulates the information accordingly.

Table 4.9: Linguistic variables for the negative reward

Description	Category	Values
Latency	Low	500 ms ≤La< 750 ms
	Normal	750 ms ≤La< 1 s
	High	1 s ≤La< 5 s
	Peak	5 s ≤La
Availability	Low	95% < Av ≤ 98%
	Normal	90% < Av ≤ 95%
	High	80% < Av ≤ 90%
	Peak	Av ≤ 80%
Packet Loss	Low	2% ≤ PL < 4%
	Normal	4% ≤ PL < 8%
	High	8% ≤ PL < 20%
	Peak	20% ≤ PL

Table 4.10. Positive Reward

Inputs	Reward	Minimum	Mean	Maximum
Latency	Positive	499 ms	249	0s
Availability	Positive	99 %	99.5%	100%
Packet Loss	Positive	1 %	0.5 %	%

Table 4.11. Scores for the service of the performance.

Description	Score
Peak	-2
High	-1
Normal	0
Low	1
Pass	2

Table 4.12: Group Rewards

Group	Score
Low	-1
Normal	-2
High	-3
Peak	-4
Pass	1

Table 4.13 Simulation Configurations

Computer Information	
Windows Edition	Windows 8.1 Single Language
Processor	Intel ® Core ™ i5-4200M CPU @ 2.50 GHZ 2.50 GHZ
Installed Memory (RAM)	8 GB
System Type	64 Bits Operating System , x64 based processor
Disk Drives	1 Terabyte
Display Adapters	Nvidia GeForce GT 740M
Network Interface Card	Qualcomm Atheros AR8161 PCI-E Gigabit Ethernet Controller
Wireless Interface Card	Qualcomm Atheros AR956x Wireless Network Adaptor
Simulation Software	MATLAB Release R2015a
Fuzzy Q-Learning Model	Github License [108]
Data files	Public access [139]. Details available at Appendix D
ISP observation on QoS	Public access [140]. Details of SLA segmentation available at Appendix E.

Table summarises the executions of experiments. As for the Q-Learning part, it is the extension of fuzzy values and has three Q-learning factors. The runs evaluated the groups of Small, Medium and Large of the Learning Rate and Small and Medium of Epsilon and Lambda.

Table 4.14. Categories of the experiments

Categories	No of iterations	Type of Comparison	
Latency vs Ability	500	Small Epsilon and Small Lambda	Small Learn Rate
			Medium Learn Rate
			Large Learn Rate
		Large Epsilon and Large Lambda	Small Learn Rate
			Medium Learn Rate
			Large Learn Rate
Latency vs Packet Loss	500	Small Epsilon and Small Lambda	Small Learn Rate
			Medium Learn Rate
			Large Learn Rate
		Large Epsilon and Large Lambda	Small Learn Rate
			Medium Learn Rate
			Large Learn Rate
Packet Loss vs Ability	500	Small Epsilon and Small Lambda	Small Learn Rate
			Medium Learn Rate
			Large Learn Rate
		Large Epsilon and Large Lambda	Small Learn Rate
			Medium Learn Rate
			Large Learn Rate

Below are the values for the categories of epsilon, lambda and alpha.

Table 4.15. Categorisation of the Q-Learning Factors

Q-Learning Factor	Categories	
Epsilon	Small	0.1
	Large	1.0
Lambda	Small	0.1
	Large	1.0
Learn Rate (Alpha)	Small	0.1
	Medium	0.5
	Large	1.0

The final step was to update the correct reward values and to ensure that the conditions were according to the rule base values. The overall configuration for the reward calculator is available in Appendix F.

Reward Calculator Embedded within MATLAB Code (Excerpt)

```
if (current_state(1)>= 0.5 && current_state(1) <0.75 )|| (current_state(2) > 95 &&
current_state(2) <=98)
    reward =-1;
%  Latency Normal
    elseif (current_state(1)>= 0.75 && current_state(1) <1 )|| (current_state(2) > 90
&& current_state(2) <=95)
    reward =-2;
   %Latency High
     elseif (current_state(1)>= 1 && current_state(1) <5 )|| (current_state(2) > 80
&& current_state(2) <=90)
    reward =-3;
     %Latency Peak
     elseif (current_state(1)>= 5  )|| (current_state(2) < 80)
    reward =-4;
     % Latency Pass
    elseif (current_state(1)<=0.5 )|| (current_state(2) > 98)
    reward =1;
      %if (current_state(2)<=SLA(1)) % response time SLO has not been violated
 %   reward=1;
elseif (current_state(2)<=old_state(2))&&(old_action>0) ||
(current_state(1)<=old_state(1))&&(old_action>0) % violated but has been
improved due to the action
    reward=0; % not either penalize nor give positive reward
   %else %violated and has been dropped from last time
    %reward=exp((98)-current_state(2))/98-1; % a negative reward between [-1 0)
        %reward = -1;
   %end
end
end
```

4.3.2 Experimental Results

In this experiment, we demonstrated two main issues of this research study, which were uncertainties and adaptation through a series of experimental assessments. The outcome of this was the defined contribution of the research to answer the following questions:

- **Research Question (RQ)2.**
  How can the QoS provision of ISPs architectures be achieved using an autonomic computing approach?
  Fuzzy Q-Learning was applied as the adaptation and optimisation algorithm used to handle this phase and the experiments with a static and dynamic combination in the rule base has been demonstrated.
- **Research Question (RQ)3.**
  What are the approaches to autonomously self-configure and support QoS terms?
  At this stage, the static fuzzy rule base approach was compared with Fuzzy Q-Learning to handle uncertainties and in further

experiments, to handle adaptations from the input file and to interact with the stable Q-Learning algorithm.

4.3.2.1 Uncertainties (RQ2)

The ability of fuzzy logic to react to the robust values of QoS parameters, which are associated with the defined rule base, is demonstrated in Figure 13-15. The learning rate was then calculated from the end process of defuzzification using the fuzzy toolbox. The change in the learning rate occurred when the input of the QoS parameters reflected the linking rule.

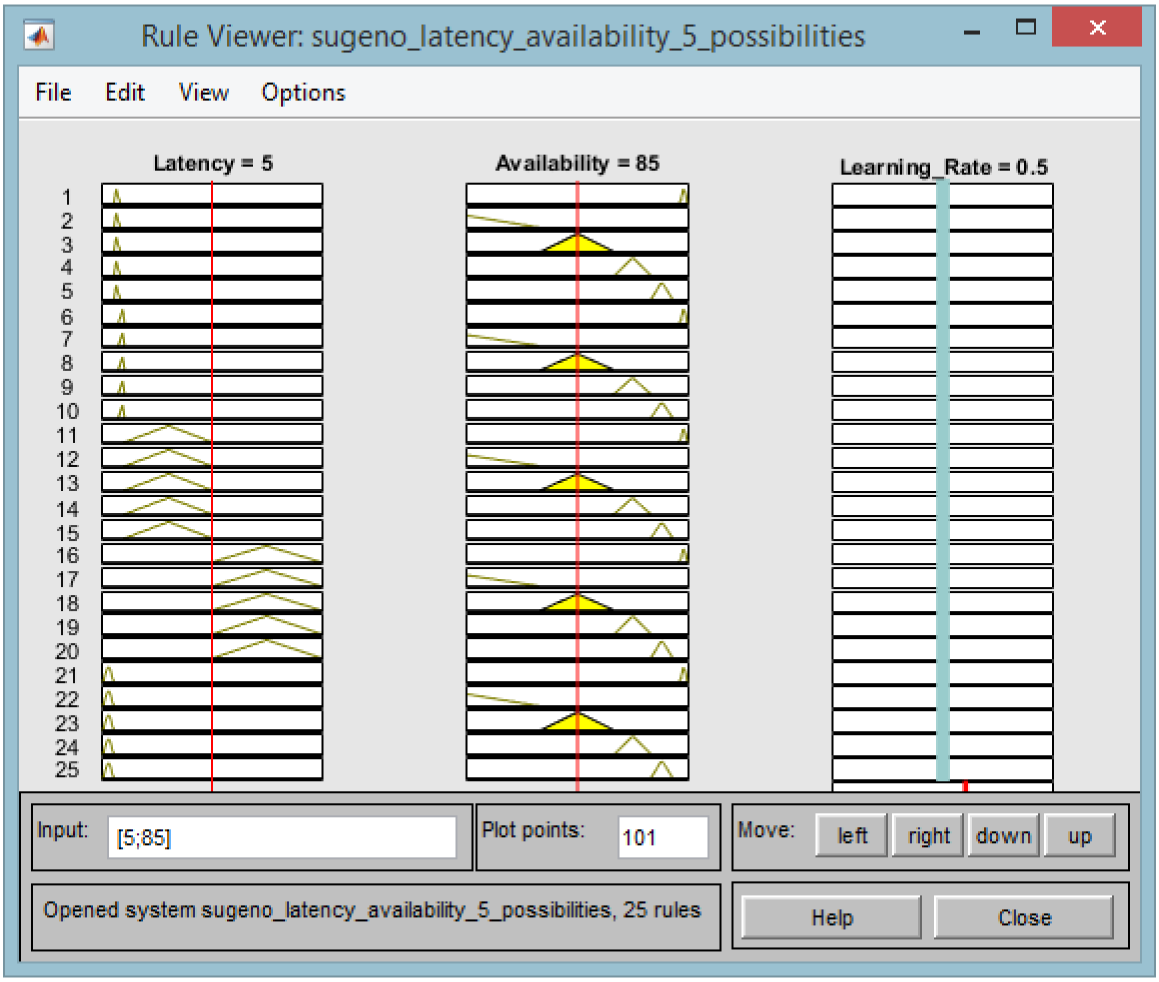


Figure 4.16. Learning Rate with the Latency = 5 and Availability = 85

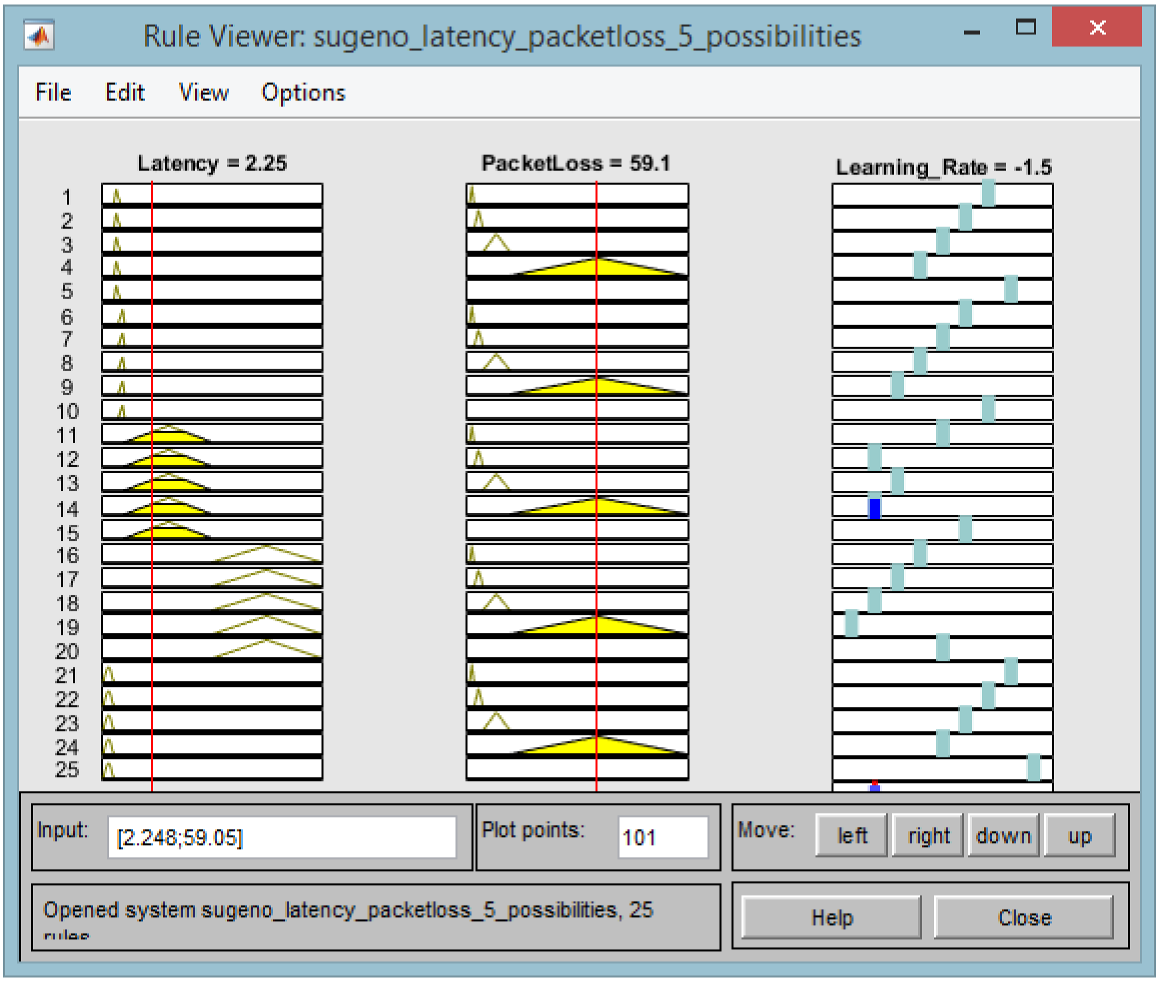


Figure 4.17. Learning Rate with the Latency =2.25 and Packet Loss = 59.1

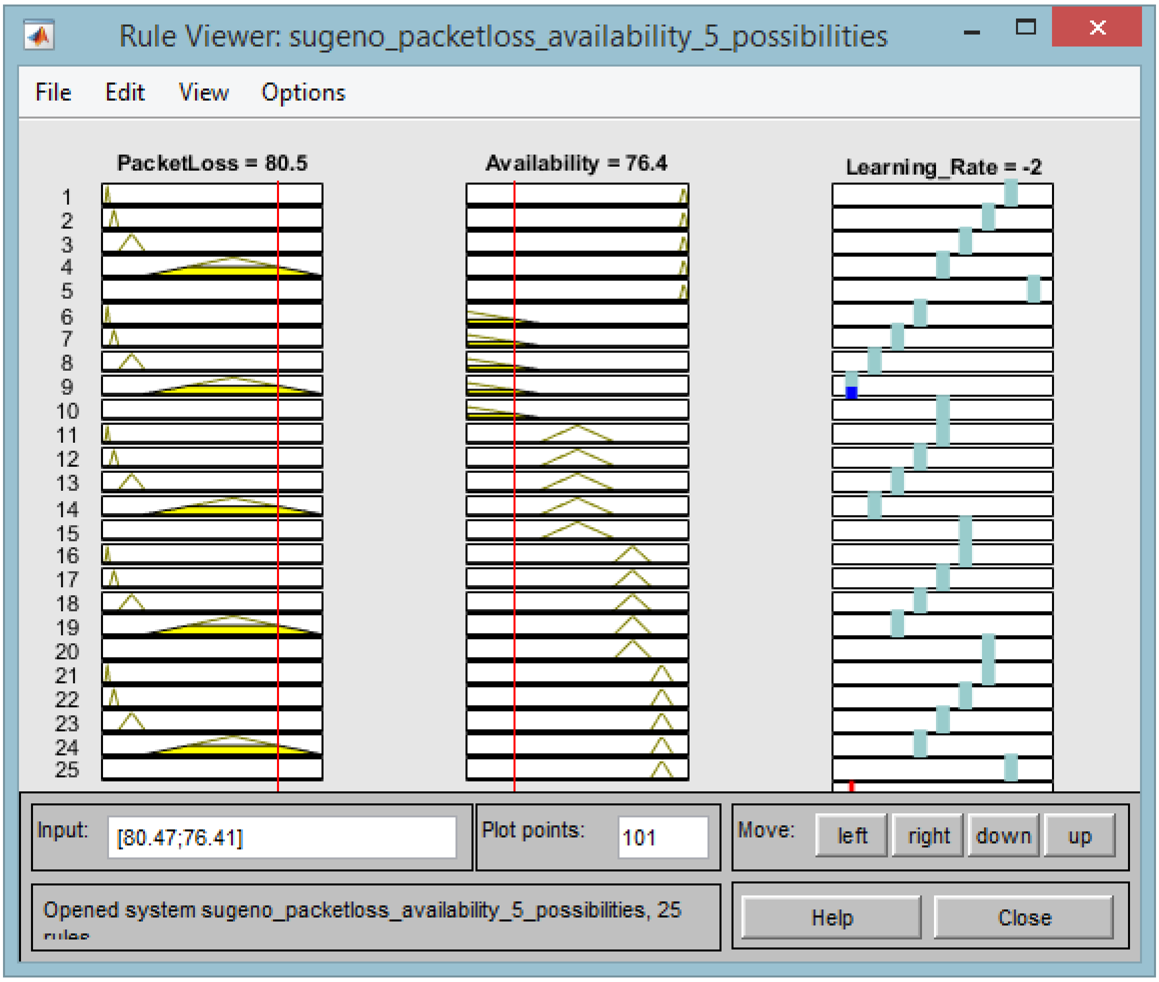


Figure 4.18. Learning Rate with the Packet Loss = 80.5 and Availability = 76.4

As Figure 4.17-4.18 shows, the values of the learning rate changed to negative due to the poor performance of the QoS parameters in the static inputs. The inputs in Figure 4.17 showed that the Latency was 2.25 and Packet Loss was 59.1, which meant that the learning rate was -1.5. This is due to the Latency itself, which was high and the Packet Loss was at its Peak. In this run, it activated rule 14 in the fuzzy inference system.

Figure 4.18 shows another combination of Packet Loss, which is 80.5, and Availability is 76.4. This totalled to -2. The learning rate is different in every combination and produced both negative and positive learning abilities as illustrated in Figure 4.16.

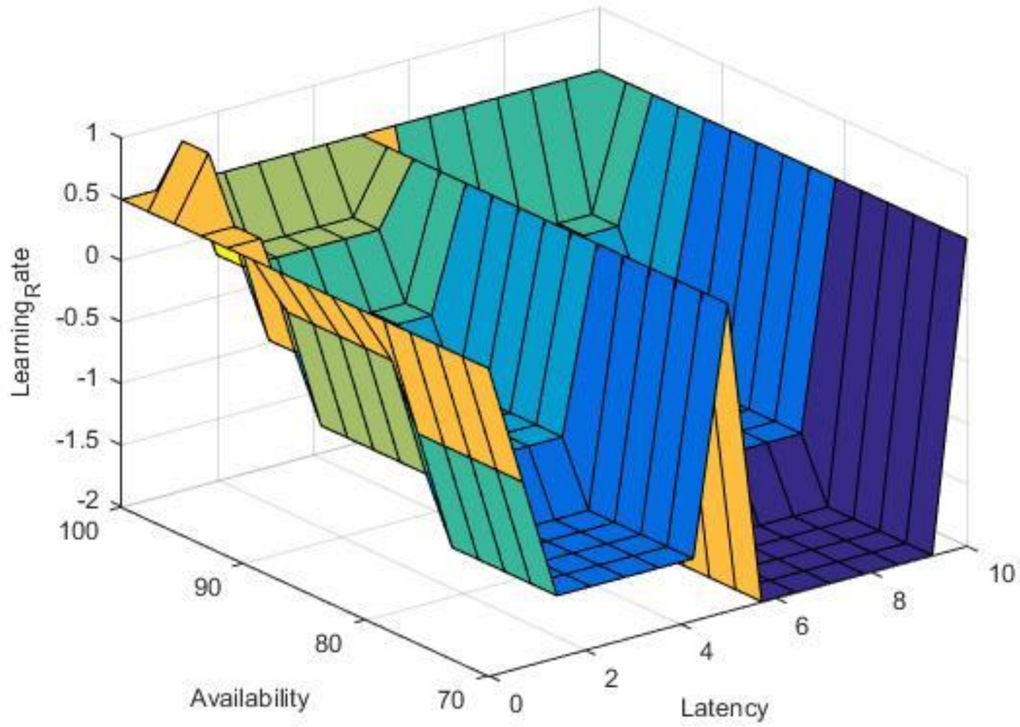


Figure 4.19: Normal Combination of Latency and Availability

Figure 4.19 shows the combination of latency and availability with normal combination.

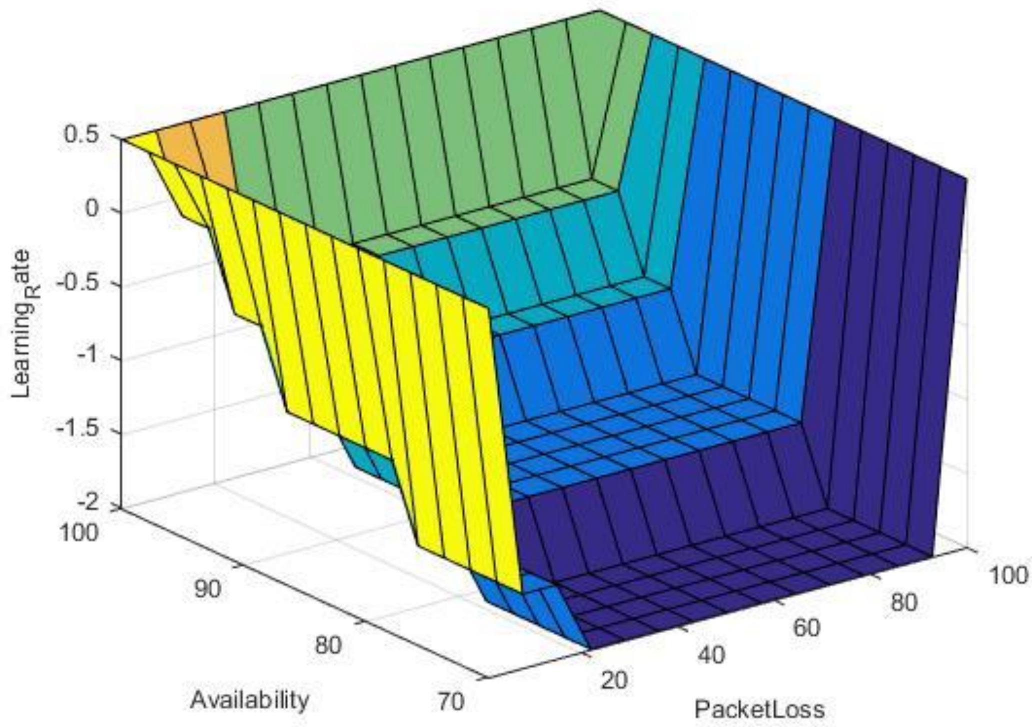


Figure 4.20: Normal Combination of Availability and Packet Loss

Figure 4.20 shows the combination of latency and availability with normal combination.

As for the dynamic inputs from the data file, the static graph in Figure 4.19-4.20 shows the normal categories of latency versus availability and packet loss versus availability. Throughout the experiment, there were no available rules fired for Packet Loss and Latency using the data file.

Therefore, the results are limited to two combinations, which are Latency versus Availability and Availability versus Packet Loss. In Figure 4.21-4.23, all of them were tested with the Small, Medium and Long values of the learning rate. The outcome for the Small learning rate in Figure 4.23 shows that most of the values are still negative and that the learning rate performance increasing to positive with a higher learning rate and ability to handle uncertainties.

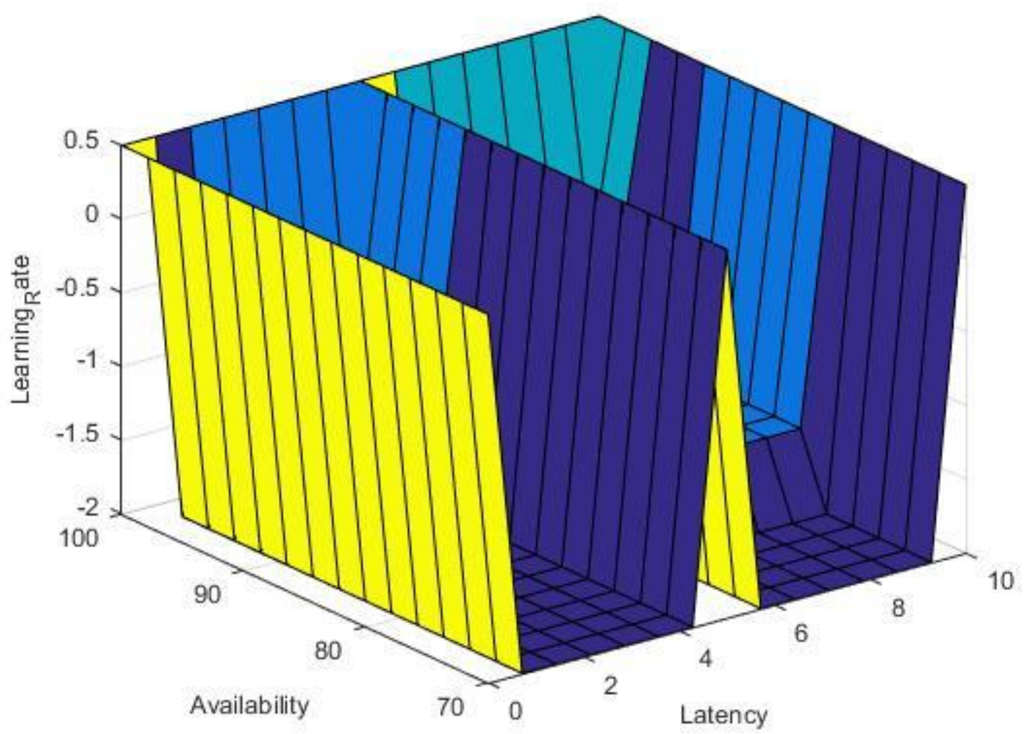


Figure 4.21: Small group with Alpha 0.1

In Figure 4.21 small group accessed with the alpha 0.1. The alpha value set to 0.1 to justify the learning rate are low. QoS Parameters applied are availability and latency.

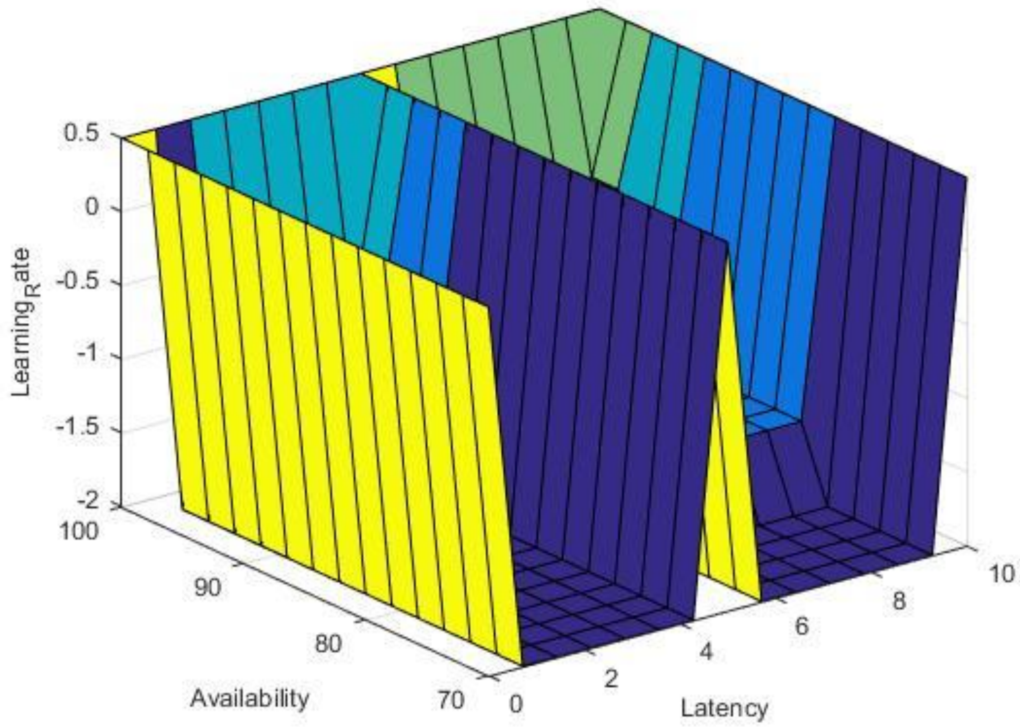


Figure 4.22: Small group with Alpha 0.5

In Figure 4.21 small group accessed with the alpha 0.5. The alpha value set to 0.5 to justify the learning rate are medium. QoS Parameters applied are availability and latency.

