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Modeling network traffic on a global network-centric system with artificial neural networks

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MODELING NETWORK TRAFFIC

ON A GLOBAL NETWORK-CENTRIC SYSTEM

WITH ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This dissertation proposes a new methodology for modeling and predicting network traffic. It features an adaptive architecture based on artificial neural networks and is especially suited for large-scale, global, network-centric systems. Accurate characterization and prediction of network traffic is essential for network resource sizing and real-time network traffic management. As networks continue to increase in size and complexity, the task has become increasingly difficult and current methodology is not sufficiently adaptable or scaleable. Current methods model network traffic with express mathematical equations which are not easily maintained or adjusted. The accuracy of these models is based on detailed characterization of the traffic stream which is measured at points along the network where the data is often subject to constant variation and rapid evolution. The main contribution of this dissertation is development of a methodology that allows utilization of artificial neural networks with increased capability for adaptation and scalability. Application on an operating global, broadband network, the Connexion by Boeing® network, was evaluated to establish feasibility. A simulation model was constructed and testing was conducted with operational scenarios to demonstrate applicability on the case study network and to evaluate improvements in accuracy over existing methods.

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LIST OF ACRONYMS AND NOMENCLATURE

Symbol/Acronym	Description
a	Semi-Major Axis
a	Variance Coefficient in Norros Equation
AAAI	Assoc. for the Advancement of Artificial Intelligence
AM	Ante Meridiem
ANA	All Nippon Airways
ANN	Artificial Neural Networks
ARINC	American Radio Incorporated
ARPANET	Advanced Research Projects Agency Network
AS	Antenna Subsystem
ASME	American Society of Mechanical Engineering
ATC	Air Traffic Control
B	Buffer Size in Norros Equation
BA	British Airways
bps	bits per second
BS	Bachelor of Science
C	Capacity
C3I	Communications Command Control and Intelligence
C4ISR	Command Control Comm. Intel. Surveillance & Recon.
CAD	Computer Aided Design
CAIDA	Cooperative Association for Internet Data Analysis
CAL	China Airlines
CBB	Connexion by Boeing
CCRP	Command and Control Research Program
CDS	Cabin Distribution System
CI	Computational Intelligence
COTS	Commercial Off The Shelf
CRISP-DM	Cross-Industry Standard Process for Data Mining
CS	Control Subsystem

CSIM	Capacity Simulation
CSU	Control Subsystem Unit
DARPA	Defense Advanced Research Projects Agency
D-BIND	Deterministic Bounding Interval-length Dependent
DBS	Direct Broadcast Satellite
dBW	Decibel Watt
DC	District of Columbia
DLH	Lufthansa Airlines
DNA	Deoxyribonucleic Acid
DNS	Domain Name System
DoD	Department of Defense
DoDAF	DoD Architecture Framework
DTR	Data Transceiver and Router
e	Eccentricity
ε	Cell Loss Rate in Norros Equation
EBO	Effects Based Operations
ECG	Electro-Cardiogram
EEG	Electro-Encephalogram
EIRP	Effective Isotropic Radiated Power
ENN	European Neural Network Society
EOC	Enterprise Operations Center
etc	et cetera
fBm	Fractional Brownian Motion
FLM	Forward Link Modulator
FRD	Forward Receive Demodulator
FTP	File Transfer Protocol
GB	Giga-Byte
GERTS	Ground Receive Transmit Subsystem
GHz	Giga-Hertz
GIG	Global Information Grid
GMT	Greenwich Mean Time

GPS	Global Positioning System
H	Hurst Parameter in Norros Equation
H	Header
HAN	Home Area Network
H-BIND	Hybrid Bounding Interval-length Dependent
Hz	Hertz
i	Inclination
i	internet
I	Internet
IANA	Internet Assigned Numbers Authority
IDEF	Integrated DEFinition Methods
IEEE	Institute of Electrical and Electronics Engineers
IFE	In-Flight Entertainment
in.	Inches
INCOSE	International Council On Systems Engineering
INNS	International Neural Network Society
IP	Internet Protocol
ISO	International Standards Organization
ISP	Internet Service Provider
IUS	Interim Upper Stage
JAL	Japan Airlines
JNNS	Japanese Neural Network Society
JPO	Joint Program Office
κ	Constant
k	Neuron
KAL	Korean Airlines
KB	Kilo-Byte
Kbps	Kilo-Bits per Second
KDD	Knowledge Discovery in Databases
KM	Kilo-Meter
KU-Band	11 – 18 GHz Band in the Electromagnetic Spectrum

LAN	Local Area Network
L-Band	1 – 2 GHz Band in the Electromagnetic Spectrum
lbs	Pounds
ln	Natural Logarithm
LRBP	Long Range Business Plan
LRU	Line Replaceable Unit
LSI	Launch Systems Integration
m	Mean bit rate in Norros Equation
MAN	Metropolitan Area Network
Max.	Maximum
MB	Mega-Byte
Mbps	Mega-Bits per Second
MHz	Mega-Hertz
MISP	Mobile Information Services Provider
MPEG	Moving Picture Experts Group
MS	Master of Science
MVAR	Modified Allan Variance
MW	Mega-Watt
n	Right Ascension of the Ascending Node
n	Iteration
NCO	Network-Centric Operations
NCOIC	Network-Centric Operations Industry Consortium
NCS	Network-Centric System
NCW	Network-Centric Warfare
NES	Network Equipment Subsystem
NLANR	National Laboratory for Applied Network Research
nm	Nautical Miles
NMS	Network Management System
NMTF	Network Monitoring Task Force
NN	Neural Network
NOC	Network Operations Center

NORAD	North American Aerospace Defense Command
NORTHCOM	Northern Command
OAG	Official Airline Guide
OASD	Office of the Secretary of Defense
OODA	Observe Orient Decide Act
OSD	Office of the Secretary of Defense
OSI	Open Systems Interconnection
PC	Personal Computer
PCA	Principle Components Analysis
PhD	Philosophy Doctorate
PM	Post Meridiem
QoS	Quality of Service
RF	Radio Frequency
RFS	RF Subsystem
RLD	Return Link Demodulator
RMA	Revolution in Military Affairs
RTS	Receive and Transmit Subsystem
RTT	Round Trip Time
Rx	Receive
SARM	Strategic Architecture Reference Model
SAS	Scandinavian Airlines
S-BIND	Statistical Bounding Interval-length Dependent
SEBoK	Systems Engineering Book of Knowledge
SIA	Singapore Airlines
SL	Sea Launch
SLAC	Stanford Linear Accelerator Center
SOM	Self-Organizing Map
SoS	System-of-Systems
STD	Standard
TCP	Transmission Control Protocol
TOD	Time of Day

TV	Television
Tx	Transmit
UDP	User Datagram Protocol
UMR	University of Missouri – Rolla
US	United States
USA	United States of America
USAF	United States Air Force
USAFA	United States Air Force Academy
USC	University of Southern California
USN	United States Navy
USSR	Union of Soviet Socialist Republics
v	Volts
v	True Anomaly at Epoch
VoIP	Voice over Internet Protocol
VPN	Virtual Private Network
w	Argument of Perigee
WAN	Wide Area Network
WEKA	Waikato Environment for Knowledge Analysis

1. INTRODUCTION

1.1. OVERVIEW

The world has become increasingly complex and the trend is accelerating. This is especially true for large-scale networks and global communication systems. The emergence of network empowered SoSs (system-of-systems), often called NCSs (network-centric systems), is a good example. These network empowered NCSs tend to be large in scale, complex in nature, global in scope, and constantly evolving. As a result, different aspects of NCSs, such as behavior, characteristics, and architectures, are extremely difficult to model.

Modeling network traffic typifies the difficulty. It's a great challenge to model something so dynamic and subject to change. Yet accurate knowledge of network traffic is essential to the design and operation of the network. During the design phase, and for expansion planning, models are used to simulate the traffic stream and predict future needs. This allows for accurate sizing of the network. During the operational phase, models are used to predict future data rates based on real-time data. This allows for efficient and timely QoS (quality of service) management. In both cases accuracy is vital.

It's the complex, dynamic nature of network traffic that makes the modeling task so difficult. Traffic characteristics vary according to location on the network, applications in use, and time or date of measurement. Unforeseen evolution of network technology results in continuous change, forcing constant updates to model parameters. In addition, the unpredictable behavior of users contributes significant amounts of uncertainty.

Computationally intelligent adaptive modeling techniques are needed in order to capture the dynamically changing and constantly evolving features of these large-scale complex systems. Currently methodology for modeling network traffic is not sufficiently adaptable or scalable. Simulations based on ANNs (artificial neural networks), with the ability to adapt, generalize, and model non-linearities, have the potential for significant improvements in accuracy and ease of maintainability.

1.2. PROBLEM DEFINITION

1.2.1. Increasingly Complex Systems. Complexity in systems exists when it becomes impossible or difficult to define or predict the overall characteristics or behavior of a system based on characteristics, behavior, and relationships between individual elements [Moffatt, 2004; Smith, 2006]. Large-scale global networks are a good example of complex systems. Even a thorough understanding of the individual elements within the network does not lead to an easy understanding of the system behavior as a whole. This creates special challenges when it comes to developing accurate architectures and models.

Take the human body as an example of a complex system, as illustrated in Figure 1-1. Scientific research has lead to entire fields of study based on various biological systems of the human body - such as the cardiovascular system, the respiratory system, the nervous system, the reproductive system, the skeletal system, the digestive system, the muscular system, and others. Much is known and documented about the characteristics, form, and function of these individual biological systems, yet knowledge of individual systems does not allow one to view the human person as a whole and predict or understand human behavior. No two humans are alike and no two humans react, learn, or grow in the same manner.

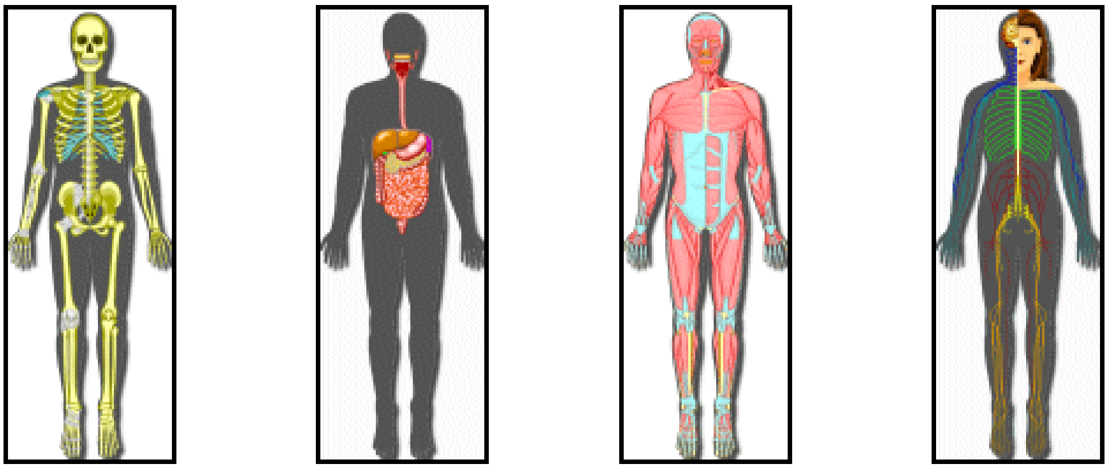


Figure 1-1 Complex Systems

In the modern technology oriented society of today, man-made systems are continuing to grow more and more complex. The advent of the global Internet has fostered the growth of complexity by facilitating the flow and availability of information in previously unforeseen quantities, enhancing the capability of humankind to learn and create, leading to rapid growth in all fields of scientific endeavor. The importance of information cannot be over estimated. As it is often stated, “Information is power,” [Alberts and Hayes, 2003a].

Although the ready availability of information has led to the development of increasing complex systems, the abundance of information has not made it easier to model these systems. On the contrary, the complexity of systems has grown to the point where the task of modeling and understanding large-scale system behavior has become too vast and complex a task for the human mind to encompass in all its variety, detail, complexity, and unpredictability.

According to Edward Smith, "In reality, we must deal not just with a complex system but with a complex adaptive system, one that not only changes unpredictably, but also adapts to its external environment in similarly unpredictable ways, [Smith, 2006]."

1.2.2. Emergence of Network-Centric Systems. Along with the growth of complexity in systems, the growth of the Internet and large-scale networks has provided the emergent technology necessary for the development and deployment of truly large-scale, network enabled systems, called SoSs (system-of-systems). A SoS is composed of components which are large independent systems in and of themselves. A NCS (network-centric system) is a type of SoS oriented towards providing network services.

These large NCSs have become an increasing dominant factor in world affairs, for both military operations and commercial endeavors. Major General Dale Meyerrose, director of NORTHCOM (Northern Command) and NORAD (North American Aerospace Defense Command), says, "Net centricity is the future … the next set of change agents [Meyerrose, 2004]." Carl O'Berry, vice president of network-centric architectures at Boeing, cites Joint Vision 2020 calling for all systems to have the ability to operate as nodes in a global environment, [O'Berry, 2005].

Take a modern battle group as an example of an NCS, illustrated in Figure 1-2 [from Dagli and Miller, 2003]. This battle group might include field troops, tanks, artillery, aircraft, helicopters, satellites, and more. It would also include logistics support, medical support, communication units, command structure, press units, intelligence gathering units, and transportation units. It might include allied coalition units from the armies of foreign nations. A network allows all these units in the battle group to operate as a SoS through use of a common information grid and a networked flow of information. This flow of information allows for shared awareness, collaboration, interoperability, and self-synchronization. The method of operation shifts from platform centric to network centric.

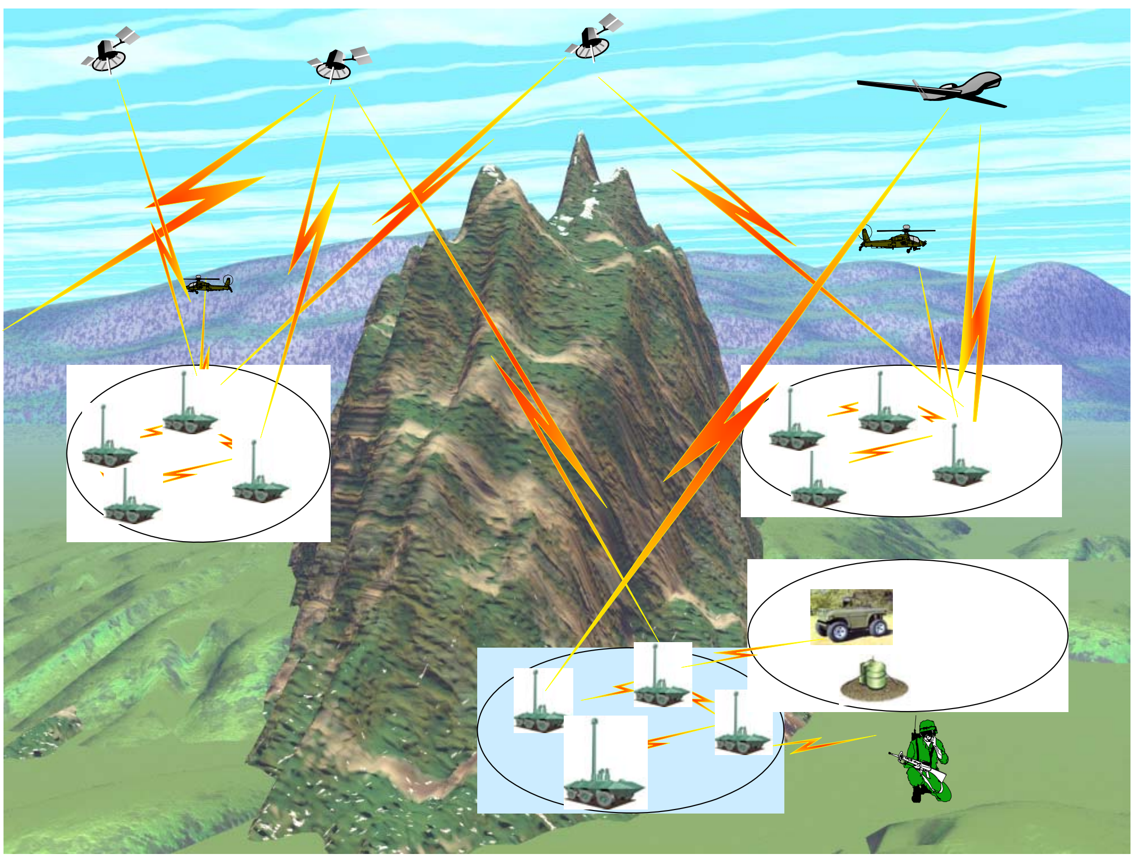


Figure 1-2 Network-Centric Battlegroup

These features, although very desirable, make for extreme difficulty when trying to develop or model the architecture with conventional non-adaptive techniques. When feature are constantly changing and adapting and evolving, a model that doesn't change or adapt or evolve will soon become outdated and soon become woefully inadequate.

1.2.3. Complex Network Traffic. Network traffic on an NCS typifies the problem. Network traffic is complex and constantly changing and evolving; consequently, very difficult to model. Figure 1-3 illustrates the variability exhibited by even a simple set of eighteen individuals in a short six minute span of network traffic.

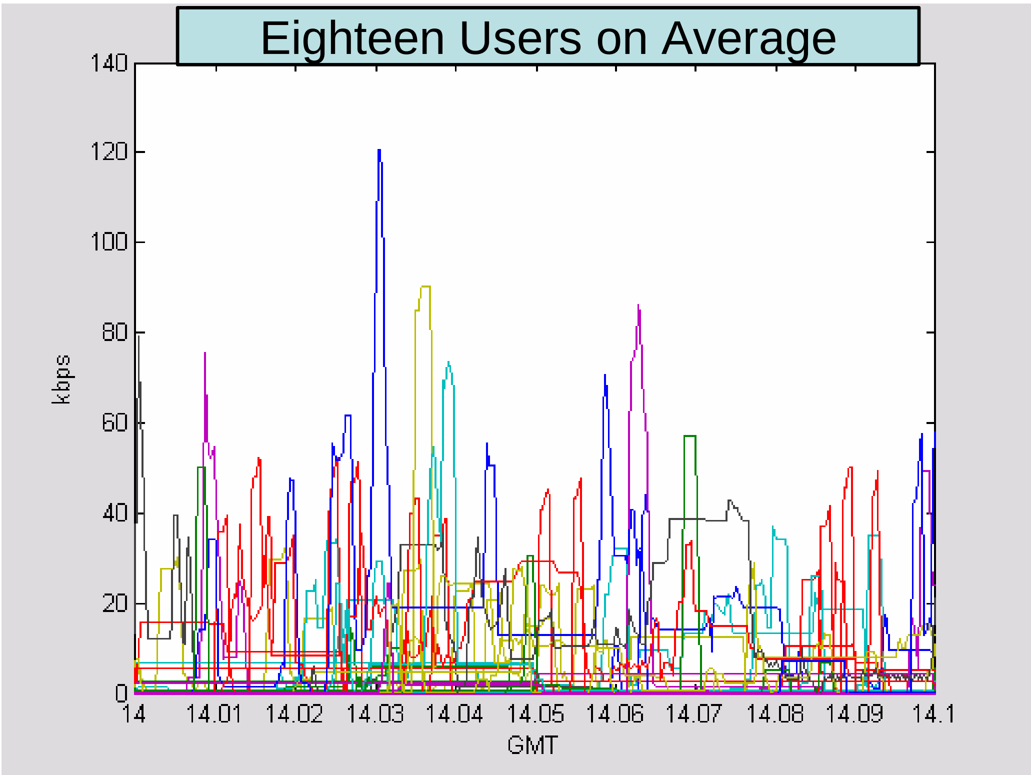


Figure 1-3 Internet Data Traffic on an NCS

Network traffic on a large NCS is likely to be different for various systems of the SoS. For example, data traffic to and from an F-15 fighter jet is likely to have vastly different characteristics than data traffic between infantry soldiers or data traffic for an Apache helicopter. Network traffic would also be different depending upon the situation. For example, an M1A2 Abrams tank would likely have moderate steady state traffic while in cruise operations moving towards the battlefield and heavy high bursty traffic while engaged in combat.

As the networks evolve and new applications and technology become available, new protocols also result in changing traffic characteristics. Emergent capabilities arise as users learn and develop new techniques and uses for available services and for any number of evolving features.

All of this makes accurate modeling extremely difficult, yet it is of utmost importance. One of the primary uses of these models is to predict network needs to allow capacity planning for sizing of the network.

The task is similar to the supply and demand scenario faced by electrical power companies. They have a wide variety of different users, all with unique demand characteristics, from the small individual household to the large industrial factory. To supply the power they tend to have a variety of electrical sources - hydroelectric, petroleum, nuclear, natural gas, coal, solar, etc. Demand varies over time with peaks and lulls, but outages are not looked upon kindly. The problem facing the electrical company is how much capacity is needed, or how big to make the electrical grid so that all the demand is met with the most cost effective means. Everything depends upon accurate demand modeling and precise prediction of usage. Figure 1-4 [from PPRP, 2005] illustrates with a typical load profile, this one from Maryland in the Delmarva peninsula service area.

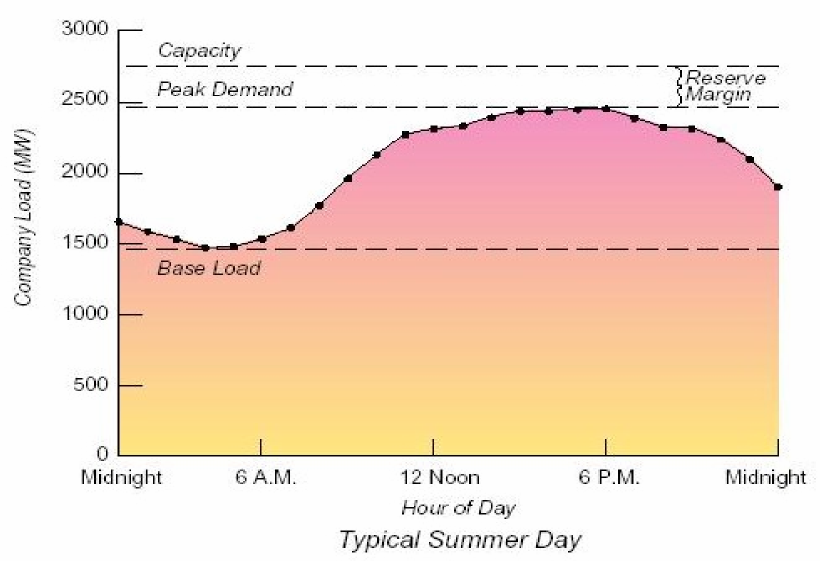


Figure 1-4 Power Load Profile

The same need for accurate capacity modeling exits with regards to network traffic on a large NCS. There is a wide variety of different types of users with a multitude of possible applications and physical devices. The data bandwidth flow, or load, varies over time and there is strong motivation not to be undersupplied, which would cause loss of link and/or degradation of the QoS (quality of service). The problem is how much capacity, or how big to make the pipe over which the data traffic must flow. Everything depends upon accurate capacity modeling and precise prediction of usage. Figure 1-5 illustrates with a projected bandwidth load profile for the CBB NCS.

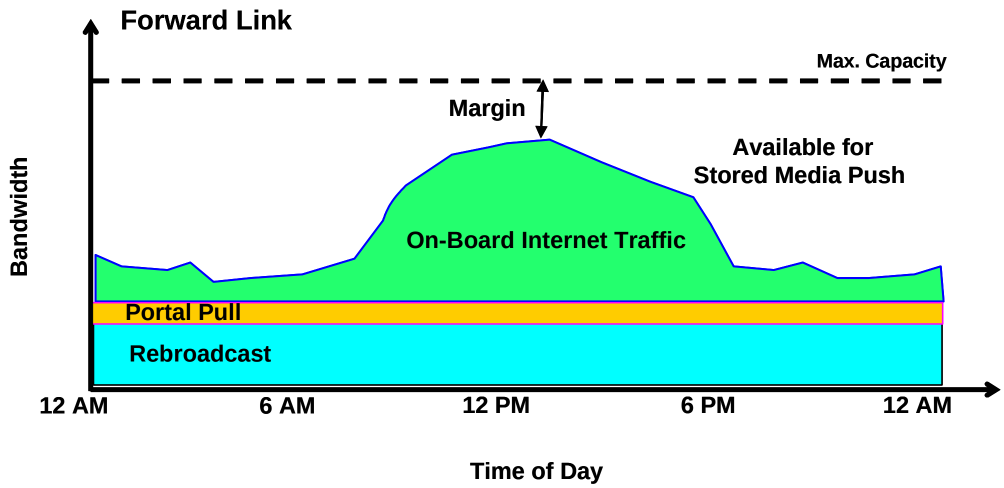


Figure 1-5 Bandwidth Demand

Unfortunately, despite the increasingly volatile nature of network data traffic, the capacity modeling algorithms of today are not adaptable or scaleable enough to deal with network traffic variability, evolution, and uncertainty.

1.3. ADAPTIVE MODELING WITH COMPUTATIONAL INTELLIGENCE

An adaptive architecture is proposed as the means to address these problems. Fortunately, a set of intelligent computing methodologies, known collectively as CI (Computational Intelligence), has arisen with the advent of computers in response to the difficulty of modeling and analyzing extremely complex systems and incredibly large amounts of data. CI has successfully been applied to many fields and applications, such as data mining, pattern recognition, prediction, association, machine learning, optimization, noise filtration, logic and reasoning, neuroscience, and robotics. CI methodologies are useful for addressing difficulties of complexity, non-linearity, generalization, imperfect data, changing data, immense quantities of data, and system evolution. CI methodologies are especially valuable in addressing problems when the scope of complexity extends beyond the capabilities of the human mind and it becomes hard to foresee potential solutions or predict emergent capabilities. CI includes fields such as fuzzy logic, artificial neural networks, and genetic algorithms.

Large NCSs stand to benefit greatly from an adaptive architecture based on CI. Since a large NCS is constantly changing and evolving, and tends to be too complex for human control, it stands to reason that architectures and models need to change and evolve also, or in other words, to adapt.

1.4. RESEARCH OBJECTIVES

The objective of this research was to examine the feasibility and develop an adaptive architecture based on ANNs for modeling network traffic on large-scale NCSs for increased adaptability, scalability, and accuracy in predicting network demand. An adaptive ANN model was developed for and applied to the CBB broadband network. System output consists of time-history bandwidth traces defining the capacity needs of the network. As the NCS expands, changes, or adapts, the ANN model is re-trained and updated to allow adaptation in response to the evolving NCS.

1.5. CONNEXION BY BOEING CASE STUDY

CBB (Connexion by Boeing) was chosen as the case study for an NCS for three reasons. First, and most important, it has all the characteristics and features of a large-scale, complex, global, broadband NCS. Second, CBB network data was made available to UMR (University of Missouri – Rolla) for the research project. Third, mobile aircraft Internet data traffic, such as that provided by CBB, is new territory. Mobile aircraft Internet data traffic has never before been made available for academic research and presented an excellent opportunity for original investigation in an emerging field.

The CBB network provides two-way, high-speed, broadband Internet data services for commercial airline passengers through shared broadband satellites in geo-synchronous orbit. Network control is managed through a network operations center which monitors service usage to increase or decrease capacity in order to maintain QoS as user demand fluctuates. Figure 1-6 illustrates the overall CBB Block 1 operational architecture (DoDAF OV-1). Section 6 of this dissertation gives a more detailed description of the CBB NCS.

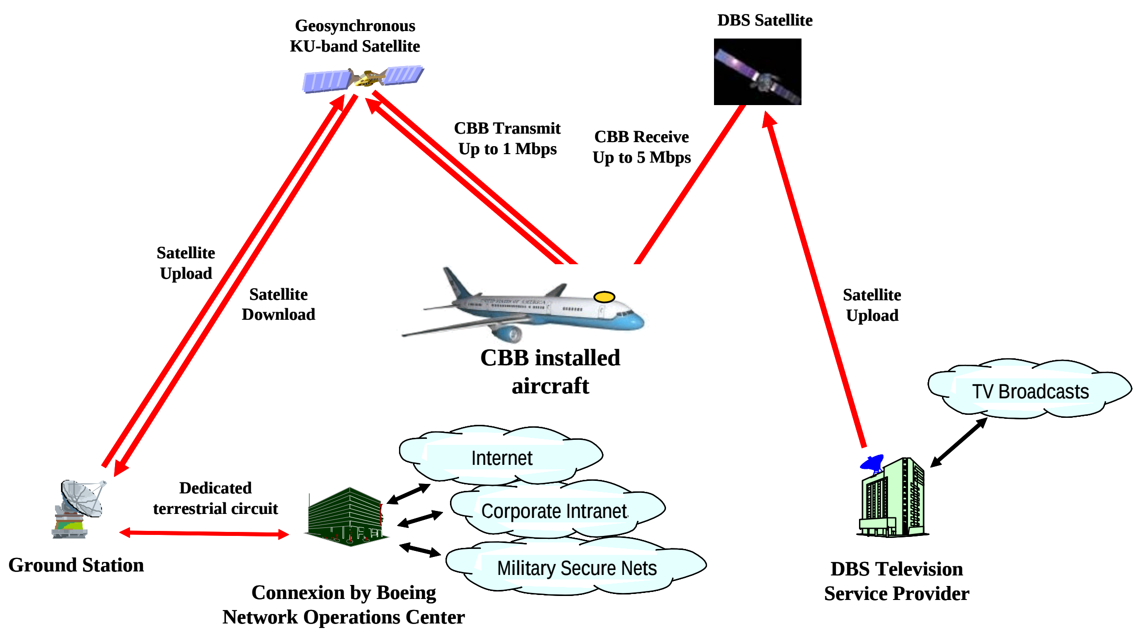


Figure 1-6 Connexion by Boeing Architecture

1.6. METHODOLOGY

Three major activities were undertaken to accomplish the objectives of this research project, as shown in Figure 1-7. Things were not so simple as to merely take an existing non-adaptive architecture, replace the capacity algorithm with an adaptive ANN capacity predictor, and call it good. A methodology for extracting, evaluating, and transforming network data into a condition compatible with ANN simulation had to be developed. This was accomplished in step 1 through use of a rigorous data mining process. Step 2 involved development of an ANN bandwidth predictor and it's incorporation into a bandwidth capacity simulation. Step three involved simulation testing to confirm feasibility and compare accuracy against existing methodology.

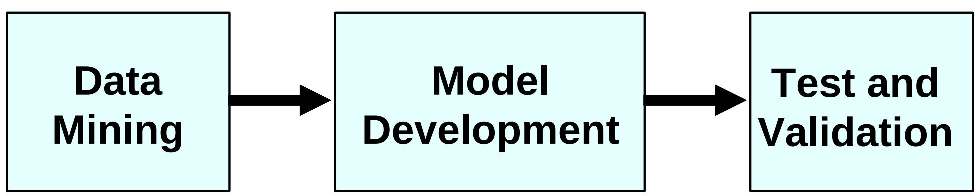


Figure 1-7 Dissertation Methodology

1.7. CONTRIBUTIONS TO LITERATURE

There are several contributions resulting from this Ph.D. dissertation research project conducted through the University of Missouri – Rolla.

- A data mining methodology for decomposing network traffic data into a form compatible with computationally intelligent simulation techniques.
- Data extraction algorithms and processes for the CBB network. These processes allow users to extract network data from multiple data warehouses for trending analysis and research on network characteristics. The processes could be adapted for use on other similar networks.
- Decomposition of CBB network traffic into flight route bandwidth traffic traces. These traffic traces were used for ANN simulation and also for evaluation of flight and user characteristics.
- An adaptive architecture that uses computational intelligence for modeling network traffic. The architecture uses artificial neural networks and was demonstrated on an operating network.
- A working ANN model that predicts network traffic traces for the CBB case study network. Input vectors were composed of selected flight attributes. The output vector was composed of points on the time history of a bandwidth traffic trace. The network was composed of two hidden layers with 39 neurons each, an input layer with 10 attributes, and an output layer with 17 neurons.
- An adaptive simulation architecture that utilizes the ANN bandwidth predictor. The simulation models operational scenarios with user selected flights, flight routes, and satellite coverage areas. Network data is used as inputs and the simulation predicts satellite transponder needs using the ANN bandwidth predictor.

1.8. SECTION ORGANIZATION

Section 1: Introduction to the research topic - the problem to be addressed, a proposed solution, and contributions to literature.

Section 2: Literature review of network-centric systems – their importance, basic characteristics, examples, and applicability to this research project.

Section 3: Literature review of the Internet and capacity modeling techniques – development, basic features, techniques, and applicability to this research project.

Section 4: Literature review of artificial neural networks – algorithms and applications and applicability to this research project.

Section 5: Literature review of data mining - techniques and applications and applicability to this research project.

Section 6: Description of the CBB global NCS - the case study NCS used to provide data for this research project. Includes a description of the CBB capacity simulation for modeling and predicting network traffic.

Section 7: Data mining CBB network traffic and the development of bandwidth traffic traces to enable ANN based simulation.

Section 8: Development of the ANN based bandwidth predictor and the results of simulation testing to establish the feasibility of using ANN based simulation. Includes a comparison against existing methods.

Section 9: Conclusion.

2. NETWORK-CENTRIC SYSTEMS LITERATURE REVIEW

2.1. RELEVANCE OF NCS TO THIS RESEARCH

The goal of this research project was to investigate the feasibility of using computational intelligence for modeling network traffic on a global NCS (Network-Centric System) to allow accurate and adaptable prediction of bandwidth demand for the NCS. Network enabled systems are becoming more and more common. Networks provide the enabling technology that allows large-scale endeavors for many military and commercial applications. These NCSs, constantly changing and evolving because of their very nature, are driving the need for adaptive architectures such as the ones investigated and proposed in this dissertation.

Due to the complex and evolutionary nature of NCSs, and the likely probability of widespread use in the future, the need for adaptive architectures that can change and evolve has become critical. The adaptive architecture proposed by this dissertation was developed in an effort to study and define ways to address the special needs of NCSs, which were described in this section.

Carl O'Berry, as the newly appointed chairman of the executive committee of an international consortium formed to promote network-centric operations, said, "I can think of no system or user that wouldn't benefit from having the ability to participate on a global network," and "it is my prediction that NCO will eventually involve every domain in our lives, forever [O'Berry, 2005]."

The literature review in this section includes: 1) an overview of what Network-Centric Systems are, including a brief description of systems, the importance of networking, the flow of information within a NCS, domains of operation, the global information grid, and some challenges and issues, 2) a description of several architecture frameworks, focusing primarily on the DoD Architectural Framework, and 3) a review of successful examples of NCSs, including the CBB case study.

2.2. CHARACTERISTICS OF NETWORK-CENTRIC SYSTEMS

An NCS is a system oriented towards providing network services. The world is evolving from the Industrial Age to the Information Age and the driving force behind this evolution is the ability of computers and networks to facilitate the flow of vast quantities of information. David S. Alberts, Director of Research at OASD-C3I (Office of the Secretary of Defense) said, "Information Technology is the DNA of the Information Age – the fundamental building block of dominant competitors [Alberts et al., 2002a]."

The value of information has long been recognized as vital to the success of nearly all aspects of human endeavor. This is equally true in business or military environments. Vice Admiral Arthur K. Cebrowski of the U.S. Navy postulates that "We are in the midst of a revolution in military affairs (RMA) unlike any seen since the Napoleonic Age, [Cebrowski and Garstka, 1998]." He quotes Admiral Jay Johnson, Chief of Naval Operations, calling this change "a fundamental shift from what we call platform-centric warfare to something we call network-centric warfare," and says "it will prove to be the most important RMA in the past 200 years [Cebrowski and Garstka, 1998]."

Research into the development of new processes and enabling technology to facilitate the move towards network-centricity is accelerating. Many of the definitions and characteristics are still evolving and will continue to evolve with time; however, there is little doubt net-centric capability will be the driving force of the future for large scale multi-national and multi-organizational systems. "Although the broad tapestry of network-centric concepts is still emerging, there is clear evidence that a shift to network-centric operations has begun, [Alberts et al., 2002a]."

2.2.1. System Concepts. To understand the concept of NCS it is important to first have good working definitions of different types of systems, from small to large, from simple to complex, from homogeneous single purpose systems to large system-of-systems that are composed of multiple independent acting systems.

2.2.1.1 Systems. The generally accepted definition of a system is any assemblage of components that results in capabilities or functions not available from the individual components by themselves. A system is a collection of components that operate together to accomplish some purpose. The INCOSE (International Council of Systems Engineering) definition of a System contained in the SEBoK (Systems Engineering Book of Knowledge) Guide is, "A construct or collection of different elements that together produce results not obtainable by the elements alone [Leibrandt, 2004]." It further clarifies that the value of the system is typically created by the relationship of how the parts are connected [Leibrandt, 2004]. A systems engineer is someone who will "define, develop, and deploy systems, [Sage and Armstrong, 2000; Shared, 1996; Swift, 2003a]." Systems engineering is used through all phases of the program life-cycle, from design and development, through integration, and including verification and validation [Sheared and Herndon, 1996; Swift, 2003b].

2.2.1.2 Complex systems. A simple system can be easily defined and understood, regardless of the size of the system. The characteristics and behavior can typically be deduced from the characteristics of the components. A complex system is one in which the behavior of the overall system cannot easily be understood or deduced from the characteristics of the components. The interaction of the components produces behavior not present in the components by themselves [Moffat, 2004].

This resultant behavior is called emergent behavior and is a natural product of complex systems. Emergent behavior, properties, and characteristics emerge from the synergy of parts and their interactions [McConnell, 2000; McConnell, 2001]. Because of emergent properties and behaviors, it becomes important to have architectures that can model change and adapt.

An example of a complex system is an ecological system - such as a woodland area. These complex ecological systems have a wide variety of components ranging from bacteria life, to insect life, to plant life, to animal life, and are hosted by a constantly changing environment. As the different parts interact, the behavior of the woodland system as a whole is hard to predict based on the actions of the individual parts alone. New emergent behavior constantly appears resulting in continuously unpredictable change. Another example is the economic system of a modern industrial country. There are a multitude of components – businesses, manufacturing, supplier, consumer, service, sales, etc. The components interact on a continuous basis and are constantly changing and evolving and being driven by external forces like taxes, competitors, customers, regulations, and others. The system is complex, always changing, and extremely hard to model or understand.

2.2.1.3 System-of-Systems. There are many different definitions of a SoS (system-of-system). Simple early definitions of a SoS revolved around size and complexity of the overall system and geographic distribution. Some argued that any large system could by definition be called a SoS simply by defining its individual subsystems as systems in and of themselves or by saying the capabilities of the whole are greater than the sum of the individuals [Arnold and Brook, 2001; Roe, 1999]. An example presented by Kaffenberger is an orchestra. If all components work in tune the performance can be much larger than the sum of the individual performers alone [Kaffenberger and Ruedige, 2001].

Another definition describes a SoS as a system made up of interdependent systems which must be evaluated as a whole and that evolve over time. This evolution of the individual systems could be self evolution, joint evolution, or emergent evolution [Carlock et al., 2001; Chen and Clothier, 2003].

Another definition of a SoS, first proposed by Mark Meier of Aerospace Corporation, describes a SoS as a large collaboration of systems with two main characteristics. The first main characteristic is that a SoS is composed of individual systems capable of operating by themselves for their own purposes, such that if any of these individual systems were disconnected, the SoS would continue to operate with or without them. The second main characteristic is that the individual systems have their own separate management and operate towards their own purposes rather than the purpose of the whole [Maier, 1999]. Future references to a SoS in this dissertation will be based on this definition.

Thomas Sanders, system-of-systems engineering study chairman of the USAF scientific advisory board, describes SoS engineering in a report on the subject as, “The process of planning, analyzing, and integrating the capabilities of a mix of existing and new systems into a system-of-systems capability that is greater than the sum of the capabilities of the constituent parts. This process emphasizes the process of discovering, developing, and implementing standards that promote interoperability among systems developed via different sponsorship, management, and primary acquisition processes [Sanders, 2005].”

Some good examples of this type of SoSs are integrated air defense systems, the Internet, and intelligent transport systems [Maier, 1999]. Another good example is the state of Washington's public education system. Each individual school district is a large system in and of itself. Each school district operates separately and under its own management. The individual school districts set their own educational goals, collect taxes, hire teachers, pick textbooks and courses to teach, build school buildings, conduct maintenance, operate cafeterias, run buses, and set their own policies. Individual school districts could operate independently if required. However, the benefits to students in Washington are greater because of the overall state school system. Students have the ability to transfer between school districts, are taught according to state educational standards, have state certified and trained teachers, and receive recognition of graduation credentials statewide.

2.2.2. Importance of Networks. The power of an NCS is based on the use and application of networks and it’s the growth of network and computer technology that has provided the emergent capabilities necessary to allow for the powerful NCS systems of today and the future. Starting from mainframe computers, society has experienced rapid development to PCs (personal computers), then to client-servers, to the Internet, and now to network-centric computing [Alberts et al., 2002a]

The Boeing SARM (strategic architecture reference model) defines a network as "A collection of data processing products that are connected by communication media for information exchange between locations [Jones et al., 2003]." Metcalfe's Law states that the power or value of a network increases exponentially as the square of the number of nodes [Alberts et al., 2002a]. Figure 2-1 illustrates this concept. The network's potential for value rises exponentially as the size of the network expands.

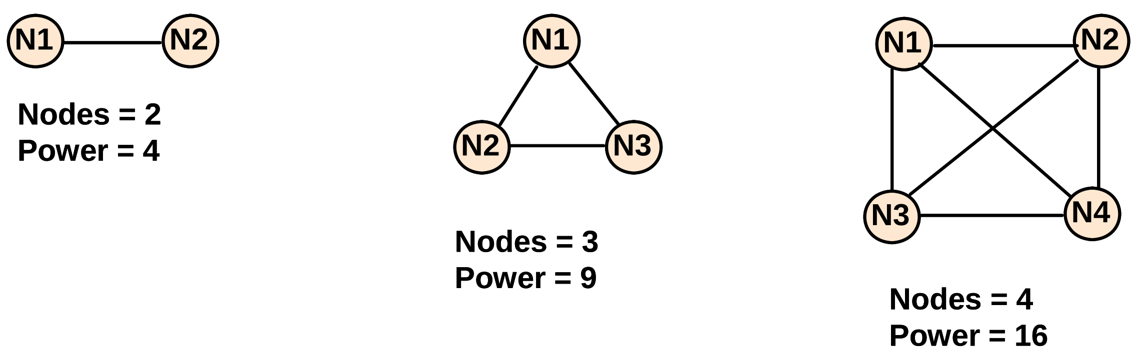


Figure 2-1 Power of Networks

However, in a NCS, it's not about the network but how the network is used. A successful NCS must translate the power of the network and information into operational capability through increased reach, shared awareness, and improved collaboration

[Alberts et al., 2002b]. To accomplish this the NCS will seek to go beyond the properties of a system and achieve the properties of a network [Alberts, 2003b].

2.2.3. Flow of Information. The importance of information cannot be overstated. The DoD (Department of Defense) Joint Vision 2010 and 2020 both specifically focus on the power of information as an enabler of combat power for the future [Alberts, 2003b]. It has also been repeatedly stated that, "Information is power," [Alberts and Hayes, 2003a].

Sun Tzu and Carl von Clausewitz both recognized the importance of information on the field of battle [Alberts and Hayes, 2003a]. Sun Tzu said, "Know the enemy and know yourself; in a hundred battles you will never know peril. When you are ignorant of the enemy but know yourself, your chances of winning or losing are equal. If ignorant of both your enemy and yourself, you are certain in every battle to be in peril." Carl von Clausewitz said, "The general unreliability of all information presents a special problem: all action takes place, so to speak, in a kind of twilight … like fog … The commander must work in a medium which his eyes cannot see, which his best deductive powers cannot always fathom; and which, because of constant changes, he can rarely be familiar."

2.2.3.1 Traditional flow of information. The traditional process for passing information can best be described as a "push" process. The burden was upon the owner of the information to identify interested parties and then determine and implement a means to provide the information to those parties [Alberts and Hayes, 2003a]. The military provided information to identified parties through commands, intelligence, or doctrine [Alberts, 2003b].

Decision making was based on the OODA (observe, orient, decide, act) loop. The first two steps in the OODA loop can be called situational awareness. The first step in the OODA loop is observe, the collection of information on the environment and competitors. The second step is orient, the processing, analysis, and dissemination of that information and also information about your own condition. The third step is decide, determining a course of action. Finally, the fourth step is called act, putting the decision into action [Potts, 2004].

2.2.3.2 Network-centric flow of information. In a world equipped with the global Internet and the ability for almost anyone to create their own web pages and information portals and to post whatever information they desire, processes for the flow of information are evolving from a "push" process to a "pull" process. The burden is shifted from the owner of the information trying to identify where to push his information, to the receiver where interested parties identify sources of desired or needed information [Alberts and Hayes, 2003a].

Decision making is more effective in this type of environment. In a robust NCS you have improved information sharing. This leads to a higher quality of information and shared situational awareness. This enables collaboration and self-synchronization and enhances sustainability and speed of action. The end result is a dramatic increase in effectiveness [Potts, 2004].

2.2.3.3 Information superiority. The DoD in Joint Pub 2-13 defines information superiority as "The ability to collect, process, and disseminate an uninterrupted flow of information while exploiting and/or denying an adversary's ability to do the same [Alberts et al., 2002a; Shelton, 2000]." This is accomplished by getting the "right information to the right people at the right time in the right form while denying an adversary the ability to do the same [Alberts et al., 2002b]." The DoD Joint Vision claims information superiority should be at the core of every military activity and is the key enabler of victory [Shelton, 2000]. Information superiority is not just confined to military operations and systems. Business operation and enterprises are equally as dependant upon information and the business that obtains information superiority is in a position to out perform and even dominate competitors.

Information superiority is achieved and a competitive advantage is obtained from exploiting the three dimensions of information superiority. These dimensions are relevant information, timely information, and superior information, as illustrated in Figure 2-2 [adapted from Alberts et al., 2002a].

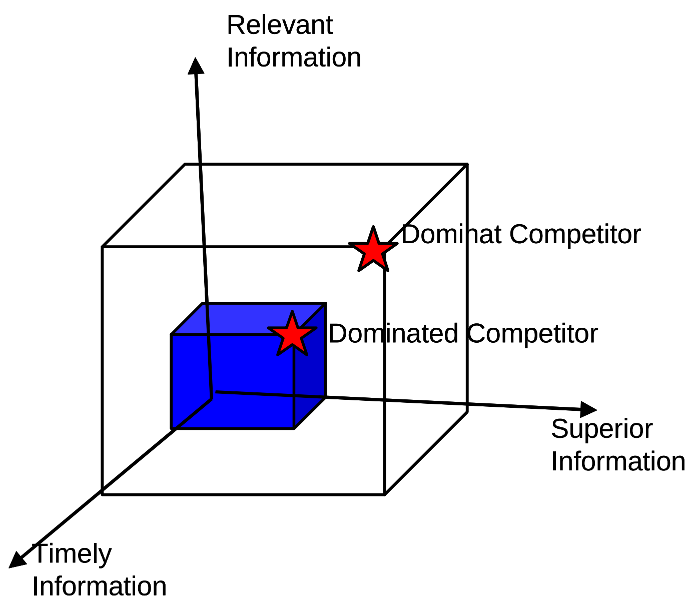


Figure 2-2 Dimensions of Information Superiority

The ability to use information is also undergoing a profound change. Alberts describes this based on the principles of richness and reach [Alberts et al., 2002b]. Richness is an aggregate measure of the quality (content, accuracy, timeliness, relevance). Reach is an aggregate measure of how that information is shared. In the past, during the Industrial Age, there was an inverse relationship between the two because of technological limitations with sharing. The richer the information the less reach, the more the reach the less richness. Now, with the Information Age, the greater ability to disseminate information coincides with greater richness in information available for extraction. Figure 2-3 illustrates the change.

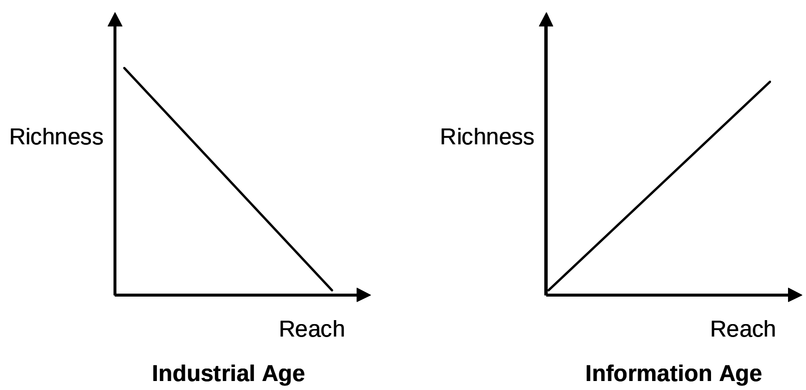


Figure 2-3 Information Usability

2.2.4. Domains of Operation. There are three domains of operation within network-centric operations - the information domain, the physical domain, and the cognitive domain. The physical domain can be thought of as reality. It includes the environment and all physical things, both your systems and other systems, whether a part of the system or factors affecting the system. The information domain is where information is developed and shared. This includes the network. The Cognitive Domain is where the thinking takes place. This includes perceptions, awareness, understanding, beliefs, values, sense making and decision making [Alberts et al., 2002b]. Figure 2-4 illustrates the relationship of how these domains interact.

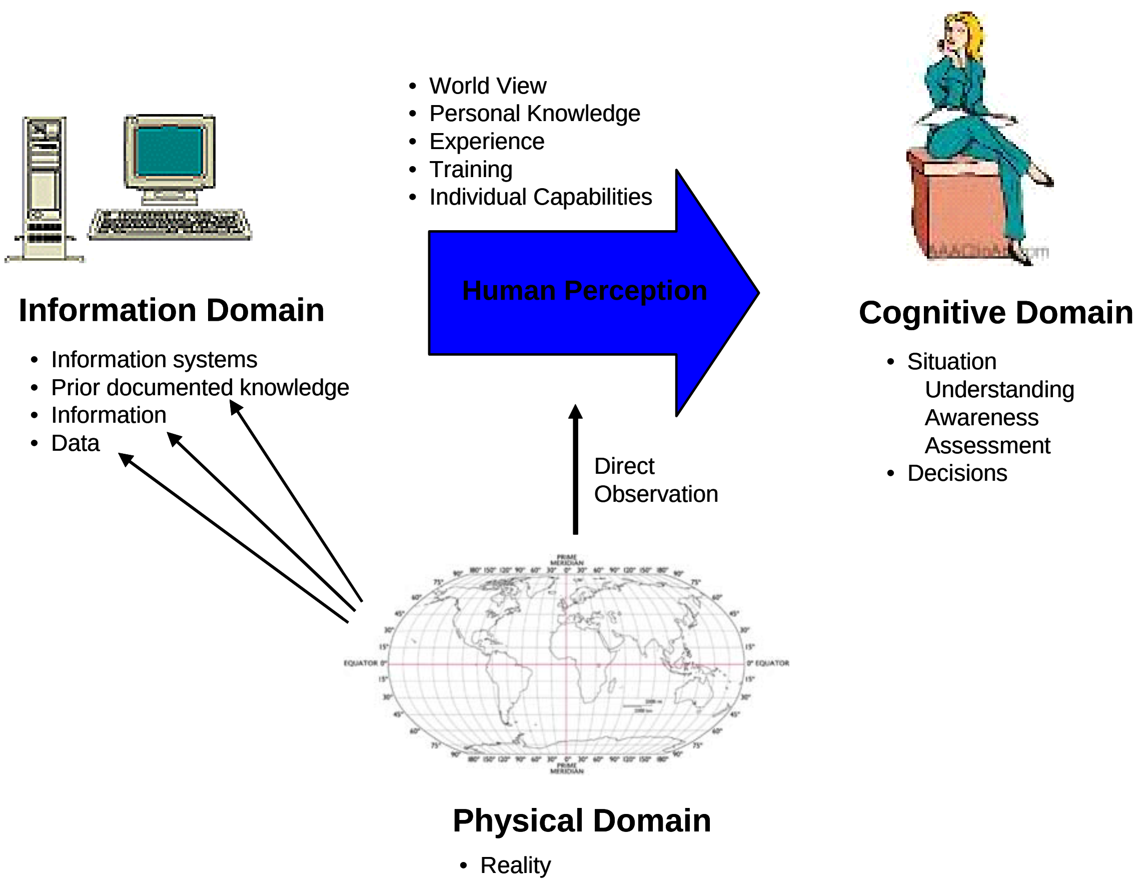


Figure 2-4 NCS Domains of Operation

2.2.5. Desired Characteristics. Operating within these domains there are several desirable characteristics that enhances and/or evolve naturally from efficient network-centric systems. These include shared awareness, collaboration, synchronization, self-synchronization, and interoperability.

2.2.5.1 Shared awareness. This is a state in the cognitive domain when two or more are able to develop a similar awareness of a situation [Alberts et al., 2002b]. Shared awareness is one of the key benefits of network-centric operations and is also a critical factor if the benefits of the network are to be realized. Without shared awareness the systems are not able to operate towards mutually beneficial goals or objectives.

2.2.5.2 Collaboration. This is a state in the cognitive domain where two or more plan together towards a common goal [Alberts et al., 2002b]. Now that the shared awareness has been developed, collaboration can take place to develop plans for the implementation of the goals and objectives.

2.2.5.3 Synchronization. This is a state in the physical domain where two or more act together [Alberts et al., 2002b]. Now that the shared awareness and collaboration have been achieved, this is the capability for joint action on those goals and objectives, as is illustrated in Figure 2-5 [adapted from Alberts et al., 2002b].

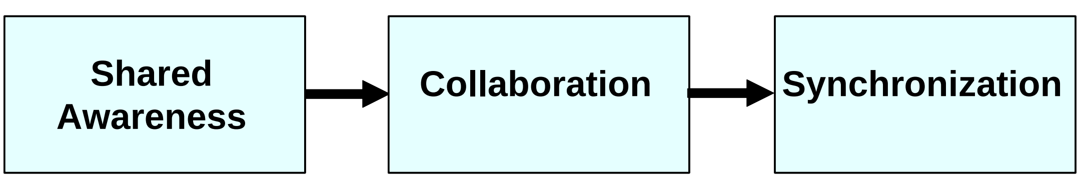


Figure 2-5 Joint Operations

2.2.5.4 Self-synchronization. Self-synchronization is one of the most useful features that arises from network-centricity. It is the ability for individual units to self-organize at the unit level, from the bottom up, rather than commanded synchronization which flows from the top down. An excellent description of self-synchronization is given by Vice Admiral Cebrowski of the USN, "Self-synchronization is the ability of a well-informed force to organize and synchronize complex warfare activities from the bottom up ... self-synchronization is enabled by a high level of knowledge of one's own forces, enemy forces, and all appropriate elements of the operating environment. It overcomes the loss of combat power inherent in top-down command directed synchronization characteristic of more conventional doctrine and converts combat from a step function to a high-speed continuum [Cebrowski and Garstka, 1998]."

In order to enable self-synchronization, Alberts proposes four conditions that must be present [Alberts and Hayes, 2003a]:

- Clear understanding of purpose
- High quality information and high level of shared awareness
- Competence at all levels
- Trust in the information and all parties involved

2.2.5.5 Interoperability. Interoperability is an essential characteristic of network-centric operations and systems. The Boeing SARM defines interoperability as the ability of elements or systems to provide services to and services from other elements or systems in order to increase effectivity [Jones and Sizelove, 2003]. The DoD Joint

Vision 2020 calls interoperability a mandate for joint forces and defines it as “the ability of systems, units, or forces to provide services to and accept services from other systems, units, or forces and to use the services so exchanged to enable them to operate effectively together [Shelton, 2000].”

Carl O’Berry claims its “critical that all industry begin to design systems that have the ability to interoperate [O’Berry, 2005].” He describes it like DNA, the coding inherent in every cell of the body that allows it to join and interact with other cells within the body’s network [O’Berry, 2005].

2.2.6. Global Information Grid. The concept of a GIG (global information grid) was developed by the DoD as a means for achieving information superiority. "The GIG is a single, secure grid providing seamless end-to-end capabilities to all warfighters, national security, and support users [Logan, 2003]."

Moffat foresees the GIG as "a distributed environment that includes all types of computers situated at locations all around the world as appropriate with varying needs for power, environment, and space. This distributed environment will be integrated via a transport layer that enables these processors to exchange information, dynamically share workloads, and cooperatively process information on behalf of (and transparent to) users. The GIG will make information and related services available to any and all connected entities (nodes) that are ‘net ready’. Competitive market mechanisms will ensure that users have access to the information and services that they want when, where, and how they want it [Moffat, 2004]."

The Boeing SARM defines the GIG as "a globally interconnected, end-to-end set of information capabilities, associated processes and personnel for collecting, processing, storing, disseminating, and managing information on demand to users, policy makers, and support personnel [Jones and Sizelove, 2003].

2.2.7. Challenges and Issues. There are many issues and challenges to overcome and address when developing, deploying, operating, and evolving large network-centric systems. Some familiar categories are complexity, trustworthiness, interoperability, management, information overload, and accounting for evolutionary growth.

2.2.7.1 Complexity. Network-centric systems are usually large scale and globally dispersed. They are frequently system-of-systems. Interdependencies and interfaces are not easily understood and the functionality has greater degrees of complexity.

2.2.7.2 Trustworthiness. Network-centric systems must address the same trustworthiness issues as any system or component, only on a much larger and much more complex scale. These include quality, reliability, availability, survivability, and maintainability.

2.2.7.3 Interoperability. Network-centric systems face the added challenge of having all components and systems interoperate with a host of other components and systems. Legacy systems are frequently included which may not have been designed or built to the same requirements or standards.

2.2.7.4 Management. Network-centric systems face a multitude of management difficulties stemming from geographically dispersed, developed, designed, and fielded systems. The management team is usually multi-service or multi-company, may be multi-national, and is usually geographically dispersed. Management is forced into more of a participative mode rather than a directive mode.

2.2.7.5 Information overload. The most commonly cited potential problem with Network-centric systems is the potential for information overload [Potts, 2002]. However, this may not be as big a problem as expected. With a global network the individual is responsible for pulling the information needed rather than having information pushed at them [Alberts and Hayes, 2003a]. With network technology the shift has gone from an information push to an information pull environment.

A tank in a valley will not necessarily be overwhelmed by detailed information about the entire battlefield. The individual tank need only pull required information, such as detailed information about the valley in which it is situated, less information about the next valley (enemy movements, strike coordinates), and even less but key information about the entire battlefield (retreat or advance of supporting forces).

2.2.7.6 Evolutionary growth. The Network-centric system must make allowances for growth on an evolutionary basis. Nothing will ever be static and everything will always be in a state of flux and change. Emergent capabilities and functions are sure to arise and propagate. The potential for confusion and error is great, but it is the capability for evolutionary growth that forms the real power of network-centric system.

2.3. ARCHITECTURE FRAMEWORKS

An architecture, simply put, is a way of describing something and an architectural framework is a common set of rules for how to describe it. An architecture framework could be likened to a set of building codes that all the architects must adhere to in designing and constructing their own buildings in order to use the infrastructure of a city [O'Berry, 2005]. It's a common approach. It allows all the pieces to fit and work together. It allows for order within the prescribed universe. For SoSs and NCSs a architecture framework is essential.

An architecture, according to the DoD integrated architecture panel, 1995, based on IEEE STD 610.12, is "the structure of components, their relationships, and the principles and guidelines governing their design and evolution over time [DoDAF, 2003]."

According to Cebrowski, an architecture needs to "provide sufficient information to assure that component systems will fit into the architecture, while simultaneously trying to avoid over specifying the architecture and overly constraining the system designers [Cebrowski and Garstka, 1998]."

An architecture framework provides guidance for the development of architectures to ensure interaction and interoperability among systems. Different approaches that can be taken, such as structured analysis concepts [Wagenhals et al., 2000] or object oriented concepts [Bienvenu et al., 2000].

2.3.1. DoD Architecture Framework. The DoDAF (Department of Defense Architecture Framework) was developed to define "a common approach for DoD architecture description, development, presentation, and integration for both warfighting operations and business operations and processes [DoDAF, 2003]. "The initial impetus for the Framework came from the Defense Science board, who determined in the early 1990s that one of the key means for ensuring interoperable and cost effective military systems is to establish comprehensive architectural guidance for all of DoD [Sowell, 2000].”

There are four main components of the DoD Architecture Framework - architecture views, products and data, universal guidance, and common references. The three architecture views, as illustrated in the DoDAF figure displayed in Figure 2-6 below [from DoDAF, 2003], are the operational architecture view, the systems architecture view, and the technical architecture view.

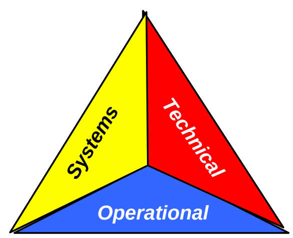


Figure 2-6 DoD Architecture Framework Views

2.3.2. Other Architecture Frameworks. Other architectures frameworks of note are the Zachman Framework, the Federal Enterprise Architecture Framework, and the Treasury Enterprise Architecture Framework. Also of interest was the formation in September 2004 of the Network-Centric Operations Industry Consortium dedicated to the promotion and development of an industry wide network-centric framework.

2.3.2.1 Zachman Framework. The Zachman Framework is based on describing an enterprise in a matrix format. Columns represent various aspects of the enterprise and rows represent different views. It provides the opportunity for detailed analysis via a variety of different views to allow for the development of a comprehensive architecture [Sowell, 2000].

2.3.2.2 Federal Enterprise Architecture Framework. The Federal Enterprise Architecture Framework provides guidance on architecture for multi-organizational functional segments of the federal government. The architecture is divided into a business view and a design view. The business view is divided into sections for data, applications, and technology [Sowell, 2000].

2.3.2.3 Treasury Enterprise Architecture Framework. The Treasury Enterprise Architecture Framework is based on the Zachman Framework matrix with rows and columns. The columns are condensed into four views – infrastructure view, organizational view, information view, and functional view. The rows are organized into four perspectives - planner perspective, owner perspective, designer perspective, and builder perspective.

2.4. EXAMPLE NCS'

"In the commercial sector, dominant competitors have developed information superiority and translated it into a competitive advantage by making the shift to network-centric operations. They have accomplished this by exploiting information technology and co-evolving their organizations and processes to provide their customers with more value. This co-evolution of organization and process is being powered by a number of mutually reinforcing, rapidly emerging trends that link information technology and increased competitiveness [Alberts et al., 2002a]."

2.4.1. Manufacturing. The Boeing 777 commercial airplane program and Dell® computers [Alberts et al., 2002a], both introduced and used new network-centric information systems for inventory control and were able to translate the results into increased productivity, reduced production time, and reduced inventory.

2.4.2. Retail. Wal-Mart® with precision retailing was able to use network-centric systems based on shared information throughout a common network to facilitate and speed the supply chain differential and implement flow-through logistics to deliver products to the right stores at the right times based on up to date information about customer purchases and re-supply availability throughout the chain. The chain from suppliers to warehouses to the stores to the shelves and finally, to the consumers evolved into a vast integrated operation empowered by a network-centric precision retaining process [Alberts et al., 2002a; Cebrowski and Garstka, 1998] [Byrnes, 2005].

2.4.3. Air Traffic Control. ATC (air traffic control) is rapidly developing into one large nation-wide NCS using net-centricity to enable rapid information sharing on the location of all air traffic and to make surveillance data available to all ATC organizations and also outside agencies, such at the Department of Homeland Security and also the military. “The next generation of U.S. air traffic control will have to be network-centric to enable data to move freely from one system to the next and across organizational boundaries, say ATC specialists [Hughes, 2006].

