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for Sustainable Development

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MODELING ENERGY CONSUMPTION OF A SWITCH USING FUZZY-RULE CLASSIFIER

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ABSTRACT

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Modeling Energy Consumption of a Switch Using Fuzzy-Rule Classifier

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The energy consumption of IT equipments is becoming an issue of increasing importance. In particular, network equipments such as routers and switches are major contributors to the energy consumption of internet. Therefore it is important to understand how the relationship between input parameters such as bandwidth, number of active ports, traffic-load, hibernation-mode and their impact on energy consumption of a switch.

In this paper, the energy consumption of a switch is analyzed in extensive experiments. A fuzzy rule-based model of energy consumption of a switch is proposed based on the result of experiments. The model can be used to predict the energy saving when deploying new switches by controlling the parameters to achieve desired energy consumption and subsequent performance. Furthermore, the model can also be used for further researches on energy saving techniques such as energy-efficient routing protocol, dynamic link shutdown, etc.

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This thesis is dedicated to my parents who have given me the opportunity of an education from best institutions and support throughout my life, also to my elder and younger sisters who have always stood by me and dealt with all of my absence from many family occasions with a smile. Last but not least, I would like to address my appreciation to all of my family, relatives, and friends, without whom none of my success would be possible.

Alifia Fithritama

Nancy, 20 May 2015

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LIST OF SYMBOLS AND ABBREVIATIONS

ACL	Access Control List
ASIC	Application-Specific Integrated Circuit
CF	Confident Factor
CLI	Command Line Interface
DECC	Department of Energy and Climate Change
DEFRA	Department for Environment, Food & Rural Affairs
EDF	*Electricité de France*
EEE	Energy Efficient Ethernet
€	Euros
FRC	Fuzzy Rule Classifier
GA	Genetic Algorithm
Gb/s	Gigabit per second
Gbps	Gigabit per second
GHG	Green House Gas
GUI	Graphic User Interface
GW	Giga Watt
IEA	International Energy Agency
ISP	Internet Service Providers
ICT	Information and Communication Technology
kWh	kilo Watt hour
kVA	kilo Voltage-Ampere
LAN	Local Area Network
MBF	Membership Function
Mb/s	Megabit per second
Mbps	Megabit per second
MIB	Management Information Base
MISO	Multi Input Single Output
MSS	Minimum Segment Size
MW	Mega Watt
NIC	Network Interface Card

NN	Neural Network
PC	Personal Computer
POE	Power over Ethernet
RR	Recognition Rate
SFP	Small Form-Factor Pluggable
SNMP	Simple Network Management Protocol
SHM	Switch Hibernation Mode
SVM	Support Vector Machines
SLA	Service Level Agreement
QOE	Quality of Experiment
QOS	Quality of Service
RTE	*Réseau de Transport d'Électricité*
T&D	Transmission and Distribution
UK	United Kingdom
UNFCCC	United Nations Framework Convention on Climate Change
WRI	World Resources Institute

1. INTRODUCTION

The impact of technology development on the environment is among one of many challenges we face today. To monitor the environment and human activities (e.g. industry, building, and transport), intensive deployment of distributed smart Information and Communication Technologies (ICT) system is needed as recommended by The SMART 2020 report (The Climate Group, 2012). As the Future Internet is taking shape, it is recognized that, among other basic concepts and key aspects, sustainability should pervade the network infrastructure as a whole to such extent as to become part of the network design criteria. With this new ecology paradigm, networked design has to be globally rethought to include sustainability constraints. (Carro, et al., 2012) has analyzed the relevant literature for energy efficiency support by networks and (Drouant, et al., 2014) has proposed a framework for designing green network architecture according to ten commandments for conducting business, inspired by Biomimicry concept (Benyus, 2002).

Motivations that drive the quest for "green" networking are (1) environmental, related to the reduction of waste and pollution, the use of earth resource efficiently and the decreased impact on carbon emissions; and (2) economic, due the ever-increasing cost of energy (Rondeau, et al., 2015). Awareness of environmental problems tied to carbons and other Green House Gases (GHG) has been increased during recent years. Many scientists all around the world are discussing the damaging effect of carbon emission and their consequences on climate change. According to (Pamlin & Szomolányi, 2006), an emission volume decrease of 15-30% is required before year 2020 in order to keep the global temperature increase below 2 degree Celsius. However, the effects of carbon emission are not only related to the environmental aspect, but also to the economy as well. Furthermore, they have investigated the financial damage in perspective of current trend and also potential economic benefit that would follow the reduction of carbon emission. It projected that one-third reduction of carbon emission could generate economic benefit higher than the amount of investment required to reach this goal. This possible economic upturn has moved many governments to build greener industries both for shorter and long-term sustainable development of their countries.

In the last few years, telecom operators and Internet Service Providers (ISPs) reported a growing trend of energy consumption of their network (Bolla, et al., 2011). For example, energy consumption of the Telecom Italia network in 2006 has reached more than 2 TWh (ca. 1% of the total energy demand in Italy), increasing by 7.95% with respect to 2005, and by 12.08% to 2004 (Bianco, et al., 2007). Similar energy requirements were reported by Telecom France with 2 TWh in 2006 and by British Telecom with 2.6 TWh in 2008 (British Telecom Group, 2008). The latter absorbed about 0.7% of the total UK's energy consumption in the winter of 2007, making it the biggest single power consumer in the nation. This share on total electricity consumption on ICT sector is certainly noteworthy. It deserves attention and calls for adequate action, in particular because it is increasing fast. Electricity consumption for EU-27 will increase by around 50% within 15 years in a "business-as-usual" scenario. Particularly for Telecommunication industry, The European Commission DG INFSO report estimated that European telecoms and operators had an overall network energy requirement equal to 14.2 TWh in 2005, bound to rise to 21.4 TWh in 2010 and to 35.8 TWh in 2020, in the absence of "green network technologies" (European Comission DG INFSO, 2008).

Green networking includes the study of designing, manufacturing, using, and disposing of networking systems in efficient and effective manner. The goal of green networking are minimizing impact on the environment, achieving economic viability, and abiding ethical responsibilities (Murugesan, 2008). From engineering point of view, green networking could be seen as a way to reduce energy consumption while maintaining the same level of performance. The drivers for energy-efficient network are environmental sustainability and cost considerations (Bianzino, et al., 2012). The concern of environmental sustainability is related to carbon emission that is produced by electricity. While the cost considerations for instance the cost of electricity bills from data center operation, heat dissipation of computer processors, and limited lifetime of battery-supplied devices.

Triggered by the increase in energy price, the continuous growth of costumer population, the spreading of broadband access, and the expanding number of services, the energy efficiency issue has recently become a high-priority objective for telecom operators and Internet Service Providers (ISPs). One of the chalenge in achieving energy-efficient network is to control the energy consumption of the network. Most of the time network devices are up twenty four hours a day, seven days a week, regardless presence of the users nor the condition of the traffic itself. Therefore, to be able to use the network devices more efficiently, understanding the behaviour of the energy consumption is very important. Only when the correlation between energy consumption and the input parameters are understood, the energy consumption can be controlled effectivelly.

1.1. Goals and delimitations

As reported by ((Tucker, et al., 2008); (Zhang, et al., 2010)), switches and routers are major contributors to the energy consumption of the network, therefore research community is investigating methods to decrease the energy consumption of these devices. The objective of this study is to propose an approach for estimating energy consumption values during the identification phases of modeling the switch. The switch is analyzed as a black-box system with unknown characteristics and fuzzy logic is used to map the relation between input and output variables. For the experiment, four input variables are chosen; namely bandwidth, traffic-load, number of connections, and hibernation-mode while the output variable to be measured is the energy consumption of the switch. As a dynamic system, a switch presents non-linearity and uncertainty behaviour under different operating condition. Thus, fuzzy logic approach is selected due to its capability to represent the dynamic behavior of the switch accurately despite its complexity. After the model has been identified, the end goal is to be able to control the energy consumption of a switch using the fuzzy rules which are extracted from the experiment data.

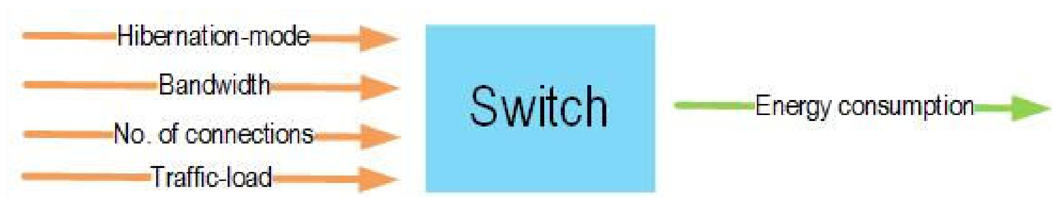

Figure 1. Blackbox approach

The main interest of this approach is to consider all the parameters of the network in the modelling step. However, since the identification phase was achieved for a specific model of switch devices, the result of the study will be dependent on the concerned model only. This limitation also involve the input variables. It means that the output that is observed is assumed to be affected by these three input variables only. If the input variables are changed to other variables, then consequently the relationsip between input and output will differ. Also, because the identification phase was achieved based on experimentation data for a specified network technology, the result of the study will be dependent on the concerned model.

1.2. Structure of the thesis

This thesis consists of seven chapters namely (1) Introduction, (2) Background and Related Works, (3) Benchmarking, (4) Modeling Energy Consumption of a Switch, (5) Results, (6) Discussion and (7) Summary respectively. Initially, chapter 1 served as an introduction material toward the study of green network. Next, chapter 2 contained the background and some previous works related to the study. Chapter 3 illustrated detail explanation about the experimentation, including the description of the experiment method, the hardware and software which are used in the experiment, and the combination of experiment scenarios. Then, chapter 4 examined the steps of modeling energy consumption of a switch using Fuzzy Rule Classifier (FRC). Afterwards, chapter 5 presented the result of the experiment along with the evaluation of the model. Chapter 6 reviewed the further analysis of the model and examined how it will be applied on the real-life scenarios. Finally, chapter 7 summarizes of what has been preceded in the previous sections and concludes the result the future possibilities in the research topic or the in the application area

2. BACKGROUND AND RELATED WORKS

This chapter describe the background of the study and some related researches in the domain of fuzzy logic, green network, and energy consumption model that had been done in the past.

2.1. Background

Network communications could be regarded as complex systems which are composed of many interconnected and distributes devices, such as routers, switches, firewalls, acess points and terminals. These network devices implement services and protocols that followed TCP/IP or UDP/IP protocol stacks. Thus, one of the challenges in managing network within the ecology paradigm is the ability to control (regulate) energy consumption efficiently and still ensure that Quality of Service (QoS) requirements is respected. In the context of controlling a large network like internet for example, an approximate approach is preferred rather than a precise one. Because the goal is not reducing the exact number of Watt power, but rather to maintain the level of energy consumption of the whole network from time to time so that it does not reach maximum power. Due to this consideration, fuzzy logic is convenient tool to identify the complex network behavior in which mathemathical representation is almost unfeasible to obtain.

Fuzzy logic provides an inference structure to apply human reasoning capabilities into artificial knowledge-based system. For this reason, fuzzy rule-based system have been successfully applied to many control problems (King & Mamdani, 1977), (Lee, 1990), (Precup & Hellendoorn, 2011). A fuzzy rule-based system provides an effective way to capture the approximate and inexact nature of the real world. Specifically, it is useful when the system is too complex for analysis by conventional quantitative techniques, or when available information of the system is qualitative, inexact, or uncertain. Theoretically, it was proven that fuzzy rule-based systems are universal approximators of any real continuous function on a compact domain to arbitrary accuracy (Wang, 1992), (Kosko, 1994), (Kreinovich, et al., 2000).

In practice, the controlling of energy consumption is usually achieved by both manually and empirically. For example, a network architect who has knowledge about the network usage behavior may use a sleeping mechanism to limit the energy consumption of the network devices during the night when the office hours has passed. However, this kind of approach is not effective to reduce energy consumption of the network devices, because in this case, the saving can only be done during the evening outside the office hours, while there is also a potential to save energy consumption during the day. Second issue is that the network architect (user) need to understand the whole picture of the network, how each component of network devices providing that they did the control manually and it can be very complex and tedious given the large size of the network. Also because of the knowledge between one user and another user could vary based on their expertise, it is likely that they might use their own evaluation instead of taking into account various condition to control the energy consumption of the network.

On the other hand, using the method that is proposed by this study, if the relations between energy consumption and input parameters are identified and taken into account, then user (in this case, a user who acts as a network administrator for example) could monitor the condition of the network and use this information to regulate the energy consumption and make the saving that are appropriate to various of scenarios, for example by limiting the active number connections, reducing the bandwidth, decreasing the traffic, or putting the node into hibernation.

This study analyze an Ethernet LAN (Local Area Network) that uses switches to connect individual stations (hosts/nodes). Switched Ethernet replaces the shared medium of legacy Ethernet (traditional Ethernet) with dedicated segment for each stations. This allows many transmission to occur simultaneously on a switched network. Switched Ethernet are becoming popular due to its effectiveness and convenience feature to extend the bandwidth of existing Ethernet. Currently, the switch replaces the repeater and provides full 10 Mb/s bandwidth (or 100 Mb/s for Fast Ethernet and 1 Gb/s for Giga Ethernet) to the rest of the network. In this experiment, a *desktop switched Ethernet* is used, in which all hosts that are connected to the switch are user PC (Personal Computer).