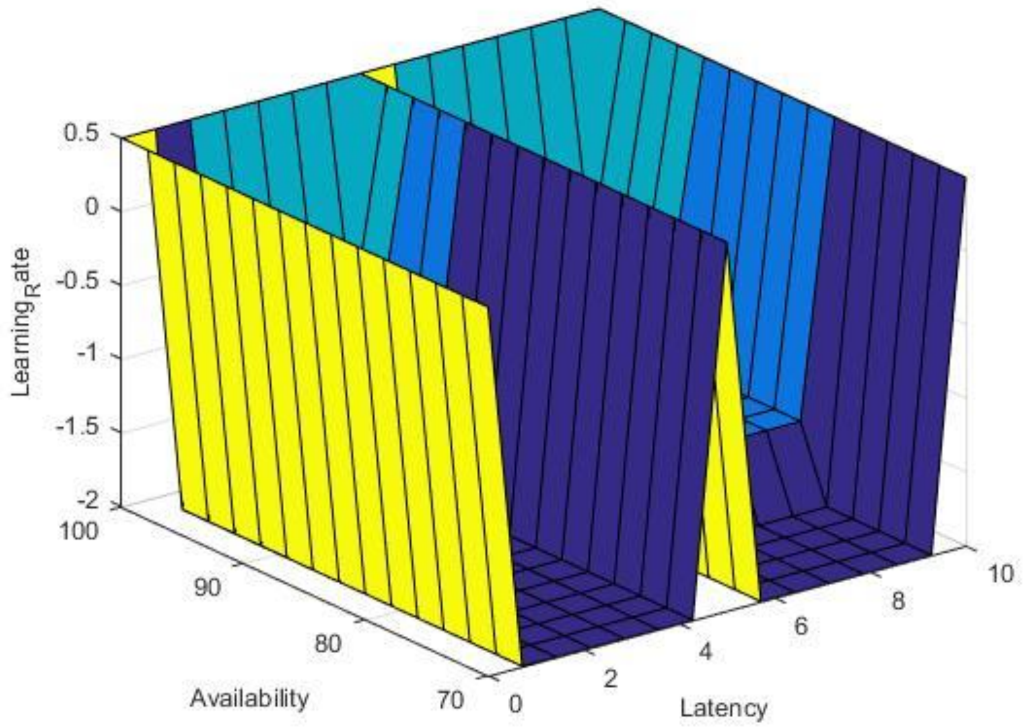


Figure 4.23: Small group with Alpha 1.0

In Figure 4.23 small group accessed with the alpha 1.0. The alpha value set to 1.0 to justify the learning rate are high. QoS Parameters applied are availability and latency.

In Figure 4.24-4.26, it demonstrates the same pattern of learning rate as the previous graph. It shows that the ability of fuzzy to react to an input file is to map it with static and dynamic inputs.

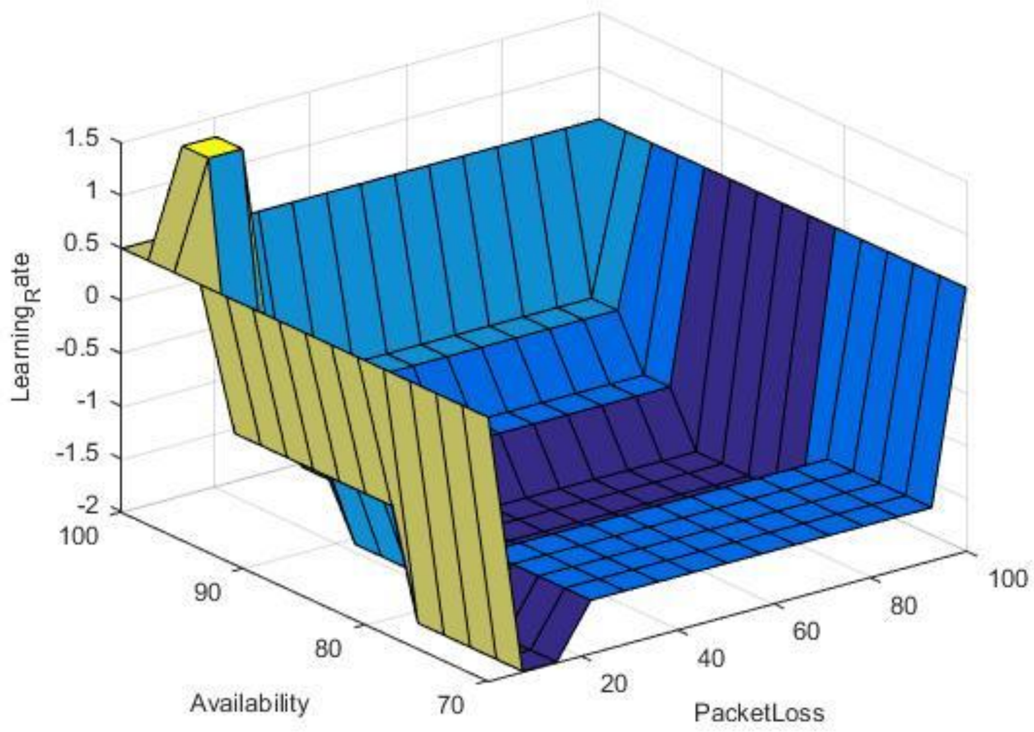


Figure 4.24: Small group with Alpha 0.1

In Figure 4.24 small group accessed with the alpha 0.1. The alpha value set to 0.1 to justify the learning rate are low. QoS Parameters applied are availability and packet loss.

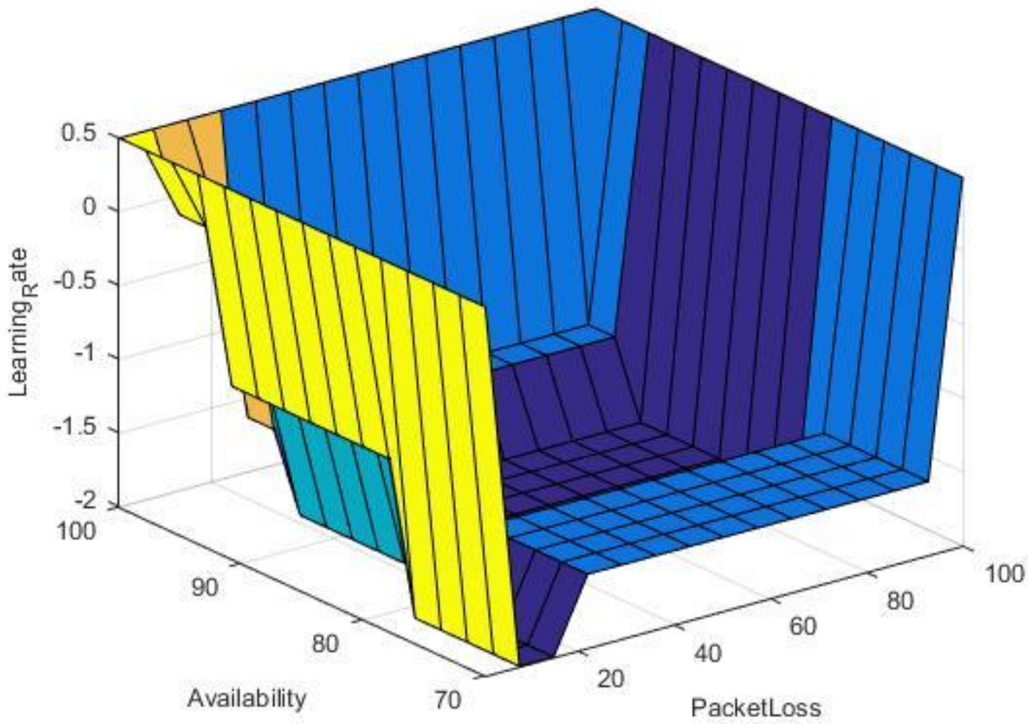


Figure 4.25: Small group with Alpha 0.5

In Figure 4.25 small group accessed with the alpha 0.5. The alpha value set to 0.5 to justify the learning rate are medium. QoS Parameters applied are availability and packet loss.

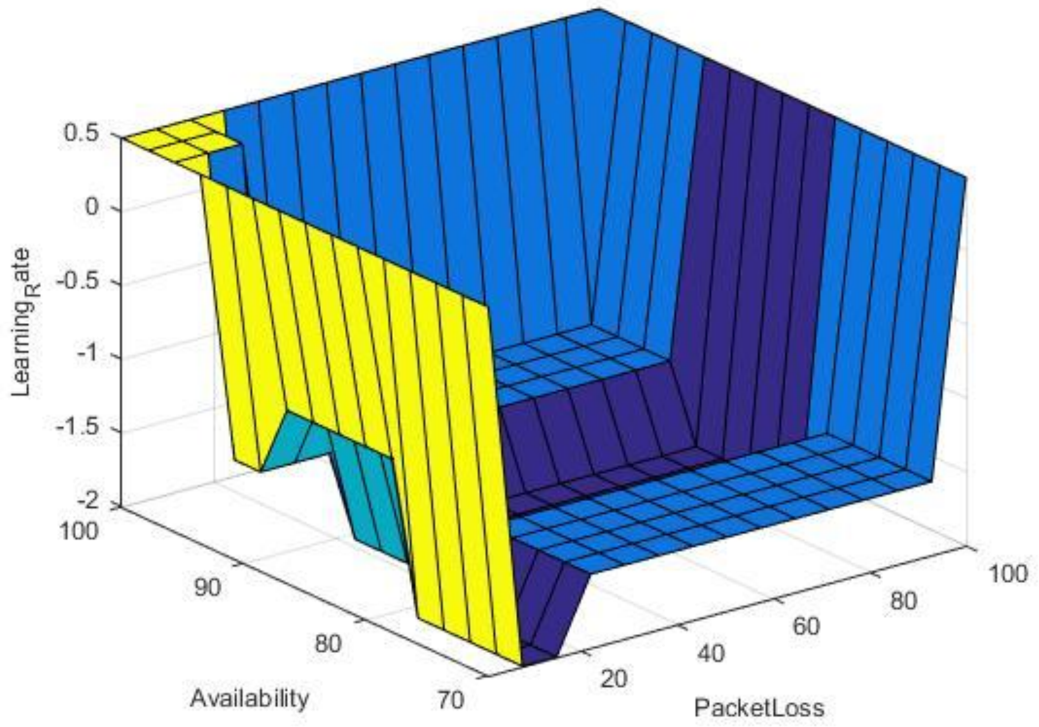


Figure 4.26: Small group with Alpha 1.0

In Figure 4.26 small group accessed with the alpha 1.0. The alpha value set to 1.0 to justify the learning rate are high. QoS Parameters applied are availability and packet loss.

4.3.2.2 Adaptation (RQ3)

This is the key output for the adaptation approach. It simply monitors, analyses, plans and executes within the iteration. There are groups of iterations such as 100, 200, 300, 400 and 500. The reason for doing this is to demonstrate the adaptation features from this experiment to deal with the input file. SLA has been defined within the combination of QoS parameters in the rule base.

As for the overall adaptation in Packet Loss and Availability, the number of rules affected has been labelled with state, rule base as the action and lastly, q-values. There were 6 cases used to measure the overall adaptation and the evolution of the q-values associated to each action. The values of Small, Medium and Large have been defined in Table 4.14 and 4.15.

Evaluation of the QoS Parameters;

i. Packet Loss versus Availability

The overall adaptation for this combination is available in Figure 4.27. The evolution of the q-values increased from case 1 to case 3 and then dropped at case 4. The value continued growing from case 5 to case 6.

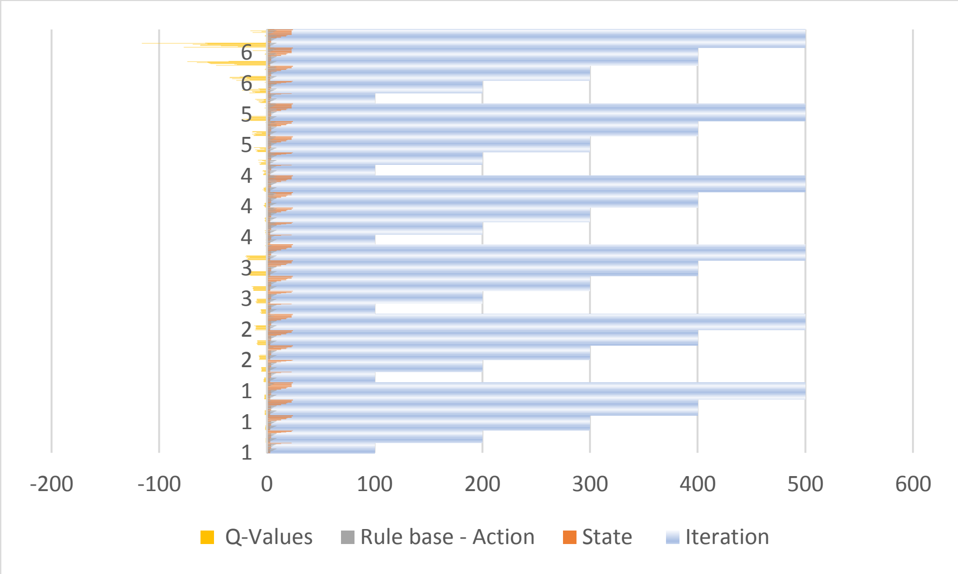


Figure 4.27: Overall adaptation Packet Loss vs Availability

1. Case 1 – Small [Epsilon and Small Lambda] versus Small Learn Rate Results available in Figure 4.28.

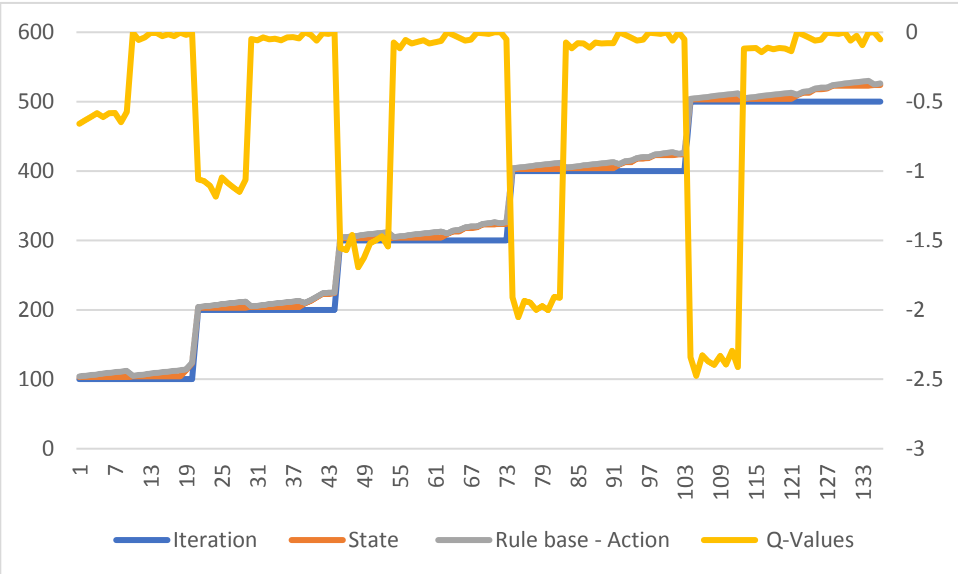


Figure 4.28: Case 1 Packet Loss vs Availability

2. Case 2– Small [Epsilon and Small Lambda] versus Medium Learn Rate Results available in Figure 4.29.

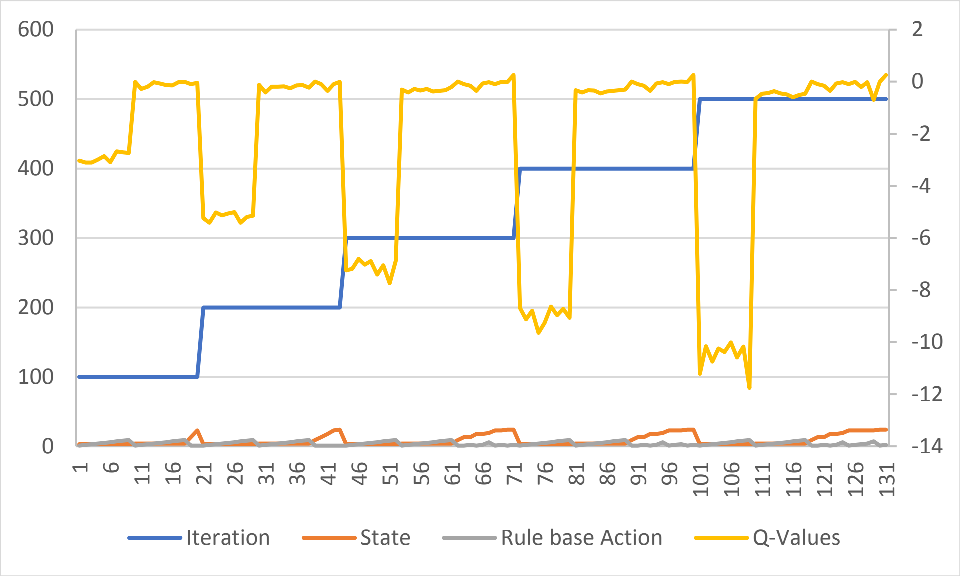


Figure 4.29: Case 2 Packet Loss vs Availability

3. Case 3– Small [Epsilon and Small Lambda] versus Large Learn Rate Results available in Figure 4.30.

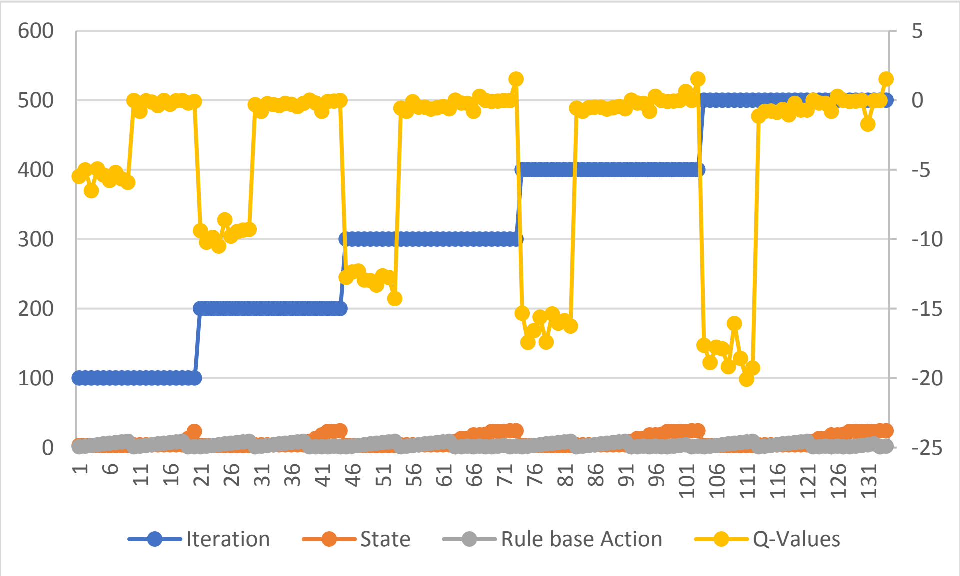


Figure 4.30: Case 3 Packet Loss vs Availability

4. Case 4– Small [Epsilon and Small Lambda] versus Small Learn Rate Results available in Figure 4.31.

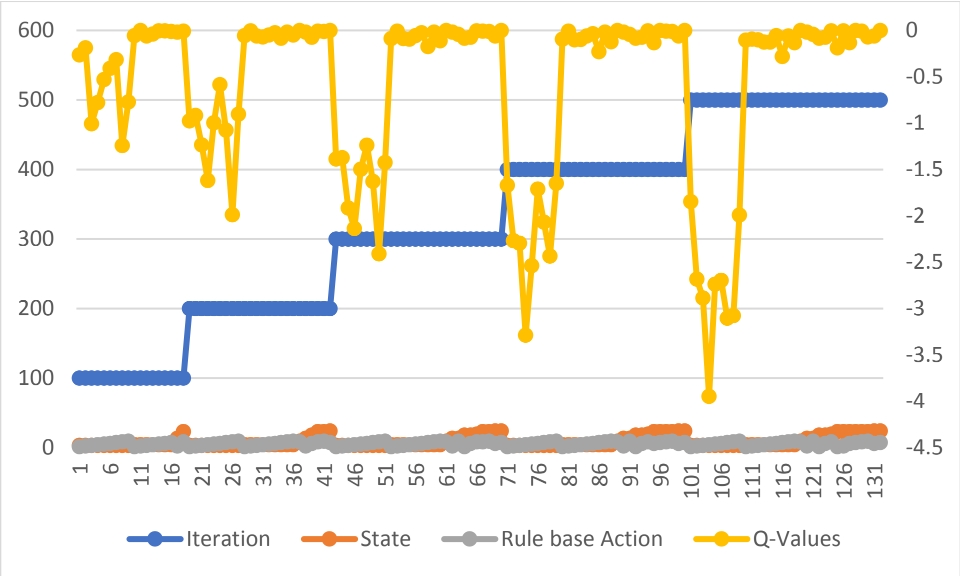


Figure 4.31: Case 4 Packet Loss vs Availability

5. Case 5 – Small [Epsilon and Small Lambda] versus Medium Learn Rate
   Results available in Figure 4.32.

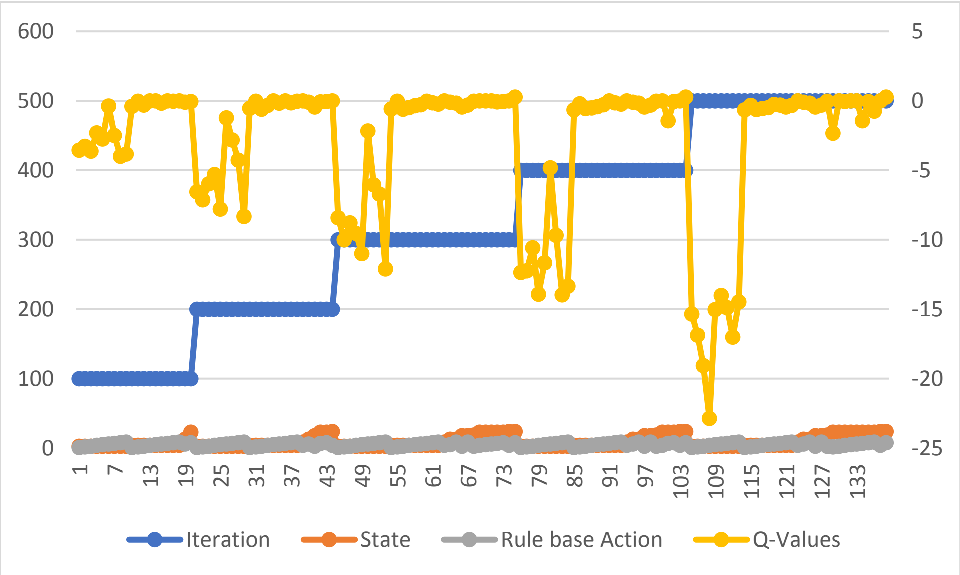


Figure 4.32: Case 5 Packet Loss vs Availability

6. Case 6– Small [Epsilon and Small Lambda] versus Large Learn Rate
   Results available in Figure 4.33.

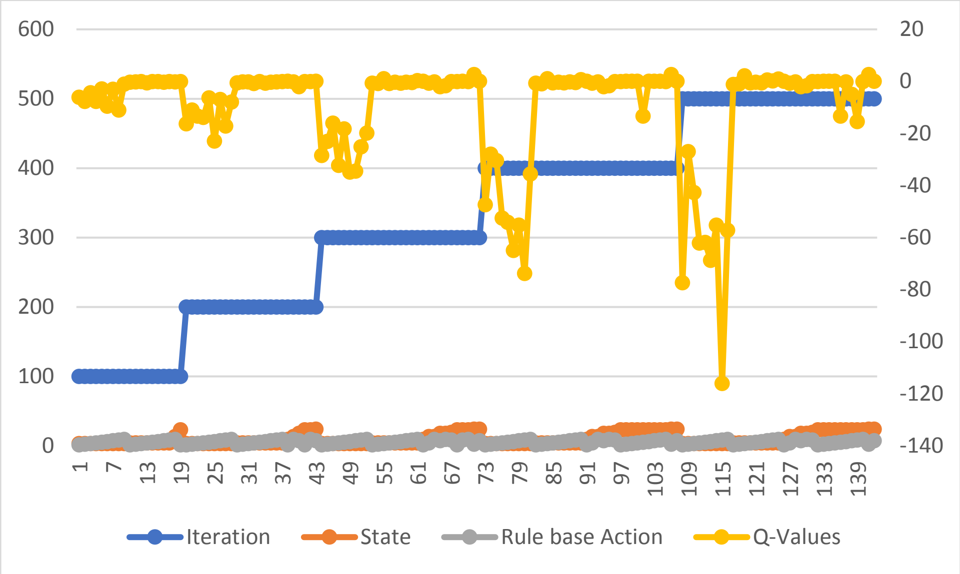


Figure 4.33: Case 6 Packet Loss vs Availability

ii. Latency versus Availability

The overall adaptation for this combination shows that from case 2 up to the end of case 3, the q-values increase with negative rewards and the output started declining from case 4. However, the q-values continue rising from case 5 until case 6. Case 6 demonstrated the highest achievement of q-values as displayed in Figure 4.34.