2.4.4. Financial. Capitol One® successfully put into operation a network-centric system for tracking and modifying consumer credit limits, which managed operational risk, focused on the market, and then aligned credit limits accordingly [Alberts et al., 2002a]. Several Financial Services businesses have greatly improved productivity and customer services by implementing network-centric systems. Some examples are Charles Schwab®, E*Trade®, and Deutsch Morgan Grenfell® [Alberts et al., 2002a; Cebrowski and Garstka, 1998]

2.4.5. Connexion by Boeing. CBB is an excellent example of a commercial profit oriented NCS. CBB is a complex, large-scale, global NCS oriented towards providing network services to its airline customers, military customers, individual passengers, and any other users that tie into the system. Section 6 of this dissertation provides a detailed description of the CBB system and its operation.

2.4.6. Military Strategy. One of the most successful users of NCSs has been the U.S. military. The DoD has gone so far as to adapt the philosophy of network-centricity as the future growth engine for all new systems and the basis of military strategy, procurement, development, and operations for the future.

The strategic concept of NCW (network-centric warfare) has evolved based on NCSs. NCW involves strategic planning centered around network based systems rather than platform based systems. The military takes into consideration all three domains (cognitive, information, and the physical), when developing military strategy and tactical plans.

A good example of NCW strategy is that described by David Potts in describing the transition of command control to the Information Age [Potts, 2004], which involves many elements and all three domains. Battlespace monitoring takes place in the physical domain and involves the collection, storage, transmission, and display of data. Awareness is in the cognitive domain and involves the recognition and filtration of pertinent data. Understanding follows awareness and involves the understanding of the significance of the data given the circumstances. Sensemaking is in the cognitive domain and involves making sense of the data, its applicability, how it can be used, and what steps to take. Command intent is communication to subordinates on actions to take. Battlespace management is action on the information and cognitive domains to pass information to carry out command intent. Synchronization is attempting to carry out command intent on the physical domain. Figure 2-7 [from Smith, 2003] illustrates the relationship of the elements involved in NCW strategic thinking and implementation.

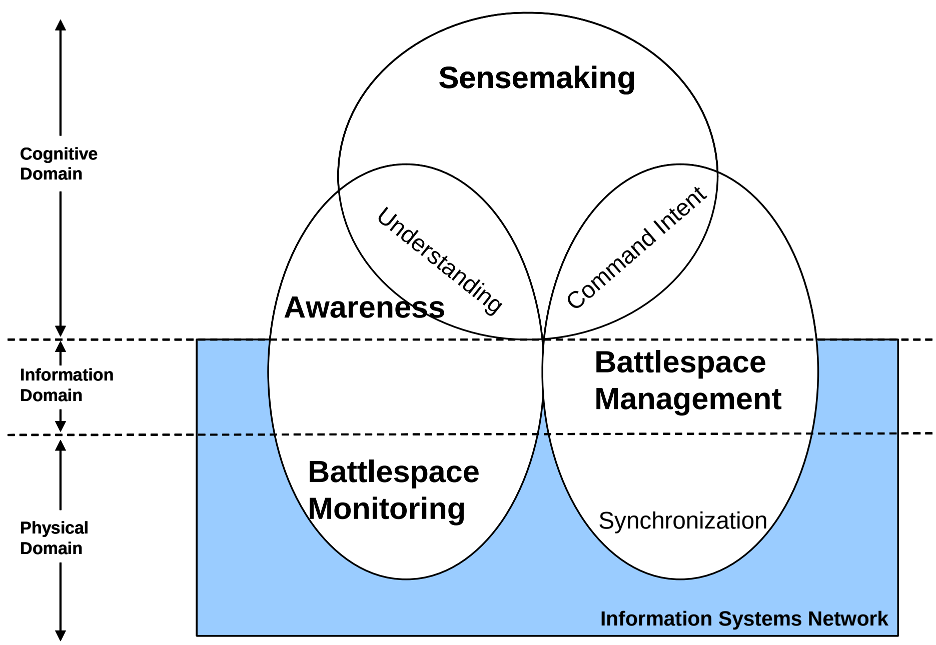


Figure 2-7 NCW Strategic Planning

EBO (effects based operations) is another doctrine of military theory that has emerged with the enhanced capabilities provided by NCSs. EBO focuses on actions and their links to behavior rather than just targets and the infliction of damage. According to the information superiority working group sponsored by the Office of the Secretary of Defense, EBO is "a coordinated set of actions directed at shaping the behavior of friends, foes, and neutrals in peace, crisis, and war [Smith, 2003]."

The scope of EBO is considerably larger than traditional military tactical strategic thinking and the capability is highly dependent upon network-centric capabilities. According to Edward Smith of the CCRP (Command and Control Research Program), "We can tap the technologies and thinking of network-centric operations to provide the four key ingredients of successful effects based operations: options, agility, coordination, and knowledge [Smith, 2003]."

An example of the constraints placed on the military when considering EBO can be seen in the following scenario during Operation Iraqi Freedom. “In Najaf, American forces faced some 2,500 Sadr militiamen with the resistance centered on the Najaf cemetery and the Shrine of the Imam Ali, the holiest place in Shi’I Islam. Because U.S. officers knew that damaging the shrines would inflame opinion in Iraq and worldwide against the Americans, both were declared exclusion areas despite the fact that they served as a tactical advantage to Sadr’s men, who used them as refuges and secure fire bases from which to mortar U.S. forces [Smith, 2006].”

2.5. SECTION SUMMARY

This section on network-centric systems provided the background on the importance of network-centricity, gave evidence of the potential power of NCSs, and described the characteristic features of an NCS. A description of systems was given, both simple and complex, and also a description of system-of-systems. Then the importance and power of the network was described. Next the flow of information in a NCS was compared to traditional flows of information. The domain of operation in a NCS was described and several features were examined, including shared awareness, collaboration, interoperability, synchronization, and self-synchronization. Then the importance of the global information grid was examined. Several issues and challenges facing NCS were then discussed, which actually provide opportunities for enhanced effectiveness when properly addressed. Architecture frameworks were addressed next, with emphasis on the DoD Architecture Framework. Other frameworks, such as the Zachman Framework were touched on also. Finally, several examples of successful NCS were reviewed; including Connexion by Boeing, which was used as the case study for this dissertation.

Due to the complex and evolutionary nature of NCSs, and the likely probability of widespread use in the future, the need for adaptive architectures that can change and evolve has become critical. The adaptive architecture proposed by this dissertation was developed in an effort to study and define ways to address the special needs of NCSs, which were described in this section.

The following section (Section 3) contains a literature review of network (Internet) theory, which is the medium through which the data and information that empowers NCSs flows. It also contains a literature review of network capacity modeling techniques and methods. An evaluation of the applicability and accuracy of these modeling techniques when applied towards NCSs, along with shortcomings and advantages, is also evaluated.

3. THE INTERNET AND CAPACITY MODELING LITERATURE REVIEW

3.1. RELEVANCE OF THE INTERNET TO THIS RESEARCH

The global Internet provides the medium over which NCS network traffic flows. All NCSs must use some type of network to convey data to and from platform nodes and the Internet provides the GIG through with which most NCSs operate. In order to model data traffic on an NCS, a good understanding of how the Internet operates and of current modeling techniques, theory and research, is needed. Also an understanding of the short-comings of non-adaptive Internet traffic models as technology moves into the age of highly-adaptive, evolving NCSs with constantly changing network traffic characteristics. The need for adaptive modeling techniques then becomes clear.

The literature review in this section includes: 1) an overview of the Internet, 2) reference architectures like the OSI model and TCP/IP model, 3) an explanation of data encapsulation, 4) traffic management theory, including resource allocation, and 5) capacity modeling. This last section on capacity modeling is very important. It includes information on the difficulty of Internet capacity modeling and describes current techniques, like fractional Brownian motion and Kelly's equation. This section also contains a detailed description of the capacity modeling methods and simulation used by CBB, along with advantages and disadvantages; and last, a description of current academic research activities and their applicability to NCSs.

3.2. OVERVIEW OF THE INTERNET

The Internet is a global network interconnecting millions of computers in a common information grid. The Internet is the vehicle that has ushered in the Information

Age by allowing global interconnection of the world. The impact to business and all facets of life has already been tremendous and the change has just begun. Bill Gates, founder of Microsoft®, says, "Business is going to change more in the next ten years than it has in the last fifty [Gates, 2005]." Bill Clinton, former president of the United States lamented that, "When I took office, only high energy physicists had ever heard of what is called the World Wide Web … now even my cat has its own page [INS, 2005]."

Internet use continues to experienced phenomenal growth in the number of users, the amounts of data being transmitted, and in generated revenue. As of the start of 2005, in the United States of America alone there were 293,271,500 recorded users. This is 68.8% of the population and the growth rate since 2000 has been 111.5%. For the world as a whole, there were 817,447,147 recorded users at the start of 2005. This is 12.7% out of a world population of 6.4 billion and the growth rate since 2000 has been 126.4% [INS, 2005]. Figure 3-1 shows the growth of Internet usage over the past 10 years from 16 million at the end of 1995 to 817 million at the end of 2004.

Besides this phenomenal growth in the number of users, the volumes of data flowing through the Internet have experienced even greater growth rates and it's predicted that the volume of traffic worldwide will nearly double annually over the next five years, from 180 petabits every day to 5,175 petabits per day by the end of 2007. This amounts to downloading and sharing information equivalent to the entire Library of Congress more than 64,000 times per day [Hong, 2004].

Besides the growth in users and volumes of data, there has also been dramatic exponential growth of revenue generated over the internet. Figure 3-2 illustrates the growth from .008 billion dollars in 1994 to 1,234 billion dollars in 2002 [Hong, 2004].

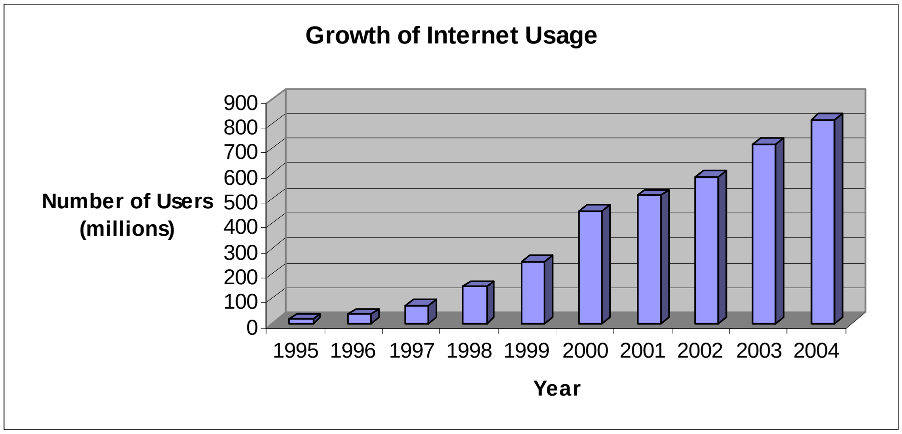


Figure 3-1 Internet Growth Over the Past Ten Years

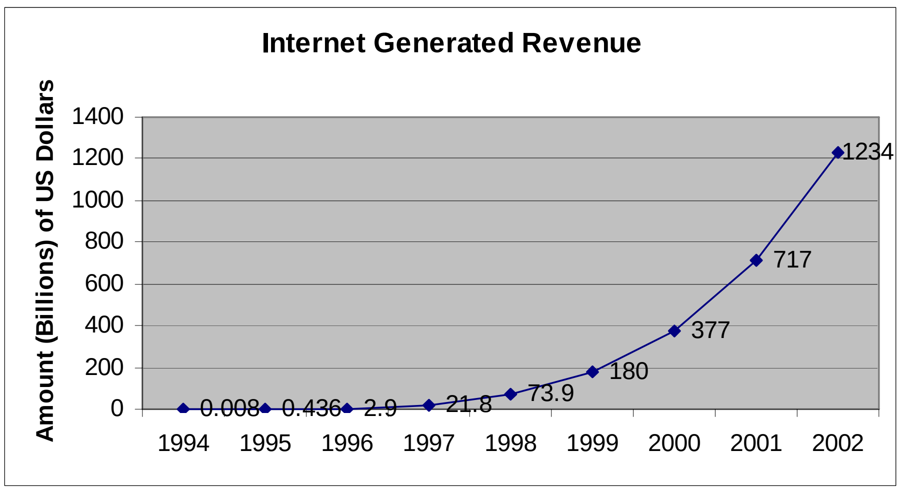


Figure 3-2 Growth in Internet Generated Revenue

3.2.1. Computer Networks. A network is a system that provides connectivity between computers for the transfer of data. It is a collection of computer hosts and associated communication equipment all tied together for the transmission of information. Networks tend to have sources and destinations, transmitters and receivers, and a communication medium to carry the data.

There are many kinds of networks as you go from small to large to global. A HAN (home area network) is typically confined to one individual house. A LAN (local area network) and is a small network usually belonging to one building or campus and extends up to 1 km. A MAN (metropolitan area network) usually belongs to a city and typically extends up to 10 km. A WAN (wide area network) is anything larger, and can be global in reach.

A collection of interconnected networks is called an internetwork or an internet with a small 'i'. Nodes that implement the network are called switches and nodes that use the network are called hosts. The Internet is designated with a capital 'I' when referring to the entity that composes the vast global collection of networks in use by people throughout the globe. Figure 3-3 illustrates the differences between a network, an internet, and the Internet.

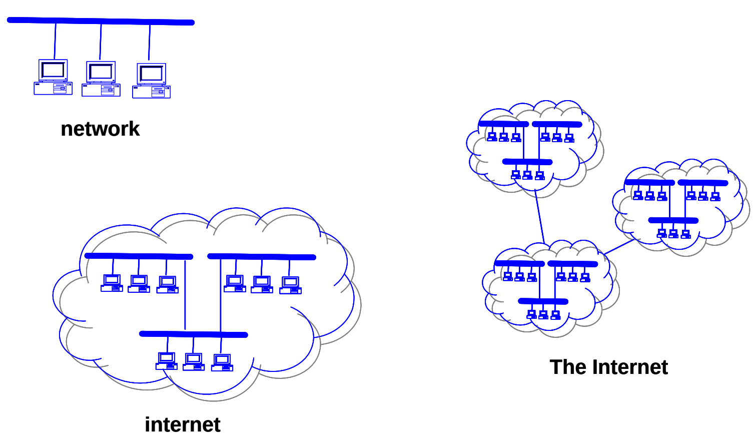


Figure 3-3 Networks and the Internet

3.2.2. The Internet. The Internet is not simply a large network, but is a vast collection of networks that use common protocols and provide common services [Tanenbaum, 2003]. It was first created as a DoD project by DARPA (Defense Advanced Research Projects Agency) wanting to develop a secure communication network that could survive nuclear attack. The resulting product was called the ARPANET (Advanced Research Projects Agency Network). Initially only selected universities and the DoD were connected but soon other countries and universities were creating their own networks patterned after the ARPANET. In the 1980s the DNS (domain name system) was created to organize domains and IP (Internet protocol) addresses. Eventually everything was interconnected and the network infrastructure was handed over to industry where it has evolved into the Internet of today.

3.3. REFERENCE ARCHITECTURES

To reduce complexity the Internet was designed in layers. This allows the decomposition of the Internet into manageable components and provides for a modular design. Each level is defined as an abstraction. Peterson defines it in this way, "The idea of an abstraction is to define a unifying model that can capture some important aspect of the system, encapsulate this model in an object that provides an interface that can be manipulated by other components of the system, and hide the details of how the object is implemented from the users of the object [Peterson and Davie, 2003]."

A protocol is the agreement of rules on how different entities within a layer communicate among themselves. The main elements of a protocol are syntax, semantics, and timing. Syntax includes details about the physical communication structure and format. Semantics includes information about how to control the communication. Timing includes information about the flow of information.

Architectures were developed to describe the rules and agreements for layering the Internet. There are two common reference architectures - the OSI model and the TCP/IP model.

3.3.1. OSI Reference Architecture. The OSI (open systems interconnection) reference architecture was based on a proposal by the ISO (International Standards Organization) as the first step towards international standardization of the protocols defining rules for various layers of the Internet [Tanenbaum, 2003]. It was based on rules for connecting open systems for communication with other open systems and has seven layers. Figure 3-4 illustrates the seven layers of the OSI architecture. Each layer represents a different abstraction and has a different function. The goal is to minimize communication between layers and reduce complexity. Designers writing software that operates within one of the layers need not be concerned with protocols of other layers but only with the protocols of the layer within which their software or application operates.

3.3.1.1 Physical layer. The purpose of the physical layer is to transmit the raw bits of data over a physical link. It is often called a bit pipe. It operates by converting data into waveforms at the source and then reconverting at the destination. Design issues involve mechanical and electrical interfaces and the physical transmission medium.

3.3.1.2 Data link layer. The purpose of the data link layer is to act as an interface between the network and the physical medium. It is often called a packet pipe. It collects the data into frames, transmits them sequentially, and performs error detection and flow control. Design issues involve confirming reliability, regulating traffic, and controlling access.

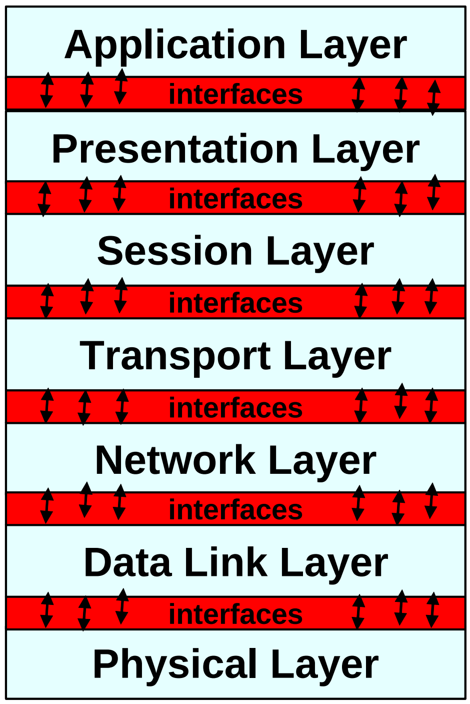


Figure 3-4 Seven Levels of the OSI Architecture

3.3.1.3 Network layer. The purpose of the network layer is routing of the packets from source to destination. Routes can be static and fixed or they can be dynamic and constantly changing. The process can be as simple as looking at a destination, consulting a table, and forwarding. Or it could involve a process to map a route for each group of packets which could be different for fragmented portions of the same data. Design issues involve congestion and interconnection between networks.

3.3.1.4 Transport layer. The purpose of the transport layer is message control. It is concerned with process to process, the exchange of data between end systems. It splits data into smaller units if necessary, accounts for different types of hardware, passes data to the network layer, and ensures the message is correctly re-assembled. Design issues involve losses, duplications, and quality of service.

3.3.1.5 Session layer. The purpose of the session layer is the establishment of identity. It allows users on different machines to establish sessions with each other. Design issues involve dialog control and management.

3.3.1.6 Presentation layer. The purpose of the presentation layer is control of the format of the data being sent. It is concerned with the actual information rather than the bits being sent. Design issues involve formatting, compression, and encryption.

3.3.1.7 Application layer. The purpose of the application layer is providing the means for various application programs to use the network. Examples are browsers, email, chat, streaming media, and file transfer.

3.3.2. TCP/IP Reference Architecture. The TCP/IP (transmission control protocol / Internet protocol) reference model was the one used for the original ARPANET, predecessor of today's Internet, which is in widespread use today. Like the OSI model, the TCP/IP model is also based on layers and encapsulation and standard protocols; however, the TCP/IP model has fewer layers than the OSI model, the protocols tend to cross multiple layers at times, and the network layer can only support connectionless routing. Figure 3-5 illustrates the TCP/IP layers.

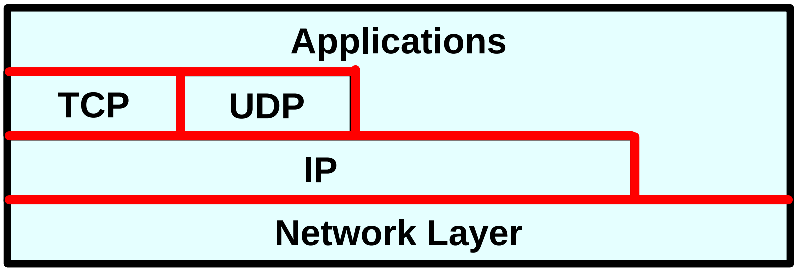


Figure 3-5 TCP/IP Model Architecture

3.4. DATA ENCAPSULATION

Encapsulation describes the means by which the Internet passes information. The body of the message being sent is called a payload. This payload reaches the first layer and is framed or encapsulated with a header and sometimes a footer. The header and footer contain information for protocol control, error detection, and address information.

The encapsulated data, with the header and footer from the first level, goes to the next level and another header and/or footer gets added and the data is again encapsulated. This process repeats as the data goes through all seven layers and gets encapsulated at each layer.

Finally, the message reaches the destination. To get there, the bottom layer unencapsulates the outer most layer and receives information vital to the operation of that layer. The message goes to the next layer for another unencapsulation and so on until the final payload message is stripped free. In this way each layer receives the information it needs for the operations that it is concerned with. Figure 3-6 [adapted from Tanenbaum, 2003] illustrates encapsulation and unencapsulation of data.

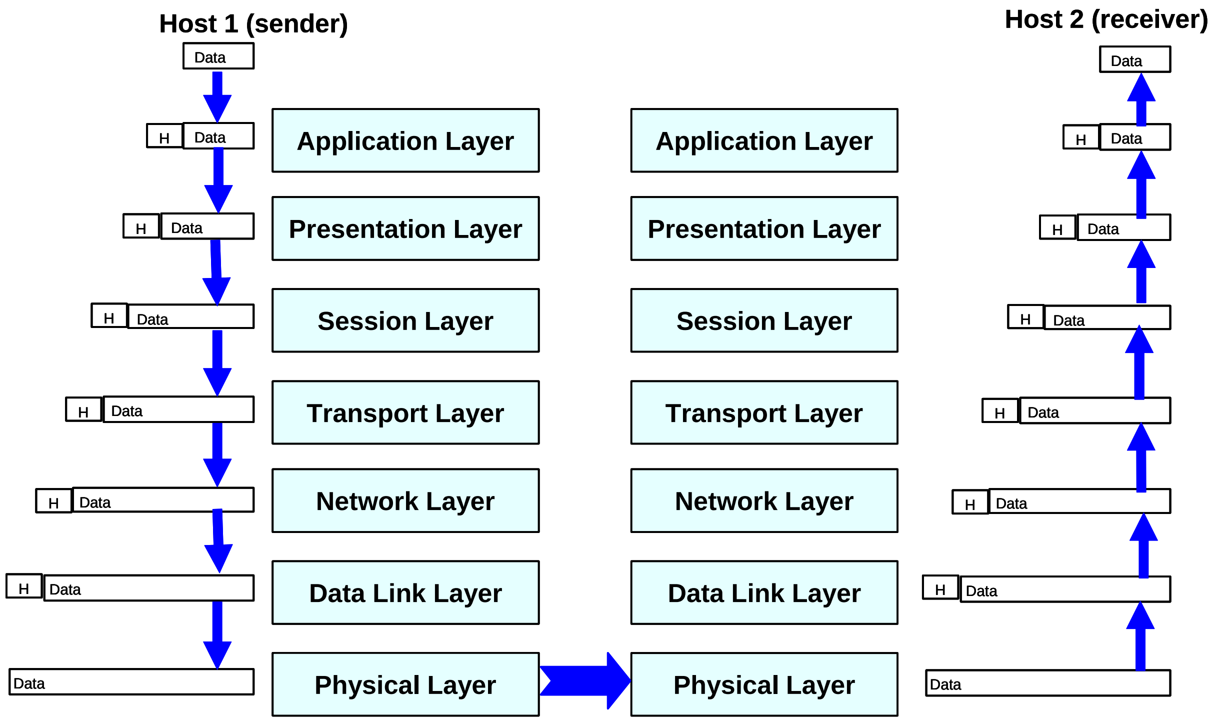


Figure 3-6 Encapsulation

3.5. TRAFFIC MANAGEMENT

3.5.1. Flow Control. Flow control is performed by the receiving device in an effort to limit or eliminate congestion. Congestion occurs when a switch has so many packets queued up waiting for output that it has to start dropping packets. This forces the sending device to perform re-transmissions. Different protocols use different methods to perform flow control.

3.5.1.1 Request reply. A common but simple method is the request and reply method. The sender sends a message and must then wait for a reply or acknowledgement before another may be sent. This method is not the most efficient.

3.5.1.2 Sliding window. Another common method is the sliding window method. The receiver has a buffer where it can store messages that have not yet been processed. The window is the remaining space in the buffer and slides smaller as the buffer fills up. As long as the window is big enough, the sender can keep sending messages without waiting for the associated acknowledgements. As the receiver processes the messages it slides the window larger.

3.5.2. Error Control. A vital function of the Internet is to ensure the message, in its final form, is received by the host without error. There are several methods employed for error control and often retransmissions are required. One common but simple method, according to various schemes, the sender inserts bits and the receiver checks for these bits to see if any errors have been made during transmission. If it finds an error then a retransmission is required. The request reply and sliding window flow control methods are also good for error control. They work on the basic premise that if acknowledgements are not received then retransmit.

3.5.3. Resource Sizing. Resource sizing is an important aspect of Internet traffic management. This has to do with sizing of the physical devices for the transmission of data. This includes the size of switches and buffers, sending and receiving devices, and also the transmission link or physical medium. Types of links include twisted pair wire, coax cable, optical fiber, and satellite transmission.

For CBB, a key resource question was that of satellite transponder management. CBB uses satellite links between customer aircraft and the ground stations where connectivity to the Internet is made. The size of the pipe provided to the customer is a function of the number of satellite transponders that have been leased to provide service for a specified area. In order to make accurate determinations of how many transponders to lease, CBB must have accurate capacity models to forecast how big the network pipe, in this case number of satellite transponders, must be.

Depending upon the peak number of aircraft flying within a particular region, CBB leases enough transponders to provide the required service. Figures 3-7 through 3-9 illustrate how the pipe size in a region can be grown to accommodate more aircraft by adding more transponders.

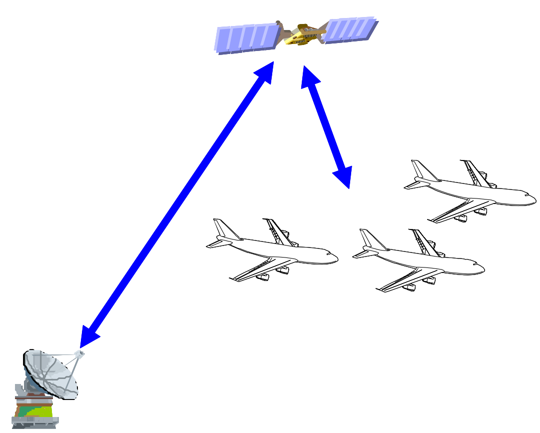


Figure 3-7 Single Transponder Coverage

As the business grows and more aircraft become equipped with CBB systems and more customers on the aircraft use the service, the demand for bandwidth grows, outstripping the capability of a single transponder. The size of the network must grow and additional transponders are leased to meet increased demand, as illustrated in Figure 3-8.

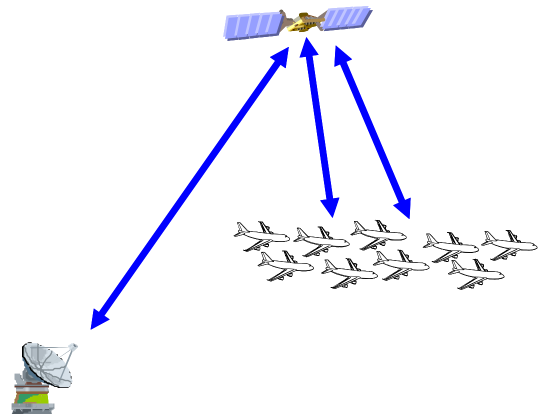


Figure 3-8 Additional Transponders

As the business grows further the demand for bandwidth grows, exceeding the capability of all the transponders on a given satellite. The size of the network must grow further and additional satellites are leased to meet increased demand, as illustrated in Figure 3-9.

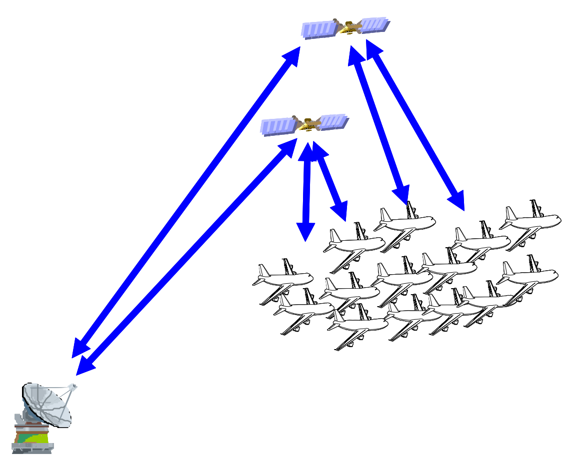


Figure 3-9 Additional Satellites

3.5.4. Performance. There are three measurements of network performance. These are bandwidth, latency, and the delay-bandwidth product, as illustrated in Figure 3-10. Bandwidth can be though of as the width of a hollow pipe. Latency is the length of the hollow pipe. Delay-bandwidth product is the volume of the hollow pipe.

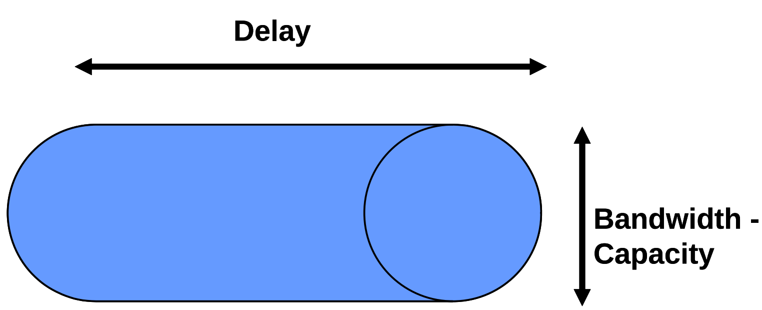


Figure 3-10 Network Performance Pipe

3.5.4.1 Bandwidth. Bandwidth, also called throughput, is the width of the network pipe, the data rate or channel capacity, and is measured in bits per second. It is the number of bits that can be transmitted over the network in a certain period of times. "It is sometimes useful to think of bandwidth as how long it takes to transmit each bit of data. On a 10-Mbps network, for example, it takes 0.1 microseconds to transmit each bit [Peterson and Davie, 2003]."

3.5.4.2 Latency. Latency, measured in time, is the delay in the signal, how long it takes a message to travel the length of the network. Latency is typically expressed in terms of RTT (round trip time). Latency is composed of three components –

propagation time, transmission time, and queuing time. Propagation time is a function of the speed of sound, which varies according to the medium, like copper wire or optical fibers. It is a measure of how fast one single bit can travel the given distance. Transmission time is the size of the pipe divided by the bandwidth. It is a measure of the time it takes to transmit a unit of data and is a function of the network bandwidth and the size of the packet. Queuing time accounts for delays in the network.

3.5.4.3 Delay-bandwidth product. The delay-bandwidth product is simply the delay (in seconds) times the bandwidth (in bits per second). The product is the capacity of the pipe from the sender to the receiver and back (in bits) [Tanenbaum, 2003]. This is a measure of the total size or capacity of the pipe. Large delay times can be compensated for by expansion of bandwidth. Limited bandwidth capability can be compensated for by reductions to delay factors, like reducing congestion.

3.5.5. Quality of Service. QoS (quality of service) is a measure of the user experience. From the user's point of view, good QoS is a function of transaction speed, size capability, availability, and reliability. According to Weibin Zhao of Columbia University, "We define QoS as providing service differentiation and performance assurance for Internet applications [Zhao et al., 2002]."

3.6. CAPACITY MODELING

Accurate modeling of network traffic is essential to the design and operation of large-scale networks. During network design, and for upgrade considerations, models are used to simulate the traffic stream and predict future needs. This allows for accurate sizing of the network. During operations, models are used to predict future rates based on real-time data. This allows for efficient and timely QoS management. This dissertation research deals with the first case, which is modeling network traffic for simulation and prediction of network demand to allow for efficient and accurate sizing of the network.

3.6.1. Difficulties in Modeling Internet Traffic. Modeling Internet traffic, with all of its size and variety, is extremely challenging, and there is still no general consensus as to the best and most effective method. It is especially difficult to develop and maintain a model that can provide reliable and accurate representation when the traffic is constantly changing and evolving. Yet this is exactly the environment in which a large-scale NCS has to operate, an environment that is vast, constantly changing, and is often different at various points on the network.

Current methods model network traffic through mathematical equations representing effective bandwidth. These models express network traffic as a function of fractional Browning Motion, based on theories developed by Ilkka Norros [Norros, 1995]. The accuracy of these models is dependent upon measured data characteristics, which are often not very accurate themselves [Cleveland and Sun, 2000; Li et al., 2004; Qian et al., 2004], are difficult to collect and correctly characterize [Bregni, 2004; Cleveland and Sun, 2000; Floyd and Kohler, 2003; Fomenkov et al., 2004; Li et al., 2004; Park et al., 2005; Qian et al., 2004; Yousefi'Zadeh, 2002], are subject to constant change, and vary according to time, circumstance, and location [Bianchi et al., 2004; Brownlee and Claffy, 2002; Li et al., 2004; Qian et al., 2004; Rodriques and Guardieiro, 2004; Swift and Dagli, 2007c].

In addition to all these difficulties, the vast amounts of data flowing over even the smallest of networks make it difficult to perform meaningful capture and analysis of enough data to provide statistically correct characterization of the whole. Many researchers argue against even trying to come up with all encompassing models for global networks [Floyd and Kohler, 2003], challenge conventional assumptions about the basic nature of Internet traffic [Bianchi et al., 2004; Cao et al., 2001; Cleveland and Sun, 2000; Floyd and Kohler, 2003; Fomenkov et al., 2004; Rodriques and Guardieiro, 2004; Swift and Dagli, 2007b], or expound on the enormous difficulties of accurately modeling something so complex [Bregni, 2004; Cleveland and Sun, 2000; Floyd and Kohler, 2003; Fomenkov et al., 2004; Li et al., 2004; Park et al., 2005; Qian et al., 2004; Yousefi'Zadeh, 2002].

Compounding this problem, network service providers tend to regard all data collected through their service as proprietary trade secrets and guard against free dissemination [Park et al., 2005]. This greatly limits the availability of data to researchers and modelers.

Marina Formenkov of CAIDA (Cooperative Association for Internet Data Analysis) states, "Internet traffic is the result of interaction among millions of users, hundreds of heterogeneous applications, and dozens of sophisticated protocols. The technical components of the Internet are complex in themselves, and they are augmented by a general unpredictability and diversity of the human components [Fomenkov et al., 2004]."

"We wouldn't recommend trying to construct a single model of the global Internet … Researchers should instead concentrate on modeling properties relevant to their research, and finding valid simplifications or abstractions for other properties [Floyd and Kohler, 2003]."

"Internet traffic data are ferocious. Their statistical properties are complex and databases are very large. The protocols are complex and introduce feedback into the traffic system. Added to this is the vastness of the Internet network topology. This challenges analysis and modeling [Fomenkov et al., 2004]."

Many basic assumptions are made to construct the models and these assumptions are often called into question by others. Examples of some typical model assumptions are: assumptions of how Internet traffic flows work, assumptions that traffic flows live for a long time and transfer a lot of data, assumptions on simple topologies, assumptions that there is only one congested link in a traffic flow, assumptions about sharing of RTTs, assuming most data traffic is one-way, and assuming reverse-path traffic is rarely congested. "All of these modeling assumptions affect simulation and experimental results, and therefore our evaluations of research. But none of them are confirmed by measurement studies, and some are actively wrong [Floyd and Kohler, 2003]."

Add to this the difficulty in measuring and recording and evaluating Internet data. It is extremely difficult to understand and characterize something that you cannot measure. "The lack of good measurements, lack of tools for evaluating measurement results and applying their results to models, and a lack of diverse and well-understood simulation scenarios based on these models are holding back the field [Floyd and Kohler, 2003].

The modeler is faced with the overwhelming task of continuously performing data collection and constantly conducting detailed analysis in order to capture changing characteristics throughout all portions of the network. Values measured and derived from data collected at a point in Amsterdam might be totally different from data collected in nearby Paris, or especially in far away Hong Kong. Data collected on users during work hours could be different from data collected on users at night or on weekends. Data from teenagers could have different characteristics from adults, data from men compared to women or to children, and from engineers compared to accountants or librarians. Data in January compared to July could be different. Data on web-surfers or emailers might be different from people viewing media clips or from multi-tasking users. Data collected one day could be entirely out of date by the following year, or month, or perhaps even the next day. The potential for variety is endless [Swift and Dagli, 2007c].

Modeling based upon computing techniques employing artificial intelligence, especially those with the capability for self-learning and self-adaptation, would not only save modelers countless hours in re-sampling and updating parameters, but would tend to be significantly more accurate.

3.6.2. Internet Traffic Data Sources. There are three major sources of Internet Traffic Data for use in the development of models and an innumerable host of independent point sources [Hong, 2004].

The NLANR is the National Laboratory for Applied Network Research. Its primary goals are "to encourage the creation of Internet traffic metrics … to create a collaborative research and analytic environment … to foster the development of advanced methodologies and techniques for: traffic performance and flow characterization, simulation, analysis, and visualization [NLANR, 2005]."

CAIDA is the Cooperative Association for Internet Data Analysis. It's goals are "to encourage the creation of Internet traffic metrics … to create collaborative research and analytic environment in which various forms of traffic data can be acquired, analyzed, and shared … to foster the development of advanced methodologies and techniques for traffic performance and flow characterization, simulation, analysis, and visualization [CAIDA, 2005]."

The SLAC NMTF is the Stanford Linear Accelerator Center Network Monitoring Task Force. Its primary goals are to act as a focus group for energy sciences sites in the area of network monitoring, share network monitoring information, and determine what tools and applications are needed [SLAC, 2005].

CBB was used as the source of data for this case study instead of these terrestrial sources. Using CBB allowed the analysis of data sets representing all locations on an operating NCS rather than just traffic flowing by a few selected nodes on the Internet.

3.6.3. Current Modeling Techniques – History and Development. The first step in modeling Internet traffic is an understanding of the basic characteristics of the traffic stream [Cleveland and Sun, 2000] and most modeling techniques of today express network traffic as a function of fractional Brownian motion, which was first proposed by Ilkka Norros of Finland in 1994 [Norros, 1995]. This methodology is based on two key assumptions: self-similarity and long range dependence.

Will E. Leland discovered the self-similarity characteristic of Internet traffic in 1993 [Crovella and Bestavros, 1997; Leland et al., 1994]. Up until then, Internet traffic was modeled as a Poisson process and all analysis was based on the Poisson or Markov modulated distributions. The Poisson methods assumed characteristic burst lengths, which allowed the traffic to be smoothed by averaging over long time scales. However, as actual data became more available, measurements of Internet traffic indicated this was not the case [Gong et al., 2005; Park et al., 2005]. It was found that measured traffic displayed significant amounts of burstiness along different scales and perhaps even an intensification of burstiness as the number of sources increased, contrary to what was then the common perception. Figure 3-11 illustrates [from Leland et al., 1994] the burstiness typically found in early network traffic, as published in the paper by Will Leland [Leland et al., 1994].

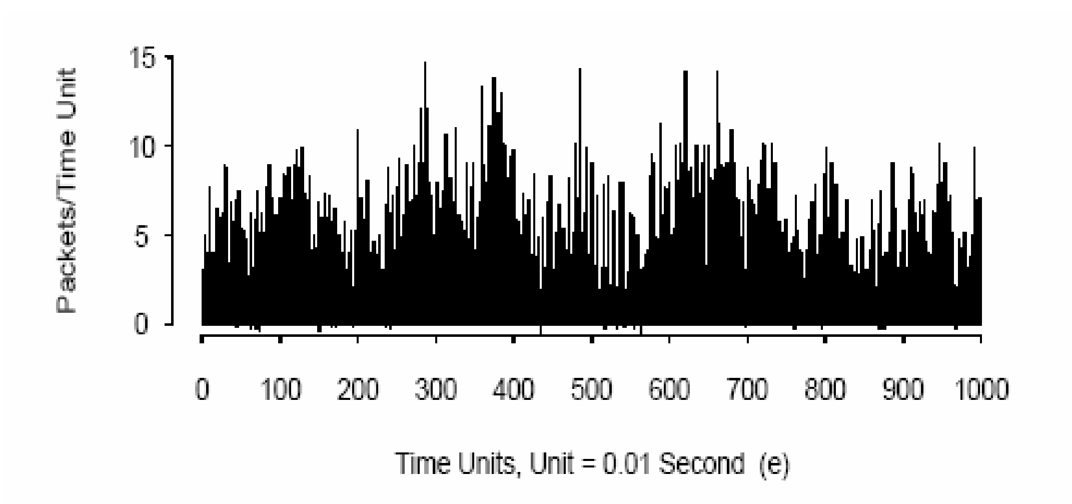


Figure 3-11 Burstiness in Internet Traffic

Self-similarity means the same shape is exhibited over varying ranges of scale. The classical example used to illustrate this feature is the well known fractional called the Sierpinski triangle [Connors, 2005]. The same shape is maintained as the scale expands or contracts. Figure 3-12 [from Connors, 2005] illustrates the relationship in scale of Sierpinski triangles, which are self-similar.

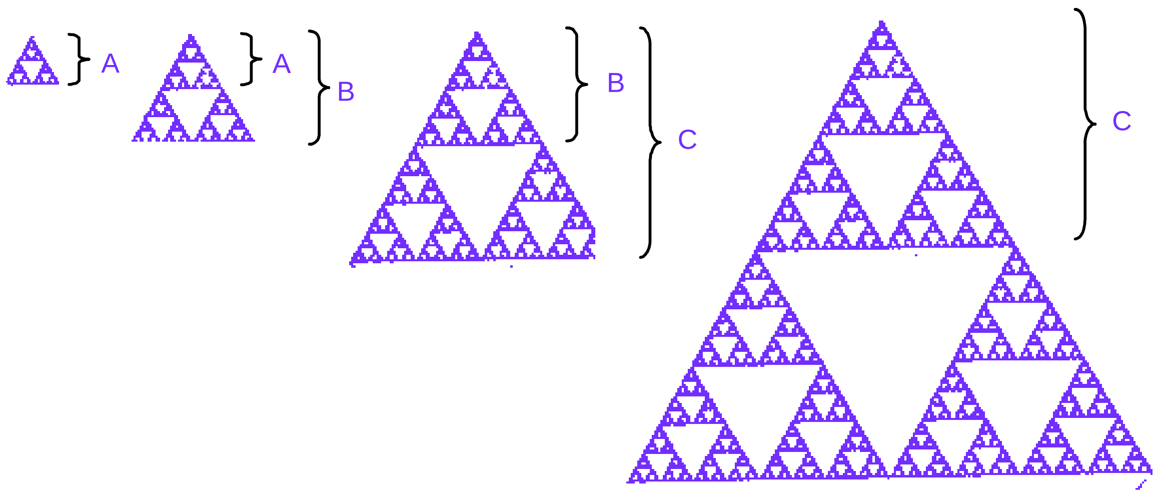


Figure 3-12 Sierpinski Triangles

Self-similarity for Internet traffic is typically expressed by examining segments of traffic on a time-history at varying scales. To be self-similar, the traffic would have to exhibit the same burstiness at varying scales. For example, Internet traffic for an airline flight that is bursty over the entire flight would also be bursty to the same degree over a one hour segment of the flight, then again over a one minute segment from the previous segment, over a one second segment, and so forth. Oznur Ozkasap and Mine Caglar of Istanbul, Turkey, give a good definition within the domain of network traffic, "Self-similarity can shortly be described as the scale invariance of the bursty behavior, observed ubiquitously in the network traffic [Ozkasap and Caglar, 2006]."

After Leland's discovery of the self-similar characteristic of Internet traffic, Norros developed his methodology by quantifying the burstiness of the traffic. "Traffic sources are bursty, i.e. they are not transmitting continuously but have silent or low-activity periods alternating with periods of high activity [Norros, 1995]." Figure 3-13 illustrates the burstiness of traffic. This plot is for the one-way traffic of only fifty users and is averaged over 1 second intervals.

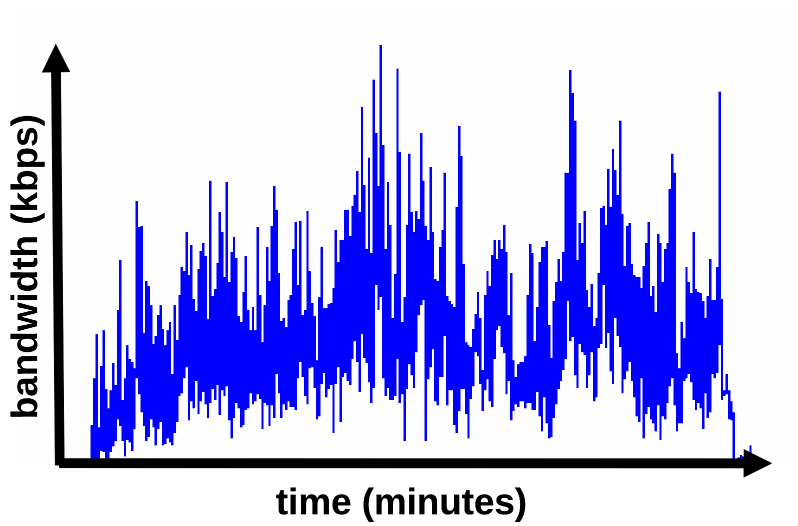


Figure 3-13 Bursty Internet Traffic for 50 Users

Ilkka Norros proposed aggregating and modeling Internet traffic by relating it to fractional Brownian motion [Li et al., 2004; Norros, 1995], and this is the most common method for modeling network bandwidth still in use today [Bianchi et al., 2004]. Ilkka Norros described his model as "an abstract model for aggregated connectionless traffic, based on the fractional Brownian motion [Norros, 1995]." Norros said, "Insight into the parameters is obtained by relating the model to an equivalent burst model [Norros, 1995]." He also said, "It is a self-similar model [Norros, 1995]" and "Internet traffic is self-similar [Norros, 1995]."

The second most common type of models are based on theories and equations developed by Frank Kelly of England [Kelly, 1991]. He developed stochastic based mathematical equations for aggregating and modeling Internet traffic [Kelly, 1991; Li et al., 2004]. Kelly felt that traffic has distinct sources and effective bandwidth must be associated with each source and the queue can limit the number of sources served so that their effective bandwidths sum to less than the capacity of the queue [Kelly, 1991].

A lesser group of methods is based on D-BIND (deterministic bounding interval-length dependant) theory proposed by Edward Knightly of the United States [Knightly and Shroff, 1997; Knightly and Zhang, 1997]. His method is based on quality of service admission controls.

Current research in the field is directed mostly towards improvements and enhancements to these methods in an attempt to add flexibility and adaptability to the models as Internet traffic becomes more and more diverse and unpredictable [Bianchi et al., 2004; Bregni, 2004; Brownlee and Claffy, 2002; Li et al., 2004; Qian et al., 2004; Rodriques and Guardieiro, 2004].

Other models include the on-off models, Gaussian models, leaky bucket, Poisson models, probabilistic models, Markovian models, other fractional Brownian motion models, D-BIND, and S-BIND [Qian et al., 2004; Baldi et al., 2003; Li et al., 2004, Knightly and Zhang, 1997; Knightly and Shroff, 1997] . Much research has come out of Bell Labs® on modeling the non-stationary characteristics of Internet traffic explaining that certain traffic (packet and connection) characteristics tend locally toward Poisson where other time series characteristics (packet sizes, transferred file sizes, and connection round trip times) tend toward independent [Cleveland and Sun, 2000; Cao et al., 2001; Cao et al., 2002a; Cao et al., 2002b]."

Returning to the most common type, Fractional Brownian motion models are founded on the assumptions of self-similarity and long-range dependence. Early experimental measurements tended to validate self-similarity [Bregni, 2004]. This was especially true for bursty Internet traffic composed mostly of web-surfing [Bianchi et al., 2004], the most common use of the Internet at the time. The more bursty the traffic, then the closer it comes to approximating pure Brownian motion.

According to Wei-Bo Gong of the University of Massachusetts [Gong et al., 2005], "Fractional Browning motion (fBm) is an example of a self-similar process. A process X(t) is said to be an fBm if the increment process is normally distributed with mean zero and variance t^{2H}. The covariance of the process is described by

$$E\left[X(s)X(t)\right] = \frac{1}{2}\left(s^{2H} + t^{2H} - \left|s-t\right|^{2H}\right) \tag{3.1}$$

where H is the self-similarity parameter."

For the network traffic, self-similarity implies consistency over varying time sets. "In a self-similar random process, a dilated portion of a realization (sample path) has the same statistical characterization as the whole. 'Dilating' is applied on both amplitude and time axes of the sample path [Bregni, 2004]."

Long range dependence, or long memory, is defined as a slow decay in correlations. With regards to Long-Range Dependence, Norros said, "The degree of the short-term predictability of the traffic model is clarified through an exact formula for the conditional variance of a future value given the past [Norros, 1995]." In other words, "Long-Range Dependence is a long-memory model for scaling observed in the limit of largest time scales [Bregni, 2004]."

Network traffic bandwidth is typically expressed in terms of capacity, C, defined as the maximum rate for data transfer. At a given instant of time, t, a link is either transmitting at capacity or is idle. The capacity of the network path, consisting of N links, $L_1 ... L_N$, is defined as [Angrisani et al., 2006]:

$$A(t, \Delta t) = \min_{i=1...N} \frac{1}{\Delta t} \int_{t}^{t+\Delta t} C_i (1 - u_i(\tau)) d\tau \tag{3.2}$$

where $C_1 ... C_N$, are link capacities and the values $u_1(t) ... u_N(t)$ are percentages of link utilization [Angrisani et al. 2006].

A mathematical expression, based on assumptions of self-similarity and fractional Brownian motion, is derived. The following Norros based equation, as used by the CBB network, illustrates one such example for modeling capacity [Erramilli and Couch, 2001; Swift, 2004b]:

$$C = m + \left(\kappa(H)\sqrt{-2\ln(\varepsilon)}\right)^{1/H} a^{1/(2H)} B^{-(1-H)/H} m^{1/(2H)} \tag{3.3}$$

where $$\kappa(H) = H^{H}(1-H)^{(1-H)} \qquad (3.4)$$

m = Mean Bit Rate (bps)

a = Peakiness (bps)

ε = Cell Loss Rate

B = Buffer Size (bits)

H = Hurst Parameter

C = Capacity or Effective Bandwidth (bps)

Arrivals of packets or bits are correlated over long periods of time. The correlations are modeled as Gaussian noise. The mean bit rate, m, is the mean bit rate per user. The peakiness, a, or variance coefficient, is closely related to the variance of traffic and is a measure of the magnitude of fluctuations in the traffic. The cell loss rate, ε, is a constant sized for the system to be modeled. The buffer size, B, is derived from the peak capacity of the system and the maximum queuing delay. The Hurst parameter, H, is a measure of the rate of decay of correlations. The three parameters, m, a, and H, together make up a measure of the self-similarity of the aggregate traffic.

Five general difficulties arise when applying this methodology to complex, large-scale, global networks. First, the accuracy is dependant upon exact characterization of the traffic stream which is usually not very accurate [Cleveland and Sun, 2000; Li et al., 2004; Qian et al., 2004]. Second, the derived mathematical expression cannot be assumed to apply throughout all segments of the network [Swift and Dagli, 2007c]. Third, it becomes a tremendous challenge to collect, evaluate, and constantly update measured data for input to the model [Bregni et al., 2004; Cleveland and Sun, 2000; Floyd and Kohler, 2003; Fomenkov et al., 2004; Li et al., 2004; Park et al., 2005; Qian et al., 2004; Yousefi'Zadeh, 2002]. Some of the input values are difficult to extrapolate from the data, especially self-similarity and long-range dependence parameters such as the Hurst parameter and other self-similar characterizations [Bregni, 2004]. Fourth, the data is in a state of constant change and evolution [Bianchi et al., 2004; Brownlee and Claffy, 2002; Li et al., 2004; Qian et al., 2004; Rodriques and Guardieiro, 2004]. Fifth, the traffic must be self-similar, which may not be a good assumption for today's traffic [Rodriques and Guardieiro, 2004; Swift and Dagli, 2007b].

These models are based on regularity and do not support non-regularities [Bianchi et al., 2004], are based on self-similarity which may not hold as true today as in the past [Rodriques and Guardieiro, 2004; Swift and Dagli, 2007b], and are dependent on accurately estimating statistical quantities of the traffic to characterize self-similarity, such as the Hurst parameter, which is very difficult to accurately measure and is subject to change [Bregni, 2004; Park et al., 2005].

3.6.4. Model Under Evaluation. The CBB network simulation utilizes the Norros equation described above in Equation 3 and 4 above to simulate Internet data traffic on the CBB network and predict network demand.

3.6.4.1 Advantages. There are three advantages gained when using the Norros fractional Browning Motion model: 1) widespread acceptance, 2) ease of modeling, and 3) accurate bursty traffic approximation.

Widespread acceptance is important; it indicates a proven methodology with less risk. Ease of modeling is important too. All that is required is a few lines of software code to implement the mathematical equation. The difficulty comes in determining good input parameters that correctly characterize the traffic all through the network, but implementation of the algorithm is easy. Accurate bursty traffic approximation is also important and fractional Browning motion gives a good estimation of bursty traffic; unfortunately, there has been a trend away from bursty traffic as more steaming media applications come on-line [Swift and Dagli, 2007b].

3.6.4.2 Disadvantages. Section 3.6.1 describes the disadvantages in great detail. These problems are especially acute when trying to model network traffic on large-scale NCS systems. It becomes a difficult task to determine the parameters for initial input to the Norros equation and them continuously monitor for changes and update. Accurately determining traffic characteristics to estimate self-similarity and long-range dependence, such as the Hurst parameter, are especially difficult [Bregni, 2004]. The current CBB simulation uses the same characteristics globally and some of the parameters are based on terrestrial statistics due to the lack of sufficient, accurate, network data.

The trend away from self-similarity can possibly best be explained by the changing nature of Internet traffic. In the past it was estimated that web-surfing, which tends to be very bursty, accounted for over 95% of the traffic. Today there are more and more peer-to-peer applications that have more constant mean-to-peak variance in data rates. These applications are not bursty in nature and tend to consume high percentages of the available network bandwidth. Even though these new less bursty applications are becoming more and more common and comprise a greater percentage of the traffic each year, little is known about the traffic characteristics of these low bursty, high delay sensitive, applications [Qian et al., 2004].

Studies from the Pew Research Institution have found a major shift in user habits among Americans since the advent of higher speed broadband. These users, estimated at roughly 21% of Internet users now, tend to engage in multiple activities when on the Internet [Horrigan and Rainie, 2005]. An example would be a user that is web surfing at the same time they are listening to streaming audio music and also engaging in Internet chat. Surveys show these users are 3.5 to 4.75 times more likely to use steaming media, such as watching a video clip, listening to live music, or watching a movie, and 2.8 to 5.5 times more likely to do downloading of games, video, pictures, music, or movies, in a given day [Horrigan and Rainie, 2005].

The trend is away from highly bursty web-surfing traffic. New applications are appearing on a regular basis. Interactive gaming, for example, is becoming more and more prevalent. Another example is the production, uploading, downloading, and viewing of amateur video clips. Approximately 16% of users have gone online to view web-cam images [Rainie, 2005b], 27% say they have downloaded either music or video files [Madden and Rainie, 2005], and 29% have downloaded podcasts from the web [Rainie and Madden, 2005a]. In addition, users of today are just as likely to go online to view web based classes or training as to download music [Horrigan and Rainie, 2005]. Many of the major universities archive class lectures for later viewing and some even broadcast live.

Figure 3-14 was taken from a data sample of 65 users with an average of 18 active at one time. The figure illustrates the great variety in usage patterns between different individuals. Some have very bursty traces and others have fairly constant data rates for considerable spans of time.

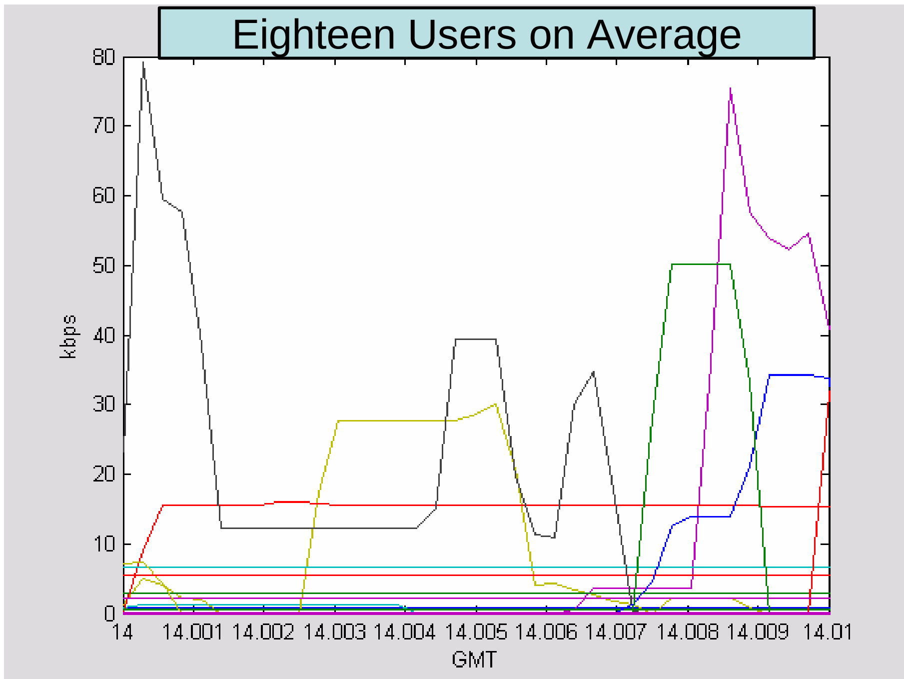


Figure 3-14 Individual Internet Traces

3.6.5. Direction of Research. Current research is applied towards improving upon existing methods based upon fractional Browning Motion, such as those postulated by Norros Theory, Kelly's Equations, or D-BIND Theory.

One proposal involves a different way of computing Brownian Motion. "Instead of computing mono-fractional Browning motion we compute multi-fractional Browning motion by using a time dependant Holder function instead of the Hurst parameter. The value of the Holder exponent at a given time indicates the degree of traffic burstiness [Bianchi et al., 2004]."

Another proposal involves using different profiles for TCP (transmission control protocol) and UDP (user datagram protocol) when calculating the Hurst parameter. It also proposed working at the flow level so the fractal nature of Internet traffic can be ignored when computing Hurst parameter and a simple Poisson shot-noise process [Rodriques and Guardieiro, 2004].

Another proposal involves using a unified model rather than one model for each traffic flow as per Kelly's equation. It investigated use of dynamic weighted round robin scheduling [Li et al., 2004].

One proposal suggested that instead of D-BIND (deterministic bounding interval-length dependent) method, using a confidence-level based statistical S-BIND traffic model for inputs to a hybrid gamma H-BIND algorithm. This method may be good for both low and high bursty traffic [Qian et al., 2004].

Another proposed use of MAVAR (modified Allan variance) to estimate the power-law spectrum and thus the Hurst parameter, instead of log-scale diagram techniques based on wavelet analysis. The MAVAR is a well-known time-domain tool originally studied for frequency stability characterization [Bregni, 2004].

Another proposal involved characterization based on flows rather than size. Current methods center around network elephants, which are large file transfers, and network mice, which are small volume transfers. A new method was proposed based on streams, either Dragonflies or Tortoises. Dragonflies composed 45% of Internet traffic in his studies, lasting less than 2 seconds, and carried 50-60% of data. Tortoises last longer than 15 minutes but only compose 2% of Internet traffic, yet they too carry 50-60% of the total data on a link [Brownlee and Claffy, 2002].

The major goal of these research efforts is an attempt to improve upon existing Internet traffic modeling techniques, or an attempt to make them applicable to more than one condition or environment at a time. The direction of research is indicative of a generally well understood need to make Internet traffic models more flexible to change and different types of traffic. An adaptive model would do just that.

Research into the use of ANNs for modeling network traffic centers around real-time network QoS management, sampling to predict data rates as they occur [Tong et al., 2004; Yousefi'Zadeh, 2003]. This is the type not under investigation by this study which is instead concerned with prediction of demand for resource sizing. These network management modeling methods depict network traffic as a time series:

$$X = (x_i : I = 0, 1, 2\ldots) \qquad (3.5)$$

Given the current and past observed values of X_i, the model is used to predict a future value. Most of this research, due to the changing complexity of the Internet when viewed as a whole, restricts the data under investigation to a single application, such as studies investigating use of ANNs to model MPEG (moving picture experts group) video streams [Bhattacharya et al., 2003; Chang and Hu, 1997; Doulamis et al., 2000; Doulamis et al., 2003] or to model traffic queuing delays [Yousefi'Zadeh, 2002].

Research into the use of ANNs for modeling and simulating network traffic to determine resource sizing needs, expressing the traffic as composite bandwidth, as described in this paper, is largely unexplored.

3.7. SECTION SUMMARY

This section on the Internet and capacity modeling provided the background on how the Internet works, which is the medium through which NCS data flows to achieve network-centricity. It also gave a description of the two most common Internet architecture models, the OSI and the TCP/IP. Then encapsulation was described to provide understanding of the type of data being used for this research project and also details on traffic management which included performance parameters and QoS.

This section also provided background on capacity modeling. The problems encountered when modeling something as vast and complex as the Internet were described. Then current modeling techniques were presented, along with advantages and disadvantages, and also research into improvements and enhancements. Greater detail was given to the Norros model using fractional Brownian motion which is the model currently employed by CBB.

Since current models tend to be self-similar and non-adaptive, it is becoming more and more difficult to accurately model global systems that are network-centric, complex, changing, and evolving. This defines the need for an adaptive model based on computationally intelligent modeling techniques.

The following section (Section 4) contains a literature review of artificial neural network modeling techniques which form the vehicle for modeling used in this dissertation research project. After reviewing in previous sections the nature of NCS systems and the networks that enable them, and how traffic is modeled on those networks, the next section discusses artificial neural networks, the method of computational intelligence uses by this dissertation research project for adaptive modeling of NCS network traffic.

4. ARTIFICIAL NEURAL NETWORK LITERATURE REVIEW

4.1. RELEVANCE OF ANNS TO THIS RESEARCH PROJECT

As systems become more and more complex, it became impossible for designers to conceptualize and develop solutions without computing software tools. As these systems developed further levels of complexity, with the advent of the Internet and SoSs and NCSs, they developed dynamic characteristics, experience constant change, and often display unforeseen emergent characteristics and behaviors. These added levels of complexity are driving the need for computationally intelligent software tools.

ANNs (artificial neural networks) are a form of computational intelligence used for pattern recognition or data classification and subsequently for prediction. They perform well in mediums where non-adaptive algorithms have difficulty, such as modeling non-linearities, generalizing to account for faulty input data, data mining, data compression, and signal processing for difficult situations such as voice recognition and image processing [Franklin, 2003]. The power of the ANN derives from its ability to learn (the means of adaptation) and to generalize [Haykin, 1999; Sohn and Dagli, 2003a]. They are well suited for the challenge of modeling network traffic, especially traffic from highly complex NCS systems where traffic characteristics are constantly evolving and are difficult to model with conventional means.

The literature review in this section includes: 1) an overview of typical ANN architecture, in particular the perceptron type neural network that was used in this dissertation research, 2) a description of alternative types of neural networks and also genetic algorithms, and 3) a review of successful example applications in the use of ANNs.

4.2. OVERVIEW OF ARTIFICIAL NEURAL NETWORKS

Neural networks, also known as artificial neural networks or neurocomputing, are biologically inspired intelligent computing techniques that can be used very effectively for classification. Unlike traditional computing techniques which simply process information, neural networks learn and adapt in a manner similar to the human brain. Neural networks are based on the following assumptions [Ham and Kostanic, 2001], [Fausett, 1994]:

- Information processing occurs at nodes called neurons
- Signals are passed between neurons over connection links
- Each connection link has an associated weight
- Each neuron applies an activation function

For this study a simple feed-forward perceptron neural network with back-propagation learning was used. This type of neural network is fairly simple and easy to implement. Other more complex types of neural networks were considered, but the gains in accuracy did not justify the added complexity. The perceptron proved entirely capable. In an operational environment, as long as performance is satisfactory, the simpler the better.