This study examines the energy consumption model of a wired Ethernet switch. At the basic level, an Ethernet switch is similar to a bridge with many ports. However, unlike bridge, the switch does not flood every packets out of its port, but rather read the destination address of the packet so that it only reaches intended recipient. Because the only devices in the segment are the switch and the end station, the switch look up every transmission before it reaches another node. The switch then forwards the frame over appropriate segments.

In this study, Cisco Catalyst 2960X switch (Cisco, 2014) is used to create the Ethernet LAN for the experiment. It has 24 Gigabit Ethernet ports and 4 Gigabit SFP (Small Form-Factor Pluggable) uplinks. The 2960-Xseries switches support both IEEE 802.3af POE (Power over Ethernet) and IEEE 802.3at PoE+ (up to 30W per port) to power up standards-compliant PoE/PoE+ end devices such as IP phones, wireless access points, sensors, switches, etc. Most importantly, Cisco Catalyst 2960X switch is chosen because it has been analyzed to be one of the ”greenest switch” in the market that consumed 55% less energy in Watts/Gb/s and save over 50% in annual energy operating costs compared to the industry average (Miercom, 2013).

Cisco Catalyst 2960X switch offers various power-saving features such as Cisco *EnergyWise* (Cisco, 2004), a wide temperature operating range and variable-speed cooling fans. Also, it supports IEEE 802.3az EEE (Energy Efficient Ethernet) (Christensen, et al., 2010) that enables ports to dynamically sense idle periods between traffic bursts and quickly switch the interfaces into a low power idle mode, thus reducing power consumption. As reported in (Miercom, 2013), the 2960-X model reduced up to 29.3% energy consumption (13.1 Watt) with EEE enabled. Another interesting functionality supported by Cisco Catalyst 2960-X is Cisco SHM (Switch Hibernation Mode) (Cisco, 2015), a feature which puts the switch in sleep (ultra low power mode) during periods of idle or very-low traffic in which it can be scheduled using Cisco *EnergyWise* compliant management software. Cisco SHM allowed a significant 84% of power reduction from 44.3 Watt at link idle to only 7.2 Watt at idle for the Catalyst 2960-X.

2.2. Related Works

Since it was initially introduced by Lotfi Zadeh (Zadeh, 1975), many studies about fuzzy logic control in various industry application had been published ((Zadeh, 1973); (King & Mamdani, 1977); (Sugeno, 1985); (Lee, 1990); (Precup & Hellendoorn, 2011)).

In the network domain, some studies on using fuzzy set theory and fuzzy logic have also been published. These studies present models of relationship between users and communication network, such as Quality of Experience (QoE) model (Hamam, et al., 2008) , QOS model (Fernandez, et al., 2002) with regards of Service Level Agreement (SLA). Moreover, fuzzy logic methods have also been applied to QoS management in wireless sensors (Feng, et al., 2007) and mobile ad-hoc network (Khoukhi & Cherkaoui, 2008).

A study about the comparison of energy consumption of access network revealed that among current wired (DSL, HFC, PONs, FTTN, PtP) and wireless (WiMAX and W-CDMA) technology, the optical access networks are the most energy efficient (Baliga, et al., 2011). Furthermore, some researchers have been studied about modelling of energy consumption of network. However, the studies have been focused on the wireless technology (ad-hoc or cellular network). Some examples are: (Zhu, et al., 2003), (Carvalho, et al., 2004), (Heni, et al., 2010), and (Decreusefond, et al., 2013).

Few studies have been carried out about energy consumption model of wired network. In (Reviriego, et al., 2012) and (Vishwanath, et al., 2014), authors propose a specific equation for estimating energy consumption of a network architecture based on switched-Ethernet technology. However, the equation was obtained in empirical way and therefore it lack of structured methodology and may be too simple. A more generic power model design of ICT systems was proposed by (Beister, et al., 2014). However, this approach does not guarantee that the resulted model was complete regarding the domain it is used in. In addition, it also lacks of formal means to validate the resulting model. A study about analytical model on the power management of networked devices (PCs, servers, set-top boxes, etc) has been submitted by (Bruschi, et al., 2014). Another similar study has been done about modeling energy consumption of a switch using other method than Fuzzy Rule

Controller (FRC) which is Design of Experiment (Hossain, 2015).

The originality of the research presented in this study compared to the previous works are: (1) the identification of network behaviour (in this case, the energy consumption of a switch) using series of experiments based on real-life scenarios; (2) the use of automatic modelling for fuzzy rule controller rather than human expertise. Here, the fuzzy rules in form of linguistic term are automatically generated after the identification phase. The relevant fuzzy rules are then selected based on the confidence index; and (3) the integration of ecology (sustainability) paradigm into network design.

3. BENCHMARKING

This chapter consists of two parts: (1) Methodology; and (2) Data Set Generation. The first part described the methodology used in this study on how to obtain the energy consumption model. The latter explained about the generation of sample data sets from experimentation.

3.1. Methodology

The methodology used in this study is shown in **Figure 2** below.

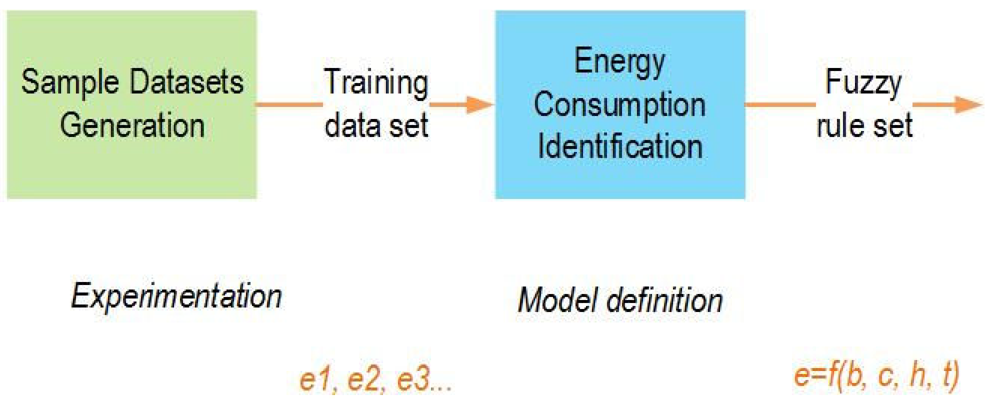

Figure 3. Methodology

The first step is generating sample datasets to identify the energy consumption of the switch without referring to human expertise. The datasets are generated by experimentation. Section 3.2 will explains the data set generation in details. The sample data sets of energy consumption (*e1,e2,e3,...*) in relation to the controllable parameters which consist of bandwidth (*b1,b2,b3*), number of connections (*c1, c2, c3*), hibernation mode (*h1, h2*), and traffic-load (*t1,t2,t3*).

The next step is to analyze the sample datasets to define a model of energy consumption of the switch. Linguistic variables are first defined according to the application requirements as described in section 4.2. Afterwards, fuzzy rule set is generated based on the linguistic rules and data sets as illustrated in section 4.3. The fuzzy rules associates energy consumption characteristic to a configuration level of bandwidth, number of connection, hibernation mode, and input bytes.

Generally, after the fuzzy identification step is accomplished, the model is then used to build a fuzzy-based controller. A controller based on the fuzzy rule set generated from previous step that will select value on a given network component to achieve desired energy consumption level. In the framework of this study, it means that the controller determines the level of bandwidth, number of connection, hibernation mode, and input bytes that provides expected level of energy consumption.

To illustrate the propose methodology, consider the application context adopted as a case study for the experimentation . An Ethernet witch is fixed to interconnect user end devices (PC no.1 until PC no.24) and support the relevant real-time traffic sent between them. This switch support the IEEE 802.3az EEE (Christensen, et al., 2010) and Switch Hibernation Mode (SHM) (Cisco, 2015). As a case study of the proposed methodology, the throughput (bandwidth) data rate of the link is set to be 10 Mb/s (Megabit per second) , 100 Mb/s, or 1 Gb/s (Gigabit per second). To simulate the real-time traffic, a traffic generator software called *JPerf* ((Richasse, 2009); (Parson & Griffith, n.d.)) is used to send TCP traffic between one host and another (in a pair of client-server). The traffic load is diverged by varying the sliding window parameter on *Jperf* software (Reid, 2008). As the result, the generated traffic is ranged from as low as 4 Mb/s up to 17,000 Mb/s at the highest rate. *Powerspy2* (Alciom, 2013) sensor is used to measure the energy consumption of the monitored switch. The data of energy consumption is sent in real-time via bluetooth with accuracy of 0.01 Watt. In addition, the Graphic User Interface (GUI) also provided the graphic, table, and other necessary information such minimum, maximum, standard deviation, and average value of power consumption

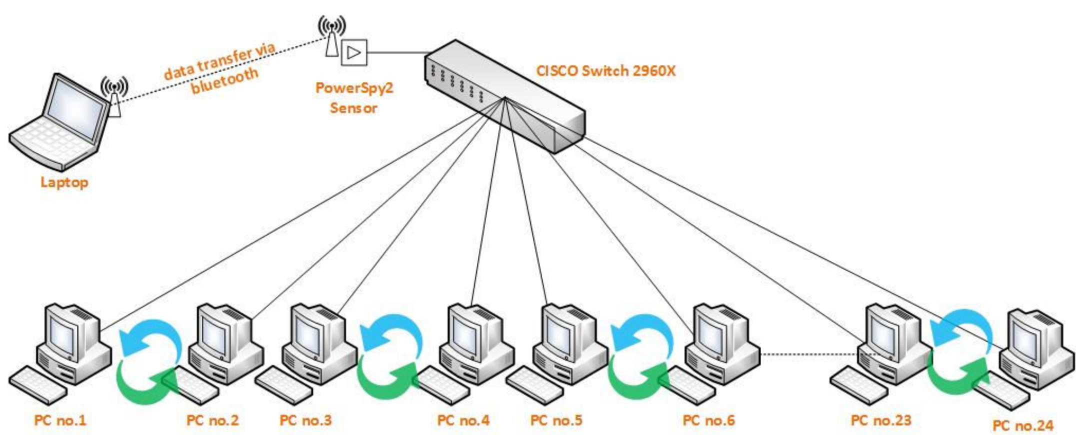

Figure 4. Application context and network of interest

The application requires that the energy consumption remain low regardless of the condition of the network. Therefore the objective for the network administrator is to tune the switch parameters (such that bandwidth, number of connection, traffic-load, and hibernation-mode) so that energy consumption remain on a low level. It should be noted that the key operational cost (Barroso, et al., 2009) of data center is energy consumed in network and is an aggregated consumption of end-user devices which is significant due to the large number of devices inside the data center (The Climate Group, 2012). Meaning that, the more devices are up and running, the higher is the energy consumption of the network, and so does the operational cost of the data center. Furthermore, it has been observed that energy consumption is in many cases almost independent of the system load (Barroso & Hölzle, 2007). This results in poor energy efficiency for lightly-loaded systems. Thus, the energy-efficiency can be significantly improved by making energy consumption proportional to the system load.

3.2. Data Set Generation

At first, to serve as a starting point, the energy consumption of a switch with 0 host connected is measured. Afterwards, the experiment continues by arranging small network with 2 hosts at initial and then increase linearly to 4 hosts, 6 hosts, 8 hosts, 10 hosts and so on until all 24 hosts are connected. There are three possible bandwidth settings which are 10 Mb/s, 100 Mb/s, and 1 Gb/s. For simplicity, in each given scenario, all ports are set to be in the same bandwidth. Each of the host makes a pair with its neighbor host and simultaneously sends and receives TCP traffic (hence, each host acted as server and client at the same time). The amount of traffic generated is varied to produce different level of traffic loads (high traffic load, medium traffic load, and low traffic load). The categorization of traffic load into low, medium, and high was explained in detail in **Figure 11**. *Fuzzification* of traffic load on Section 4.3 Fuzzy Rule Classifier (FRC) setting. Each of the experiment lasts for 15 minutes before the energy consumption value is taken. After some trials, 15 minutes period is considered to be the most effective to wait for the Powerspy2 sensor to stabilize the value of energy consumption. The experiment scenario is illustrated in **Figure 4** below.