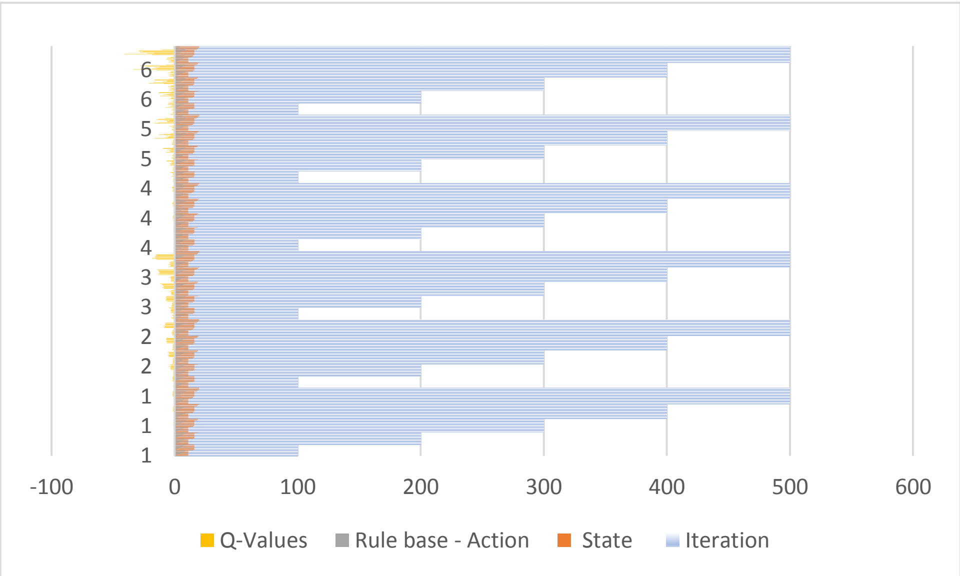


Figure 4.34: Overall adaptation Latency and Availability

1. Case 1 – Small [Epsilon and Small Lambda] versus Small Learn Rate Results available in Figure 4.35.

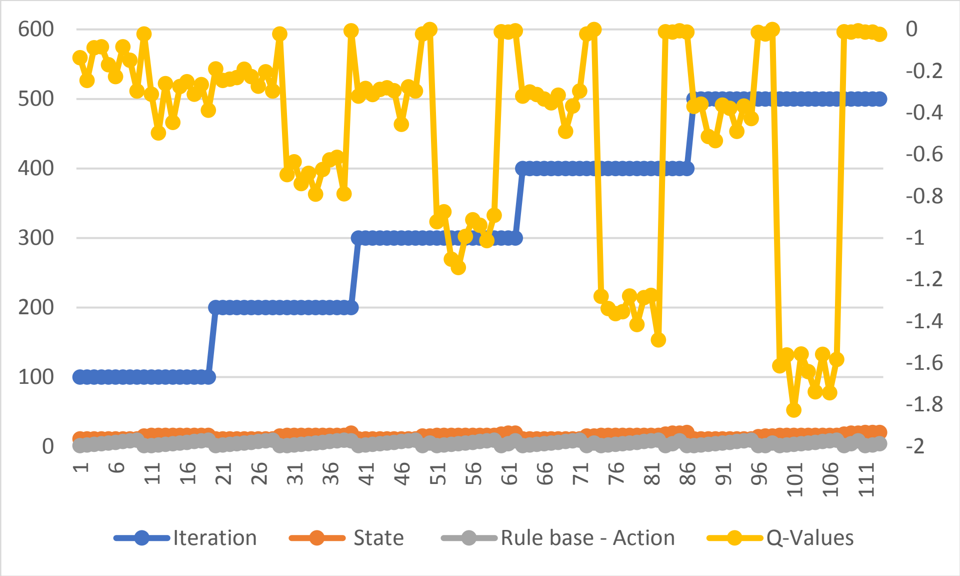


Figure 4.35: Case 1 Latency vs Availability

2. Case 2– Small [Epsilon and Small Lambda] versus Medium Learn Rate Results available in Figure 4.36.

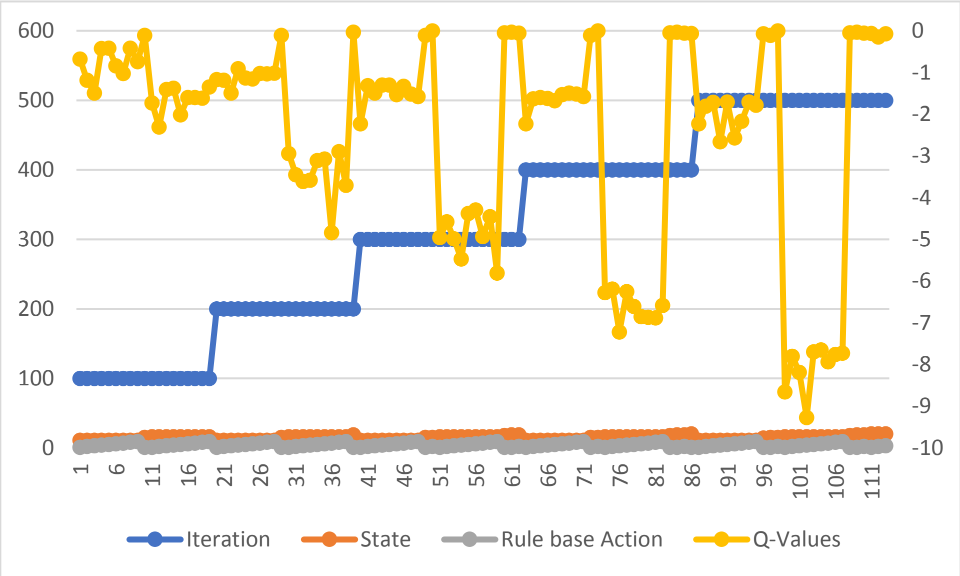


Figure 4.36: Case 2 Latency vs Availability

3. Case 3– Small [Epsilon and Small Lambda] versus Large Learn Rate Results available in Figure 4.37.

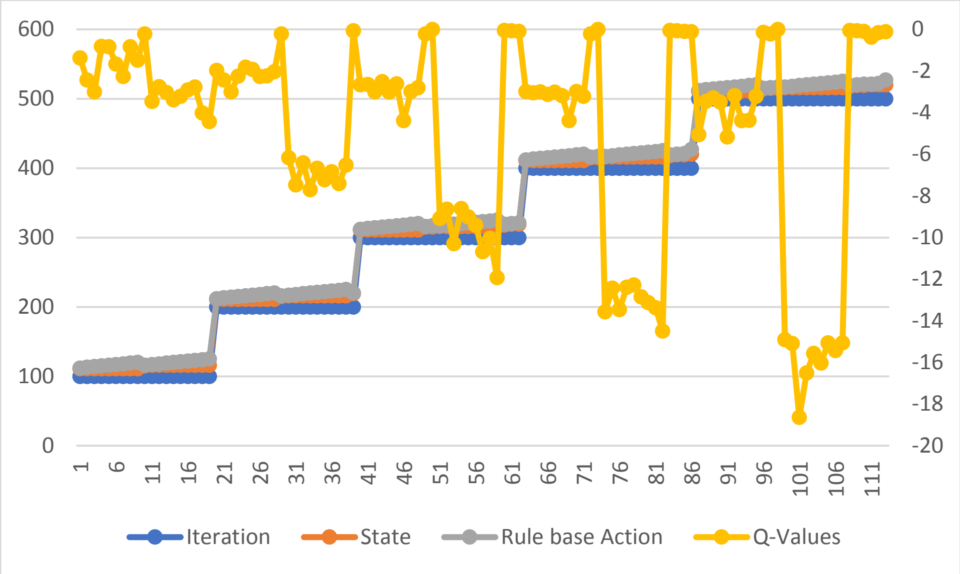


Figure 4.37: Case 3 Latency vs Availability

4. Case 4– Small [Epsilon and Small Lambda] versus Small Learn Rate Results available in Figure 4.38.

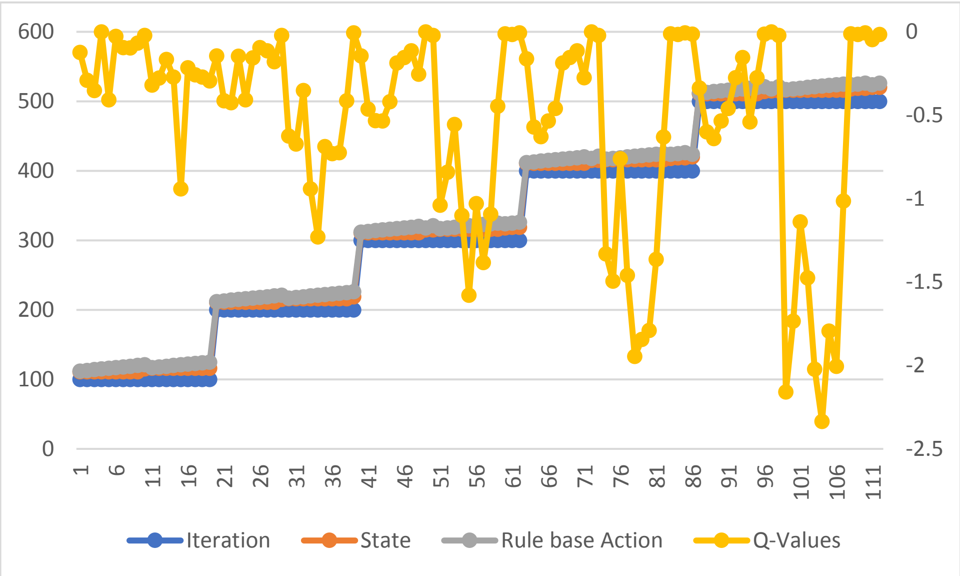


Figure 4.38: Case 4 Latency vs Availability

5. Case 5 – Small [Epsilon and Small Lambda] versus Medium Learn Rate Results available in Figure 4.39.

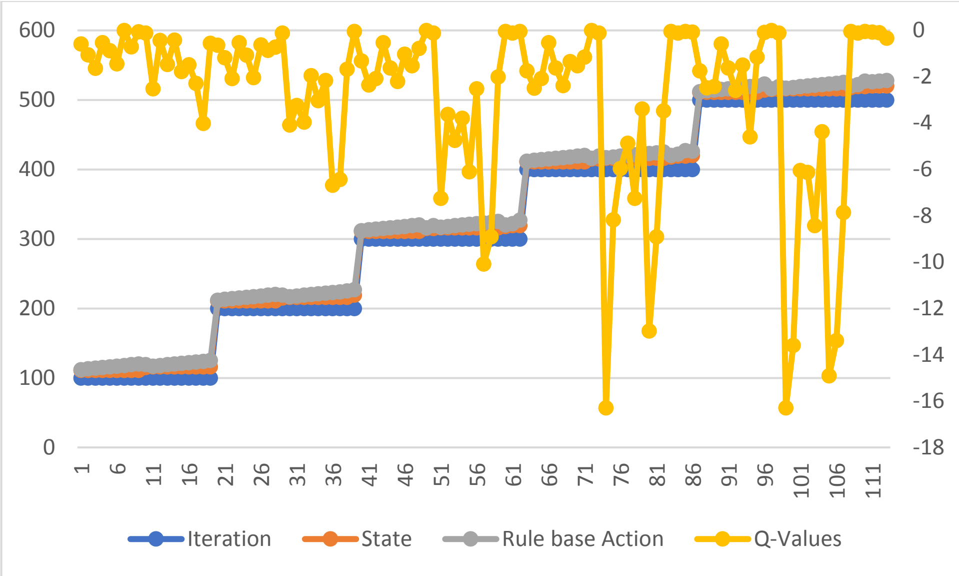


Figure 4.39: Case 5 Latency vs Availability

6. Case 6 – Small [Epsilon and Small Lambda] versus Large Learn Rate

Results available in Figure 4.40.

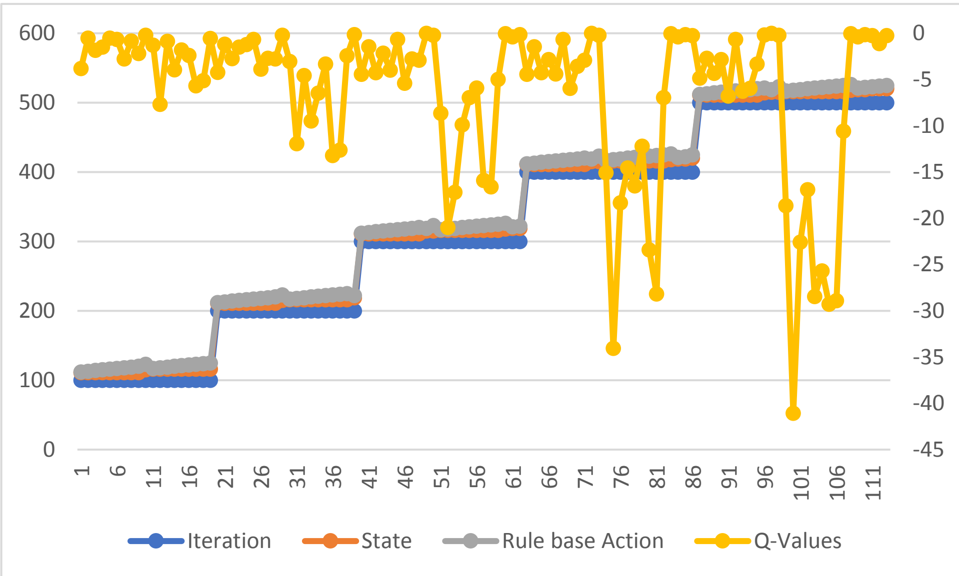


Figure 4.40: Case 6 Latency vs Availability

In this experiment, there are no matched conditions for the other pair of QoS parameters, which is Latency versus Packet Loss. A separate experiment was executed to prove that the Fuzzy Q-Learning algorithm is capable of handling this combination with synthetic data as the input.

4.4 Evaluation

In this section, we have evaluated the final results against the proposed MAPE-K framework to justify the effectiveness of this research study. The output of the two sets of comparison shows the adaptations undergone with the same pattern of the evolution of q-values.

4.4.1 Experimental Analysis

In the analysis, we can focus on the effectiveness of the adaptation by concentrating on the q-learning factors. Epsilon. lambda and learn rate. As for case 1 to case 3 in first and second QoS parameter executions, the Lambda and Epsilon were fixed to Small which is 0.1 and Large at 1.0, whereas the values for Learn Rate were 0.1, 0.5 and 1.0 respectively for Small, Medium and Large. On the other hand, the value for Epsilon and Lambda was increased to 1.0 to represent Large for cases 4, 5 and 6.

The pattern of the learning rate for cases 1 to 3 and 4 to 6 are consistent due to learn rate value having been restarted to match the Epsilon and Lambda comparison, which is Small and Large. As a benchmark for case 1 to 3 for both cases, it shows that the q-value evolution increased for the Large combination of Epsilon and Lambda compared to the Small combination. The same result appears for case 4 to 6 in the Large combination as well.

As for the Latency and Availability analysis, in the first iteration for each case, the states affected were 11,15, and 16 and the q-values increased with negative rewards for the match cases. For the last iteration of 500 in every case for Latency and Availability, the number of states that developed increased to additions of 14, 18,19, and 20. This additional increment has shown that different values of lambda, epsilon and the learn rate does affect the matched states with additional negative rewards.

However, in the second scenario for Latency and Packet Loss, the q-values were zeroes due to input from the data files. The available data is not in line with the setup rule base, therefore there is no available learning rate recorded.

In last scenario, the pattern of the first 100 iterations compared to 500 was identical to Packet Loss and Availability. It starting with state 3,4,13 and 14 for the first 100 iterations, and ended with additional states 9,18,19,23 and 24.

Epsilon in a nutshell is the q-learning factor for exploration or exploitation. The value starts from 0.1 for the lowest exploration and 1.0 for the highest. Lambda is the accumulated reward for each state in q-learning, in order to collect the most possible reward for their actions based on the given policy. In this case, q-learning is the off-policy learner; it learns the optimal policy independently.

With the given explanation, it shows that the q-values able to integrate the optimal policy from the lowest Lambda and Epsilon and started to increase the learning rate and vice versa in the Large comparison.

4.4.2 Discussion

In this experiment, the results really inclined towards the establishment of RQ2 and RQ3, which was to process uncertainties and adaption. MATLAB is a great tool for this research together with the implementation of Fuzzy Q-Learning algorithm.

The proposed enhanced Fuzzy Q-Learning architecture in Figure 4.9 was able to map along with the MAPE-K framework and the Q-Learning model as introduced along with the other architectural components. This is an important contribution to the research, which is integral, to pair the whole framework with the established research [108-110].

The number of fuzzy rules are clearly affected throughout this exercise based on the QoS and Q-Learning parameters. For instance, the overall 125 rules for each 5 times iterations oriented to better adaptation due to Q-Learning parameters.

The further discussion of this result available in the following chapter.

4.5 Summary

The experiment tackled the major issues of uncertainties and adaptation. The major concern is whether the next part of Q-Learning is able to integrate the Fuzzy values into their learning process. The contribution of this experiment was the ability to identify the affected rules, which were fixed from the SLA case study [139-140] and its ability to the optimal policy and update the algorithm.

This approach helps ISP in maintaining their SLA, and monitors their affected rules. It provides qualitative adaptive rules to the enhanced framework in Figure 4.9 and updates the knowledge base for better decision-making.

Chapter 5

Comparison, Discussion and Overall Assessment

In this chapter, the contents have addressed the comparison, discussion and overall assessment of the conducted experiments. Section 5.1 is the motivation of this experiments, whereas Section 5.2 explains the results analysis of the three experiments. The overall discussion is available in Section 5.3 and a comparison with other's research has been done in Chapter 5.4. The limitation and summary have been addressed respectively in Section 5.5 and Section 5.6.

5.1 Experiments Motivation

The entire experiments were based on three core motivations, which are autonomic computing, uncertainties and adaptation to learning abilities. The elaborations for each motivation are as below.

- *Autonomic Computing*
  This is the target environment of this research, whereby the solution is able to acts as an autonomic element. The concept of autonomics exists in the global and local elements. Each of these elements are able to perform self-features such as negotiations, routing and adaptations. Opnet is a proven item of Telco simulation software for forecasting, performance and maintenance. In the first experiment, it was justified that the setup architecture with BGP routing technology was able to connect different geographical subnet locations and exchanged the packets successfully. This is identical to the idea of global and local autonomic elements.

- *Uncertainties*
  In the second experiment, the prime motivation was to apply categories of SLA into IF condition in the rule base approach, which is available within the fuzzy toolbox. This toolbox belongs to MATLAB and the defined rules are able to interact with different combinations of QoS parameters, namely Packet Loss, Latency and Jitter. The results from the experiment were really tailored to the intended objective and it does suggest that the next motivation is the learning rate of each rule.

- *Adaptation*

  In the last experiment, the motivation was to apply the real case studies of SLA and ISP performances. The targeted outcome was to prove that the MAPE-K framework is workable and able to manage learning abilities though a number of iterations. Besides that, the other motivation was to ensure that the learn rates varied from one case to another. This is applicable with the different setup of the Q-Learning factors together with the different combinations of QoS parameters.

5.2 Results Analysis

The early analysis has been discussed in the Chapter 4 and Chapter 5 on the outcomes of the executed experiments. However, the connections of each experiment with a thorough analysis has been discussed separately and, in this section, we present the full analysis and its significance.

5.2.1 First Experiment – Autonomous Routing Protocol

In this experiment, there were two scenarios; one with BGP and another one without BGP. BGP is a routing technique that allows for a neighbours' discoveries, connecting with other BGPs and sharing their resources. The resources include the IP address, the advertisement of their BGP router's IP address and their neighbours IP. The setup was based on ISP architecture and the assumptions of each ISP were located in different regions with dedicated subnets. T3 line was applied as the standard transmission from the ISP and the speed was up to 45 MB per second. The assessment has been categorised into three parameters as below.

I. **Throughput**

   Two logical subnets have been included as per Figure 3.20 and Figure 3.21. Figure 3.20 is the illustration of the BGP architectures and Figure 3.21 is non-BGP. The point to point throughput performance was measured for the outgoing packets rather than incoming packets. The results for non-BGP are as per Figure 3.22 and the direct comparison is available in Figure 3.23 for BGP. From the results, it was demonstrated that non-BGP performance for point to point throughput in early transmissions is efficient compared to BGP. However, after 4 minutes, the BGP performance improved and became more stable compared to non-BGP. It shows that the autonomic computing environment is stable and consistent compared to the non-autonomic approach.

II. **Response Time**

   As for the response time, it measured the upload response time and download response time. The simulation was based on an email server configured using Opnet network simulation software. Within the configuration, there were various servers, one of which was an email server. There were a number of workstations from different regions that were electronically connected. The method applied in this simulation was profiling performance for each workstation based on the email response time. Average response time for email download in Figure 3.26 and Email Uploads in Figure 3.27 were both consistently efficient for the BGP approach. The BGP performance for email downloads was constantly reading 0.0.24 seconds from the start of the 2 minutes simulation until the end. However, for non-BGP, the response time fluctuated from one period to another.

III. Delay

In this assessment, the delay measures are in the following application;

- Email
- Streaming
- Http

As demonstrated in Figure 3.28, although the delays between BGP and non-BGP are slightly equal, the consistencies of BGP are stable from the beginning of the simulation until the end.

5.2.2 Second Experiment – Handling uncertainties using rule base

The focus of this experiment is based on the ISPs and broker architecture. At this stage, the research has been narrowed down to focus on the rule base within ISP, and the existence of the broker is to justify the perimeters of this study. The MAPE-K framework has been introduced and applied conceptually in this experiment. The self-features are a vital approach in autonomic computing.

Figure 3.20 illustrates the renegotiation process within self-adaptive brokerage and fits the assumptions of the research context in the ISP architecture. The connection of MAPE-K framework to the rule base is demonstrated in Figure 3.21 as the goal management layer in the abstract model. A suitable policy within MAPE-K will be iterated to enhance and update according to the current framework.

The Adaptation model layer was introduced with **THREE (3)** adaptation rules to connect with the other conceptual autonomic elements using control data and functional components as per Figure 3.22 and Figure 3.23. In this approach, the autonomic element refers to ISP. The rules are:

I. Suitable Adaptation rule has been learned
II. The environment changed – another approach to the goal
III. Or another rule is applicable

SLA case studies were presented in this experiment. They carried **SIX (6)** QoS performance parameters and **TWO (2)** for the fault repair. The details are available in Table 3.5. In the defined fuzzy rules in Table 3.7, only one rule examined what is the increase bandwidth for different combinations of jitter, Packet Loss and Delay. An example of an ‘If’ statement is below.

IF Jitter is Poor AND Packet Loss is Critical, AND Latency is High, Then Increased Bandwidth is High.

The rule base was applied in the Fuzzy toolbox within MATLAB software with defined Packet Loss, Latency and Jitter membership function. The generated results are based on the static input and simulation. The first comparison was Packet Loss versus Jitter.

The result shows that a state of urgency to increase bandwidth when the fuzzy rules are equal to jitter is poor and that packet loss is critical. On the other hand, the demands for increased bandwidth is less demanding in the event of jitter being high quality and when packet loss is low.

In the second comparison between Latency and Packet Loss, the result was that there was no urgent request for bandwidth increase if latency is low and packet loss is low. The graph available in Figure 3.36 is a match with the rule base defined in Table 3.7, for the continued effects to occur between latency versus packet loss.

The same consistency was applied in the last comparison between Latency versus Jitter. It was a match with the objectives related to using fuzzy logic as the approach to handle uncertainties in the next step in the MAPE-K framework.

5.2.3 Third Experiment – Uncertainties and Adaptation

In the last experiment, it was an extension of second experiment which highlighted uncertainties and the ability of MAPE-K to handle the adaptation together with the self-learning showcase. Fuzzy Q-Learning was the adopted algorithm for this experiment. According to the generated results from the public data files and SLA case studies, the results have been segmented into three QoS combinations. The **THREE (3)** QoS parameters are Packet Loss, Availability and Latency, and these have been further categorised into different sets of Q-Learning factors. The analysis of the results are:

I. **Packet Loss versus Availability**

II. **Latency versus Availability**

The analysis was applied for both Packet Loss versus Availability and Latency versus Packet Loss. The experiments were conducted with SIX (6) cases and the overall adaptation result was that the lowest Learn Rate produced the lowest Q-values. Although the same high learn rate was applied in both case 3 and case 6, the q-values in case 6 grew dramatically due to the higher values of Lambda and Epsilon in case 6. To be exact, the values in case 3 for Epsilon and Lambda were both 0.1, whereas in case 6, both were 1.0. The higher the value from 0.1 towards 1.0 represents the exploration and better reward function in the q-learning algorithm.

III. **Latency versus Packet Loss**

In this exercise, there were no match rules concerning using the public access input files.

The outcome of these three experiments was to prove that the adaptation of self-learning utilising a Fuzzy Q-Learning algorithm is able to address the third research question. It is self-explanation as to how the different q-learning factors react accordingly to the accumulated learning rate, rewards and exploration.

5.3 Overall Discussion

The overall experiments demonstrate the intended results in relation to the defined research questions and expected contributions. The first experiment was able to address the autonomous computing environment and the relationship of the ISP architecture within the simulation. The research progressed to the second experiment to understand the adaptation layer, abstract model, autonomic elements, SLA, QoS and later, adopted a fuzzy rule base into the fuzzy toolbox within MATLAB.

The static data shows that fuzzy rules are able to interact with the uncertainties and this justifies proceeding with the adaptation approach.

With the fuzzy rules approach and when it is applied in real case studies, the combination of QoS has been changed accordingly. In the Fuzzy Q-Learning approach, every combination of rules is the state and the target is the action. These are the two main parameters in the Q-Learning besides reward, exploration and learn rate. The affected rules with the iteration of 500 will reach the convergence and later be updated to the existing framework.

The process is tailored to the MAPE-K framework and the ongoing iteration enhances the available rules.

5.4 Comparison of the research approaches with related work

In this section, there are three major domains in the works that relate to this thesis' approaches, namely:

i. Autonomic Management (Closest comparison – Table 5.1)
ii. SLA (Closest comparison – Table 5.2)
iii. Machine Learning (Closest comparison – Table 5.3)

Table 5.1 displays the closest comparison to the autonomic management elements against this research studies' activities. Only two out of ten applied an ISP architecture and most of the adaptation was done using an autonomic manager in predicting and controlling the actions. The proposed intervention in this framework is unsupervised and it is in line with other major research works in the literature. One of the major contributions of this research is SLA management within ISP, and this is not present in the entirety of the compared research.

Whereas in Table 5.2, the research limitations have been addressed with suggestions for improvements. It is highlighted in the fourth, fifth and sixth columns as to how the improvements can be made. My approach is the combination of the MAPE-K framework, and it is able to adaptively relate to the identified service objective in the SLA. This iterative process produced an adaptive environment, and this is a major contribution in this thesis.

Lastly in Table 5.3, the comparison is between the machine learning approaches. The comparison covers six elements which are adaptive, integration with fuzzy, optimisation, external knowledge, policies and SLA. The closest algorithm is Sarsa and it is identical to the Q-Learning approach. However, Sarsa itself is more on exploitation, and this thesis focused on learning with exploration together with the Q-learning elements such as learning rate, epsilon and lambda. Q-Learning demonstrates safe exploration with fuzzy uncertainty abilities. It is an ideal execution for the adaptation.

Table 5.1. Comparison of Closest Research Reviews – Autonomic Management

Ref	**ISPs Architectures**	**Autonomic Management Properties (Self-Configuration, Self-Optimisation, Self-Healing and Self-Protection)**	**Human Intervention in the framework**
[76]	Using Web Server Environment	Carrying out of an autonomic manager in predicting the next sequence or actions based on previous behaviour. The autonomic manager will choose one or more appropriate actions of anticipation.	Each element will deliver its own associated policies that will help the autonomic manager to decide on the following course of action. Human Intervention = **Unsupervised**
[77]	No	Using autonomic elements called SelfLet. This element is able to communicate from one component to another to work within the complex infrastructure. This model is able to understand the specifying behaviour, abilities and goals of each component. It will direct them to the autonomic manager that is able to understand the entirety of the components.	It works on the Model called SelfLet. Human Intervention = **Unsupervised.**
[78]	No	Autonomic Management approaches to identify the preferred uses of existing policies or learn new policies.	Applying a Reinforcement Learning Model to accommodate the alterations. Human Intervention: **Unsupervised**
[79]	Future Internet Networks, such as wireless	Using a cognition cycle to adapt the adaptive network management. Cognitive network managers are able to interpret the previous events	Using a Cognitive Cycle Process Human Intervention: **Unsupervised.**

	network issues	in the circle and this works for betterment in the hereafter.	
[80]	ISPs (Tiered Infrastructure)	No elements of adaptive management. Using an Autonomous System within the ISP to understand the routing table sizes and churn rates.	Connect ISPs using inter-domain concepts to grow worldwide as a topology. Human Intervention: **Unsupervised**
[81]	Cloud Computing Environment	Using Hierarchical Autonomic (HA) – SLAs. Within this approach, each SLA is expected to have its own control mechanism to increase SLA validity without compromising the response time. Using autonomic features to show the self-management SLA.	Using SLAs attributes to connect one SLA and another. Human Intervention: **Unsupervised**
[82]	Cloud Networking Environments	Using autonomic management features to establish NaaS and IaaS services. The architecture ensures the self-establishment between cloud managers.	Using SLA as the medium between the Cloud Service Provider and Cloud Service User. Human Intervention: **Unsupervised**
[83]	Cloud Networking Environments	A novel policy-based adaptive approach to solve the issues of contract between provider and customer. It will then provide a contract template embedded with the policy to adapt to the changes of service provision and the participant’s requirements.	Using SLA to ensure satisfaction between both parties. Human Intervention: **Unsupervised**
[84]	Cloud Computing Environments	Presented with self-manageable architecture to ensure less violations in the contract of SLA between providers and subscribers. The research was based on the SLA-based service virtualisation that provides an easy process in its execution.	Using SLAs to ensure satisfaction between both sides. Human Intervention: **Semi Supervised**
[32]	Intra Network	The interaction uses events as the skeleton between one autonomic element to another. Events allow one to precisely monitor the status of the execution of the algorithm skeletons.	Using Algorithm skeletons as the feature for self-configuration and self-optimisation. Human Intervention: **Unsupervised**

This Research	To provide a solution for ISPs Architecture.	System will fully utilise the autonomic management features to ensure that it is able to adapt to the changes and available resources. With that approach, SLAs will be the mainstream contract or template that is transparent between the providers and their partners, which will have be back to the subcarriers and subscribers.	To present robust autonomic management with the ability to be semi-supervised from the initial start. The system will further mitigate the process with an unsupervised approach using the MAPE-K framework.

Table 5.2: Comparison of Closest Research Reviews – SLA

	Research Features				
Reference	**Research Problems**	**Contributions**	**What they do not do**	**How Can I Improve**	**My Contributions**
[96]	There is no tool for the ISPs to gain optimal link prices.	a) Introduce a selective exploration rule and a Learning Automata (LA) for stationary and non-stationary environment for ISPs. b) Use a formal method to calculate the inter-domain routing within ISPs with two scenarios. c) Two pricing model available; utility model and cost model.	Full MAPE-K Framework and evaluation of the agreement between ISPs. This is very crucial to identify any metrics which cannot be fulfilled throughout the SLA.	Incorporate the inter-domain services between ISPs and bind them with SLA. A further framework should be exhibited to ensure that the signed SLA will actively monitor the agreed terms and any violations will be subject to the agreement of both parties.	An inter-domain architecture with the presence of MAPE-K framework to ensure the SLA terms actively monitor for any violations.
[101]	To have a renegotiation approach within a cloud-	Using two approaches; a) Bargaining-based negotiation b) Offer generation-based negotiation	The solution is for one cycle not through the	To have a dynamic Service Level Objective (SLO) that	To ensure that the renegotiation will all of the possible

	based system to ensure flexibility and scalability.	Ability to generate multiple offer SLA parameters within one round during negotiation	MAPE-K framework, whereby the SLA Manager will act as the autonomic element to supervise the running agreements.	is adaptive to the agreements during renegotiation. This will then avoid any violation.	inputs from the other providers and that the enhancement of the SLO will be thoroughly monitored.
[102]	To have a renegotiation protocol with multi-round capabilities. It can cater for the network environment such as message lost, delayed, duplicated and reordered.	A clear definition of the protocols have been established. There are three main contributions under protocol specification such as a) Protocol Messages (RenegotiationQuoteRequest, RengotiationQuote , Renegotiation Offer, RenegotiatioOfferAck, RenegotiationAccept, RenegotiationReject, RenegotiationNotPossible) b) Protocol Behaviours i) Customer Behaviour ii) Resource Provider Behaviour c) Handling Inconsistencies	This protocol, although it is a thorough process, does not apply in any of the case studies, especially in the MAPE-K framework.	To evaluate the proposed protocol with the MAPE-K framework. This exercise can prove the consistency of the framework with the running of the research activities.	The MAPE-K framework will have a thorough renegotiation protocol to ensure the stability of the entire process.