4.2.1. Biological Construction. The human brain is made up of basic cellular units called neurons. These neurons have synapses and dendrites. The dendrites are extensions of the neurons that connect to other neurons and allow for the passage and amplification of electrical pulses or brain signals. The synapses are stops that either halt the signal by remaining dormant or else fire to allow passage of a signal to other neurons. All together they form a network that selectively allows electrical pulse signals to travel about the brain.

“When a connection (dendrite) is very strong, the importance of the neuron from which this connection comes has an important role in the network, or on the other hand, when a connection is very narrow, the importance of the neuron from which the connection comes from is less high. Through this process the neural network stores information in the pattern of connection weights [Franklin, 2003].”

For ANN models, the neurons are simulated by nodes and connections. The nodes simulate the function of a synapses by use of an activation function which sums the inputs from connecting nodes and only fires if the total signal exceeds a threshold according to the properties of the activation function. The dendrites are simulated by connections between nodes with weighting that mimics the strength of the dendrite. The ANN structure, composed of a network of activation function nodes and weighted connections, is very similar to the brain with neurons consisting of synapses and dendrites.

Training of the neural network simulates learning in the human brain. The brain learns by perceiving the environment and storing information in memory. The ANN learns by training patterns passed through the network causing memory through adjusting weights on the network connections.

4.2.2. Basic Neural Network Structure. Pioneers in the development of ANN techniques started with Warren S. McCulloch and Walter Pitts who developed the McCulloch-Pitts neuron based on the neuron of a brain, but without learning. Then

Donald Hebb developed the first learning process based on information stored in the weights of networks. Then Frank Rosenblatt developed the perceptron neural network with adaptive behavior. Then Bernard Windro developed the adaline. Webos developed the back-propagation algorithm for training. Amari developed recurrent networks. Finally, John Hopfield started the age of modern neural networks with his publication on the applications and capabilities of neural networks for pattern recognition [Ham and Kostanic, 2001].

The basic perception feed-forward neural network with back-propagation learning is arranged with an input layer, then hidden layer or layers, and finally, an output layer. The neural network learns through training data sets. An example neural network, a basic feed-forward perceptron with two hidden layers, is shown in Figure 4-1. It has four attributes in the input vector, two hidden layers with activation functions, and an output layer with two elements in the output vector.

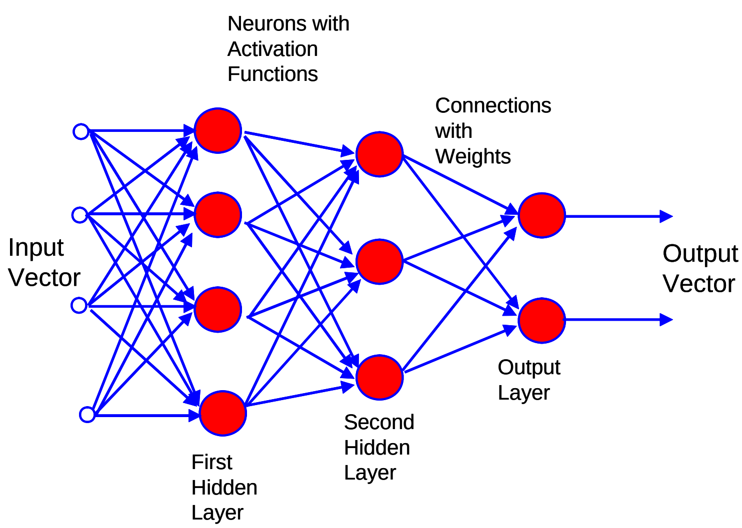


Figure 4-1 Feed-Forward Perceptron Neural Network

Simple scalar weighting is applied to the network connections and activation functions are used at the nodes instead of biological thresholds. The most common type is the sigmoid activation function [Franklin, 2003], Equation 4.1. Other functions include the hard limit activation function, the linear transfer function, the log-sigmoid activation function, and the tangent-sigmoid activation function [Demuth and Beale, 2001, Ham and Kostanic, 2001].

$$Y = \frac{1}{1+e^{-x}} \tag{4.1}$$

4.2.3. Back-Propagation Learning. Neural networks learn and adapt through learning algorithms. The most common means is through back-propagation. The training data is passed through the system which then back-propagates to determine errors and then adapts by adjusting weights. "Back propagation performs a gradient descent in the solution space to reach a global minimum – the theoretical solution with the lowest possible error – along the steepest vector of the error surface [Sohn and Dagli, 2003a]." Once the errors become small enough to meet specified criteria, the neural network can operate without the back-propagation and be used for data classification or pattern recognition.

The basic process involves computing the error signal by comparing ANN output to the known values. The error signal is simply the output signal of output neurons minus a target output. The error signal is used to drive corrective adjustments to the weights of the connection leading to each neuron to bring that neuron's output signal closer to the target. The process is repeated until the error signal falls within the limits of a defined parameter or else reaches steady state. Figure 4-2 illustrates the calculation of the error signal. Equations 4.2 through 4.6 show the calculation process for updating the weights on the network connections [Ham and Kostanic, 2001; Haykin, 1999; Sohn and Dagli, 2003a].

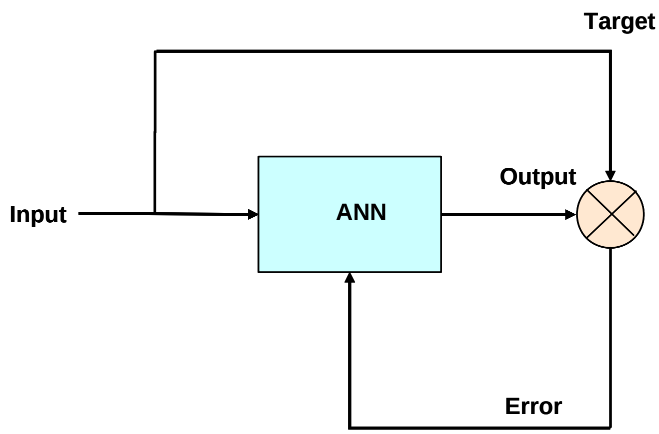


Figure 4-2 Error Signal

X(n) = input signal

Y(n) = output signal

T(n) = target signal

E(n) = error signal

W(n) = weight

n = iteration

k = neuron

η = learning rate

The input is the same as the target: $X_k(n) = T_k(n)$ (4.2)

The error is the target minus the output: $E_k(n) = T_k(n) - Y_k(n)$ (4.3)

Typical minimizing function: $\zeta_k(n) = 0.5E_k^2(n)$ (4.4)

Adjustment to the weight: $\Delta W_k(n) = \eta E_k(n) X_k(n)$ (4.5)

Updated value of the weight: $W_k(n+1) = W_k(n) + \Delta W_k(n)$ (4.6)

There are two types of learning for neural networks. The first is called supervised learning, which is the process described in back-propagation, where solution training sets are supplied and error signals are determined to adjust the weights. The second is called unsupervised learning, where the network is not provided any training sets and must develop its own solutions based on dependencies within the data [Ham and Kostanic, 2001, Haykin, 1999].

4.3. OTHER TYPES OF NEURAL NETWORKS

There are several other types of neural networks besides the standard feed-forward perceptron. These include counter-propagation neural networks, radial basis function neural networks, Kohonen self-organizing map neural networks, genetic algorithms, and hybrids.

4.3.1. Counter-Propagation Neural Networks. Counter-propagation neural networks function as a bi-directional look-up table which maps in both directions between the input and output vector patterns when in training. It has a big advantage over the feed-forward perceptron neural network in speed of convergence during training because of the bi-directional update of the weights. A disadvantage is that is requires more neurons to achieve the same level of accuracy.

Figure 4-3 [adapted from Sohn and Dagli, 2003a] illustrates the basic structure for a simple counter-propagation neural network which maps both ways. The neurons in the cluster layer receive inputs from both X and Y input vectors and output to X and Y output vectors.

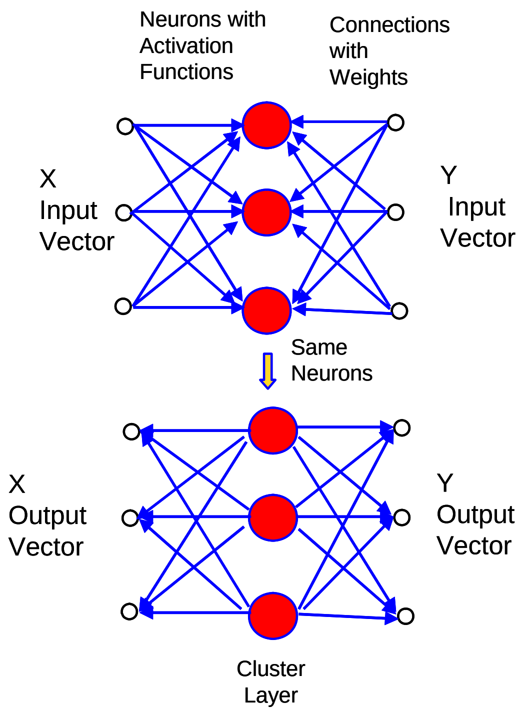


Figure 4-3 Counter-Propagation Neural Network

Counter-propagation neural networks are often used in place of feed-forward perceptron neural networks in cases where speed of the training becomes an issue. Sometimes they are used as prototypes and then later replaced with feed-forward perceptron neural networks.

For the CBB traffic modeling case of performing classification, the basic feed-forward perceptron neural network was selected over a counter-propagation neural network because there was no reason to suspect the ability to generalize might be a problem and for simplification purposes.

4.3.2. Radial Basis Function Neural Networks. Radial basis function neural network operates differently but are also well suited for both classification and pattern recognition and prediction. The radial basis function neural network has only one hidden layer. Instead of iteratively comparing the networks prediction for each sample with the actual known output, a radial basis function neural network computes Euclidean distance between the input vector and the center of basis functions of neurons in the hidden layer. Figure 4-4 [adapted from Sohn and Dagli, 2003a] shows the structure for a basic radial basis function neural network.

This type of neural network would probably work just as well as a feed-forward perceptron. The radial basis function neural network tends to have a simpler architecture in that it contains only one hidden layer but they often require more neurons in the hidden layer than the feed-forward perceptron neural network. Because they only need one hidden layer they are often easier to design and to train. They work best with lots of training vectors and are not as well suited to larger applications.

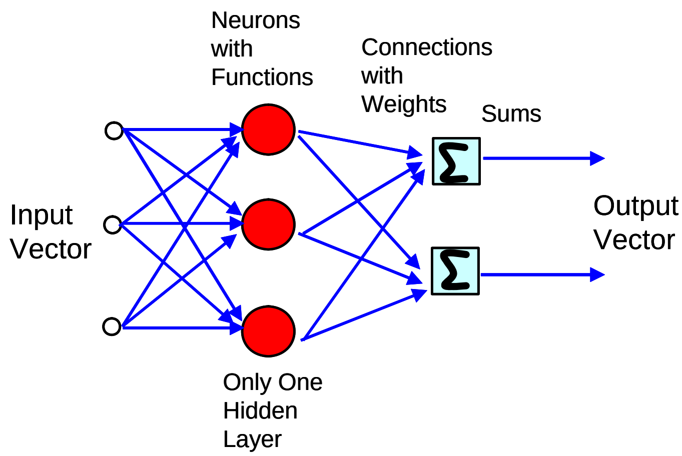


Figure 4-4 Radial Basis Function Neural Network

For the CBB traffic modeling case the basic feed-forward perceptron neural network was chosen over the radial basis function neural networks because of the variety of potential categories. With the radial basis function network a large number of training vectors for each and every category is required and this would increase data collection requirements.

4.3.3. Kohonen Self-Organizing Map Neural Networks. The SOM (self-organizing map) was developed by Professor Teuvo Kohonen of the Academy of Finland [Kohonen, 1989]. This is a clustering technique that uses unsupervised neural network algorithms. Like other types of neural networks, the SOM has the ability to learn from its environment and adapt. The output is a topological map of features. In the SOM every input is mapped to every neuron. Figure 4-5 illustrates a SOM structure [adapted from Ham and Kostanic, 2001].

The main use of SOM neural networks is to develop clusters or categories that might not be obvious to the observer. The key advantage is that the output does not have to be known beforehand and no target variables are needed. SOM neural networks are also useful for mapping a multi-dimensional data into two dimensions which is easier to visualize.

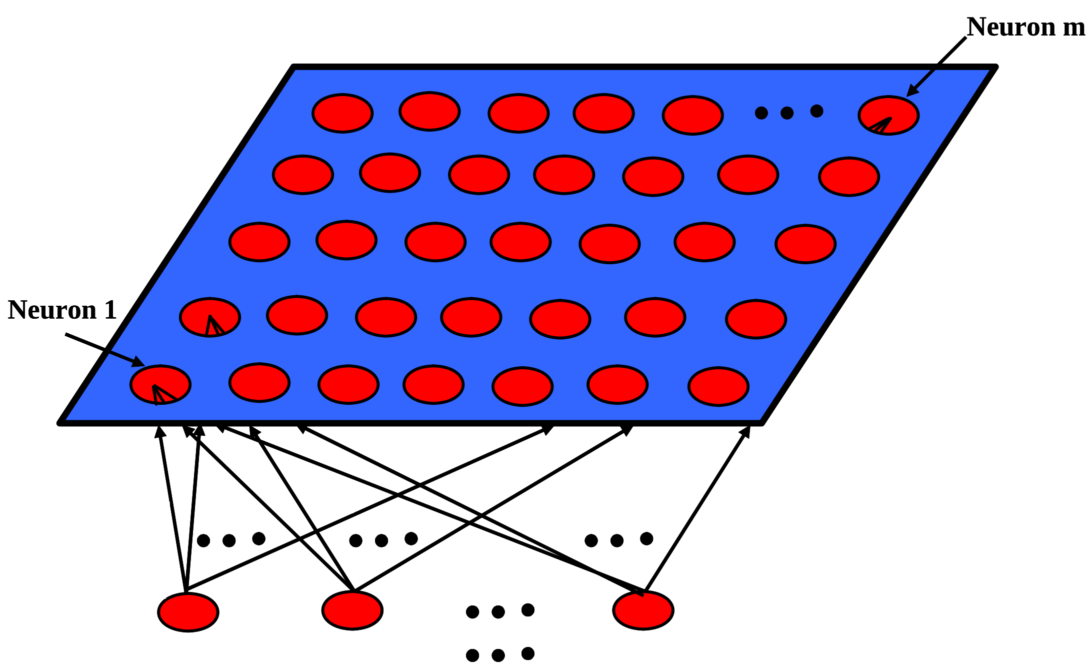


Figure 4-5 Mapping of Neurons in a Kohonen SOM

For a given input set or vector the SOM finds the closest vector in the weight matrix. The SOM then finds all weight vectors within a specified range and updates only those vectors within that range. Then another input is run through the network. This continues with decreasing learning rates and range until the network converges. Figure 4-6 illustrates the convergence [adapted from Ham et al., 2001].

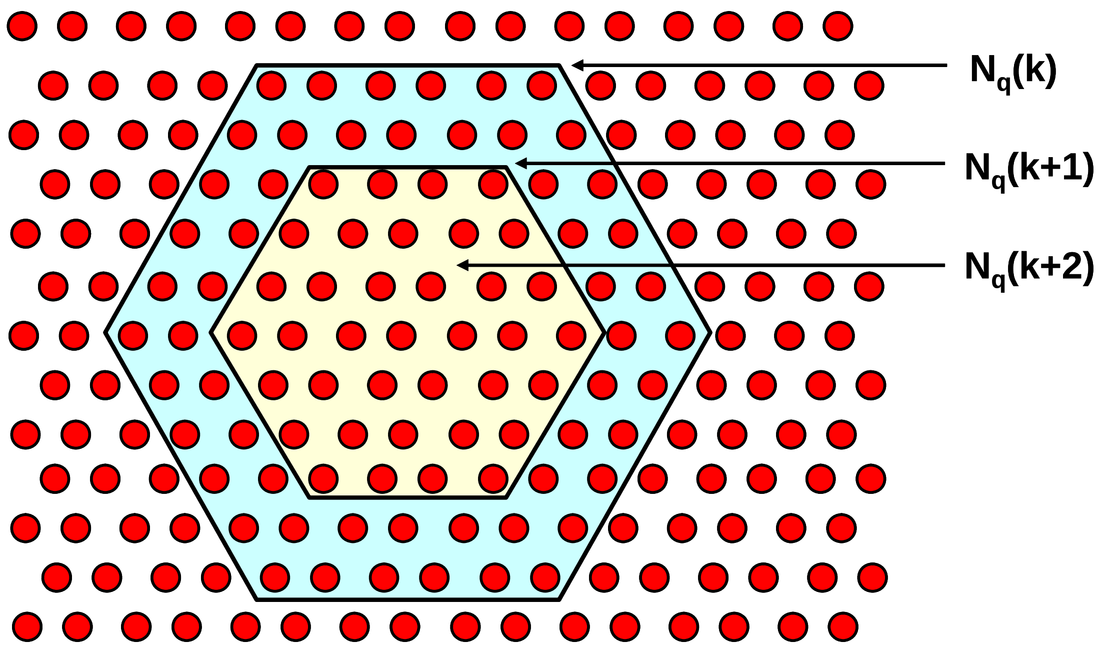


Figure 4-6 Convergence of Mapping in a Kohonen SOM

The SOM learns both the distribution and the topology of the input vectors. The neurons can be arranged in different topologies, such as gridtop, hextop, or random. The topology is reduced as the network converges. Upon completion of training, the SOM can categorize inputs onto the topology [Fausett, 1994, Ham and Kostanic, 2001; Swift and Dagli, 2004a].

For the CBB traffic modeling case, the basic feed-forward perceptron neural network was chosen over the SOM neural networks because of the ready availability of well defined outputs that could be used for supervised learning and because the simulation model was based on classification and prediction rather than clustering or mapping, which is the main function of a SOM neural network.

4.3.4. Other Techniques. Some other methods that can be used for classification and prediction include decision trees, genetic algorithms, K-means, Bayesian classification, fuzzy logic, and others. When looking at the different types of classification methods one has to not only consider accuracy but also ease of implementation, computational speeds, robustness in the face of noise, scalability, and interpretability.

4.3.5. Genetic Algorithms. Genetic algorithms are evolutionary algorithms that use biologically derived techniques such as inheritance, mutation, natural section, and crossover. Candidate solutions are called individuals or chromosomes. The solution state of individuals is typically encoded as a binary valued string where each bit represents a gene and the vector or string represents a chromosome. The optimization algorithms act on a population of individuals to cause evolution towards a better solution through natural selection of the fittest. The evolution starts from a population of completely random chromosomes. Each evolution is called one generation. The fitness of the population is evaluated. Based on fitness some individuals are selected. The chromosomes of the individual are modified by mutation or recombination, and a new population of offspring is formed. This new population is then acted on during the next generation or iteration of the algorithm in a similar manner. Termination conditions include things like – a fixed number of generations, a chromosome satisfies minimum criteria, computing time limit reached, or successive iterations not producing better results [Ham and Kostanic, 2001; Li et al., 2005; Sohn and Dagli, 2003a]. Figure 4-7 [adapted from Sohn and Dagli, 2003a] illustrates the flow.

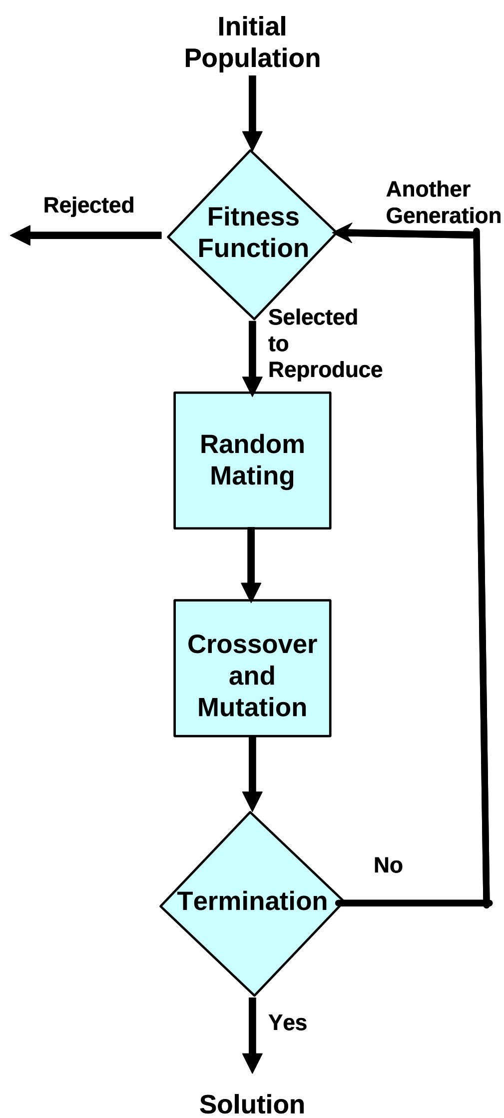


Figure 4-7 Genetic Algorithms

It is very possible that genetic algorithms would be a useful tool for the CBB traffic modeling case and would be as good as neural networks. Genetic algorithms are known for rapidly locating good solutions even for difficult search spaces. However, there would be several difficulties to overcome. Genetic algorithms do not operate well on dynamically changing data sets. They tend to converge towards early solutions which may not be valid for later data. This would be a problem with the complex CBB case where the complexity of data requires multiple large data sets to cover all the possibilities and the initial data fed into the system might be region by region rather than a global mix. New techniques for solving this short coming include increasing genetic diversity to prevent early convergence by increasing the probability of mutation or by injecting random elements into the gene pool called random immigrants. Another difficulty lies in determination of the fitness function. Genetic algorithms cannot solve the problem if there is no way to effectively judge the fitness of an answer. For the CBB traffic model case, which is global, it is hard to visualize a single good fitness function, which cannot be a simple mathematical function but needs to in some way represent performance relating to the real problem [Ham and Kostanic, 2001; Li et al., 2005; Sohn and Dagli, 2003a].

4.3.6. Evolving Critical Neural Network Architectures. The evolving critical neural networks architecture developed by Dr. Sunghwan Sohn involves the use of multiple feed-forward neural networks and also genetic algorithms [Sohn and Dagli, 2003a]. The neural networks are connected by way of a basic schema for combining outputs [Li et al., 2005; Sohn and Dagli, 2003a, Sohn, 2003b] as seen in Figure 4-8 [adapted from Sohn and Dagli, 2003a].

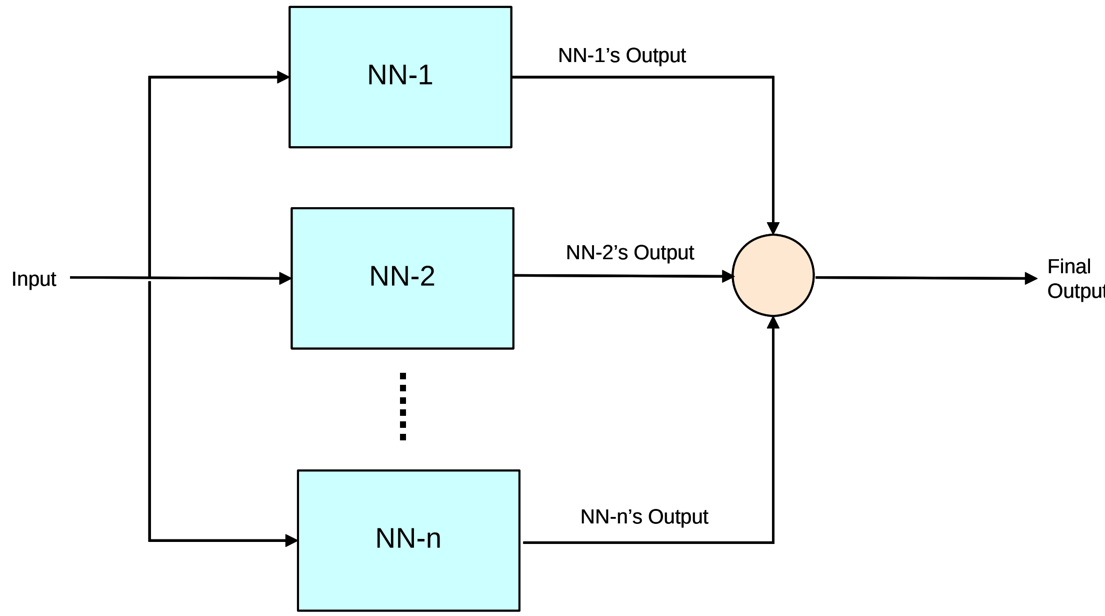


Figure 4-8 Hybrid of Neural Networks and Genetic Algorithms

Genetic algorithms are used to find an optimized feature subset and to find an optimal network architectures and for combining. Using genetic algorithms the individual neural network is independently translated into a network structure, and then trained by back-propagation with a fitness measure. In the combining phase all the individual or selected individual networks in the last generation are used as sub networks and aggregated to determine a final result. Crossover is used to exchange architecture elements between neural networks. Mutation changes feature selection and links [Ahmed, et al., 2004, Li et al., 2005; Sohn and Dagli, 2003a]. Figure 4-9 [from Sohn and Dagli, 2003a] illustrates a genetic algorithm architecture.

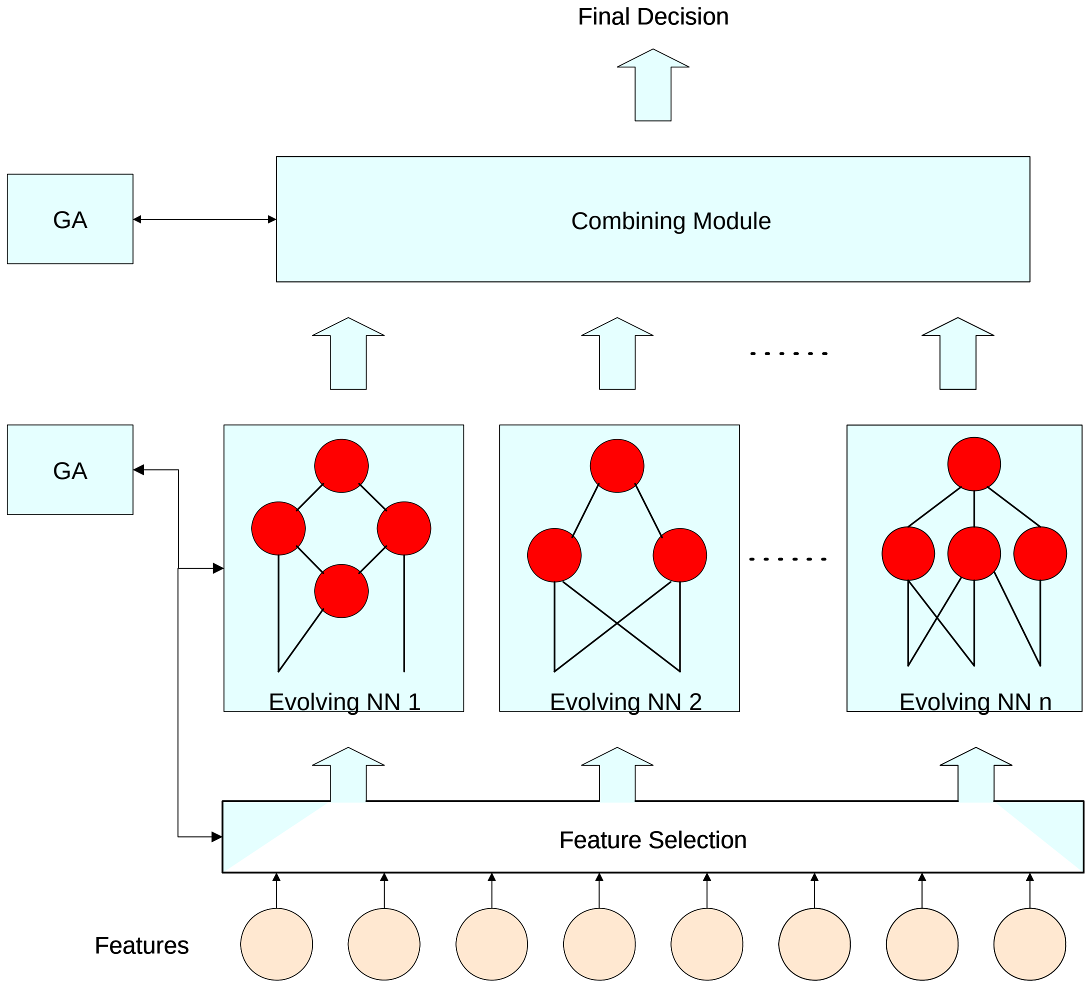


Figure 4-9 Evolving Critical Neural Networks

This type of evolving neural networks architecture would add several features that would be valuable in accommodating changes in flight or customer behavior.

- More adaptable
- Easier to set up

- Greater accuracy
- More robust
- Greater scalability

There are some limitations. Genetic algorithms in Dr. Sohn's evolving neural network architecture require long learning times when trying to optimize the neural network architecture. With large data sets or large neural networks the time required for obtaining convergence could become excessive [Ahmed, et al., 2004, Li et al., 2005; Sohn and Dagli, 2003a].

This type of evolving critical neural network architecture would have a better application for modeling Internet traffic in an operational setting. It could prove valuable in the case where you are monitoring the traffic real-time and trying to adjust the capacity on a real-time basis. In this case the real-time traffic might be quite similar to the stock market, with a predicable component and a non-predictable component. It would take some research to tell. If it was, then using this adaptive critical neural network architecture with reinforcement learning might be advantageous over conventional trending or statistical methods.

4.4. SUCCESSFUL APPLICATIONS OF ANNs

"The field of neural networks is now extremely vast and interdisciplinary, drawing interest from researchers in many different areas such as engineering (including biomedical engineering), physics, neurology, psychology, medicine, mathematics, computer science, chemistry, and economics [Ham and Kostanic, 2001]."

4.4.1. Electronics and Communications. Neural networks have been successfully used for code sequence prediction, integrated circuit layout, failure analysis, voice synthesis, translation, vision systems, image and data compression, and automated information services [Demuth and Beale, 2001].

4.4.2. Entertainment. Neural networks have been successfully used for animation and special effects, speech recognition, and text to speech synthesis [Demuth and Beale, 2001].

4.4.3. Financial. Neural networks have been successfully used for loan appraisals, mortgage screening, bond ratings, credit analysis, insurance policy applications, market analysis, bond ratings, to identify abnormal credit card activity, and for advise when trading on the stock market [Demuth and Beale, 2001; McNellis, 2005].

4.4.4. Manufacturing and Design. Neural networks have been successfully used for manufacturing process control, machine diagnostics, inspection systems, quality analysis, maintenance analysis, robotics, [Demuth and Beale, 2001].

4.4.5. Medical. Neural networks have been successfully used for breast cancer analysis, EEG (electro-encephalogram) and ECG (electro-cardiogram) analysis, and prosthesis design [St. Clair et al., 2000].

4.4.6. Military. Neural networks have been successfully used for weapon steering, target tracking, sensor recognition, noise suppression, and signal and image identification [Demuth and Beale, 2001].

4.4.7. Transportation. Neural networks have been successfully used for aircraft autopilot control systems, flight path simulation, aircraft and automobile fault detection, automotive consumer warranty analysis, and truck routing and scheduling systems [Demuth and Beale, 2001].

4.4.8. Novelty Applications. One study demonstrated the effectiveness of using neural networks to automate the detection of rail defects to reduce problems associated with rail maintenance [St. Clair et al., 2000].

Another study demonstrated a neural network method for classifying signal modulation types. This allows a receiver to autonomously choose among modulation types in order to extract the correct information from a signal [Shull and St. Clair, 2000].

Another study demonstrated how a Kohonen self-organizing map could be applied something as common as individual yard care [Swift and Dagli, 2004a]. Data was collected on the health of the yard by splitting up the grassy areas into a grid. The grass was rated in the following characteristics: length of grass, density of grass, presence of clover or dandelion weeds, presence of moss, and the color of the grass. Figure 4-10 [from Swift and Dagli, 2004a] illustrates the lawn grid and the development of the input attributes.

The SOM developed its own classification categories and a topology map. The output was information a lawn care provider could use to tailor application of expensive yard care products, such as: water, fertilizer, lime, weed killer, and moss out. Figure 4-11 [from Swift and Dagli, 2004a] illustrates the mapping.

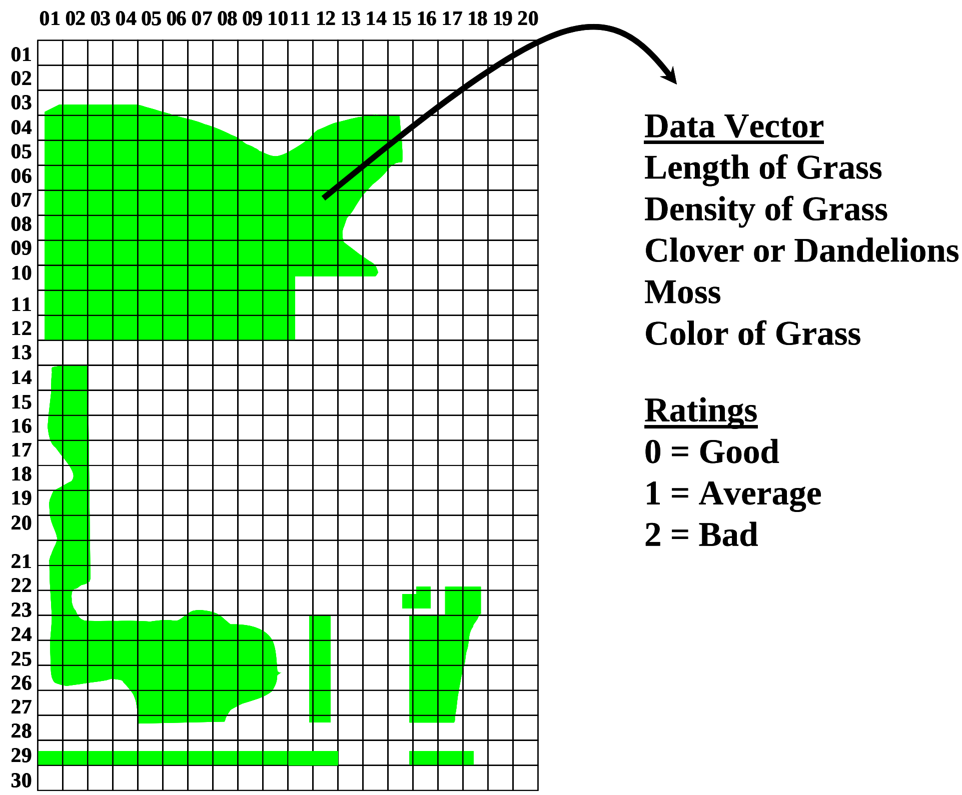


Figure 4-10 Lawn Grid for a SOM Neural Network

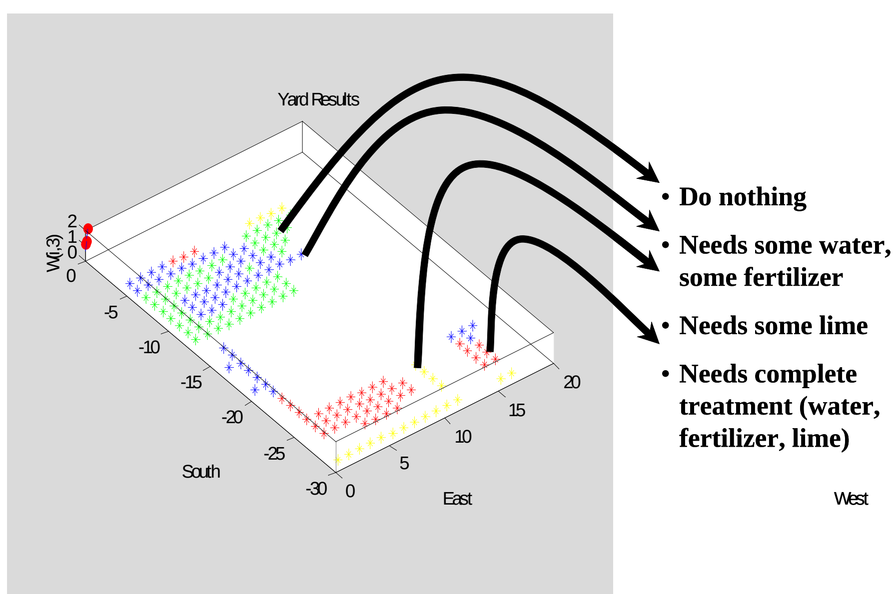


Figure 4-11 Topology Mapping from a Kohonen SOM

4.4.9. Fields of Research Emphasis. Editors for the Neural Networks Journal, the official journal of the INNS (International Neural Network Society), the ENNS (European Neural Network Society), and the JNNS (Japanese Neural Network Society), discuss topics of particular interest in Special Issues. In 2005 there were five special issues: 1) applications of learning and data-driven methods to earth sciences and climate modeling, 2) brain mechanisms of imitation learning, 3) advances in self-organizing maps, 4) neurobiology of decision making, and 5) brain and attention. In 2007 there were four special issues: 1) echo state networks and liquid state machines, 2) computational intelligence in earth and environmental sciences, 3) advances in neural networks research, and 4) consciousness and brain [Grossberg et al., 2007]. The application of neural networks for modeling network traffic bandwidth for traffic as a whole has been mostly unexplored.

4.5. SECTION SUMMARY

This section on artificial neural networks provided the background on the importance and use of ANNs, the type of computational intelligence used in this dissertation research project. It gave a description of the structure of ANNs, relationship to the human brain, and learning methods. Particular attention was given to feed-forward perceptron ANNs, the type used in this research. Other types of ANNs, such as counter-propagation, radial basis function, Kohonen self-organizing maps, genetic algorithms, and evolving critical neural networks were also described.

Because network traffic on large-scale NCSs is so complex and subject to change, mathematical algorithms are not adaptive or scalable enough to maintain accuracy. This defines the need for adaptive modeling techniques based on computational intelligence, such as ANNs, with the ability to adapt through learning and to generalize, allowing for greater accuracy in prediction of network bandwidth needs.

The following section (Section 5) contains a literature review of data mining techniques which form an integral part of this dissertation research project. After reviewing in previous sections the nature of NCS systems and the networks that enable them, and how ANNs operate, the next section evaluates data mining, the means by which network traffic data can be evaluated to see if an adaptive ANN system could be deployed.

5. DATA MINING LITERATURE REVIEW

5.1. RELEVANCE OF DATA MINING TO THIS RESEARCH PROJECT

In order to model or build a computationally intelligent ANN model for network traffic on a global NCS, an initial first step involves extracting the necessary data and transforming it into a form compatible with ANN simulation techniques.

The data mining process was used in this research project to not only obtain, transform, and evaluate the data; but also to extract knowledge from the data and to develop relevant input vectors for use in training and operating the ANN. The ability to successfully categorize the data, not only gives the ability to vary the traffic model, but also to evolve the model as the NCS evolves.

The literature review in this section includes: 1) an overview of data mining, 2) a description of the data mining process, 3) a description of important tools, techniques, and algorithms, and 4) a review of successful example applications in the use of data mining, including the CBB case study.

5.2. OVERVIEW OF DATA MINING

Data mining is a process for the discovery of new information from large data sources. Data mining is typically used in situations where the evaluation of information would be too complicated or extremely time consuming via conventional means and which, for all practicable purposes, render human analysis nearly impossible. Data mining emerged as a discipline with the growth of databases technology capable of storing vast quantities of data.

KDD (knowledge discovery in databases) is sometimes used as a name for the same process as data mining, since the purpose of data mining is not merely to mine or extract data, but to also to analyze that data for the development of knowledge. Some literature differentiates between the two, referring to KDD as the entire process and data mining to the modeling step only, but for the purposes of this dissertation they will be considered the same.

Usama Fayyad, a recognized early pioneer and expert in the field of data mining, co-chair of the First International Conference on Knowledge Discovery and Data Mining in 1994, 1995, and 1996, editor-in-chief of the journal, *Data Mining and Knowledge Discovery,* said, "Knowledge Discovery in Databases (KDD) and Data Mining are concerned with the extraction of high-level information (knowledge) from low-level data (usually stored in large databases) [Fayyad, 1997]." It has also been described by recognized experts as "The nontrivial extraction of implicit, previously unknown, and potentially useful information from data [Frawley et al., 1992]."

As society entered the knowledge age scalability became a problem. The technology for collecting and storing data, mostly through advances in database technology, has far outpaced traditional methods of data analysis based mostly on human interaction. Although databases provide lookup capabilities for the extraction of specific information, the ability to understand and analyze is beyond the scope of database programs [Fayyad et al., 1996a].

Han and Kamber claim, "The major reason that data mining has attracted a great deal of attention in the information industry in recent years is due to the wide availability of huge amounts of data and the imminent need for turning such data into useful information and knowledge [Han and Kamber, 2001]."

5.3. DATA MINING PROCESS

The entire data mining process can be described in a series of steps. First is selection, resulting in target data, then preprocessing, resulting in preprocessed data, then transformation, resulting in transformed data, then data mining, resulting in patterns and or models, and finally, interpretation/evaluation, resulting in knowledge. Figure 5-1 illustrates the entire process [Fayyad et al., 1996b].

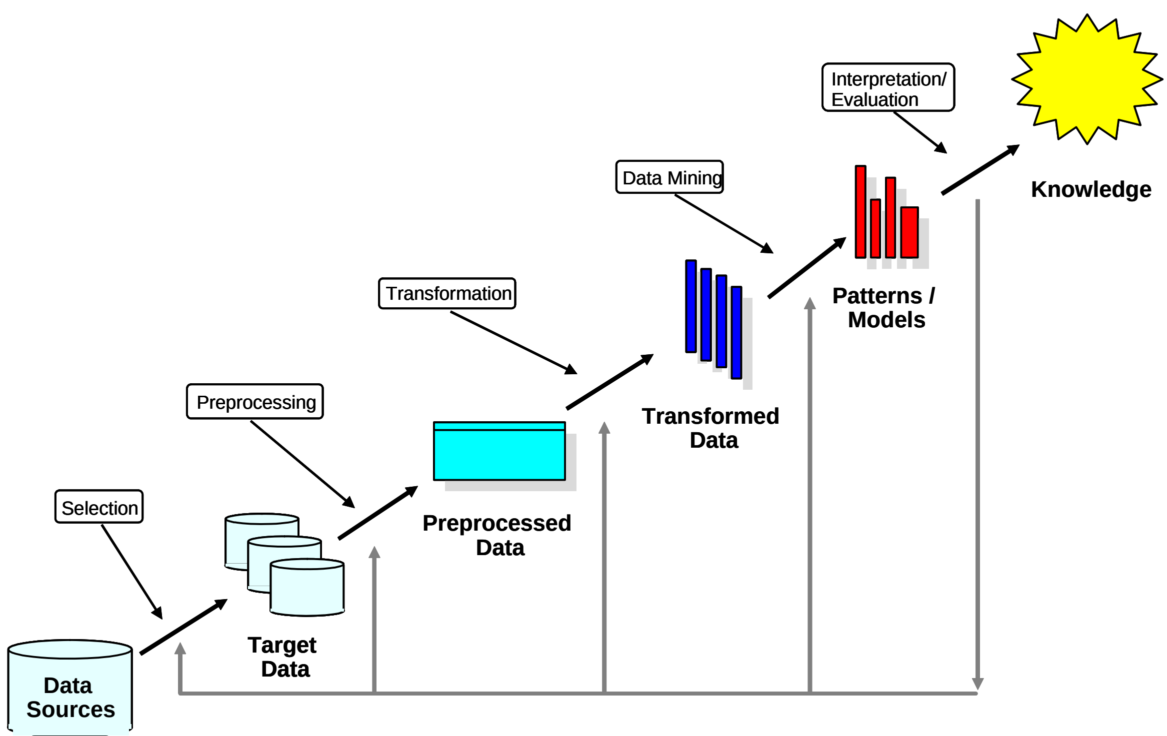


Figure 5-1 Data Mining Process

5.3.1. Selection. This is the first and possibly most important step in the entire process. In the selection step relevant data is extracted from the source. According to the Two Crows Corporation® data mining document [Two Crows, 1999] there are two keys to success in data mining. The first is understanding the problem you are trying to solve and the second is using the right data.

A mistake in the selection can totally skew results. If important relevant information is not included in the selection, then the results would be inconclusive or invalid. Conversely, if extraneous information is included in the selection, then the process becomes larger and more expensive than needed, and the results could also be inconclusive or invalid.

The key to selection is a goal or purpose. The user must have an idea of the expected outcome. There are two types of outcomes, descriptive and predictive [Ham and Kostanic, 2001]. Descriptive outcomes involve identifying and determining applicable characteristics and patterns from the data. Predictive outcomes involve using the patterns and characteristics to predict future behavior.

5.3.2. Preprocessing. Preprocessing, also called cleaning, is a preparatory step where the selected data is manipulated to remove errors and inconsistencies in the data set. A major source of error is noise, usually introduced by the data collection system. True noise, different from outlier data, has no relationship to the actual data being collected and should be filtered out as much as possible. A good example would be background noise generated by the device motors of a tape recorder. Suspect or inconsistent data must also be addressed. A smaller, but purer data set is better than a larger data set with erroneous information. Erroneous data would include any data outside the normal which would indicate errors or inappropriate information. Examples might be atypical situations, such as fault conditions, or atypical environmental inputs. Preprocessing also includes filling in missing values or throwing out incomplete sets.

5.3.3. Transformation. Transformation is preparation of the data set for use by the analysis tools. This includes activities such as smoothing, aggregation, generalization, normalization or attribute/feature construction. Smoothing is typically done by binning. Aggregation, or data reduction, is combining data. Generalization is replacing with higher level concepts. Normalization is scaling. Attribute/feature construction is adding additional attributes [Han and Kamber, 2001].

5.3.4. Data Mining. The data mining step involves the use of analytical data tools to evaluate the data sets and extract and organize relevant information. There are intelligent methods and statistical methods. The intelligent methods include machine learning tools such as C4.5 decision trees and also neural networks. The statistical methods include tools that perform correlation, regression, and clustering.

5.3.5. Interpretation and Evaluation. The data mining process does not replace the need for interpretation and evaluation. Data mining is merely a powerful tool that improves the capabilities of the analysis but does not remove the need for a skilled analysis [Two Crows, 1999]. During this step the results of the data mining is turned into knowledge. One key aspect of this step is presentation of the results in a way that successfully conveys the knowledge learned in a manner that is informative and easy to understand.

5.4. DATA MINING TOOLS AND ALGORITHMS

There are many kinds of tools that can be used for data mining and they fall into a variety of categories [Ham and Kostanic, 2001]: There is descriptive, where you determine data characteristics or features. There is association analysis, where you develop association rules and determine support and confidence for outcomes. There is classification and predictions, where you describe and predict. There is cluster analysis, where you group. There is outlier analysis, where you determine objects that don't comply with general behavior. There is evolution analysis, where trends are evaluated over time. There is interestingness, where you evaluate understandability, validity, usefulness, and novelty.

There is a great variety of tools available for each of these categories and the key is to know what is available and the types of results each can provide. The following sections provide a brief description of some of the most useful tools available.

5.4.1. CRISP-DM. The CRISP-DM (cross-industry standard process for data mining) approach can best be described as a methodology. It represents an attempt to define a cross industry standard process for data mining. The user is lead through a hierarchical process, from the top level to the bottom level, in building a model to perform data mining. The following paragraphs define the CRISP-DM methodology for setting up a data mining project [Chapman et al., 2000].

Top level data mining tasks are organized into phases. The phases are as follows: 1) Business understanding - what are the objectives and requirements from a business perspective, 2) Data understanding - the collection and evaluation of the data, 3) Data preparation - preparation of the data, 4) Modeling - use of a tool or tools for automated analysis, 5) Evaluation - testing validity of the model, and 6) Deployment - using the model and also presentation of results. Figure 5-2 [from Chapman et al., 2000] illustrates the CRISP-DM phases.

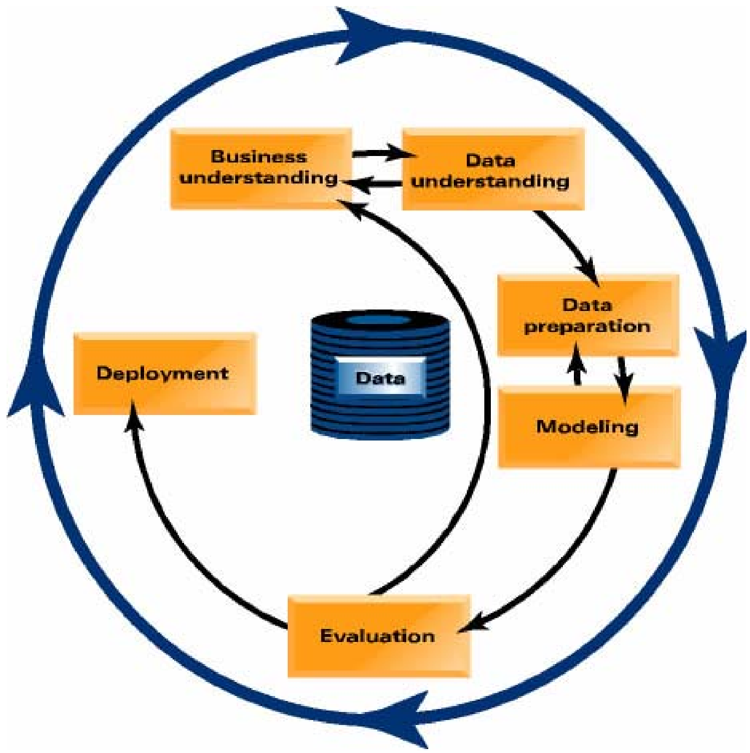


Figure 5-2 CRISP-DM Top Level Phases

The second level is called the generic level, where all the top level phases are broken down into specific tasks general enough to cover all the possible situations. The third level is called the specialized level, where action tasks are developed to accomplish each of the second level general tasks. The fourth level is called process instance, where a record of the actions, decisions and results of an engagement are recorded.

5.4.2. WEKA. The Weka software collection is composed of machine learning algorithms for data mining. Weka was developed at the University of Waikato in New Zealand. Weka stands for Waikato environment for knowledge analysis. The program is freely available on the World Wide Web at http://www.cs.waikato.ac.nz/ml/weka/ [Witten and Frank, 2000].

5.4.3. C4.5 Decision Tree. The decision tree is an attribute based classification method. The C4.5 program generates a decision tree to perform the function. Each data set falls through the decision tree and takes a path that ends in a class. The decision tree is self-generated based on a determination of highest gain paths. There are only two components to a decision tree. The first component is a decision node. At the decision node a test is performed on a single attribute. One path or another is then taken depending upon the outcome. The second component is a leaf. This is the end of a particular path and is the resulting class of the data being tested [Quinlan, 1992]. Figure 5-3 illustrates a fictional decision tree based upon polling data about voter characteristics comparing potential candidate the person would vote for. The tree could be written in logical statements as follows:

if age < 25

if not employed then vote for B

else if employed

if in school none then vote for B

if in school part time then vote for A

if in school full time then vote for B

else if age > 25

if not male then vote for B

else if male

if owns < 10K stock then vote for B

else if owns > 10K stock then vote for A

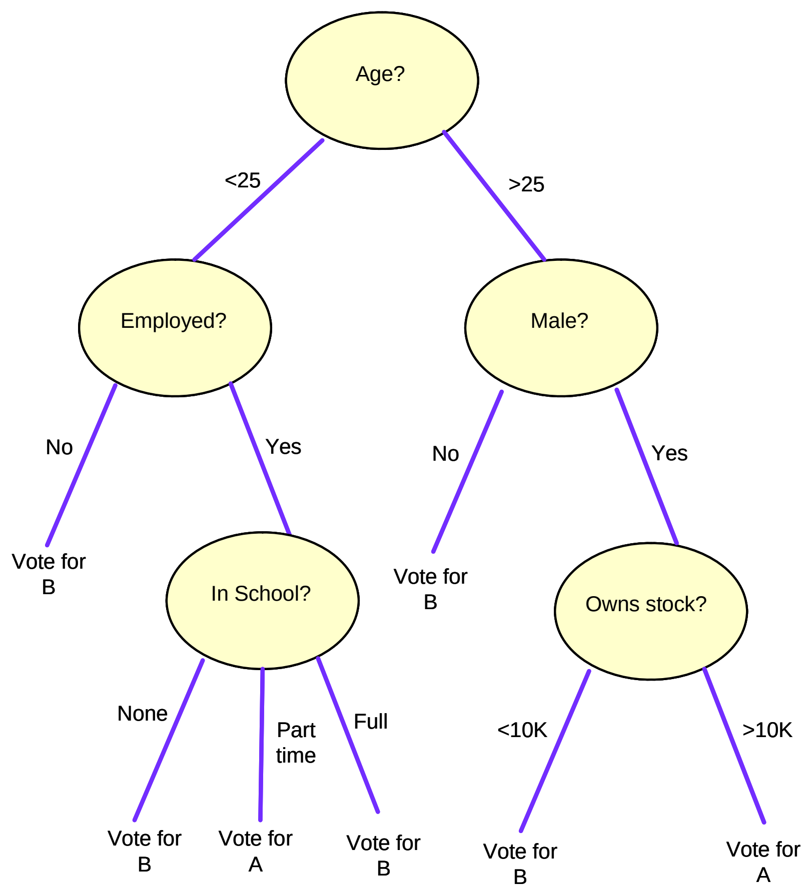


Figure 5-3 Voter Preference Decision Tree

From the decision tree a classification category is produced. A sample set run through the decision tree will yield the number of cases reaching each node and the number of classification errors at the node.

5.4.4. Principle Component Analysis. PCA (principle component analysis) is a data compression method. The object of PCA is to reduce the dimensionality of the data set while still capturing the variability. PCA projects a data set onto a smaller dimension space with highly independent attributes. The process consists of capturing principle components by determining the largest eigenvector of the covariance matrix. In most cases a small number of principle components can capture 90% or more of the variance [Hand et al., 2001].

5.4.5. Regression. Regression techniques are a statistical method of evaluating data. Regression techniques include linear regression, linear least squares, polynomial regression, exponential regression, and logistic regression. Regression is often used for data sets with complicated attributes. The method tries to determine the relationship between independent variables by means of a function. Outputs include the goodness fit, linearity, homoscedasity, analysis of variance, and probabilities [Burden and Faires, 2004; Gillett, 1976].

5.4.6. Apori Approximation. Apori approximation is used for pruning. This method counts the items to determine large groupings. Next it counts pairs and again determines large sets. Then it counts triplets and on and on. Every subset of a frequent item set has to also be frequent, if not it is dropped [Ham and Kostanic, 2001].

5.4.7. Artificial Neural Networks. ANNs were previous described in Section 4 of this dissertation. The feed-forward perceptron ANN with back-propagation training is the type of ANN selected for this dissertation research project to use for modeling NCS network traffic. It was chosen over other types of ANNs, like counter-propagation, radial basis function, Kohonen self-organizing maps, genetic algorithms, and evolving critical ANNs, mainly because of its simplicity and ease of use. The perceptron type of neural network proved capable of performing the required tasks so the more complicated ANNs, even though more efficient in some applications, were not necessary.

5.4.8. K-Means. This is a clustering algorithm based on statistical equations. K equates to the number of clusters or groups. The algorithm determines clusters so that the centers of the clusters are as widely separated as possible [Ham and Kostanic, 2001].

5.5. SUCCESSFUL APPLICATIONS OF DATA MINING

There have been many successful applications of data mining tools, techniques, and processes. This has been especially true in recent years when the use of data mining has grown beyond the domain of computer scientists, statisticians, and business analysts [Kohavi and Provost, 2001].

Kohavi proposed five criteria that could be applied to a project to evaluate the potential for successful application of data mining [Kohavi and Provost, 2001]:

- Data with rich descriptions
- Large volumes of data
- Controlled and reliable data collection

- Ability to evaluate results
- Ease of integration with existing processes

5.5.1. Text and Graphics Applications. Much research has gone into the development of text searching tools for data mining. A entire subfield called text data mining has emerged to develop tools and techniques [Baldi et al., 2003; Castillo and Serrano, 2003; Hearst, 1999; Zheng et al., 2003]. A follow up application was to apply data mining techniques to graphics search engines based on vectors like those found in CAD (computer aided design) drawings [Fisher and St. Clair, 2001]. Data mining is also being applied to other forms of multimedia, such as: MPEG, videos, audio recordings, photos, and others [Petrushin et al., 2003]. Each application under development tends to spin off a multitude of other application uses. For example, video data mining uses have moved from the produced commercial data sources, such as news videos, recordings, and movies, to private individual data sources, such as webcams, surveillance videos, and home recorded videos [Petruchin et al., 2003].

5.5.2. Electronic Commerce. Electronic commerce has emerged as an important field that benefits greatly from the use of data mining techniques [Kohavi and Provost, 2001; Menasce and Virgilio, 2000]. One of the main reasons is that the data from electronic commerce is so easily collectable, and there is so much more information to be mined compared to live commerce, and the results have direct application to the businesses involved.

5.5.3. Web Content. Data mining is being successfully applied to evaluate the effectiveness of web content and also to provide tools for search engines to use [Baldi et al., 2003; Chau et al., 2002; Menon and Dagli, 2003; Scime, 2004]. This has become increasing important as the types and structure of web pages proliferates.

5.5.4. Fraud Detection. Data mining has been also been successfully employed in the use of fraud detection. Techniques of back-propagation neural networks, Bayesian analysis, and C4.5 algorithms have all been used [Phua et al., 2003]. This is a valuable application for insurance and credit card companies.

5.5.5. Geospatial Information and Mapping. Data mining is also being used to evaluate geospatial information being collected by advanced technology for remote sensing and surveying. These data mining tools have the ability to automatically transform masses of geographic data into useful information [Buttenfield et al., 2000].

5.5.6. Network-Centric Systems. Large-scale network-centric systems, by their very nature, tend to produce large amounts of data that are conductive to the application of data mining techniques. NCSs are dependent on the continuous flow of these large amounts of data to all the various units throughout the system. Being able to analyze, categorize, and understand this data is essential to the development, operation, and management of the NCS. The CBB NCS is a good example.

5.5.7. Connexion by Boeing NCS. Data mining techniques proved very effective in the evaluation process of analyzing data flowing through the CBB system. The amounts of data being collected on a daily basis were beyond the scope of evaluation by human or statistical means. See the next section (Section 6) for a complete description of how the data mining process was applied to CBB. Comparing CBB to the five criteria suggested by Kovhavi for determining if projects stand to benefit from data mining [Kovhavi et al., 2001]:

- The header data being collected on each user transaction had a large variety of useful attributes for evaluation.
- There was a tremendous amount of data being collected every day. Files containing 15 minute segments of transactions were 10-250 MB each and contained over 65,000 lines each.
- Network sniffers were able to collect reliable data of sufficient quantities for evaluation.
- Perl and Matlab scripts were developed for evaluation and consistent results were produced.
- No new data collection processes were needed.

5.6. SECTION SUMMARY

In this section on data mining the groundwork was laid for the process to be used in the CBB case study for extracting knowledge from raw data flowing through the CBB network. A description of data mining was provided, which is the "extraction of high-level information (knowledge) from low-level data (usually stored in large databases) [Fayyad, 1997]."

Each step in the process was described, including selection, preprocessing, transformation, data mining, and interpretation/evaluation. Important tools, processes, and algorithms of data mining were reviewed: CRISP-DM, Weka, C4.5 decision tree, principle component analysis, regression, apori approximation, neural networks, and K-means. Successful example applications of data mining were presented.

In previous sections the composition of NCSs, the network that enables their complex operations, ANNs for adaptive modeling, and now data mining for extraction and evaluation of the data were all reviewed. In the following section (Section 6) the details of the CBB NCS used for this case study is described and then in the following section (Section 7) data mining techniques covered in this section are applied to the CBB NCS in an attempt to extract useful knowledge and prepare the data for ANN simulation.

6. CONNEXION BY BOEING REVIEW

6.1. RELEVANCE OF CBB TO THIS RESEARCH PROJECT

CBB (Connexion by Boeing) was chosen as the case study network for this research for a variety of reasons. First, CBB is an excellent example of an operating, large-scale, complex, network-centric system. It exhibits the power and benefits of being network-centric enabled. It also faces the problems that challenge a complex NCS, one of which is the difficult task of building and maintaining accurate models and simulations. CBB is a system-of-systems. CBB is also an NCS, providing global broadband network services to its customers. The data collection and network traffic capacity modeling features of the CBB system are challenged by the constant change and evolving characteristics of the traffic stream. Because of all this, CBB stands to benefit from an adaptable architecture for modeling network data traffic such as the ANN based simulation proposed by this dissertation.

Another reason CBB was chosen as the case study for this dissertation was because access to actual CBB network data was made available to the University of Missouri - Rolla for this research project. CBB presented the unique opportunity to perform research on a new, previously unstudied, emerging NCS system, one that is typical of the future in large-scale systems dependant upon network-centricity. It was an opportunity to perform research in an emerging field. The data being investigated, mobile Internet data traffic, had not previously been made available for academic research.

The literature review in this sections includes: 1) a review of the CBB System, which includes the overall architecture, 2) a description of the services provided to customers, 3) a description of the major subsystems, which includes the airborne segment located upon the airplanes, the space segment satellites and transponders and a brief introduction to orbital mechanics, and also the terrestrial segment with the ground stations, data centers, and customer service centers, 4) a description of the CBB data collection system, and 5) a description of the current CBB network capacity simulation which is not very adaptive.

6.2. OVERVIEW OF THE CBB SYSTEM

CBB is a MISP (mobile information services provider) that was launched by the board of directors of the Boeing Company in February 2000 and in October 2000 CBB became a separate business unit of the Boeing Company. CBB was created to address the market created by the connectivity needs of air travelers (business, recreational, and military), who in the past had been isolated from the ground while traveling. To accomplish this CBB developed a global NCS to provide two-way, high-speed, broadband, Internet and Intranet data services for passengers and crew on CBB equipped aircraft.

The CBB system provides a shared broadband satellite link that operates as a party-line in which users share satellite transponder links. The network uses existing satellites in geosynchronous orbit, existing ground uplink/downlink stations, and existing DBS satellite TV networks. Network control is managed through the CBB NOC (network operations center). Figure 6-1 illustrates the overall CBB Block 1 System architecture.