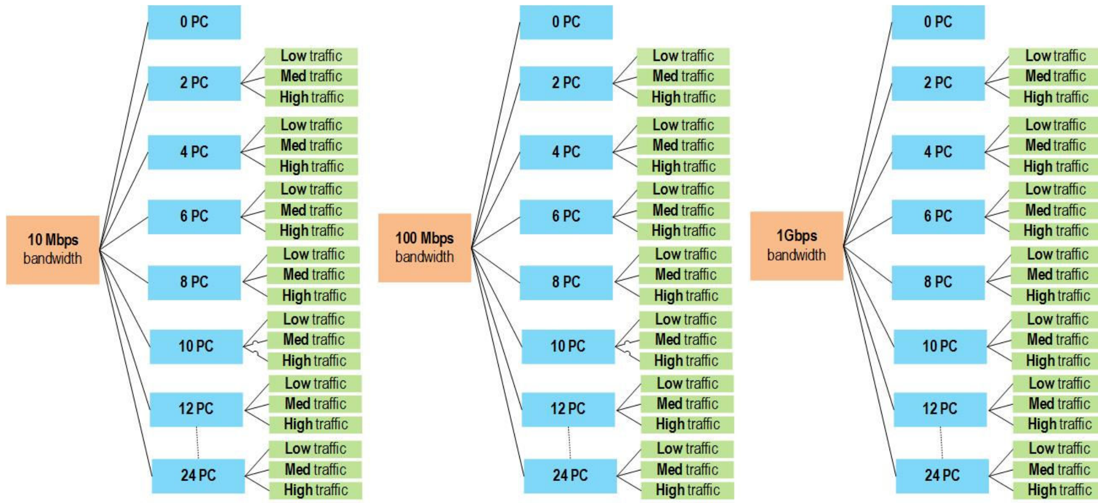

Figure 5. Experiment scenarios

The experiment is conducted considering TCP protocol because TCP can be considered as the most commonly used layer-4 protocol for network applications such as HTTP, FTP, and SMTP. TCP manages network performance by controlling how much data is sent in each packet (Minimum Segment Size = MSS), how many packets are sent before receiving an acknowledgement (Window Size) and how much memory is allocated to send and receive traffic flow buffers (Buffer Length). The analogy of TCP is identical to a shipping company which define how much weight can be loaded in each box, how many boxes can go on each truck, and how many boxes can wait in the loading docks at both sender and receiver end.

JPerf has features to adjust the values of MSS, Window Size, and Buffer Length by selecting the parameter in Graphic User Interface (GUI). By adjusting these values, the impact changes on throughput can be observed. As stated in IPerf User Documentations (Vivien, n.d.), the most fundamental tuning issue for TCP is Window Size which control how much data can be in the network at one point. For example, changing Window Size from the default value of 8 Kbyte to 64 Kbyte over a Gigabit Ethernet LAN resulted in a nearly three-time increase in throughput. However, there are also some situations where reducing the Window Size may improve throughput. This is because TCP, as a reliable protocol, retransmit packets should data loss occurs. On a slower network (a network with low data rate) with many retransmissions due to packet loss, throughput can be upgraded by sending smaller amounts of data between acknowledgments. Thus, it minimizes the possibility of congestion due to packet retransmission.

To check the incoming and outgoing packets, *Wireshark* (Lamping, et al., 2004) is used to monitor the network interface of each PC. *Wireshark* is network packet analyzer software that captures all incoming and outgoing packets and displays them with detail information such as protocol type, source address, destination address, etc. To get the amount of incoming traffic on the switch, Cisco MIB (Management Information Base) is used to display the value of incoming bytes at real time. The MIB value is accessed via SNMP (Simple Network Management Protocol) connection to the switch. To save substantial amount of network resource, SNMP traps instead of SNMP requests are used to direct the notification from MIB (Cisco, 2006).

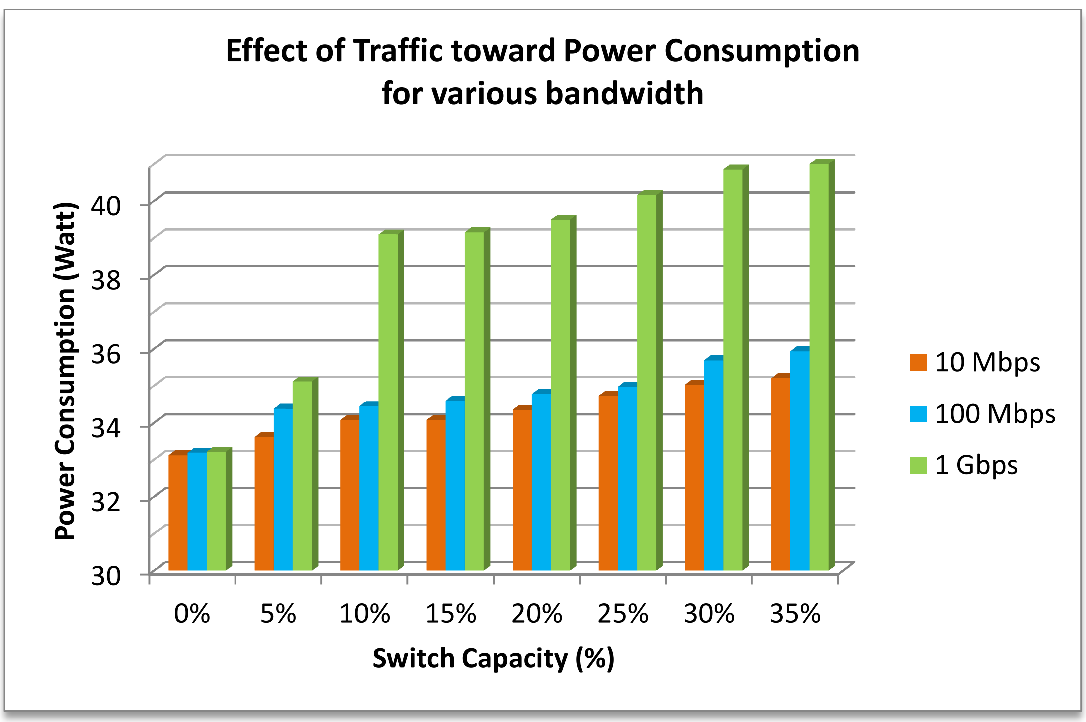

Figure 6. Effect of Traffic toward Power Consumption of a Switch

Measurement-based studies to date ((Chabarek, et al., 2008); (Mahadevan, et al., 2009); (Ward, et al., 2012)) showed that device power consumption increases fairly linearly from an idle power (i.e., under zero load) to a maximum power (i.e., under full load).

Furthermore, the idle power is typically in excess of 80% to 90% of the maximum power. This was in line with the result from the experiment as depicted in **Figure 5**. The power profile had the tendency to increase in line with the increasing amount of traffic. Moreover, the idle power was 94% (10 Mb/s bandwith) , 92% (100 Mb/s bandwidth) and 80% (1 Gb/s bandwidth) of the maximum power consecutively. From the graph, it showed that the higher the bandwidth, the bigger impact made by the traffic toward power consumption.

Figure 6 depicted the relation of power consumption of the switch and number of connected PC for different bandwidths (10 Mb/s, 100 Mb/s, and 1 Gb/s). The graph showed a linear relation between energy consumption and number of connected PC. As the number of connected PC increased, the the power consumption was also increase accordingly. However, the bandwidth affected significant amount of increase in power consumption. The higher the bandwidth, the bigger the jump difference of energy consumption. As it can be seen from the graph, the green bar (hence the 1 Gb/s) had the most significant increment in energy consumption each time the number of connected PC are increased. Whereas the red (10 Gb/s) and blue bar (100 Gb/s) showed only small amount of hike.

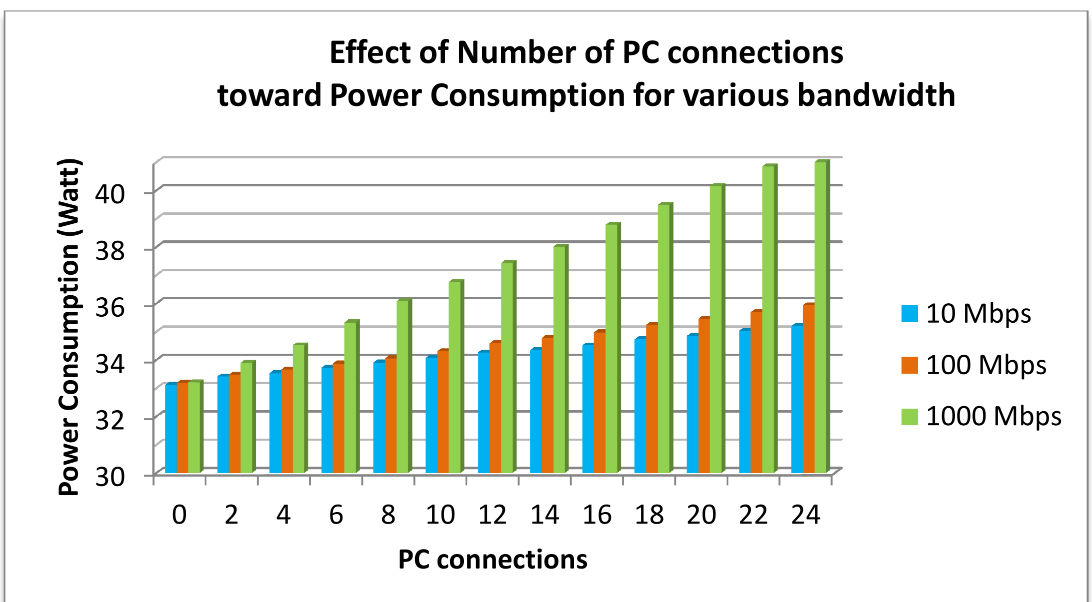

Figure 7. Effect of PC connection toward Power Consumption of a Switch

The next experiment was about the Switch Hibernation Mode (SHM) that can saves energy during off-hours. The SHM puts the switch to sleeps, consuming less energy. The SHM scenario was used to illustrate the non-office hours in which the users are not active and therefore the switch can be put into sleep to save the energy. Similar to previous arrangement, the experiment is done by connecting 2 hosts at initial and then increase linearly to 4 hosts, 6 hosts, 8 hosts, 10 hosts and so on until all 24 hosts are connected. However, in this experiment, because the switch was going to be hibernated, the hosts did not send any traffic to each other. It only simply connected to the switch without sending or receiving any traffic (idle with link). After the hosts were connected, waited for 5 minutes and then put the switch into hibernation mode using Cisco *EnergyWise* (Cisco, 2004) management software. When the switch was completely slept, energy consumption was measured using the *Powerspy2* sensor. After that, switch was woken up and procedure was repeated for the next scenario. The experiment scenario is illustrated in **Figure 7** below.

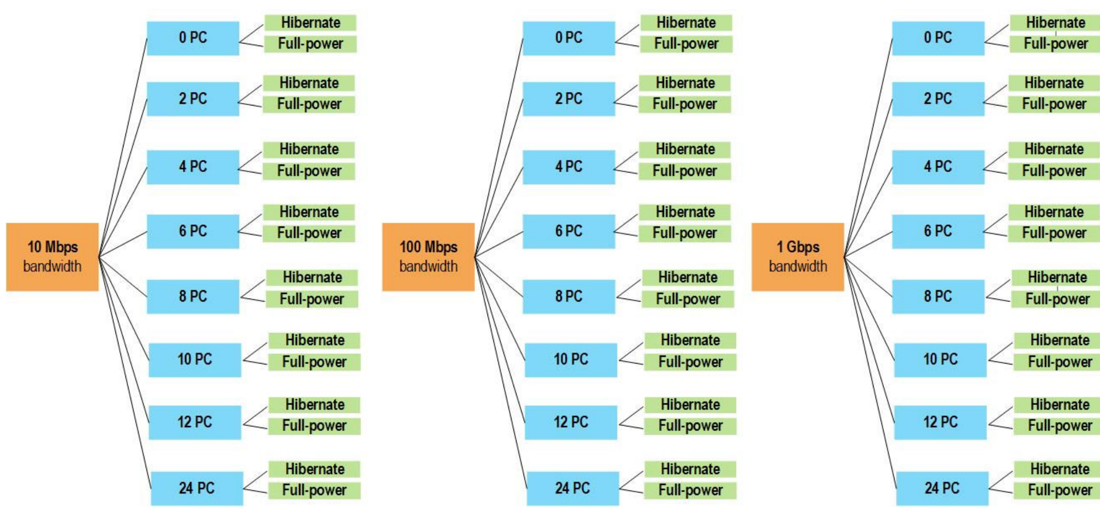

Figure 8. Experiment scenarios for Switch Hibernation Mode (SHM)

EnergyWise used a set of power levels to manage the power usage of network devices. A power level is a measure of energy consumed by devices in *EnergyWise* network. It indicated the state of an entity. Actions in response to change request of power level were interpreted by the entity locally. The power level range from 0 to 10 as written in **Table 1** below. The default value is level 10 (full-power) but a Cisco switch does not support level

0 because a switch cannot be turned off completely, otherwise it would be unreachable from *EnergyWise* manager. By this definition, a hibernated switch was actually assigned to a power level 1, and conversely, when a switch was woken up, it was assigned to a power level 10 (ibid).

Table 1. EnergyWise power level

Category	Level	Description
Operational	10	Full
	9	High
	8	Reduced
Standby	7	Medium
	6	Frugal
	5	Low
	4	Ready
	3	Standby
Non-operational	2	Sleep
	1	Hibernate
	0	Shut off

As previously explained, Cisco Catalyst 2960-X, 2960-CX, and 3560-CX Series Switches can be put into hibernation mode when not in use. They were put into hibernation mode by two ways: (1) by using a Cisco *EnergyWise* management tool to schedule the hibernation time; or (2) by using Command Line Interface (CLI) query to activate hibernation immediately. On the other hand, switches operational state can be returned in two ways: (1) again by using Cisco *EnergyWise* management tool to schedule the wake up time; or (2) by pressing the Mode button manually to activate wake-up events instantly.

As shown in **Table 2** below, Cisco Catalyst 2960-X, 2960-CX, and 3560-CX Series Switches only supported power levels 1 and 2 to 10 to keep them in hibernation mode and fully powered, respectively. In hibernation mode, the switches powered off most of the hardware components in the data path. CPU cores, application-specific integrated circuit (ASIC), and connected PoE devices were all powered off. Soon after switches were powered on again, they went through a complete reload.