Table 5.3. Comparison of Closest Research Reviews – Machine Learning

	Q-Learning	Sarsa	Deep Learning	Neural Network	My Contributions
Adaptive	Yes [115] [114] [127]	Yes [127]	Yes	Yes [112]	Yes
Integration with Fuzzy	Yes [123] [110] [128][107]	Yes [129]	Not Available	Not Available	Yes
Optimisation	Yes [124] [125] [126] [127]	Yes [124] [125] [126] [127]	Yes	Yes	Yes
External Knowledge (connect with admission control)	Yes	Yes	Not Available	Not Available	Yes
Policies (Feedback, Rewards, Penalties, QoS)	Yes [off policy] [111] [113] [15]	Yes [on policy] [111] [15]	Not Specific	Not Specific	Yes
SLA	Yes	Yes	Not Available	Yes [112]	Yes
Fuzzy	Yes [108]	Yes [109]	Not Specific	Not Specific	Yes

5.5 Limitations

In this research, there are five identified limitations that can be future work done by other researchers in the computer network domain or any generic application of research using the MAPE-K framework and Machine Learning. The lists and explanations are below.

i) *Implementation of global and local autonomic elements to synchronise the resources.*
In this research, adaptation really focuses on the local autonomic element which is available in the ISP architecture. The element itself is connected with admission control and the SLA manager. The extension to the global elements can really benefit the entire ISP architecture and allow it to be able to perform complex processes among them.

ii) *Renegotiation protocol between brokers in the ISP*
There is no renegotiation that took place in this research. This idea has been examined in the early research stages within the different case studies. However, the objective is to apply the adaptation to a single ISP architecture, and renegotiation is among the next elements to be analysed in future research.

iii) *Subscriber profiling to plan for costing and resource management*
In this research, the process is based on the iteration and it relies on the MAPE-K framework. However, ISP is unable to identify the

specific subscribers during the executions. With the profiling feature, it will be a great extension to this research to identify the subscriber pattern and for the ISP to be able to forecast subscription activity.

iv) *To integrate with levels of ISPs*
In the various levels of ISP tiers, the integration amongst them is very important for ongoing business. By having this in future research, the entire ISP architecture will really have benefited from this approach. The feedback system will be automated as well as the escalated system. Important decisions can be made instantly and help them to prevent any unwanted situations. This will also produce a great subscriber profiling database.

v) *Integration with other machine learning algorithms*
In this thesis, the execution is based on Q-Learning and it mainly covers the exploration features within the mentioned QoS and Q-Learning elements. It will be a more robust and dynamic comparison if the research can be extended to other machine learning algorithms, either in the same domain of Reinforcement Learning or extended to supervised and unsupervised learning. The results will be able to cross-examine the chosen algorithm with another such as Sarsa, Bayesian, N-Gram, Dynamic Programming, Deep Learning and etc.

5.6 Summary

The overall of this chapter has highlighted the research comparison with another prominent research in different domains, and later discussed how this research is different and what the contributions are that have been made by this research. Prior to that is the discussion on the results and lastly, the limitations of the research. Some of the items discussed in the limitations have been examined in the early research stages and excluded due to on-going research refinement. The items will be further explained in the next chapter as a suggestion for future work.

Chapter 6

Conclusion and Future Work

In the last chapter, the author has addressed two major concerns which are the conclusion and future work to do with this research. Section 6.1 explains about the research summary followed by Section 6.2 on the research contributions. The final section is 6.3 on the future work direction of this research. Lastly, the summary is available in Section 6.4.

6.1 Research Summary

In this thesis, there are three major domains which are interconnected and have been carefully discussed either in the objectives, methodologies, results analysis and lastly, in the evaluation. The three domains are SLA, Adaptive framework and Machine Learning.

The combinations present within the objectives adaptively handle the SLA management within ISP. It is a common issue in the ISPs to have overwhelming service requests by the subscribers. It is important for them to learn how to manage the resources efficiently to get along with daily business.

This research holds that the adaptive features, such as self-management, react in the iteration process and suggest appropriate actions for the running policies. This is known as fuzzy rules, based on the selected case studies. The results overcome the conventional feedback on admission control and automate monitoring and penalties on the affected policies. The output of this is the adaptation manager that acts as autonomic element to works autonomously within ISPs to ensure their resources are actively monitors, analyse, plan and perform necessary executions based on the running knowledge base.

The implementation of MAPE -K and Fuzzy Q-Learning in the mathematical simulation software provides a steady result to do with the uncertainties and learning ability. Each of the SLA combinations have been converted into State in the Q-Learning algorithm with the proper rewards and actions mechanism. The iteration process within the MAPE-K framework proved that the affected rules updated accordingly, and the factors depend on a combination of QoS parameters and Q-Learning metrics.

Three research questions were carefully crafted and addressed in this thesis to identify the research contributions and the significance of the results to the body of knowledge. Each of research questions falls under a different contribution category such as architecture, framework and analysis. On the last note of this research summary, we addressed the limitations of this research in **Section 5.5** and has put forward further recommendations to other researcher to consider tabulated items as their next research agenda.

6.2 Research Contributions

There are three major contributions of this thesis summarised in the following list:

1. **Introduce an adaptive architecture and adaptation manager for monitoring and responding to SLA terms within the ISP identify the current resources and limitations.**
   The proposed enhanced architecture able to provide feedback system during the iterations. It reacts on the given SLA and updated the affected rules accordingly. The adaptation and learning abilities of defined policies demonstrated accordingly with the combination of QoS and Fuzzy Q-Learning parameters.
   This autonomic element can either placed as local or global depending on the requirements. In this research, there are other connected elements such as Admission Control, SLA Manager and Broker to automate the ISPs architectures. The solution helps admission control to update the status to SLA Manager either accept or reject on any SLAs offered. The correct justification benefits the entire ISP architecture to prevent any unwanted situations such as penalties, poor performance and in excess of utilization on the resources.

2. **Implement the MAPE-K framework with fuzzy Q-learning to handle the adaptation and learning abilities.**
   The MAPE-K framework itself designed to support adaptation with the correct implementation. In this research the algorithm Fuzzy Q-Learning applied, and the result demonstrated accordingly to the planned objectives. The combined algorithms able to demonstrates uncertainties and learning abilities to the whole adaptation designs. These three elements, MAPE-K, Fuzzy and Q-Learning reacts positively on given requirements such as SLA and it provides effective feedback system to the architecture.

6.3 Future Work Directions

This final section is focused on the improvements and suggestions to do with this research limitations, which have been highlighted in the previous chapter. There are three main objectives on future work directions and the explanations are below.

i) *Application of Fuzzy Sarsa*
Sarsa is another popular method in Reinforcement Learning besides the selected Q-Learning in this thesis. In contrast, it is on

policy method compared to off policy in Q-Learning. It learns the Q-Values based on the action performed by the current policy, rather than greedy policy. The major difference is that Sarsa applies the exploration in the actions from one state to another.

ii) *Application with another Machine Learning Division such as Supervised, Unsupervised methods and Neural Networks.*
This thesis focused on Reinforcement Learning due to the nature of the research such as case studies, SLA, ISP architecture and the scale of the data. The extension of this research into other machine learning divisions will certainly produce different results and provide complex analysis. It could eventually merge different algorithms from different machine learning divisions into prominent research activities and results.

iii) *To perform negotiation features for each adaptation manager in the ISP*
Since the adaptation manager is one of the autonomic elements in the ISP architecture, the unit itself is able to perform negotiations among the elements. The results of this negotiations provide better autonomic environment to the ISP architecture and reduce the workload that is currently present at admission control and in the SLA manager.

iv) *To automate multiple SLA scenarios within the ISP*
This future work suggestion is to enable ISP deals with multiple SLA scenarios in the MAPE-K framework. The continuous adaptation to the incoming SLAs will eventually help ISP manage unwanted situations such as penalties and growing QoS parameters in the SLAs.

v) *To provide instant feedback features to the ISP*
The MAPE-K framework is able to execute a quality feedback system and this can be done instantly with the proper programming methods. This feedback is able to resolve a lot of growing issues in ISP in its daily executions. It really helps them in preventive exercise and deals in organised approaches.

6.4 Summary

This chapter addresses the thesis research summary, contributions and lastly the future work directions. The future work directions are very much connected with the research limitations and how they can be addressed for improvements in the near future by other interested researchers.

List of References

1. Social, W. A. (2014). Global digital statistics 2014. *Retrieved April*, *8*, 2014.
2. [Online]. Available : http://www.internet.org/
3. F. W. K. - and T. J. -, “A Survey on QoS in Next Generation Networks,” *Int. J. Adv. Inf. Sci. Serv. Sci.*, vol. 2, no. 4, pp. 91–102, Dec. 2010.
4. K. Kritikos, M. Carro, B. Pernici, P. Plebani, C. Cappiello, M. Comuzzi, S. Benrernou, I. Brandic, A. Kertész, and M. Parkin, “A survey on service quality description,” *ACM Comput. Surv.*, vol. 46, no. 1, pp. 1–58, Oct. 2013.
5. Ezhilchelvan, P. D., & Shrivastava, S. K. (2004). A model and a design approach to building QoS adaptive systems. In *Architecting Dependable Systems II* (pp. 215-238). Springer, Berlin, Heidelberg.
6. Sarmadi, S., Li, M., & Chellappan, S. (2017, November). On the feasibility of profiling internet users based on volume and time of usage. In *2017 IEEE 9th Latin-American Conference on Communications (LATINCOM)* (pp. 1-6). IEEE.
7. Anala, M. R., & Shobha, G. (2012). Application of Autonomic Computing Principles in Virtualized Environment. In *First International Conference on Information Technology Convergence and Services (ITCS 2012)* (p. 203208).
8. Ahuja, K., & Dangey, H. (2014, February). Autonomic Computing: An emerging perspective and issues. In *2014 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)* (pp. 471-475). IEEE.
9. Farokhi, S. (2014, May). Towards an sla-based service allocation in multi-cloud environments. In *2014 14th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing* (pp. 591-594). IEEE.
10. Groleat, T., & Pouyllau, H. (2012). Distributed learning algorithms for inter-nsp sla negotiation management. *IEEE Transactions on Network and Service Management*, *9*(4), 433-445.
11. Xia, Y., Zhou, M., Luo, X., & Zhu, Q. (2013, August). A comprehensive QoS determination model for Infrastructure-as-a-Service clouds. In *2013 IEEE International Conference on Automation Science and Engineering (CASE)* (pp. 122-127). IEEE.
12. Dai, W., & Jordan, S. (2013, September). Modeling ISP tier design. In *Proceedings of the 2013 25th International Teletraffic Congress (ITC)* (pp. 1-9). IEEE.
13. Dai, W., & Jordan, S. (2013, December). Design and impact of data caps. In *2013 IEEE Global Communications Conference (GLOBECOM)* (pp. 1650-1656). IEEE.
14. Lee, S. C., & Lui, J. C. (2008). On the interaction and competition among Internet service providers. *IEEE Journal on Selected Areas in Communications*, *26*(7), 1277-1283.
15. H. Alshaer, T. Ernst, and a. de La Fortelle, “A QoS architecture for provisioning high quality in intelligent transportation services,” *2012 IEEE Netw. Oper. Manag. Symp.*, pp. 595–598, Apr. 2012.
16. Barenco, C. J., Saloña, A. A., & Moreno, J. I. (2000). An architecture of QoS services for a Core Internet Network over DTM. In *1st European Conference on Universal Multiservice Networks. ECUMN'2000 (Cat. No. 00EX423)* (pp. 351-359). IEEE.

17. Eze, T., Anthony, R., Walshaw, C., & Soper, A. (2012, March). Autonomic computing in the first decade: trends and direction. In *Proceedings of the Eighth International Conference on Autonomic and Autonomous Systems (ICAS)* (p. 16).
18. Femminella, M., Francescangeli, R., Reali, G., Lee, J. W., & Schulzrinne, H. (2011). An enabling platform for autonomic management of the future internet. *IEEE Network*, *25*(6), 24-32.
19. R. M. Bahati and M. a. Bauer, "Towards adaptive policy-based management," *2010 IEEE Netw. Oper. Manag. Symp. - NOMS 2010*, pp. 511–518, 2010.
20. R. M. Bahati and M. a. Bauer, "Adapting to Run-Time Changes in Policies Driving Autonomic Management," *Fourth Int. Conf. Auton. Auton. Syst.*, pp. 88–93, Mar. 2008.
21. a. Ouda, H. Lutfiyya, and M. Bauer, "Towards Automating the Adaptation of Management Systems to Changes in Policies," *2006 IEEE/IFIP Netw. Oper. Manag. Symp. NOMS 2006*, pp. 1–4, 2006.
22. Computing, A. (2006). An architectural blueprint for autonomic computing. *IBM White Paper*, *31*(2006), 1-6.
23. Badis Tebbani and Issam Aib , *" GXLA a Language for the Specification of Service Level Agreements ", IFIP International Federation for Information Processing 2006*, LCNS 4195, pp. 201-214 , 2006.
24. K. Angelopoulos, V. E. Silva Souza, and J. Pimentel, "Requirements and architectural approaches to adaptive software systems: A comparative study," *2013 8th Int. Symp. Softw. Eng. Adapt. Self-Managing Syst.*, pp. 23–32, May 2013.
25. S. Chauhan, A. Sharma, and P. S. Grover, "Developing self managing software systems using agile modeling," *ACM SIGSOFT Softw. Eng. Notes*, vol. 38, no. 6, pp. 1–3, Nov. 2013.
26. Šerbedžija, N., Bureš, T., & Keznikl, J. (2013, September). Engineering autonomous systems. In *Proceedings of the 17th Panhellenic Conference on Informatics* (pp. 128-135). ACM.
27. Perez-Palacin, D., Mirandola, R., & Merseguer, J. (2011, June). Software architecture adaptability metrics for QoS-based self-adaptation. In *Proceedings of the joint ACM SIGSOFT conference--QoSA and ACM SIGSOFT symposium--ISARCS on Quality of software architectures--QoSA and architecting critical systems--ISARCS* (pp. 171-176). ACM.
28. W. Yang, C. Xu, Y. Liu, C. Cao, X. Ma, and J. Lu, "Verifying self-adaptive applications suffering uncertainty," *Proc. 29th ACM/IEEE Int. Conf. Autom. Softw. Eng. - ASE '14*, pp. 199–210, 2014.
29. A. Agne, M. Happe, A. L. Osch, and C. Plessl, "Self-Awareness as a Model for Designing and Operating Heterogeneous Multicores," vol. 7, no. 2, 2014.
30. K. Ahuja and H. Dangey, "Autonomic Computing: An emerging perspective and issues," *2014 Int. Conf. Issues Challenges Intell. Comput. Tech.*, pp. 471–475, Feb. 2014.
31. Pabón, G., & Henrio, L. (2014, February). Self-Configuration and Self-Optimization Autonomic Skeletons using Events. In *Proceedings of Programming Models and Applications on Multicores and Manycores* (p. 21). ACM.

32. Gittens, M., Lutfiyya, H., & Bauer, M. (2004, November). An extended operational profile model. In *15th International Symposium on Software Reliability Engineering* (pp. 314-325). IEEE..
33. Philippe, L., McCann, J. A., & Diaconescu, A. (2013). Autonomic Computing–Principles Design and Implementation. In *Undergraduate Topics in Computer Science Series*. Springer.
34. Courcoubetis, C., Dramitinos, M., & Stamoulis, G. D. (2012, July). Internet interconnection assured quality services: Issues and strategic impact. In *2012 Future Network & Mobile Summit (FutureNetw)* (pp. 1-9). IEEE.
35. Ezhilchelvan, P. D., & Shrivastava, S. K. (2004). A model and a design approach to building QoS adaptive systems. In *Architecting Dependable Systems II* (pp. 215-238). Springer, Berlin, Heidelberg.
36. Krutz, R. L., & Vines, R. D. (2010). *Cloud security: A comprehensive guide to secure cloud computing*. Wiley Publishing.
37. M. J. Katchabaw, H. L. Lutfiyya, and M. a. Bauer, "Usage based service differentiation for end-to-end quality of service management," *Conf. Proc. 2003 IEEE Int.*, pp. 513–520, 2003.
38. Patel.Z.M, Dalal,U.D, " Performance Evaluation and Comparison of Queue Scheduling schemes for WiMAX under heterogeneous traffic", Circuits, Controls and Communications (CCUBE), 2013 International conference on , pp.1-5, IEEE, December 2013.
39. K. Kritikos, M. Carro, B. Pernici, P. Plebani, C. Cappiello, M. Comuzzi, S. Benrernou, I. Brandic, A. Kertész, and M. Parkin, "A survey on service quality description," *ACM Comput. Surv.*, vol. 46, no. 1, pp. 1–58, Oct. 2013.
40. Campbell, A., Aurrecoechea, C., & Hauw, L. (1996). A review of QoS architectures. *ACM Multimedia Systems Journal*, *6*, 138-151.
41. H. Alshaer, T. Ernst, and a. de La Fortelle, "A QoS architecture for provisioning high quality in intelligent transportation services," *2012 IEEE Netw. Oper. Manag. Symp.*, pp. 595–598, Apr. 2012.
42. D. Ardagna, G. Casale, M. Ciavotta, J. F. Pérez, and W. Wang, "Quality-of-service in cloud computing: modeling techniques and their applications," *J. Internet Serv. Appl.*, vol. 5, no. 1, p. 11, 2014.
43. C. Aurrecoechea, A. T. Campbell, and L. Hauw, "A survey of QoS architectures," *Multimed. Syst.*, vol. 6, no. 3, pp. 138–151, May 1998.
44. Bahati, R. M., & Bauer, M. A. (2004, April). Quality of service provisioning for VoIP applications with policy-enabled differentiated services. In *2004 IEEE/IFIP Network Operations and Management Symposium (IEEE Cat. No. 04CH37507)* (Vol. 1, pp. 335-348). IEEE.
45. Barenco, C. J., Saloña, A. A., & Moreno, J. I. (2000). An architecture of QoS services for a Core Internet Network over DTM. In *1st European Conference on Universal Multiservice Networks. ECUMN'2000 (Cat. No. 00EX423)* (pp. 351-359). IEEE.
46. Bezruk, V. M., & Bukhanko, A. N. (2013, September). Required quality of service provision based on the resilient telecommunication topologies. In *2013 23rd International Crimean Conference" Microwave & Telecommunication Technology"* (pp. 422-423). IEEE.
47. Chalmers, D., & Sloman, M. (1999). A survey of quality of service in mobile computing environments. *IEEE Communications surveys*, *2*(2), 2-10.
48. de Sousa Chaves, F., Abbas-Turki, M., Abou-Kandil, H., & Romano, J. M. T. (2013). Transmission power control for opportunistic QoS provision in

wireless networks. *IEEE Transactions on Control Systems Technology*, *21*(2), 315-331.

49. Krile, S., & Perakovic, D. (2006, June). Bandwidth optimization in SLA negotiation process. In *Joint IST Workshop on Mobile Future, 2006 and the Symposium on Trends in Communications. SympoTIC'06.* (pp. 36-39). IEEE.
50. Kim, B., Chae, H., Han, T., & Jeong, Y. (2004, February). Bandwidth broker signaling for service level negotiation over heterogeneous ipv4/ipv6 diffserv networks. In *The 6th International Conference on Advanced Communication Technology, 2004.* (Vol. 2, pp. 1097-1102). IEEE.
51. Hamze, M., Mbarek, N., & Togni, O. (2014, February). Autonomic brokerage service for an end-to-end cloud networking service level agreement. In *2014 IEEE 3rd Symposium on Network Cloud Computing and Applications (ncca 2014)* (pp. 54-61). IEEE.
52. Simao, J., & Veiga, L. (2013, December). Flexible slas in the cloud with a partial utility-driven scheduling architecture. In *2013 IEEE 5th International Conference on Cloud Computing Technology and Science* (Vol. 1, pp. 274-281). IEEE.
53. Rodier, L., Auger, D., Cohen, J., & Pouyllau, H. (2013, October). SLA learning from past failures, a Multi-Armed Bandit approach. In *Proceedings of the 9th International Conference on Network and Service Management (CNSM 2013)* (pp. 277-283). IEEE.
54. Liu, D., Kanabar, U., & Lung, C. H. (2013, May). A light weight SLA management infrastructure for cloud computing. In *2013 26th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)* (pp. 1-4). IEEE.
55. Famaey, J., Latré, S., Wauters, T., & De Turck, F. (2012, April). An SLA-driven framework for dynamic multimedia content delivery federations. In *2012 IEEE Network Operations and Management Symposium* (pp. 1241-1247). IEEE.
56. El-Atawy, A., & Samak, T. (2012, April). End-to-end verification of QoS policies. In *2012 IEEE Network Operations and Management Symposium* (pp. 426-434). IEEE.
57. [Online] . Available : https://learningnetwork.cisco.com/servlet/JiveServlet/downloadImage/102-15624-2-116729/310-238/OSI.png
58. [Online]. Availabe : http://www.perpettersson.me/sweden-and-the-internet-2012/
59. [Online]. Available : http://ids.nic.in/jces%20tnl%20oct%202008/Q%20of%20S/Bandwidth%20Broker.JPG
60. Sahadeva, K., Kumar, S., & Sharma, A. (2012). A new SDLC framework with autonomic computing elements. *International Journal of Computer Applications*, *54*(3).
61. Li, X. J., Zhou, B., & Dong, J. X. (2005, July). Self-learning histograms for changing workloads. In *9th International Database Engineering & Application Symposium (IDEAS'05)* (pp. 229-234). IEEE.
62. Abu Bashar, Geradd Parr, Sally MCClean , Bryan Scotney and Detlelf Nuck , *“ Application of Bayesian Network for Autonomic Network*

Management", Journals of Networks and Systems Management , Vol 22, Issues 2, pp. 174-207, April 2014.

63. Manish Parashar, Salim Hariri, "Autonomic Computing: Concepts , Infrastructures and Applications ", CRC Press, 568 Pages , 15 December 2006.
64. Sankar.S.G,Kumar.A, " Analysis and Simulation of Queuing Models for reservation based bandwidth access with large propagation delays ",Personal Wireless Communication, 1999 IEEE International Conference on , pp 140-144, 1999.
65. Patel.Z.M, Dalal,U.D, " Performance Evaluation and Comparison of Queue Scheduling schemes for WiMAX under heterogeneous traffic", Circuits, Controls and Communications (CCUBE), 2013 International conference on , pp.1-5, IEEE, December 2013.
66. Michael D. Schroeder , Andrew D. Birrell, Michael Burrows, Hal Murray and Roger M. Needham *," Autonet : A High Speed, Self-Configuring Local Area Network Using Point to Point Links " , IEEE Journal On Selected Areas In Communication* , vol 9 , no. 8, pp. 1318-1335, October 1991.
67. J.M. Garcia and J. Duato , *"An Algorithm for Dynamic Reconfiguration of a Multicomputer Network "*, In *Proceeding of the Third IEEE Symposiums on Parallel and Distributed Processing 1991*, December 1991, pp. 848 – 855.
68. Brendan Jennings , Sven van der Meer , Sasitharan Balasubramaniam, Dmitri Botvich, Michael O Foghlu and William Donnelly *," Towards Autonomic Management of Communications Networks ", IEEE Communications Magazine* , Vol. 45 , No. 10, pp. 112-121, October 2007.
69. Xuan Liu, Parikshit Juluri and Deep Medhi *," An Experimental Study on Dynamic Network Reconfiguration in A Virtualized Network Environment Using Autonomic Management", IEEE/ IFIP International Symposium on Integrated Network Management (ICM2013): Mini-Conference* , pp. 616-622, 2013.
70. Ramkumar Cherukuri , Xuan Liu , Andy Bavier, James P.G. Sterbenz and Deep Medhi , *" Network Virtualization in GpENI: Framework , Implementation and Integration Experience ", Proceedings of 3rd IEEE/IFIP International Workshop on Management of the Future Internet (ManFI)* , Dublin , Ireland , May 27 ,2011.
71. James P.G. Sterbenz, Deep Medhi , Byrav Ramamurthy, Caterina Scoglio, David Hutchison, Bernhard Plattner , Tricha Anjali, Andrew Scoot, Cort Buffington, Gregory E. Monaco, Don Gruenbacher, Rick McMullen, Justin P. Rohrer, John Sherrell, Pragatheeswaran Angu, Ramkumar Cherukuri , Haiyang Qian and Nidhi Tare *," The Great Plains Environment for Network Innovation (GpENI): A programmable Testbed for Future Internet Research ",* In *Proceeding of 6th International Conference on Testbeds and Research Infrastructure for the Development of Networks & Communities (Trident Com)* Berlin, Germany , May 2010, pp. 428-441.
72. Thomas Gamer, Marcus Scholler and Roland Bless , *" An Extensible System for Network Anomaly Detection", IFIP International Federation for Information Processing 2006*, LCNS 4195, pp. 97-108, 2006.
73. J. Elias , F. Martignon and A. Capone , *" An Efficient Dynamic Bandwidth Allocation Algorithm for Quality of Service Network*", IFIP International*

Federations for Information Processing 2006, LCNS 4195 , pp. 132-145, 2006.

74. Juan J. Alcaraz, Mario Lopez Martinez, Javier Vales Alonso and Joan Garcia Haro *," Bandwidth Reservation as a Coexistence Strategy in Oppurtinistic Spectrum Access Environments ", IEEE Journal On Selected Areas in Communications* , Vol. 32, No. 3, March 2014.
75. R. M. Bahati, M. a. Bauer, and E. M. Vieira, "Adaptation Strategies in Policy-Driven Autonomic Management," *Third Int. Conf. Auton. Auton. Syst.*, pp. 16–16, Jun. 2007.
76. Devescovi, D., Di Nitto, E., & Mirandola, R. (2007, November). An infrastructure for autonomic system development: the selflet approach. In *Proceedings of the twenty-second IEEE/ACM international conference on Automated software engineering* (pp. 449-452). ACM.
77. R. M. Bahati and M. a. Bauer, "An Adaptive Reinforcement Learning Approach to Policy-Driven Autonomic Management," *2009 Fifth Int. Conf. Auton. Auton. Syst.*, pp. 135–141, 2009.
78. A. Kousaridas, G. Nguengang, J. Boite, and V. Conan, "An experimental path towards Self- Management for Future Internet Environments," pp. 95–104, 2010.
79. Nozaki, Y., Tuncer, H., & Shenoy, N. (2012, June). ISP tiered model based architecture for routing scalability. In *2012 IEEE International Conference on Communications (ICC)* (pp. 5817-5821). IEEE.
80. M. Sarfraz, M. Z. Hussain, and M. Ishaq, "HA-SLA: A Hierarchical Autonomic SLA Model for SLA Monitoring in Cloud Computing," *J. Softw. Eng. Appl.*, vol. 06, no. 03, pp. 114–117, 2013.
81. M. Hamze, N. Mbarek, and O. Togni, "Self-establishing a Service Level Agreement within autonomic cloud networking environment," *2014 IEEE Netw. Oper. Manag. Symp.*, pp. 1–4, May 2014.
82. Z. Zhang, L. Liao, H. Liu, and G. Li, "Policy-based adaptive service level agreement management for cloud services," *2014 IEEE 5th Int. Conf. Softw. Eng. Serv. Sci.*, pp. 496–499, Jun. 2014.
83. a. Kertesz, G. Kecskemeti, and I. Brandic, "An interoperable and self-adaptive approach for SLA-based service virtualization in heterogeneous Cloud environments," *Futur. Gener. Comput. Syst.*, vol. 32, pp. 54–68, Mar. 2014.
84. [Online] . Available : http://www.everest-ist.upc.es/Imagenes/TechnicalApproach2.gif
85. [Online] . Available : http://cdn.ttgtmedia.com/digitalguide/images/Misc/ts_bgp_1.gif
86. [Available] . Online : http://blog.octo.com/wp-content/uploads/2012/01/publish_tasks.png
87. [Available] . Online : https://www.uni-marburg.de/fb12/verteilte_systeme/forschung/pastproj/crossware/odin-3.png
88. [Available]. Online : http://www.cisco.com/en/US/technologies/tk648/tk362/tk920/images/0900aecd8023ca9e_null_null_null_09_27_04-4.jpg
89. [Available]. Online : http://sisinflab.poliba.it/swottools/mobile-user-profiler/jquery-lightbox-0.5/photos/architecture.png
90. [Available] . Online : http://imtech.com/Content/ImtechICT%20UK/Logos/Allotbandwidth.gif

91. Mehdi Bahrami, Payam Noor, Peyman Arebi, *" A Binomial Heap for Self-Recognition in Exclusive Management on Autonomic Grid Networks", 2010 Second International Conference on Computational Intelligence , Communication Systems and Networks*, pp. 326-329, IEEE, 2010.
92. Mehdi Bahrami, Peyman Arebi, Hossen Bakhshizadeh, Hamed Barangi , *" A Novel Self-Reconfiguration Method for Autonomic Grid Networks Case Study : Advisor Labor Law Software Application", Advanced in Information Sciences and Service Sciences* , Vol 3, Number 5, pp. 262-269, June 2011
93. [Online]. Available : http://www.cse.yorku.ca/~aaw/Sotirios/BinomialHeapAlgorithm.html
94. Norton, W. B. (2001, May). Internet service providers and peering. In *Proceedings of NANOG* (Vol. 19, pp. 1-17).
95. Vrancx, P., Gurzi, P., Rodriguez, A., Steenhaut, K., & Nowé, A. (2015). A reinforcement learning approach for interdomain routing with link prices. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*, *10*(1), 5.
96. Kohli, M. (2011). *An Enhanced Goal-Oriented Decision-Making Model for Self-Adaptive Systems* (Master's thesis, University of Waterloo).
97. Defazio, Aaron, and Thore Graepel. "A comparison of learning algorithms on the arcade learning environment." *arXiv preprint arXiv:1410.8620* (2014).
98. Brys, Tim, et al. "Policy transfer using reward shaping." *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2015.
99. Pulakka, Kimmo. "A dynamic control system for adjusting prices and quality of service in DS enabled networks." *Network Control and Engineering for QoS, Security and Mobility*. Springer US, 2003. 241-252.
100. Hani, A. F. M., Paputungan, I. V., & Hassan, M. F. (2015). Renegotiation in service level agreement management for a cloud-based system. *ACM Computing Surveys (CSUR)*, *47*(3), 51.
101. Sharaf, S., & Djemame, K. (2015). Enabling service-level agreement renegotiation through extending WS-Agreement specification. *Service Oriented Computing and Applications*, *9*(2), 177-191.
102. Sidhanta, S., Golab, W., Mukhopadhyay, S., & Basu, S. (2016, May). OptCon: An Adaptable SLA-Aware Consistency Tuning Framework for Quorum-based Stores. In *Cluster, Cloud and Grid Computing (CCGrid), 2016 16th IEEE/ACM International Symposium on* (pp. 388-397). IEEE.
103. Subasi, O., Di, S., Balaprakash, P., Unsal, O., Labarta, J., Cristal, A., ... & Cappello, F. (2017, September). MACORD: Online Adaptive Machine Learning Framework for Silent Error Detection. In *Cluster Computing (CLUSTER), 2017 IEEE International Conference on* (pp. 717-724). IEEE.
104. Li, J., Qiu, M., Ming, Z., Quan, G., Qin, X., & Gu, Z. (2012). Online optimization for scheduling preemptable tasks on IaaS cloud systems. *Journal of Parallel and Distributed Computing*, *72*(5), 666-677.
105. Gujarati, A., Elnikety, S., He, Y., McKinley, K. S., & Brandenburg, B. B. (2017, December). Swayam: distributed autoscaling to meet SLAs of machine learning inference services with resource efficiency. In *Proceedings of the 18th ACM/IFIP/USENIX Middleware Conference* (pp. 109-120). ACM.