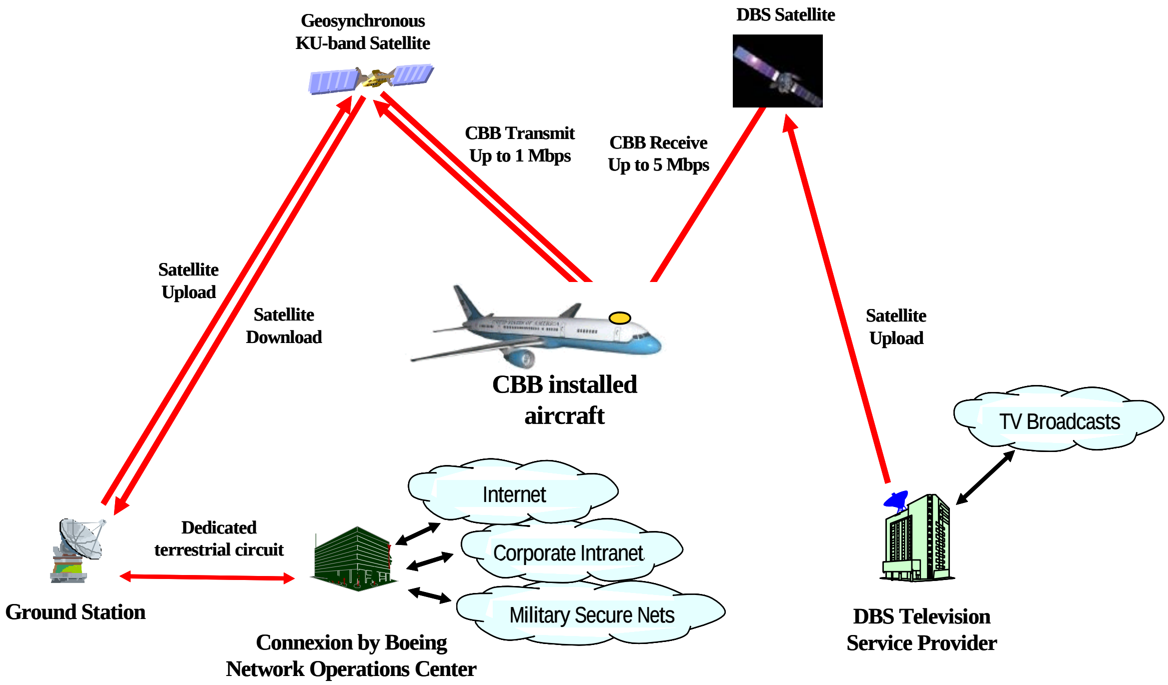


Figure 6-1 CBB Block 1 Architecture

It should be noted that CBB commercial service to airline customers officially ended on January 1, 2007. However, the service is still continuing for the government component of the business and is called Boeing Broadband SatCom Network. The center of operations is at the NOC still in Kent, Washington. The service was discontinued for financial reasons and not for technical reasons. The CBB network was up and operational. All the data collected from the CBB network for this dissertation research project was collected prior to discontinuation of the commercial service and the descriptions provided in this section apply to that period of operation. The research is still applicable for proving the feasibility of adaptive ANN architectures for modeling network traffic on large-scale global NCS, which CBB was.

6.3. SERVICES AVAILABLE TO CUSTOMERS

CBB provides one group of services to the aircraft for operational purposes and another group of services to the passengers on-board the aircraft. The passenger services can be grouped into the data services or television services.

6.3.1. Passenger Data Services. The CBB passenger data service operates similar to standard ISPs (Internet service providers) on the ground. Depending on how the aircraft is configured, the passenger connects to the aircraft LAN (local area network), known as a CDS (cabin distribution system), via wireless connection from their laptop or by plugging their laptop computer into a standard RJ45 port located by their seat. The passenger then opens a web browser (such as Netscape®, Microsoft Internet Explorer®, or Mozilla Foxfire®) and the CBB splash page, the home page portal, automatically opens. A connection is placed via satellite and ground station links to the CBB data center which provides an ISP interface to the Internet. The passenger also has the capability to connect to corporate or government Intranets through standard VPN (virtual private network) protocols. Some of the standard passenger uses include:

- Internet access for web-surfing
- Access to personal and corporate e-mail accounts
- Access to private restricted corporate Intranet files
- Access to government/military secure nets
- Travel and destination information
- Airline information
- Internet chat service

- File transfer protocol for sending and receiving files
- Interactive Internet gaming
- Streaming media services, audio and video
- Telnet connectivity
- Voice over IP connection
- Video teleconferencing, for government and private jets only

6.3.2. Airline Data Services. Data services are also available to the airline for use in operational activities. These services are restricted to airline crew members in the course of conducting official airline business. Some of the standard airline uses include:

- Scheduling
- Weather updates
- Cabin crew applications
- Aircraft health monitoring
- Flight data services

6.3.3. Passenger Television Services. Live television is also available to the passengers. The CBB TV service is available by satellite link through airline subscription to DBS (direct broadcast satellite) TV providers (such as DirecTV® or Dish Network®). Free to air television programming that resides within the CBB frequency bandwidth is also available. Live TV is routed from CBB antennas and receivers to the aircraft IFE (in flight entertainment) system for viewing on live TV displays located in various zones within the aircraft. These zones can be configured individually for independent viewing of different TV channels within the zones. Channel selection is via remote control or from a master control panel.

6.4. AIRCRAFT SEGMENT

The CBB trials utilized Block I hardware on the subject aircraft. Block I aircraft hardware consists of three major subsystems – the AS (antenna subsystem), the RTS (receive and transmit subsystem), and the CS (control subsystem). Table 6-1 shows the standard approximate overall weight and power consumption numbers.

Table 6-1 Block I Specifications

System	Weight (lbs)	Power (Watts)
AS	350	1,800
RTS	100	600
CS	50	250
Install Provisioning	450	0
Totals	950	2,650

Data is passed to and from the aircraft and corresponding satellite via the AS. Data is passed to and from the users through the RTS, CS, and Aircraft LAN or IFE. Figure 6-2 illustrates the Block I physical architecture for the aircraft segment.

6.4.1.1 Receive antenna. The receive antenna is a phased array antenna that receives KU-band satellite signals in the range of 11.7 – 12.2 GHz. The antenna is composed of an array of steerable antenna modules.

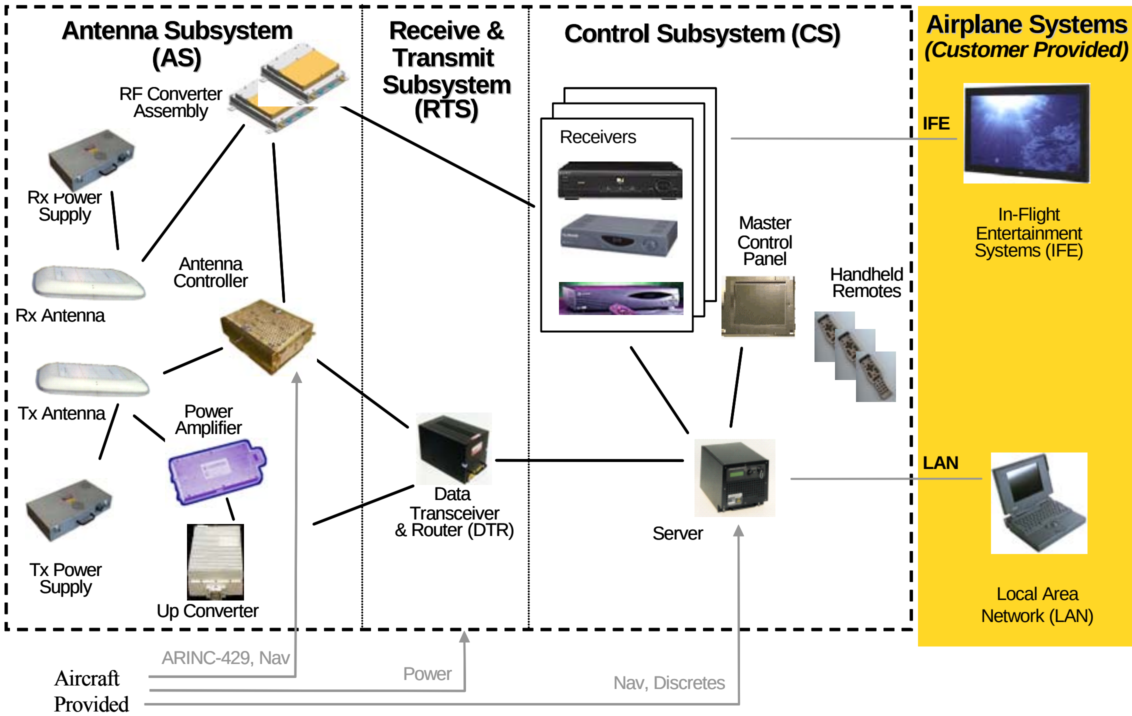


Figure 6-2 Aircraft Segment Architecture

6.4.1.2 Transmit antenna. The transmit antenna is also a phased array antenna. It transmits to KU-band satellites in the range of 14.0 – 14.5 GHz.

6.4.1.3 RF converter assembly. The RF converter assembly takes KU-band signals from the Receive Antenna and down converts to L-band. The RF Converter Assembly also performs linear polarization.

6.4.1.4 Rx and Tx power supply. The receive and transmit power supply units take 115V, 3 phase, 400 Hz power from aircraft sources and provides power to the receive and transmit antenna units respectively and also to other AS units.

6.4.1.5 Power amplifier. The power amplifier amplifies the signal to provide a high power output for the transmit antenna.

6.4.1.6 Up converter. The up converter receives input for transmission to the ground and converts the signal from the L-band range of 950-140 MHz to the KU-band range of 14.0-14.5 GHz.

6.4.1.7 Antenna controller. The antenna controller provides antenna module pointing. It also performs status functions.

6.4.1.8 Installation. Several constraints had to be taken into consideration when determining antenna locations on the airplane fuselage. Aerodynamic loads are most severe over the aft half of the wings. Tail shadow constraints prevent a location aft of the wings. Any existing antennas have to be evaluated to insure non-interference of transmissions. The transmit signal cannot be too close to the tail or the tail might scatter the signal. Radiation exposure hazards require strict adherence to a safety exclusion zone around the aircraft to protect maintenance and service personnel when the aircraft is on the ground. Structural seams on the fuselage have to be avoided. Finally, interior space constraints in the aircraft overhead must be evaluated since several associated boxes must be located under the antennas. Figure 6-3 illustrates a notional example of relative installation locations.

Separation constraints required a minimum of 80 inches between antennas to preclude transmit signals from interfering with receive signals. Cable length restrictions allowed no more than 75 feet separation. Another consideration on separation was the potential for fuselage bending. The transmit antenna uses the receive antenna for pointing purposes and hence they must be aligned parallel to each other along the crown of the fuselage. Figure 6-4 illustrates antenna size dimensions and also the separation requirements for the Block 1 antennas. The antennas are placed along the aircraft centerline on top of the fuselage. A six lug antenna installation kit was developed and deployed specifically for the phased array antennas used by the CBB program, as show in Figure 6-5.

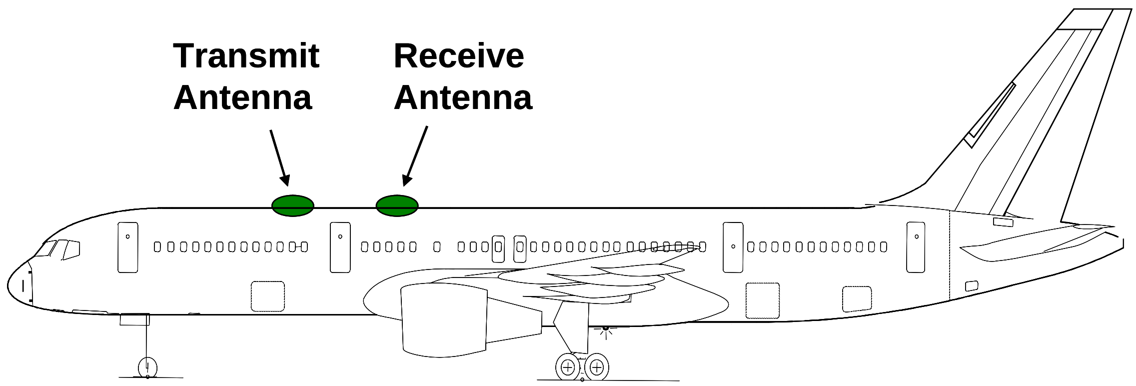


Figure 6-3 Antenna Locations

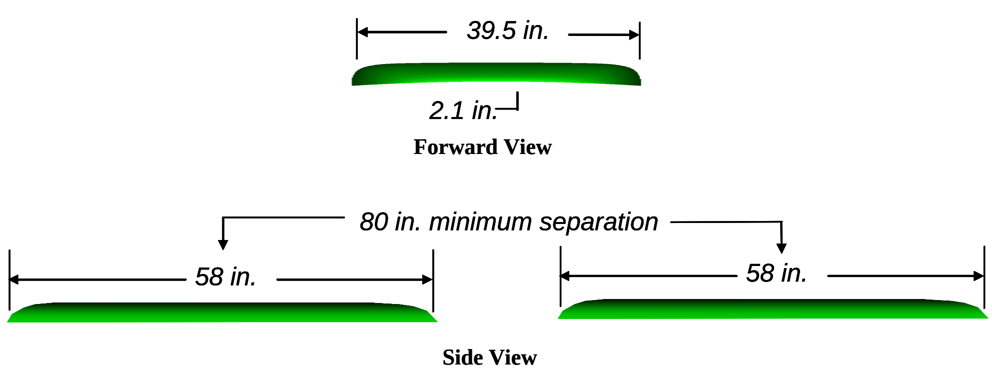


Figure 6-4 Antenna Dimensions

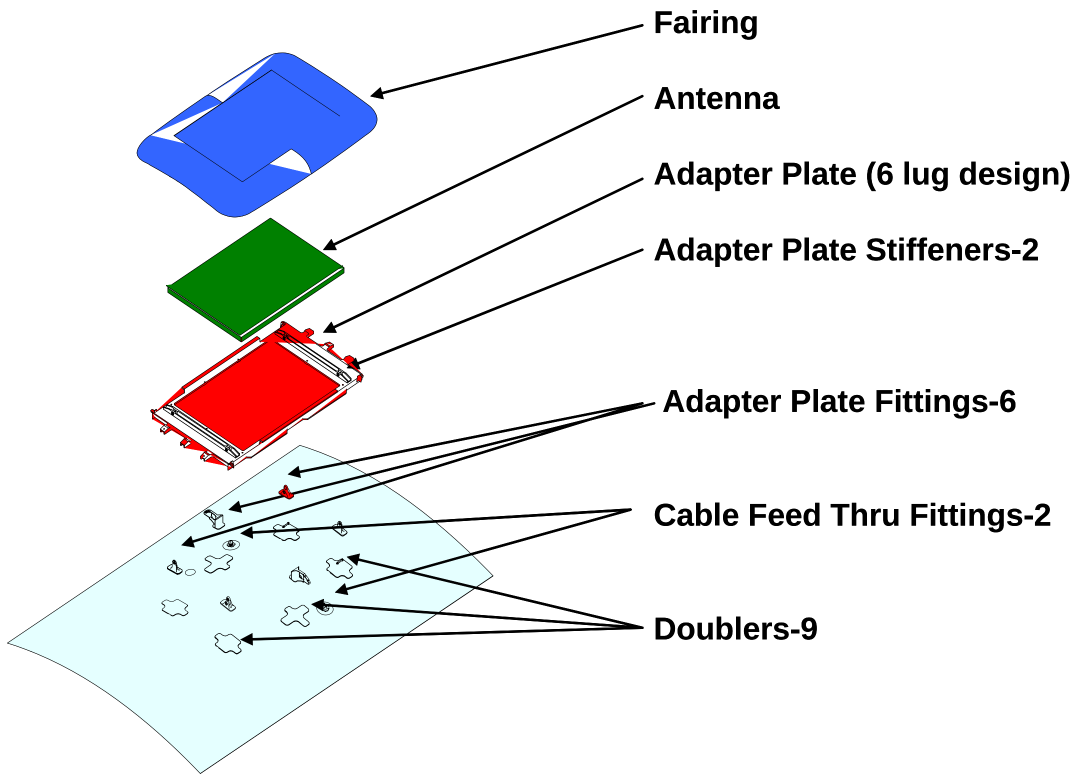


Figure 6-5 Antenna Installation Kit

6.4.2. Receive and Transmit Subsystem. The RTS provides signals to and from the AS and CS. It is composed of a DTR (data transceiver and router) and the TV receivers and switches.

The DTR contains integrated receiver decoders. It receives L-band RF signals from the AS. These signals are split and distributed with the DTR and back to the antenna controller. The DTR also passes data signals to the CS for decoding and routing to and from the aircraft LAN.

The TV receivers are standard COSTS (commercial off-the-shelf) television receivers. They receive commercial television signals from the AS and use audio-video switches to distribute live television programming to the aircraft IFE allowing for independent channel selection in each aircraft zone.

6.4.3. Control Subsystem. The CS is composed of a server and a control panel. It also has associated power supply units and an electronic control unit. The control panel allows aircraft personnel to choose between various data and television settings. An RF remote control is also provided for ease of channel switching.

6.5. SPACE SEGMENT

The space segment is composed of leased KU-band transponders on geosynchronous satellites that provide relay linkage between CBB equipped airlines and the Ground Segment. Figure 6-6 illustrates the relationship between the satellites and the ground segment.

Figure 6-6 Satellite Constellation

6.5.1. Satellites. The use of space based transponders allows global coverage on a scale not readily achievable by terrestrial based relay systems. "The wide-area coverage feature combined with the ability to deliver relatively wide bandwidths with a consistent level of service make satellite links attractive [Elbert, 1977]." The use of satellites has become increasingly common and is now considered an essential feature for global communication enterprises. "Many large companies have built their foundations on satellite services such as cable TV, data communications, information distribution, maritime communications, and remote monitoring. For others, satellites have become a hidden asset by providing a reliable communications infrastructure [Elbert, 1977]."

In 1991 there were only 18 launch vehicle families in operation, almost all operating inside the USA (United States of America) or the USSR (Union of Soviet Socialist Republics). Europe's space launch program was in its infancy. At the end of 2003 there were 31 launch vehicle families. Europe and China are now major players alongside the USA and Russia [Isakowitz and Hopkins, 2004]. Major launch sites in the USA at Cape Canaveral and Vandenberg and in the former USSR at Baikonour and Plesetsk have been compliment by the French launch site at Kourou, the Chinese sites at Jiuquan and Xichang, the Japanese site at Tanegashima, the Indian site at Sriharikota, a new USA mobile launch platform Sea Launch Odyssey for ocean launches, and a host of smaller capacity vehicle sites [Isakowitz and Hopkins, 2004].

6.5.2. Orbital Elements. The science of astrodynamics has it's foundation on Kepler's Laws, which provided the first explanation of planetary motion. These laws apply equally well to satellite orbits. Kepler's Laws are as follows [Bate et al., 1986]:

- Planets follow an elliptical orbit around the sun. The sun is located at one of the two focus of the ellipse.
- A line connecting a planet to the sun will sweep out equal areas from the orbital plane in equal amounts of time.
- The square of the revolutionary period of a planet is proportional to the cube of its mean orbital distance from the sun.

There are six classical orbital elements used to describe the orbit of any satellite. The first five orbital elements describe the orbit and the sixth pinpoints the position of the satellite. Figures 6-7 and 6-8 [adapted from Bate et al., 1986] illustrate the orbital elements [Bate et al., 1986; Geyling and Westerman, 1971].

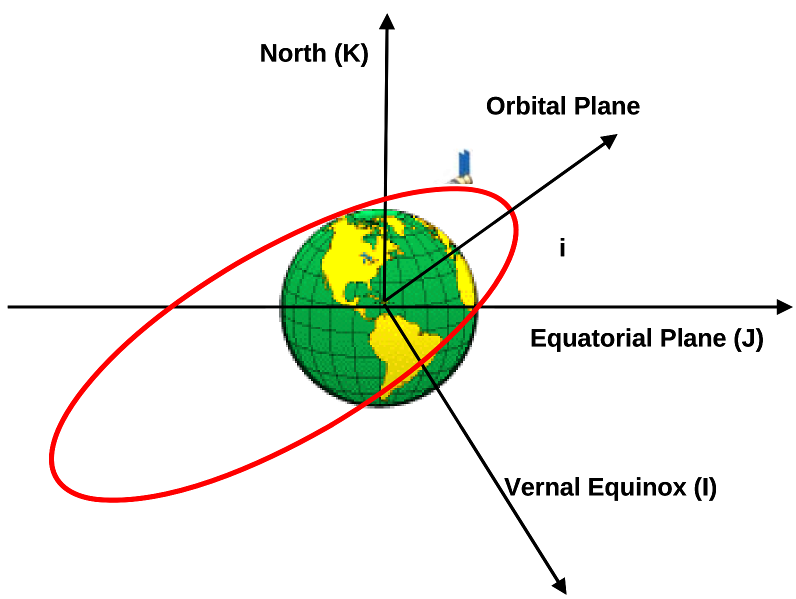


Figure 6-7 Orbital Plane

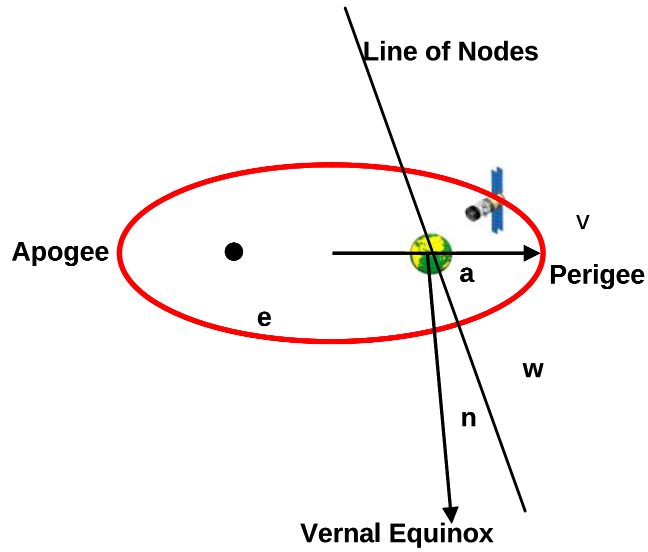


Figure 6-8 Orbital Elements

The six classical orbital elements are as follows:

- a = Semi-major Axis: Defines the size of the orbit. The distance between Perigee (the point on the orbit closest to the earth) and the center of the orbit.
- e = Eccentricity: Defines the ellipticity or shape of the orbit. Equals the distance from the center of the earth to apogee (the point on the orbit farthest from the earth) minus a, all divided by a.
- i = Inclination: Defines how much the orbit is inclined. Equals the angle between the equatorial plane and the orbital plane.
- n = Right Ascension of the Ascending Node: Defines the orientation of the orbital plane to space. Equals the angle between vernal equinox (a

vector fixed to stellar space) and the point where the orbit crosses the equatorial plane going north.

- w = Argument of Perigee: Defines the orientation of the orbital plane to the rotating the earth. Equals the angle between right ascension of the ascending node and perigee.
- v = True Anomaly at Epoch. Defines the location of the satellite in the orbit. Equals the angle between perigee and the satellite.

Constellations are groups of satellites located in orbits at regular intervals to provide coordinated coverage. CBB leases KU-band transponders to form a satellite constellation in geosynchronous orbits. Satellites in geosynchronous orbits circle the earth once each day in circular orbits, matching the rotation of the earth at an altitude of 19,230 nm above the surface of the planet. This orbit allows the satellite to hang over a spot on the earth if the orbital plane is at the equator. If the orbital plane is inclined, the ground trace becomes a figure eight curve tracing north and south around a spot on the earth's surface. [Bate et al., 1986; Geyling and Westerman, 1971] Figure 6-9 [adapted from Bate et al., 1986] illustrates a geosynchronous equatorial orbit.

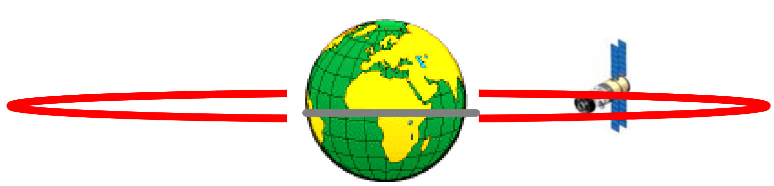


Figure 6-9 Geosynchronous Orbits

6.5.3. Operating Frequencies and Bandwidth. For the CBB Block I system, operating frequencies are in the KU-band. Uplink frequencies from the ground to the aircraft range between 11.7 GHz and 12.2 GHz. Downlink frequencies from the aircraft to the ground range between 14.0 GHz and 14.5 GHz.

6.5.4. Forward Link. The CBB leased KU-band transponders on a geosynchronous satellite delivers four channels of forward link data to regions on the earth within the coverage footprint of the satellite. All aircraft flying within the region receive the shared signal through their receive antenna and filter out that portion of the signal destined for IP addresses on their aircraft. Up to 5 Mbps of data can be received by each aircraft.

6.5.5. Return Link. Separate CBB leased KU-band transponders on the same satellite receives one channel of return link data from each aircraft to the ground. The signal is sent to the satellite from the transmit antenna on the aircraft. Up to 1 Mbps of data can be transmitted by each aircraft.

6.6. TERRESTRIAL SEGMENT

The terrestrial segment is composed of satellite uplink/down facilities, or ground station gateways, which are located in Littleton in the USA, Leuk in Switzerland, Moscow in Russia, and Iberaki in Japan. The terrestrial network control and customer service facilities are located in Irvine, California and Kent, Washington. The main facilities are the network operations center, the enterprise operations center, and the data center. Communication with the satellites is via RF uplink and downlink. Communication between the gateways and along the ground network between terrestrial centers is through dedicated leasing of standard telecommunication T1 or T3 landlines. Figure 5-6 in Section 6-5 illustrates the architecture.

6.6.1. Ground Station Gateways. The ground station gateways used in the CBB network are privately owned facilities where CBB leases services from a supplier for communication routing and signal processing of data between the data center and the satellites. Leasing arrangements include physical facilities, communication equipment, and personnel services at the gateway. The gateway receives and transmits IP encapsulated data and control and status information to and from the satellites. Space is provided at the gateway for leased supplier equipment and also CBB furnished equipment.

6.6.1.1 CBB equipment. At each gateway, CBB provides a GRTS (ground receive transmit subsystem) which operates much like a modem. The GRTS is composed of the FLM (forward link modulator), the RLD (return link demodulator), and the FRD (forward receive demodulator). The FLM performs data compression, encryption, error correction encoding, spreading, and modulation. The RLD performs data decompression, decryption, decoding, despreading, and demodulation. The FRD performs the same function only for a signal used for test and monitoring. The GRTS interfaces with the DTR on-board the aircraft. Also at each gateway CBB provides an NES (network equipment subsystem) composed of switches, routers, and firewall equipment.

6.6.1.2 Supplier equipment. At each gateway the supplier provides an RFS (RF subsystem) which transmits and receives signals to and from the KU-band satellites. The RFS includes ground antennas, amplifiers, up converters, down converters, and splitters. The RFS receives and transmits Ku-band signals to and from the satellites, in both horizontal and vertical polarization. The RFS outputs or receives an L-band signal to and from the GRTS. The supplier also provides the facility infrastructure which includes power, heating, ventilation, air conditioning, emergency backup systems, and security systems.

6.6.2. Terrestrial Centers. The CBB network is composed of data centers, a network operations center, the enterprise operations center, and the network infrastructure backbone. It provides direct access to system elements and connectivity to terrestrial based networks around the globe. A digital NMS (network management system) monitors performance of network applications and of the infrastructure servers and routers. The CBB terrestrial centers interface with the public Internet, corporate VPNs and also government secure networks. Figure 6-10 illustrates the physical architecture showing how these terrestrial centers interface with the rest of the CBB System.

6.6.2.1 Data centers. The main CBB data center is located at Irvine, California. Regional data centers are located around the globe and provide similar functions as the main data center. The data center performs data collection, data distribution, database management, application hosting, and network management. Security management is also provided, which includes activity monitoring, encryption, firewalls, intrusion detection. Data is stored in the data center and accessed, forwarded, pulled, merged, and copied as needed to provide for customer services and network operations and management.

6.6.2.2 Network operations center. The NOC (network operations center) is located in Kent, Washington. The NOC performs control and monitoring functions for the CBB Network. This includes configuration management, security management, fault detection, and the collection of system metrics. The NOC tracks all daily system activities and proxies monitoring of the entire network.

6.6.2.3 Enterprise operations center. The EOC (enterprise operations center) is located in Irvine, California. The EOC provides content management and delivery services for the customer, user registration and account setup, billing functions and account management, a 24 hour 7 day a week customer care services for question and problem resolution relating to billing or technical difficulties, product support for hardware repair or exchange, maintenance, training, spares and directions, and also business operations.

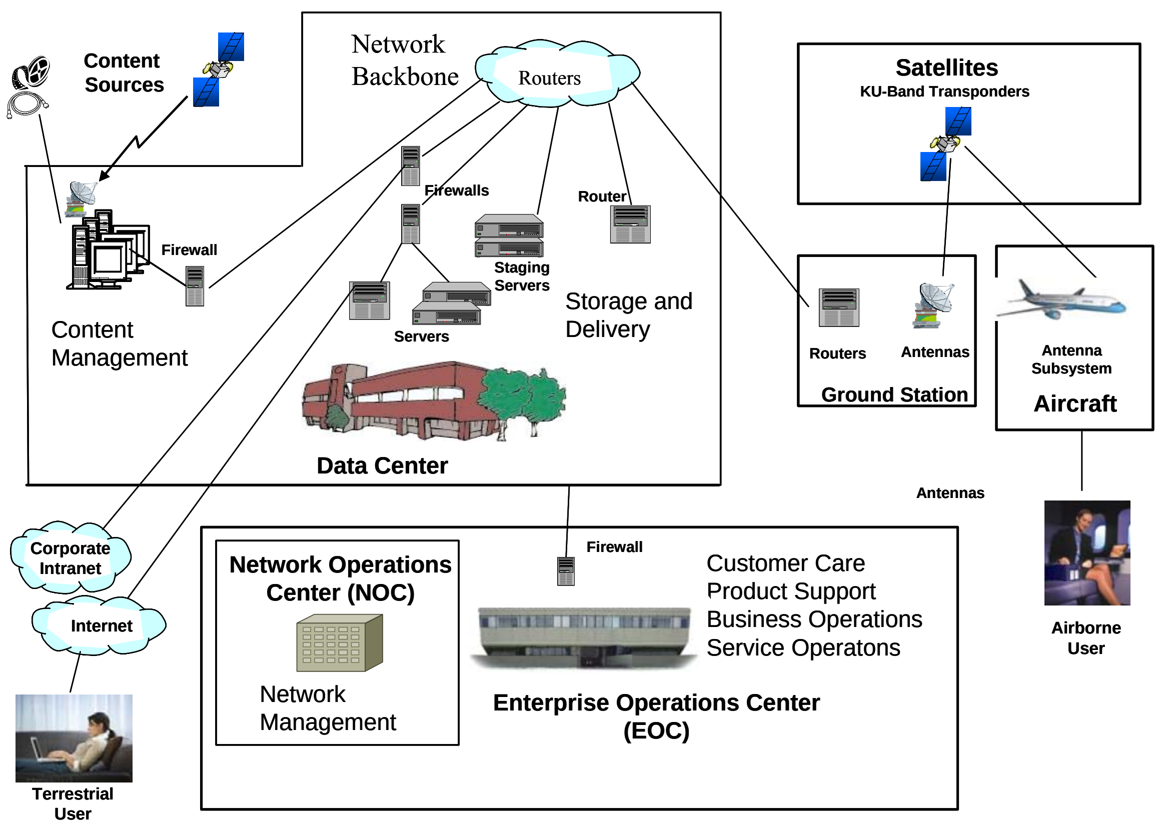


Figure 6-10 Terrestrial Centers

6.7. CBB CAPACITY MODEL

The biggest operational expense for the CBB program is incurred in the leasing of KU-band transponders on geosynchronous satellites. In order to assure adequate coverage of CBB customer bandwidth needs these transponder leases must be procured well in advance. Consequently the accurate forecast of transponders requirements can have significant impact on the business success of the program and is a critical factor in business decisions.

Too few transponders and CBB would either have to reduce the QoS (quality of service) or else deny service. Neither option is acceptable. To reduce the QoS by a reduction of bandwidth to the aircraft would cause a noticeable slowing to the user and cause considerable customer dissatisfaction. To deny service to regions or individuals or applications, would deny customers and revenue and also cause considerable customer dissatisfaction. When customers do not receive the promised and paid for service, they are unlikely to want to repeat the experience. No amount of advertising can compensate for the bad publicity ensuing from dissatisfied customers and the resultant loss of future customers and revenue.

Too many transponders and CBB would be expending limited budget in a waste of money that could be used elsewhere. Considering the slim profit margins most enterprises operate with, this could endanger the viability of the entire program.

6.7.1. Overview. The CBB network CSIM (capacity simulation) estimates the number of transponders needed to support projected customer demand. Figure 6-11 illustrates inputs and outputs of the CSIM utilized by CBB.

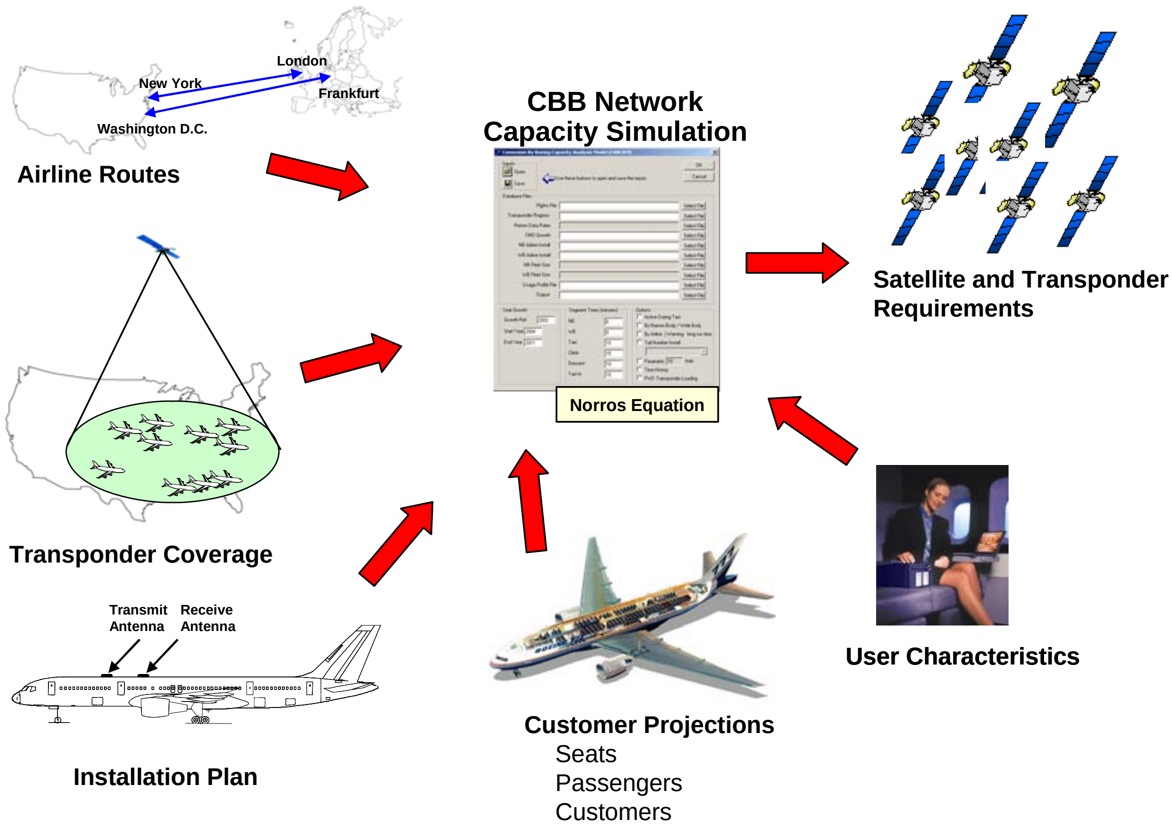


Figure 6-11 CBB Capacity Simulation

6.7.2. CSIM Modules. A variety of inputs are required for use by the CSIM. The input modules can be broken down as follows: airline routes, transponder coverage, installation plan, customer projections, user characteristics, core, and finally, transponder/satellite requirements.

6.7.2.1 Airline routes. The first module determines the location at a given time for all user selected airplanes or sets of airplanes as they traverse flight routes around the globe. Data is derived from the OAG (Official Airline Guide®). The OAG gives the commercial airline flight schedules which can then be fed into the CSIM in database format. This gives the origination and destination airports for all flights and also the departure and arrival times. Flight routes can be computed so that the location of any airplane at any given time can be estimated and simulated. In order to size the network to accommodate peak traffic, the CSIM uses the busiest week in the busiest month of the year, the second week in August.

6.7.2.2 Transponder coverage. The second module determines the location of KU-band satellites, transponder availability, and coverage areas. Transponder coverage areas are determined by first calculating the achievable data rates for the particular transponder. This is based on the satellite location, signal characteristics such as bandwidth and EIRP (effective isotropic radiated power), atmospheric interference, loss, and airplane antenna characteristics. The signal reception area varies in strength according to latitude and longitude with the greater strength towards the center and a lessening of signal strength towards the edges. The boundaries are then defined based on the area a particular transponder will support with a particular data rate. When an airplane flies into the transponder service area, its antennas are configured to automatically point to the associated satellite for reception to or from the particular transponder. When the airplane flights out of the region, it is configured to point towards another satellite and associated transponder. Figure 6-12 illustrates a fleet of aircraft flying through a transponder coverage zone. Figure 6-13 illustrates the coverage for HotBird® Satellite. Note that the signal strength dissipates as coverage is expanded.

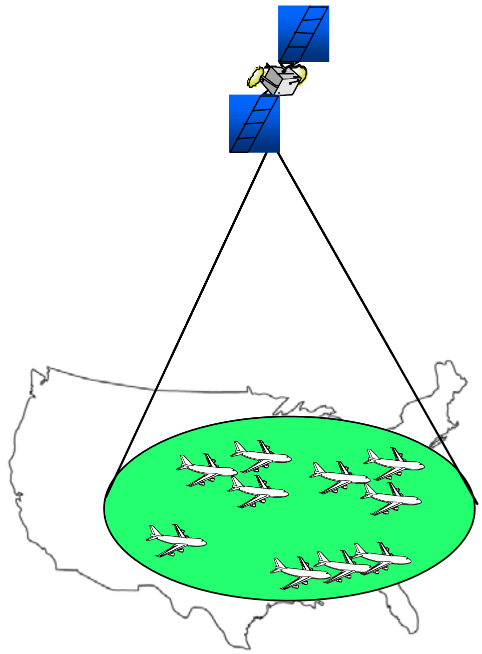


Figure 6-12 Transponder Service Coverage Area

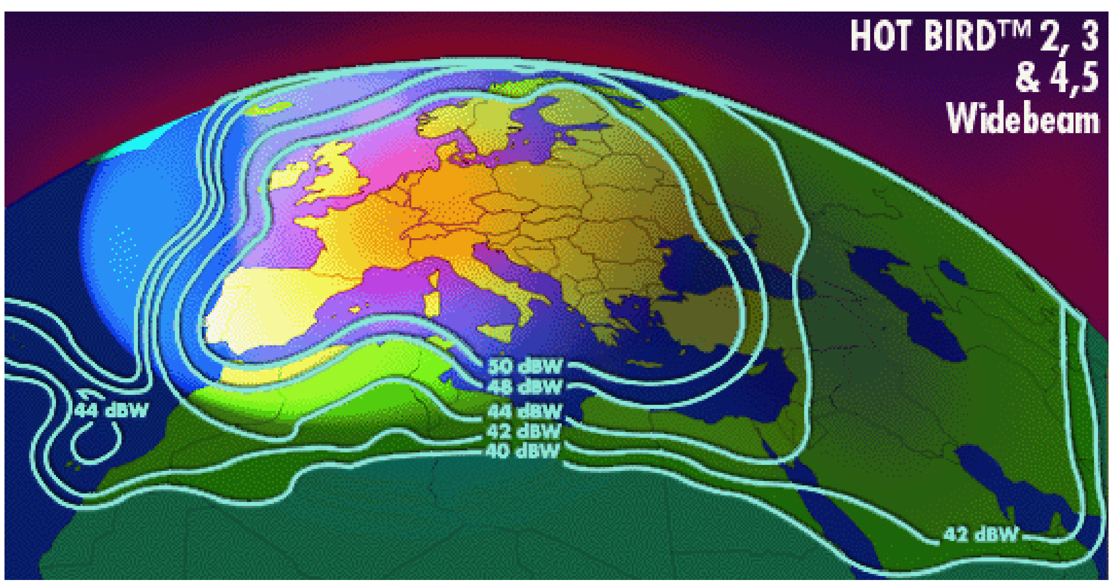


Figure 6-13 Hot Bird Service Coverage Area

6.7.2.3 Installation plan. The third module determines which of those airplanes have the CBB equipment installed. Planning falls into three categories. Aircraft with CBB installed, aircraft on contract and scheduled for installation, and aircraft projected for installation.

For installed aircraft it is simply a matter of matching the installed aircraft to the flight routes. Since the OAG doesn't correlate tail numbers a Monte Carlo distribution is applied to all the routes of a particular airline using the same model aircraft. For example, if five out of ten 747-400 aircraft in an airline's fleet have CBB installed, then the Monte carol routine randomly selects which five and varies it through the week.

For aircraft with scheduled installation dates, the uncertainty goes up as plans often change and schedules have a tendency to slip. For these aircraft the CSIM matches the schedule to airline routes as it projects out through the years. The further out the year, the greater the uncertainty.

For aircraft with marketing projected installation dates the uncertainty goes up considerable higher. For these aircraft the LRBP (long range business plan) is used. This is not only dependent on schedules, which may slip, but on marketing and sales, and is applied to airlines which CBB has not been sold too but which marketing and sales have on the capture plan.

6.7.2.4 Customer projections. The fourth module is an estimation based on several factors and is used to estimate how many customers are using the CBB Internet service at any given moment.

The first factor is number of seats on the aircraft. this can easily be obtained from the OAG which relates the type of aircraft on a given route and knowing the seat configuration used by the particular airline.

The second factor is occupancy, which is an estimation of how many of those seats are filled with passengers and how many are empty. Airline occupancy tends to be around 80% in the worst case month of the year.

The third factor is customers, those passengers which have signed on to use the CBB network data service. Again the simulation is dependant on marketing and sales projections. The market penetration would be small the first year, but would tend to increase over the years as the CBB system matures, until a saturation level is reached. Then further increases in market penetration would have to be driven by new product or service introductions, such as VoIP or Interactive Gaming.

The fourth factor is activity, how many of those customers are actually using the system at a particular moment. Some may have the service on during the entire flight listening to online music and others for only a short period in order to check email. Some may be active off and on, stopping during the meal service, or to take a nap, or for any number of reasons. The service will typically be available once the plane reaches 10,000 feet of altitude and will remain available until the plane starts to descend for landing and again crosses the 10,000 feet level. It is assumed that the shorter the flight, the higher the activity factor. If a customer signs on during a 2 hour flight they will probably use all the time and may have an 80% activity factor. If they sign on during an 8 hour flight, they would probably do other things also and may only have a 50% activity factor. The average number of simultaneous users that are using the CBB system on a particular flight at a particular moment may now be calculated.

Figure 6-14 illustrates with an example Boeing 747-400. The airplane model has approximately 400 seats. A load factor of 80% results in 320 passengers on the airplane. A market penetration rate of 20% results in 64 customers signing on to use the CBB service during the flight. Finally, an activity factor of 25% results in an average of 16 simultaneous users during the flight.

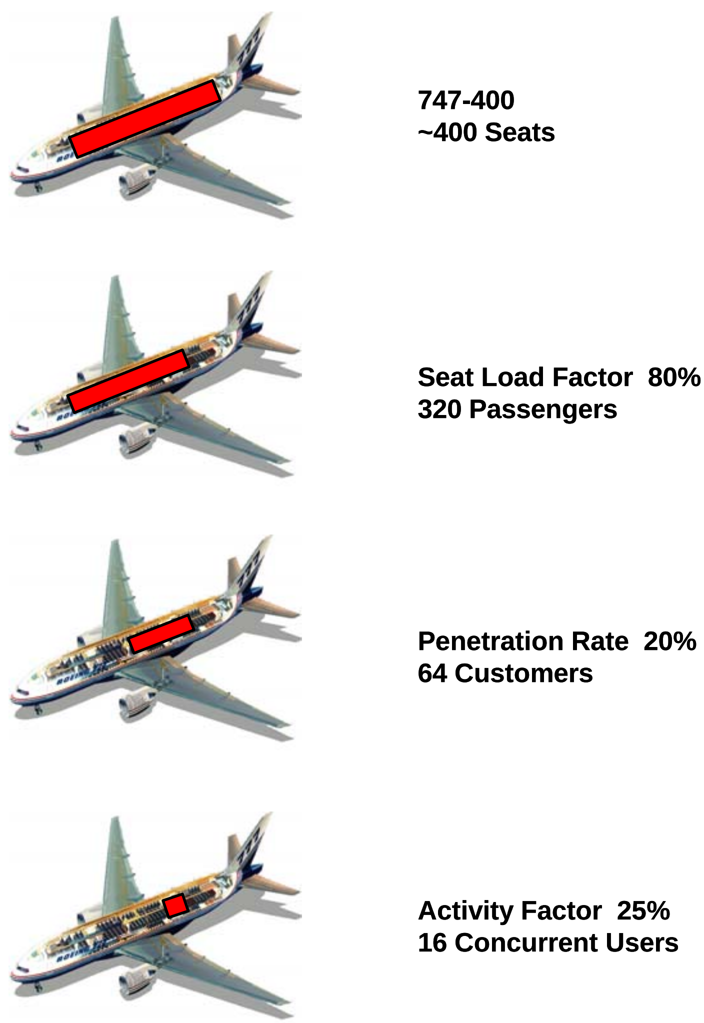


Figure 6-14 Calculation of Simultaneous Users

6.7.2.5 User characteristics. The fifth module estimates the Internet usage characteristics of the individual users. The key parameters are, mean bit rate, mean to peak variance of bit rate, and the asymmetry between the forward link and the return link, and self-similarity parameters like the Hurst parameter. This is a really hard thing to estimate, as described in detail in Section 3.6.1., and new simulation proposed by this dissertation research project proposes deleting this module because of the inaccuracy of estimating user characteristics.

Accuracy of these models is dependent upon measured data characteristics, which are often not very accurate themselves [Cleveland and Sun, 2000; Li et al., 2004; Qian et al., 2004], are difficult to collect and correctly characterize [Bregni, 2004; Cleveland and Sun, 2000; Floyd and Kohler, 2003; Fomenkov et al., 2004; Li et al., 2004; Park et al., 2005; Qian et al., 2004; Yousefi'Zadeh, 2002], are subject to constant change, and vary according to time, circumstance, and location [Bianchi et al., 2004; Brownlee and Claffy, 2002; Li et al., 2004; Qian et al., 2004; Rodriques and Guardieiro, 2004; Swift and Dagli, 2007c].

6.7.2.6 CSIM core. The CSIM Core utilizes inputs from all the previous modules and performs two important functions. First it determines how many users are active within any given transponder zone based on where the passengers are, the transponder coverage, what planes are flying, the location of the planes, how many people on each plane is using the service, and the user characteristics of those people. Second it utilizes the Norros equation developed by Ilkka Norros of Finland [Norros, 1995] to aggregate the traffic and calculate the bandwidth needed to support demand on the network. Section 4.6.4 contains a detailed description of the Norros equation uses by

CBB, its variables and constants, its derivation, and standard uses. The Norros equation, as used by CBB, is repeated below in equations 6.1 and 6.2:

$$C = m + \left(\kappa(H)\sqrt{-2\ln(\varepsilon)}\right)^{1/H} a^{1/(2H)} B^{-(1-H)/H} m^{1/(2H)} \tag{6.1}$$

where $$\kappa(H) = H^{H}(1-H)^{(1-H)} \tag{6.2}$$

m = Mean Bit Rate (bps)

a = Peakiness (bps)

ε = Cell Loss Rate

B = Buffer Size (bits)

H = Hurst parameter

C = Capacity (bps)

The output of the CSIM is the satellite and transponder requirements, which define the size of the network. This output is typically shown in matrix format detailing a transponder count needed for each satellite. The CSIM makes sure the number of transponders for a given satellite does not exceed the number of transponders available on that satellite and in many cases more than one satellite may be needed for a coverage region. Projections are made for future years based on projected growth in the number of customers and in their user characteristics. Table 6-2 is an example of how the CSIM output is displayed.

Table 6-2 CSIM Transponder Requirements Count

	2005	2006	2007	2008	2009	2010	....
Satellite #1							
Satellite #2							
Satellite #3							
Satellite #4							
Satellite #5							
Total							

6.8. SECTION SUMMARY

This section described the CBB global network, the NCS which was chosen for this case study. This section gave a review of the CBB architecture, a description of the services offered, a description of the major subsystems and segments, and a description of the CBB capacity simulation used for modeling network traffic and predicting demand.

CBB was shown to be a complex, large-scale, network-centric system whose main function is providing network services. CBB exhibits much of the power and benefits of being network-centric but is also facing the typical problems of an NCS. The data collection and capacity simulation function of CBB must deal with the typical NCS challenges of constant change and evolving characteristics. The current CBB capacity simulation is not adaptive or scalable enough.

This section concludes the literature review portion of the dissertation. The following section (Section 7) contains the results of the data mining study conducted with actual CBB network data to determine if the data could be used for ANN simulation. The following section (Section 8) gives the results of simulation testing comparing an adaptive ANN based simulation to the current Norros equation based simulation.

7. DATA MINING THE CBB NETWORK

7.1. OVERVIEW OF DATA MINING CBB NETWORK DATA

In this section the methodology and results from data mining network traffic on the CBB network is presented. Data from the CBB trials was used for development of a data mining methodology specific to network traffic and to validate the feasibility of transforming network data into a format compatible with ANN simulation methodology. The objective was to interpret and transform the data into a form that could be used for construction of a computationally intelligent simulation with adaptive capabilities. The methodology developed in this section was then applied to operational network data to construct an ANN simulation and run validation testing and also simulation comparison against existing CBB modeling methodology.

The methodology developed in this section follows the guidelines outlined in Section 5, which are the recognized standard steps for data mining: selection, preprocessing, transformation, data mining, and interpretation/evaluation, as shown previously in Figure 5-1 [adapted from Fayyad, 1996b].

The following subsections match the process steps, starting with the data sources, and then following with selection, preprocessing, transformation, data mining, and finally, interpretation/evaluation. Each of these steps was tailored for implementation on the CBB network and the methodology would most likely be adaptable for data mining network traffic in general. The end result is information ready for simulation testing and analysis. Figure 7-1 illustrates how the standard data mining process was implemented by this research project on the CBB network.

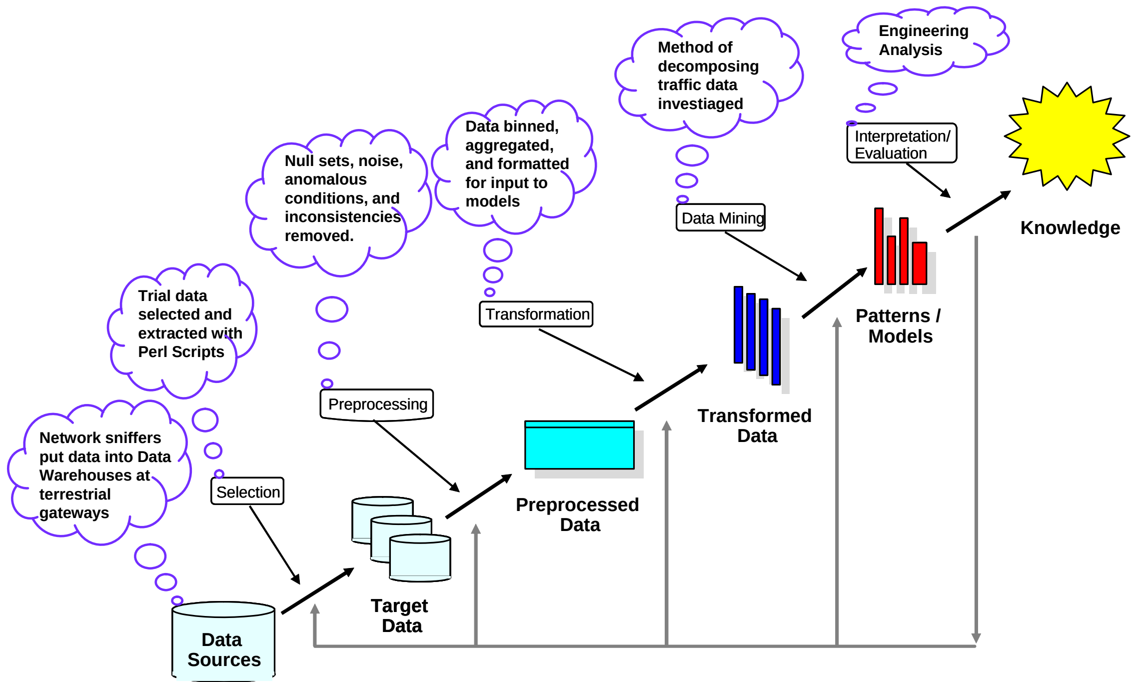


Figure 7-1 Data Mining the CBB Network

7.2. DATA SOURCES

Network traffic from the CBB NCS was collected by commercially purchased network sniffers which were configured to monitor and collect network header traffic as it passed through designated points on the network. Internet header information was placed into data warehouses for storage and retrieval, for presentation of statistics and trends, and for use in analysis and studies.

7.2.1. Network Sniffers. The network sniffers utilized by CBB were the Niksun NetVCR® units. These are commercially available, passive, network traffic, data monitoring units that monitor, collect, and analyze Internet header information as it passes through the unit [Niksun, 2003]. The NetVCRs were placed at each terrestrial ground station gateway in order to capture all data passing through the gateways going to or from the satellite transponders on its way to or from the aircraft. The one used during the CBB trials was located at the Littleton, Colorado Ground Station. During full-scale operations, units were placed at each gateway, to include Littleton, Colorado; Leuk, Switzerland; Moscow, Russia; and Iberaki, Japan. The NetVCRs were configured to monitor, collect, and analyze real-time packet and bit rate network traffic for both the forward and the return links.

7.2.2. Data Warehouses. Data warehouses are utilized at each gateway for storage and retrieval of data collected by the NetVCR units. A variety of reports and data cubes were developed for visualization and presentation of statistics. This allows easy monitoring of the system performance, trending analysis, and gives a professional reporting capability for management review. In addition to this, the raw data was also available for retrieval from the data warehouses for more comprehensive studies, such as the one conducted for this dissertation.

7.2.3. Data Collected. Raw header data was used in this study to analyze user characteristics and to build an adaptive architecture for modeling. The header information from the NetVCR network sniffers is analyzed through a Niksun application called MakeExport®. This application calculates relevant statistics from header information [Niksun, 2003]. The header statistics were then stored into the data warehouses. Traffic information is collected on each and every IP transaction by every user throughout the entire CBB network.

The raw data is collected by NetVCR through MakeExport in 15 minute segments throughout the day. Each file of zipped data was approximately 100 KB in size during the CBB trials, which was limited to only four flight routes. This amounted to approximately 9.6 GB of data per day. During the course of a month this is approximately 288 GB of data.

7.3. SELECTION

The first step in the data mining process was to select what, out of all this data, was to be analyzed and to extract that data from the source. This results in the target data. Two Crows corporation cites the proper selection of data as one of the two keys to success in data mining [Two Crows, 1999]. It is essential to have an idea of where you are going in order to make the proper selection. The intent of this dissertation research project was to find a way to accurately model the traffic stream bandwidth to allow for accurate sizing of the network. Enough data would need to be collected to allow for analysis, development of the model, and testing.

7.3.1. Sample Selection. Data from the CBB trials was selected for this initial data mining part of the dissertation study. The CBB Block 1 antenna system and associated hardware were installed on two 747-400 aircraft, one belonging to Lufthansa Airlines (DLH) and the other to British Airways (BA). Trials were conducted wherein passengers with laptops on commercial flights were provided access to the Internet through the CBB system. DLH trials were conducted on Flights 418 and 419 between Rhein-Main Airport at Frankfurt, Germany and Dulles International Airport at Washington D.C., USA. The CBB service was provided free of charge to the DLH passengers. BA trials were conducted on Flight 175, 177, 112, 113 and 116 between Heathrow Airport at London, England and John F. Kennedy International Airport at New

York, USA. Passengers on the BA flights were charged for the service, starting at 20 £ (about 30 dollars) per flight, although the price was varied near the end of the trial period to test for pricing sensitivities.

The Lufthansa Airlines trial started on January 15, 2003 and lasted until April 18, 2003, for a total of 94 days. There were 155 flight legs flown for 626,000 flight miles. There were 1,110 hours of operational time, out of which the CBB system was operational 980 hours and down 130 hours. During the trials there were 7 aircraft LRU (line replaceable unit) failures, several ground LRU failures, and 434 anomaly events logged. Overall CBB availability was approximately 90%, airline and customer satisfaction was high, and the DLH trial was declared a great success. The decision was made to continue with full-scale launch and Lufthansa Airlines subsequently signed a service agreement with CBB for the installation of CBB equipment and the provision of CBB service on more than 80 commercial wide body aircraft [Swift, 2004b].

The British Airways trial started on February 20, 2003 and lasted until March 16, 2003, for a total of 86 days. There were 95 flight legs flown for 328,510 flight miles. There were 520 hours of operational time, out of which the CBB system was operational 478 hours and down 42 hours. During the trial there was 1 aircraft LRU failure, 1 preventive maintenance activity, several ground LRU failures, and 118 anomaly events logged. Overall CBB availability was approximately 92%, airline and customer satisfaction was high, and the BA trial was also declared a great success. During the BA trial passengers were charged to use the system and there were a total of 245 paying customers [Swift, 2004b]. Figure 7-2 illustrates the flight routes.

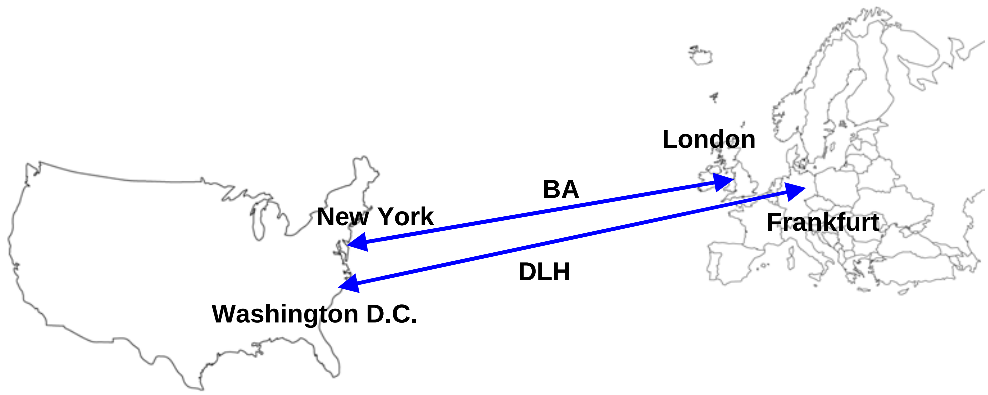


Figure 7-2 Airline Flight Routes Used During CBB Trials

The following differences between trial conditions and later operational conditions must be taken into consideration when evaluating any data resulting from the trial:

- Block 1 antenna system used during trial
- CBB network still in development
- Free laptop computers offered to some DLH passengers
- No charge for service by DLH
- Novelty of first time use
- High level of publicity by DLH
- Only four routes (Frankfurt to Washington DC, Washington DC to Frankfurt, London to New York, and New York to London)

- Limited passenger types (mostly German, English, and East Coast Americans)
- Special FlyNet® attendants available to assist DLH passengers

Four trail routes were selected for data mining and for development of the initial adaptive ANN simulation. The DLH flights were thought to be representative of where CBB might be in terms of customer load by 2011 and the BA flights were thought to be representative of where CBB might be during the initial year of operation. During the trials there was enough data collected on these representative flights to be equivalent to 10% of the entire Library of Congress.

7.3.2. Extraction. Each CBB equipped aircraft is assigned, by the NOC, a group of IP addresses. These IP addresses are subsequently available for assignment by the aircraft server to individual users. For example, the airplane used by DLH for the trials had the IP range of 10.255.255.1 through .254, and the aircraft used by BA for the trials had the IP range of 10.255.254.1 through .254. During the trials there were only two airplanes used and they flew the same flight routes each day. During operational services it became a more complicated matter as dozens of aircraft became equipped with CBB antennas and different aircraft began to fly all different routes for various days.

Knowing the IP address of a flight, the day of a flight, and the scheduled departure and arrival times, a Perl® script was written to extract the Internet header traffic for that individual flight.

These output files from the Perl scripts were stored in matrix format with one row for each IP transaction accomplished during the flight. The files were typically 5,000 –

15,000 KB in size and were stored as .csv files since they exceeded the Microsoft Excel® limits of 66,000 lines. Table 7-1 shows an example of just six transactions from one of the generated .csv files.

Table 7-1 Parsed Transaction Data Sample

Year (start)	Day of the year (start)	Month (start)	Day (start)	Hour (start)	Minute (start)	Second (start)	Year (end)	Day of the year (end)	Month (end)	Day (end)
2004	146	5	25	10	7	54.20751095	2004	146	5	25
2004	146	5	25	10	7	54.02042007	2004	146	5	25
2004	146	5	25	10	7	57.04566407	2004	146	5	25
2004	146	5	25	10	7	57.08757305	2004	146	5	25
2004	146	5	25	10	7	59.96775699	2004	146	5	25
2004	146	5	25	10	7	44.24736691	2004	146	5	25
2004	146	5	25	10	8	0.7883811	2004	146	5	25

Hour (end)	Minute (end)	Second (end)	#Start Time	End Time	Physical Port	Source IP	Dest IP	Source Port	Dest Port	Protocol
10	7	57.54984903	1.08548E+15	1.08548E+15	sf0	216.65.241.1	193.24.35.33	34698	443(https)	6(tcp)
10	7	58.22063899	1.08548E+15	1.08548E+15	sf0	216.65.241.4	66.213.246.11	3132	80(http)	6(tcp)
10	7	58.42899799	1.08548E+15	1.08548E+15	sf0	216.65.241.4	66.213.246.11	3133	80(http)	6(tcp)
10	8	0.423316956	1.08548E+15	1.08548E+15	sf0	216.65.241.1	193.24.35.33	34700	443(https)	6(tcp)
10	8	1.527039051	1.08548E+15	1.08548E+15	sf0	216.65.241.4	66.213.246.11	3134	80(http)	6(tcp)
10	8	2.473232985	1.08548E+15	1.08548E+15	sf0	216.65.241.1	193.24.35.35	34672	2004(mailbox)	6(tcp)
10	8	2.77421093	1.08548E+15	1.08548E+15	sf0	216.65.241.254	204.153.10.199	55524	80(http)	6(tcp)

Source TOS	Dest TOS	Source Pkts	Dest Pkts	Source Bytes	Dest Bytes	Round Trip Time	Response Time	Source Rexmit %	Dest Rexmit %
16	0	10	9	1528	1061	0.623861	0.047013	0	0
16	0	14	18	1458	20217	0.675939	0.987019	0	0
16	0	5	5	960	532	0.551267	0.239416	0	0
16	0	8	9	1384	1061	0.58217	0.047146	0	0
16	0	5	5	977	532	0.540139	0.428999	0	0
16	0	12	10	1625	1970	0.653589	0.049362	0	0
16	0	6	4	607	750	0.582232	0.289825	0	0

7.3.3. Target Data. The resulting target data was then stored in matrix format with each row representing an IP user transaction and each column an attribute of that transaction. There was one matrix for each flight on a particular day. Table 7-2 lists the attributes collected for each IP transaction, the column titles.

Table 7-2 Internet Traffic Transaction Attributes

Year (start)	**Day (end)**	**Source IP**
Day of Year (start)	**Hour (end)**	**Protocol**
Month (start)	**Minute (end)**	**Source Packets**
Day (start)	**Second (end)**	**Destination Packets**
Hour (start)	**#Sart Time**	**Source Bytes**
Minute (start)	**#End Time**	**Destination Bytes**
Second (start)	**Day (end)**	**Round Trip Time**
Year (end)	**Hour (end)**	**Response Time**
Day of Year (end)	**Minute (end)**	**Source Retransmit**
Month (end)	**Second (end)**	**Destination Retransmit**

7.4. PRE-PROCESSING

Preprocessing, also called cleaning, is a preparatory step where the selected data is manipulated to remove errors and inconsistencies in the data set. It was found that several preprocessing actions had to be employed with the data collected from the CBB network.

7.4.1. Format Manipulation for Consistency. Different gateways used different formats for the data. Some were compressed using bzip2® and others with gzip®. Some placed the server designation in the title and others did not. Some put the date designation at the beginning and others at the end. The first task was to remove inconsistencies and put all the data titles and data in a consistent structure. This was a time consuming task considering the magnitude of the data.