Table 2. EnergyWise level available for C2960-X

EnergyWise Mode	**EnergyWise Level**
Switch on	2 to 10
Switch in hibernation	1

Figure 8 below illustrated the relationship between power consumption of the switch and the hibernation mode for various of bandwidth (10 Mb/s, 100 Mb/s, and 1 Gb/s) and various number of connected PCs. According to (Cisco, 2015), Catalyst 2960X-24TD-L in hibernation mode consumed up to 82% less power than it did in active mode. However, this was not the case in our experiment. Even though it is true that the graph showed a significant decrease in power consumption of the switch, the maximum saving was only 50.94% for 1 Gb/s with 24 PC connected. Even though instability occured, the trend suggested that the more number of connected PCs, the more energy saving (in term of percentage) was achieved using hibernation mode. This is because when the PC is connected, the ports became active and thus consume energy. Since the energy consumption during hibernation mode is more or less stable (around 19 to 21 Watt), thus the more energy that consumed during idle state, the larger the gap.

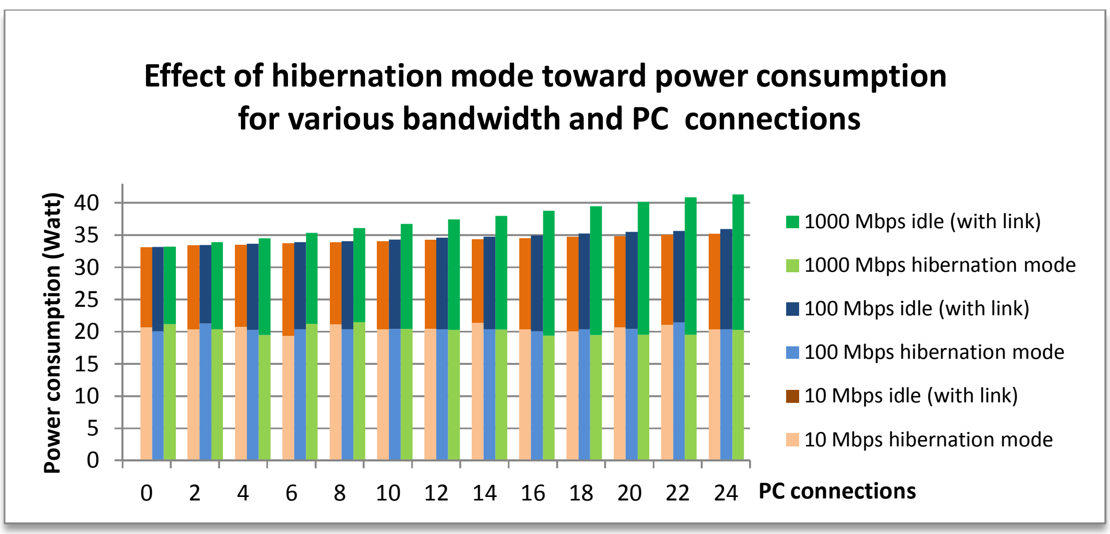

Figure 9. Effect of hibernation mode toward power consumption

Table 3. Amount of power saving by hibernation mode

PC	10 Mb/s	100 Mb/s	1 Gb/s
0	37.47%	39.47%	36.21%
2	38.90%	36.54%	39.90%
4	37.96%	39.72%	43.57%
6	42.38%	39.81%	39.91%
8	37.51%	40.17%	40.46%
10	40.17%	40.54%	44.43%
12	40.37%	41.06%	45.86%
14	37.67%	41.47%	46.49%
16	40.81%	42.51%	50.04%
18	42.13%	42.18%	50.65%
20	40.60%	42.40%	51.34%
22	39.73%	40.00%	52.22%
24	42.04%	43.34%	50.94%

Except for 10 Mb/s setting, the largest energy saving for 100 Mb/s and 1 Gb/s bandwitdh were achieved when 24 PCs were connected; 43.34% and 50.94% respectively. As for 10 Mb/s, the largest energy saving was 42.38% with 6 PCs connected. Almost similar to the effect of number of PC connected, the bandwidth has also affect the energy saving. The trend suggested that the higher the bandwidth, the more energy saving was achieved. The reason is likely identical to the influence of energy consumed by active ports. As the bandwidth increase, the more energy needed to power up the switch ports, thus increasing the gap between the power in idle state and the power in hibernation mode. The amount power saving (in percentage) was given in **Table 3.**

4. MODELLING ENERGY CONSUMPTION OF A SWITCH

The overall objective of this study is to model the energy consumption of a switch using Fuzzy Rule Classifier (FRC), with the end goal of being able to tune the energy consumption of the switch to minimize it while still maintaining performance for the users. FRC is basically any classifier that uses fuzzy sets and more precisely fuzzy logic (fuzzy rules) in the course of its training phase and prediction phase. A classifier is an algorithm of pattern recognition that assigns a class label to an object based on the object description via a series of learning (training). The object description appears in the form of a vector containing values of the features (or attributes) which is presumed to be relevant for the classification task. The classifier learns to make the prediction (estimation) of a class label using a training data set. Once training phase has been completed, the classifier could be used to estimate the output of undiscovered input data that are not part of the training data set.

FRC is selected due to following reasons: (1) A rapid preliminary study on the relationship between energy consumption of a switch, bandwidth, number of connections, input bytes, and hibernation mode showed non-linearities. And FRC is well-adapted to model a system with non-linear characteristics. (2) User requirement can be expressed by non-experts in network. For example, instead of using technical terms such as Ethernet, Fast-Ethernet, or Giga-Ethernet, users can define the bandwidth with linguistic term such as as low, medium, or high bandwidth accordingly. (3) FRC facilitates the identification of network behavior and reuses this identification result to control the energy consumption tuning. In addition, the result of the identification phase can be used to predict or estimate the output of the system in accordance with given input. (4) FRC is flexible enough to enable the prediction and classification task using limited dataset. It can be built using expert opinion, data, or both. Example of application included rare disease, terrorist activities, natural disasters. (5) FRC could take heterogeneous input, either continuous or discrete values. (6) FRC provides easy interpretation because the model is a rule set.

4.1. Identification Method

The identification method consists of applying pattern recognition procedure to classify different classes of output to obtain the link between the inputs and the output. This link modelize the switch behaviour. In this study, the bandwidth, number of connection, traffic load and hibernation mode are considered as inputs, and the energy consumption of the switch is considered as output of the classification.

The use of black box methods such as Neural Networks (NN) (Tou, et al., 2009) or Support Vector Machines (SVM) (Hao, et al., 2007) do not qualify the required interpretability. Thus the rule-based system is chosen ((Nauck & Kruse, 1999) ; (Nauck, 2003) ; (Roubos, et al., 2003)) , which is more likely to be appropriate in network context.

Figure 9 shows an overview of FRC which is build on two steps: (1) training step to build the model, and (2) generalization step to classify unknown data. The training step is divided into two levels: (1) fuzzification to define fuzzy linguistic variables, and (2) fuzzy rule generation which is accomplished through iterative steps to adjust the model.

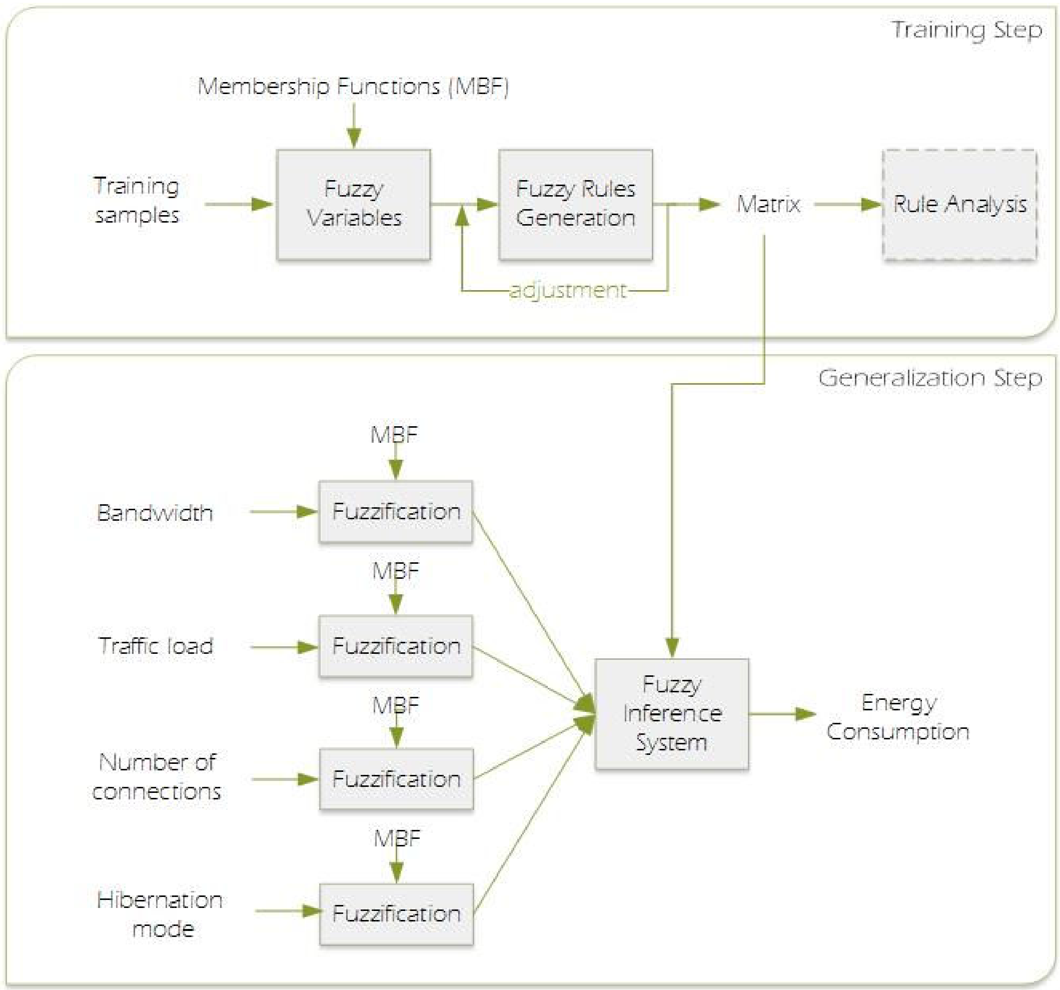

Figure 9. Overall description of FRC

4.2. Fuzzy Linguistic Variable Definition

Fuzzzification is an important concept in fuzzy logic theory. *Fuzzification* is the process where the crisp values are converted into fuzzy values. The fuzzy values are formed based on the uncertainties which are presented in the crisp values. The conversion of fuzzy values is represented by the membership function (MBF) (Chen & Pham, 2001). In *fuzzification* step, the number of variable terms, their distribution on the universe of discourse, and the shape of MBF diagram are defined.

The goal of this step is to translate numerical inputs into linguistic variables. In this study, the tuple (*V*,*X*, *Tv*) represents the following:

- V is the input variables (bandwidth, connections, hibernation, traffic-load) defined in the referential X.
- X is the *Universe of Discourse*; a range containing all possibility entities refferred to in a discourse
- Tv is the vocabulary selected to define the linguistic value of V.
- The bandwidth here refered to the settings (configuration) on interface in the Cisco switch ports, the PC network card interfaces, and the UTP communication cables. The bandwidth consists of discrete values of 10 Mb/s (low), 100 Mb/s (medium), and 1000 Mb/s (high). Thus, $X_{bandwidth} = \{10,100,1000\}$ and fuzzy sets are singletons: $T_{bandwidth} = \{low, medium, high\}$.
- The number of PC connections referred to the number of hosts in the network. PC connections are even number between 2 and 24. Where 2-8 PCs is considered as low number of connections, 10-16 PCs is medium number of connections, and 18-24 PCs is high number of connections. Thus, $X_{connections} = \{2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24\}$ and $T_{connections} = \{low, medium, high\}$.
- The hibernation mode refered to the Switch Hibernation Mode (SHM) feature on Cisco 2960-X series. Hibernation mode only has two states, either on (1) or off (0). Thus, $X_{hibernation} = \{0, 1\}$ and $T_{hibernation} = \{off, on\}$.
- The traffic-load is the percentage of input bytes on the active ports over the total capacity of the switch corresponding to the used bandwidth. The value of traffic-load is continuous number that range between 0 to 100%. The traffic load of 0-5% is considered as low traffic-load, 5-25% is considered as medium traffic-load, and above 25% is considered as high traffic-load. Thus, $X_{ctraffic\text{-}load} = \{1,...,100\}$ and $T_{traffic\text{-}load} = \{low, medium, high\}$.

The finite or infinite set of $Tv = \{A_1, A_2,...\}$ contains the normalized fuzzy sub-sets of X used to characterized the variable V. Each Ai is defined by a degree of belonging $\mu_{Ai}(x)$ which range between 0 and 1. The height of the fuzzy set A is the maximum value of the membership function (MBF) $max\ (\mu_A(x))$. The *crossover point* of MBF is the elements in universe whose membership value is equal to 0.5, $\mu_{Ai}(x) = 0.5$ (Sivanandam, et al., 2007).

4.3. Fuzzy Rule Classifier (FRC) Settings

The setting of FRC concerns with the *fuzzification* step and has significant influence on classification result. FRC setting considers the distribution of terms in the universe of discourse and the shape of membership function (MBF) diagram.