106. Glorennec, P. Y. (1994, June). Fuzzy Q-learning and dynamical fuzzy Q-learning. In *Fuzzy Systems, 1994. IEEE World Congress on Computational Intelligence., Proceedings of the Third IEEE Conference on* (pp. 474-479). IEEE.
107. Jamshidi, Pooyan, et al. "Fuzzy Self-Learning Controllers for Elasticity Management in Dynamic Cloud Architectures.", 2016.
108. Arabnejad, H., Pahl, C., Jamshidi, P., & Estrada, G. (2017, May). A comparison of reinforcement learning techniques for fuzzy cloud auto-scaling. In *Cluster, Cloud and Grid Computing (CCGRID), 2017 17th IEEE/ACM International Symposium on* (pp. 64-73). IEEE.
109. Arabnejad, H., Jamshidi, P., Estrada, G., El Ioini, N., & Pahl, C. (2016, September). An auto-scaling cloud controller using fuzzy q-learning-implementation in openstack. In *European Conference on Service-Oriented and Cloud Computing* (pp. 152-167). Springer, Cham.
110. Groléat, T., & Pouyllau, H. (2011, May). Distributed inter-domain SLA negotiation using Reinforcement Learning. In *12th IFIP/IEEE International Symposium on Integrated Network Management (IM 2011) and Workshops*(pp. 33-40). IEEE.
111. Sikora, Tomasz D., and George D. Magoulas. "Neural adaptive control in application service management environment." *Evolving Systems* 4.4 (2013): 267-287.
112. Mijumbi, R., Gorricho, J. L., Serrat, J., Claeys, M., De Turck, F., & Latré, S. (2014, May). Design and evaluation of learning algorithms for dynamic resource management in virtual networks. In *2014 IEEE Network Operations and Management Symposium (NOMS)* (pp. 1-9). IEEE.
113. Yu, L., Zhili, W., Lingli, M., Jiang, W., Meng, L., & Xue-song, Q. (2013, June). Adaptive web services composition using q-learning in cloud. In *2013 IEEE Ninth World Congress on Services* (pp. 393-396). IEEE.
114. Pouyllau, Hélia, and Giovanna Carofiglio. "Inter-carrier SLA negotiation using Q-learning." *Telecommunication Systems* 52.2 (2013): 611-622.
115. Leitner, Philipp, et al. "Data-driven and automated prediction of service level agreement violations in service compositions." *Distributed and Parallel Databases* 31.3 (2013): 447-470.
116. Verma, Dinesh C. "Supporting service level agreements on IP networks." (1999).
117. Lamali, Mohamed Lamine, et al. "Risk-aware sla negotiation." *Proceedings of the 7th International Conference on Performance Evaluation Methodologies and Tools*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2013.
118. Kohli, Manbeen. "An Enhanced Goal-Oriented Decision-Making Model for Self-Adaptive Systems." (2011).
119. Defazio, Aaron, and Thore Graepel. "A comparison of learning algorithms on the arcade learning environment." *arXiv preprint arXiv:1410.8620* (2014).
120. Brys, Tim, et al. "Policy transfer using reward shaping." *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent*

Systems. International Foundation for Autonomous Agents and Multiagent Systems, 2015.

121. Pulakka, Kimmo. "A dynamic control system for adjusting prices and quality of service in DS enabled networks." *Network Control and Engineering for QoS, Security and Mobility*. Springer US, 2003. 241-252.
122. Boumehraz, Mohamed, and Khier Benmahammed. "Tuning Fuzzy Inference Systems by Q-Learning." (2014).
123. Corazza, Marco, and Andrea Sangalli. "Q-Learning and SARSA: a comparison between two intelligent stochastic control approaches for financial trading." *University Ca'Foscari of Venice, Dept. of Economics Research Paper Series No* 15 (2015).
124. Brys, Tim, et al. "Policy transfer using reward shaping." *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2015.
125. White, Martha, and Adam White. "A Greedy Approach to Adapting the Trace Parameter for Temporal Difference Learning." *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2016.
126. Erev, Ido, and Greg Barron. "On adaptation, maximization, and reinforcement learning among cognitive strategies." *Psychological review*112.4 (2005): 912.
127. Galindo-Serrano, Ana, and Lorenza Giupponi. "Self-organized femtocells: a Fuzzy Q-Learning approach." *Wireless networks* 20.3 (2014): 441-455.
128. Tokarchuk, L., J. Bigham, and L. Cuthbert. "Fuzzy sarsa: An approach to fuzzifying sarsa learning." *Proceedings of the International Conference on Computational Intelligence for Modeling, Control and Automation*. 2004.
129. Głowaty, G. (2013). Enhancements of fuzzy Q-learning algorithm. *Computer Science*, *7*(4), 77.
130. Dayan, P., & Watkins, C. J. C. H. (1992). Q-learning. *Machine learning*, *8*(3), 279-292.
131. Wu, L., Garg, S. K., & Buyya, R. (2012). SLA-based admission control for a Software-as-a-Service provider in Cloud computing environments. *Journal of Computer and System Sciences*, *78*(5), 1280-1299.
132. Pierre Yves Glorennec and Lione Jouffe : Fuzz Q-Learning . Proc. Sixth IEEE International Conference on Fuzzy Systems (Fuzz-IEEE’97), Barcelona 1997, pp. 659-662
133. Caironi, P. V., & Dorigo, M. (1997). Training and delayed reinforcements in Q-learning agents. *International journal of intelligent systems*, *12*(10), 695-724.
134. Bersini, H. (1993). Reinforcement learning and recruitment mechanism for adaptive distributed control. In *Artificial Intelligence in Real-Time Control 1992* (pp. 467-473).

135. Ribeiro, C. H. C. (1999, July). A tutorial on reinforcement learning techniques. In *Supervised Learning Track Tutorials of the 1999 International Joint Conference on Neuronal Networks*.
136. Berenji, H. R. (1996, September). Fuzzy Q-learning for generalization of reinforcement learning. In *Fuzzy Systems, 1996., Proceedings of the Fifth IEEE International Conference on* (Vol. 3, pp. 2208-2214). IEEE.
137. Leng, J., Fyfe, C., & Jain, L. (2006, October). Teamwork and simulation in hybrid cognitive architecture. In *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems* (pp. 472-478). Springer, Berlin, Heidelberg.
138. SLA Case Study IRAN . Retrieved from https://www.apt.int/sites/default/files/Upload-files/SATRC/WGNET02/SATRC-WG-NET02-08_Service_Level_Agreements.pdf
140. Data for ISP Performance. Retrieved from https://www.ofcom.org.uk/research-and-data/telecoms-research/broadband-research/
141. https://blog.twitter.com/engineering/en_us/topics/open-source/2016/reinforcement-learning-for-torch-introducing-torch-twrl.html
142. Mitchell, Tom Michael. *The discipline of machine learning*. Vol. 9. Pittsburgh, PA: Carnegie Mellon University, School of Computer Science, Machine Learning Department, 2006.
143. PeeringDB Website. Retrieved from http://www.peeringdb.com
144. Marilly, Emmanuel, Olivier Martinot, Stéphane Betgé-Brezetz, and Gérard Delègue. "Requirements for service level agreement management." In *IEEE Workshop on IP Operations and Management*, pp. 57-62. IEEE, 2002.
145. Moler, Cleve. "Parallel MATLAB: Multiple processors and multiple cores." *The MathWorks News & Notes* (2007).
146. Falkenberg, Eckhard D. "A framework of information system concepts." International Federation for Information Processing, 1998.
147. Pedrycz, Witold, and Fernando Gomide. *An introduction to fuzzy sets: analysis and design*. Mit Press, 1998.
148. Jamshidi, P., Ahmad, A., & Pahl, C. (2014, June). Autonomic resource provisioning for cloud-based software. In *Proceedings of the 9th international symposium on software engineering for adaptive and self-managing systems* (pp. 95-104). ACM.
149. Mendel, J. M., John, R. I., & Liu, F. (2006). Interval type-2 fuzzy logic systems made simple. *IEEE transactions on fuzzy systems*, *14*(6), 808-821.
150. Wu, D. (2012). On the fundamental differences between interval type-2 and type-1 fuzzy logic controllers. *IEEE Transactions on Fuzzy Systems*, *20*(5), 832-848.
151. Mendel, Jerry M., Hani Hagras, and Robert I. John. "Standard background material about interval type-2 fuzzy logic systems that can be used by all authors." (2006).

Appendix A
PeeringDB

PeeringDB is the free access information available over the Internet. The provided information is useful to understand the connection from layers of ISPs. As for example the ISP – TELEKOM MALAYSIA BERHAD is one of the Tier 1 ISP in Malaysia and it has multiple connections with another ISP through the public peering exchange points.

Figure A.1 illustrates the connection of TELEKOM MALAYSIA BERHAD with local and international ISPs through public peering exchange point. Figure A.2 shows the information about Malaysia Internet Exchange, the function of the exchange is to connect all local ISPs in Malaysia as intranet-based connections. It helps the ISP to overcome the unwanted fees for extra routing to access information within different routing among local ISPs.

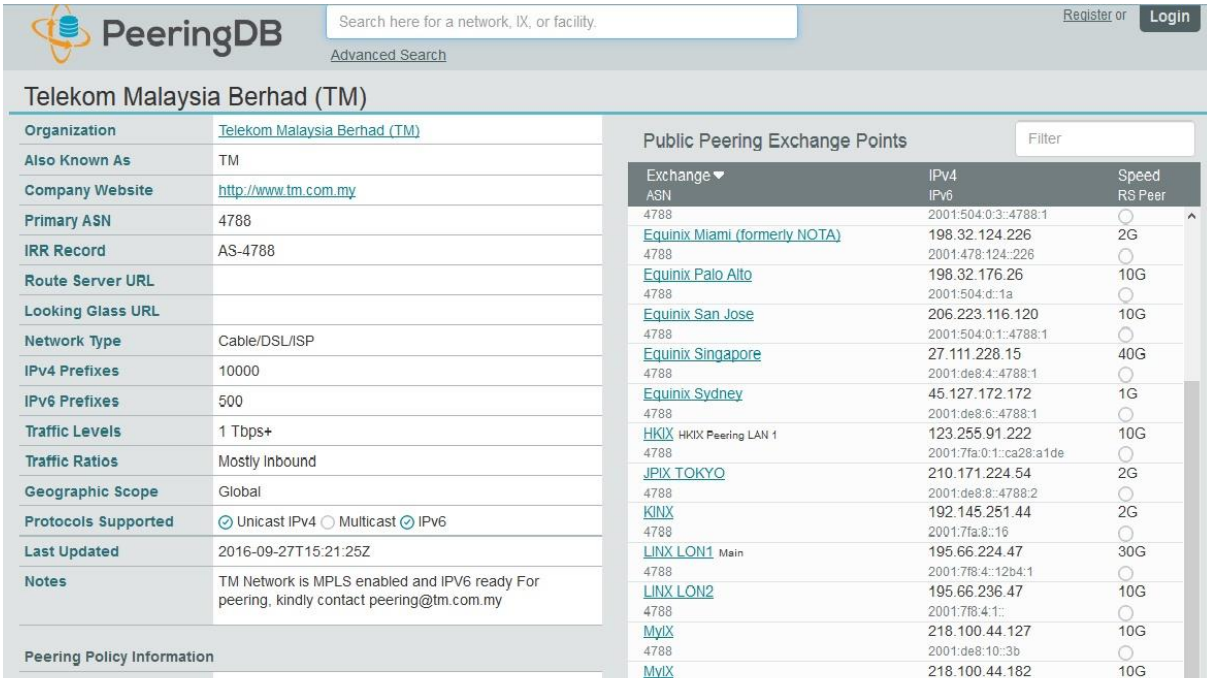


Figure A.1 Telekom Malaysia Berhad - ISP

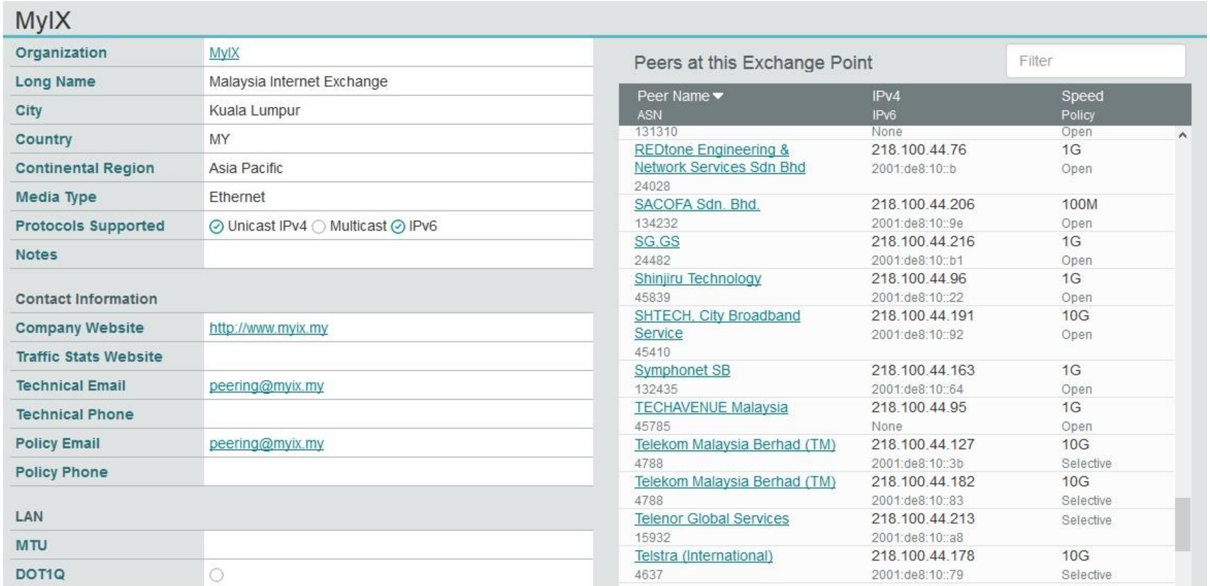


Figure A.2 Malaysia Internet Exchange

Figure A.3 displays the information about Virgin Media ISP, it is among the tier 1 ISP in United Kingdom. Both Virgin Media and TELEKOM MALAYSIA BERHAD connected through London Internet Exchange as displayed in Figure A.4.

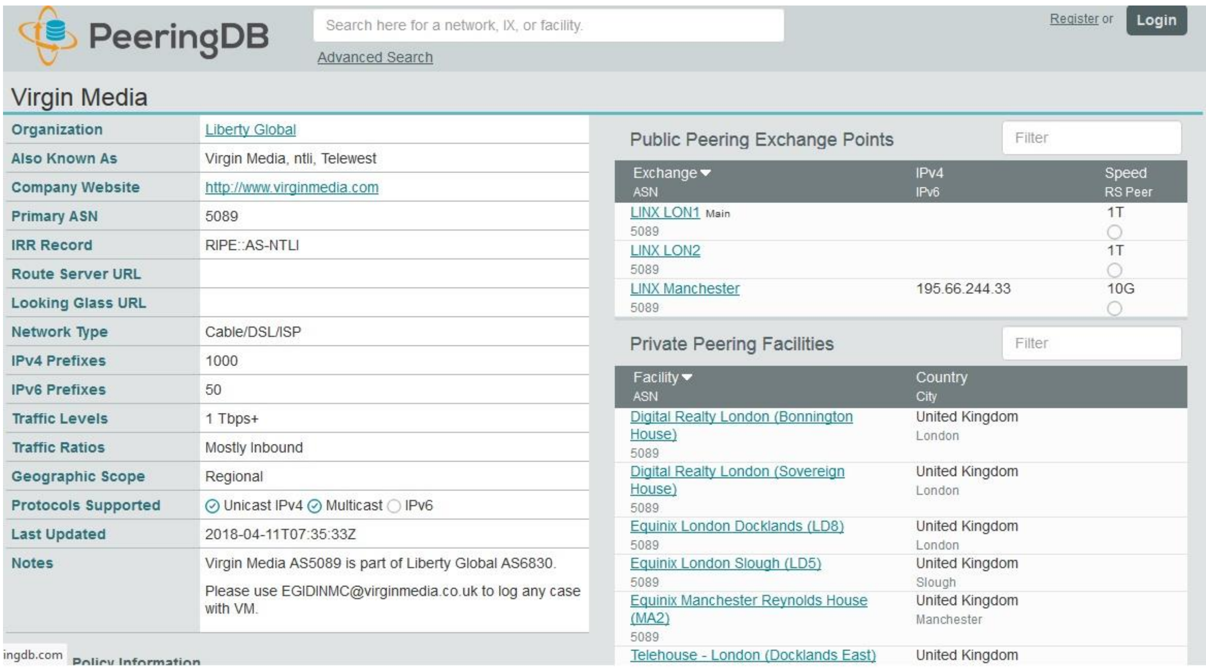


Figure A.3 Virgin Media - ISP

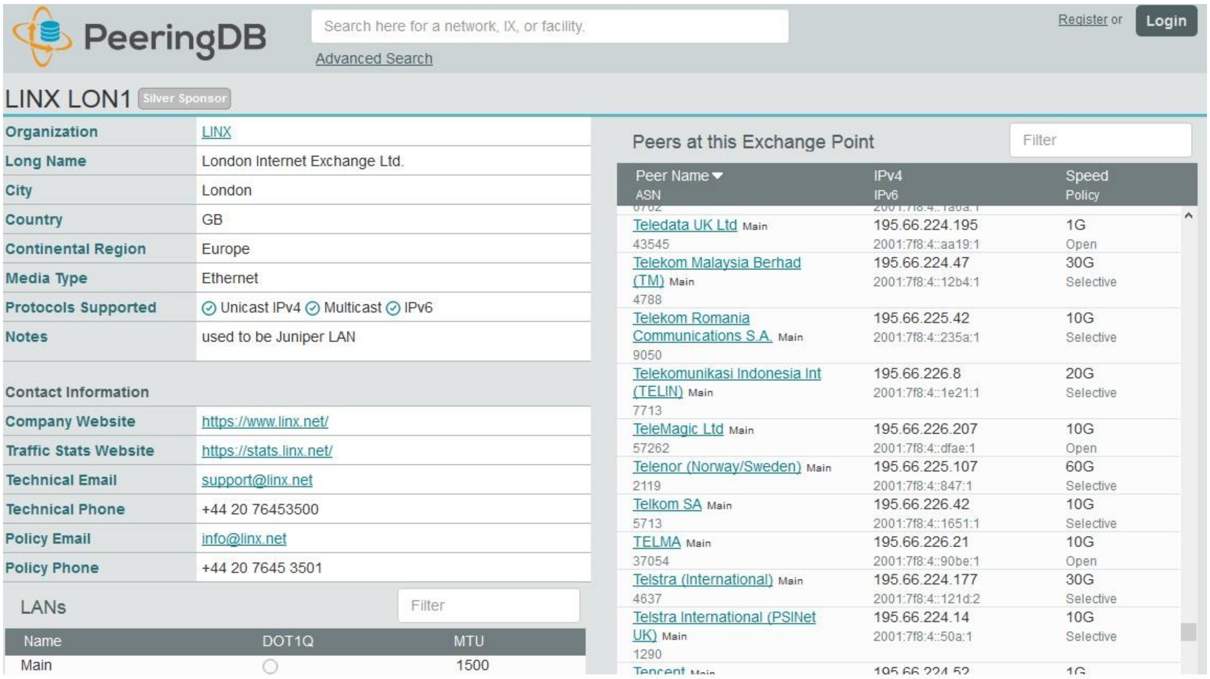


Figure A.4 London Internet Exchange

Appendix B

Fuzzy Rule Base Approach

This is the list of fuzzy rule base applied in this thesis.

Rule	Antecedents			Consequent(Evaluation on the service)					Weighted Total
	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	2	1	**2.00**
2	Low	Pass	Normal	0	0	1	1	1	**1.50**
3	Low	Pass	High	0	1	0	1	1	**1.00**
4	Low	Pass	Peak	1	0	0	1	1	**0.50**
5	Low	Pass	Pass	0	0	0	1	2	**2.50**
6	Low	Peak	Low	1	0	0	2	0	**0.00**
7	Low	Peak	Normal	1	0	1	1	0	**-0.50**
8	Low	Peak	High	1	1	0	1	0	**-1.00**
9	Low	Peak	Peak	2	0	0	1	0	**-1.50**
10	Low	Peak	Pass	1	0	0	1	1	**0.50**
11	Low	High	Low	0	1	0	2	0	**0.50**
12	Low	High	Normal	0	1	1	1	0	**0.00**
13	Low	High	High	0	2	0	1	0	**-0.50**
14	Low	High	Peak	1	1	0	1	0	**-1.00**
15	Low	High	Pass	0	1	0	1	1	**1.00**
16	Low	Normal	Low	0	0	1	2	0	**1.00**
17	Low	Normal	Normal	0	0	2	1	0	**0.50**
18	Low	Normal	High	0	1	1	1	0	**0.00**
19	Low	Normal	Peak	1	0	1	1	0	**-0.50**
20	Low	Normal	Pass	0	0	1	1	1	**1.50**
21	Low	Low	Low	0	0	0	3	0	**1.50**
22	Low	Low	Normal	0	0	1	2	0	**1.00**
23	Low	Low	High	0	1	0	2	0	**0.50**
24	Low	Low	Peak	1	0	0	2	0	**0.00**
25	Low	Low	Pass	0	0	0	2	1	**2.00**
1	Normal	Pass	Low	0	0	1	1	1	**1.50**
2	Normal	Pass	Normal	0	0	2	0	1	**1.00**
3	Normal	Pass	High	0	1	1	0	1	**0.50**
4	Normal	Pass	Peak	1	0	1	0	1	**0.00**
5	Normal	Pass	Pass	0	0	1	0	2	**2.00**
6	Normal	Peak	Low	1	0	1	1	0	**-0.50**
7	Normal	Peak	Normal	1	0	2	0	0	**-1.00**
8	Normal	Peak	High	1	1	1	0	0	**-1.50**
9	Normal	Peak	Peak	2	0	1	0	0	**-2.00**

10	Normal	Peak	Pass	1	0	1	0	1	**0.00**
11	Normal	High	Low	0	1	1	1	0	**0.00**
12	Normal	High	Normal	0	1	2	0	0	**-0.50**
13	Normal	High	High	0	2	1	0	0	**-1.00**
14	Normal	High	Peak	1	1	1	0	0	**-1.50**
15	Normal	High	Pass	0	1	1	0	1	**0.50**
16	Normal	Normal	Low	0	0	2	1	0	**0.50**
17	Normal	Normal	Normal	0	0	3	0	0	**0.00**
18	Normal	Normal	High	0	1	2	0	0	**-0.50**
19	Normal	Normal	Peak	1	0	2	0	0	**-1.00**
20	Normal	Normal	Pass	0	0	2	0	1	**1.00**
21	Normal	Low	Low	0	0	1	2	0	**1.00**
22	Normal	Low	Normal	0	0	2	1	0	**0.50**
23	Normal	Low	High	0	1	1	1	0	**0.00**
24	Normal	Low	Peak	1	0	1	1	0	**-0.50**
25	Normal	Low	Pass	0	0	1	1	1	**1.50**
1	High	Pass	Low	0	1	0	1	1	**1.00**
2	High	Pass	Normal	0	1	1	0	1	**0.50**
3	High	Pass	High	0	2	0	0	1	**0.00**
4	High	Pass	Peak	1	1	0	0	1	**-0.50**
5	High	Pass	Pass	0	1	0	0	2	**1.50**
6	High	Peak	Low	1	1	0	1	0	**-1.00**
7	High	Peak	Normal	1	1	1	0	0	**-1.50**
8	High	Peak	High	1	2	0	0	0	**-2.00**
9	High	Peak	Peak	2	1	0	0	0	**-2.50**
10	High	Peak	Pass	1	1	0	0	1	**-0.50**
11	High	High	Low	0	2	0	1	0	**-0.50**
12	High	High	Normal	0	2	1	0	0	**-1.00**
13	High	High	High	0	3	0	0	0	**-1.50**
14	High	High	Peak	1	2	0	0	0	**-2.00**
15	High	High	Pass	0	2	0	0	1	**0.00**
16	High	Normal	Low	0	1	1	1	0	**0.00**
17	High	Normal	Normal	0	1	2	0	0	**-0.50**
18	High	Normal	High	0	2	1	0	0	**-1.00**
19	High	Normal	Peak	1	1	1	0	0	**-1.50**
20	High	Normal	Pass	0	1	1	0	1	**0.50**
21	High	Low	Low	0	1	0	2	0	**0.50**
22	High	Low	Normal	0	1	1	1	0	**0.00**
23	High	Low	High	0	2	0	1	0	**-0.50**
24	High	Low	Peak	1	1	0	1	0	**-1.00**
25	High	Low	Pass	0	1	0	1	1	**1.00**
1	Peak	Pass	Low	1	0	0	1	1	**0.50**
2	Peak	Pass	Normal	1	0	1	0	1	**0.00**
3	Peak	Pass	High	1	1	0	0	1	**-0.50**
4	Peak	Pass	Peak	2	0	0	0	1	**-1.00**
5	Peak	Pass	Pass	1	0	0	0	2	**1.00**
6	Peak	Peak	Low	2	0	0	1	0	**-1.50**
7	Peak	Peak	Normal	2	0	1	0	0	**-2.00**
8	Peak	Peak	High	2	1	0	0	0	**-2.50**

9	Peak	Peak	Peak	3	0	0	0	0	**-3.00**
10	Peak	Peak	Pass	2	0	0	0	1	**-1.00**
11	Peak	High	Low	1	1	0	1	0	**-1.00**
12	Peak	High	Normal	1	1	1	0	0	**-1.50**
13	Peak	High	High	1	2	0	0	0	**-2.00**
14	Peak	High	Peak	2	1	0	0	0	**-2.50**
15	Peak	High	Pass	1	1	0	0	1	**-0.50**
16	Peak	Normal	Low	1	0	1	1	0	**-0.50**
17	Peak	Normal	Normal	1	0	2	0	0	**-1.00**
18	Peak	Normal	High	1	1	1	0	0	**-1.50**
19	Peak	Normal	Peak	2	0	1	0	0	**-2.00**
20	Peak	Normal	Pass	1	0	1	0	1	**0.00**
21	Peak	Low	Low	1	0	0	2	0	**0.00**
22	Peak	Low	Normal	1	0	1	1	0	**-0.50**
23	Peak	Low	High	1	1	0	1	0	**-1.00**
24	Peak	Low	Peak	2	0	0	1	0	**-1.50**
25	Peak	Low	Pass	1	0	0	1	1	**0.50**
1	Pass	Pass	Low	0	0	0	1	2	**2.50**
2	Pass	Pass	Normal	0	0	1	0	2	**2.00**
3	Pass	Pass	High	0	1	0	0	2	**1.50**
4	Pass	Pass	Peak	1	0	0	0	2	**1.00**
5	Pass	Pass	Pass	0	0	0	0	3	**3.00**
6	Pass	Peak	Low	1	0	0	1	1	**0.50**
7	Pass	Peak	Normal	1	0	1	0	1	**0.00**
8	Pass	Peak	High	1	1	0	0	1	**-0.50**
9	Pass	Peak	Peak	2	0	0	0	1	**-1.00**
10	Pass	Peak	Pass	1	0	0	0	2	**1.00**
11	Pass	High	Low	0	1	0	1	1	**1.00**
12	Pass	High	Normal	0	1	1	0	1	**0.50**
13	Pass	High	High	0	2	0	0	1	**0.00**
14	Pass	High	Peak	1	1	0	0	1	**-0.50**
15	Pass	High	Pass	0	1	0	0	2	**1.50**
16	Pass	Normal	Low	0	0	1	1	1	**1.50**
17	Pass	Normal	Normal	0	0	2	0	1	**1.00**
18	Pass	Normal	High	0	1	1	0	1	**0.50**
19	Pass	Normal	Peak	1	0	1	0	1	**0.00**
20	Pass	Normal	Pass	0	0	1	0	2	**2.00**
21	Pass	Low	Low	0	0	0	2	1	**2.00**
22	Pass	Low	Normal	0	0	1	1	1	**1.50**
23	Pass	Low	High	0	1	0	1	1	**1.00**
24	Pass	Low	Peak	1	0	0	1	1	**0.50**
25	Pass	Low	Pass	0	0	0	1	2	**2.50**

Combinations between 125.