A process improvement that resulted from this study was for CBB to implement consistent data storage at all their gateways. This provided considerable cost savings for the program.

7.4.2. Null Flights and Null Users. Another required task was to remove flights from the mix that had no users. Then another task was to remove users from the mix that had no data flow. An example was someone who signed on to view the service options and was given an IP address but made no off-board Internet transactions. The removal of null flights and null users was accomplished by use of software filters.

7.4.3. Overhead. It also became necessary to remove data transactions not made by individual users. These overhead transactions were made by the system for various health and status monitoring functions or for system server uploads. This was accomplished by removing the overhead sub-addresses. For example, on DLH 10.255.255.1 was reserved for the DTR modem, 10.255.255.2 for the CSU, and 10.255.255.17 for the airline portal. That left 10.255.255.18 and up for real users.

7.4.4. Anomalous Conditions. It was also discovered that another source of data corruption was anomalous flights. These were caused by hardware or software problems during the flight that would make the service unavailable to users for a period of time. Also human error caused anomalous conditions, such as days where the attendants were late in turning on the system. These flights were deleted since anomalous conditions with the equipment or service would probably cause atypical behavior on the part of the users. The user might get discouraged if there were problems signing on and might not use the system at all even once it became available again. Or the user might try to accomplish all planned tasks in a shorter available time period and have higher than typical data rates. A 95% availability number was used and any flights with less than 95% availability were discarded.

7.4.5. Missing Data. Another source of problems were with the data collection system which occasionally experience collection anomalies and problems. Any flight with gaps in the data flow was considered corrupt and was also discarded.

7.4.6. Noise in the Data. Filters had to be applied to eliminate noise. There was noise found in two forms. The first was data rates of small magnitude and the second was data rates of high magnitude but very short durations.

7.5. TRANSFORMATION

Transformation is preparation of the data set for use by the analysis tools. It includes activities such as smoothing, aggregation, generalization, normalization, and attributes construction.

7.5.1. Flight Profiles. The data was in the format of transactions and there were over 66,000 transactions per flight. Multiply this by the number of flights and this was too large a data set for meaningful analysis. It was decided to aggregate the data into sample sets, still per flight, by time histories rather than by transactions. A Perl script binning program was written to bin the data by number of bytes per time period of the day. This resulted in a data rate time-history for the flight. The data was also broken down to the individual user level so that a time-history was also collected for each individual user on each flight. In addition, data was collected by application, such as web surfing, email, and online gaming.

The data was now in matrix format with each row representing a 1 second interval in TOD (time of day) and each column the bytes used by an individual user and also a column for the aggregated flight kbps, or the sum of the users.

7.5.2. Binning Intervals. The next task was to decide at what level to bin the data. The NetVCR filters collected the data every one thousands of a second. The CBB data cubes were performing calculation at the 15 minute bin size, which is the industry standard. Some aggregation was necessary because of the enormity of the data, but binning tends to smooth out the peakiness characteristic of the data, an important characteristic for Internet traffic modeling. A small study was performed to asses the effects of binning. Binning intervals of 1 second, 1 minute, 5 minutes, 10 minutes, 15 minutes and 30 minutes were assessed. Figure 7-3 illustrates time histories for the same flight at different bin sizes. Because of the dramatic loss of peakiness, bin sizes of one second were used for the collection of data for this research study.

7.5.3. Time of Day Conversion. Some flights crossed midnight or the International Date Line and this had to be taken into account. For example a flight might depart at 17:00 GMT (Greenwich mean time) and arrive at 05:00 GMT. The simple solution was to add 24 hours to the time value for any values prior to the departure time.

7.5.4. Final Sample Set. There were four flight routes selected from the CBB trials for use in developing the data mining methodology and for use in developing the adaptable architecture for modeling traffic. Sample flights were taken from each of the four flights. Additional operational flight routes were used in subsequent simulation testing to validate the model and assess accuracy and adaptability.

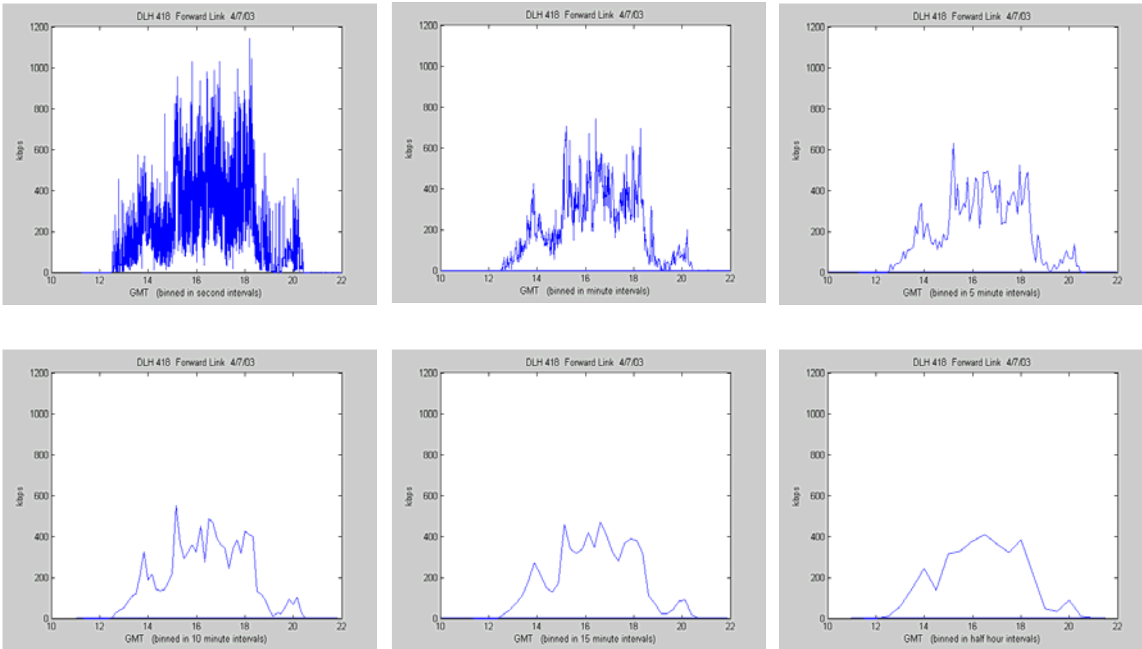


Figure 7-3 Smoothing Effects of Bin Size

7.5.4.1 DLH 418 flights from Frankfurt to Washington D.C. Thirty-nine flights on DLH 418, traveling from Germany to the United States, were selected for this study. DLH Flight 418 is a day route, which departed at approximately 1:10 PM (local) and arrived at approximately 3:55 PM (local). Out of the 94 days during the DLH trial, there were 50 days where CBB service availability was over 95%. Flights with less than 95% availability were not included in the study since anomalies would bias customer activity patterns away from the norm. Of the 50 remaining flights there was no NetVCR data available on one of the days. Once the data was plotted, an additional 10 flights were eliminated due to missing blocks of user activity, probably caused by DLH system problems or data collection anomalies. This left 39 good flights for the study. An example traffic trace is shown in Figure 7-4 for April 7, 2003. During this flight, there was a total of 601 MB of data sent to the airplane over the forward link. Average data flow was approximately 171 kbps. The peak data flow (95th percentile) was approximately 471 kbps [Swift, 2004].

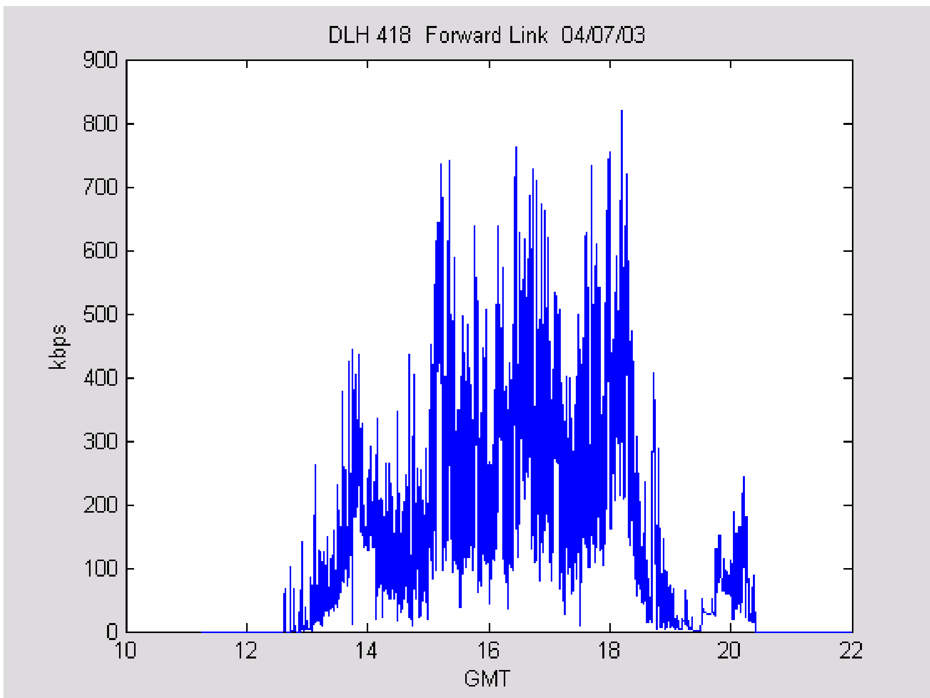


Figure 7-4 Sample DLH 418 Bandwidth Trace

7.5.4.2 DLH 419 flights from Washington D.C. to Frankfurt. Thirty-one flights on DLH 419, traveling from the United States to Germany, were selected for this study. DLH Flight 419 is a night route, which departed at approximately 5:55 PM (local) and arrived at approximately 7:35 AM (local). Out of the 94 days during the DLH trial, there were 36 days where CBB service availability was over 95%. Flights with less than 95% availability were not included in the study since anomalies would bias customer activity patterns away from the norm. Once the data was plotted, an additional 5 flights were eliminated due to missing blocks of user activity, probably caused by DLH system problems or data collection anomalies. This left 31 good flights for the study. An example traffic trace is shown in Figure 7-5 for March 8, 2003. During this flight, there was a total of 311 MB of data sent to the airplane over the forward link. Average data flow was approximately 106 kbps. The peak data flow (95th percentile) was approximately 296 kbps [Swift, 2004].

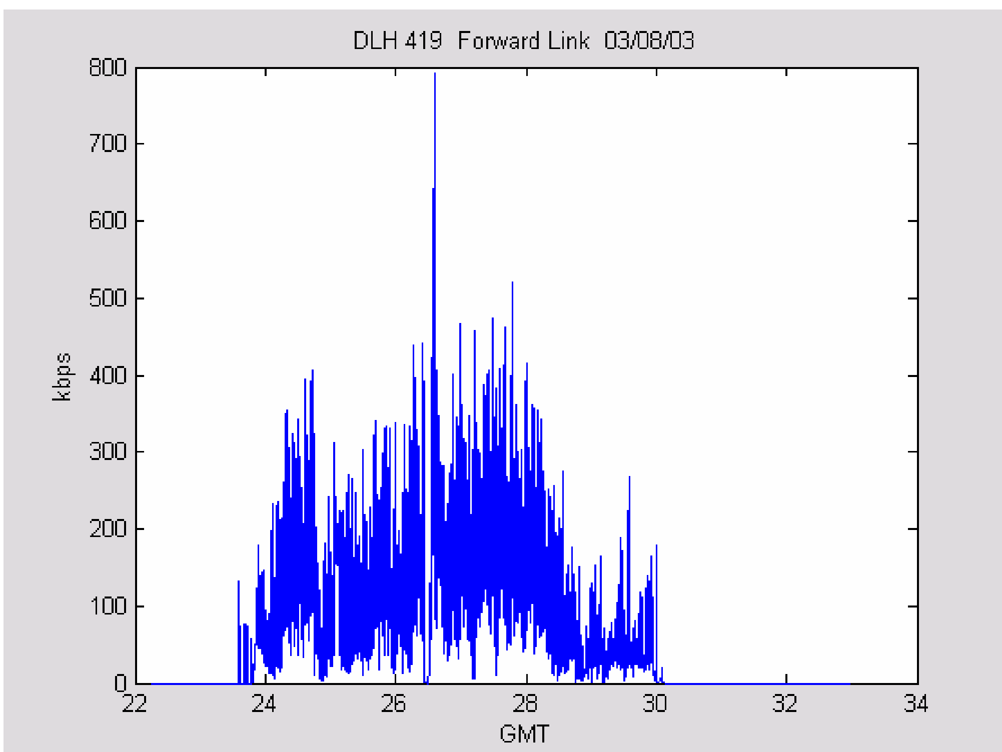


Figure 7-5 Sample DLH 419 Bandwidth Trace

7.5.4.3 BA 175 flights from London to New York. Forty-five flights on BA 175, traveling from England to the United States, were selected for this study. BA Flight 175 is a day route, which departed at approximately 11:00 AM (local) and arrived at approximately 1:50 PM (local). Out of the 85 days during the BA trial, usable NetVCR flight data was available for 45 days. An example is traffic trace shown in Figure 7-6 for May 6, 2003. During this flight, there was a total of 66 MB of data sent to the airplane over the forward link. Average data flow was approximately 22 kbps. The peak data flow (95th percentile) was approximately 72 kbps [Swift, 2004].

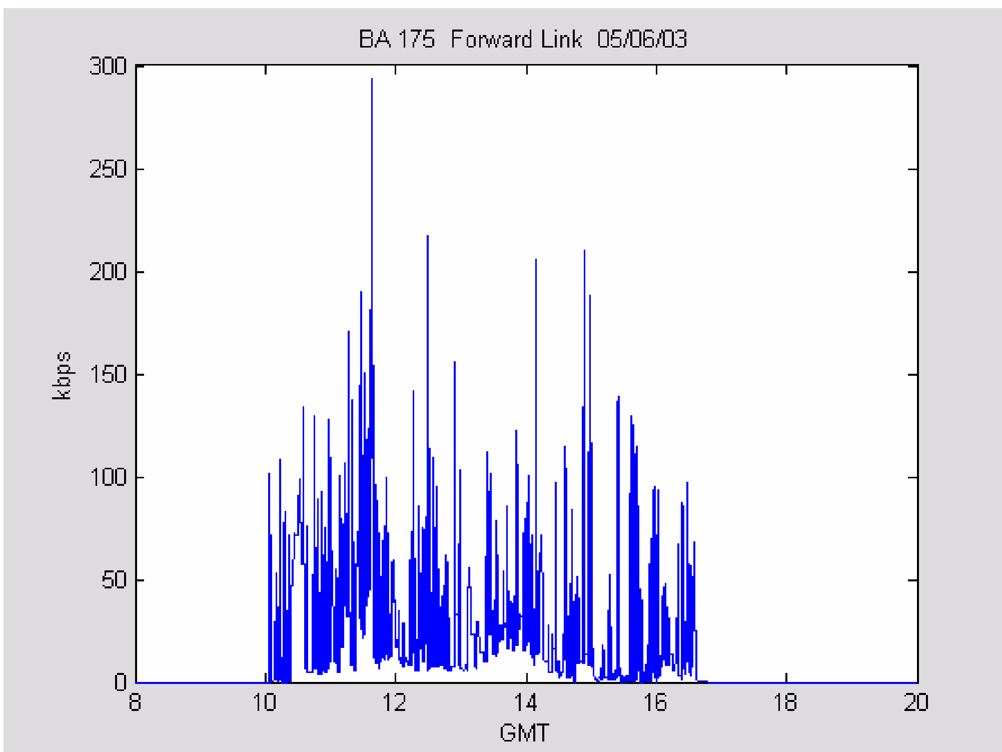


Figure 7-6 Sample BA 175 Bandwidth Trace

7.5.4.4 BA 112 flights from New York to London. Twenty-six flights on BA 112, traveling from the United States to England, were selected for this study. BA Flight 112 is a night route, which departed at approximately 6:30 PM (local) and arrived at approximately 6:25 AM (local). Out of the 85 days during the BA trial, usable NetVCR flight data was available for 26 days. An example traffic trace is shown in Figure 7-7 for May 2, 2003. During this flight, there was a total of 42 MB of data sent to the airplane over the forward link. Average data flow was approximately 17 kbps. The peak data flow (95th percentile) was approximately 71 kbps [Swift, 2004].

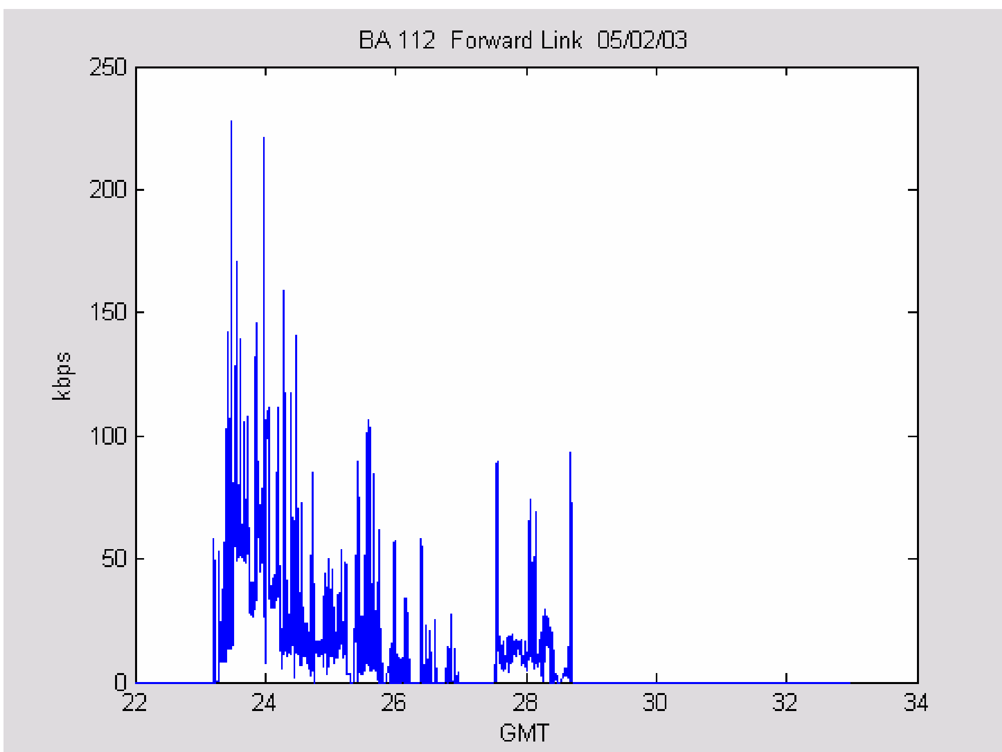


Figure 7-7 Sample BA 112 Bandwidth Trace

7.6. DATA MINING

The first and perhaps most difficult step in developing a neural network model for predicting network traffic, is to explore the decomposition of available traffic data. The data must be put into a format that consists of repeatable patterns which the ANN can be trained to recognize and predict. In this case the patterns were to consist of time-history bandwidth traffic traces. The ANN could then be trained to output vectors representing these traffic traces. An ANN would also have the capability to generalize for errors or unexpected differences in the input data, and would also have the ability to adapt through re-training. Three methods of decomposition were investigated:

- By individual users traffic traces
- By application traffic traces
- By common usage traffic traces

7.6.1. Individual User Traffic Traces. The first attempt was to try and decompose the data into time-history vectors based on individual user traffic traces. Bandwidth traces for single users were easily obtained by parsing on individual IP addresses. However, two major problems surfaced and this method had to be rejected. The diversity between individual users was too extreme to manage, even among small sample sets, and the data traces of users tended to vary from day to day and were not repeatable. Figure 7-8 displays a sample of the data illustrating the jumble of users frequently seen on Internet traffic. Figure 7-9 illustrates further by increasing the scale.

Note some users are fairly steady state and others exhibit considerable peakiness. Each line represents a different user.

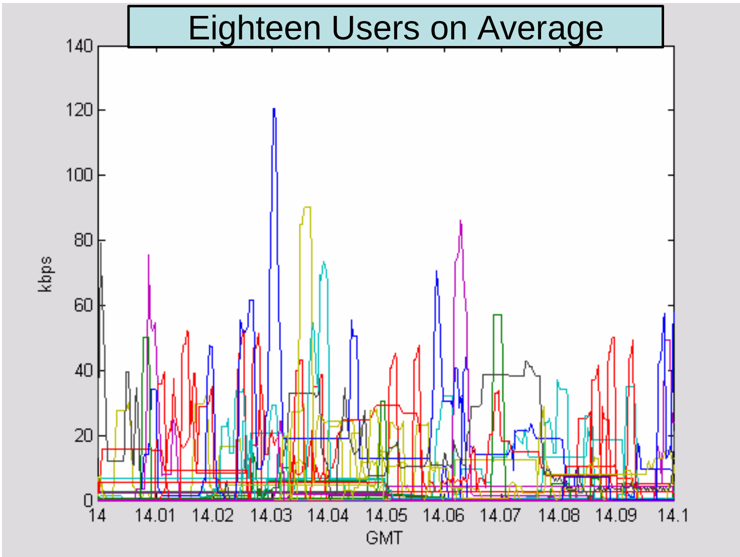


Figure 7-8 Typical Internet Traffic Trace – 0.1 hours

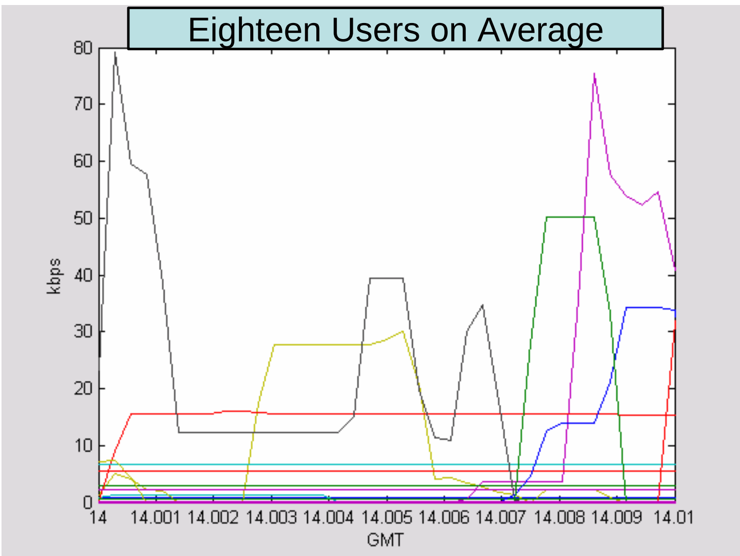


Figure 7-9 Typical Internet Traffic Trace – 0.01 hours

Parsing out a single user also revealed changing patterns by the individual user even during the course of a single session. Figure 7-10 shows a twelve hour period for one user during a flight and Figure 7-11 shows a 30 minute segment for the same user at an increased scale. Exhibited in the data are dead times of inactivity of varying lengths, times of high and low burstiness, and times of sustained constant data rates. These changing characteristics are due to varying activities of the user, such as times of high or low activity, or when using different applications, such as email, web surfing, or streaming media. Therefore, in addition to each user being different, there is variance in usage characteristics for the same individual during a session.

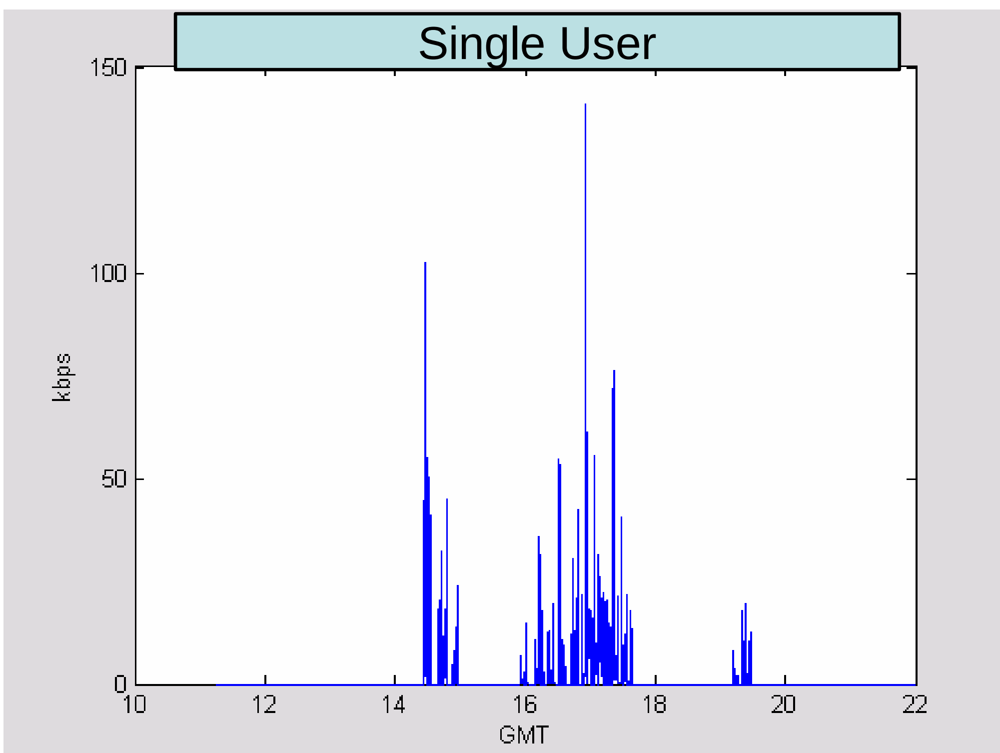


Figure 7-10 Single User Traffic Trace – 12 hours

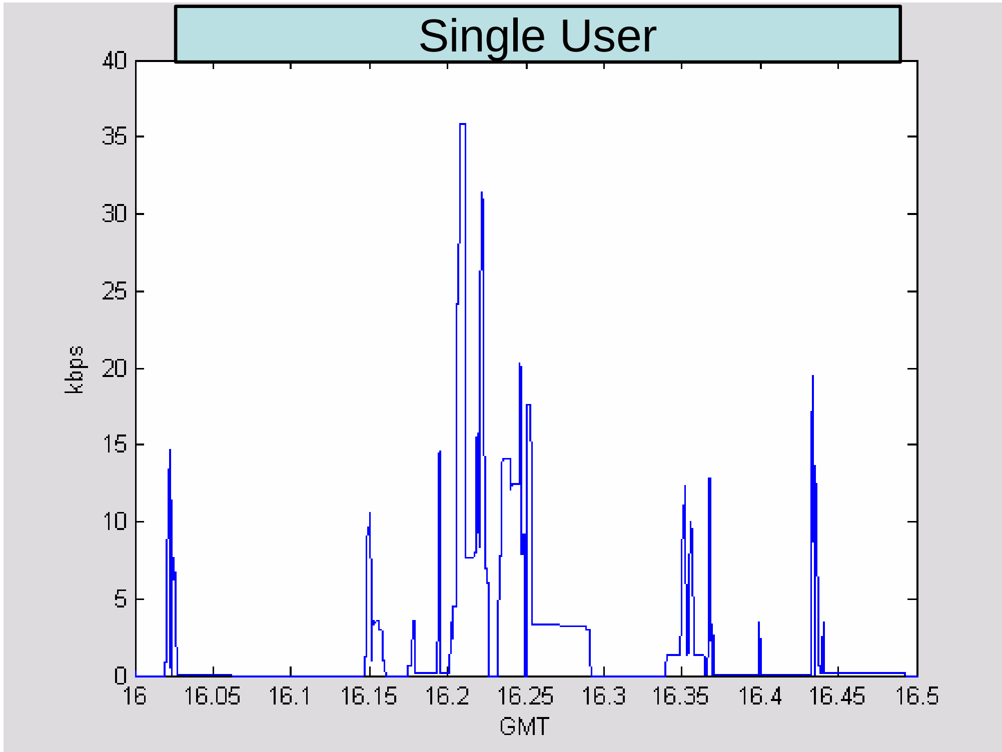


Figure 7-11 Single User Traffic Trace – 0.5 hours

Fuzzy logic or Kohonen self-organizing maps could possibly be used to develop patterns or groupings of individual users not readily discernable, but these groupings would have the same difficulty with changing patterns from day to day. Since the individual user traffic traces were unstable and did not follow repeatable patterns, decomposition by individual user was rejected.

7.6.2. Application Traffic Traces. The next attempt at decomposing network data into time-history vectors was to try by application traffic traces. These appeared promising since different applications, such as web surfing vs. email, have recognizably different characteristics and would hopefully be consistent over time and location. For example, a person doing Internet chat on a Lufthansa Airlines flight over Berlin would likely have similar Internet traffic characteristics with a person doing Internet chat on a Japanese Airlines flight over Tokyo. The same would be true with audio streaming or any other application. There were ten applications selected for parsing in an attempt to see if this could produce repeatable useable traffic traces. The selected applications were: web surfing traffic, email traffic, FTP (file transfer protocol) traffic, VPN (virtual private network) traffic, news traffic, chat traffic, telnet traffic, VoIP (voice over IP) traffic, media traffic like streaming video or audio, and interactive gaming traffic.

Individual IP addresses could not be used to parse out this type of Internet traffic, like in the previous attempt, instead parsing was based on protocol and port. These are defined by the IANA (Internet Assigned Numbers Authority), and are published on the web. The IANA is "dedicated to preserving the central coordinating functions of the global Internet for the public good, [IANA, 2004]." The port numbers are divided into three ranges, the well known ports, the registered ports, and the dynamic and/or private ports. A study was done to determine protocols and ports applying to each application. It was recognized the choices made would not be all inclusive, but it was hoped they would capture at least 90% of the traffic for a given application.

- **Web Surfing.** There were 8 protocol port pairs chosen for characterizing web surfing Internet traffic. These included ports 80, 280, 443, and 8080 for both TCP and UDP and were titled World Wide Web for HTTP, http-mgmt, http protocol over TLS/SSL, and http alternate [IANA, 2004].

- **Email.** There were 50 protocol port pairs chosen for characterizing email Internet traffic. These included ports titled Simple Mail Transfer, POP3, Remote Mail Checking Protocol, XNS Mail, NI Mail, Mail Q, QuickMail Transfer Protocol, MCS Fastmail, and others [IANA, 2004].
- **FTP.** There were 28 protocol port pairs chosen for characterizing FTP Internet traffic. These included ports titled FTP Default Data, FTP Control, NI FTP PFTP, UTS FTP, GSI FTP, MFTP, ODETTE FTP, and others [IANA, 2004].
- **VPN.** There were 12 protocol port pairs chosen for characterizing VPN Internet traffic. These included ports titled PPTP, NI FTP, ISAKMP, Socks, and others [IANA, 2004].
- **News.** There were 16 protocol port pairs chosen for characterizing news Internet traffic. These included ports titled TAC News, Network News Transfer Protocol, Readnews, NetNews, NewsEdge, and others [IANA, 2004].
- **Chat.** There were 74 protocol port pairs chosen for characterizing chat Internet traffic. These included ports titled Chat, Internet Relay Chat Protocol, IDEAFARM-CHAT, Instant Service Chat, Netchat, Redwood Chat, HotU Chat, Yo.net, PR Chat, America-Online, IRCU, OnLive, Italk Chat System, and others [IANA, 2004].
- **Telnet.** There were 16 protocol port pairs chosen for characterizing telnet Internet traffic. These included ports titled Telnet, SU/MIT Telnet

Gateway, Remote Telnet Service, SkyTelnet, TC1-Telnet, SCPI-Telnet, and others [IANA, 2004].

- **VoIP.** There were 18 protocol port pairs chosen for characterizing VoIP Internet traffic. These included ports titled BSQUARE-VOIP, h323hotstcall, MSICPP, PRP, IUA, NetIP VoIP Assessor, and others [IANA, 2004].
- **Media.** There were 16 protocol port pairs chosen for characterizing streaming media Internet traffic. These included ports titled MS-Streaming, YO.net main service, IATP, ARCP, APCNECMP, and others [IANA, 2004].
- **Gaming.** There were 70 protocol port pairs chosen for characterizing gaming Internet traffic. These included ports titled Doom, IM Games, IberiaGames, GameGen1, Evolution, Compaq, TAPPI BoxNet, Redstorm, Netrek, GameLobby, Xbox, NetMIke, Ironstorm, Quake, GameSmith, Tera Base, and others [IANA, 2004].

Running individual traces by application category proved successful and the individual categories do make logical sense. Figure 7-12 illustrates the traffic races for six of the applications. It appears that they could be distinguishable and would probably hold the same characteristics throughout the network.

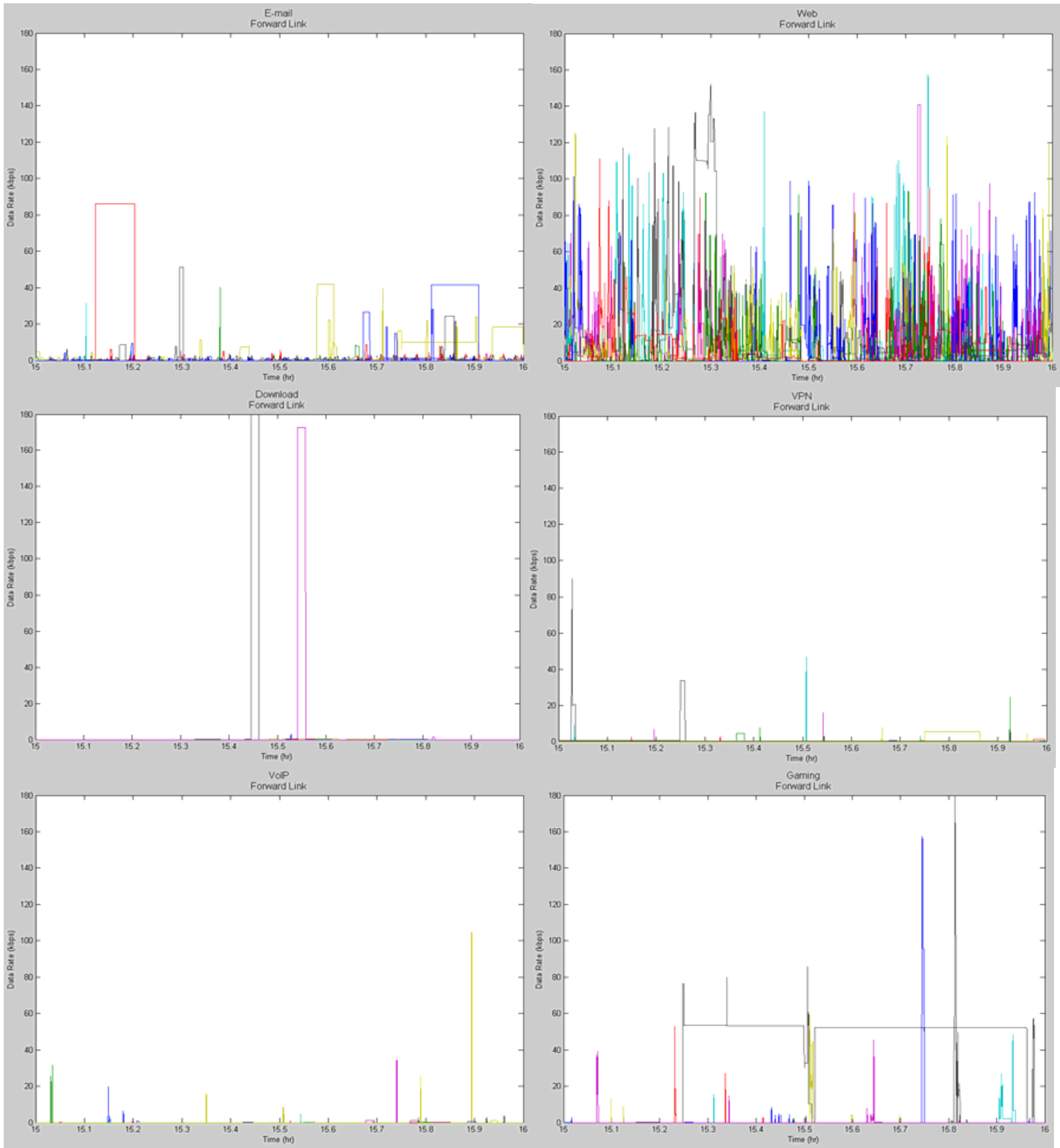


Figure 7-12 Application Traffic Traces

Unfortunately, two major problems were recognized when evaluating implementation. A considerable increase in software programming and also run time was necessary to decompose the network traffic by application. More important than this, the lists of which ports and protocols that go with which applications was imprecise and subject to change. Because of the difficulty in defining and maintaining accurate and complete listings of port designations for the various applications, and recognizing the distinct possibility that some key ports might be missed, this method of decomposition was also rejected.

7.6.3. Common Usage Traffic Traces. The third attempt at decomposing the network data was to try less granularity and to investigate traffic traces of common usage groups. Decomposition by similar airline flight route was selected for the subject network and traffic data was collected on several thousand flights for a variety of different routes. Users on each aircraft have the same IP subnet addresses and traffic traces were obtained by matching aircraft IP subnets to published flight schedules.

This method of decomposition was found to be acceptable. The individual flights on similar flight routes were consistent from day to day and were quite distinct from each other. Traffic traces were developed by taking all the flights of a particular type flight route, normalizing to the same start time, and then computing the average. Some example plots of various sizes and shapes are shown in Figure 7-13. Note how each is unique from the others. Appendix A contains plots for the thirty standard flight routes used in this study.

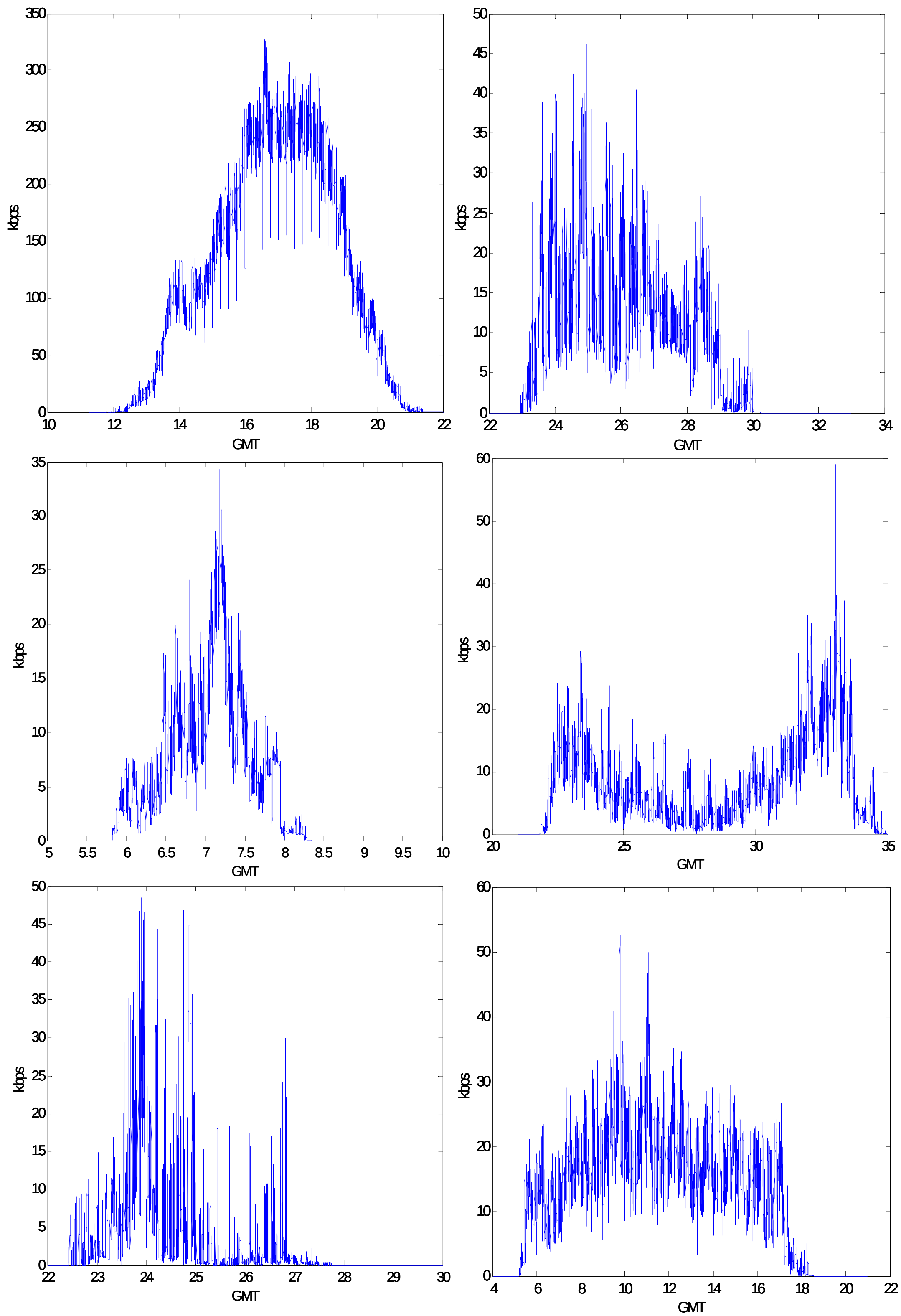


Figure 7-13 Flight Route Traffic Traces

7.7. INTERPRETATION AND EVALUATION

Data mining is merely a tool, although powerful, that improves the capabilities of the analysis but does not remove the need for a skilled analysis [Two Crows, 1999]. During this step the data mining information is turned into knowledge. This will be covered in the Section 8 through simulation development and testing.

7.8. APPLICABILITY TO OTHER NETWORK-CENTRIC SYSTEMS

The question arises as to whether or not the same data mining methodology could be applied to other NCSs and whether or not data traffic on other NCSs could also be broken down into distinct categories made up of the traffic traces of similar types of users.

7.8.1. Network-Centric Battlegroup. Consider the network-centric battlegroup discussed in a previous section (Section 1.2.2) as illustrated in Figure 7-14 [from Dagli and Miller, 2003]. The same data mining methodology that was applied to decompose the CBB NCS's network traffic could also be applied to decomposing the battlegroup's network traffic. Data could be collected during mock war trials or during previous battlegroup engagements and stored in database warehouses. The data could be extracted based on IP addresses like the CBB NCS, then preprocessed and transformed as appropriate. The data could then be aggregated into categories similar to the CBB NCS but yet unique to the battlegroup NCS. Instead of different flight route traffic traces, the categories could be different military platform traffic traces. For example, data traffic to and from an F-15 fighter jet is likely to have vastly different characteristics than data traffic between infantry soldiers, and the data traffic for an Apache helicopter is likely to be even more different. Network traffic would also be different depending upon the situation. For example, an M1A2 Abrams tank would likely have light steady state traffic while in cruise operations moving towards the battlefield and heavy bursty traffic while engaged in battle. In this manner the methodology developed for data mining the CBB NCS could also be applied to network-centric battlegroup. The result would be data traffic traces that could be used in simulation for traffic modeling and bandwidth demand prediction.

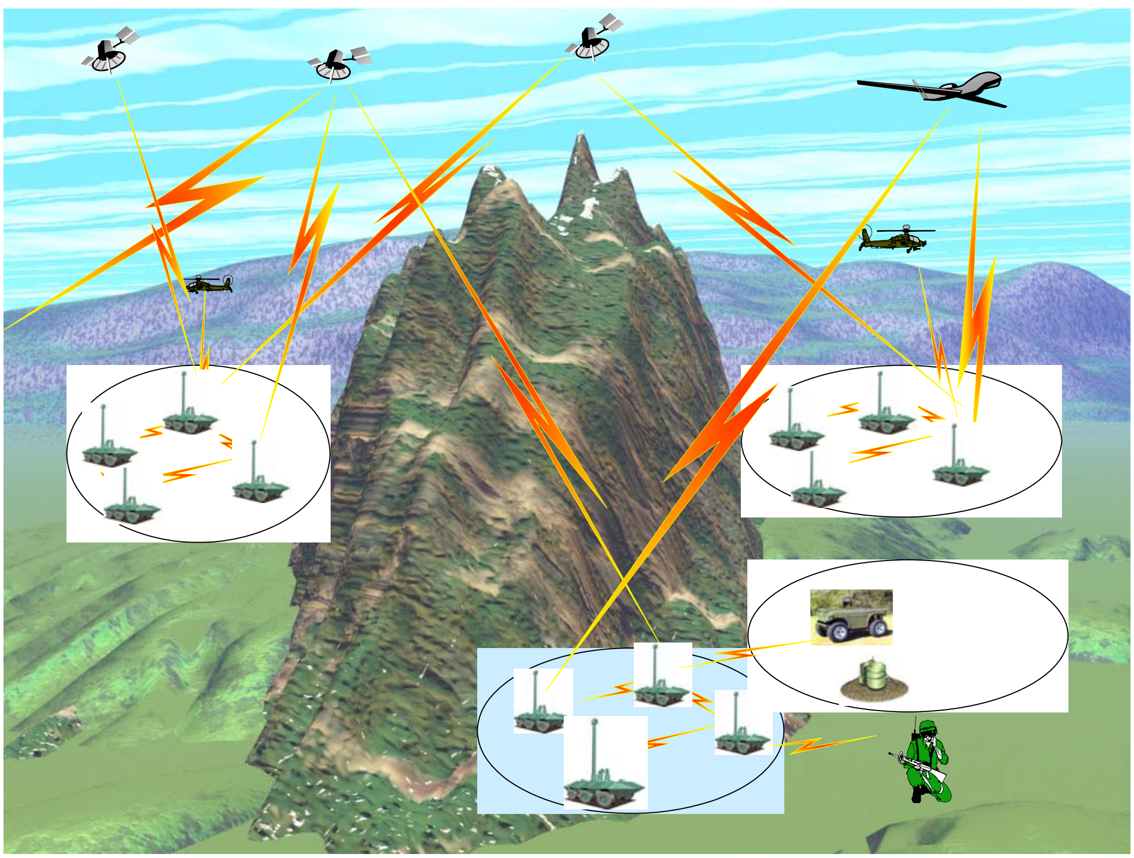


Figure 7-14 Network-Centric Battlegroup

7.8.2. Naval Group. Consider a navel carrier group, as seen in Figure 7-15 [NavSource, 2007], consisting of an aircraft carrier, battleships, cruisers, submarines, fighter aircraft, etc. A similar methodology could be applied to develop characteristic traffic traces for individual classes of ships. During war gaming exercises planners could predict the network demand based on the number and type of vehicles assigned to the group.

Figure 7-15 Abraham Lincoln Aircraft Carrier Naval Group

7.8.3. Commercial Ventures. There are many examples of large companies operating in a network-centric environment that that could use the same methodology to predict bandwidth needs for their networks. These would include retail stores, banking operations, trucking and other transportation companies, and in particular Internet service providers for cellular phones, cable and satellite television, and computers.

7.9. SECTION SUMMARY

In this section the methodology and results from data mining network traffic on the CBB network were presented. Each step of the data mining process was described as CBB network data was selected, extracted, preprocessed, transformed, and data mined for relevant traffic traces. The same methodology was then applied to operational CBB network traffic data to supply input data for the testing of the ANN based simulation.

Now that a method has been developed for decomposing CBB network data into categories compatible with ANN simulation, the next step was to build an ANN based simulation and compare results to current methodology. The following section (Section 8.0) proposes an adaptive model for Internet traffic modeling based on artificial neural networks.

8. ANN SIMULATION

8.1. OVERVIEW OF SIMULATION DEVELOPMENT AND TESTING

In this section an adaptive architecture for network traffic modeling based on artificial neural networks is presented. In the previous section (Section 7) a methodology was proposed for data mining network traffic to determine patterns in the data compatible with ANN simulation. For the CBB network it was time-history traffic traces based on various flight route types, such as Atlantic routes, trans-Asia routes, Far East routes, etc. In this section ANNs are used to build a network bandwidth simulation based on these traffic traces. The simulation is then used to predict network bandwidth demand.

First the simulation is described, including the substitution of the ANN predictor in place of the Norros equation module. Then the architecture of the ANN predictor is described. Next the accuracy of the ANN predictor is evaluated and simulation testing results are presented comparing the ANN based simulation to current methodology with the Norros equation.

8.2. SIMULATION ARCHITECTURE

The purpose of the simulation is to predict network bandwidth demand. This allows for efficient and accurate sizing of the network. The CBB NCS network was used as the case study for this dissertation. The ability to predict bandwidth demand allows for cost efficient leasing of transponders on geo-synchronous satellites. This allows for cost effective sizing of the network. Figure 8-1 (adapted from Swift, 2004b] illustrates a bandwidth trace.

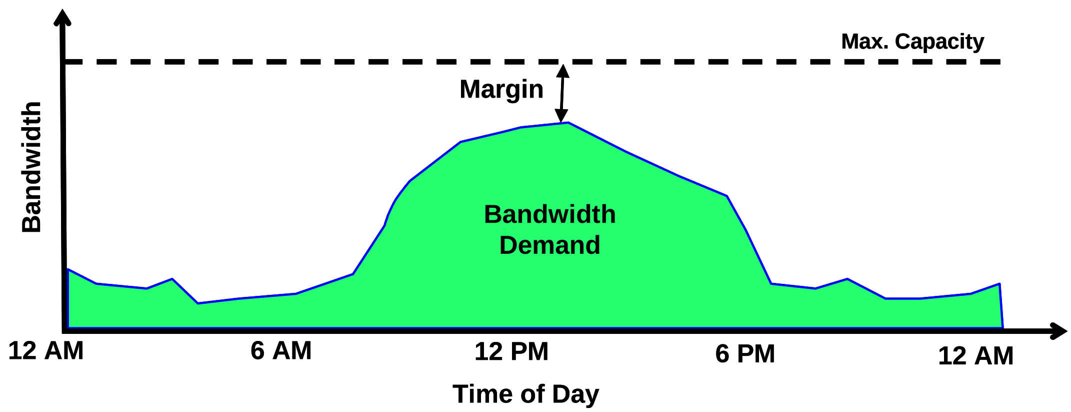


Figure 8-1 Bandwidth Load Profile

To predict bandwidth demand, a CBB network CSIM (capacity simulation) is currently used. In the current CSIM, predicted user characteristics are the primary input. Other inputs are used to determine how many users are in a specified transponder region at any given moment and how many are using the system at that moment. The CSIM uses a Norros based equation, which models Internet traffic based on fractional Brownian motion, to compute the bandwidth needs. This output is then used to determine how many satellite transponders to lease in order to effectively size the network. Figure 8-2 shows a top level block diagram of CSIM inputs and outputs.

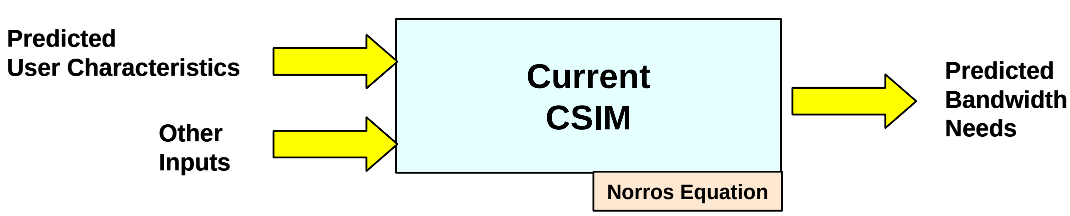


Figure 8-2 Current CSIM Inputs and Outputs

The proposed adaptive architecture utilizes artificial neural networks, which are a recognized form of computational intelligence, in place of the Norros equation. Artificial neural networks are capable of learning and of generalizations. Instead of using predicted user characteristics, the adaptive neural network uses actual traffic traces taken from data collected off the network. Figure 8-3 shows the proposed block diagram.

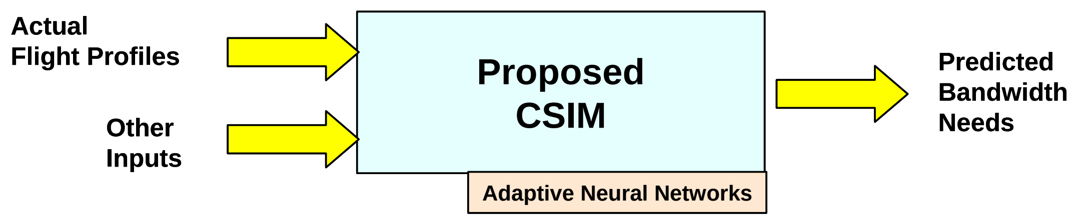


Figure 8-3 Proposed ANN Simulation Inputs and Outputs

The operational overview architecture (DoDAF OV-1) for the current CSIM simulation is shown in Figure 8-4. The key input is user characteristics and the Norros equation is used to compute bandwidth demand for each transponder region. Other inputs include airline routes so the location of aircraft at a given time are known, transponder coverage areas, installation plans to determine which planes are equipped with CBB antennas, and customer projections to determine how many users will be connected to the CBB network at one time. Section 6.7 contains a complete description of the current CBB CSIM and discusses each of the modules and how they interface and the outputs and inputs.

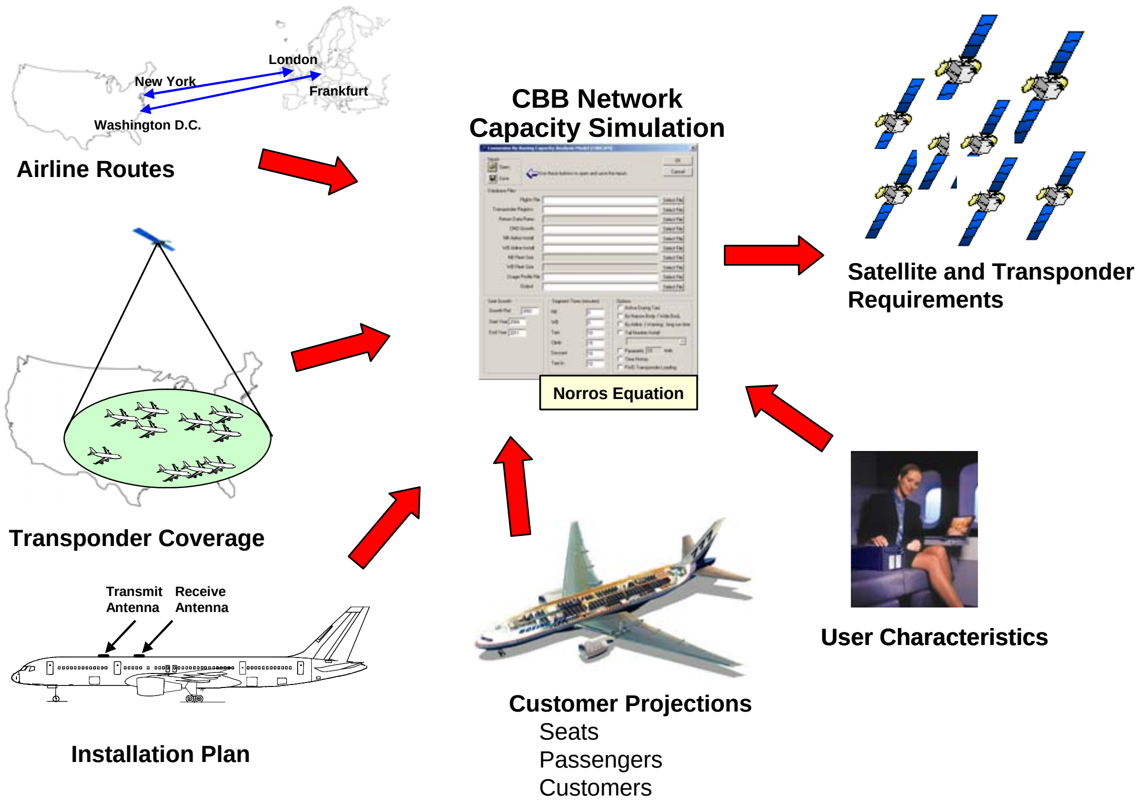


Figure 8-4 Current CSIM Architecture

There are several weakness. One is the level of uncertainty. Several of the input parameters are estimations. Another is use of the Norros equation. Values used for input to the Norros equation are difficult to obtain and are of questionable accuracy. Also the Norros equation is based on self-similarity which may not hold true for modern NCSs. Another weakness is a lack of adaptability and scalability. The Norros equation is held constant throughout the network. In reality, network traffic varies according to location on the network, time of day, applications in use, user habits, and other factors. The network characteristics are also constantly evolving and changing.

The operational overview architecture (DoDAF OV-1) for the proposed ANN based CSIM simulation is shown in Figure 8-5. Bandwidth traffic traces are substituted as the key input parameter to the CSIM core instead of user characteristics. These bandwidth traffic traces are generated by the ANN predictor. Other inputs are still needed to determine which type of equipped aircraft is in a given transponder region at a given moment in time. The CSIM core simply aggregates a composite value for any given moment of time to generate system bandwidth demand profiles.

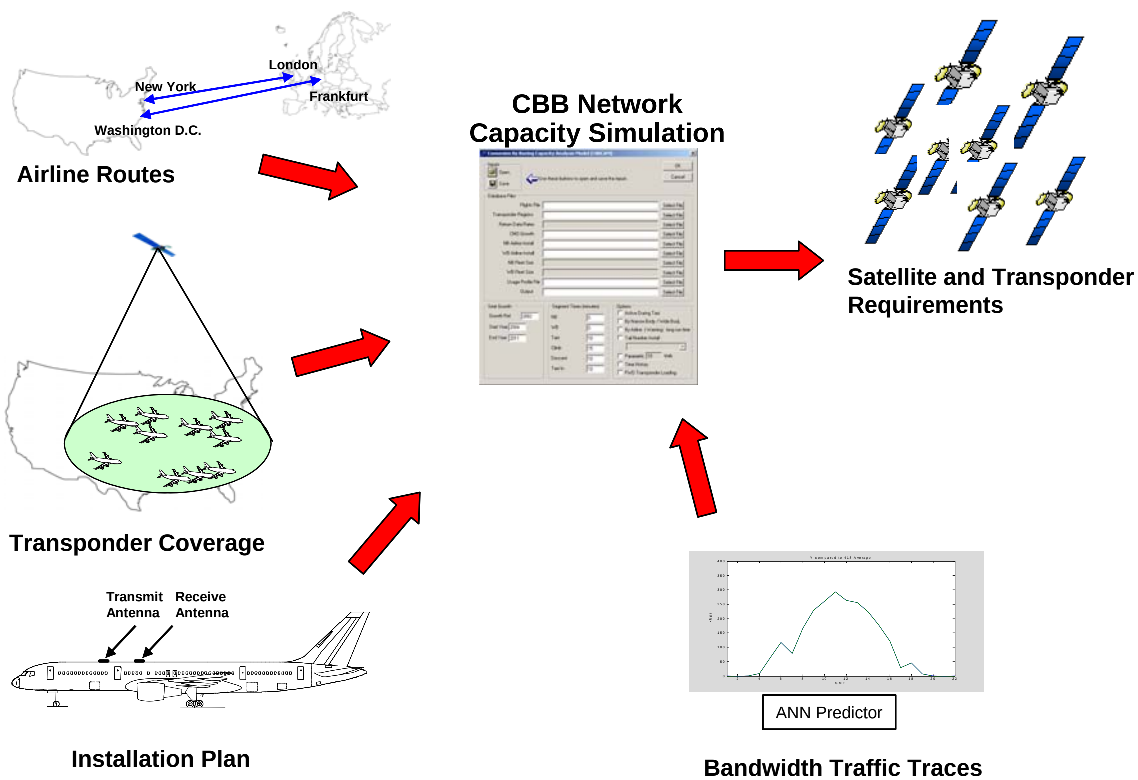


Figure 8-5 Proposed CSIM Architecture

There are several strengths. One is a decrease in uncertainty. Several of the input parameters which were estimates are no longer required - such as user characteristics (for input to the Norros equation) and penetration rate projections (estimating how many of the available passengers will connect to the network). Another strength is variability. The input profiles will be different for different regions of the globe and different types of aircraft and different flight durations and for several other factors. Another strength is adaptability. The neural networks will adapt to change through learning as the CBB system evolves.

8.3. ANN Predictor

Neural networks, also known as ANNs (artificial neural networks) or neurocomputing, are biologically inspired intelligent computing techniques that can be used very effectively for classification and prediction. Unlike traditional techniques which simply process information, neural networks learn and adapt in a manner similar to the human brain [Ham and Kostanic, 2001].

This sub-section describes the ANN predictor developed for simulation modeling of network traffic demand. The previous sub-section described how the ANN predictor is used by the overall CSIM simulation, along with other inputs, to predict network traffic demand. The disadvantages of the current methodology were discussed in Section 3. Sub-secton 8.4 describes the development of the simulation and the integration of the ANN predictor into the simulation in place of the current Norros equation modules. The results of simulation testing and a comparison between the ANN predictor and current simulation methodology are presented in Section 4 also.

8.3.1. Ground Rules. There were three ground rules used in development of the neural network model:

- Inputs for the neural network would come from values currently being collected by the network sniffers and data warehouses in use by CBB.
- The neural network would have the capability for learning through real network data, to allow for the ability to change and adapt.
- The output would be in a form that could be used to predict bandwidth demand by the simulation, which is the whole reason for modeling network data traffic on an NCS.

8.3.2. Purpose. The goal of the ANN predictor development effort was to build an ANN that could recognize flight route types from flight route attributes and then output corresponding bandwidth traffic traces that correctly represent the demand. These flight route bandwidth traffic traces had been selected from the data decomposition data mining process (Section 7) and would serve as output vectors from the ANN predictor to the CSIM core, and also for training of the ANN. The inputs vectors would consist of key attributes that would enable the neural network to accurately output the bandwidth traffic trace of a given flight route. Figure 8-6 illustrates the top level block diagram. The outputs could then be summed by the simulation to give the predicted total bandwidth needed for any number of flights operating concurrently according to published departure and arrival schedules.

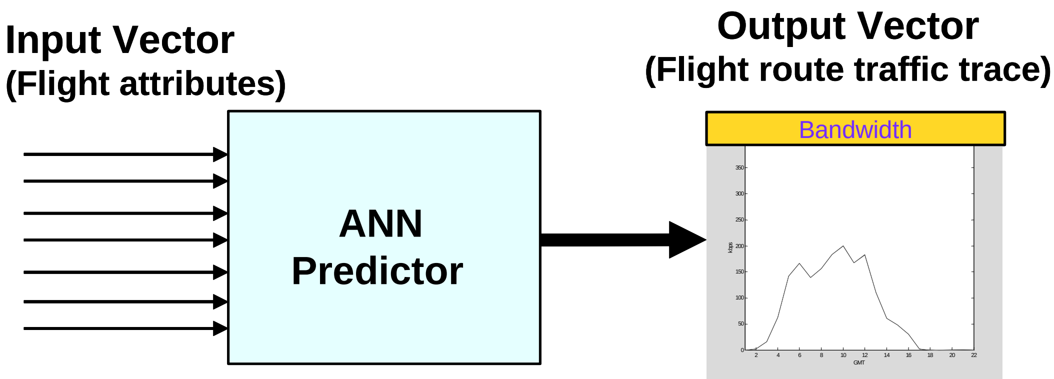


Figure 8-6 ANN Predictor Inputs and Outputs

8.3.3. Input Vectors. A study was conducted to determine key attributes that could be used to form the ANN input vectors. These input attributes would have to be sufficient enough to allow the ANN predictor to generate a predicted bandwidth profile. The following criteria were used:

- Contribution to model accuracy
- Reliability
- As few as possible
- Easily obtainable

First an IDEF analysis was performed on the CBB network examining all potential attributes. IDEF stands for integrated definition methods. According to the IDEF website [IDEF, 2005], IDEF is a methodology designed to help model the functions (activities, actions, processes, and operations) of a system or enterprise.

Federal Publication 183, “Integration Definition for Function Modeling (IDEF0)” contains the standard, which is issued by the National Institute of Standards and Technology after approval from the Secretary of Commerce.

The model consists of a hierarchical series of diagrams, text, and glossary. Functions are represented on the diagram by boxes. Interfaces are represented by arrows. Figure 8-7 [adapted from IDEF, 2005] illustrates the overall scheme.