Generally, there are three basic shape of membership function, which are *triangular*, *trapezoidal*, and *Gaussian*. However, these shapes can be combined, for example a *trapezoid-triangular* membership function is a combination of *trapezoidal* with a *triangular* in the middle. It is important to note that the choice of membership function shape can affect the recognition rate. In this study, the trapezoid-triangular membership function is used because it tends to produce better results (Bombardier & Schmitt, 2010) .

The other difficulty lies in choosing the position of the membership function that defines the linguistic terms. One characteristic is represented by distributed terms in its definition field, called *Universe of Discourse*. In fact, there are various methods to assign the membership values to fuzzy variables. The assignment can be performed by using intuition or by using algorithms/ logical procedures.

The assignment based on the intuition relies on the human expert's own intelligence and understanding to develop the membership functions. This method called *expert fuzzification*. The number of terms and their position are determined from human expert interpretation of the data or from expert knowledge about industrial context. The *expert fuzzification* permits reduction of the number of rules. The advantage of this method is the interpretability of the rule set and the ease of rule modification manually. However, the disadvantage is that a human expert needs to set up the FRC to fix the number and the position of each variable and their membership function (Bombardier, et al., 2007).

A method proposed in (Bombardier, et al., 2013) imposes a number of terms equal to the number of output classes and calculates the locations of the kernels using the input data that belongs to the main class of their terms. The slope and position of term support are defined with a cross for a membership degree equal to 0.5. The main interests of this approach are (1) to provide a high recognition rate with a minimal number of terms and (2) to improve interpretability of the obtained rule set. However, this method is inappropriate to use in this study since the output variable (energy consumption) has three terms (low, medium, high) but one of the input variable which is hibernation mode has only two terms (on and off).

On the other hand, the assignment based on algorithm is performed to achieve an *automatic fuzzification*, for example by using Neural Network, Genetic Algorithm (Cordon, et al., 2004), clustering algorithms (de Carvalho, 2007) or rank ordering process (Sivanandam, et al., 2007). However, these techniques require a large amount of data during the learning process. Another *automatic fuzzification* method based on the study of output classes typicality (Forest, et al., 2006) can be used in the case of reduced sample datasets (Schmitt, et al., 2007). The equation of typicality measurement is provided in Appendix 2. Nonetheless, the drawback of this method is it generates a large number of terms. Using *automatic fuzzification* method, only numerical data is needed to split the *Universe of Discourse* of each parameter of the characteristic vector. The convenience of this method is the simplicity of the use and tuning of the system. For example, if the users of the Fuzzy Rule Classifier (FRC) are not experts, and therefore they often prefer a quick configuration of recognition module.

A simpler way to choose is to use a regular distribution of the terms in the *Universe of Discourse*. Hence the *Universe of Discourse* is split into regular parts according to the number of linguistic terms. This method is called *regularly distributed fuzzification*. The number of terms is chosen empirically from test on input data in relation to the application field and is generally odd and small values. However, it should be noted that despite of its simplicity, *regularly distributed fuzzification* may provide more terms than are needed, thereby increasing the number of generated rules and the complexity of the model.

The number of fuzzy rules is given by the following formula (Bombardier & Schmitt, 2010).

$$\textbf{Number of rules} = \prod_{v=1}^{N} Card(Tv) \tag{1}$$

With *N* is the number of feature and *Card(Tv)* is the number of terms for variable *V*. Using the formula above, the total number of rules generated in this study with 4 kinds of input variables: bandwidth (3 terms), connections (3 terms), hibernation (2 terms), and traffic-load (3 terms) are $3 \times 3 \times 2 = 54$ rules as listed in **Table 4.**

For this study, a combination of method is used for fuzzification to ensure the maximum recognition rate. For example, an *expert fuzzification* method with singleton membership function is used to represent bandwidth variable, mainly because the values consist of only three discrete values. Fuzzy singleton is a fuzzy set which support a single point in *Universe of Discourse* with a membership function of one. For traffic-load variable, *adapted fuzzification* method is used due to the non-symmetric shape and large spread of the sample sets. For PC-connection variable, a *regularly distributed fuzzification* with triangular-trapezoidal membership function is chosen, because of the uniform distribution of the sample sets. For the same reason, hibernation-mode variable also used *regularly distributed fuzzification* with triangular membership function. The membership function diagrams of four input variables are given on **Figures 10-13**.

Figure 10. Fuzzification of bandwidth

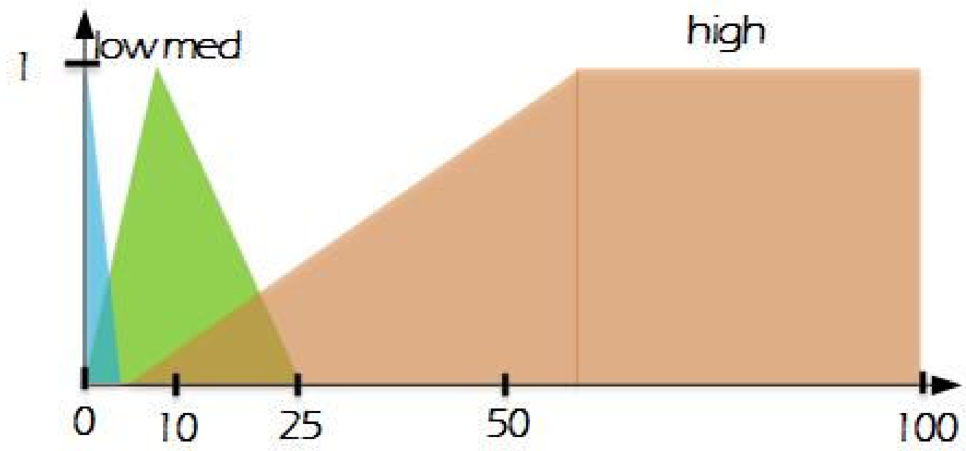

Figure 11. Fuzzification of traffic-load

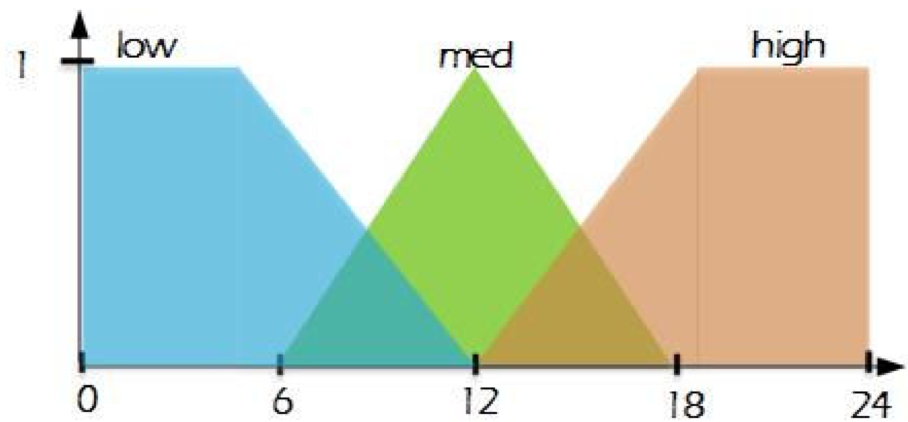

Figure 12. Fuzzification of number of connections

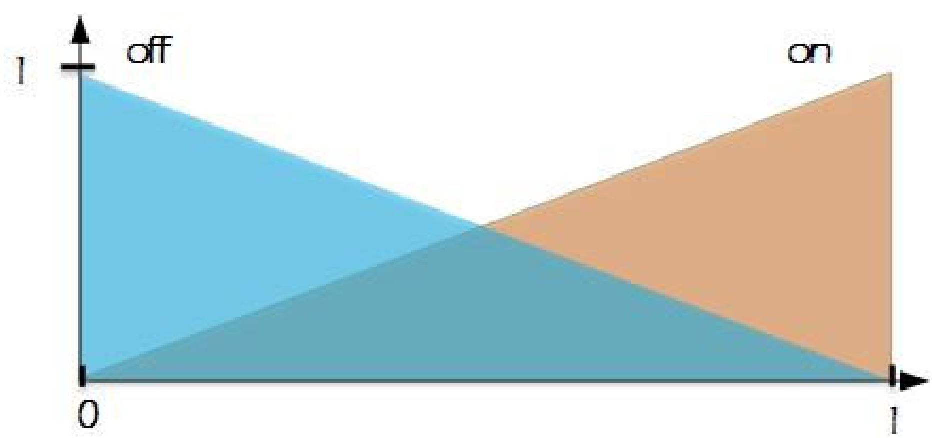

Figure 13. Fuzzification of hibernation mode

In this study, the membership function for the output variable *Energy*, called the energy consumption of switch is initialized with respect to the data analysis of the training sample set. The symbolic vocabulary then associated with variable *Energy* is T_{energy} = *{low, medium, high}*. Thus, the linguistic variable of energy consumption is split into three terms or fuzzy sets and this variable is characterized by a vector composed of three membership degrees: $[\mu_L(x), \mu_M(x), \mu_H(x)]$ as shown in **Figure 14** below. Instead of using the real value, a percentage value is used for easy conversion where $X_{energy} = \{0,...,100\}$. The minimum value of energy consumption is 0% when the switch is turn off, while100% is the maximum value obtained from the experiment which is around 41 Watt. At first, the division of the classes are distributed evenly. However, when the hibernation mode is active, the power consumption ranges between 19 to 21 Watt which are translated into 47% to 52% of maximum power. Therefore, the threshold limit has been empirically adjusted to achieve higher recognition rate. Low power consumption is defined from 0% to 50% of maximum power. Medium power consumption is defined in the range of 51% to 85% of maximum power. Lastly, high power consumption is anywhere more than 85% of maximum power. **Figures 14** below depict the fuzzification of energy consumption.

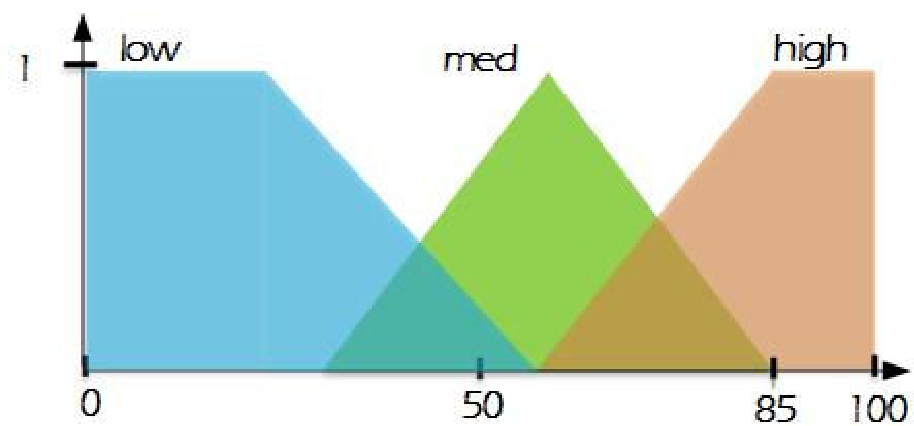

Figure 14. Fuzzification of energy consumption

5. RESULTS

This section contain the results of the modeling process which is the fuzzy rules. The model which consists of a set of fuzzy rules will be presented along with the evaluation method to assess the goodness of the model in terms of recognition rate.

5.1. Fuzzy Rule Set Generation

The next step after fuzzification is to generate a "IF..THEN..." fuzzy rule set from datasets. If two linguistic variables are considered for input (V_1, V_2) and one for output (Z_3), the general form of the associated fuzzy rule is (Zadeh, 1975):

$$\textbf{IF } V_1 \text{ is } A_i \textbf{ AND } V_2 \text{ is } A_j \textbf{ THEN } Z \text{ is } C_k \qquad (2)$$

Where V_1 and V_2 are the input variables defined on X_1 and X_2 ; and Z is the linguistic variable of output defined on Y (energy consumption: "low" for example). A_i and A_j € Tv (chosen vocabulary: "low" and "high" for example). C_k is the output class of kth.

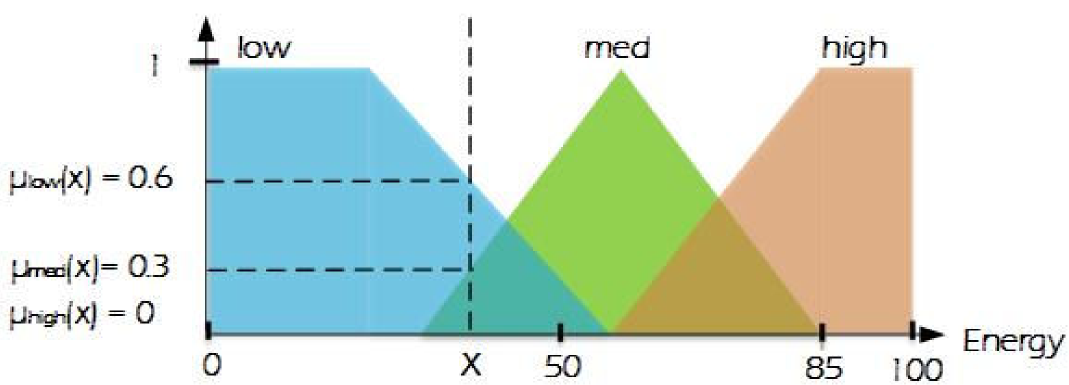

Figure 105. Example of fuzzification of energy consumption parameter into three terms

Several methods can be used to automatically generate the linguistic rules, including Genetic Algorithm (Alcala, et al., 2007), Decision Tree Method (Marsala, 2000), Wang and Mendels algorithm Algorithm (Wang & Mendel, 1992), and Ishibuchi algorithm Algorithm (Ishibuchi, et al., 1992). In this study, Ishibuschi algorithm is used, which its inference mechanism is build based on Larsen Model. The entire algoritm is given in Appendix. This inference is more adapted than Mamdani's, especially when several premises are available (Berthold, 2003). This inference uses conjunctive reasoning mechanism. Each rule is activated in parallel, and a maximum disjunction operator is used to aggregate partial conclusion and determine the final decision. The final output is selected by exempting the rule which gives the highest response. This inference mechanism gives an interpretation and semantics (Dubois & Prade, 1996) and assures the consistency of rule base (Dubois & Prade, 1997) . If there is no information being processed (the input space is not covered by the rule set), then the output gives an *unknown* class.