1. Latency vs Availability

Rule	Antecedents	Consequent(Evaluation on the service)	Weighted Total

	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	1	1	**1.50**
2	Low	Pass	Normal	0	0	0	1	1	**1.50**
3	Low	Pass	High	0	0	0	1	1	**1.50**
4	Low	Pass	Peak	1	0	0	1	1	**0.50**
5	Low	Pass	Pass	0	0	0	1	1	**1.50**
6	Low	Peak	Low	1	0	0	1	0	**-0.50**
7	Low	Peak	Normal	1	0	1	1	0	**-0.50**
8	Low	Peak	High	1	0	0	1	0	**-0.50**
9	Low	Peak	Peak	1	0	0	1	0	**-0.50**
10	Low	Peak	Pass	1	0	0	1	0	**-0.50**
11	Low	High	Low	0	1	0	1	0	**0.00**
12	Low	High	Normal	0	1	0	1	0	**0.00**
13	Low	High	High	0	1	0	1	0	**0.00**
14	Low	High	Peak	1	1	0	1	0	**-1.00**
15	Low	High	Pass	0	1	0	1	0	**0.00**
16	Low	Normal	Low	0	0	1	1	0	**0.50**
17	Low	Normal	Normal	0	0	1	1	0	**0.50**
18	Low	Normal	High	0	0	1	1	0	**0.50**
19	Low	Normal	Peak	0	0	1	1	0	**0.50**
20	Low	Normal	Pass	0	0	1	1	0	**0.50**
21	Low	Low	Low	0	0	0	2	0	**1.00**
22	Low	Low	Normal	0	0	0	2	0	**1.00**
23	Low	Low	High	0	0	0	2	0	**1.00**
24	Low	Low	Peak	0	0	0	2	0	**1.00**
25	Low	Low	Pass	0	0	0	2	0	**1.00**
26	Normal	Pass	Low	0	0	1	0	1	**1.00**
27	Normal	Pass	Normal	0	0	1	0	1	**1.00**
28	Normal	Pass	High	0	0	1	0	1	**1.00**
29	Normal	Pass	Peak	0	0	1	0	1	**1.00**
30	Normal	Pass	Pass	0	0	1	0	1	**1.00**
31	Normal	Peak	Low	1	0	1	0	0	**-1.00**
32	Normal	Peak	Normal	1	0	1	0	0	**-1.00**
33	Normal	Peak	High	1	0	1	0	0	**-1.00**
34	Normal	Peak	Peak	1	0	1	0	0	**-1.00**
35	Normal	Peak	Pass	1	0	1	0	0	**-1.00**
36	Normal	High	Low	0	1	1	0	0	**-0.50**
37	Normal	High	Normal	0	1	1	0	0	**-0.50**
38	Normal	High	High	0	1	1	0	0	**-0.50**
39	Normal	High	Peak	0	1	1	0	0	**-0.50**
40	Normal	High	Pass	0	1	1	0	0	**-0.50**
41	Normal	Normal	Low	0	0	2	0	0	**0.00**
42	Normal	Normal	Normal	0	0	2	0	0	**0.00**
43	Normal	Normal	High	0	0	2	0	0	**0.00**
44	Normal	Normal	Peak	0	0	2	0	0	**0.00**
45	Normal	Normal	Pass	0	0	2	0	0	**0.00**
46	Normal	Low	Low	0	0	1	1	0	**0.50**
47	Normal	Low	Normal	0	0	1	1	0	**0.50**

48	Normal	Low	High	0	0	1	1	0	**0.50**
49	Normal	Low	Peak	0	0	1	1	0	**0.50**
50	Normal	Low	Pass	0	0	1	1	0	**0.50**
51	High	Pass	Low	0	1	0	0	1	**0.50**
52	High	Pass	Normal	0	1	0	0	1	**0.50**
53	High	Pass	High	0	1	0	0	1	**0.50**
54	High	Pass	Peak	0	1	0	0	1	**0.50**
55	High	Pass	Pass	0	1	0	0	1	**0.50**
56	High	Peak	Low	1	1	0	0	0	**-1.50**
57	High	Peak	Normal	1	1	0	0	0	**-1.50**
58	High	Peak	High	1	1	0	0	0	**-1.50**
59	High	Peak	Peak	1	1	0	0	0	**-1.50**
60	High	Peak	Pass	1	1	0	0	0	**-1.50**
61	High	High	Low	0	2	0	0	0	**-1.00**
62	High	High	Normal	0	2	0	0	0	**-1.00**
63	High	High	High	0	2	0	0	0	**-1.00**
64	High	High	Peak	0	2	0	0	0	**-1.00**
65	High	High	Pass	0	2	0	0	0	**-1.00**
66	High	Normal	Low	0	1	1	0	0	**-0.50**
67	High	Normal	Normal	0	1	1	0	0	**-0.50**
68	High	Normal	High	0	1	1	0	0	**-0.50**
69	High	Normal	Peak	0	1	1	0	0	**-0.50**
70	High	Normal	Pass	0	1	1	0	0	**-0.50**
71	High	Low	Low	0	1	0	1	0	**0.00**
72	High	Low	Normal	0	1	0	1	0	**0.00**
73	High	Low	High	0	1	0	1	0	**0.00**
74	High	Low	Peak	0	1	0	1	0	**0.00**
75	High	Low	Pass	0	1	0	1	0	**0.00**
76	Peak	Pass	Low	1	0	0	0	1	**0.00**
77	Peak	Pass	Normal	1	0	0	0	1	**0.00**
78	Peak	Pass	High	1	0	0	0	1	**0.00**
79	Peak	Pass	Peak	1	0	0	0	1	**0.00**
80	Peak	Pass	Pass	1	0	0	0	1	**0.00**
81	Peak	Peak	Low	2	0	0	0	0	**-2.00**
82	Peak	Peak	Normal	2	0	0	0	0	**-2.00**
83	Peak	Peak	High	2	0	0	0	0	**-2.00**
84	Peak	Peak	Peak	2	0	0	0	0	**-2.00**
85	Peak	Peak	Pass	2	0	0	0	0	**-2.00**
86	Peak	High	Low	1	1	0	0	0	**-1.50**
87	Peak	High	Normal	1	1	0	0	0	**-1.50**
88	Peak	High	High	1	1	0	0	0	**-1.50**
89	Peak	High	Peak	1	1	0	0	0	**-1.50**
90	Peak	High	Pass	1	1	0	0	0	**-1.50**
91	Peak	Normal	Low	1	0	1	0	0	**-1.00**
92	Peak	Normal	Normal	1	0	1	0	0	**-1.00**
93	Peak	Normal	High	1	0	1	0	0	**-1.00**
94	Peak	Normal	Peak	1	0	1	0	0	**-1.00**
95	Peak	Normal	Pass	1	0	1	0	0	**-1.00**
96	Peak	Low	Low	1	0	0	1	0	**-0.50**

97	Peak	Low	Normal	1	0	0	1	0	**-0.50**
98	Peak	Low	High	1	0	0	1	0	**-0.50**
99	Peak	Low	Peak	1	0	0	1	0	**-0.50**
100	Peak	Low	Pass	1	0	0	1	0	**-0.50**
101	Pass	Pass	Low	0	0	0	0	2	**2.00**
102	Pass	Pass	Normal	0	0	0	0	2	**2.00**
103	Pass	Pass	High	0	0	0	0	2	**2.00**
104	Pass	Pass	Peak	0	0	0	0	2	**2.00**
105	Pass	Pass	Pass	0	0	0	0	2	**2.00**
106	Pass	Peak	Low	1	0	0	0	1	**0.00**
107	Pass	Peak	Normal	1	0	0	0	1	**0.00**
108	Pass	Peak	High	1	0	0	0	1	**0.00**
109	Pass	Peak	Peak	1	0	0	0	1	**0.00**
110	Pass	Peak	Pass	1	0	0	0	1	**0.00**
111	Pass	High	Low	0	1	0	0	1	**0.50**
112	Pass	High	Normal	0	1	0	0	1	**0.50**
113	Pass	High	High	0	1	0	0	1	**0.50**
114	Pass	High	Peak	0	1	0	0	1	**0.50**
115	Pass	High	Pass	0	1	0	0	1	**0.50**
116	Pass	Normal	Low	0	0	1	0	1	**1.00**
117	Pass	Normal	Normal	0	0	1	0	1	**1.00**
118	Pass	Normal	High	0	0	1	0	1	**1.00**
119	Pass	Normal	Peak	0	0	1	0	1	**1.00**
120	Pass	Normal	Pass	0	0	1	0	1	**1.00**
121	Pass	Low	Low	0	0	0	1	1	**1.50**
122	Pass	Low	Normal	0	0	0	1	1	**1.50**
123	Pass	Low	High	0	0	0	1	1	**1.50**
124	Pass	Low	Peak	0	0	0	1	1	**1.50**
125	Pass	Low	Pass	0	0	0	1	1	**1.50**

2. Latency vs Packet Loss

Rule	Antecedents			Consequent(Evaluation on the service)					Weighted Total
	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	2	0	**1.00**
2	Low	Pass	Normal	0	0	1	1	0	**0.50**
3	Low	Pass	High	0	1	0	1	0	**0.00**
4	Low	Pass	Peak	1	0	0	1	0	**-0.50**
5	Low	Pass	Pass	0	0	0	1	1	**1.50**
6	Low	Peak	Low	0	0	0	2	0	**1.00**
7	Low	Peak	Normal	0	0	1	1	0	**0.50**
8	Low	Peak	High	0	1	0	1	0	**0.00**
9	Low	Peak	Peak	1	0	0	1	0	**-0.50**
10	Low	Peak	Pass	0	0	0	1	1	**1.50**
11	Low	High	Low	0	0	0	2	0	**1.00**
12	Low	High	Normal	0	0	1	1	0	**0.50**

13	Low	High	High	0	1	0	1	0	**0.00**
14	Low	High	Peak	1	0	0	1	0	**-0.50**
15	Low	High	Pass	0	0	0	1	1	**1.50**
16	Low	Normal	Low	0	0	0	2	0	**1.00**
17	Low	Normal	Normal	0	0	1	1	0	**0.50**
18	Low	Normal	High	0	1	0	1	0	**0.00**
19	Low	Normal	Peak	1	0	0	1	0	**-0.50**
20	Low	Normal	Pass	0	0	0	1	1	**1.50**
21	Low	Low	Low	0	0	0	2	0	**1.00**
22	Low	Low	Normal	0	0	1	1	0	**0.50**
23	Low	Low	High	0	1	0	1	0	**0.00**
24	Low	Low	Peak	1	0	0	1	0	**-0.50**
25	Low	Low	Pass	0	0	0	1	1	**1.50**
26	Normal	Pass	Low	0	0	1	1	0	**0.50**
27	Normal	Pass	Normal	0	0	2	0	0	**0.00**
28	Normal	Pass	High	0	1	1	0	0	**-0.50**
29	Normal	Pass	Peak	1	0	1	0	0	**-1.00**
30	Normal	Pass	Pass	0	0	1	0	1	**1.00**
31	Normal	Peak	Low	0	0	1	1	0	**0.50**
32	Normal	Peak	Normal	0	0	2	0	0	**0.00**
33	Normal	Peak	High	0	1	1	0	0	**-0.50**
34	Normal	Peak	Peak	1	0	1	0	0	**-1.00**
35	Normal	Peak	Pass	0	0	1	0	1	**1.00**
36	Normal	High	Low	0	0	1	1	0	**0.50**
37	Normal	High	Normal	0	0	2	0	0	**0.00**
38	Normal	High	High	0	1	1	0	0	**-0.50**
39	Normal	High	Peak	1	0	1	0	0	**-1.00**
40	Normal	High	Pass	0	0	1	0	1	**1.00**
41	Normal	Normal	Low	0	0	1	1	0	**0.50**
42	Normal	Normal	Normal	0	0	2	0	0	**0.00**
43	Normal	Normal	High	0	1	1	0	0	**-0.50**
44	Normal	Normal	Peak	1	0	1	0	0	**-1.00**
45	Normal	Normal	Pass	0	0	1	0	1	**1.00**
46	Normal	Low	Low	0	0	1	1	0	**0.50**
47	Normal	Low	Normal	0	0	2	0	0	**0.00**
48	Normal	Low	High	0	1	1	0	0	**-0.50**
49	Normal	Low	Peak	1	0	1	0	0	**-1.00**
50	Normal	Low	Pass	0	0	1	0	1	**1.00**
51	High	Pass	Low	0	1	0	1	0	**0.00**
52	High	Pass	Normal	0	1	1	0	0	**-0.50**
53	High	Pass	High	0	2	0	0	0	**-1.00**
54	High	Pass	Peak	1	1	0	0	0	**-1.50**
55	High	Pass	Pass	0	1	0	0	1	**0.50**
56	High	Peak	Low	0	1	0	1	0	**0.00**
57	High	Peak	Normal	0	1	1	0	0	**-0.50**
58	High	Peak	High	0	2	0	0	0	**-1.00**
59	High	Peak	Peak	1	1	0	0	0	**-1.50**
60	High	Peak	Pass	0	1	0	0	1	**0.50**
61	High	High	Low	0	1	0	1	0	**0.00**

62	High	High	Normal	0	1	1	0	0	-0.50
63	High	High	High	0	2	0	0	0	-1.00
64	High	High	Peak	1	1	0	0	0	-1.50
65	High	High	Pass	0	1	0	0	1	0.50
66	High	Normal	Low	0	1	0	1	0	0.00
67	High	Normal	Normal	0	1	1	0	0	-0.50
68	High	Normal	High	0	2	0	0	0	-1.00
69	High	Normal	Peak	1	1	0	0	0	-1.50
70	High	Normal	Pass	0	1	0	0	1	0.50
71	High	Low	Low	0	1	0	1	0	0.00
72	High	Low	Normal	0	1	1	0	0	-0.50
73	High	Low	High	0	2	0	0	0	-1.00
74	High	Low	Peak	1	1	0	0	0	-1.50
75	High	Low	Pass	0	1	0	0	1	0.50
76	Peak	Pass	Low	1	0	0	1	0	-0.50
77	Peak	Pass	Normal	1	0	1	0	0	-1.00
78	Peak	Pass	High	1	1	0	0	0	-1.50
79	Peak	Pass	Peak	2	0	0	0	0	-2.00
80	Peak	Pass	Pass	1	0	0	0	1	0.00
81	Peak	Peak	Low	1	0	0	1	0	-0.50
82	Peak	Peak	Normal	1	0	1	0	0	-1.00
83	Peak	Peak	High	1	1	0	0	0	-1.50
84	Peak	Peak	Peak	2	0	0	0	0	-2.00
85	Peak	Peak	Pass	1	0	0	0	1	0.00
86	Peak	High	Low	1	0	0	1	0	-0.50
87	Peak	High	Normal	1	0	1	0	0	-1.00
88	Peak	High	High	1	1	0	0	0	-1.50
89	Peak	High	Peak	2	0	0	0	0	-2.00
90	Peak	High	Pass	1	0	0	0	1	0.00
91	Peak	Normal	Low	1	0	0	1	0	-0.50
92	Peak	Normal	Normal	1	0	1	0	0	-1.00
93	Peak	Normal	High	1	1	0	0	0	-1.50
94	Peak	Normal	Peak	2	0	0	0	0	-2.00
95	Peak	Normal	Pass	1	0	0	0	1	0.00
96	Peak	Low	Low	1	0	0	1	0	-0.50
97	Peak	Low	Normal	1	0	1	0	0	-1.00
98	Peak	Low	High	1	1	0	0	0	-1.50
99	Peak	Low	Peak	2	0	0	0	0	-2.00
100	Peak	Low	Pass	1	0	0	0	1	0.00
101	Pass	Pass	Low	0	0	0	1	1	1.50
102	Pass	Pass	Normal	0	0	1	0	1	1.00
103	Pass	Pass	High	0	1	0	0	1	0.50
104	Pass	Pass	Peak	1	0	0	0	1	0.00
105	Pass	Pass	Pass	0	0	0	0	2	2.00
106	Pass	Peak	Low	0	0	0	1	1	1.50
107	Pass	Peak	Normal	0	0	1	0	1	1.00
108	Pass	Peak	High	0	1	0	0	1	0.50
109	Pass	Peak	Peak	1	0	0	0	1	0.00
110	Pass	Peak	Pass	0	0	0	0	2	2.00

111	Pass	High	Low	0	0	0	1	1	**1.50**
112	Pass	High	Normal	0	0	1	0	1	**1.00**
113	Pass	High	High	0	1	0	0	1	**0.50**
114	Pass	High	Peak	1	0	0	0	1	**0.00**
115	Pass	High	Pass	0	0	0	0	2	**2.00**
116	Pass	Normal	Low	0	0	0	1	1	**1.50**
117	Pass	Normal	Normal	0	0	1	0	1	**1.00**
118	Pass	Normal	High	0	1	0	0	1	**0.50**
119	Pass	Normal	Peak	1	0	0	0	1	**0.00**
120	Pass	Normal	Pass	0	0	0	0	2	**2.00**
121	Pass	Low	Low	0	0	0	1	1	**1.50**
122	Pass	Low	Normal	0	0	1	0	1	**1.00**
123	Pass	Low	High	0	1	0	0	1	**0.50**
124	Pass	Low	Peak	1	0	0	0	1	**0.00**
125	Pass	Low	Pass	0	0	0	0	2	**2.00**

3. Packet Loss vs Availability

Rule	Antecedents			Consequent(Evaluation on the service)					Weighted Total
	Latency	Availability	Packet Loss	-2	-1	0	1	2	
1	Low	Pass	Low	0	0	0	1	1	**1.50**
2	Low	Pass	Normal	0	0	1	0	1	**1.00**
3	Low	Pass	High	0	1	0	0	1	**0.50**
4	Low	Pass	Peak	1	0	0	0	1	**0.00**
5	Low	Pass	Pass	0	0	0	0	2	**2.00**
6	Low	Peak	Low	1	0	0	1	0	**-0.50**
7	Low	Peak	Normal	1	0	1	0	0	**-1.00**
8	Low	Peak	High	1	1	0	0	0	**-1.50**
9	Low	Peak	Peak	2	0	0	0	0	**-2.00**
10	Low	Peak	Pass	1	0	0	0	1	**0.00**
11	Low	High	Low	0	1	0	1	0	**0.00**
12	Low	High	Normal	0	1	1	0	0	**-0.50**
13	Low	High	High	0	2	0	0	0	**-1.00**
14	Low	High	Peak	1	1	0	0	0	**-1.50**
15	Low	High	Pass	0	1	0	0	1	**0.50**
16	Low	Normal	Low	0	0	1	1	0	**0.50**
17	Low	Normal	Normal	0	0	2	0	0	**0.00**
18	Low	Normal	High	0	1	1	0	0	**-0.50**
19	Low	Normal	Peak	1	0	1	0	0	**-1.00**
20	Low	Normal	Pass	0	0	1	0	1	**1.00**
21	Low	Low	Low	0	0	0	2	0	**1.00**
22	Low	Low	Normal	0	0	1	1	0	**0.50**
23	Low	Low	High	0	1	0	1	0	**0.00**
24	Low	Low	Peak	1	0	0	1	0	**-0.50**
25	Low	Low	Pass	0	0	0	1	1	**1.50**
26	Normal	Pass	Low	0	0	0	1	1	**1.50**
27	Normal	Pass	Normal	0	0	1	0	1	**1.00**

28	Normal	Pass	High	0	1	0	0	1	**0.50**
29	Normal	Pass	Peak	1	0	0	0	1	**0.00**
30	Normal	Pass	Pass	0	0	0	0	2	**2.00**
31	Normal	Peak	Low	1	0	0	1	0	**-0.50**
32	Normal	Peak	Normal	1	0	1	0	0	**-1.00**
33	Normal	Peak	High	1	1	0	0	0	**-1.50**
34	Normal	Peak	Peak	2	0	0	0	0	**-2.00**
35	Normal	Peak	Pass	1	0	0	0	1	**0.00**
36	Normal	High	Low	0	1	0	1	0	**0.00**
37	Normal	High	Normal	0	1	1	0	0	**-0.50**
38	Normal	High	High	0	2	0	0	0	**-1.00**
39	Normal	High	Peak	1	1	0	0	0	**-1.50**
40	Normal	High	Pass	0	1	0	0	1	**0.50**
41	Normal	Normal	Low	0	0	1	1	0	**0.50**
42	Normal	Normal	Normal	0	0	2	0	0	**0.00**
43	Normal	Normal	High	0	1	1	0	0	**-0.50**
44	Normal	Normal	Peak	1	0	1	0	0	**-1.00**
45	Normal	Normal	Pass	0	0	1	0	1	**1.00**
46	Normal	Low	Low	0	0	0	2	0	**1.00**
47	Normal	Low	Normal	0	0	1	1	0	**0.50**
48	Normal	Low	High	0	1	0	1	0	**0.00**
49	Normal	Low	Peak	1	0	0	1	0	**-0.50**
50	Normal	Low	Pass	0	0	0	1	1	**1.50**
51	High	Pass	Low	0	0	0	1	1	**1.50**
52	High	Pass	Normal	0	0	1	0	1	**1.00**
53	High	Pass	High	0	1	0	0	1	**0.50**
54	High	Pass	Peak	1	0	0	0	1	**0.00**
55	High	Pass	Pass	0	0	0	0	2	**2.00**
56	High	Peak	Low	1	0	0	1	0	**-0.50**
57	High	Peak	Normal	1	0	1	0	0	**-1.00**
58	High	Peak	High	1	1	0	0	0	**-1.50**
59	High	Peak	Peak	2	0	0	0	0	**-2.00**
60	High	Peak	Pass	1	0	0	0	1	**0.00**
61	High	High	Low	0	1	0	1	0	**0.00**
62	High	High	Normal	0	1	1	0	0	**-0.50**
63	High	High	High	0	2	0	0	0	**-1.00**
64	High	High	Peak	1	1	0	0	0	**-1.50**
65	High	High	Pass	0	1	0	0	1	**0.50**
66	High	Normal	Low	0	0	1	1	0	**0.50**
67	High	Normal	Normal	0	0	2	0	0	**0.00**
68	High	Normal	High	0	1	1	0	0	**-0.50**
69	High	Normal	Peak	1	0	1	0	0	**-1.00**
70	High	Normal	Pass	0	0	1	0	1	**1.00**
71	High	Low	Low	0	0	0	2	0	**1.00**
72	High	Low	Normal	0	0	1	1	0	**0.50**
73	High	Low	High	0	1	0	1	0	**0.00**
74	High	Low	Peak	1	0	0	1	0	**-0.50**
75	High	Low	Pass	0	0	0	1	1	**1.50**
76	Peak	Pass	Low	0	0	0	1	1	**1.50**

77	Peak	Pass	Normal	0	0	1	0	1	**1.00**
78	Peak	Pass	High	0	1	0	0	1	**0.50**
79	Peak	Pass	Peak	1	0	0	0	1	**0.00**
80	Peak	Pass	Pass	0	0	0	0	2	**2.00**
81	Peak	Peak	Low	1	0	0	1	0	**-0.50**
82	Peak	Peak	Normal	1	0	1	0	0	**-1.00**
83	Peak	Peak	High	1	1	0	0	0	**-1.50**
84	Peak	Peak	Peak	2	0	0	0	0	**-2.00**
85	Peak	Peak	Pass	1	0	0	0	1	**0.00**
86	Peak	High	Low	0	1	0	1	0	**0.00**
87	Peak	High	Normal	0	1	1	0	0	**-0.50**
88	Peak	High	High	0	2	0	0	0	**-1.00**
89	Peak	High	Peak	1	1	0	0	0	**-1.50**
90	Peak	High	Pass	0	1	0	0	1	**0.50**
91	Peak	Normal	Low	0	0	1	1	0	**0.50**
92	Peak	Normal	Normal	0	0	2	0	0	**0.00**
93	Peak	Normal	High	0	1	1	0	0	**-0.50**
94	Peak	Normal	Peak	1	0	1	0	0	**-1.00**
95	Peak	Normal	Pass	0	0	1	0	1	**1.00**
96	Peak	Low	Low	0	0	0	2	0	**1.00**
97	Peak	Low	Normal	0	0	1	1	0	**0.50**
98	Peak	Low	High	0	1	0	1	0	**0.00**
99	Peak	Low	Peak	1	0	0	1	0	**-0.50**
100	Peak	Low	Pass	0	0	0	1	1	**1.50**
101	Pass	Pass	Low	0	0	0	1	1	**1.50**
102	Pass	Pass	Normal	0	0	1	0	1	**1.00**
103	Pass	Pass	High	0	1	0	0	1	**0.50**
104	Pass	Pass	Peak	1	0	0	0	1	**0.00**
105	Pass	Pass	Pass	0	0	0	0	2	**2.00**
106	Pass	Peak	Low	1	0	0	1	0	**-0.50**
107	Pass	Peak	Normal	1	0	1	0	0	**-1.00**
108	Pass	Peak	High	1	1	0	0	0	**-1.50**
109	Pass	Peak	Peak	2	0	0	0	0	**-2.00**
110	Pass	Peak	Pass	1	0	0	0	1	**0.00**
111	Pass	High	Low	0	1	0	1	0	**0.00**
112	Pass	High	Normal	0	1	1	0	0	**-0.50**
113	Pass	High	High	0	2	0	0	0	**-1.00**
114	Pass	High	Peak	1	1	0	0	0	**-1.50**
115	Pass	High	Pass	0	1	0	0	1	**0.50**
116	Pass	Normal	Low	0	0	1	1	0	**0.50**
117	Pass	Normal	Normal	0	0	2	0	0	**0.00**
118	Pass	Normal	High	0	1	1	0	0	**-0.50**
119	Pass	Normal	Peak	1	0	1	0	0	**-1.00**
120	Pass	Normal	Pass	0	0	1	0	1	**1.00**
121	Pass	Low	Low	0	0	0	2	0	**1.00**
122	Pass	Low	Normal	0	0	1	1	0	**0.50**
123	Pass	Low	High	0	1	0	1	0	**0.00**
124	Pass	Low	Peak	1	0	0	1	0	**-0.50**
125	Pass	Low	Pass	0	0	0	1	1	**1.50**

Appendix C
Transformation of Rule Base into Accumulated Service Performance

The following information are the accumulated service performance values which mapped to the rule base.

A. Latency vs Availability

There are two inputs which are Latency and Availability and the output is AccumulatedServicePerformance.