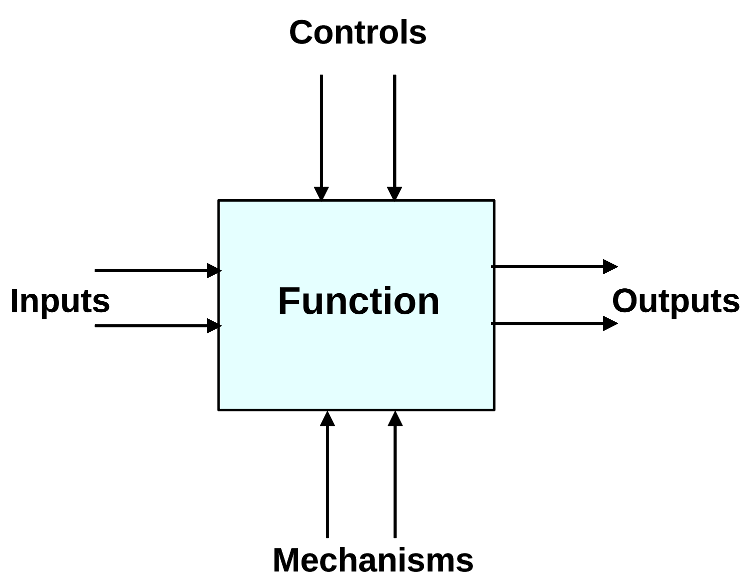


Figure 8-7 IDEF Inputs and Outputs

The first diagram in an IDEF model is the A-0 model diagram which is the top level context diagram. Figure 8-8 is a top level context diagram, A-0, for the CBB network CSIM simulation.

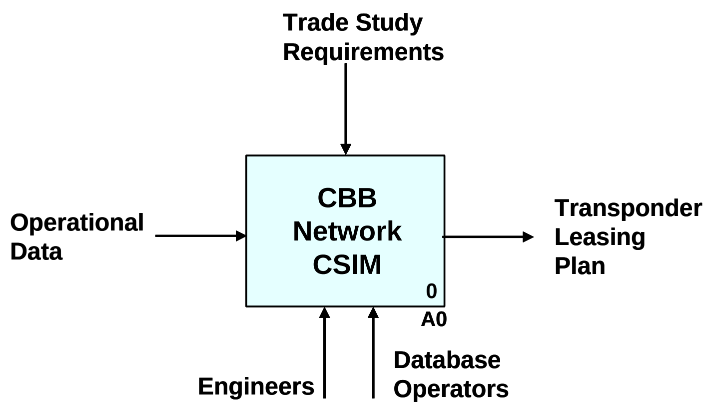


Figure 8-8 IDEF A0 Top Level Context Diagram for CBB CSIM

The next level diagram in the hierarchy is a child diagram of the function block for the top level context diagram. This is the A0 diagram shown below in Figure 8-9.

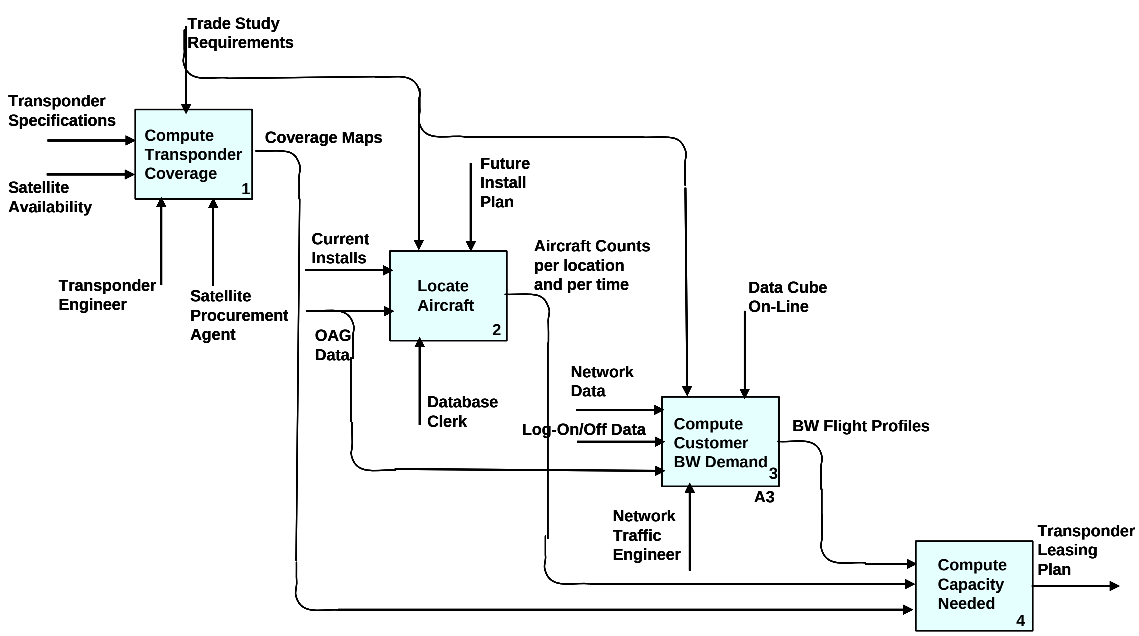


Figure 8-9 IDEF Child Diagram of Functional Block A0 for CBB CSIM

The next level diagram in the hierarchy is a child diagram of function block number 3, which is the one labeled Compute Customer BW Demand. This is the A3 diagram shown below in Figure 8-10.

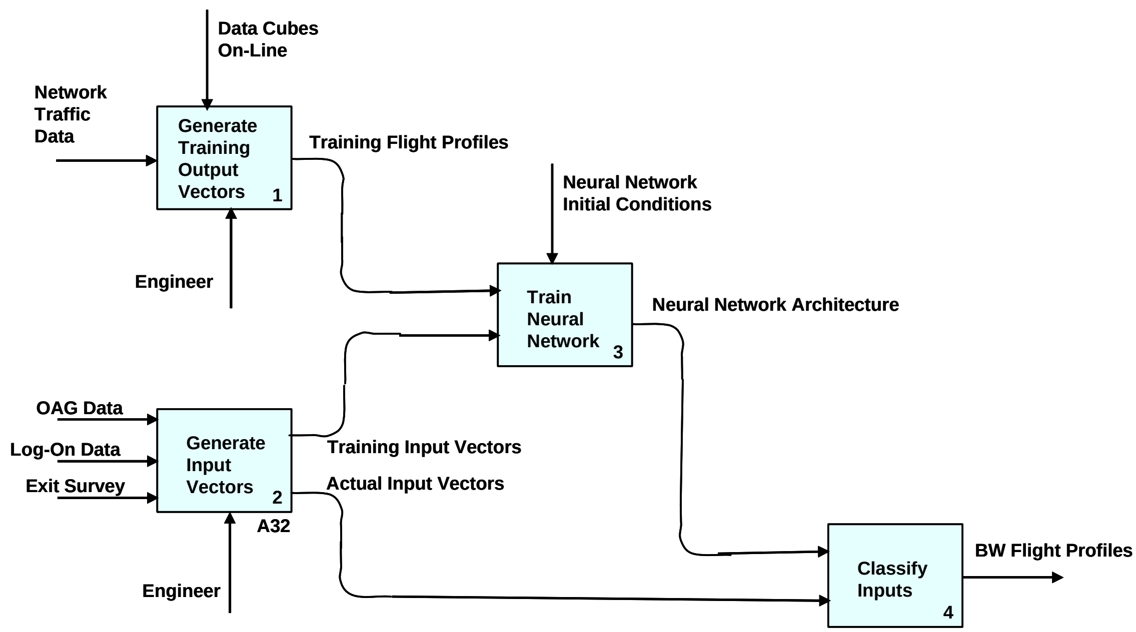


Figure 8-10 IDEF Child Diagram of Functional Block A3 for CBB CSIM

The next level diagram in the hierarchy is a child diagram of function block number 2, which is the one labeled Generate Input Vectors. This is the A32 diagram shown below in Figure 8-11.

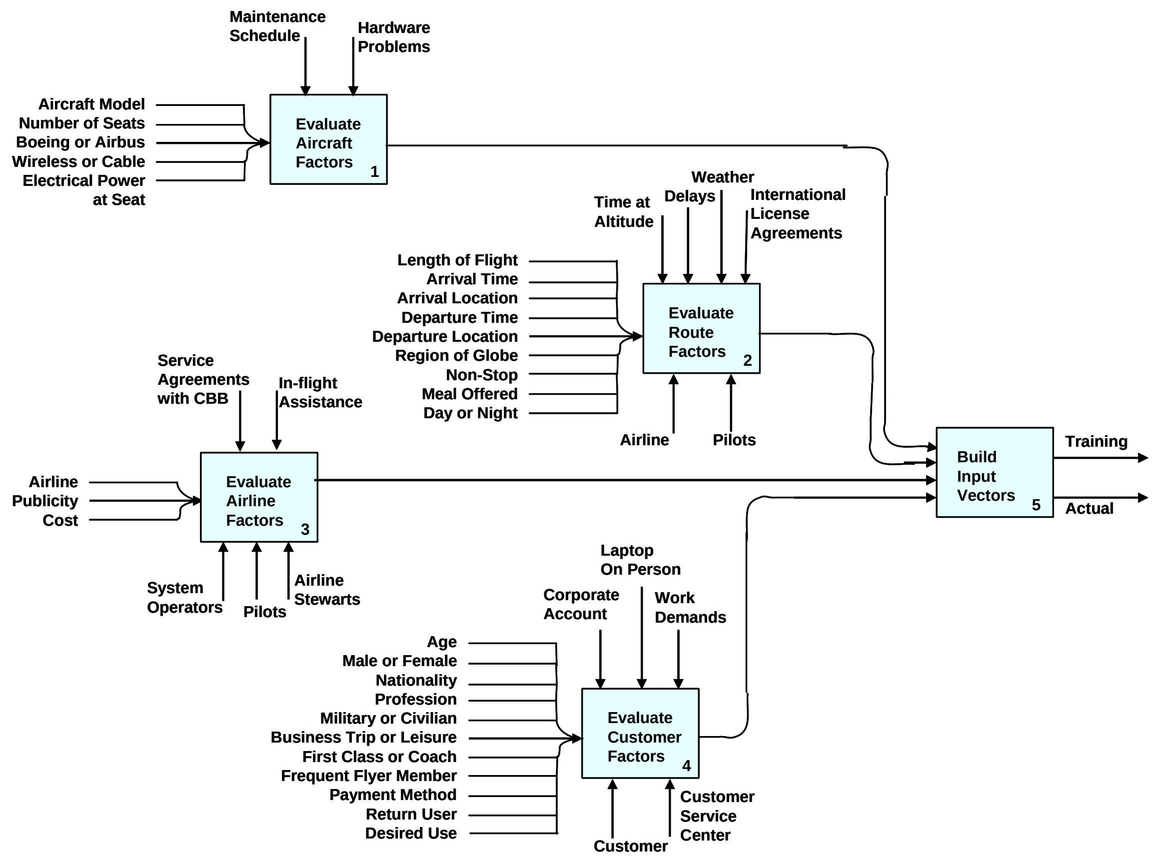


Figure 8-11 IDEF Child Diagram of Functional Block A32 for CBB CSIM

Table 8-1 contains the resultant attributes and the levels that were considered for each factor identified above in the A32 diagram. Column two also contains examples shown in parenthesis.

Table 8-1 Attributes from IDEF Study

Factor	Level
Aircraft Model	Two levels, nominal, aircraft model (747), version (747-400)
Number of Seats	One level, integer (397 seats)
Boeing or Airbus	One level, binary (Boeing/Airbus)
Wireless or Cable	One level, binary (wireless/cable)
Electrical Power	One level, binary (yes/no)
Length of Flight	One level, continuous number (9:45:30 = 9.758 hours)
Arrival Time	One level, continuous number (21:45:30 = 21.758 hours)
Arrival Location	One level, nominal, major airports only (LAX)
Departure Time	One level, continuous number (12:45:30 = 12.758 hours)
Departure Location	One level, nominal, major airports only (SEA)
Region of Globe	One level, nominal, major regions only (Atlantic)
Non-Stop	One level, binary (yes/no)
Meal Offered	One level, binary (yes/no)
Day or Night	One level, binary (day/night)
Airline	One level, nominal, airline designators (United Airlines)
Publicity	One level, binary (yes/no)
Cost	One level, continuous number ($29.50)
Age	One level, integer, round to years (21)
Male or Female	One level, binary (male/female)
Nationality	One level, nominal, countries (France)
Profession	One level, integer number (yes/no)
Military or Civilian	One level, binary (military/civilian)
Business or Leisure	One level, binary (business/leisure)
First Class or Coach	One level, binary (first class/coach)
Frequent Flyer	One level, binary (yes/no)
Payment Method	One level, nominal (credit card)
Return User	One level, binary (yes/no)
Desired Use	One level, nominal, primary use only (web surfing)

Attributes identified through the IDEF study were examined according to the study criteria, pivot tables were built, and rankings by gain (Quinlin, 1992), per the Equation 8.1, were performed.

$$Gain(T) = \sum_{j=1}^{k} \frac{freq(C_j, T)}{|T|} * \log_2\left(\frac{freq(C_j, T)}{|T|}\right) \tag{8.1}$$

Where freq(C,T) is the number of cases in T belonging to class C and |T| is the number of cases in set T. Eight key attributes were selected to form the input vectors for the ANN predictor as listed in Table 8-2.

Table 8-2 Selected Attributes

Number of users
Airline
Aircraft model (seats)
Length of flight (total minutes)
Departure time (local)
Arrival time (local)
Departure location
Arrival location

Note that length of flight is not the difference between arrival and departure times, which are a reflection of the time of day since they were calculated in local time and most flights crossed multiple time zones. Also, departure and arrival location had to each be broken into latitude and longitude for input to the model, which raised the total to 10 attributes.

After data cleaning, manipulation of format, and normalizing, the 10 attributes listed in Table 8-3 were combined into time-history input vectors for training the neural networks to perform pattern recognition and output flight route traffic traces.

Table 8-3 Input Vector Attributes

Number of users
Airline
Aircraft model (seats)
Length of flight (total minutes)
Departure time (local)
Arrival time (local)
Departure location latitude
Departure location longitude
Arrival location latitude
Arrival location longitude

8.3.4. Output Vectors. Output vectors from the ANN predictor are the flight route bandwidth traffic traces developed in the data decomposition data mining study described in Section 7. These bandwidth traffic traces are input to the CSIM core for aggregation and calculation of the total network's bandwidth demand. Thirty typical types of flights routes were chosen for the study to give a global representation. The bandwidth traffic traces were developed by taking a composite average of all the collected data for those flights over the course of the study. These time series traffic traces, composed of data points every second, were binned into 17 intervals of one hour each and normalized to equivalent numbers of users.

Figure 8-12 illustrates by comparing the composite trace, with data points every second, to the derived output vectors, with points binned in hour intervals. Figure 8-13 illustrates for a different flight route and Figure 8-14 for a third.

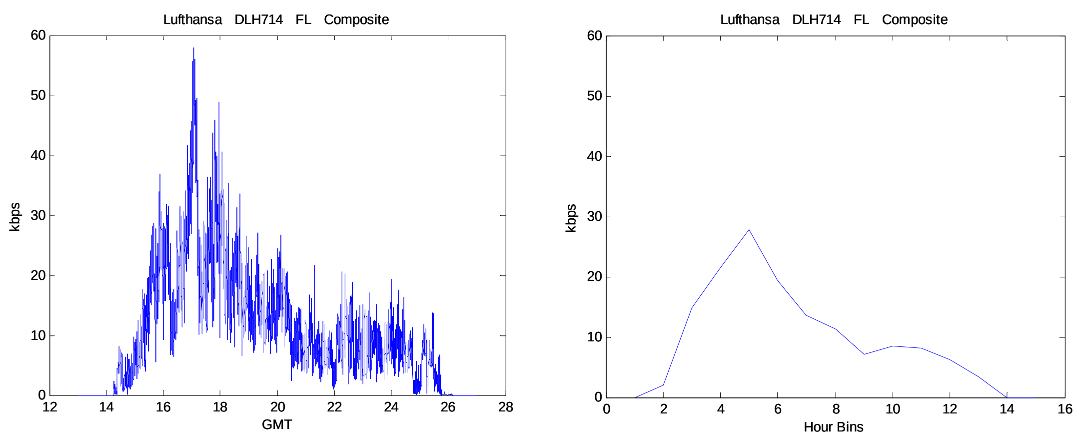


Figure 8-12 Composite Data Binned to 1 Hour for DLH 714

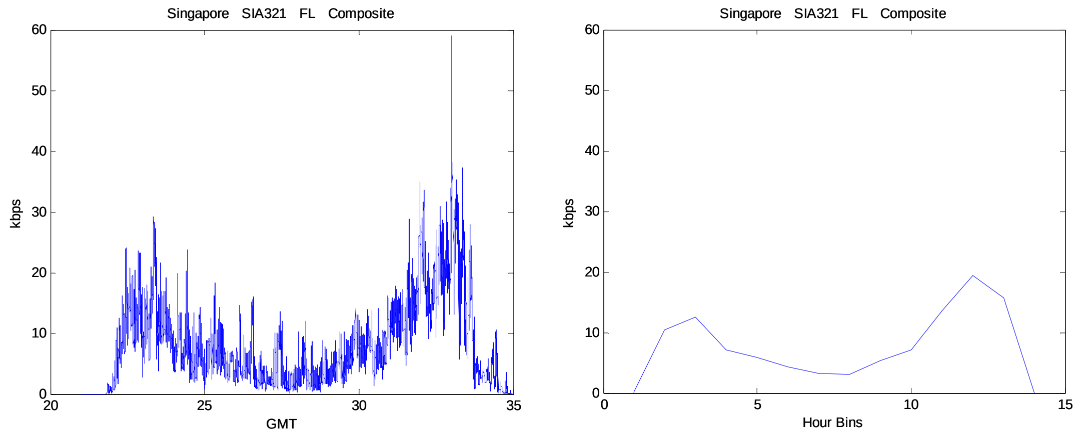


Figure 8-13 Composite Data Binned to 1 Hour for SIA 321

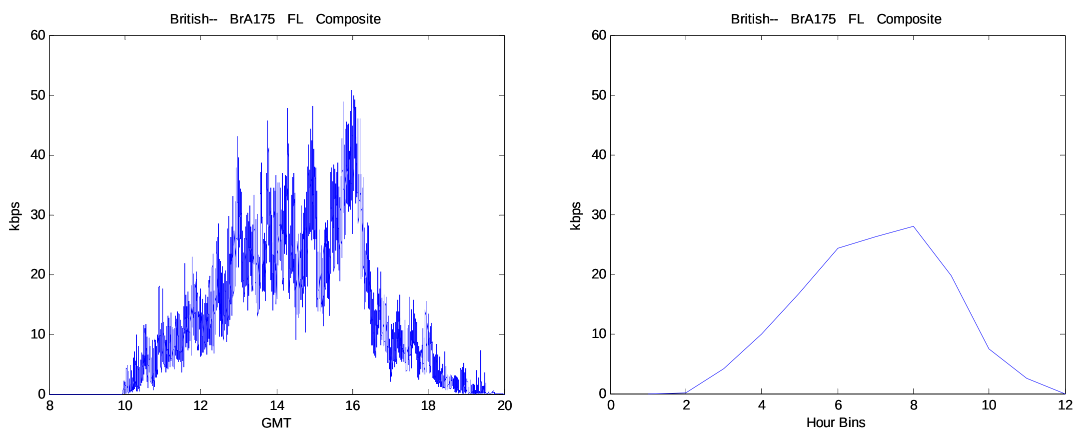


Figure 8-14 Composite Data Binned to 1 Hour for BA 175

Figure 8-15 illustrates a set of 6 output data sets representing flight route traffic traces for six long haul flights. Each line represents a different flight route. Notice how they are each distinct from the other. Figure 8-16 illustrates for 6 mid-range flight routes and Figure 8-17 illustrates for 6 short range flight routes. Individual graphs for all the flight routes are contained in Appendix A.

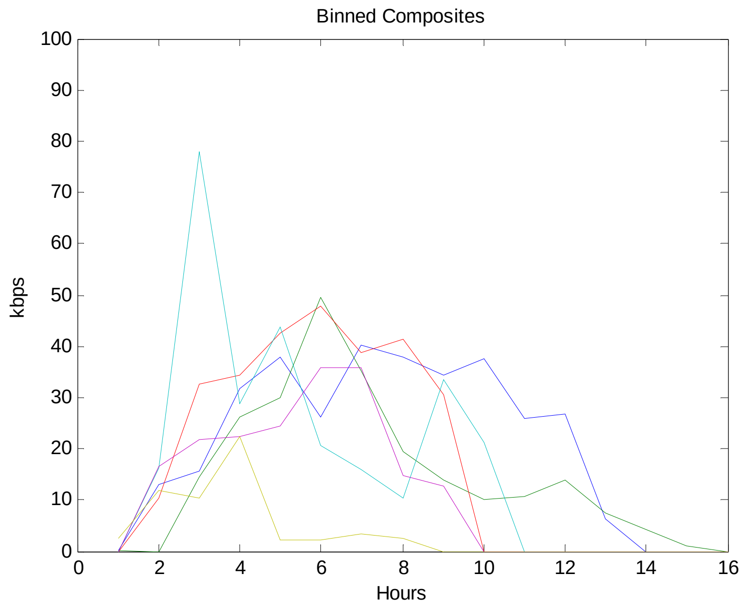


Figure 8-15 Output Vectors for 6 Flight Route – Long Range

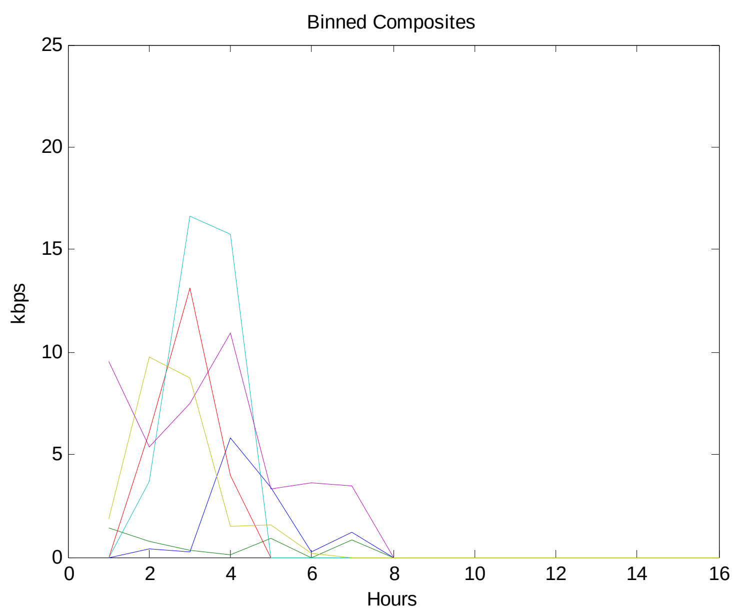


Figure 8-16 Output Vectors for 6 Flight Route – Mid-Range

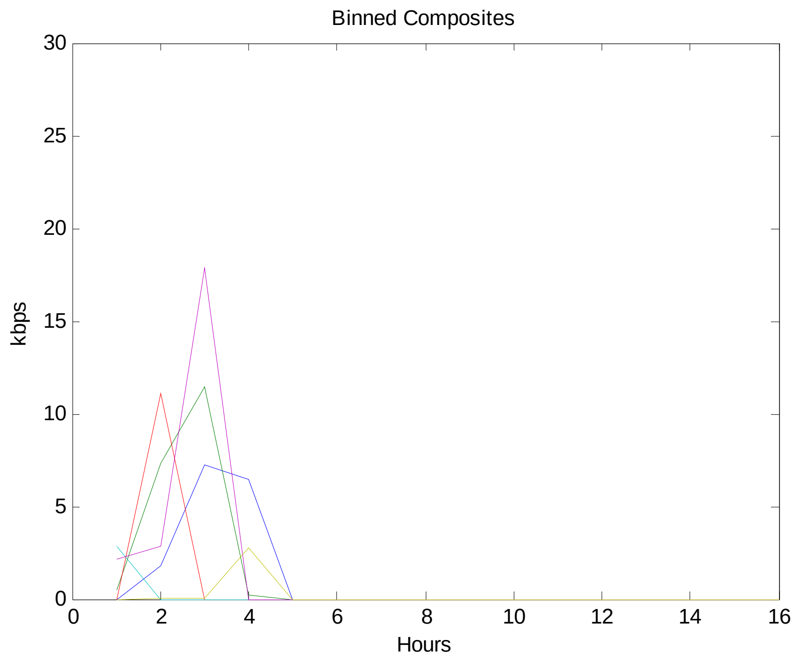


Figure 8-17 Output Vectors for 6 Flight Route – Short Range

It should be noted here that the ANN predictor has a natural advantage over the Norros equation. The ANN predictor outputs actual flight profiles that vary in scale whereas the Norros equation outputs a constant value. This is typical of current modeling techniques based on mathematical equations which are not very adaptable. Figures 8-18 and 8-19 illustrate the Norros equation estimates compared to actual bandwidth traffic. A constant value does not provide a very good representation.

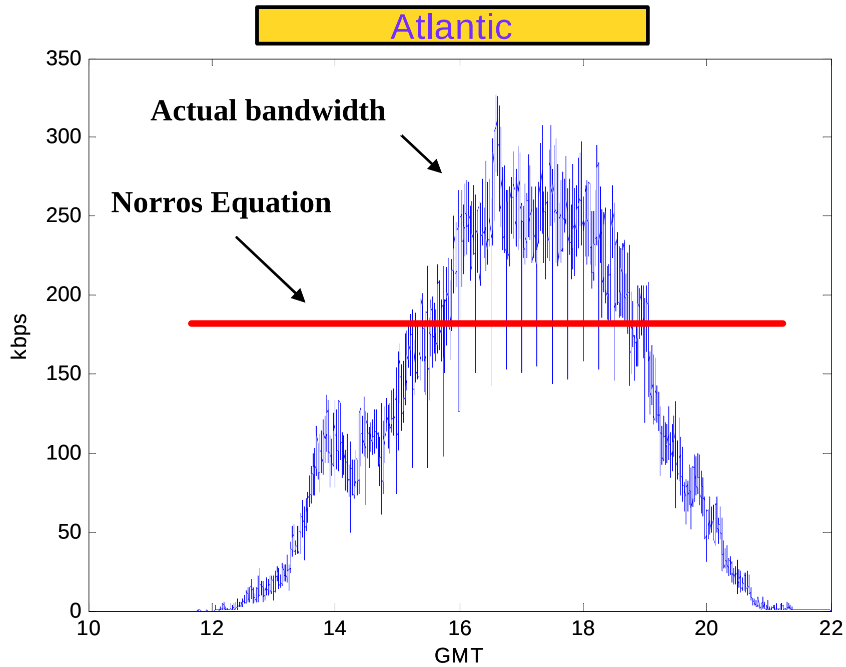


Figure 8-18 Norros Equation Estimate – Example 1

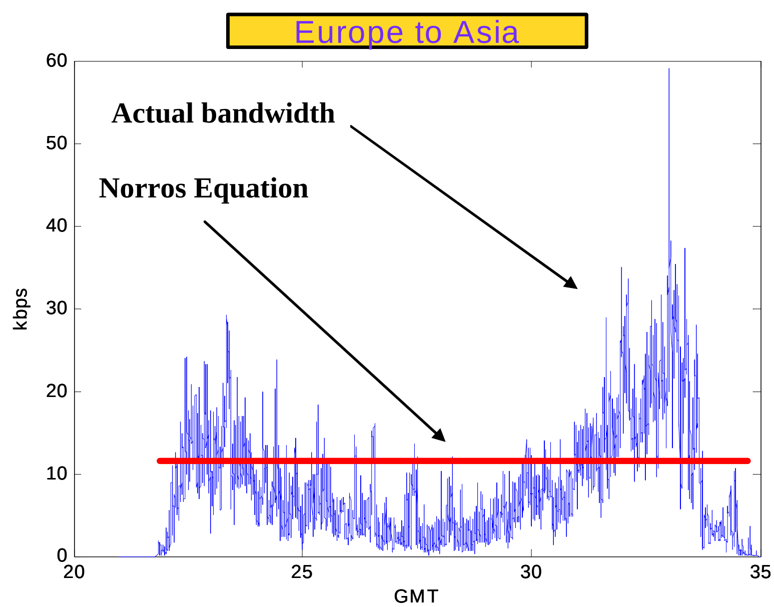


Figure 8-19 Norros Equation Estimate - Example 2

8.3.5. ANN Structure. A simple multi-layer feed-forward perceptron with back-propagation learning was used for the ANN predictor. Table 8-4 details the structure of the neural network and Figure 8-20 illustrates the network structure. Other types of neural networks were investigated, such as counter-propagation neural networks, radial basis function neural networks, Kohonen self-organizing maps, genetic algorithms, and evolving critical neural networks. Some are more accurate but the added complexity did not justify the gain, see Section 4-3, and the simple feed-forward perceptron with back-propagation learning proved sufficient. However, a second hidden layer did have to be added to the perceptron network structure to minimize the effects of noise as the number of input cases increased.

Table 8-4 Neural Network

Type	Feed-forward perceptron
Input Vectors	10 neurons
First Hidden Layer	39 neurons
Activation function	Tangent-sigmoid
Second Hidden Layer	39 neurons
Activation function	Logarithmic-sigmoid
Output Layer	17 neurons
Activation function	Pure linear
Training	Back-propagation
Training Algorithm	Levenberg-Marquardt
Convergence Criteria	e-5

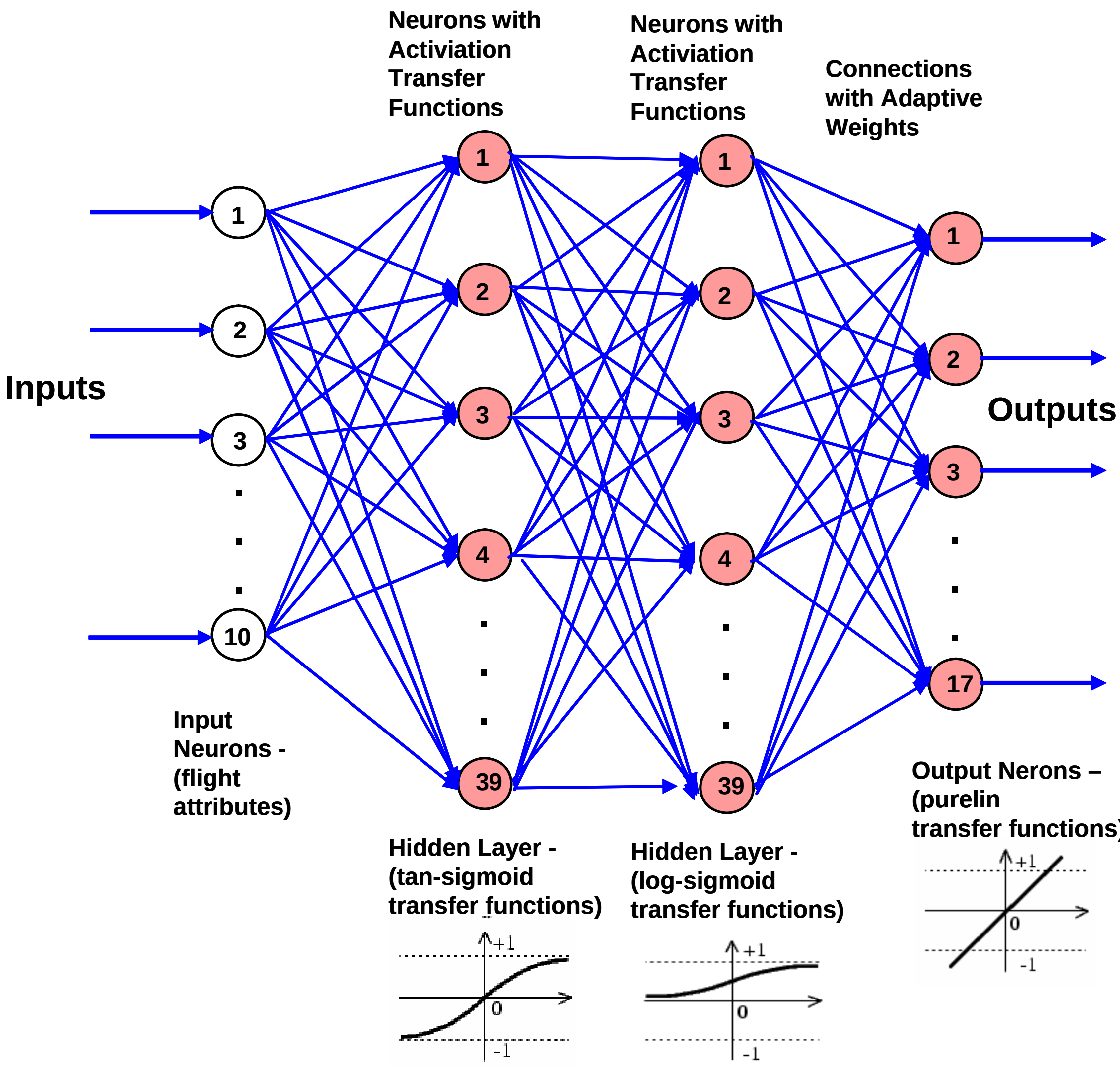


Figure 8-20 ANN Structure

The feed-forward perceptron assigns activation functions to the neurons and weights to the network lines. Once the perceptron has been trained through a learning algorithm it processes input vectors, in this case a vector of 10 flight route attributes, and then generates the output vector, in this case a vector of 17 points defining the bandwidth traffic trace for that flight route. Figure 8-21 illustrates the block diagram.

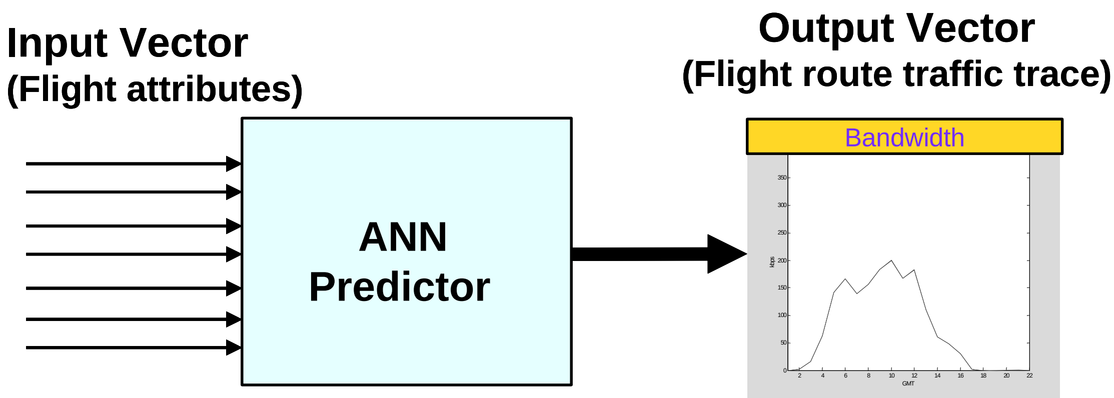


Figure 8-21 Feed-forward Perceptron

Three activation functions were used. Tangent-sigmoid was used on the first hidden layer. It generates an output between +1 and -1 as the neuron's net input goes from negative to positive infinity [Demuth and Beale, 2001]. Logarithmic-sigmoid was used on the second hidden layer. It generates output between +1 and 0 as the neuron's net input goes from negative to infinity [Demuth and Beale, 2001]. A linear activation function was used on the output layer. It outputs the neuron's net input without modification.

Back-propagation learning involves a set of iterations. First a training vector is passed through the network to determine the error between the desired output and the network's output in its current state. Then the weights on the network lines to each neuron are adjusted according to a scaling factor towards lower local error. This process is back-propagated through the network until all the weights are adjusted. Then another training iteration takes place. This continues until the error criteria have been reached or the network stabilizes. The Levenberg-Marquardt training algorithm adjusts weights on network lines in the direction of the negative gradient to minimize error. It uses the Jacobian matrix of first derivatives of the network errors with respect to the weights and biases [Ham and Kostanic, etc]. For this simulation all modules were developed with Matlab® version 6.0 with the Neural Network Toolbox® version 4.0 [Demuth and Beale, 2001; Hanselman and Littlefield, 2001].

8.4. PERFORMANCE EVALUATION

ANN simulation performance evaluation consisted of two main parts. The first part was accuracy testing of the ANN predictor, described in Section 8.3, for all 30 flight routes and then comparing output from the ANN predictor against estimates from the Norros equation, described in Section 6.7.2.6, Equations 6.2 and 6.2. Details on the development of the Norros equation as a mathematical representation are contained in Section 3.6.3 and a discussion of the advantages and disadvantages in Section 3.6.4. Table 8-5 lists the thirty standard flight routes used for performance evaluation. The chart contains flight numbers, which are in pairs to and from selected cities. The chart also contains airline name and designation, origination city and designation, destination city and designation, departure time local, arrival time local, and the aircraft designator, from which the size of the aircraft and number of seats can be determined.

Table 8-5 Flight Routes

	Flight Number	Airline	Origination	Destination	Departure	Arrival	Aircraft
1.	DLH 418	Lufthansa Airlines (LH)	Frankfurt (FRA)	Washington D.C. (IAD)	13:10	15:55	744
2.	DLH 419	Lufthansa Airlines (LH)	Washington D.C. (IAD)	Frankfurt (FRA)	17:55	7:35	744
3.	BA 175	British Airways (BA)	London (LHR)	New York (JFK)	11:00	13:50	744
4.	BA 112	British Airways (BA)	New York (JFK)	London (LHR)	18:30	6:25	744
5.	DLH 452	Lufthansa Airlines (LH)	Munich (MUC)	Los Angeles (LAX)	11:10	14:25	343
6.	DLH 453	Lufthansa Airlines (LH)	Los Angeles (LAX)	Munich (MUC)	16:35	12:50	343
7.	DLH 714	Lufthansa Airlines (LH)	Munich (MUC)	Tokyo (NRT)	15:30	10:00	343
8.	DLH 715	Lufthansa Airlines (LH)	Tokyo (NRT)	Munich (MUC)	12:20	17:35	343
9.	ANA 919	All Nippon Airways (NH)	Tokyo (NRT)	Shanghai (PVG)	9:50	11:55	777
10.	ANA 920	All Nippon Airways (NH)	Shanghai (PVG)	Tokyo (NRT)	13:10	16:55	777
11.	SIA 320	Singapore Airlines (SQ)	Singapore (SIN)	London (LHR)	12:40	19:10	744
12.	SIA 321	Singapore Airlines (SQ)	London (LHR)	Singapore (SIN)	22:15	18:00	744
13.	JAL005	Japan Airlines (JL)	New York (JFK)	Tokyo (NRT)	13:30	16:20	744
14.	JAL006	Japan Airlines (JL)	Tokyo (NRT)	New York (JFK)	12:00	11:25	744
15.	CAL 011	China Airlines (CI)	New York (JFK)	Anchorage (ANC)	23:55	3:25	343
16.	CAL 012	China Airlines (CI)	Anchorage (ANC)	New York (JFK)	11:20	22:10	343
17.	SAS 937	Scandinavian Airlines (SK)	Copenhagen (CPH)	Seattle (SEA)	15:35	16:35	343
18.	SAS 938	Scandinavian Airlines (SK)	Seattle (SEA)	Copenhagen (CPH)	18:55	13:25	343
19.	SAS 943	Scandinavian Airlines (SK)	Copenhagen (CPH)	Chicago (ORD)	15:30	17:30	763
20.	SAS 944	Scandinavian Airlines (SK)	Chicago (ORD)	Copenhagen (CPH)	22:15	13:30	763
21.	KAL 703	Korean Airlines (KE)	Seoul (ICN)	Tokyo (NRT)	10:20	12:35	744
22.	KAL 704	Korean Airlines (KE)	Tokyo (NRT)	Seoul (ICN)	14:55	17:20	744
23.	SIA 001	Singapore Airlines (SQ)	Hong Kong (HKG)	Singapore (SIN)	8:00	11:35	744
24.	SIA 002	Singapore Airlines (SQ)	Singapore (SIN)	Hong Kong (HKG)	17:00	20:45	744
25.	SIA 011	Singapore Airlines (SQ)	Tokyo (NRT)	Singapore (SIN)	19:10	1:00	744
26.	SIA 012	Singapore Airlines (SQ)	Singapore (SIN)	Tokyo (NRT)	9:50	17:35	744
27.	DLH 582	Lufthansa Airlines (LH)	Frankfurt (FRA)	Cairo (CAI)	10:00	15:00	332
28.	DLH 583	Lufthansa Airlines (LH)	Cairo (CAI)	Frankfurt (FRA)	16:30	19:45	332
29.	DLH 632	Lufthansa Airlines (LH)	Munich (MUC)	Riyadh (RUH)	13:55	20:25	332
30.	DLH 633	Lufthansa Airlines (LH)	Riyadh (RUH)	Munich (MUC)	3:05	8:00	332

The second part consisted of simulation runs with the ANN predictor loaded into the CSIM. Simulation runs #1 used the CBB trial data for development of the neural network structure and to test feasibility as part of a concept demonstration exercise. Simulation runs #2 used operational data for one transponder region. Simulation runs #3 increased the scale to a global model. In all cases results from the ANN based model was evaluated for accuracy and then compared against results from the Norros equation based model.

The evaluations included models of varying scales: 1) one-on-one flight route comparison, 2) concept development simulation comparison, 3) a regional simulation comparison, and 4) a global simulation comparison.

8.4.1. One-on-One Comparison. Flight route traffic traces generated by the ANN predictor were compared against expected values and then against flight route traffic traces from the Norros equation. The Norros equation outputs a constant value based on the length of flight and number of users. The ANN predictor generates a predicted bandwidth traffic trace composed of 17 points on a time-history vector. A cubic spline interpolation was used between data points for graphing purposes. Comparisons were made on all 30 representative flight routes. The neural network outputs were significantly more accurate, not only in scale, but because they vary along the horizontal axis to match the actual values, whereas the Norros equation outputs a constant value. Figures 8-22, 8-23, and 8-24 show three examples for various range flights. Plots for all the flight routes are contained in Appendix B.

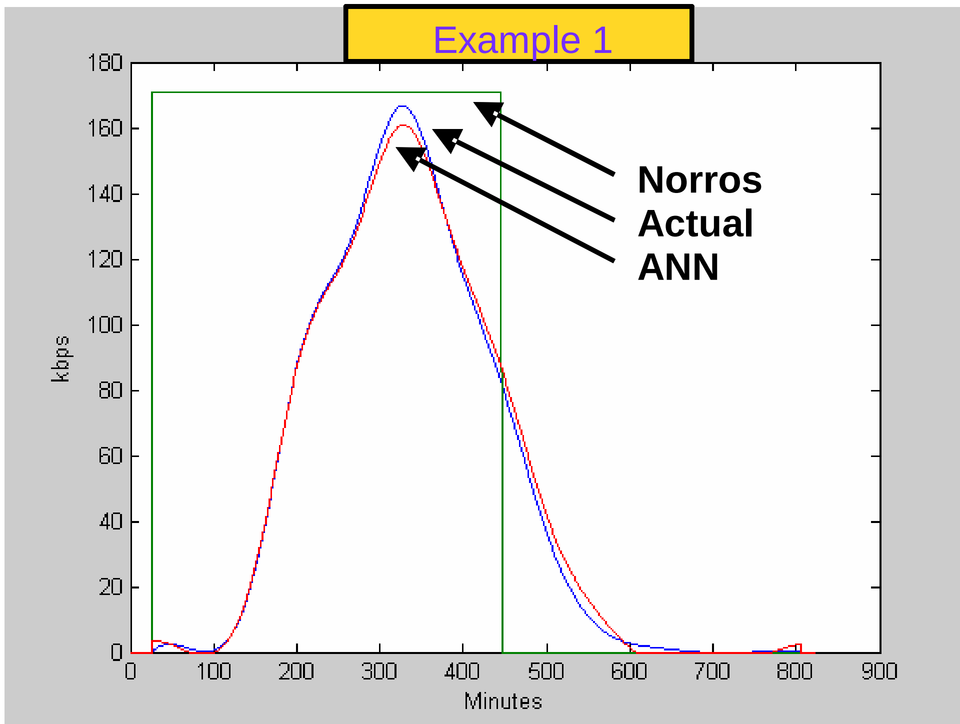


Figure 8-22 Generated Flight Route Traffic Traces – Comparison 1

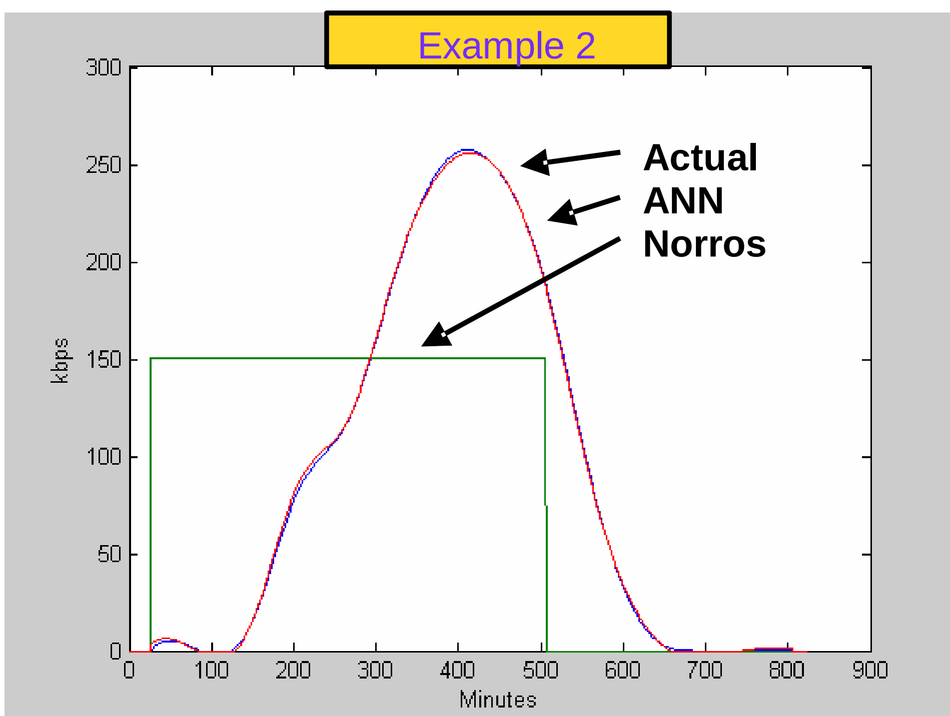


Figure 8-23 Generated Flight Route Traffic Traces – Comparison 2

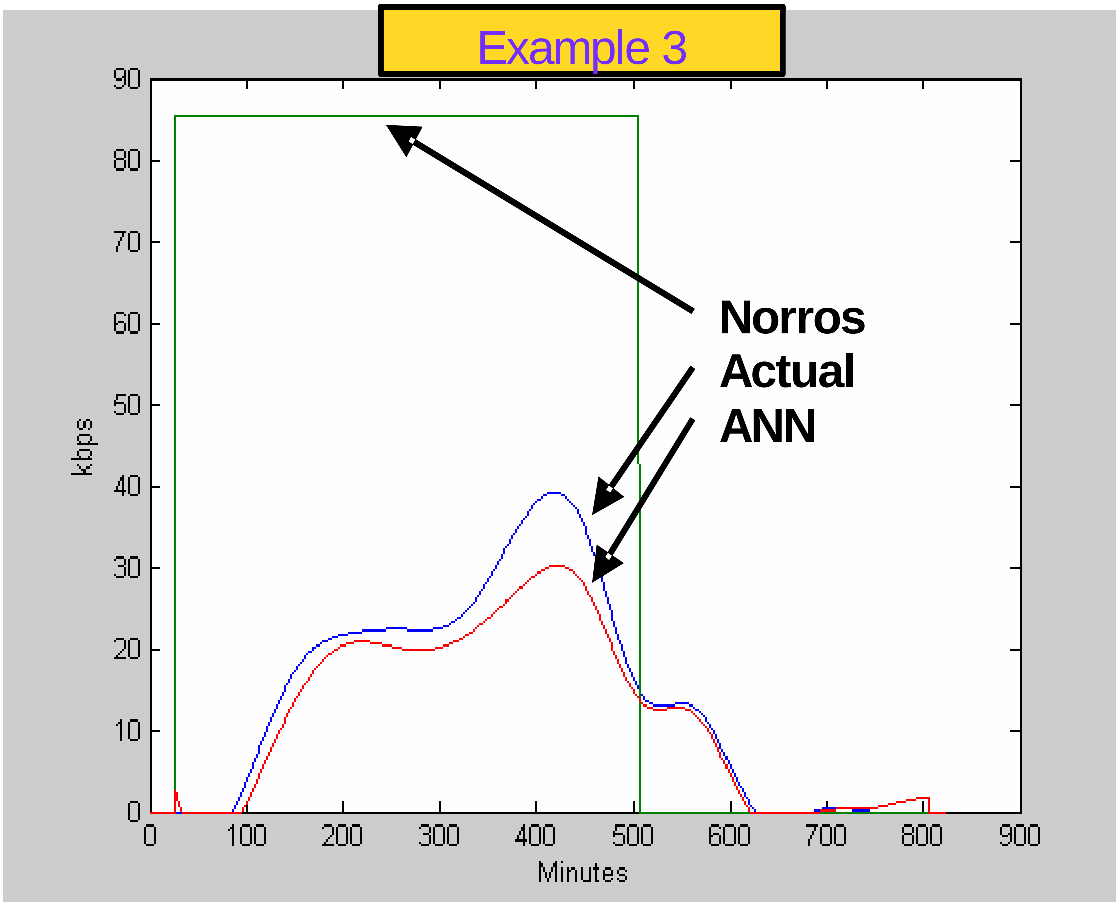


Figure 8-24 Generated Flight Route Traffic Traces – Comparison 3

The improvement in accuracy was considerable for all 30 flight routes. Average errors from the expected value for a flight route, for the Norros equation, ranged from 39.1 to 99.5 kbps with an average of 62.7 kbps. Average errors from the expected value for a flight route, for the ANN, ranged from 0 .1 to 2.6 bps with an average of 1.0 bps. Table 8-6 contains the statistics.

Table 8-6 One-On-One Comparison of Average Errors

Flight	Average Error (kbps)	
	Norros	**ANN**
1	58.2391	0.0001
2	54.1722	0.0014
3	60.2146	0.0001
4	55.8083	0.0001
5	48.1816	0.0001
6	51.3295	0.0002
7	65.8969	0.0010
8	50.6480	0.0019
9	85.7078	0.0017
10	77.3187	0.0050
11	39.0915	0.0023
12	48.8326	0.0014
13	42.3335	0.0004
14	53.2897	0.0003
15	55.0250	0.0005
16	51.7578	0.0021
17	57.2813	0.0008
18	61.9477	0.0016
19	88.7665	0.0008
20	91.8675	0.0010
21	87.4132	0.0015
22	99.5353	0.0026
23	54.1393	0.0004
24	60.4965	0.0003
25	42.0443	0.0002
26	41.0144	0.0001
27	70.1716	0.0002
28	65.9520	0.0007
29	82.1474	0.0006
30	80.3793	0.0001
Mean	62.7001	0.0010

8.4.2. Simulation #1 Results – Concept Demonstration. The initial concept demonstration simulation was configured for four trans-Atlantic flights routes and 100 flights. Figure 8-25 illustrates the routes. Each line represents two flight routes, forward and return. Start times, departure and arrival locations, and flight numbers for each of the 100 flights were loaded into the simulation.

- Lufthansa Airlines DLH 418 from Frankfurt to Washington D.C.
- Lufthansa Airlines DLH 419 from Washington D.C. to Frankfurt
- British Airways BA 175 from London to New York
- British Airways BA 112 from New York to London

Figure 8-25 Concept Demonstration Flight Routes

Estimated bandwidth demand was calculated for the Norros based simulation and the ANN based simulation. Figure 8-26 illustrates the difference in bandwidth traffic traces. The Norros equation based simulation is significantly higher than the expected value. The ANN based simulation more closely follows the expected values. Table 8-7 contains some statistics.

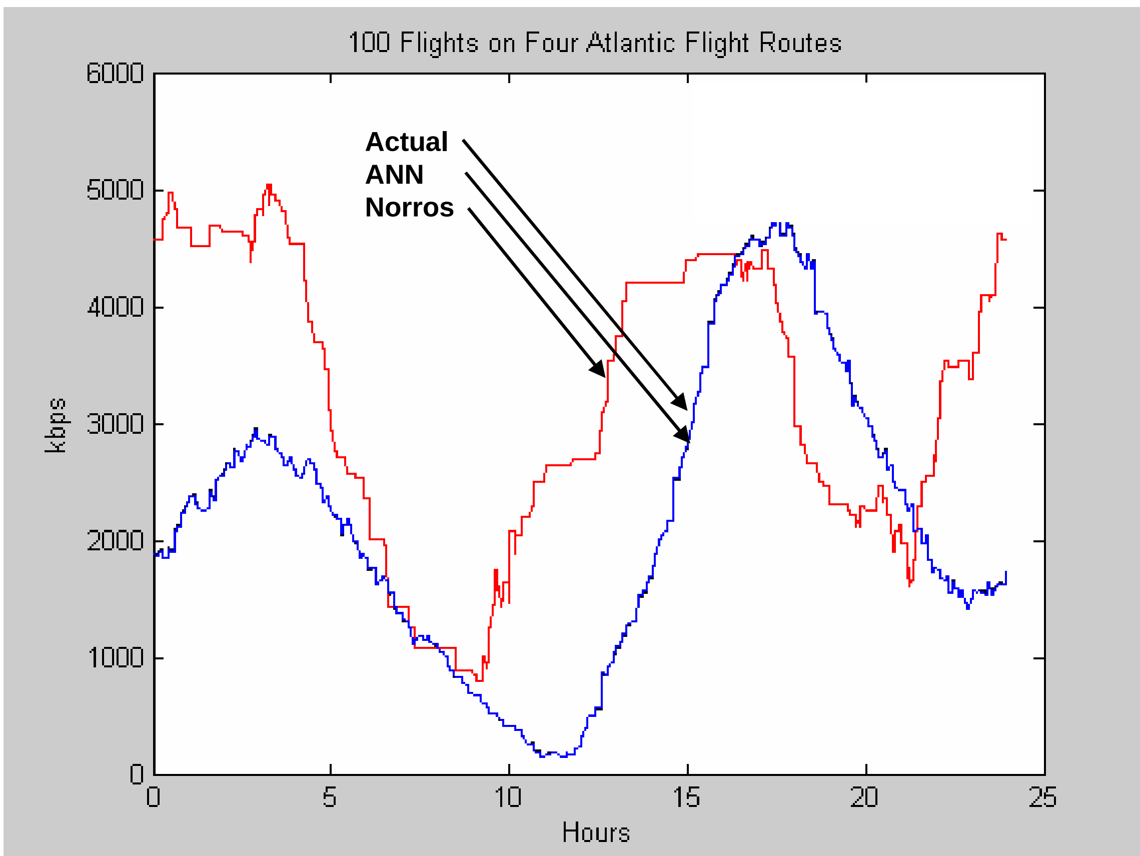


Figure 8-26 Concept Demonstration Bandwidth Traces

Table 8-7 Concept Demonstration Simulation Results

	Average Bandwidth (kbps)	Peak Bandwidth (kbps)
Actual	2,153.8	4,790.4
Norros	3,189.0	5,048.4
ANN	2,152.0	4,744.0

8.4.3. Simulation #2 Results – Regional Model. The finalized simulation was configured to use eight operational trans-Atlantic flights routes, one transponder region, and 500 flights. Figure 8-27 illustrates the routes. Each line represents two flight routes, forward and return. Start times, departure and arrival locations, and flight numbers for each of the 500 flights were loaded into the simulation.

- Lufthansa Airlines DLH 452 from Munich to Los Angeles
- Lufthansa Airlines DLH 453 from Los Angeles to Munich
- Scandinavian Airlines SAS 937 from Copenhagen to Seattle
- Scandinavian Airlines SAS 938 from Seattle to Copenhagen
- Scandinavian Airlines SAS 943 from Copenhagen to Chicago
- Scandinavian Airlines SAS 944 from Chicago to Copenhagen
- Japan Airlines JAL 005 from New York to Tokyo
- Japan Airlines JAL 006 from Tokyo to New York

Figure 8-27 Atlantic Region Flight Routes

Required bandwidth demand was calculated for the Norros based simulation and the ANN based simulation. Figure 8-28 illustrates the difference in bandwidth traffic traces. Again the Norros equation based simulation is significantly higher than the expected value. The ANN based simulation more closely follows the expected values. Table 8-8 contains some statistics.

Table 8-8 Atlantic Region Simulation Results

	Average Bandwidth (kbps)	Peak Bandwidth (kbps)
Actual	2,153.8	4,790.4
Norros	3,189.0	5,048.4
ANN	2,152.0	4,744.0

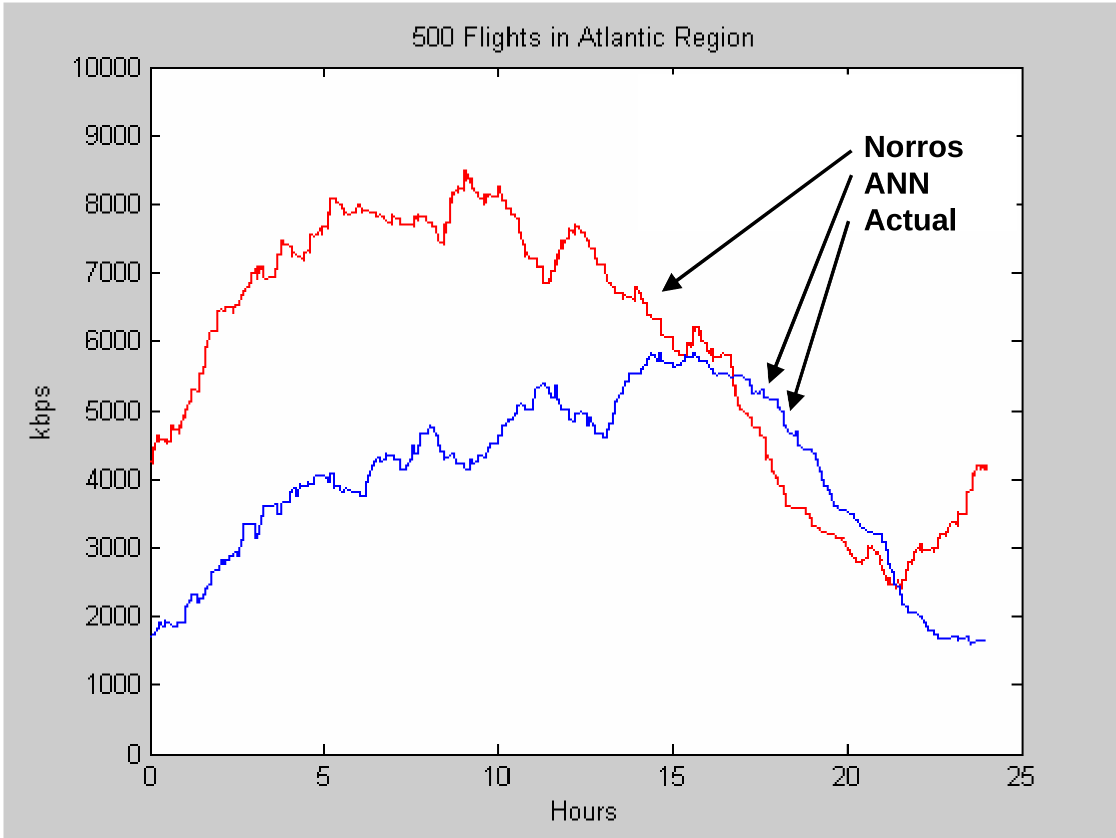


Figure 8-28 Atlantic Region Bandwidth Traces

8.4.4. Simulation #3 Results – Global Model. The finalized simulation was re-configured to use 30 flights routes around the globe, five transponder regions, and 3,000 flights. Figure 8-29 illustrates the routes. Each line represents two flight routes, forward and return. Start times, departure and arrival locations, and flight numbers for each of the 3,000 flights were loaded into the simulation.

- Lufthansa Airlines DLH 418 from Frankfurt to Washington D.C.
- Lufthansa Airlines DLH 419 from Washington D.C. to Frankfurt
- British Airways BA 175 from London to New York
- British Airways BA 112 from New York to London
- Lufthansa Airlines DLH 452 from Munich to Los Angeles
- Lufthansa Airlines DLH 453 from Los Angeles to Munich
- Scandinavian Airlines SAS 937 from Copenhagen to Seattle
- Scandinavian Airlines SAS 938 from Seattle to Copenhagen
- Scandinavian Airlines SAS 943 from Copenhagen to Chicago
- Scandinavian Airlines SAS 944 from Chicago to Copenhagen
- China Airlines CAL 011 from New York to Anchorage
- China Airlines CAL 012 from Anchorage to New York
- Lufthansa Airlines DLH 714 from Munich to Tokyo
- Lufthansa Airlines DLH 715 from Tokyo to Munich
- Japan Airlines JAL 005 from New York to Tokyo
- Japan Airlines JAL 006 from Tokyo to New York
- Singapore Airlines SIA 320 from Singapore to London
- Singapore Airlines SIA 321 from London to Singapore
- Lufthansa Airlines DLH 832 from Munich to Riyadh
- Lufthansa Airlines DLH 833 from Riyadh to Munich
- Lufthansa Airlines DLH 682 from Frankfurt to Cairo
- Lufthansa Airlines DLH 683 from Cairo to Frankfurt
- Korean Airlines KAL 703 from Seoul to Tokyo

- Korean Airlines KAL 704 from Tokyo to Seoul
- All Nippon Airways ANA 821 from Tokyo to Shanghai
- All Nippon Airways ANA 822 from Shanghai to Tokyo
- Singapore Airlines SIA 011 from Tokyo to Singapore
- Singapore Airlines SIA 012 from Singapore to Tokyo
- Singapore Airlines SIA 001 from Hong Kong to Singapore
- Singapore Airlines SIA 002 from Singapore to Hong Kong

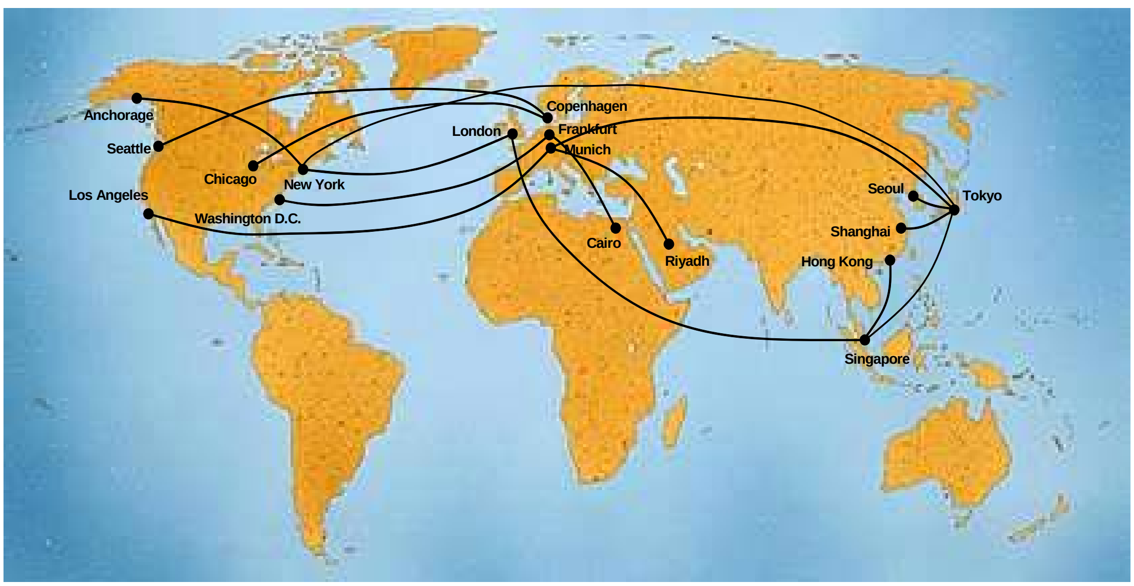


Figure 8-29 All Flight Routes

Required bandwidth demand was calculated for the Norros based simulation and the ANN based simulation. Figures 8-30 to 8-34 illustrate the difference in bandwidth traffic traces. Again the Norros equation based simulation is significantly higher than the expected value. The ANN based simulation more closely follows the expected values. Table 8-9 contains some statistics illustrating the improvements in performance comparing expected values to the values from the Norros equation based simulation and to the ANN based simulation.