Each rule is associated with a *Confident Factor* (CF) which is used for adjustment step that corresponds to the iterative part of the algorithm (Nozaki, et al., 1997). If the classification rate is inferior to a predefined threshold, the iterative procedure tunes the model. If the current sample does not match the rule, the CF coefficient decreases. Otherwise, if the sample confirms the rule, CF is increased. Therefore, the higher the CF (the closer its value to 1), the more reliable the rule is, and vice versa. Generally, a rule can be categorized as an "unambiguous" rule if the CF is more than 0.8. Otherwise, if the CF is lower than 0.8, the rule should be discarded because it corresponds to the area where the model is ambiguous and therefore the model does not well represent the actual system.

The rule set produced from iterative adjustment procedure is given in the **Table 4** below. In total, there are 54 if-then rules in the set. For example, the rule number 2 can be expressed as *if the hibernation mode is off and bandwidth is high and number of connected PC is high and traffic load is medium, then energy consumption is high*. However, after eliminating the rules with unknown results and the ambiguous rule with low CF, only 24 rules are left as described in **Table 7**. These 24 rules are the ones with high CF which are considered to express the behavior of the system, in this case the energy consumption of the switch as explained in section 6.1.

Table 4. Generated rule set

Rule	CF	Hibernate	Bandwidth	PC	Traffic load	Energy consumption
1	0.878215	off	high	med	med	high
2	1	off	high	high	med	high
3	0.970118	off	high	med	high	high
4	0.98648	off	med	high	high	high
5	1	off	high	high	high	high
6	1	on	low	low	low	low
7	1	on	med	low	low	low
8	1	on	high	low	low	low
9	1	on	low	med	low	low
10	1	on	med	med	low	low
11	0	off	high	med	low	*unknown*
12	1	on	high	med	low	low
13	0.185895	off	low	high	low	med
14	1	on	low	high	low	low
15	1	on	med	high	low	low
16	1	on	high	high	low	low
17	0	off	high	high	low	*unknown*
18	1	off	low	low	low	med
19	1	off	med	low	low	med
20	0	on	low	low	med	*unknown*
21	1	off	high	low	low	med
22	0	on	med	low	med	*unknown*
23	0.402415	off	high	low	med	med
24	0	on	high	low	med	*unknown*
25	0.788996	off	low	med	low	med
26	0	on	low	med	med	*unknown*
27	0.472969	off	med	med	med	med
28	0	on	med	med	med	*unknown*
29	1	off	med	med	low	med
30	0	on	high	med	med	*unknown*
31	0.516742	off	low	high	med	high
32	0	on	low	high	med	*unknown*
33	0.652842	off	med	high	med	high
34	0	on	med	high	med	*unknown*
35	1	off	med	high	low	med
36	0	on	high	high	med	*unknown*
37	0	off	low	low	high	*unknown*
38	0	on	low	low	high	*unknown*

39	1	off	low	low	med	med
40	0	on	med	low	high	*unknown*
41	0.267456	off	high	low	high	high
42	0	on	high	low	high	*unknown*
43	0	off	low	med	high	*unknown*
44	0	on	low	med	high	*unknown*
45	0.329606	off	med	med	high	high
46	0	on	med	med	high	*unknown*
47	1	off	med	low	med	med
48	0	on	high	med	high	*unknown*
49	0	off	low	high	high	*unknown*
50	0	on	low	high	high	*unknown*
51	0.886023	off	low	med	med	med
52	0	on	med	high	high	*unknown*
53	1	off	med	low	high	med
54	0	on	high	high	high	*unknown*

Table 5. Rule set after the *unknown* results are discarded and then re-ordered

Rule	CF	Hibernate	Bandwidth	PC	Traffic load	Energy consumption
1	0.878215	off	high	med	med	high
2	1	off	high	hig	med	high
3	0.970118	off	high	med	high	high
4	0.98648	off	med	hig	high	high
5	1	off	high	hig	high	high
6	1	on	low	low	low	low
7	1	on	med	low	low	low
8	1	on	high	low	low	low
9	1	on	low	med	low	low
10	1	on	med	med	low	low
11	1	on	hig	med	low	low
12	0.185895	off	low	high	low	med
13	1	on	low	high	low	low
14	1	on	med	high	low	low
15	1	on	hig	high	low	low
16	1	off	low	low	low	med
17	1	off	med	low	low	med
18	1	off	hig	low	low	med
19	0.402415	off	high	low	med	med
20	0.788996	off	low	med	low	med
21	0.472969	off	med	med	med	med
22	1	off	med	med	low	med
23	0.516742	off	low	high	med	high
24	0.652842	off	med	high	med	high
25	1	off	med	high	low	med
26	1	off	low	low	med	med
27	0.267456	off	high	low	high	high
28	0.329606	off	med	med	high	high
29	1	off	med	low	med	med
30	0.886023	off	low	med	med	med
31	1	off	med	low	high	med

Note: the ones highlighted in red color are considered as ambiguous rules (CF iss less than 0.8) , and therefore should be discarded.

5.2. Evaluation of the Model

The best recognition rate is achieved by low-energy consumption class with 100% recognition rate (RR). In general, the less number of sample datasets that are used in training, the worse recognition rate. However, in this case, even though low-energy consumption class has least sample datasets (only 39 out of 150 samples) compared to other classes, it still manages to have the highest recognition rate. This is mainly because the of low-energy consumption class is ranged from 19 to 21 Watt (0 to 50% of maximum power), and thus can only occur when the switch is in hibernation mode. Therefore, as long as the hibernation mode is set to 1 (on), it is almost likely that the energy consumption is always low. Hence, this class is rather easy to differentiate from others.

The second class, medium-energy consumption has slightly lower recognition rate, which is 96.61%. This is because there are 2 samples that are misclassified into high-energy consumption class. Unlike the low-energy consumption class, the medium-energy consumption class and high-energy consumption class are rather difficult to differentiate because both of them have the hibernation mode set to 0 (off). Therefore the Fuzzy Rule Classifier (FRC) must rely to other three attributes (bandwidth, number of connections, and traffic load) to determine the classification of these classes. Furthermore, because of limited available datasets, the boundary between medium and low is very small that some values are almost overlapped with one another, which can result in an ambiguous rule.

Table 6. Recognition rate per each output class

Dataset	Low	Medium	High	Total	RR
Low	39	0	0	39	100%
Medium	0	57	2	59	96.61%
High	9	2	41	52	78.85%
Total				150	**91.33%**

The worst recognition rate is obtained by the high-energy consumption class. There are couple reasons why this class has inferior recognition rate compared to the previous two classes. First, the small number of samples that obtained for this class explains the poor score. Second, it has the biggest range in the samples data which makes it more difficult to classify because of how diversely spread out the values are. The samples for high-energy consumption class have range of 6.6 (minimum value is 34.7 Watt and maximum value is 41.3 Watt). Whereas the samples for medium-energy consumption class have range of 1.5 (minimum value is 33.1 Watt and maximum value is 34.6 Watt) and the samples for low-energy consumption class have range of 2.3 (minimum value is 19.3 Watt and maximum value is 21.5 Watt).

The global rate is 91.33% (137/150), which shows good model behavior in general. Finally, the model is interesting because it shows that it is susceptible with low power consumption instead of medium or high power consumption. **Table 6** summarizes the recognition rate obtained from the rule set after the training step.

6. DISCUSSIONS

This chapter discussed two examples of application areas of the fuzzy model. The first section explained how to apply the model for predicting/ estimating value of output variable (energy consumption) given known values of input variables (bandwidth, PC-connections, traffic-load, and hibernation mode). The latter section described how to apply the model for controling the desired value of output variable (energy consumption) by tuning the input variables (bandwidth, PC-connections, traffic-load, and hibernation mode). And finally, the last section provided a case study to exemplify the saving of energy consumption, carbon emission, and electricity cost by applying the fuzzy model.

6.1. Application Area: Prediction and Estimation

Because the model obtained in this study covered all possibilities of inputs, this energy consumption model can be used for prediction and estimation. This model will be useful for network architects to design and optimize the configuration for a green network.

For a given bandwidth, PC-connections, traffic-load, and hibernation mode (input values), then energy consumption (output value) can be estimated. For example, from rule 2, it can be estimated that if hibernation mode is off and bandwidth is high and PC-connection is high and traffic-load is medium, then energy consumption is high. And so on.

From **Table 7** , it can be infered that if the hibernation mode is off, then energy consumption can be either medium or high. However if one of the others input parameter (bandwidth, traffic-load, PC-connections) is low, then the energy consumption will be low. This can be seen from rule number 16-31 on **Table 7**. That is to say that to achieve high energy consumption, all of the input parameters (bandwidth, traffic-load, PC-connections) should be either medium or high.

On the other hand, if the hibernation mode is on, most likely the energy consumption will always remain low. This is illustrated in rule number 6-15 on **Table 7**. Whatever the values of other input variables (bandwidth, traffic-load, PC-connections), if the hibernation mode is on, the energy consumption is low. This is primarily because when the switch is in hibernation, it is basically non-operative and therefore unable to send or receive any traffic. Nevertheless, some typical hibernation uses cases can be listed as follows:

(1) Offices that are closed due to public holidays and weekends. The switches can be put into hibernation mode because employees do not access the network.
(2) Retail stores that are operational during the day only, but not during the night. Thus, there is not any data traffic expected at night during off-hours.
(3) Offices where employees leave after working hours and return to the offices in the next morning (nobody stay during the night). The switches can be scheduled to hibernate immediately after office hours end, and wake up next morning when office hours start.

Table 7. Model for prediction and estimation consists of 24 fuzzy rules

Rule	CF	Hibernate	Bandwidth	PC	Traffic load	Energy consumption
1	0.878215	off	high	med	med	high
2	1	off	high	hig	med	high
3	0.970118	off	high	med	high	high
4	0.98648	off	med	hig	high	high
5	1	off	high	hig	high	high
6	1	on	low	low	low	low
7	1	on	med	low	low	low
8	1	on	high	low	low	low
9	1	on	low	med	low	low
10	1	on	med	med	low	low
11	1	on	hig	med	low	low
13	1	on	low	high	low	low
14	1	on	med	high	low	low
15	1	on	hig	high	low	low
16	1	off	low	low	low	med
17	1	off	med	low	low	med
18	1	off	hig	low	low	med
20	0.788996	off	low	med	low	med
22	1	off	med	med	low	med
25	1	off	med	high	low	med
26	1	off	low	low	med	med
29	1	off	med	low	med	med
30	0.886023	off	low	med	med	med
31	1	off	med	low	high	med

In order to do more accurate prediction/ estimation of energy consumption, a calculation could be performed using the membership function diagrams of input and output variables as described in **Figure. 10-14**, the user can make an appropriate planning to estimate the power consumption of the switch. For example, the user wants to estimate how much the power consumption of a switch that connected to 14 PCs with 100 Mb/s bandwidth and 80% of traffic-load. First, do the *fuzzification* process of the input variables (hibernation-mode, bandwidth, connections, traffic-load) using **Figure. 10-13** as below:

- Hibernation off → $\mu_{off}= 1$, $\mu_{on}= 0$
- 100 Mb/s bandwidth → $\mu_{low} = 0$, $\mu_{medium} = 1$, $\mu_{high} = 0$
- 14 PC connections → $\mu_{low} = 0$, $\mu_{medium} = 0.66$ $\mu_{high} = 0.33$
- 10% traffic-load → $\mu_{low} = 0$, $\mu_{medium} = 0.85$, $\mu_{high} = 0.15$

Second, do the inference process to extract the conclusion from the rules. Here, the Larsen model (Dubois & Prade, 1997) is used and the inference is as below:

- Rule 21 states that IF hibernation is off (1) AND bandwidth is medium (1) AND connections is medium (0.66) and traffic-load is medium i (0.85) THEN power consumption is medium (0.66)
- Rule 28 states that IF hibernation is off (1) AND bandwidth is medium (1) AND connections is medium (0.66) and traffic-load is high (0.15) THEN power consumption is high (0.15)
- Rule 24 states that IF hibernation is off (1) AND bandwidth is medium (1) AND connections is high (0.33) and traffic-load is medium (0.85) THEN power consumption is high (0.33)
- Rule 4 states that IF hibernation is off (1) AND bandwidth is medium (1) AND connection is high (0.33) and traffic-load is high (0.15) THEN power consumption is high (0.15)
- From rules above, it is inferred that power consumption is medium (0.66) and high (0.33)

Third, do the *defuzzification* process of output (energy consumption) using **Figure.14**. Here we used center of gravity to calculate the output as below:

$$\frac{(50+54+58+62+66+70+74)\ x\ 0.66\ +\ (84+88+92+96+100)\ x\ 0.33)}{(0.66\ x7)\ +\ (0.33\ x\ 5)}$$

$$= 69.93$$

Power consumption = 69.93% x 42 Watt = 29.37 Watt

From the calculation, the estimated value of power consumption is 29.37 Watt with relative error of 15.3% compared to the real value from experimentation which is 34.71 Watt.