Latency :5

Availability: 85

Observation:

Accumulated Service Performance Values	Observations
2	No combination available
1.5	No combination available
1	Availability =98 and Latency = 1
0.5	Availability = 94 and Latency = 1
0	Availability = 98 and Latency = 2 to 4
-0.5	Availability = 92 and Latency = 6 to 8 Availability = 92 and Latency 2-4
-1	Availability = 84-88 and Latency = 2 to 4
-1.5	Availability = 73-80 and Latency = 2 to 4 Availability = 80-84 and Latency 6-8
-2	Availability = 70 to 78 and Latency = 6 to 9

1. Learning Rate

   a. Learning rate with **[Epsilon 0.5] [Lambda 0.7]**

Alpha	**Latency**	**Availability**	**Accumulated Service Performance**
0.1			
0.2 (10 executions)	0.5 to 4 6-9 6-9 6-9	70-98 70-78 80-90 98	-2 -2 -1 1.5

	0.5 to 4 6-9 6-9	70-98 70-78 80-90	-2 -2 0.5
	0.5 to 4 6-9 0.5 – 4 6-9	70-90 70-90 98 98	-2 -2 1.5 2
	0.5 – 4 6-9 0.5 -4 6-9	70-90 70-78 98 85-95	-2 -2 -0.5 1
	0.5 – 4 6-9 6-9 0.5-4 6-9	70-96 70-78 82-90 98 98	-2 -2 0.5 1.5 1.5
	0.5 – 4 6-9 6-9 6-9	70-96 70-78 80-96 98	-2 -2 -1.5 0.5
	0.5 -4 6-9 6-9 0.5 - 4	70-96 70-78 82-98 98	-2 -2 1.5 1.5
	0.5 – 4 6-9 0.5-4 6-9	70-90 70-78 98 84-96	-2 -2 0 1.5
	0.5 – 4 6-9 0.5 – 4 6-9	70-90 82-90 94 96	-2 -1 -0.5 2

b. Learning rate with **[Epsilon 0.1] [Lambda 0.7]**

Alpha	**Latency**	**Availability**	**Accumulated Service Performance**
0.1			
0.2 (10 executions)	0.5 to 4 6-9 6-9 0.5 to 4	70-96 70-78 80-90 98	-2 -2 2 1
	0.5 to 4 6-9 6-9	70-96 98 70-96	-2 0 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 – 4 6-9 6-9	70-96 70-90 98	-2 -2 0

	0.5 to 4 6-9 6-9	70-96 98 70-96	-2 0 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 -4 6-9 6-9	70-96 70-78 82-94	-2 -2 -0.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 – 4 6-9 6-9	70-96 70-88 94	-2 -2 -0.5
0.3	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9	70-96 70-96 98	-2 -2 1.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
0.4	0.5 to 4 6-9 6-9	70-96 70-96 96	-2 -2 -1.5
	0.5 to 4 6-9 6-9	70-96 70-96 96	-2 -2 0
	0.5 to 4 0.5 to 4 6-9 6-9 6-9	70-96 98 70-96 96 98	-2 0.5 -2 2 0.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-96 94 98	-2 -2 0 0.5
	0.5 to 4	70-96	-2

	0.5 to 4 6-9	96 70-96	1 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9	70-96 70-96 96	-2 -2 0
	0.5 to 4 6-9	70-96 70-96	-2 -2
0.5	0.5 to 4 6-9 6-9 6-9	70-96 70-96 78-88 90-98	-2 -2 -1.5 -2
	0.5 to 4 6-9 6-9	70-96 70-94 96-98	-2 -2 -1.5
	0.5 to 4 6-9 6-9	70-96 70-94 96-98	-2 -2 0.5
	0.5 to 4 0.5 to 4 6-9	70-96 98 70-96	-2 2 -2
	0.5 to 4 0.5 to 4 6-9	70-96 98 70-96	-2 2 -2
	0.5 to 4 6-9 6-9	70-96 98 70-96	-2 2 -2
	0.5 to 4 0.5 to 4 6-9	70-96 92-94 70-96	-2 -1.5 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
0.6	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9	70-96 70-90 92-94	-2 -2 -1.5
	0.5 to 4 6-9 6-9	70-96 70-94 96-98	-2 -2 0
	0.5 to 4 6-9 6-9	70-96 70-90 92-94	-2 -2 -1.5

	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 1
	0.5 to 4 6-9	70-96 70-96	-2 -2
0.7	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92-94 96-98	-2 -2 -1.5 -1
	0.5 to 4 0.5 to 4 6-9	70-90 92-94 70-96	-2 -1.5 -2
	0.5 to 4 6-9 6-9	70-96 70-92 94-96	-2 -2 0.5
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92-94 96	-2 -2 -1.5 1
	0.5 to 4 1 to 4 6-9 6-9 6-9	70-92 94-96 70-90 92 94-96	-2 0.5 -2 0 -2
	0.5 to 4 1 to 4 6-9 6-9	70-92 96 70-96 96	-2 1 -2 0
	0.5 to 4 6-9 6-9	70-96 70-90 92	-2 -2 0.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9	70-96 70-96 82-88	-2 -2 1
0.8	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-90 92-94	-2 -2 -1.5 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-80	-2 -2

	6-9 6-9	82-88 90-96	1 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92-94 96	-2 -2 -1.5 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
0.9	0.5 to 4 6-9 6-9	70-96 70-92 94-96	-2 -2 0.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 1.2 to 4 6-9	70-92 94-96 70-96	-2 0.5 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-90 92-96	-2 -2 -0.5 -2
	0.5 to 4 6-9 6-9	70-96 70-92 94-98	-2 -2 -1.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 94-96	-2 -2 2 -2

c. Learning rate with **[Epsilon 0.2] [Lambda 0.7]**

Alpha	**Latency**	**Availability**	**Accumulated Service Performance**
0.1 (10 executions)	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92-94 96	-2 -2 -1.5 -2

	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9 6-9	70-96 70-80 82-90 92-94 96	-2 -2 -0.5 -2 1.5
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 94-96	-2 -2 0.5 -1.5
	0.5 to 4 0.5 - 4 6-9 6-9 6-9	70-92 94-96 70-90 92 94-96	-2 0.5 -2 0.5 -2
	0.5 to 4 6-9 6-9	70-96 70-92 94-96	-2 -2 0.5
	0.5 to 4 6-9 6-9 6-9 6-9	70-96 70-80 82-88 90 94	-2 -2 2 -2 1
0.2	0.5 to 4 6-9 6-9	70-96 70-80 82-90	-2 -2 1
	0.5 to 4 6-9 6-9 6-9	70-80 70-80 82-90 92-96	-2 -2 -1 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 – 4 0.5 – 4 0.5-4 6-9	70-90 92 94-96 70-96	-2 0.5 -2 -2
	0.5 to 4 0.5 - 4 6-9	70-96 92-94 70-96	-2 -1.5 -2
	0.5 to 4 0.5 - 4 6-9 6-9	70-94 96-98 70-90 92-98	-2 -1.5 -2 -1.5
	0.5 -4 6-9	70-96 70-96	-2 -2
	0.5 to 4 1.2 – 4 1.2 - 4 6-9 6-9	70-90 92 94-96 70-90 92-94	-2 1 0.5 -2 -1.5

	6-9	96-98	-2
	0.5 – 4 6-9	70-96 70-96	-2 -2
0.3	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 90-96	-2 -2 1 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 0.5 - 4 6-9 6-9 6-9	70-92 96-98 70-90 92-94 96-98	-2 -1.5 -2 0 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 92	-2 -2 1.5 1
	0.5 to 4 6-9 6-9	70-96 70-90 94	-2 -2 1
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 96	-2 -2 2 -1
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 96	-2 -2 0 -2
	0.5 to 4 1.2 to 4 6-9 6-9	70-90 92 70-94 96	-2 1 -2 -1
	0.5 to 4 6-9	70-96 70-96	-2 -2
0.4	0.5 to 4 0.5 – 4 0.5 - 4 6-9	70-90 92-94 96-98 70-96	-2 -1.5 -2 -2
	0.5 to 4 1.21 - 4 6-9 6-9 6-9	70-96 92 70-80 82-88 92-96	-2 0.5 -2 1.5 -1.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 1.21 - 4 6-9 6-9 6-9	70-94 96 70-80 82-90 92	-2 1 -2 -1 2

	6-9	94-96	-2
	0.5 to 4 0.5 - 4 6-9	70-96 92-94 70-96	-2 -1.5 -2
	0.5 to 4 0.5 to 4 6-9	70-94 96 70-96	-2 0 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9 6-9	70-96 70-80 82-90 92 94-96	-2 -2 -0.5 0 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 94-96	-2 -2 0 -2
0.5	0.5 to 4 0.5 - 4 6-9	70-94 96 70-96	-2 -1.5 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 96	-2 -2 1.5 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 1.21 – 4 1.21 - 4 6-9 6-9 6-9	70-90 92 96 70-90 92 96	-2 0.5 2 -2 1.5 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9	70-96 70-90 92-94	-2 -2 -1.5
0.6	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 1
	0.5 to 4 0.5 - 4 6-9	70-90 92-94 70-94	-2 -1.5 -2

	6-9	96	-1.5
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 2 – 4 0.5 -4 6-9	70-90 92 96 70-96	-2 1 -2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 96	-2 -2 0 -2
	0.5 to 4 2 – 4 0.5 - 4 6-9 6-9	70-90 92 96 70-96 96	-2 1 -2 -2 0
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 96	-2 -2 1 -2
	0.5 to 4 0.5 - 4 6-9 6-9 6-9	70-94 96 70-90 92-94 96	-2 -1.5 -2 -1.5 -2
	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 -1.5
0.7	0.5 to 4 6-9 6-9	70-96 70-92 96	-2 -2 1
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 96	-2 -2 0 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 92-96	-2 -2 0.5 -2
	0.5 to 4 1.21-4 0.5 - 4 6-9 6-9 6-9	70-96 92 96 70-80 82-90 92-96	-2 0.5 -2 -2 -1 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 92-96	-2 -2 0 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2

	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 92	-2 -2 0.5 1
0.7	0.5 to 4 6-9 6-9	70-96 70-92 96	-2 -2 1
	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 94-96	-2 -2 1.5 0.5
	0.5 to 4 0.5 – 4 0.5 -4 6-9 6-9	70-90 92 96 70-94 96	-2 0 1.5 -2 2
	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 -1.5
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 90-96	-2 -2 1 -2
	0.5 to 4 1.21 -4 1.21-4 6-9 6-9	70-90 92 96 70-90 92-94	-2 0.5 -2 -2 -1.5
	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 -1.5
	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 0
	0.5 to 4 1.21 - 4 6-9	70-94 96 70-96	-2 0 -2
0.9	0.5 to 4 1.21 - 4 6-9 6-9 6-9	70-94 96 70-80 82-88 92-96	-2 -0.5 -2 1.5 -2
	0.5 to 4 0.5 -4 6-9 6-9 6-9	70-94 96 70-80 82-90 92-94	-2 0 -2 -1 -1.5

	6-9	96	-2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 -1.5
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 92-94	-2 -2 1.5 0.5
	0.5 to 4 0.5 - 4 6-9	70-96 92-94 70-96	-2 -1.5 -2
	0.5 to 4 1.21 - 4 6-9 6-9	70-94 96 70-94 96	-2 -1.5 -2 -1
1.0	0.5 to 4 1.21 – 4 0.5-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-90 92 96	-2 1 -2 -2 -0.5 -1.5 -2
	0.5 to 4 6-9	70-96 70-96	-2 -2
	0.5 to 4 6-9 6-9 6-9	70-96 70-96 92 96	-2 -2 0.5 -2
	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 -1.5
	0.5 to 4 6-9 6-9	70-96 70-90 94	-2 -2 1
	0.5 to 4 6-9 6-9	70-96 70-92 94-96	-2 -2 0.5
	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 92-94	-2 -2 1 -2
	0.5 to 4 6-9	70-96 70-80	-2 -2
	6-9	82-88	1.5

	6-9	92-96	-2
	0.5 to 4 6-9	70-96 70-96	-2 -2

d. Learning rate with **[Epsilon 0.3] [Lambda 0.7]**

Alpha	Latency	Availability	Accumulated Service Performance
0.1	0.5 to 4 0.5 -4 0.5 -4 6-9	70-90 92 96 70-96	-2 -0.5 1.5 -2
0.2	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-88 92-96	-2 -2 2 -2
0.3	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-90 92-96	-2 -2 -1 -2
0.4	0.5 to 4 6-9	70-96 70-96	-2 -2
0.5	0.5 to 4 6-9 6-9 6-9	70-96 70-80 82-90 92-96	-2 -2 -1 -2
0.6	0.5 to 4 0.5-4 6-9	70-94 96 70-96	-2 0 -2
0.7	0.5 to 4 6-9 6-9	70-96 70-92 96	-2 -2 2
0.8	0.5 to 4 0.5-3.5 3.5 - 4 6-9 6-9 6-9	70-90 92 92 70-90 92 96	-2 0 0.5 -2 0.5 -1.5
0.9	0.5 to 4 1.21-4 0.5-4 6-9 6-9	70-90 92 96 70-94 96	-2 0.5 -2 -2 -1.5
1.0	0.5 to 4 6-9 6-9	70-96 70-90 92-94	-2 -2 -1.5

e. Learning rate with **[Epsilon 0.4] [Lambda 0.7]**

Alpha	Latency	Availability	Accumulated Service Performance
0.1	0.5 to 4 6-9 6-9	70-90 70-94 96	-2 -2 0
0.2	0.5 to 4 1.21 - 4 6-9 6-9 6-9	70-96 96 70-90 92 96	-2 1 -2 1 -1.5
0.3	0.5 to 4 0.5-4 6-9 6-9	70-90 92 70-92 96	-2 -0.5 -2 1.5
0.4	0.5 to 4 2 -4 6-9 6-9	70-90 92 70-90 92	-2 2 -2 2
0.5	0.5 to 4 6-9 6-9 6-9	70-96 70-90 92 96	-2 -2 1 -2
0.6	0.5 to 4 0.5-4 6-9 6-9	70-90 92 70-94 96	-2 1.5 -2 -0.5
0.7	0.5 to 4 0.5-4 0.5-4 6-9 6-9	70-96 92 96 70-92 96	-2 0 -2 -2 2
0.8	0.5 to 4 0.5-3.5 3.5 - 4 6-9 6-9 6-9	70-90 92 92 70-90 92 96	-2 0 0.5 -2 0.5 -1.5
0.9	0.5 to 4 0.5-4 0.5-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-90 92 96	-2 0 -2 -2 0.5 1 -2
1.0	0.5 to 4 2-4	70-96 92	-2 1

	6-9	70-96	-2

a. Learning rate with **[Epsilon 0.5] [Lambda 0.7]**

Alpha	Latency	Availability	Accumulated Service Performance
0.1	0.5 to 4 2-4 0.5-4 6-9 6-9 6-9	70-90 92 96 70-90 92 96	-2 2 -2 -2 1.5 -2
0.2	0.5 to 4 0.5-4 6-9 6-9 6-9 6-9	70-94 96 70-80 82-88 90 96	-2 0 -2 1.5 -2 1
0.3	0.5 to 4 0.5-4 6-9 6-9	70-94 96 70-92 96-98	-2 0 -2 0.5
0.4	0.5 to 4 6-9 6-9	70-96 70-94 96	-2 -2 -1.5
0.5	0.5 to 4 0.5-4 6-9 6-9 6-9	70-94 96 70-80 82-88 96	-2 0 -2 -0.5 1.5
0.6	0.5 to 4 2-4 6-9 6-9 6-9 6-9	70-90 92 70-80 82-88 92 96	-2 1 -2 0.5 1 2
0.7	0.5 to 4 0.5-4 6-9 6-9 6-9 6-9	70-94 96 70-80 82-88 92 96	-2 -1.5 -2 1.5 -1.5 1
0.8	0.5 to 4 1.21 - 4 6-9 6-9 6-9	70-90 92-96 70-90 92 96	-2 2 -2 2 -2
0.9	0.5 to 4 0.5-4	70-90 92	-2 1

	0.5-4 6-9 6-9 6-9	96 70-90 92 96	-2 -2 0 -2
1.0	0.5 to 4 1.21-4 6-9 6-9 6-9	70-94 96 70-90 92 96	-2 0 -2 1.5 2

b. Learning rate with **[Epsilon 0.6] [Lambda 0.7]**

Alpha	Latency	Availability	Accumulated Service Performance
0.1	0.5 to 4 6-9 6-9	70-96 70-92 94	-2 -2 1
0.2	0.5 to 4 1.21 - 4 6-9 6-9 6-9	70-92 94-96 70-90 92 96	-2 0.5 -2 0 -2
0.3	0.5 to 4 0.5-4 6-9 6-9	70-90 92-96 70-80 82-96	-2 0 -2 2
0.4	0.5 to 4 2 -4 6-9 6-9 6-9 6-9	70-90 92 70-80 82-88 92-94 96	-2 1 -2 0 -1 -1.5
0.5	0.5 to 4 1.21-4 6-9 6-9 6-9	70-94 96-98 70-90 92 96	-2 0.5 -2 2 -1.5
0.6	0.5 to 4 0.5-4 6-9 6-9	70-90 92 70-94 96	-2 1.5 -2 0
0.7	0.5 to 4 0.5-4 6-9 6-9 6-9	70-94 96 70-90 92 96	-2 0 -2 0.5 0
0.8	0.5 to 4 1.21 - 4 6-9 6-9	70-94 96 70-80 82-88	-2 -0.5 -2 -1

	6-9 6-9	92 96	1.5 2
0.9	0.5 to 4 0.5-4 6-9 6-9 6-9	70-94 96-98 70-80 82-88 92-96	-2 0.5 -2 1.5 1
1.0	0.5 to 4 1.21-4 6-9 6-9 6-9 6-9	70-94 96 70-80 82-90 92 96	-2 -1.5 -2 -1.5 -1 1.5

c. Learning rate with **[Epsilon 0.7] [Lambda 0.7]**

Alpha	**Latency**	**Availability**	**Accumulated Service Performance**
0.1	0.5 to 4 2-4 0.5-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 1 -2 -2 1 1.5 2
0.2	0.5 to 4 2- 4 0.5-4 6-9 6-9 6-9	70-90 92 96 70-90 92-94 96-98	-2 1.5 -2 -2 -1 0.5
0.3	0.5 to 4 0.5-4 0.5-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 -0.5 -2 -2 2 0.5 2
0.4	0.5 to 4 0.5-4 0.5-4 6-9 6-9 6-9	70-90 92 96 70-90 92-94 96	-2 0 -1 -2 -1.5 -1
0.5	0.5 to 4 2-4 0.5-4 6-9 6-9	70-90 92 96 70-94 96	-2 1 -2 -2 -1

0.6	0.5 to 4 0.5-4 6-9 6-9 6-9 6-9	70-94 96 70-80 82-88 92-94 96	-2 -1 -2 0 -2 -1.5
0.7	0.5 to 4 0.5-4 0.5-4 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92-96	-2 1 -1 -2 0 -2
0.8	0.5 to 4 2-4 0.5-4 6-9 6-9 6-9	70-90 92 96 70-90 92 96	-2 1 -2 -2 0 -2
0.9	0.5 to 4 0.5-4 0.5-4 6-9 6-9 6-9 6-9	70-90 92-94 96 70-80 82-88 92 96	-2 -1.5 -2 -2 -0.5 1 -0.5
1.0	0.5 to 4 0.5-4 1.21-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 0 -0.5 -2 -1 1 -2

d. Learning rate with **[Epsilon 0.8] [Lambda 0.7]**

Alpha	**Latency**	**Availability**	**Accumulated Service Performance**
0.1	0.5 to 4 1.21-4 1.21-4 6-9 6-9 6-9	70-90 92 96 70-80 82-88 94	-2 1 -1 -2 0 2
0.2	0.5 to 4 1.21 - 4 6-9 6-9 6-9	70-96 96 70-90 92 96-98	-2 1 -2 -0.5 0.5
0.3	0.5 to 4 1.21-4	70-90 92-98	-2 0.5

	6-9	70-80	-2
	6-9	82-88	-0.5
	6-9	92	2
	6-9	96	-1
0.4	0.5 to 4	70-90	-2
	1.21 - 4	92	1
	1.21-4	96	0
	6-9	70-80	-2
	6-9	82-88	1
	6-9	96	-1
0.5	0.5 to 4	70-96	-2
	1.21-4	92-96	-1.5
	6-9	70-80	-2
	6-9	82-88	0
	6-9	92-94	-1
	6-9	96	-2
0.6	0.5 to 4	70-90	-2
	1.21-4	92	1
	1.21-4	96	0
	6-9	70-80	-2
	6-9	82-92	1
	6-9	96	2
0.7	0.5 to 4	70-90	-2
	1.21-4	92-96	1.5
	6-9	70-80	-2
	6-9	82-88	1.5
	6-9	92-96	-0.5
0.8	0.5 to 4	70-90	-2
	0.5-4	92-94	-0.5
	0.5- 4	96	-2
	6-9	70-80	-2
	6-9	82-90	-1
	6-9	92-94	-0.5
	6-9	96	0
0.9	0.5 to 4	70-90	-2
	6-9	70-80	-2
	6-9	82-90	1
	6-9	92-96	-2
1.0	0.5 to 4	70-90	-2
	1.21-4	92	-1.5
	1.21-4	96	1.5
	6-9	70-80	-2
	6-9	82-88	-1
	6-9	92-96	1

e. Learning rate with **[Epsilon 0.9] [Lambda 0.7]**

Alpha	**Latency**	**Availability**	**Accumulated Service Performance**

0.1	0.5 to 4	70-90	-2
	1.21-4	92	0.5
	1.21-4	96	1.5
	6-9	70-80	-2
	6-9	82-88	1.5
	6-9	92	-1
	6-9	96	2
0.2	0.5 to 4	70-90	-2
	0.5 – 4	92-94	-1
	0.5-4	96	-2
	6-9	70-80	-2
	6-9	82-88	0
	6-9	92	2
	6-9	96	-1.5
0.3	0.5 to 4	70-94	-2
	0.5-4	96	0
	6-9	70-94	-2
	6-9	92	0.5
	6-9	96	-1
0.4	0.5 to 4	70-90	-2
	1.21 -4	92	1
	6-9	70-80	-2
	6-9	82-88	0
	6-9	90-96	-1
0.5	0.5 to 4	70-90	-2
	0.5-4	92	1.5
	0.5-4	94-96	0.5
	6-9	70-80	-2
	6-9	82-88	-1
	6-9	92-96	-1.5
0.6	0.5 to 4	70-90	-2
	1.21-4	92	0.5
	0.5-4	96	-2
	6-9	70-80	-2
	6-9	82-96	0
0.7	0.5 to 4	70-96	-2
	0.5-4	96	0
	6-9	70-80	-2
	6-9	82-90	-1
	6-9	92-94	-2
	6-9	96	-0.5
0.8	0.5 to 4	70-90	-2
	1.21-3.5	92	0
	3.5 – 4	92	0.5
	1.21-4	96	-1
	6-9	70-80	-2
	6-9	82-88	2
	6-9	92	1.5
	6-9	96	-2
0.9	0.5 to 4	70-90	-2
	1.21-4	92	1

	1.21-4 6-9 6-9 6-9	94-96 70-90 92 96	-1 -2 0 2
1.0	0.5 to 4 2-4 6-9	70-96 92 70-96	-2 1 -2

a. Learning rate with **[Epsilon 1.0] [Lambda 0.7]**

Alpha	Latency	Availability	Accumulated Service Performance
0.1	0.5 to 4 1.21-4 1.21-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 0 2 -2 2 1 -2
0.2	0.5 to 4 0.5 – 4 0.5-4 6-9 6-9 6-9 6-9	70-90 92-94 96 70-80 82-88 92 96	-2 -1.5 -2 -2 -1 -2 1
0.3	0.5 to 4 0.5-4 6-9 6-9 6-9	70-94 96 70-90 92 96	-2 -0.5 -2 0.5 -1
0.4	0.5 to 4 1.21 -4 1.21-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 1 0 -2 0 1 1.5
0.5	0.5 to 4 0.5-4 0.5-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 -1.5 0 -2 2 1 2
0.6	0.5 to 4 1.21-4 6-9 6-9 6-9	70-90 92-96 70-80 82-88 92	-2 0 -2 -1 0.5

	6-9	96	0
0.7	0.5 to 4 1.21-4 1.21-4 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92-96	-2 -1 -0.5 -2 -1.5 1.5
0.8	0.5 to 4 0.5-4 0.5 – 4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 -0.5 -2 -2 1 2 -1.5
0.9	0.5 to 4 1.21-4 1.21-4 6-9 6-9 6-9 6-9	70-90 92 94-96 70-80 82-88 92 96	-2 1 0.5 -2 1 -0.5 1
1.0	0.5 to 4 1.21-4 1.21-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92 96	-2 -1.5 -0.5 -2 -1.5 1.5 -1.5

1. Discount Factor

   a. Learning rate with **[Epsilon 1.0] [Alpha 0.1]**

Lambda	**Latency**	**Availability**	**Accumulated Service Performance**
0.1	0.5 to 4 1.21-4 6-9 6-9 6-9 6-9	70-90 92-96 70-80 82-88 92 96	-2 0 -2 1 1.5 -1
0.2	0.5 to 4 1.21-4 6-9 6-9 6-9	70-90 92 70-80 82-92 96	-2 -1.5 -2 2 1.5
0.3	0.5 to 4 1.21-4	70-90 92	-2 -1.5

	1.21-4	96	1.5
	6-9	70-90	-2
	6-9	92	0.5
	6-9	96	-2
0.4	0.5 to 4	70-90	-2
	1.21-4	92	-0.5
	1.21-4	96-98	0.5
	6-9	70-80	-2
	6-9	82-88	0.5
	6-9	92	-0.5
	6-9	96	1.5
0.5	0.5 to 4	70-90	-2
	1.21-4	92	2
	1.21-4	96-98	0.5
	6-9	70-80	-2
	6-9	82-88	2
	6-9	92	-0.5
	6-9	96	2
0.6	0.5 to 4	70-90	-2
	1.21-4	92	0.5
	2.21-4	96	2
	6-9	70-90	-2
	6-9	92	0
	6-9	96	-2
0.7	0.5 to 4	70-90	-2
	1.21-4	92-96	1.5
	6-9	70-80	-2
	6-9	82-88	-0.5
	6-9	92-96	-1.5
0.8	0.5 to 4	70-90	-2
	1.21-4	92	-1.5
	1.21-4	96	0
	6-9	70-80	-2
	6-9	82-88	1.5
	6-9	92	-0.5
	6-9	96	1.5
0.9	0.5 to 4	70-90	-2
	1.21-4	92-96	-1
	6-9	70-90	-2
	6-9	92-96	0
1.0	0.5 to 4	70-90	-2
	1.21-4	92	1
	1.21-4	96-98	0.5
	6-9	70-80	-2
	6-9	82-88	2
	6-9	92-94	0.5
	6-9	96	-1

a. Learning rate with **[Epsilon 0.5] [Alpha 0.5]**

Lambda	Latency	Availability	Accumulated Service Performance
0.5	0.5 to 4 6-9 6-9 6-9 6-9	70-96 70-80 82-88 92-94 96	-2 -2 2 0.5 -2

a. Learning rate with **[Epsilon 0.6] [Alpha 0.6]**

Lambda	Latency	Availability	Accumulated Service Performance
0.6	0.5 to 4 1.21-4 1.21-4 6-9 6-9 6-9 6-9	70-90 92 96 70-80 82-88 92-94 96	-2 1 0 -2 2 0.5 1

a. Learning rate with **[Epsilon 0.7] [Alpha 0.7]**

Lambda	Latency	Availability	Accumulated Service Performance
0.7	0.5 to 4 0.5-4 0.5-4 6-9 6-9 6-9 6-9	70-90 92-94 96 70-80 82-88 92 96-98	-2 -1 -2 -2 0 -0.5 0.5

a. Learning rate with **[Epsilon 0.8] [Alpha 0.8]**

Lambda	Latency	Availability	Accumulated Service Performance
0.8	0.5 to 4 1.21-4 6-9 6-9 6-9 6-9	70-92 96 70-80 82-88 92 96	-2 2 -2 -1 1 -2

a. Learning rate with **[Epsilon 0.9] [Alpha 0.9]**

Lambda	Latency	Availability	Accumulated Service Performance

0.9	0.5 to 4 1.21-4 6-9 6-9 6-9 6-9	70-90 92-96 70-80 82-88 92 96	-2 0 -2 0.5 0 -1.5

a. Learning rate with **[Epsilon 1.0] [Alpha 1.0]**

Lambda	Latency	Availability	Accumulated Service Performance
1.0	0.5 to 4 1.21-4 6-9 6-9 6-9 6-9	70-90 92-96 70-80 82-88 92 96	-2 -1.5 -2 0.5 -2 -1.5

B. Latency vs Packet Loss

At this stage, the adaptation process is identical to any numbers of alpha , lambda and epsilon.

Learning Rate (Alpha)	Latency	Packet Loss	Accumulated Service Performance
1.0	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
0.2	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
0.3	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
0.4	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5

0.5	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
0.6	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
0.7	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
0.8	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
0.9	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5
1.0	0.5-4 0.5-4 0.5-4 6-9 6-9 6-9	8-90 95 100 8-90 95 100	-2 -1 0.5 -2 -1 0.5

C. Packet Loss vs Availability

At this stage, the adaptation process is identical to any numbers of alpha , lambda and epsilon.

Learning Rate (Alpha)	Availability	Packet Loss	Accumulated Service Performance
1.0	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
0.2	70-96 97	8-92 8-92	-2 -1

	100	8-92	0.5
0.3	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
0.4	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
0.5	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
0.6	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
0.7	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
0.8	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
0.9	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5
1.0	70-96 97 100	8-92 8-92 8-92	-2 -1 0.5

Appendix D

Data Files.