Table 8-9 Global Simulation Results

	Average Bandwidth (kbps)	Peak Bandwidth (kbps)
USA - West		
Actual	4,717.7	7,249.4
Norros	5,945.9	9,133.4
ANN	4,717.6	7,249.4
USA - East		
Actual	9,622.7	19,713.0
Norros	14,297.0	22,453.0
ANN	9,652.5	19,804.0
Mid-East		
Actual	527.3	1,895.8
Norros	2,771.1	7,319.4
ANN	527.3	1,859.3
Asia		
Actual	3,663.8	5,871.8
Norros	9,450.0	13,015.0
ANN	3,663.8	5,871.6
Far East		
Actual	332.8	1,492.6
Norros	6,674.8	22,759.0
ANN	568.5	1,609.0
Averages		
Actual	3,772.9	7,244.5
Norros	7,827.8	14,936.0
ANN	3,825.9	7,278.7

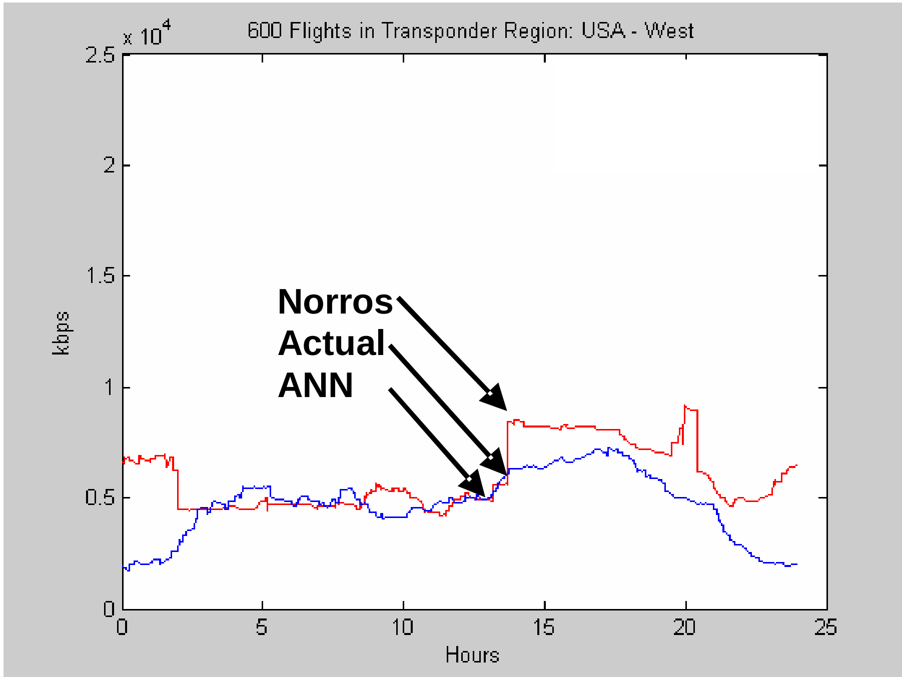


Figure 8-30 Global Region 1 Bandwidth Traces

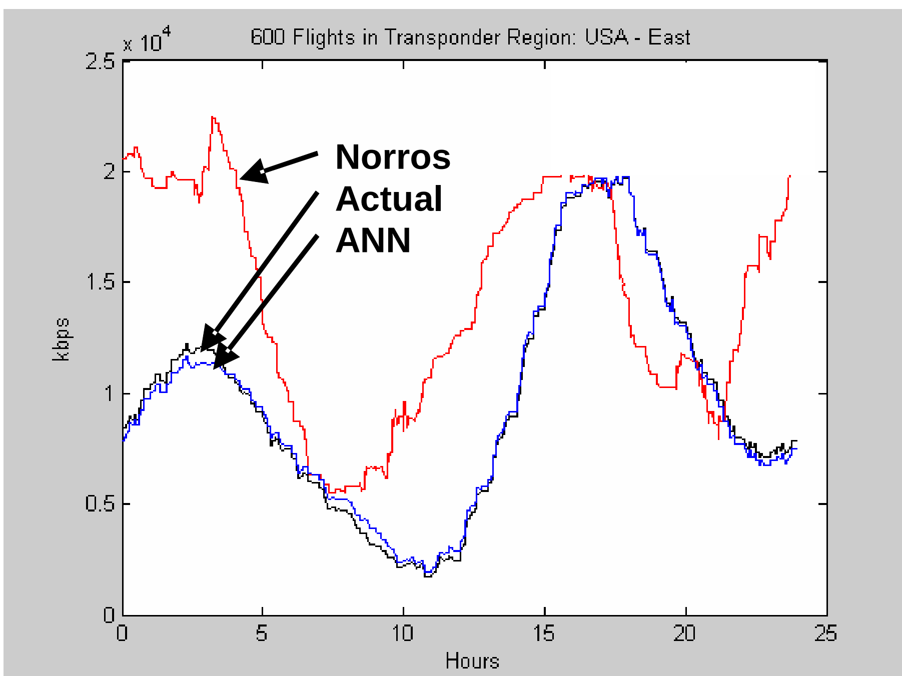


Figure 8-31 Global Region 2 Bandwidth Traces

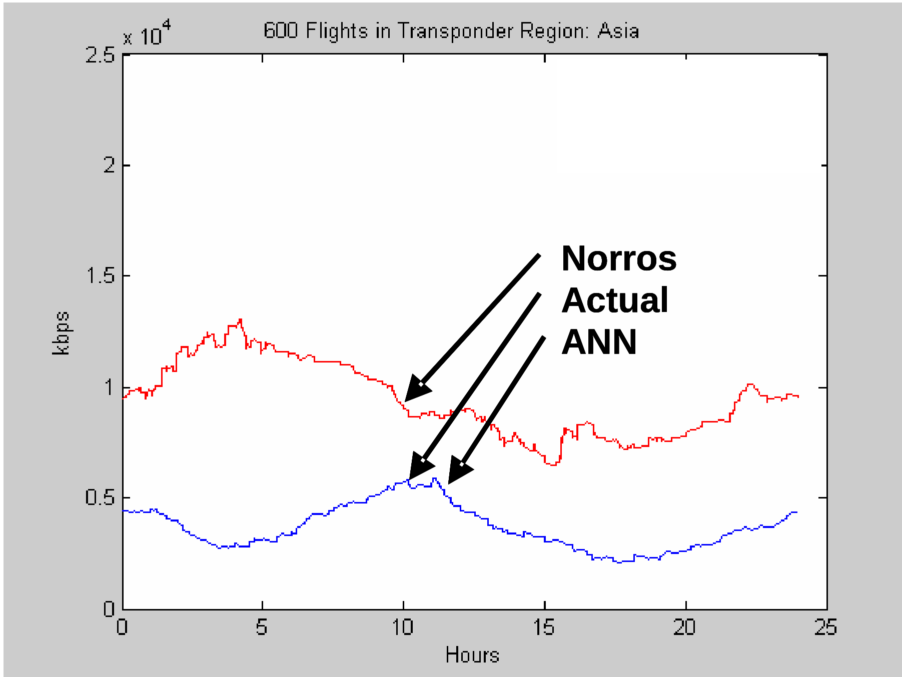


Figure 8-32 Global Region 3 Bandwidth Traces

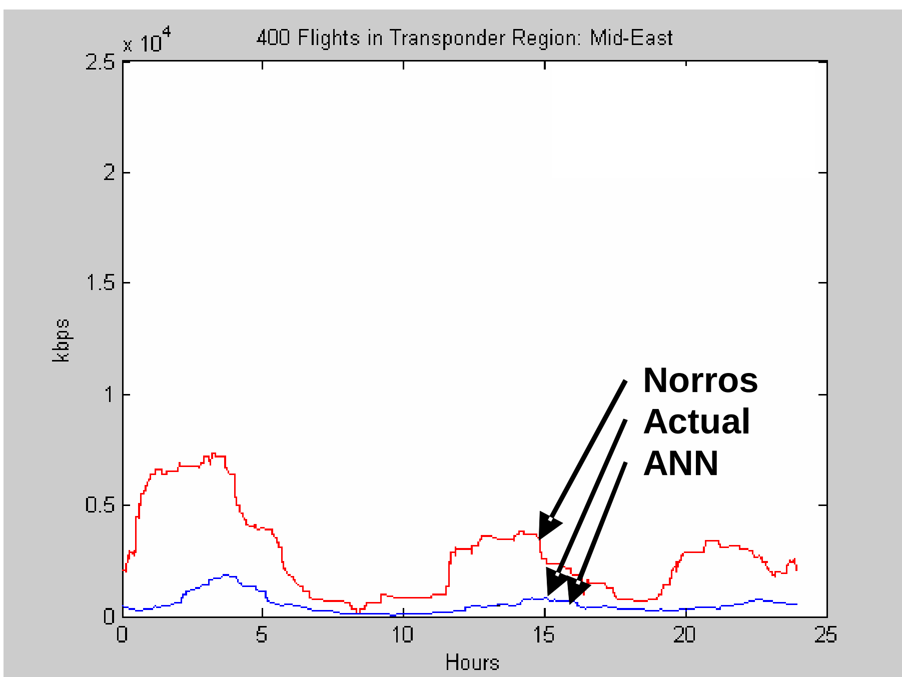


Figure 8-33 Global Region 4 Bandwidth Traces

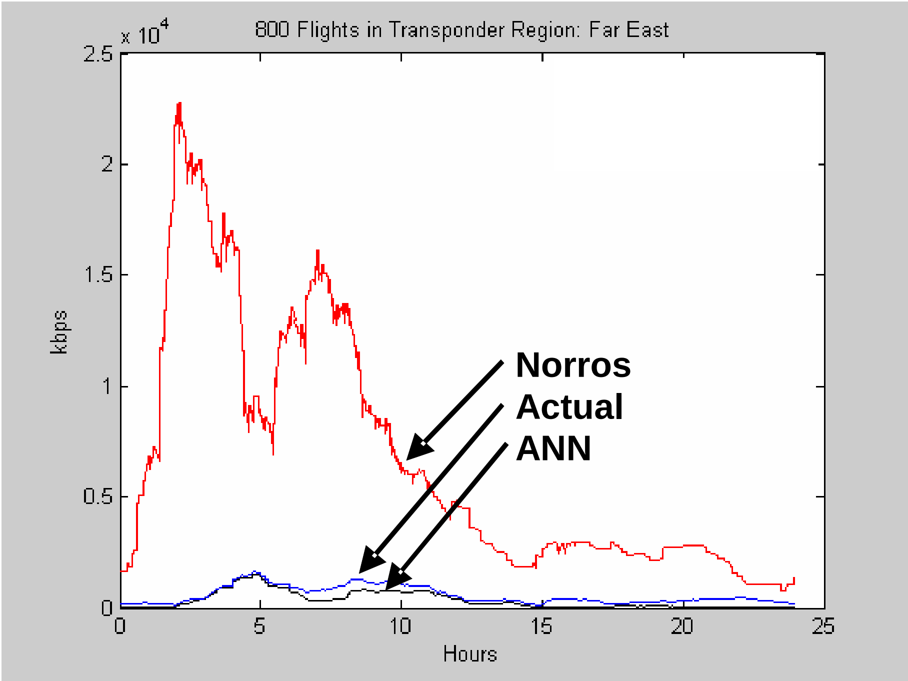


Figure 8-34 Global Region 5 Bandwidth Traces

8.4.5. Performance Evaluation Summary. In all cases, both the one-on-one comparisons and the simulation runs, the ANN predictor demonstrated clear and significantly better accuracy than the Norros equation based model which is currently in use on the CBB NCS. The Norros equation outputs a constant value, which is not a good representation, and the same Norros input parameters are used globally, due to the difficulty measuring data off the network and calculating difficult values such as the Hurst parameter. The ANN predictor uses actual network data traffic traces, which is a much better representation, and is different for each flight route. ANN adaptation can easily be performed by learning algorithms and re-training with new flight route profiles.

8.5. SECTION SUMMARY

This section introduced the adaptive artificial neural network predictor. A description of the ANN architecture was presented, including the input attribute vectors, the output traffic trace vectors, and the internal structure of the ANN, which was a feed-forward perceptron with back-propagation training. Integration of the ANN predictor into the CBB network capacity simulation was described. The CSIM is used to predict bandwidth demand for network sizing.

Then the results of performance evaluation testing were shown. The feasibility of using the ANN was demonstrated using data off the CBB network. The ANN predictor was found to be extremely accurate when compared to expected values, both for individual flight routes and for simulation runs with thousands of flights. Accuracy was compared to the model currently in use by CBB, a mathematical representation called the Norros equation. The ANN predictor was shown to be considerably more accurate.

9. CONCLUSION

9.1. SUMMARY

This dissertation research project was conducted in fulfillment of requirements for a Systems Engineering Ph.D. at the University of Missouri – Rolla in the Department of Engineering Management and Systems Engineering. The Boeing Company participated by providing the network data for the research and computing resources.

Condensed version of selected portions of this research are available in a technical paper presented at the Conference on Systems Engineering Research, CSER 2007, at Hoboken, New Jersey [Swift and Dagli, 2007a], a journal paper submitted to the Engineering Applications of Artificial Intelligence Journal [Swift and Dagli, 2007d], a journal paper submitted to the Control and Intelligent Systems Journal [Swift and Dagli, 2007e], various peer reviewed technical conference proceedings, selected Boeing documents and process, and a patent application.

An adaptive architecture is proposed for modeling network traffic on large-scale complex NCSs. The CBB NCS was used as a case study for this research project to establish the feasibility of use on an operating NCS. The proposed adaptive architecture uses artificial neural networks, a method of computational artificial intelligence. An ANN predictor was developed and integrated into the CBB capacity simulation used to predict network bandwidth demand. The ANN based simulation was tested and evaluated using actual data collected off the CBB network and compared against existing methodology.

The advantages of the proposed adaptive architecture are increased accuracy and adaptability through computational intelligence. Conventional means of modeling network traffic are not sufficiently scaleable or adaptable. They are dependent upon measured parameters off the network which are not very dependable and are subject to change. They model the traffic with mathematical expressions based on fractional Brownian motion and are based on assumptions of self-similarity, which may hold as true with the network traffic of today. With network traffic characteristics always changing and evolving, the need for models based on artificial intelligence is very real.

In order to build an adaptive ANN based model for predicting network traffic, a necessary first step is to explore the feasibility of decomposing network traffic into patterns compatible with ANN based simulation. To accomplish this task, data mining techniques were utilized and a methodology for decomposing Internet traffic on the CBB NCS case study was developed. Decomposition by user traffic traces and also by application traffic traces were investigated and rejected. Decomposition by flight route traffic traces was investigated and found to be acceptable. These patterns were then employed in the development of the adaptive ANN architecture for modeling network traffic.

The proposed ANN predictor uses a multi-layer feed-forward perceptron with back-propagation learning algorithms. The input vectors are flight attributes selected after an IDEF decomposition of the simulation. The output vectors are time-history points on the flight route bandwidth traffic traces.

The CSIM simulates airline flights by plotting flight routes on the globe based on start time, departure and arrival location, and flight number. Transponder coverage regions are also computed. The current CBB CSIM utilizes a fractional Brownian motion based Norros equation to estimate user bandwidth needs. The proposed ANN based

CSIM utilizes the ANN predictor to generate bandwidth traffic traces. The CSIM core aggregates the inputs and calculates total bandwidth demand and transponder sizing needs.

The ANN predictor was evaluated for accuracy and compared against current methodology. The ANN predictor was shown to be highly accurate in determining bandwidth traffic traces that are excellent representations of actual traffic. Feasibility of the ANN based architecture was demonstrated in a simulation environment with operational scenarios – with a small scale concept development model, with an operational regional model, and with a global model involving thousands of flights. Simulation comparisons were made against expected values and between the Norros equation based model and the ANN based model. The ANN based model was significantly more accurate. In addition to increased accuracy, the ANN based model has the capability for adaptation through learning algorithms and re-training.

Modeling network traffic on an NCS like CBB typifies the problems encountered when trying to model or architect different aspects of complex, large-scale, NCS systems. The techniques and methodology used to develop and validate the adaptive architecture for CBB can also be utilized on other NCSs.

9.2. CONTRIBUTIONS

There are several contributions resulting from this Ph.D. dissertation research project conducted through the University of Missouri – Rolla.

- A data mining methodology for decomposing network traffic data into a form compatible with computationally intelligent simulation techniques.
- Data extraction algorithms and processes for the CBB network. These processes allow users to extract network data from multiple data warehouses for trending analysis and research on network characteristics. The processes could be adapted for use on other similar networks.
- Decomposition of CBB network traffic into flight route bandwidth traffic traces. These traffic traces were used for ANN simulation and also for evaluation of flight and user characteristics.
- An adaptive architecture that uses computational intelligence for modeling network traffic. The architecture uses artificial neural networks and was demonstrated on an operating network.
- A working ANN model that predicts network traffic traces for the CBB case study network. Input vectors were composed of selected flight attributes. The output vector was composed of points on the time history of a bandwidth traffic trace. The network was composed of two hidden layers with 39 neurons each.
- An adaptive simulation architecture that utilizes the ANN bandwidth predictor. The simulation models operational scenarios with user selected flights, flight routes, and satellite coverage areas. Network data is used as inputs and the simulation predicts satellite transponder needs using the ANN bandwidth predictor.

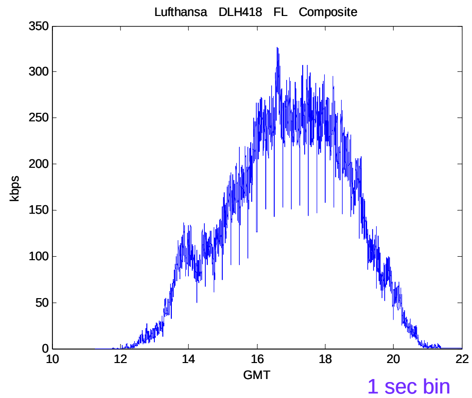
9.3. FUTURE WORK

This project utilized data mining techniques to develop useful patterns for ANN simulation of the CBB NCS network traffic. This concept could be further explored by performing similar studies on other complex large-scale NCSs. Additional research could also be performed to investigate categorizing Internet traffic in general on the world wide web.

The adaptive architecture developed for this dissertation for the CBB NCS was based on artificial neural networks. A feed-forward perceptron neural network was utilized. Further investigation could delve into the use of hybrid methods of computational intelligence that include both ANNs and genetic algorithms.

APPENDIX A

ACTUAL BANDWIDTH TRAFFIC TRACES



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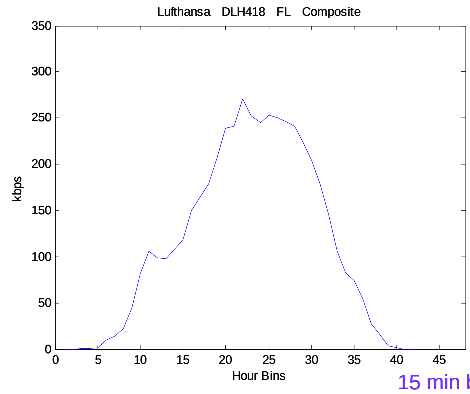

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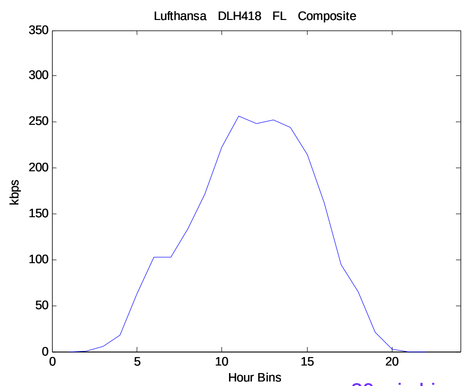

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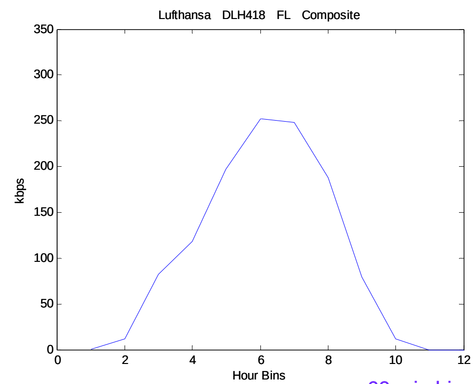

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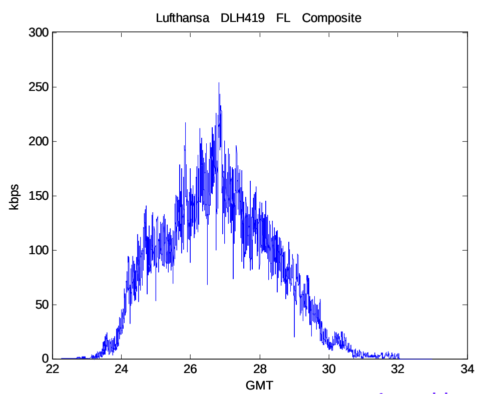

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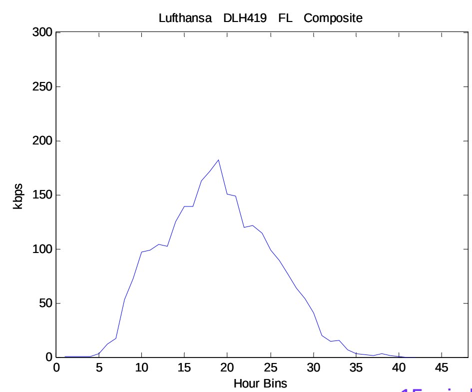

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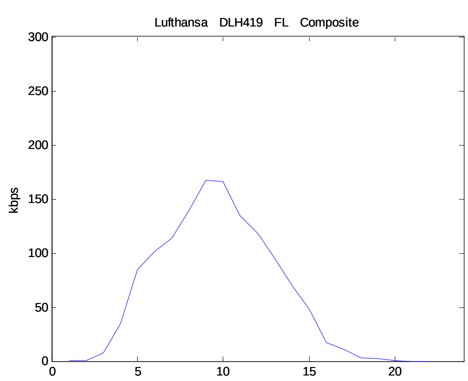

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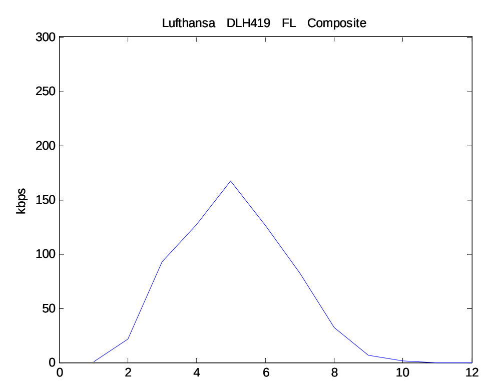

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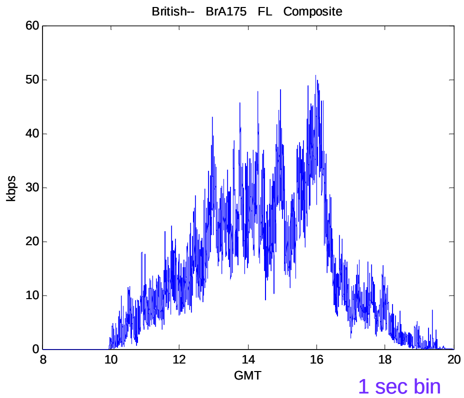
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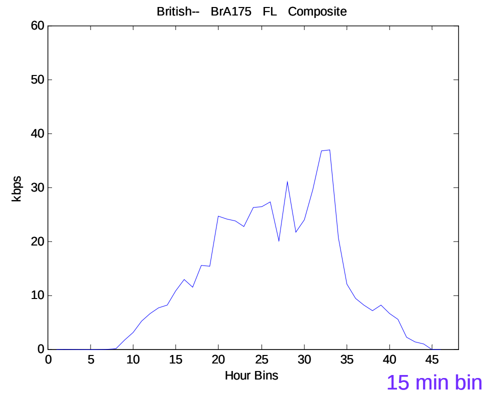
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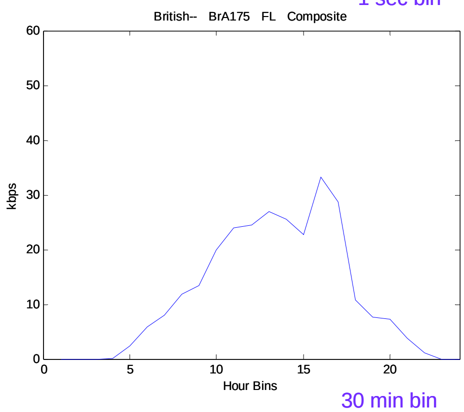
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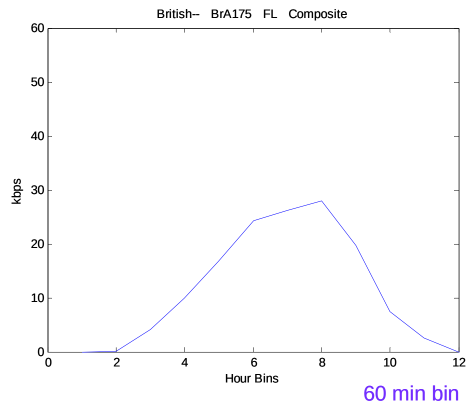
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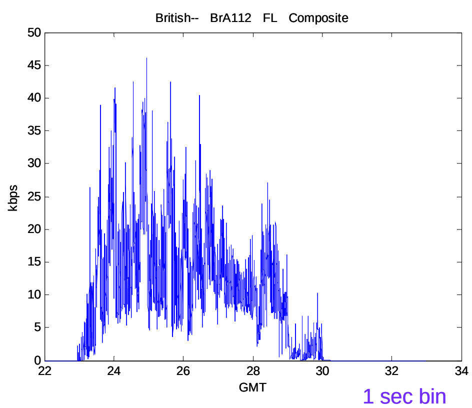
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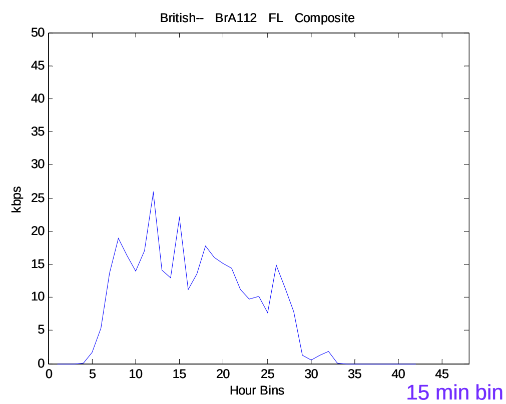
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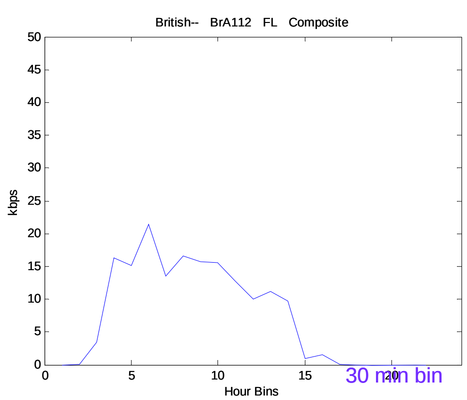
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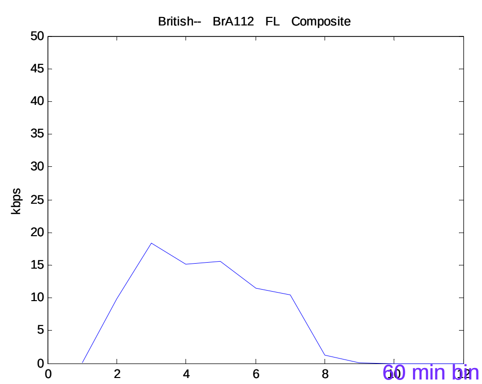
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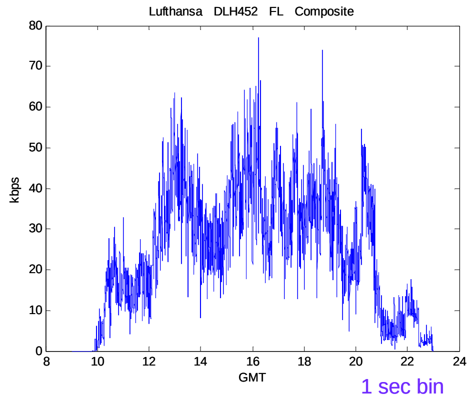

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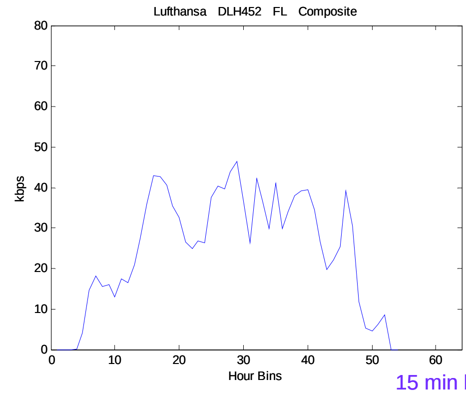

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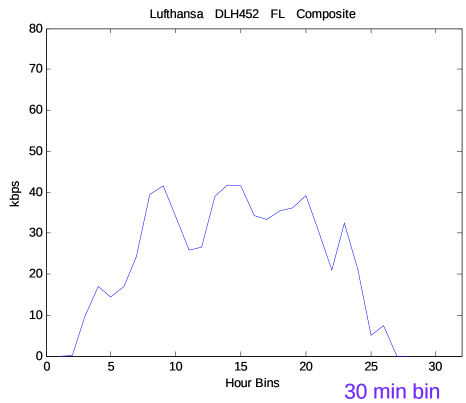

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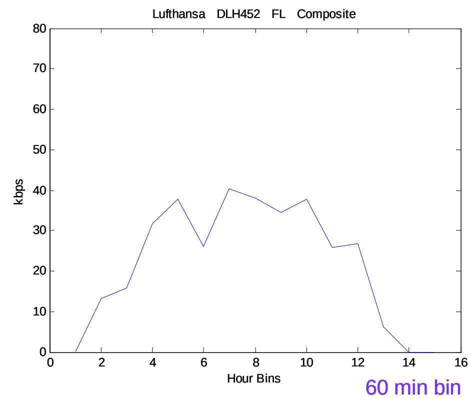

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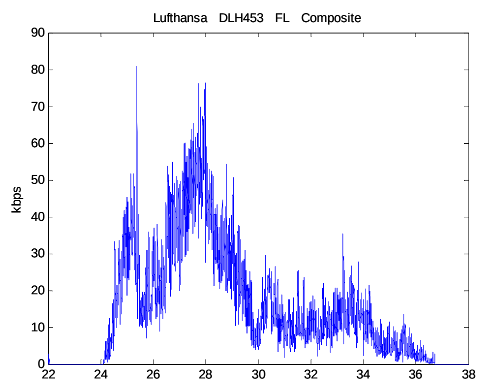

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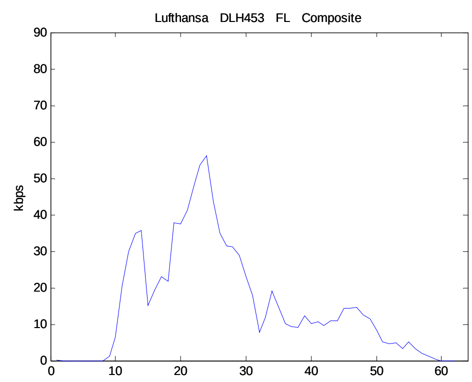

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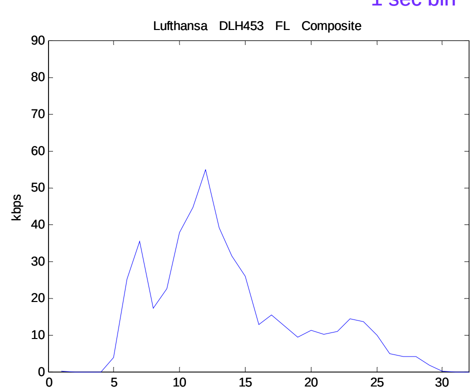

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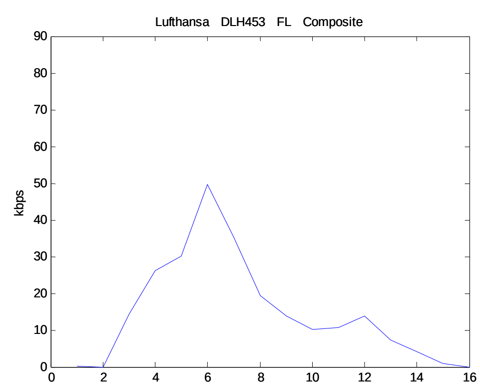

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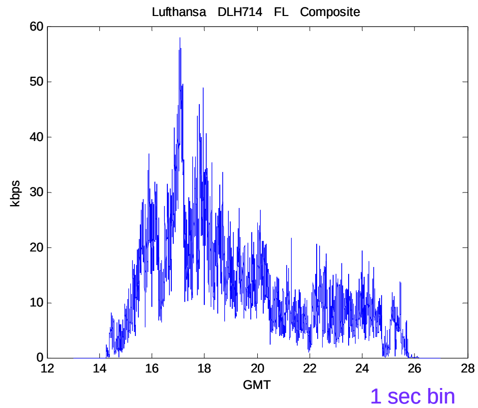

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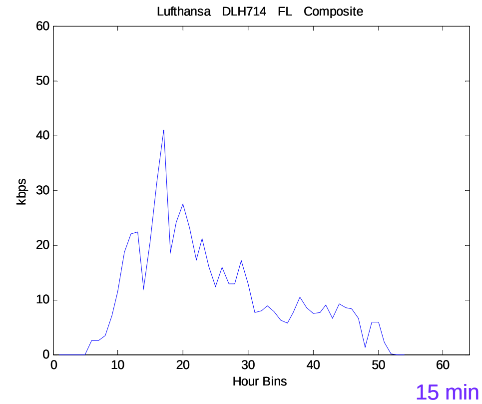

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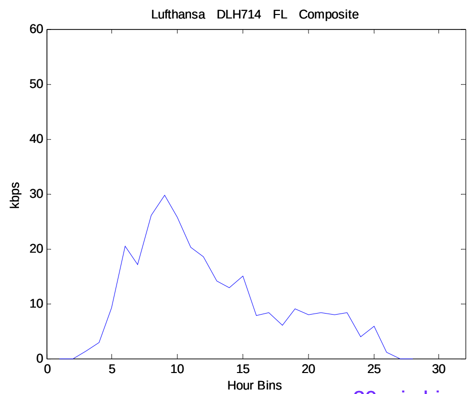

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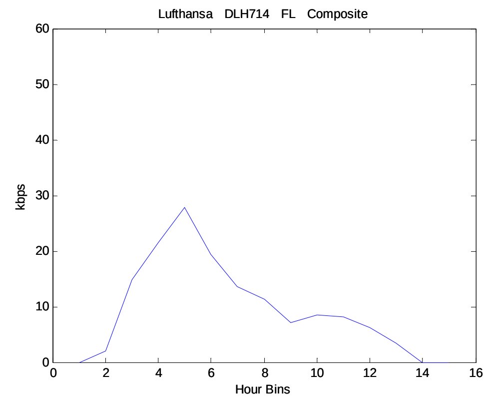

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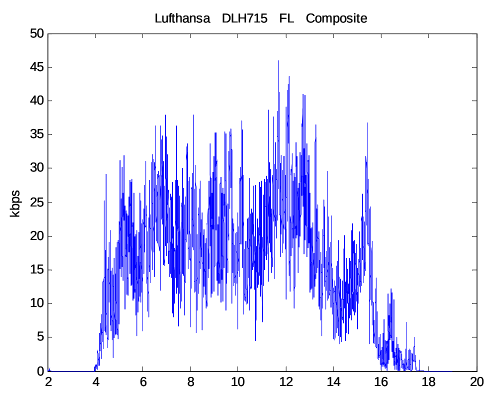

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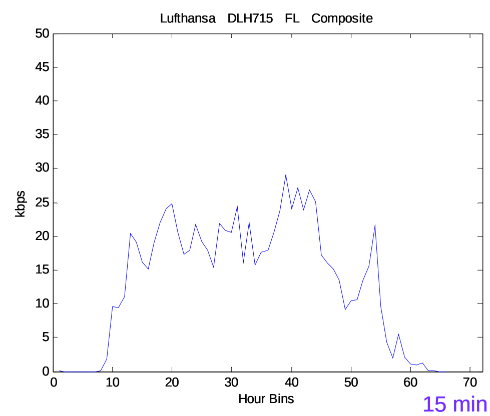

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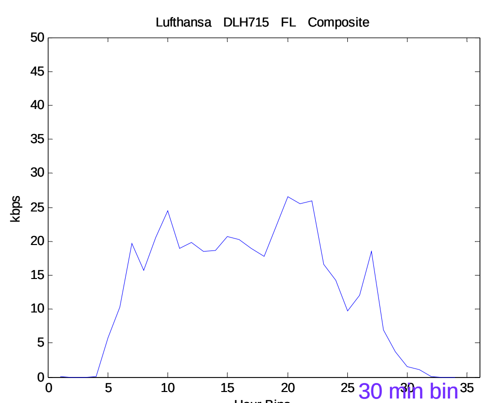

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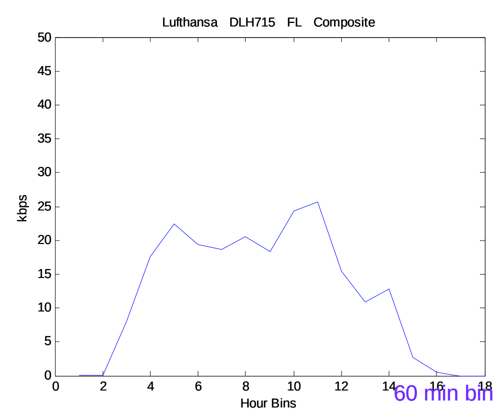

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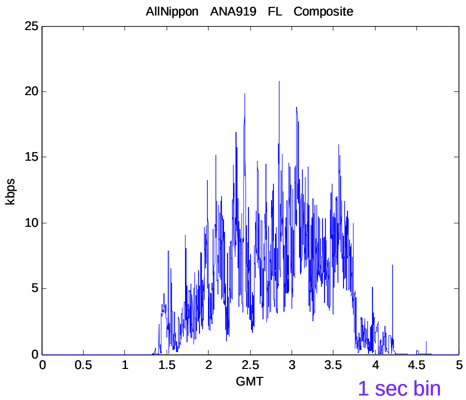

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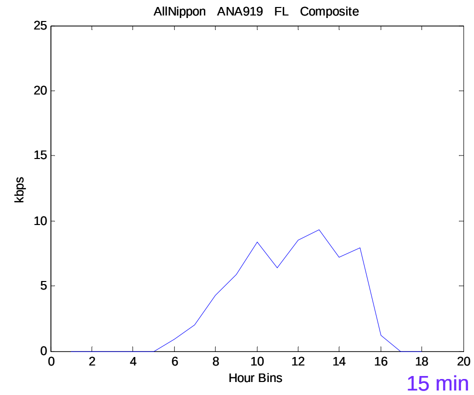

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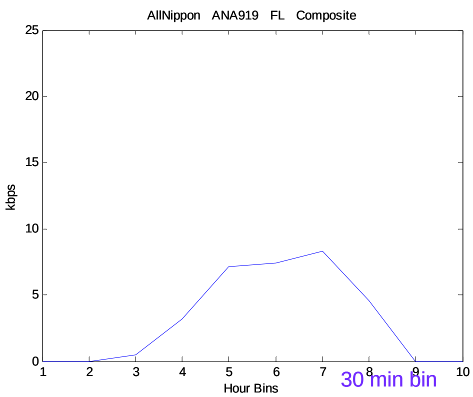

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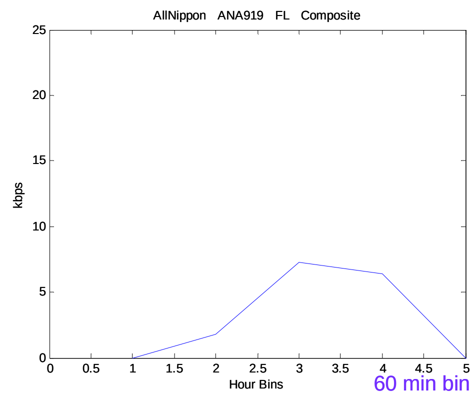

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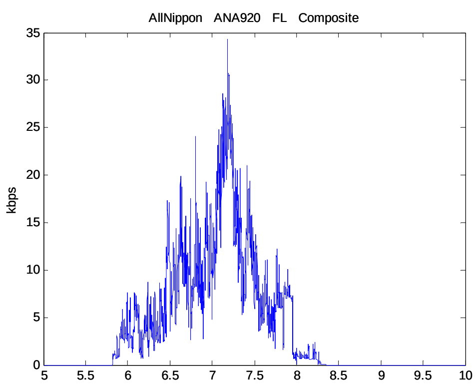

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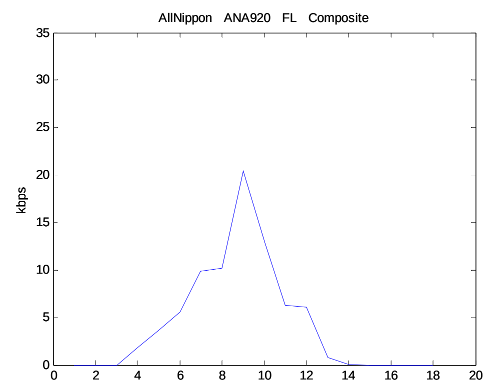

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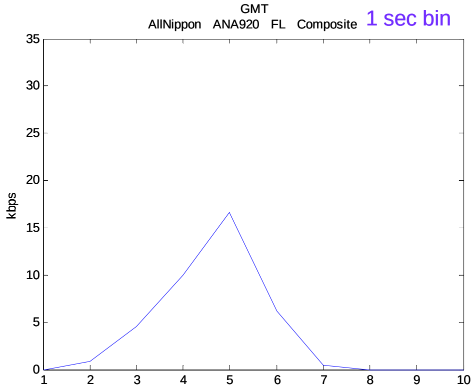

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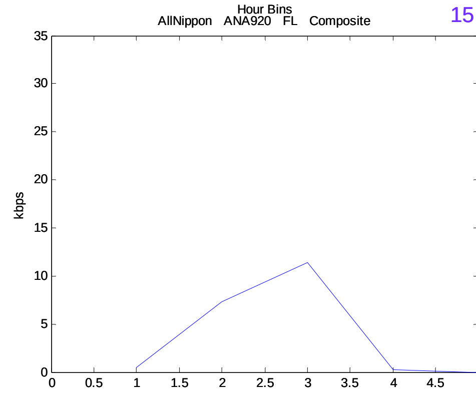

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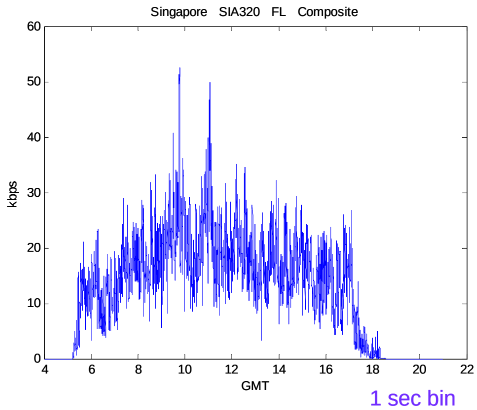

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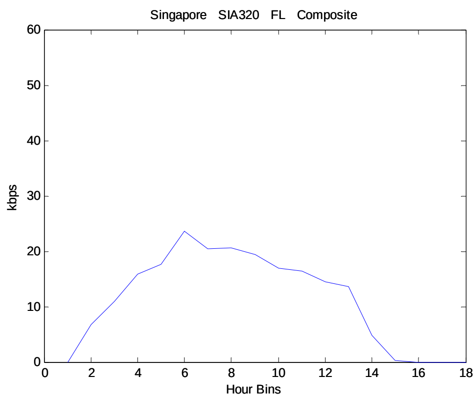

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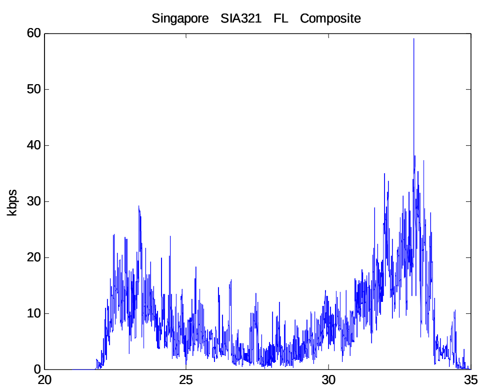

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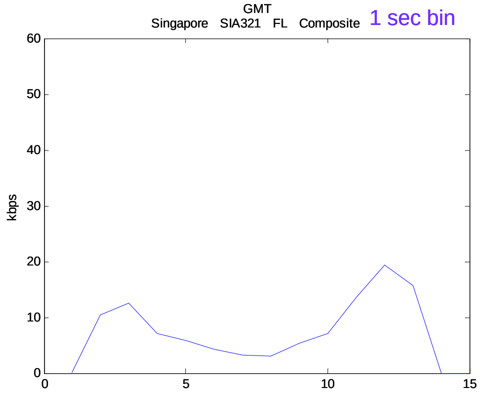

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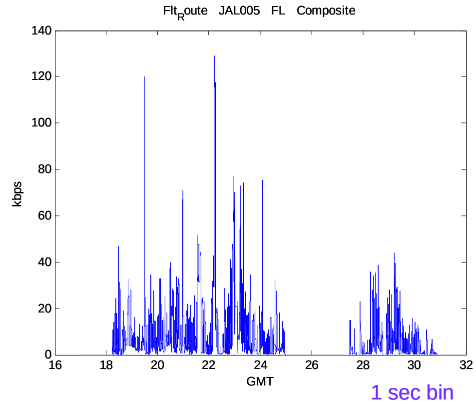

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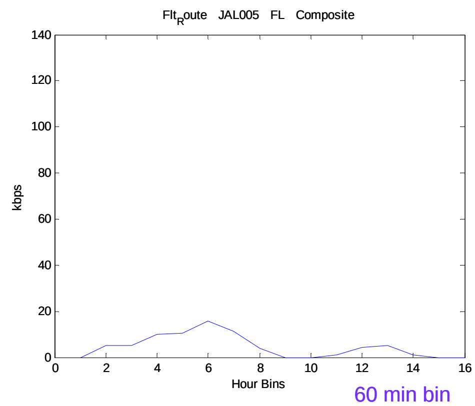

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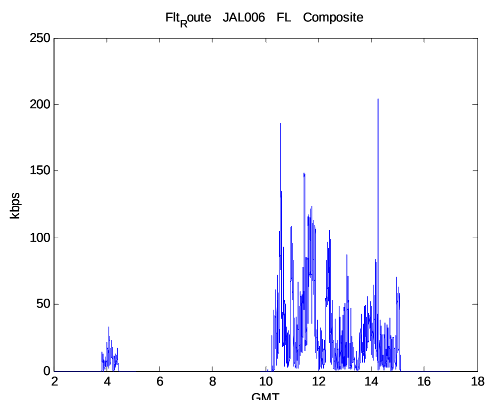

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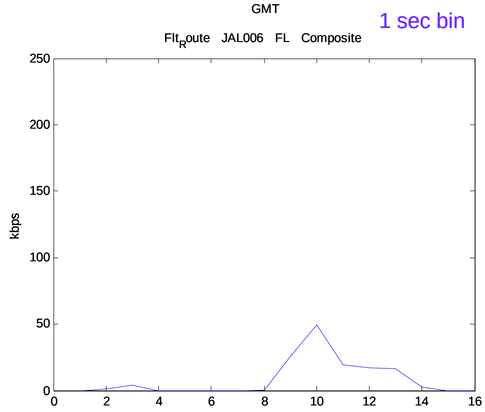

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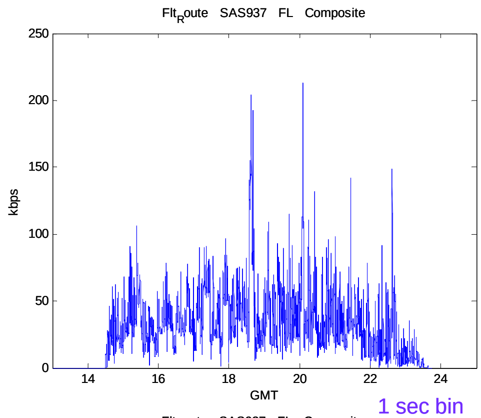

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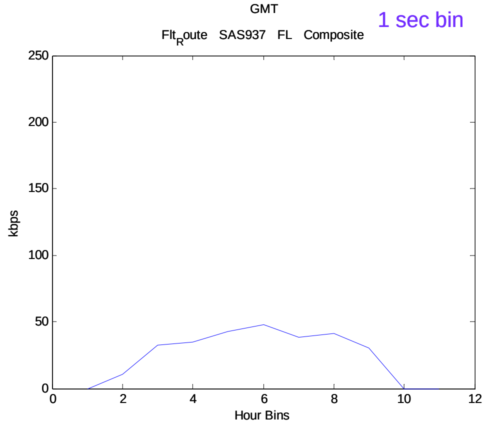

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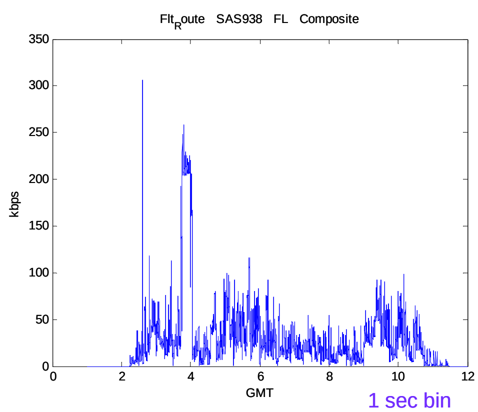

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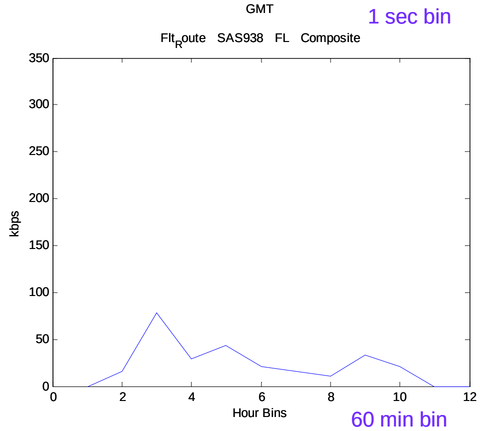

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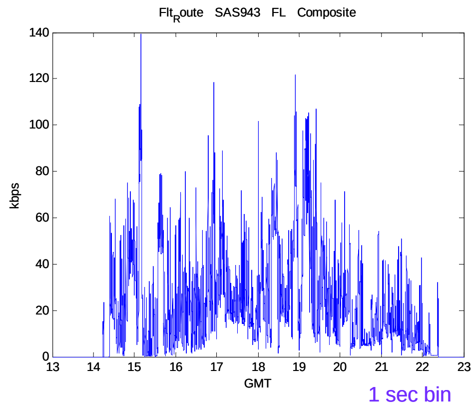
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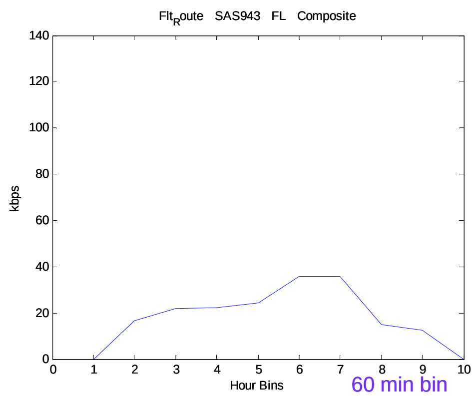
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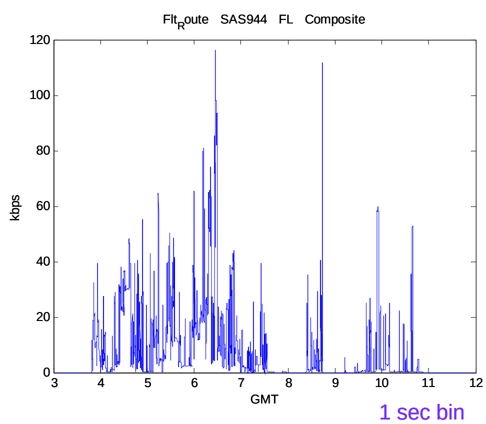
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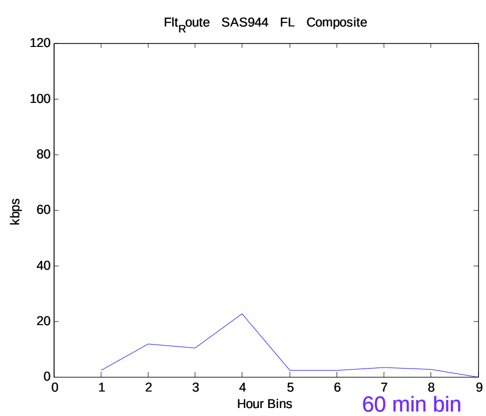
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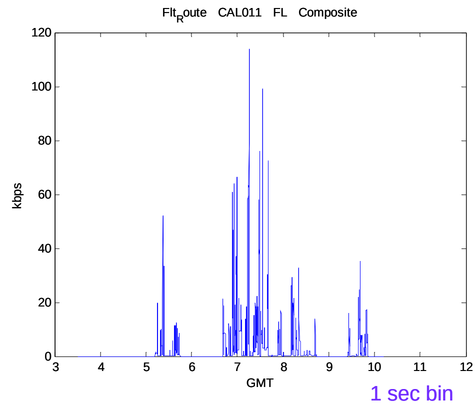
kbps
Hour Bins
60 min bin



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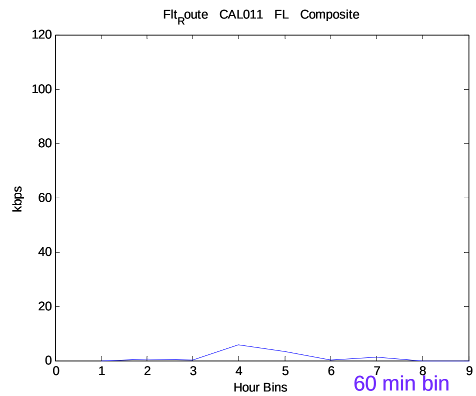

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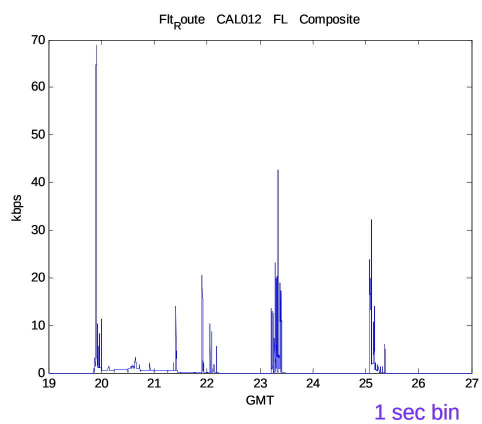

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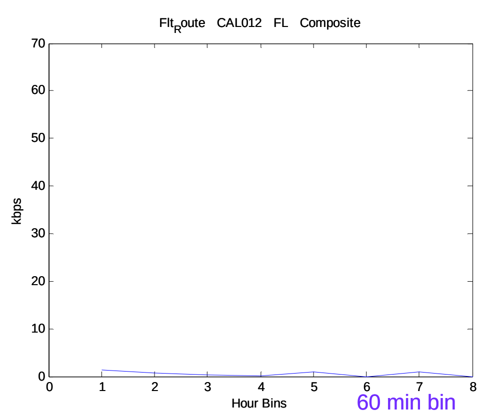

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kbps
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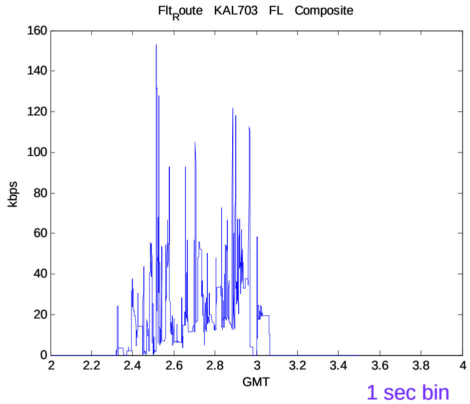
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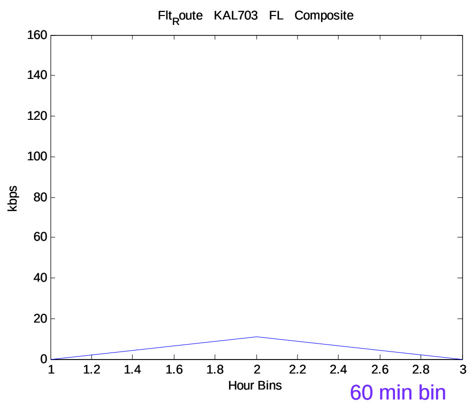
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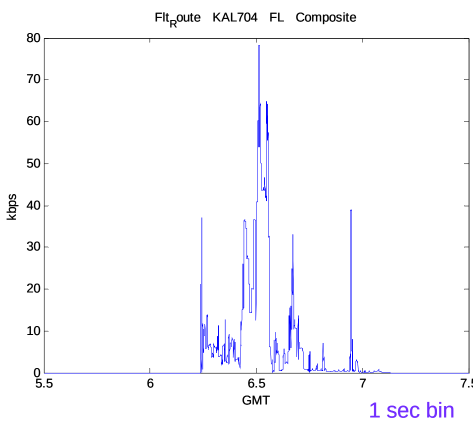
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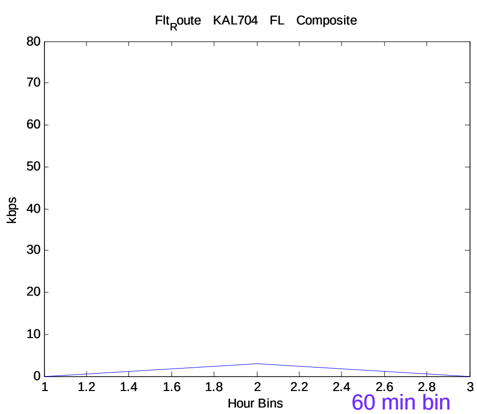
kbps
GMT
1 sec bin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kbps
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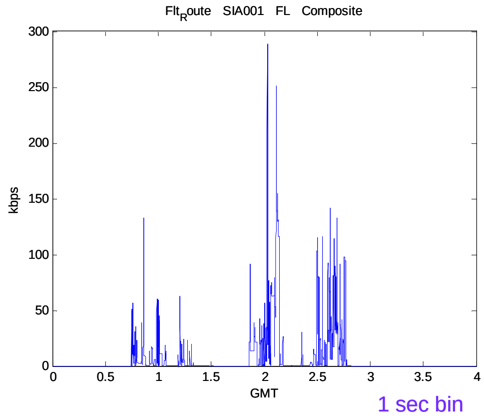
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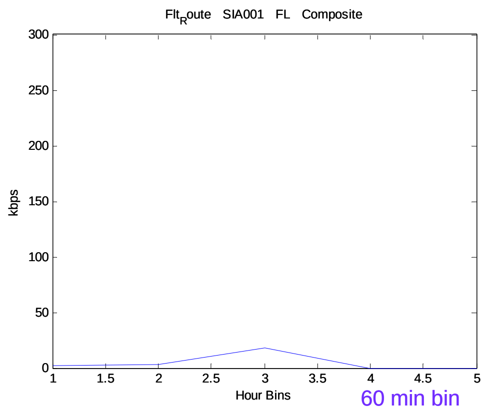
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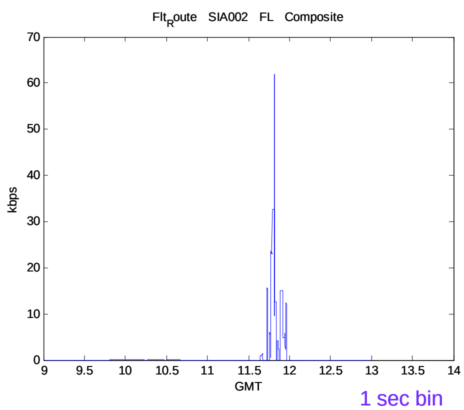
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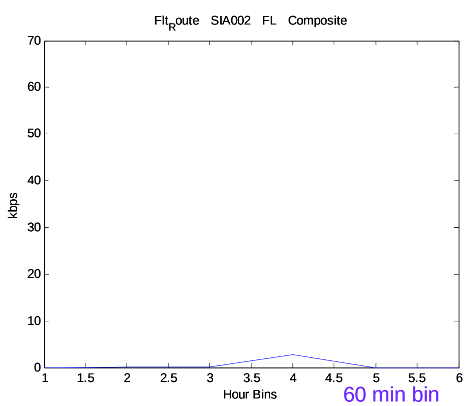
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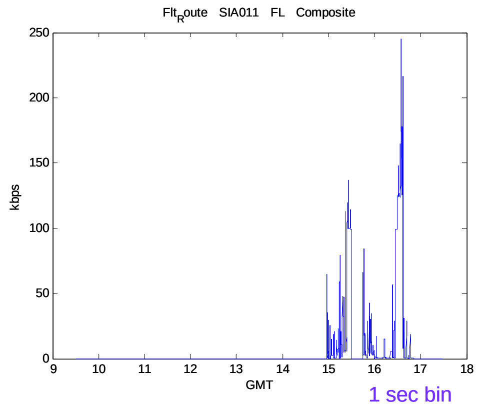
60 min bin



Flt_Route SIA011 FL Composite
kbps
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150
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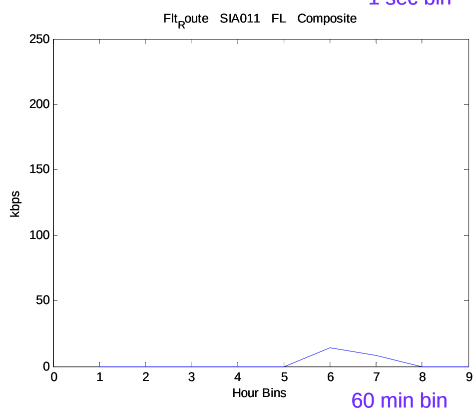
50
0
9 10 11 12 13 14 15 16 17 18
GMT
1 sec bin



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kbps
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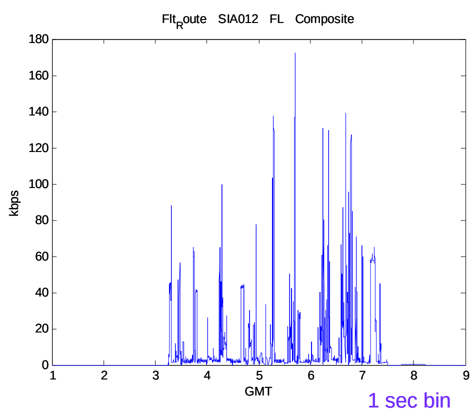
0
0 1 2 3 4 5 6 7 8 9
Hour Bins
60 min bin