6.2. Application Area: Control

The end goal of this study is to propose a model which capable to be used as a reference for controlling the energy consumption into the desired level. Fuzzy logic control has had great success in various industry application since it was initially introduced by Lotfi Zadeh (Zadeh, 1975) . However, despite of its wide application in many domains (Precup & Hellendoorn, 2011), the use of fuzzy controller it is still rarely applied in network domain.

Fuzzy controllers are particularly applicable when the identification of the control system is too complex to model using classical mathematical tools or when the knowledge of the system cannot be expressed in a numerical way (Zadeh, 1973). The main advantages of Fuzzy Control are as below (Sugeno, 1985):

(1) Simplicity, flexibility, and easy adaptation of system operation.
(2) Robustness against disturbance.
(3) Possibility of managing several objectives
(4) Facility of synthesizing views of different experts.

Nonetheless, despite of many promising advantages it may posses, fuzzy controller has some drawbacks such as it is not generic and therefore is develop for specific use case only. For example, the results presented in this study are specific to the network technology and application constraints as described.

As for the controller purpose, let us revisit the previous rules describe in section 6.1, particularly rules number 26, 29, 30, and 31 from **Table 7** which will be the main point of interest to build the strategy for tuning the energy consumption.

The top five rules in **Table 7** (rules number 1 to 5) produces output of high-energy consumption. Afterall, because the goal is to minimize energy consumption, then these rules are technically useless since high-power consumption is not preferrable at any cost. Thus, we can eliminate this rules from our concern.

Next, out of 24 rules in **Table 7**, 9 of them has output with low-energy consumption (rule 6-11,13-15). However they are all have the likeness which is all of them has hibernation mode on. It means that, to obtain a low energy consumption, simply turn the hibernation on is enough. Unfortunately, this strategy is impossible to be executed during the office hours because when the switch is put into sleep, it means that no user can access the network and do the business. Therefore this strategy is not feasible to apply.

There are ten rules left (rules number 16-18, 20-22,25-26, 29-31), all of them has output of medium energy consumption. Out of these ten, six of them has attribute of low traffic. The low traffic category means the traffic load is between 0 to 4% which can otherwise be translated into almost having no traffic at all. Again, this means that the user can not do any business activities if the load have to be kept into minimum. Thus, rule number 16-18, 20-22, 25 could not be used to tune the controller because it simply not practical.

Finally, only four rules are left as depicted in **Table 8**. These four rules are the ones which can be utilized for the fuzzy controller. All of them has output of medium energy consumption and hibernation mode set to off. Medium energy consumption can be achieved by setting the bandwidth to either low (10 Mb/s) or medium (100 Mb/s), thus high bandwidth (1 Gb/s) leads to high energy consumption. Furthermore, to keep the energy minimum, the number of connected PC must be limited to either low (0-8 PCs) or medium (9-16 PCs).

Table 8. Strategy to tune energy consumption

Rule	CF	Hibernate	Bandwidth	PC	Traffic load	Energy consumption
26	1	off	low	low	med	med
29	1	off	med	low	med	med
30	0.886023	off	low	med	med	med
31	1	off	med	low	high	med

Rule number 26 states that medium energy consumption can be obtained when hibernation is off, and bandwidth is set to low, and number of connected hosts are low, and traffic load is medium. This rule well describes the situation in the early morning when not many users have yet come to the office to start working; or during the lunch break when most people would go out to eat their lunch and do not touch their computers; or at late evening when office hour has finished and many users starts to leave the premise. In these situation, only small number of users are active and they only accessed the network occasionally for small jobs like email messaging or printing which do not require high bandwidth.

Rule number 29 and 30 are in reverse of each other in terms of bandwidth and number of connected PCs. In the scenario where traffic load is medium, energy can be kept minimum by either switching to low bandwidth or reducing number of connections. The rule number 29 fits for the situation where there are few demanding users which require high quality of service (hence provided by medium bandwidth). For example, when users conducting a business video conferencing, there might be less users who access the network because the video conference is usually held in a meeting room where participants share the same computer, however to support real time video conference in real time especially when there are multiple concurrent video calls, a sufficient bandwidth is required to ensure flawless transmission. On the other hand, rule number 30 is suitable where there are quite many users who demand the service but do not really concerned about the quality of service (hence, low bandwidth is sufficient). An example of this occasion would be the time during the busiest office hours in which the productivity is in peak. Most users in the network are active and they are carrying their activities frequently. However, since most of the office jobs are considered small tasks (e.g. call, email, or print), even a slow uplick would be sufficient to support the network.

Rule number 31 states that medium energy consumption can be achieved when hibernate is off, and traffic load is high, and bandwidth is medium, and number of connected PC are small. Compared to the previous three rules, this is the only options which permit having a high traffic load while still having a medium energy consumption. An example of scenario that suits this condition would be the time during the night when heavy-duty job is performed. Heavy tasks such as server backup, batch processing, and data mirroring would flood quite amount of traffic into the network and therefore would require a sufficient bandwidth to support the process.

6.3. Case Study

To express the interest of this study in terms of energy saving quantitatively, let us applied a scenario in a company with 100 switches installed. Each switch will have 24 Gigabit-Ethernet ports and all ports are connected to user PCs. For this study, two scenarios will be compared. Case A is a normal usage and case B is an energy-efficient usage with application of fuzzy rules explained in section 6.2 in order to save the energy. A comparison in terms of annual energy consumption, cost, and carbon emmision between case A and case B will be presented.

For both case A and case B, assumed that the switches operate 12 hours daily in five working days a week (Monday to Friday) starting from 7:00 to 19:00 during office hours. The other 12 hours at night is used for backup activity for 4 hours and idle for 8 hours. Users have no activity on weekend, so the network is idle for 48 hours during Saturday and Sunday. The user activity in a day is described in **Table 9**.

Table 9. Daily activity pattern of the users on weekdays and weekends

Time	Duration	Network usage
Weekdays		
7:00 – 9.00	2 hours	Early Morning, few people, low network activities
9:00 – 12.00	3 hours	Morning, many people, high network activities
12:00 – 14.00	2 hours	Lunch break, few people, low network activities
14:00 – 15.00	1 hour	Afternoon, video conference meeting, high network activities
15:00 – 17.00	2 hours	Late afternoon, many people, medium network activities
17:00 – 19.00	2 hours	Evening, few people, low network activities
19:00 – 23.00	4 hours	Night, system backup, high network activities
23:00 – 7.00	8 hours	Midnight, no activity, idle
Weekends		
7:00 – 7:00	24 hours	no activity

Table 10. Fuzzy rule application for case B

Time	Duration	Network usage	Rule
Weekdays			
7:00 – 9.00	2 hours	Few people, low network activities	26
9:00 – 12.00	3 hours	Many people, high network activities	5
12:00 – 14.00	2 hours	Few people, low network activities	26
14:00 – 15.00	1 hour	Video conference meeting, high network activities	29
15:00 – 17.00	2 hours	Many people, medium network activities	30
17:00 – 19.00	2 hours	Few people, low network activities	26
19:00 – 23.00	4 hours	System backup, high network activities	31
23:00 – 7.00	8 hours	Midnight, no activity	6
Weekends			
7:00 – 7:00	24 hours	no activity	6

For case A, the switches operates 24 hours in 7 days continuously, independent of network usage. While for case B, the switches will operate according to the network usage pattern. The operation of the switches applies fuzzy rules as described previously on section 6.2. **Table 10** below described the application of fuzzy rules for case B.

There are three times during the day in which the network activities is low. First is during early morning from 7:00 to 9:00 when the office is just open, only few people has reached the workspace. Second is during the midday when the lunch break occurs, most of the employees have their lunch outside the office and only few people might stay and continue their activities. Third is during evening from 17:00 to 19:00 when office hours end and many people leave the office. This situation fits the condition of low bandwidth, low number of PC-connections, and medium traffic-load, thus fuzzy rule no.26 is applied. The result is medium energy consumption.

During the morning from 9:00 to 12:00, many people arrive at the office and begin their activities. The increasing number of people results in high network load which requires high bandwidth rate, and high number of PC-connections. Therefore, fuzzy rule no.5 is applied in this situation. In the afternoon the network activities continue to be high due to the covenience time to conduct video conference meeting. In each conference meeting, many employees gather at the conference room and only one PC is required to be connected to the network. This main PC is then projected to a large screen which display the video conference to all participants in the room. To accomodate the video conference meeting, it requires a low number of PC-connections, medium bandwidth rate and medium traffi-load. Thus, fuzzy rule no.29 is applied in this situation.

The next 2 hours in the afternoon from 15:00 to 17:00, several people go back to their desks to continue their activities after the video conferences are over. This generates medium network traffic-load which required medium number of PC-connections and low bandwidth. Fuzzy rule no.30 is applied in this situation.

Night is the time for system backup which consumes a significant amount of network resources (high traffic-load). Since none of the user access the network, this means that only low number of PC-connections and medium bandwidth is required. Fuzzy rule no.31 is applied in this situation. During midnight and weekends, the network is idle and therefore the switches can be put into hibernation mode to save the energy consumption. In this case, fuzzy rule no.6 is applied.

Table 11. Description of fuzzy rules for case B

Rule	CF	Hibernate	Bandwidth	PC	Traffic load	Energy consumption
5	1	off	high	high	high	high
6	1	on	low	low	low	low
26	1	off	low	low	med	med
29	1	off	med	low	med	med
30	0.886023	off	low	med	med	med
31	1	off	med	low	high	med

Table 12. Annual usage time for weekdays for case B

Time	Duration in a day	Electricity Consumption	Annual duration time
Weekdays			
7:00 – 9.00	2 hours	30 Watt	2 hours x 5 days x 52 weeks = 520 hours
9:00 – 12.00	3 hours	40 Watt	3 hours x 5 days x 52 weeks = 780 hours
12:00 – 14.00	2 hours	30 Watt	2 hours x 5 days x 52 weeks = 520 hours
14:00 – 15.00	1 hour	30 Watt	1 hours x 5 days x 52 weeks = 260 hours
15:00 – 17.00	2 hours	30 Watt	2 hours x 5 days x 52 weeks = 520 hours
17:00 – 19.00	2 hours	30 Watt	2 hours x 5 days x 52 weeks = 520 hours
19:00 – 23.00	4 hours	30 Watt	4 hours x 5 days x 52 weeks = 1040 hours
23:00 – 7.00	8 hours	20 Watt	8 hours x 5 days x 52 weeks = 2080 hours
Weekends			
7:00 – 7:00	24 hours	20 Watt	24 hours x 2 days x 52 weeks = 2496 hours
Total			**8736 hours**

Refer to our definition of the level of energy consumption in **Figure 14** on section 4.3, the energy consumption that will be used in the calculation is assumed to be 20 Watt, 30 Watt, and 40 Watt for low, medium, and high energy consumption consecutively. So for case A, the switch always operates on full power of 40 Watt during 8736 hours in a year (24 hours x 7 days x 52 weeks). For case B, the annual usage time is given in **Table 12** below.

To measure the annual electricity (energy) consumption, the following formula is used.

$$\textit{\textbf{Annual electricity consumption}} = \textit{\textbf{Number of hardwares}} \times \textit{\textbf{Electricity consumption per harware}} \times \textit{\textbf{Total usage time per year}} \quad (3)$$

Thus, the annual electricity consumption for case A can be calculated as follows.

Annual energy consumption = (100 switches x 40 Watt x 8736 hours)

= **34.944 MW**

And, the annual electricity consumption for case B is as follows.

Annual energy consumption = (100 switches x 30 Watt x 3380 hours) + (100 switches x 40 Watt x 780 hours) + (100 switches x 20 Watt x 4576 hours)

= 10.14 MW + 3.12 MW + 9.152 MW

= **22.412 MW**

Based on our experiment, the maximum power consumption to run a 2960-X switch is approximately 42 Watt. Therefore total power supply needed to run in full capacity is around 42 Watt x 100 switches = 4.2 kW. In France, electricity are supplied mainly by the state-owned *Electricité de France* (EDF) while other alternative suppliers accounted for only 9% of residential and 22% of commercial retail market (Bayer, 2015). In line with this assumption, price of electricity (including tax) for industrial use is calculated based on 2014 blue tariff (*tariff bleu*), a base option assigned by EDF for standard industrial (non-residential) consumption band with a supply of 3 to 36 kilo Volt-Ampere (kVA) (EDF, 2014).