The following is the excerpt of data files. The full version available at https://www.ofcom.org.uk/__data/assets/excel_doc/0026/106568/UK-home-broadband-performance,-May-2017-panellist-data-without-weights.xlsx

unit_id	Ofcom Product	Type	Region	Country	Urban-Rural indicator	Distance Bands	Technology	Market Class - Geographic	JitterUp24hr	Latency24hr	PacketLoss24hr	Disconnections
814755	Sky 38	FTTC 38	London	England	Urban	0 to 250m	FTTC	3	0.23	6.71	0.00%	0.00
940494	BT 52	FTTC 52	Scotland	Scotland	Rural	0 to 250m	FTTC	1	0.21	18.18	0.03%	0.10
30458	Virgin 200	Cable 200	East Midlands	England	Semi-urban	0 to 250m	Cable	3	2.31	22.35	0.04%	0.06
2518	BT 20	ADSL 20	South West	England	Semi-urban	0 to 250m	ADSL	1	0.60	31.27	0.02%	0.10
948788	Plusnet 76*20	FTTC 76	Northern Ireland	Northern Ireland	Semi-urban	0 to 250m	FTTC	1	0.26	19.37	0.02%	0.06

821239	BT20	ADSL20	North East	England	Urban	0 to 250m	ADSL	3	0.67	22.89	0.03%	0.13
814827	BT20	ADSL20	Yorkshire & Humberside	England	Semi-urban	0 to 250m	ADSL	3	0.55	22.27	0.03%	0.13
202366	Virgin50	Cable50	West Midlands	England	Urban	0 to 250m	Cable	3	2.39	16.13	0.00%	0.00
812500	BT76	FTTC76	North West	England	Urban	0 to 250m	FTTC	3	0.24	11.97	0.27%	0.84
2374	BT52	FTTC52	Yorkshire & Humberside	England	Rural	0 to 250m	FTTC	1	0.26	12.95	0.02%	0.06
814801	Sky76	FTTC76	North West	England	Urban	0 to 250m	FTTC	3	0.25	9.51	0.05%	0.13
814851	BT52	FTTC52	London	England	Urban	0 to 250m	FTTC	3	0.35	5.79	0.01%	0.06
947164	BT20	ADSL20	Scotland	Scotland	Rural	0 to 250m	ADSL	1	0.93	44.79	0.01%	0.06
813457	Plusnet38 * 2	FTTC38	East	England	Rural	0 to 250m	FTTC	1	0.46	8.54	0.13%	0.96
821279	BT20	ADSL	Yorkshire & Hum	England	Urban	0 to 250m	ADSL	3	0.40	14.10	0.02%	0.06

		20	bersi de									
657826	Plusnet 20	ADSL20	South East	England	Semi-urban	0 to 250m	ADSL	1	0.45	18.19	0.06%	0.19
30607	Plusnet 55*10	FTTC52	South West	England	Rural	0 to 250m	FTTC	2	0.35	11.82	0.00%	0.00
660114	BT52	FTTC52	West Midlands	England	Semi-urban	0 to 250m	FTTC	1	0.32	11.90	0.01%	0.06
815611	EE76	FTTC76	North West	England	Urban	0 to 250m	FTTC	3	0.38	15.05	0.06%	0.13
821167	BT20	ADSL20	London	England	Urban	0 to 250m	ADSL	3	0.81	15.37	0.03%	0.19
48572	BT52	FTTC55	South West	England	Rural	0 to 250m	FTTC	1	0.37	9.69	0.01%	0.03
813109	BT52	FTTC52	East Midlands	England	Semi-urban	0 to 250m	FTTC	3	0.32	10.18	0.12%	0.32
942738	Sky20	ADSL20	West Midlands	England	Urban	0 to 250m	ADSL	1	0.70	21.82	0.06%	0.55
815565	Plusnet 76*20	FTTC76	North East	England	Rural	0 to 250m	FTTC	1	0.22	13.11	0.13%	0.61
948496	Plusnet	FTTC	Scotland	Scotland	Semi-	0 to	FTTC	2	0.71	19.81	0.02%	0.00

	38 * 2	38			urban	250m						
826777	EE76	FTTC76	Wales	Wales	Semi-urban	0 to 250m	FTTC	3	0.40	13.28	0.77%	0.06
947976	Plusnet20	ADSL20	Wales	Wales	Semi-urban	0 to 250m	ADSL	1	0.66	18.77	1.93%	0.06
1687	Plusnet76 * 20	FTTC76	West Midlands	England	Rural	0 to 250m	FTTC	1	0.39	15.84	0.10%	0.35
303400	Virgin200	Cable200	Scotland	Scotland	Semi-urban	0 to 250m	Cable	3	1.72	19.53	1.59%	11.87
34478	Virgin200	Cable200	South West	England	Semi-urban	0 to 250m	Cable	3	1.33	15.48	0.03%	0.16
846977	BT20	ADSL20	Yorkshire & Humberside	England	Urban	0 to 250m	ADSL	3	0.92	10.95	0.07%	0.06
812720	BT52	FTTC52	Northern Ireland	Northern Ireland	Urban	0 to 250m	FTTC	3	0.32	18.46	0.00%	0.00
947956	BT20	ADSL20	Scotland	Scotland	Rural	0 to 250m	ADSL	1	0.47	22.19	0.02%	0.06
663424	Othe	FTTC	Scotland	Scotland	Rural	0 to	FTTC	1	0.41	40.21	0.05%	0.13

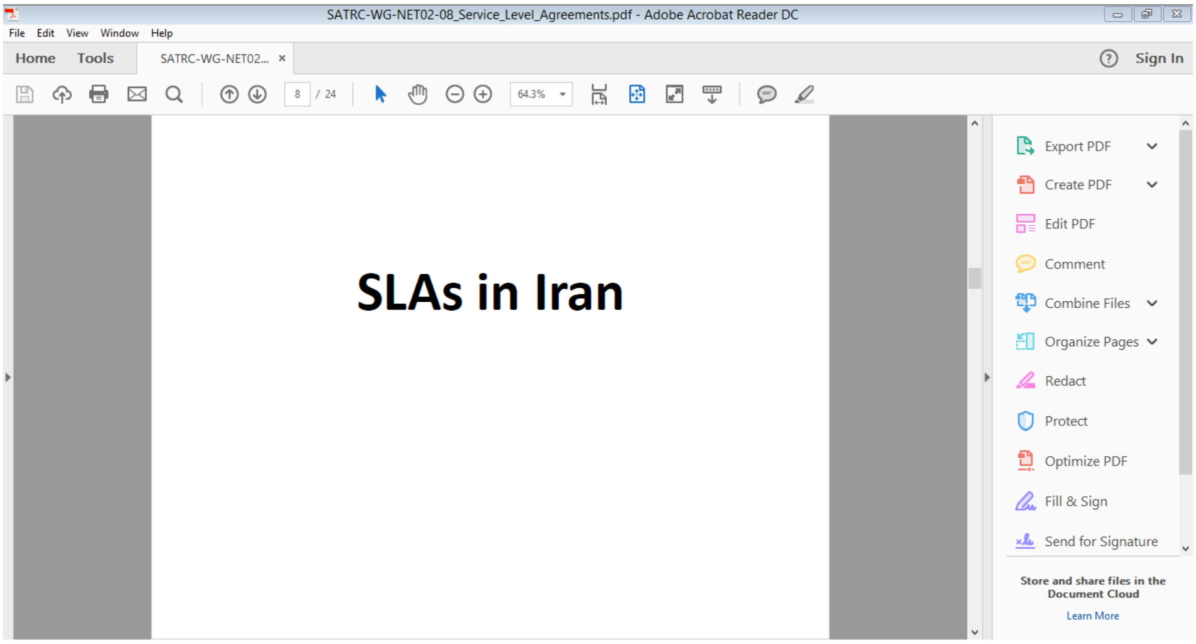
	r38	38				250m						
815103	Virgin200	Cable200	East	England	Urban	0 to 250m	Cable	3	1.78	12.22	0.01%	0.03
943184	Sky20	ADSL20	East	England	Rural	0 to 250m	ADSL	1	0.97	14.75	0.03%	0.77
947754	EE20	ADSL20	South East	England	Semi-urban	0 to 250m	ADSL	3	1.08	21.52	0.05%	0.10
26089	Sky38	FTTC38	South East	England	Semi-urban	0 to 250m	FTTC	3	0.28	7.07	0.02%	0.23
563374	Other76	FTTC76	West Midlands	England	Urban	0 to 250m	FTTC	3	0.19	12.42	0.04%	0.03
815329	EE76	FTTC76	Yorkshire & Humberside	England	Semi-urban	0 to 250m	FTTC	2	0.48	12.84	0.03%	0.00
34029	EE76	FTTC76	Wales	Wales	Semi-urban	0 to 250m	FTTC	3	0.47	17.35	0.36%	2.13
947892	KCOM75	OtherFTTC	Yorkshire & Humberside	England	Rural	0 to 250m	FTTC	4	0.30	10.62	0.01%	0.00
939786	BT52	FTTC52	Wales	Wales	Semi-urban	0 to 250m	FTTC	2	0.21	10.67	0.02%	0.08

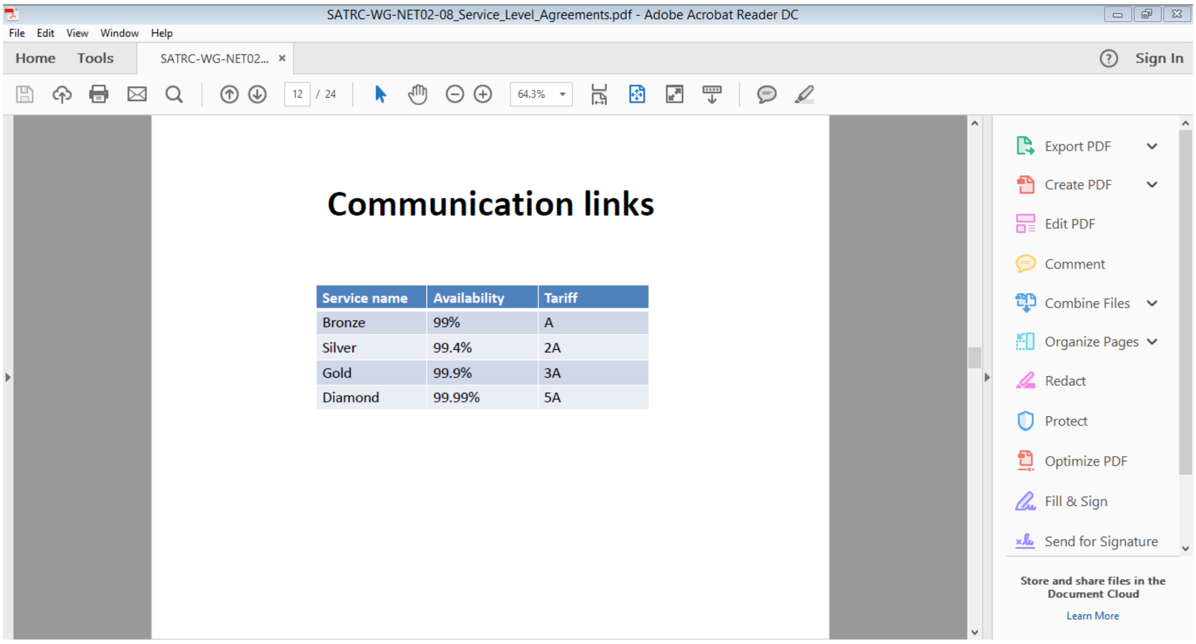
939764	BT8	ADSL8	East	England	Rural	0 to 250m	ADSL	1	1.17	18.64	0.11%	0.48
947664	Sky20	ADSL20	Scotland	Scotland	Rural	0 to 250m	ADSL	1	0.56	22.44	0.05%	0.61
830609	KCOM50	Other FTTC	Yorkshire & Humberside	England	Semi-urban	0 to 250m	FTTC	4	0.17	7.24	0.01%	0.13

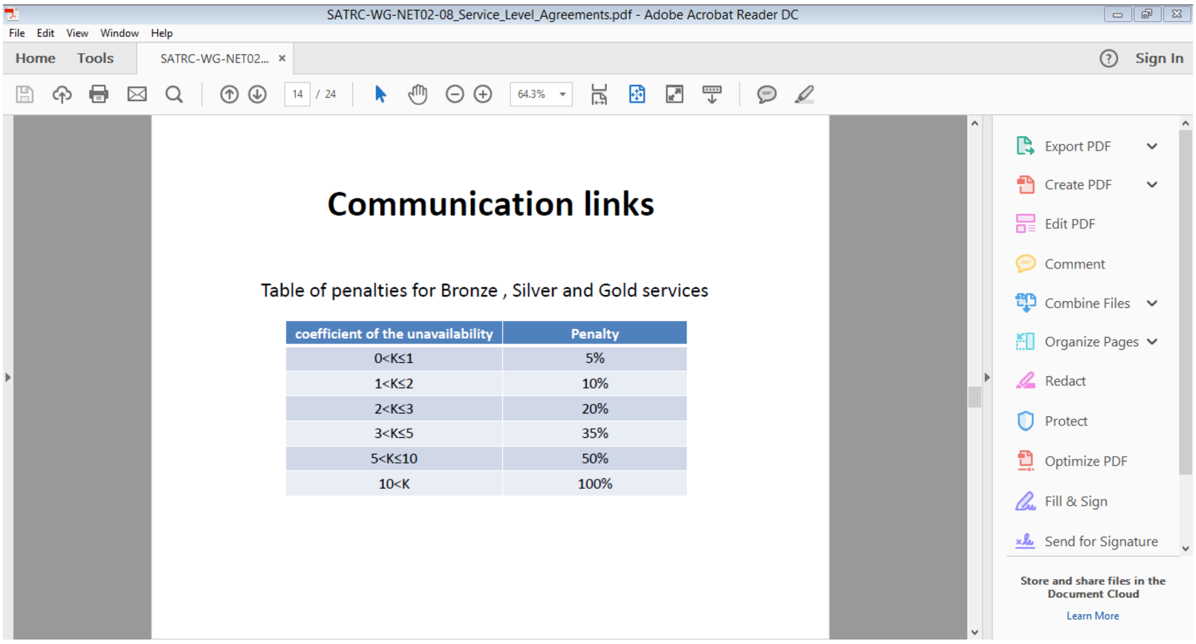
Appendix E

SLA for ISP

In the case study publicly available at [139] , the following figures are the extraction of the information and the full version at the designated reference.



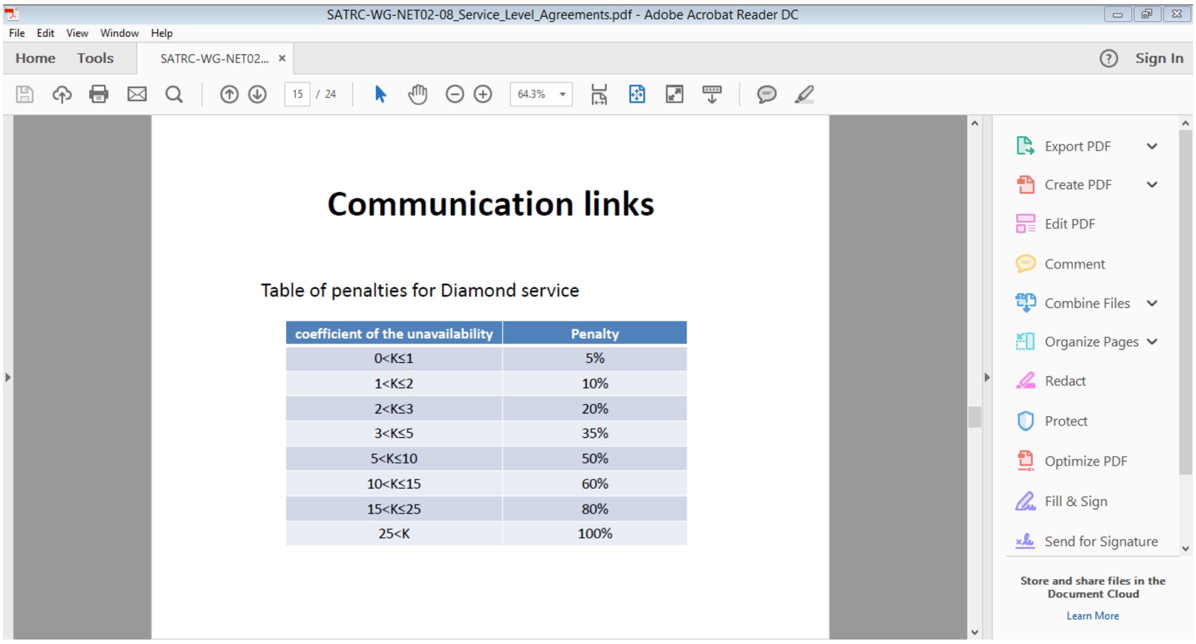




Communication links

Table of penalties for Bronze , Silver and Gold services

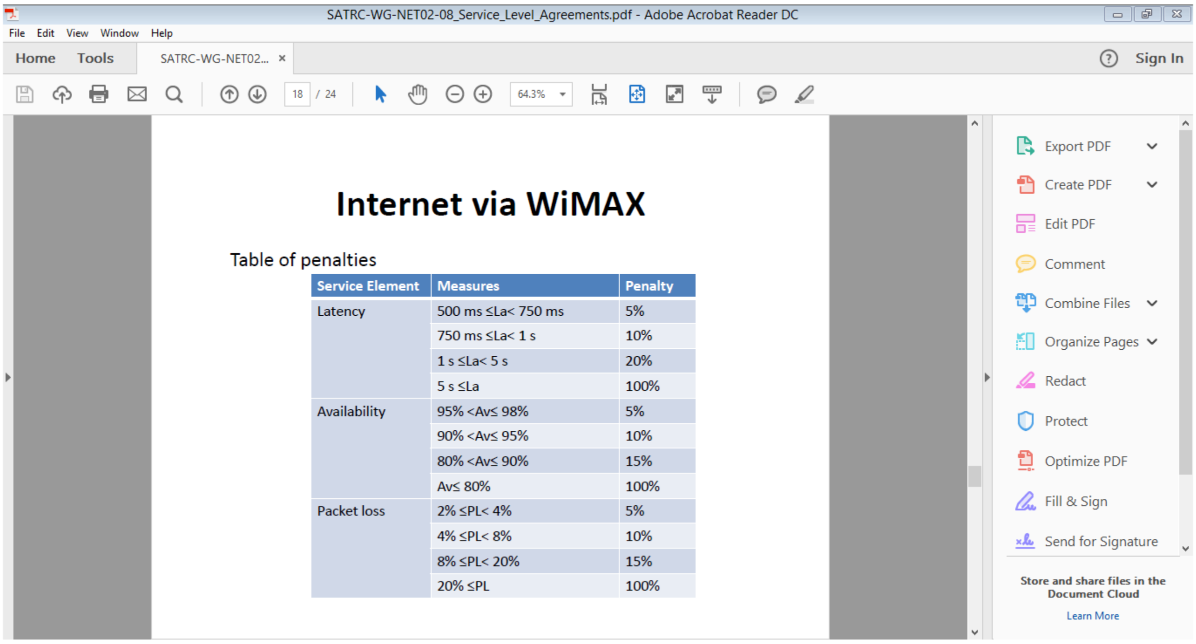
coefficient of the unavailability	Penalty
0<K≤1	5%
1<K≤2	10%
2<K≤3	20%
3<K≤5	35%
5<K≤10	50%
10<K	100%



Communication links

Table of penalties for Diamond service

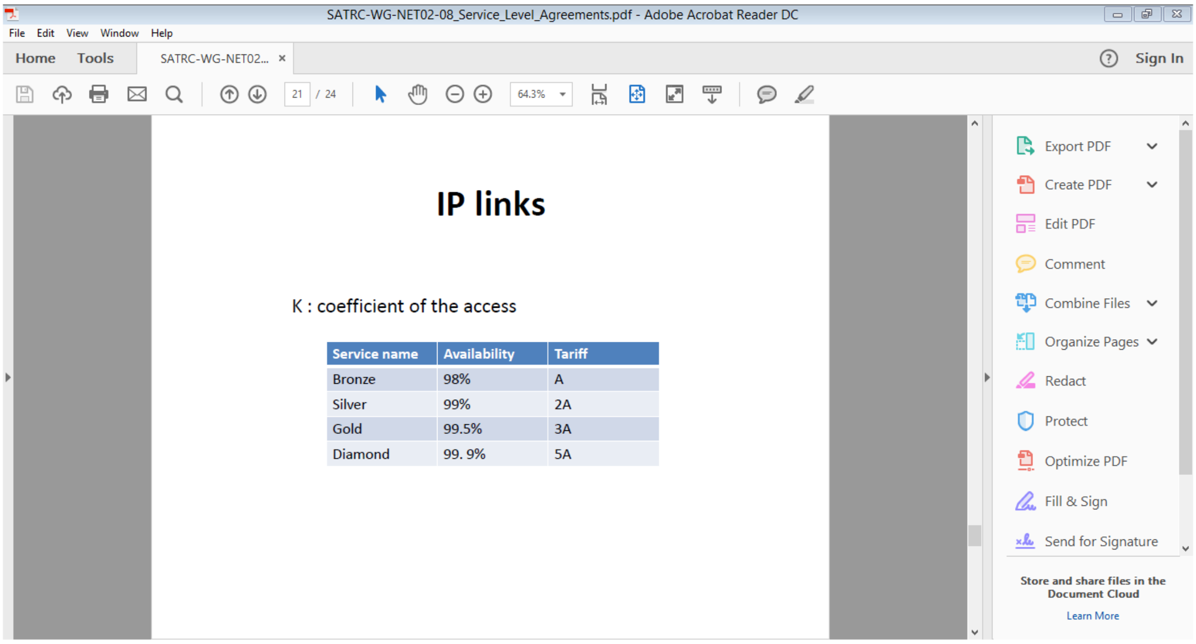
coefficient of the unavailability	Penalty
0<K≤1	5%
1<K≤2	10%
2<K≤3	20%
3<K≤5	35%
5<K≤10	50%
10<K≤15	60%
15<K≤25	80%
25<K	100%



Internet via WiMAX

Table of penalties

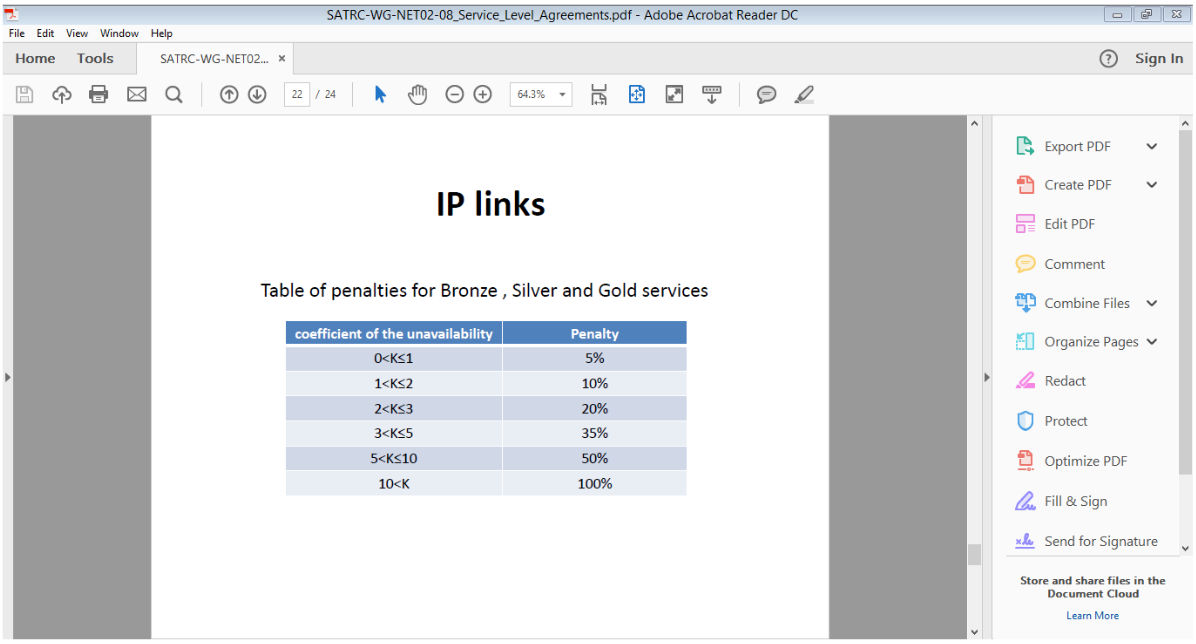
Service Element	Measures	Penalty
Latency	500 ms ≤La< 750 ms	5%
	750 ms ≤La< 1 s	10%
	1 s ≤La< 5 s	20%
	5 s ≤La	100%
Availability	95% <Av≤ 98%	5%
	90% <Av≤ 95%	10%
	80% <Av≤ 90%	15%
	Av≤ 80%	100%
Packet loss	2% ≤PL< 4%	5%
	4% ≤PL< 8%	10%
	8% ≤PL< 20%	15%
	20% ≤PL	100%



IP links

K : coefficient of the access

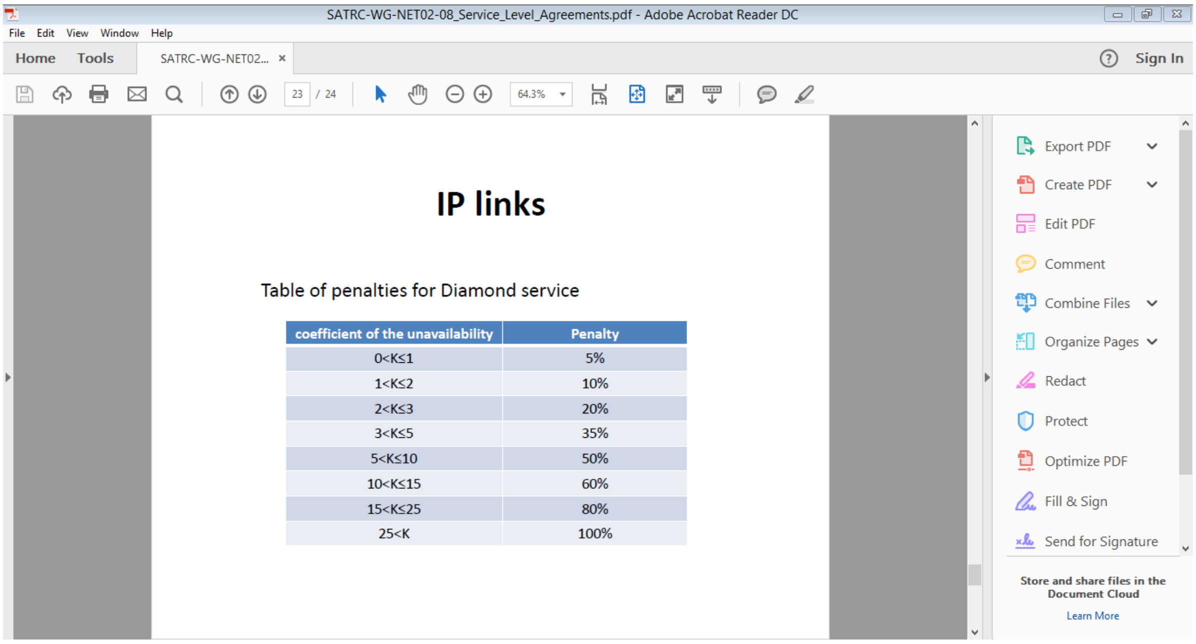
Service name	Availability	Tariff
Bronze	98%	A
Silver	99%	2A
Gold	99.5%	3A
Diamond	99. 9%	5A



IP links

Table of penalties for Bronze , Silver and Gold services

coefficient of the unavailability	Penalty
0<K≤1	5%
1<K≤2	10%
2<K≤3	20%
3<K≤5	35%
5<K≤10	50%
10<K	100%



IP links

Table of penalties for Diamond service

coefficient of the unavailability	Penalty
0<K≤1	5%
1<K≤2	10%
2<K≤3	20%
3<K≤5	35%
5<K≤10	50%
10<K≤15	60%
15<K≤25	80%
25<K	100%

Appendix F

Reward Configuration

This is the reward configuration and it is based on the code available in research executed by [108]. This is the reward function that updates the compiler the new reward system and this is different with the code produced by [108]

```
%Latency Low
if (current_state(1)>= 0.5 && current_state(1) <0.75 )
   reward = -1;
elseif (current_state(2) >= 2 && current_state(2) <4)
   reward =-1;

%  Latency Normal

    elseif (current_state(1)>= 0.75 && current_state(1) <1 )
       reward=-2;
elseif (current_state(2) >=4 && current_state(2) <8)
   reward =-2;

 %Latency High
 elseif (current_state(1)>= 1 && current_state(1) <5 )
    reward =-3;
elseif (current_state(2) >= 8 && current_state(2) < 20)
   reward =-3;

 %Latency Peak

   elseif (current_state(1)>= 5  )
      reward =-4;
elseif (current_state(2) >= 20)
   reward =-4;

 % Latency Pass
   elseif (current_state(1)<=0.5 )
      reward=1;
elseif (current_state(2) <= 1)
   reward =1;
```