The blue tariff offers a different rate for normal hours (*heures pleines)* and off-peak hours (*heures creuses)*. Since we need 4.2 kVA, we will use electricity tariff for 6 kVA supply which consists of yearly subscription (*abonnement annuel*) of 110.64 €, and a charge of 10.02 c€/kWh for normal hours and 6.18 c€/kWh for off-peak hours. The off-peak period is from 22:00 until 6:00, while the rest of the time is accounted as normal period. Energy consumption usually peaks at 19:00 when people go home and turn on heating, lights, and home appliances, while business are still consuming high amounts of electricity (Bayer, 2015). Moreover, price scheme changes according to the weather; the price during winter season is comparatively higher than it is in summer season. Annual peak demand occured during cold winter due to the significant proportion of electric heatings in buildings.

The annual operation cost is calculated using equation below.

$$\textbf{\textit{Annual cost}} = \begin{matrix}\textbf{\textit{Annual}}\\ \textbf{\textit{electricity}}\\ \textbf{\textit{consumption}}\end{matrix} \times \textbf{\textit{Electricity cost}} \qquad (4)$$

The annual cost for case A can be calculated based on **Table 13**.

Table 13. Electricity charge calculation for case A

Time	Duration in a day	Energy Consumption	Tariff	Annual duration time
Weekdays				
6:00– 22.00	16 hours	40 Watt	Normal 10.02 c€/kWh	16 hours x 5 days x 52 weeks = 4160 hours
22:00– 6.00	8 hours	40 Watt	Off-peak 6.18 c€/kWh	8 hours x 5 days x 52 weeks = 2080 hours
Weekend				
6:00– 22.00	16 hours	40 Watt	Normal 10.02 c€/kWh	16 hours x 2 days x 52 weeks = 1664 hours
22:00– 6.00	8 hours	40 Watt	Off-peak 6.18 c€/kWh	8 hours x 2 days x 52 weeks = 832 hours
Total				**8736 hours**

Therefore, annual cost for case A is as follows.

Annual cost = 110.64 € + (100 switches x 0.04 kW x 5824 hours x 10.02 c€/kWh)
+ (100 switches x 0.04 kW x 2912 hours x 6.18 c€/kWh)
= 110.64 € + 2334.26 € + 719.85 €
= **3164.75 €**

Next, the annual cost for case B can be calculated based on **Table 14.**

Table 14. Electricity charge calculation for case B

Time	**Duration in a day**	**Energy Consumption**	**Tariff**	**Annual duration time**
Weekdays				
7:00 – 9.00	2 hours	30 Watt	Normal 10.02 c€/kWh	2 hours x 5 days x 52 weeks = 520 hours
9:00– 12.00	3 hours	40 Watt	Normal 10.02 c€/kWh	3 hours x 5 days x 52 weeks = 780 hours
12:00– 22:00	10 hours	30 Watt	Normal 10.02 c€/kWh	10 hours x 5 days x 52 weeks = 2600 hours
22:00– 23:00	1 hours	30 Watt	Off-peak 6.18 c€/kWh	1 hours x 5 days x 52 weeks = 260 hours
23:00 – 6.00	7 hours	20 Watt	Off-peak 6.18 c€/kWh	7 hours x 5 days x 52 weeks = 1820 hours
6:00 – 7.00	1 hours	20 Watt	Normal 10.02 c€/kWh	1 hours x 5 days x 52 weeks = 260 hours
Weekend				
6:00– 22.00	16 hours	20 Watt	Normal 10.02 c€/kWh	16 hours x 2 days x 52 weeks = 1664 hours
22:00– 6.00	8 hours	20 Watt	Off-peak 6.18 c€/kWh	8 hours x 2 days x 52 weeks = 832 hours
Total				**8736 hours**

Therefore, annual cost for case B is as follows.

Annual cost = 110.64 € + (100 switches x 0.03 kW x 3120 hours x 10.02 c€/kWh)
+ (100 switches x 0.04 kW x 780 hours x 10.02 c€/kWh)
+ (100 switches x 0.03 kW x 260 hours x 6.18 c€/kWh)
+ (100 switches x 0.02 kW x 2652 hours x 6.18 c€/kWh)
+ (100 switches x 0.02 kW x 1924 hours x 10.02 c€/kWh)
= 110.64 € + 937.87 € + 312.62 € + 48.204 €+ 327.79 € + 385.57 €
= **2122.69 €**

To quantify the emission associated with the company's consumption of electricity, the annual energy consumption is multiplied by emission factor for electricity use in France. Emission factor is an indicator of carbon emissions generated by electricity production, expressed in grams of CO_2 per kWh produced. Majority of countries measure carbon emission from electricity consumption based on the composite electricity/heat emission factors published by International Energy Agency (IEA, 2010), which are also used for most of the grid electricity factors in the World Resources Institute (WRI) tool for emission from purchased electricity (WRI, 2011), and Department for Environment, Food & Rural Affairs /Department of Energy and Climate Change (Defra/ DECC)'s factors for non-United Kingdom (UK) countries (Defra/DECC, 2011).

However, the composite electricity/heat emission factors may not be accurate proxy for grid electricity emission because these factors include the emission from heat generation as well as electricity. Furthermore, the composite factors do not provide factors for transmission and distribution (T&D) losses or emission per kWh of electricity consumed. The "T&D losses" factor shows the emission associated with the electricity which is lost through T&D grid per kWh of electricity consumed within the country. Another limitation is that the composite factors are meant for only Carbon dioxide (CO_2) emission , and do not cover other relevant Green House Gases (GHG) according to Kyoto Protocol such as Nitrous oxide (N_2O) and Methane (CH_4) (UNFCCC, 1997). Therefore, the calculation in this paper follows the methodology for electricity-specific emission factor provided by (Ecometrica, 2011) which adresses those limitations. This methodology involves calculating the total emissions from the generation of electricity within a country and dividing that figure by the total amount of electricity produced by the country.

The electricity-specific factor for France is 0.070927465 $kgCO_2/kWh$ whereas the IEA composite electricity/heat factor is 0.082717 $kgCO_2/kWh$. The electricity-specific factor is 0.01179 $gramCO_2/kWh$ (14.3%) lower than the IEA composite electricity/heat factor (Ecometrica, 2011). This relatively high difference is expected due to the low-carbon electricity generation but high-carbon heat generation. France generates approximately 77% of its electricity from nuclear power, 13% from hydro-electric power stations, 5% from coal, natural gas, and oil, and the reminder from other renewable resources such as photovoltaics, wind, and biomass (Bayer, 2015). Because France generated its electricity mostly from nuclear plant, the carbon emission is relatively low compared to other countries. Whereas almost 100% of heat generation in France is resulted from fossil fuels or waste combustion which releases high carbon emission (IEA, 2011).

The annual carbon footprint is calculated using equation below.

$$\textbf{\textit{Annual carbon footprint}} = \textbf{\textit{Annual electricity consumption}} \times \textbf{\textit{Electricity-specific factor}} \qquad (5)$$

Thus, we can calculate the annual carbon footprint for case A as follows.

Annual carbon footprint = 34944 kWh x 0.070927465 $kgCO_2/kWh$

= **2478.49 kg**

And, the annual carbon footprint for case B is as follows.

Annual carbon footprint = 22412 kWh x 0.070927465 $kgCO_2/kWh$

= **1589.63 kg**

The result of case study illustrated that fuzzy rules can be implemented to control the network behavior in order to gain some saving in terms of energy consumption, operation cost, and carbon footprint. The result of the case study showed that case B, which illustrated the use of fuzzy rules to control the switch behavior according to user needs, consumed 36% less energy , cost 33% less money, and emmited 36% less carbon footprint than case A, which illutrated the worst case scenario where the devices is always up 24/7. The comparison of annual energy consumption, annual cost, and annual carbon footprint between case A and case B is summarized in **Table 15.**

Table 15. Summary of case A and B

	Case A	**Case B**	**Difference**
Annual energy consumption	34.94 MW	22.41 MW	36%
Annual operation cost	3164.75 €	2122.69 €	33%
Annual carbon footprint	2478.49 kg	1589.63 kg	36%

7. CONCLUSION

The purpose study is to show the use of fuzzy logic for identification, estimation/ prediction, and control of a communication network. The study addresses the topic of green network in which tuning network parameters (bandwidth, traffic-load, PC-connections, hibernation-mode) to minimize the energy consumption. The proposed approach consists of benchmarking process by analyzing the network behavior from a numerical experimentation. Instead of analytic model, Fuzzy Rule Classifier is used to identify the system hence limiting the expertise steps. The recognition rates are good considering the limited number of input data sets (150 data sets). The model is obtained from the fuzzy rules that are automatically learned by the classifier and is utilized to design a model for prediction/ estimation when deploying new switches. Furthermore, the model could also be further developed as a fuzzy controller which would be implemented in network supervisory tool.

This study provides a framework of green network services to adapt energy consumption by tuning the network parameters according to the needs of the user applications while maintaining acceptable network availability. A case study is provided to compare the amount of saving that can be obtained using energy-efficiency method based on the application of fuzzy rules. The result of case study recommended that the use of fuzzy rules to control the network operation could efficiently save 36% of energy consumption, 33% of operation cost, and 36% of carbon footprint.

In order to obtain a holistic insight, this study should be conducted with all network equipments such as routers, wireless access points, firewall, laptops, etc. For the future research, the model proposed on this study can be incorporated for various energy saving techniques such as energy efficient routing or dynamic link shutdown. To improve the model, validation using data from telecommunication companies (or ISPs) would be favorable. Also, it will be interesting to define a modeling/ controlling strategy based on more global information such QOS performance, etc.

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APPENDIX

APPENDIX 1: Ishibuchi algorithm

The outline of iterative version of the Ishibuchi rule generation algorithm is given below ((Nozaki, et al., 1997); (Ishibuchi, et al., 1992)). A fuzzy rule R_{ij}^{IJ} for two-dimensional classification problem can be written as follows:

A fuzzy rule R_{ij}^{IJ}: If x_{1p} is A_i^I and x_{2p} is A_j^J then ($x_{1p,}$ x_{2p}) belongs to Class C_{ij}^{IJ} with CF=CF_{ij}^{IJ}, i =1,2,.....I; I = 1,2,...,I_{max}; j = 1,2,...,J; J = 1,2,..., J_{max}, where C_{ij}^{IJ} is one of the M classes and CF_{ij}^{IJ} is the certainty of fuzzy rule R_{ij}^{IJ}.

(1) Calculate β_{CT} for T = 1,2,..., M. $\beta_{CT} = \sum_{X_p \in CT} \mu_i^I\,(X_{1p}) \times \mu_j^J\,(X_{2p})$

(2) Find Class X (CX) such that $\beta_{CX} = \max\{\beta_{C1}, \beta_{C2}, \dots, \beta_{CM}\}$

(3) CF_{ij}^{IJ} is determined as $CF_{ij}^{IJ} = (\beta_{CX} - \beta)/\sum_{T=1}^{M} \beta_{CT}$ where $\beta = \sum_{T=1, CT \neq CX}^{M} \beta_{CT}/(M-1)$

APPENDIX 2 : Typicality Measurement

The outline of typicality measurement *T(V)* which is used in automatic fuzzification is described below. *T(V)* is calculated from extern dissimilarity and intern likeness according to output classes ((Forest, et al., 2006); (Schmitt, et al., 2007)).

$$T(x_a^u) = \frac{RD}{RD + (1-R)(1-D)}$$

$$R(x_a^u) = \frac{\sum_{i=1}^{n} 1 \big/ d(x_a^u, x_a^{f_i})}{n}$$

$$D(x_a^u) = \frac{\sum_{i=1}^{m} 1 - d(x_a^u, x_a^{e_i})}{m}$$

Where:

x_a^u is the value of parameter *a* for sample *x*.

$x_a^{f_i}$ is the value of parameter *a* for sample *f* belonging to the same class than *x*.

$x_a^{e_i}$ is the value of feature *a* for sample *e* not belonging to the same class than *x*.

d(x,y) is the Euclidian distance.

n is the number of samples which belongs to the same class than sample *x*.

m is the number of samples which does not belongs to the same class than sample *x*.

From typicality measure (*T(V)*), correlation (*Corr*) and cross-correlation (*Xcorr*) coefficients are calculated for each output classes. The number of term is determined from ratio *Corr/Xcorr* which characterizes inter-class similarity. These terms are represented by triangular/ trapezoidal membership function and the position are obtained by computing the mean value of the samples belonging to the considered output classes.

APPENDIX 3 : Emission Factor for Electricity Consumption

The emission factor is used to calculate carbon footprint which is attributed to electricity consumption. The general principle is that the national or a European emission factor may be used. The following formula is used to calculate the emission factor (Covenant of Mayors, 2010).

$$\mathbf{EFE = [(TCE - LPE - GEP) * NEEFE + CO2LPE + CO2GEP] / (TCE)}$$

Where:

EFE	=	local emission factor for electricity [t/MWh]
TCE	=	Total electricity consumption in the local authority [MWh]
LPE	=	Local electricity production [MWh]
GEP	=	Green electricity purchases by the local authority [MWh]
NEEFE	=	national or European emission factor for electricity (to be chosen) [t/MWh]
CO2LPE	=	CO2 emissions due to the local production of electricity [t]
CO2GEP	=	CO2 emissions due to the production of certified green electricity [t]

In the exceptional case where the local authority would be a net exporter of electricity, then the calculation formula would be:

$$\mathbf{EFE = (CO2LPE + CO2GEP) / (LPE + GEP)}$$