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kbps
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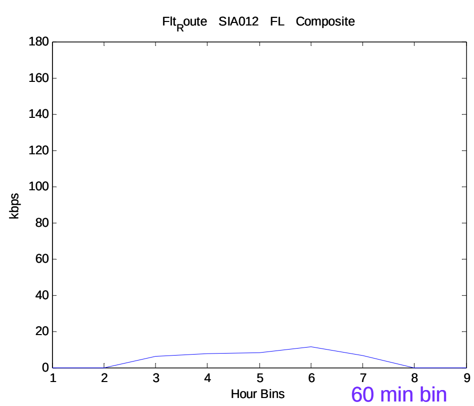
40
20
0
1 2 3 4 5 6 7 8 9
GMT
1 sec bin



Flt_Route SIA012 FL Composite
kbps
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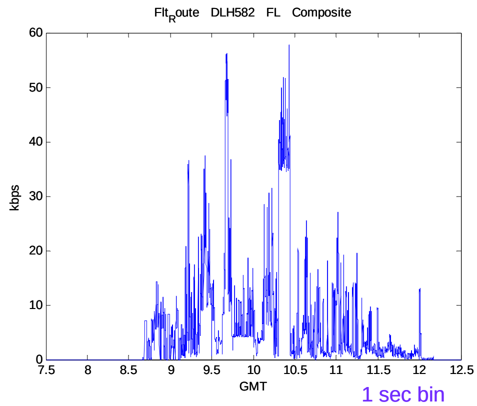
80
60
40
20
0
1 2 3 4 5 6 7 8 9
Hour Bins
60 min bin



Flt_Route DLH582 FL Composite
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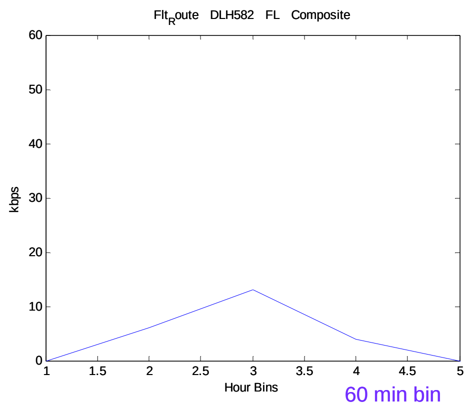

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kbps
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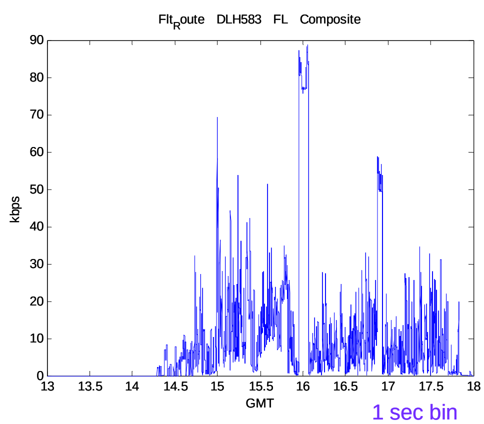
60 min bin



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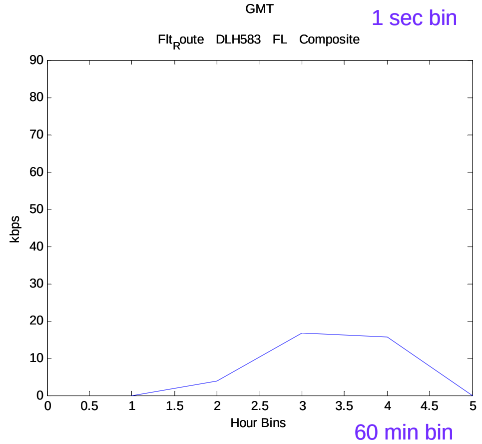
kbps
GMT
1 sec bin



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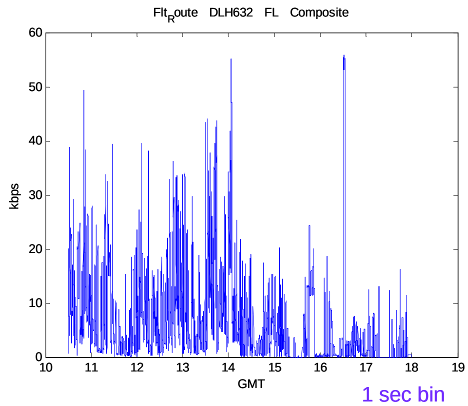
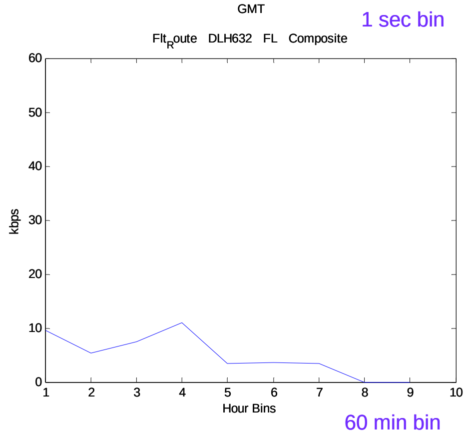
kbps
Hour Bins
60 min bin



Flt_Route DLH632 FL Composite
kbps
GMT
1 sec bin



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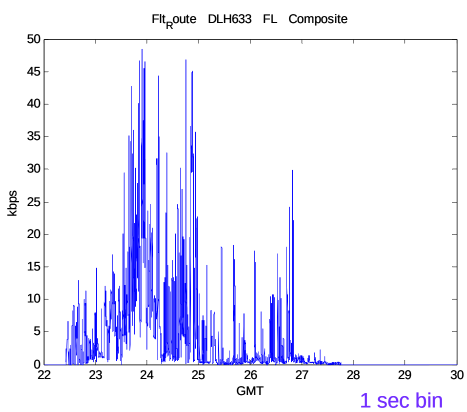
kbps
Hour Bins
60 min bin



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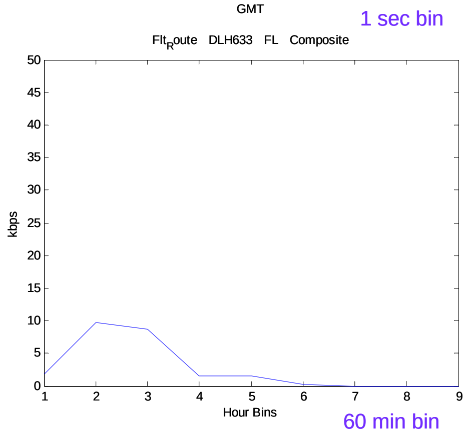
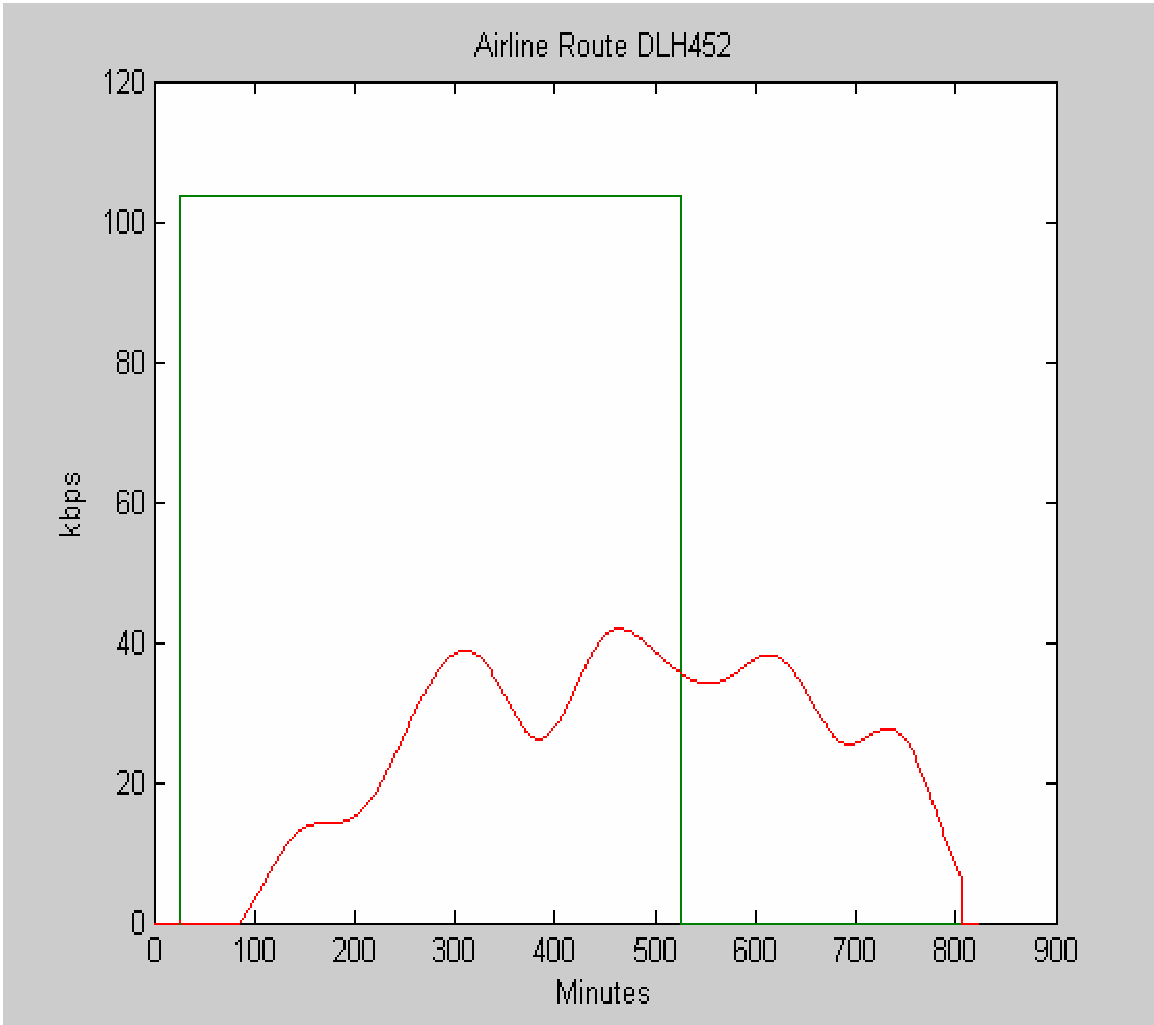
kbps
GMT
1 sec bin



Flt_Route DLH633 FL Composite
kbps
Hour Bins
60 min bin

APPENDIX B

SIMULATION TRAFFIC TRACE COMPARISONS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200
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700
800
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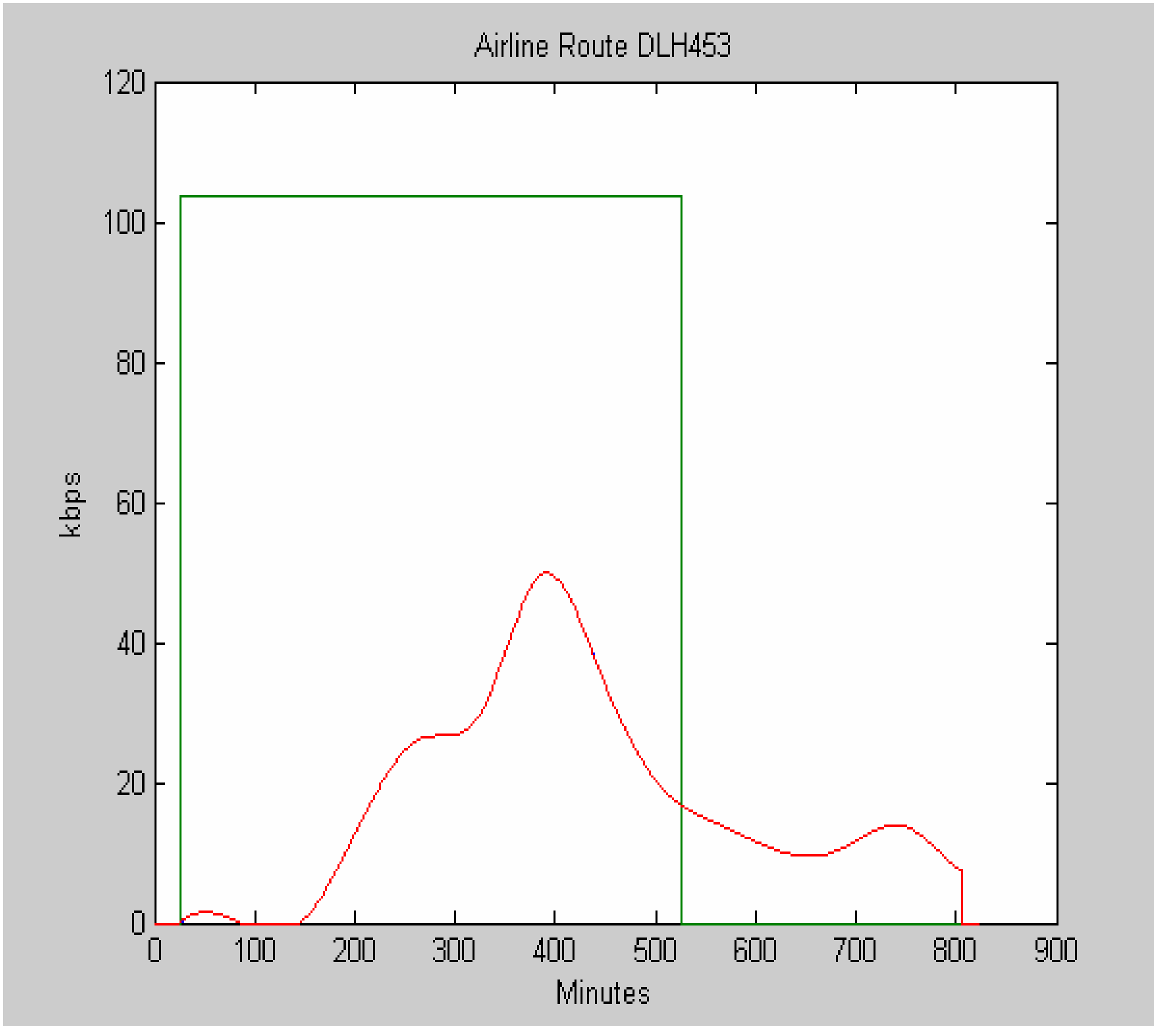
Airline Route DLH453
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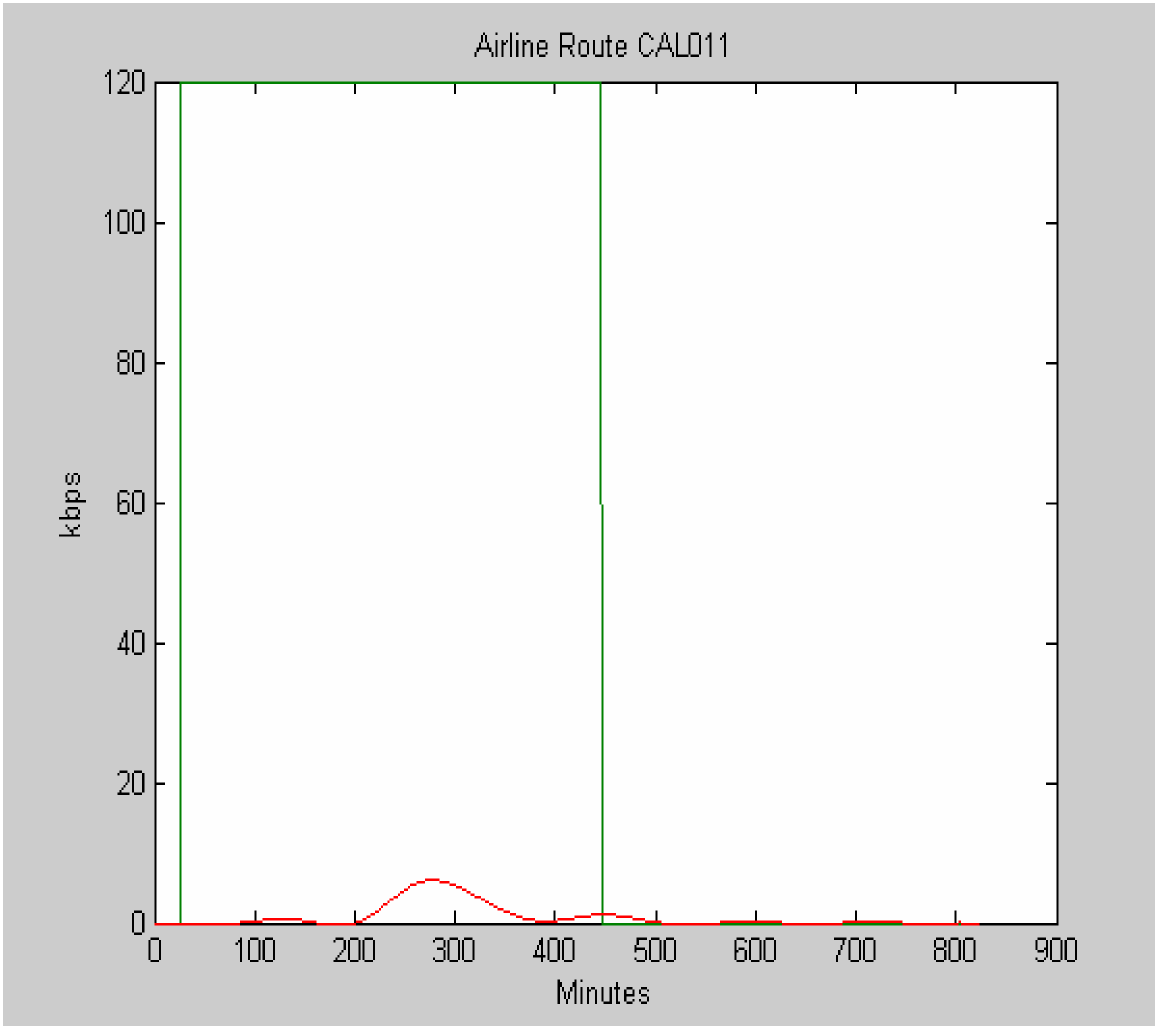
Airline Route CAL011
kbps
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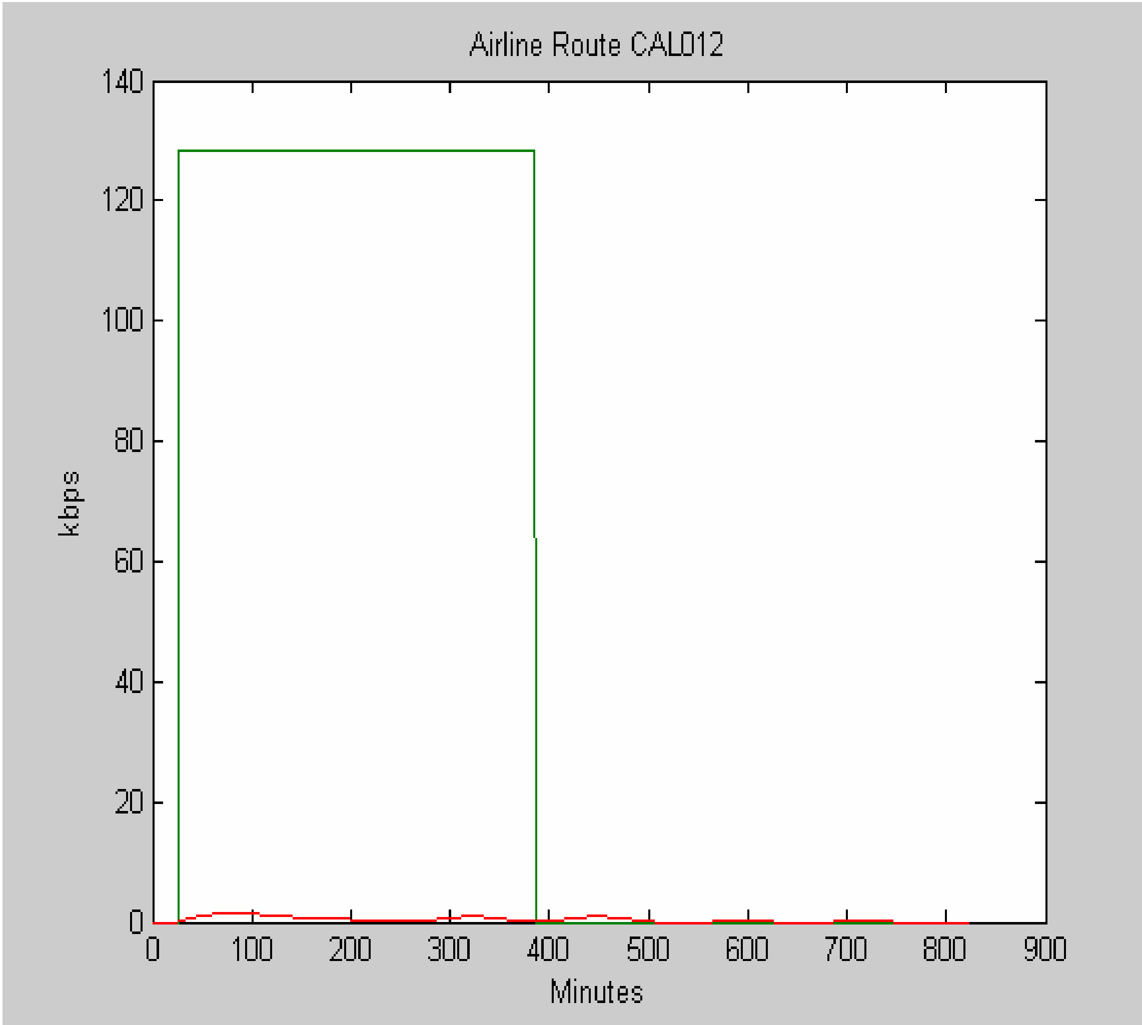
60
80
100
120
0
100
200
300
400
500
600
700
800
900



Airline Route CAL012
kbps
Minutes
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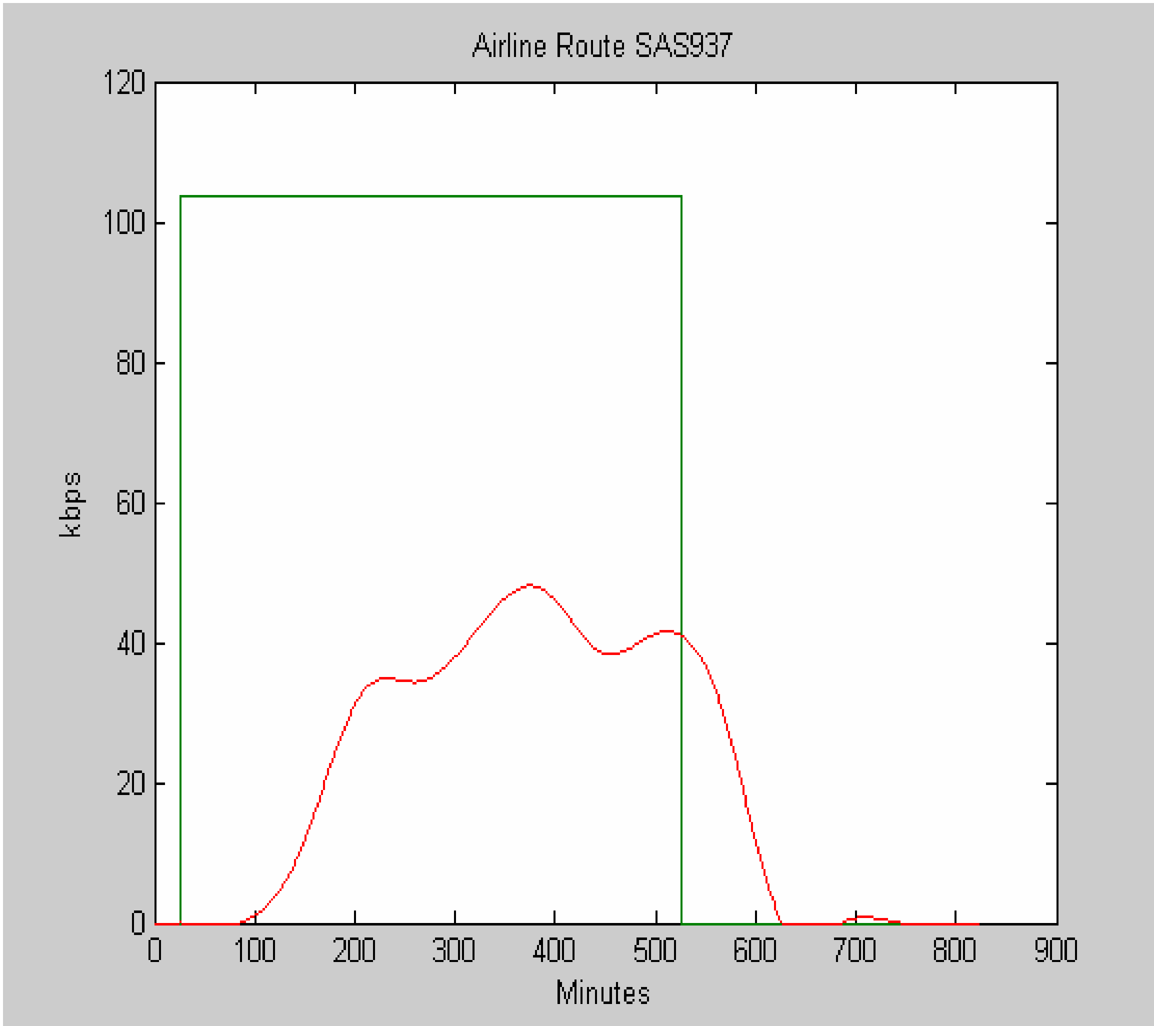
20
40
60
80
100
120
140
0
100
200
300
400
500
600
700
800
900



Airline Route SAS937
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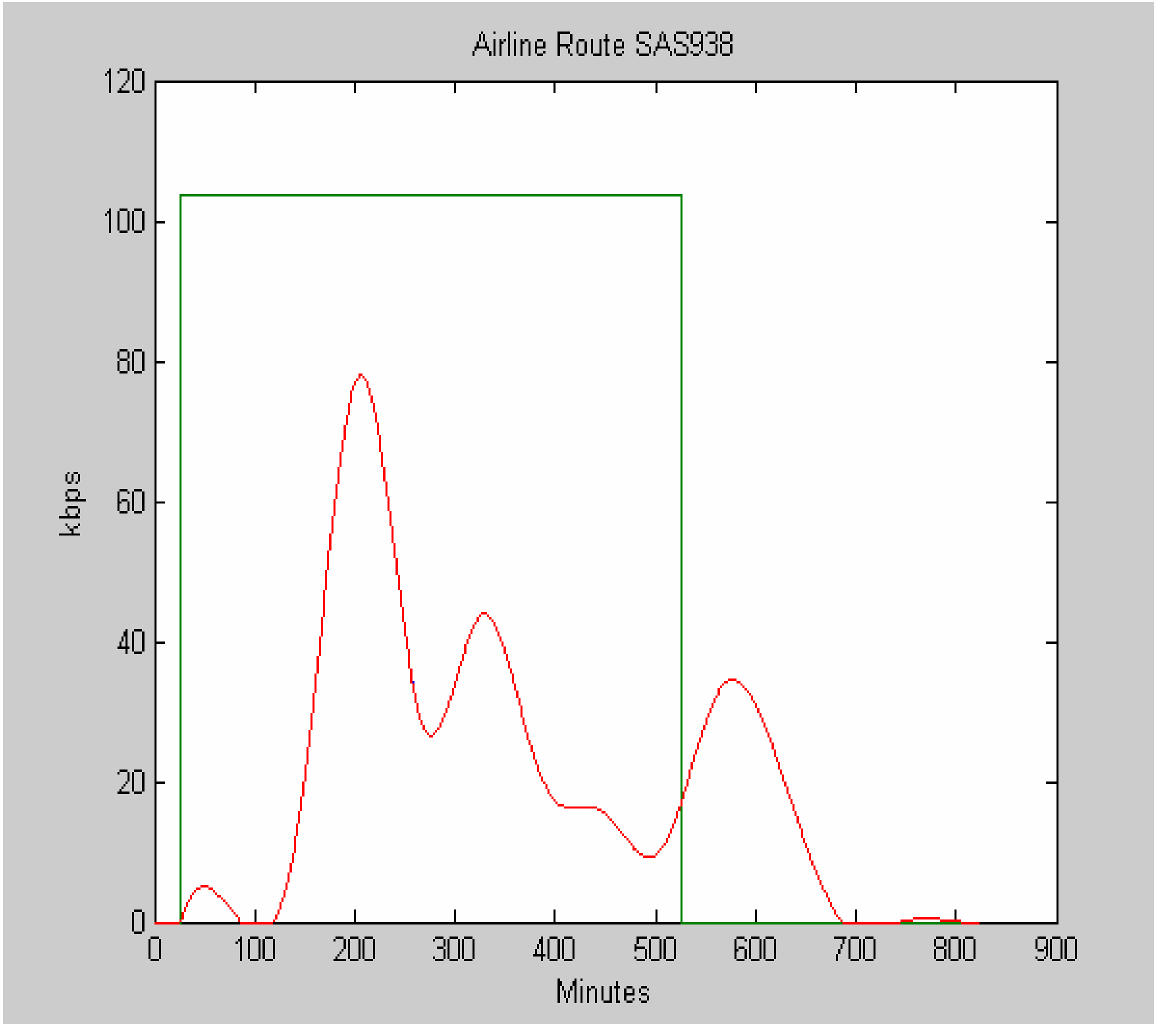
80
60
40
20
0
0
100
200
300
400
500
600
700
800
900
Minutes


Airline Route SAS938
kbps
Minutes
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20
40
60
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100
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200
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600
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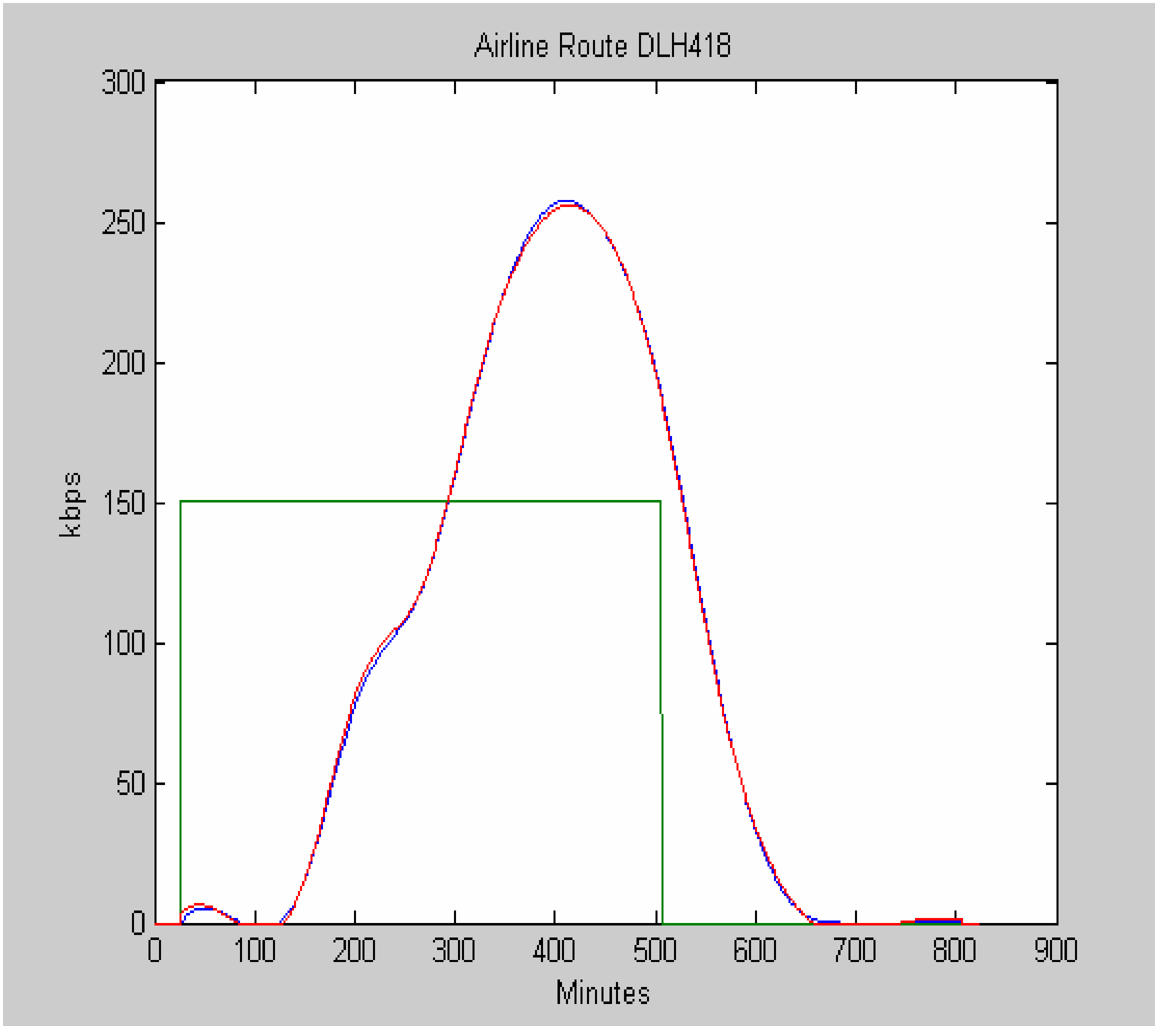
800
900



Airline Route DLH418
kbps
Minutes
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50
100
150
200
250
300
0
100
200
300
400
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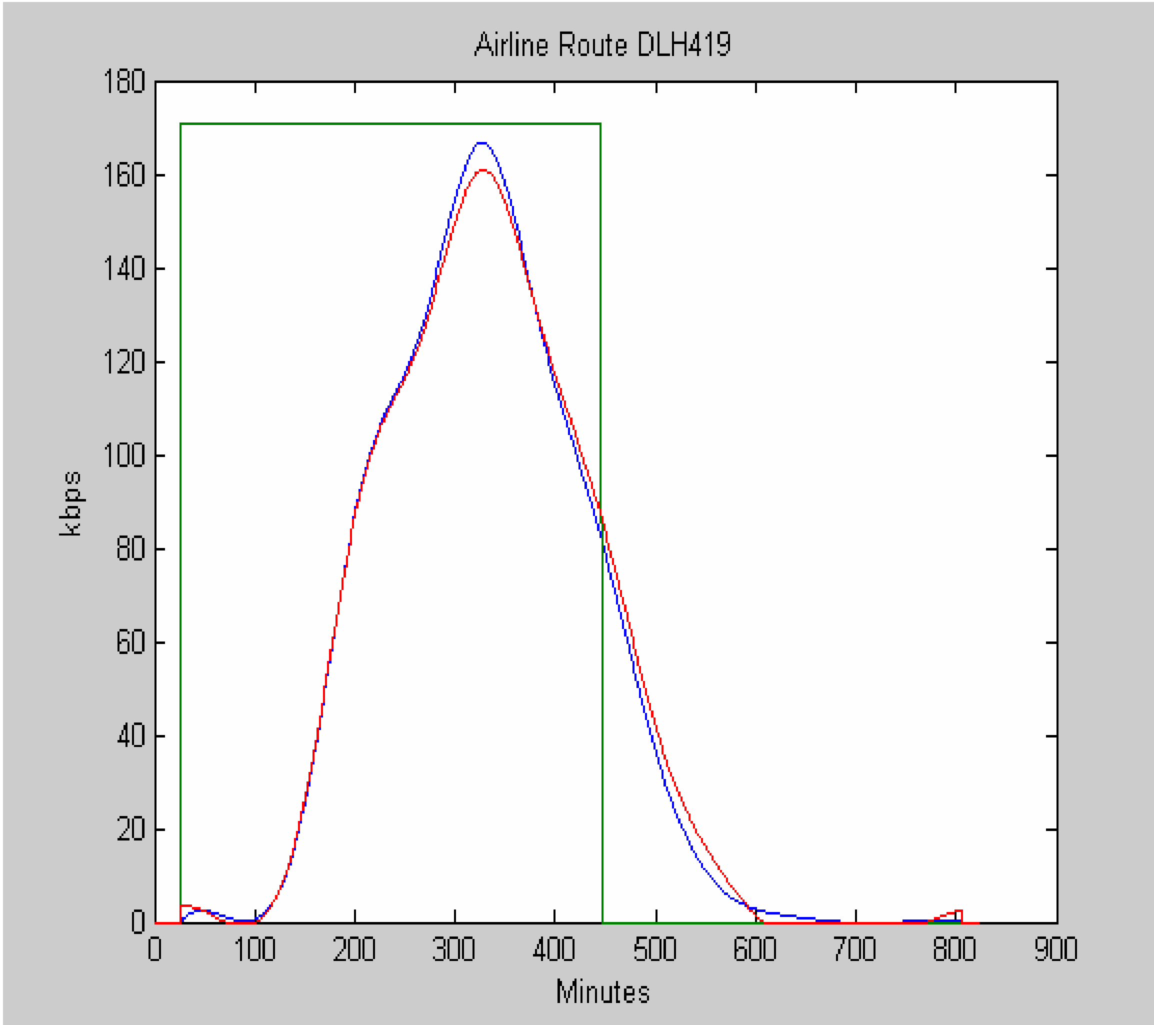
600
700
800
900


Airline Route DLH419
kbps
Minutes
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80
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40
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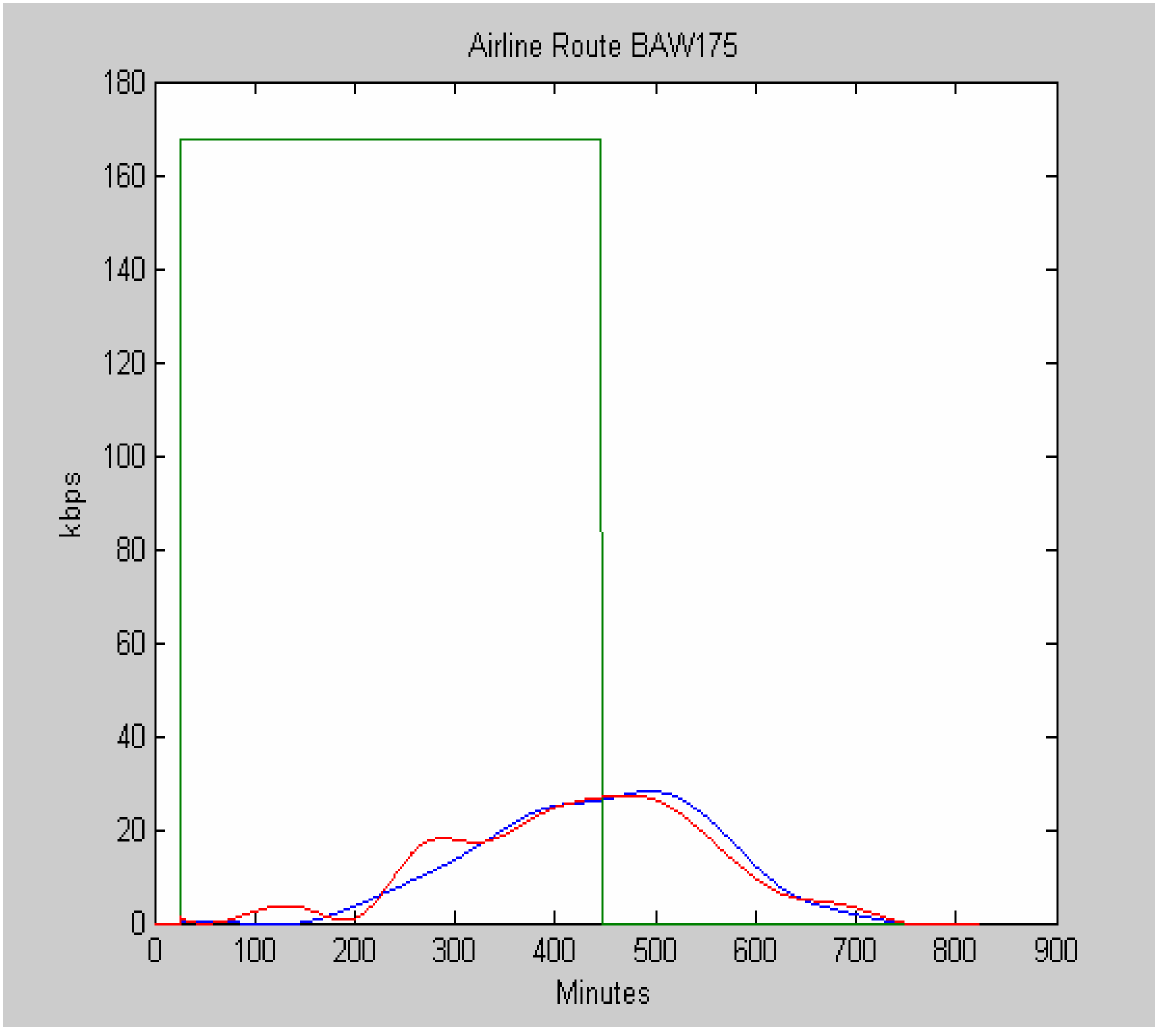
500
600
700
800
900



Airline Route BAW175
kbps
180
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120
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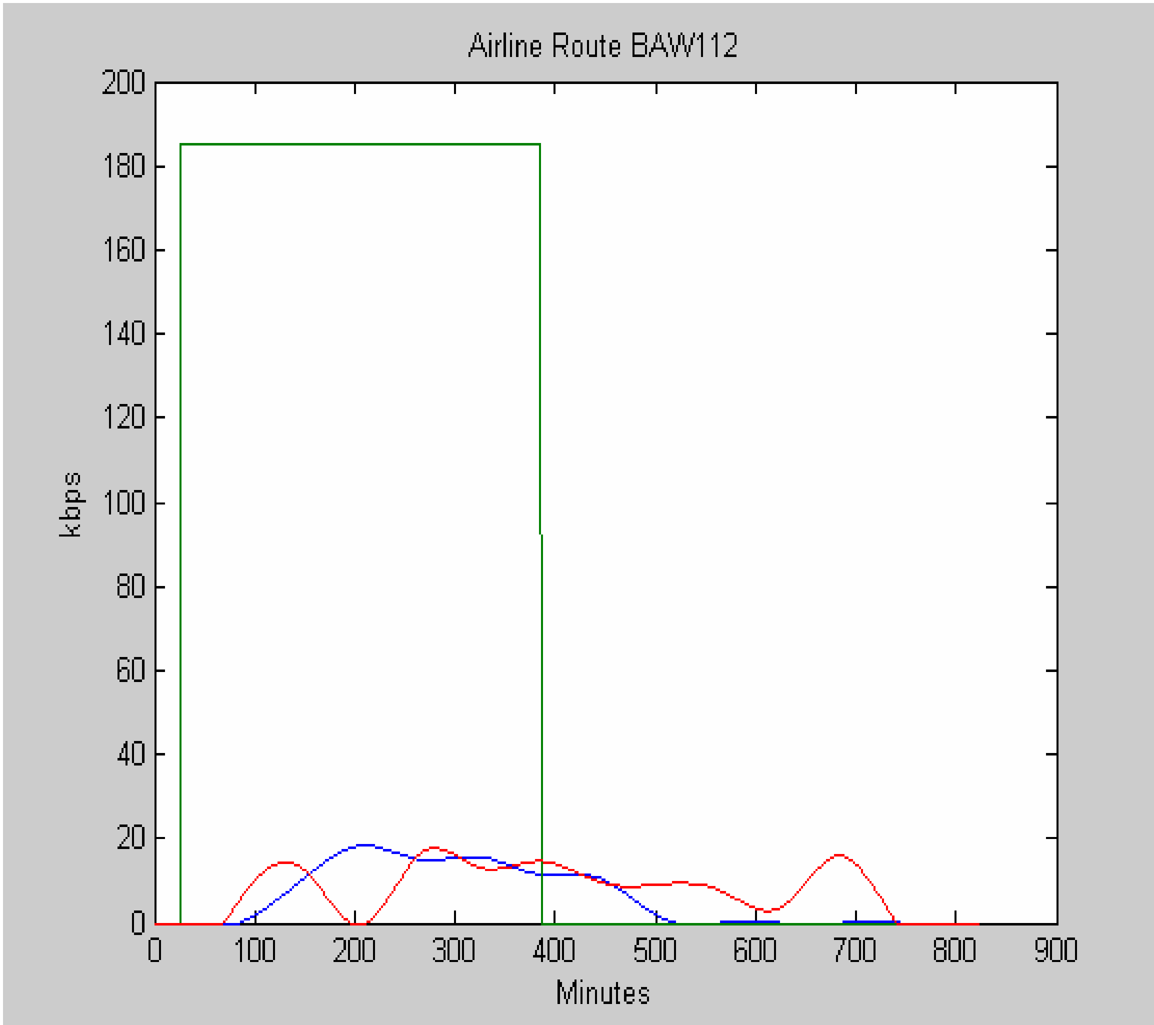
80
60
40
20
0
0
100
200
300
400
500
600
700
800
900
Minutes


Airline Route BAW112
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120
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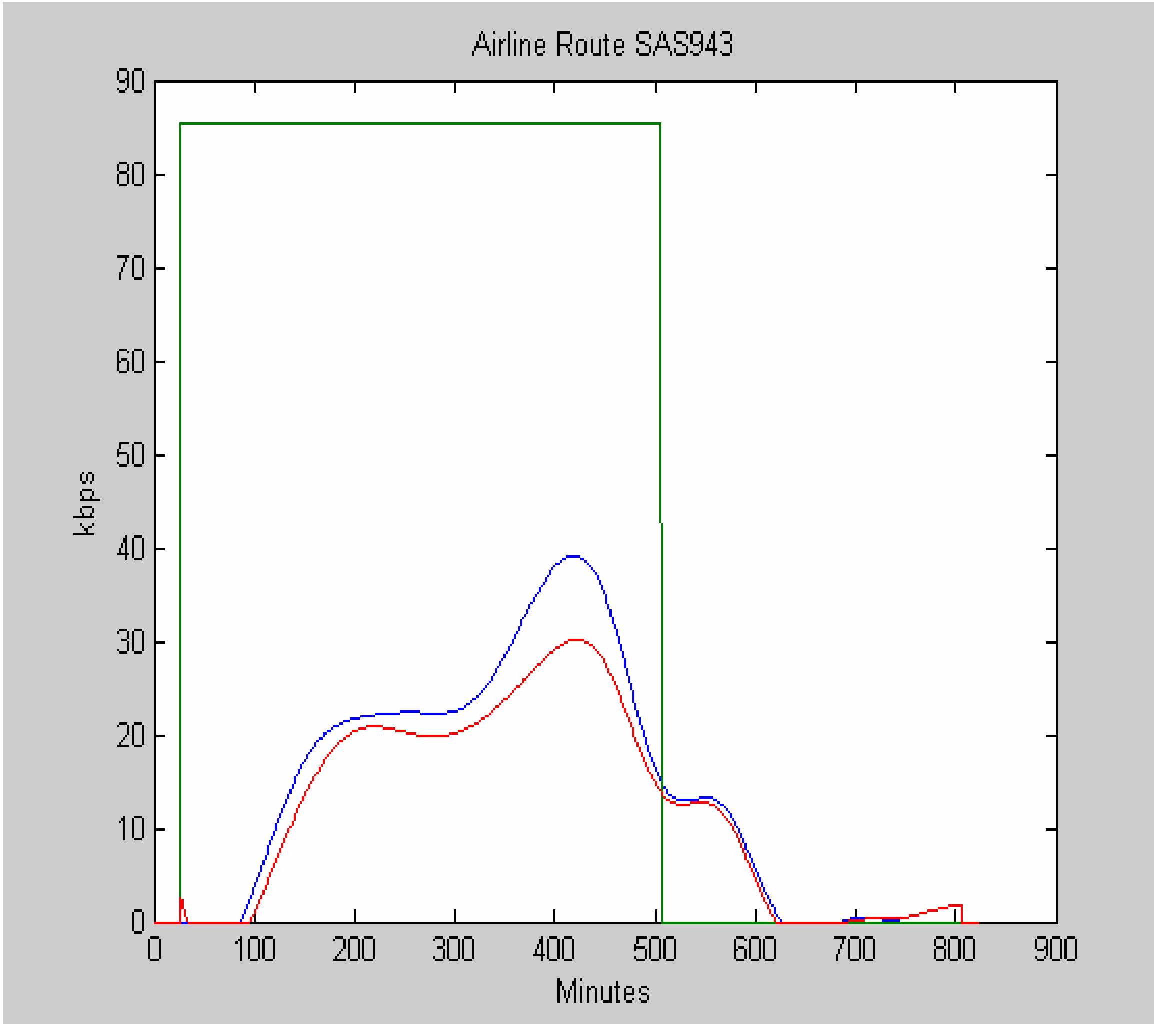
200



Airline Route SAS943
kbps
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30
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70
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200
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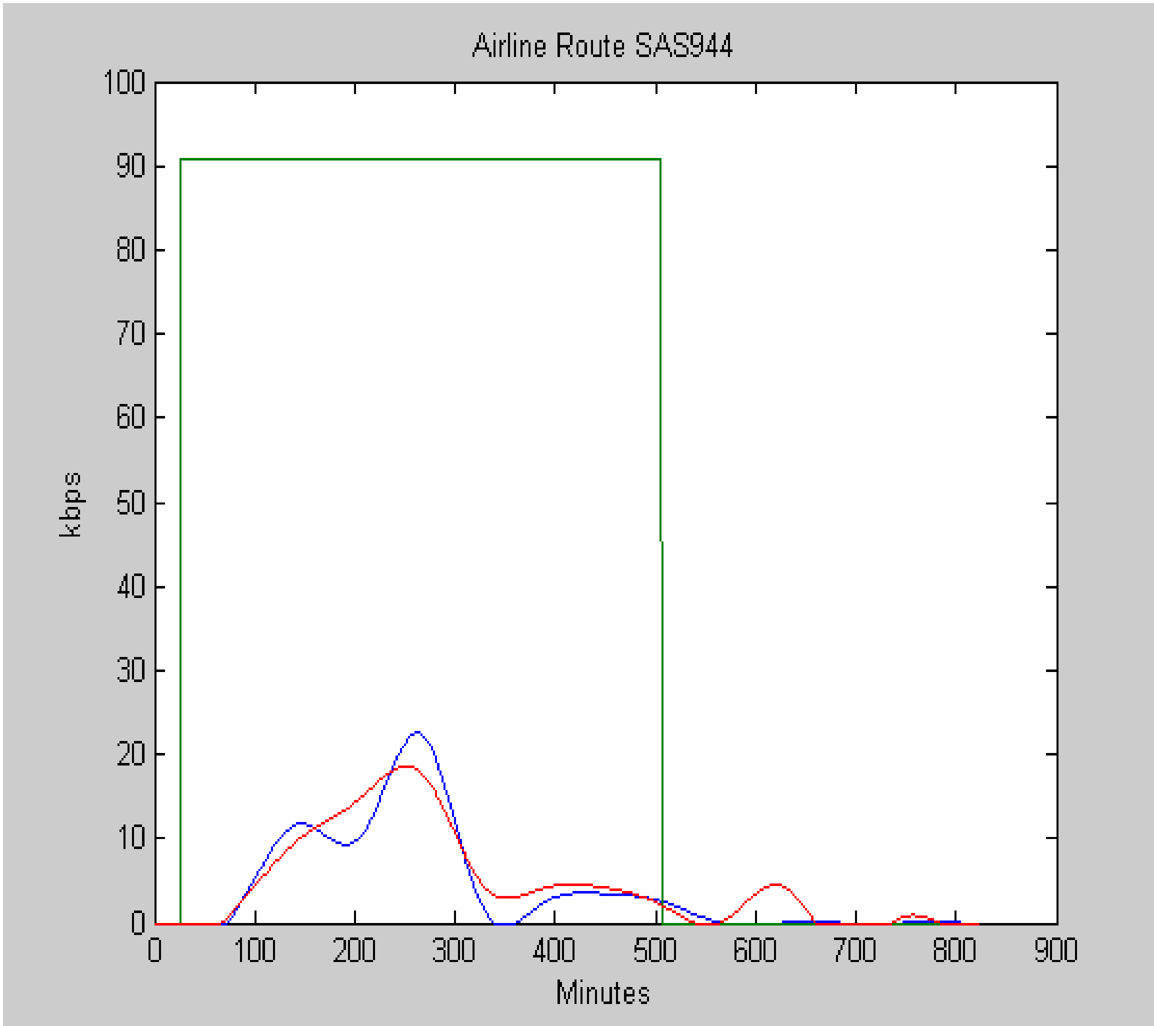
600
700
800
900


Airline Route SAS944
kbps
Minutes
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10
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50
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70
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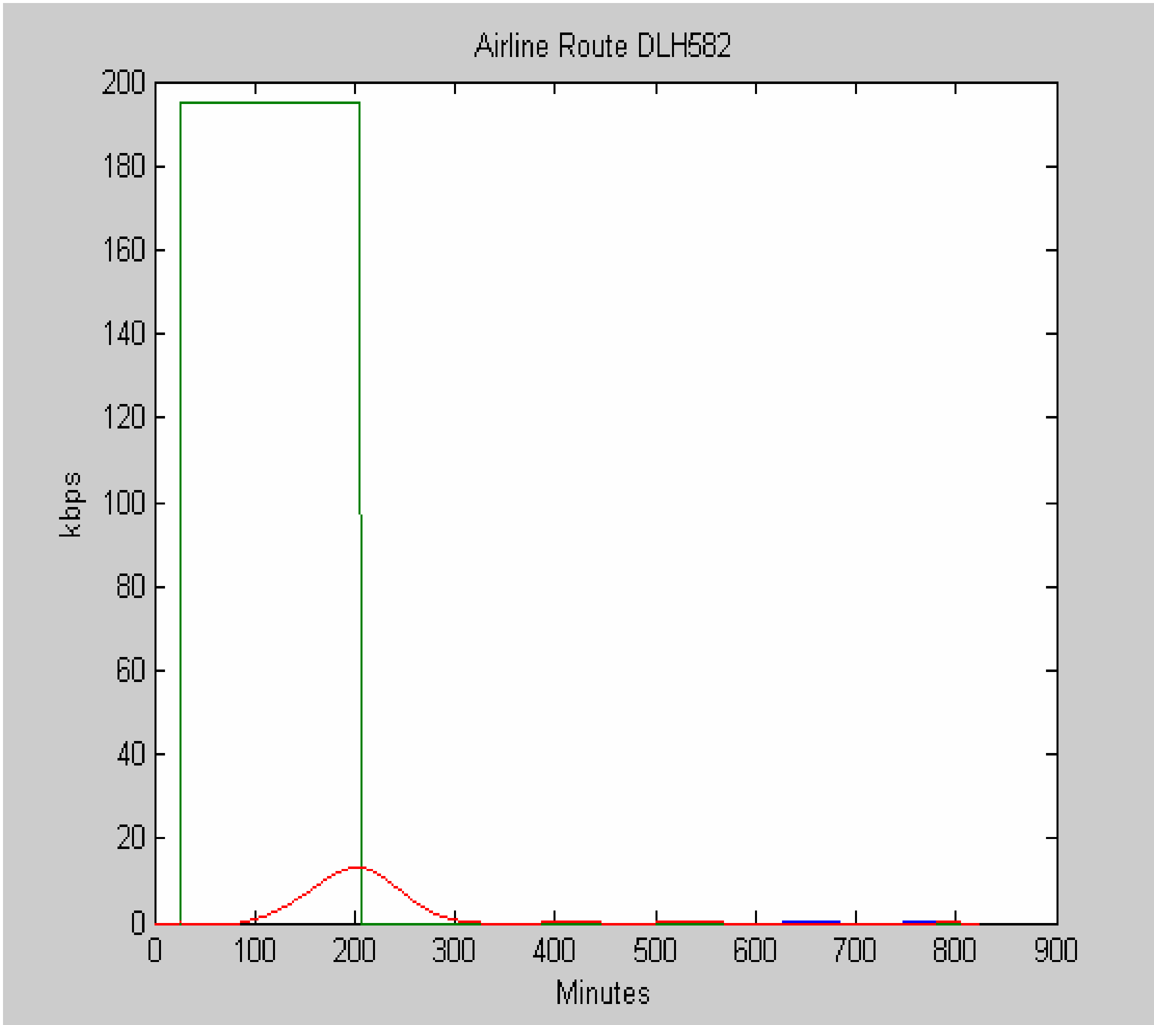
300
400
500
600
700
800
900


Airline Route DLH582
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Minutes
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300
400
500
600
700
800
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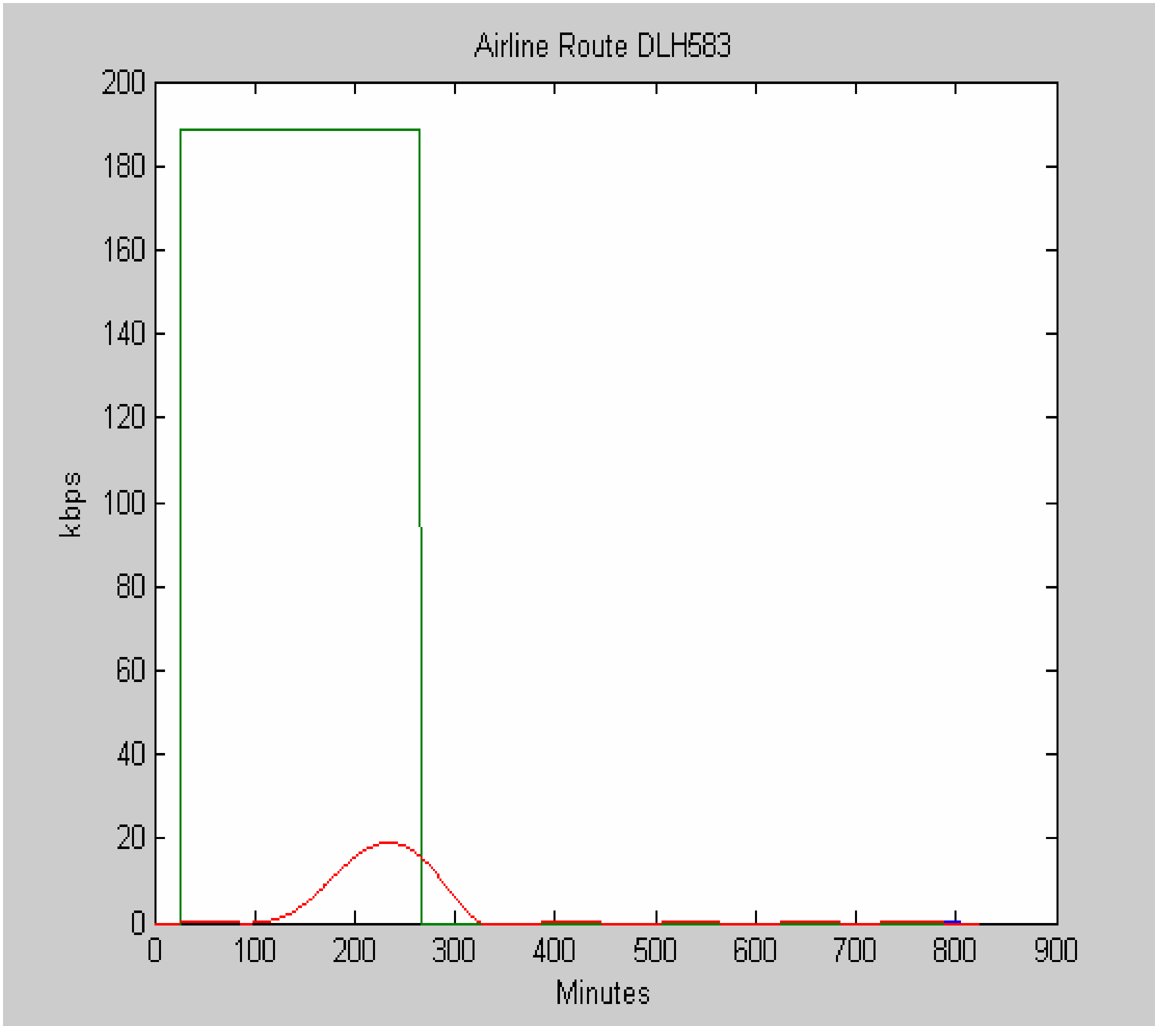
Airline Route DLH583
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600
700
800
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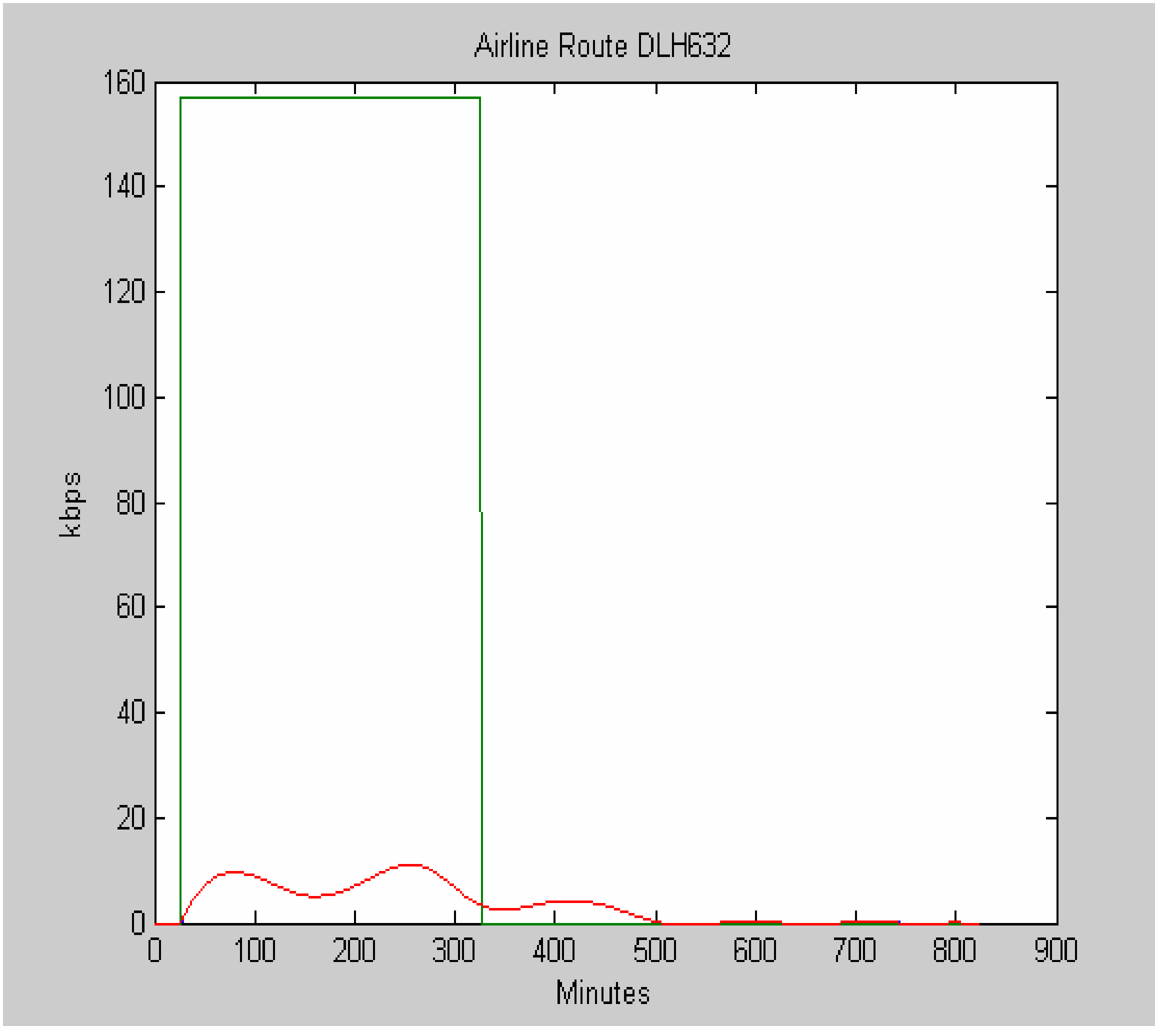
Airline Route DLH632
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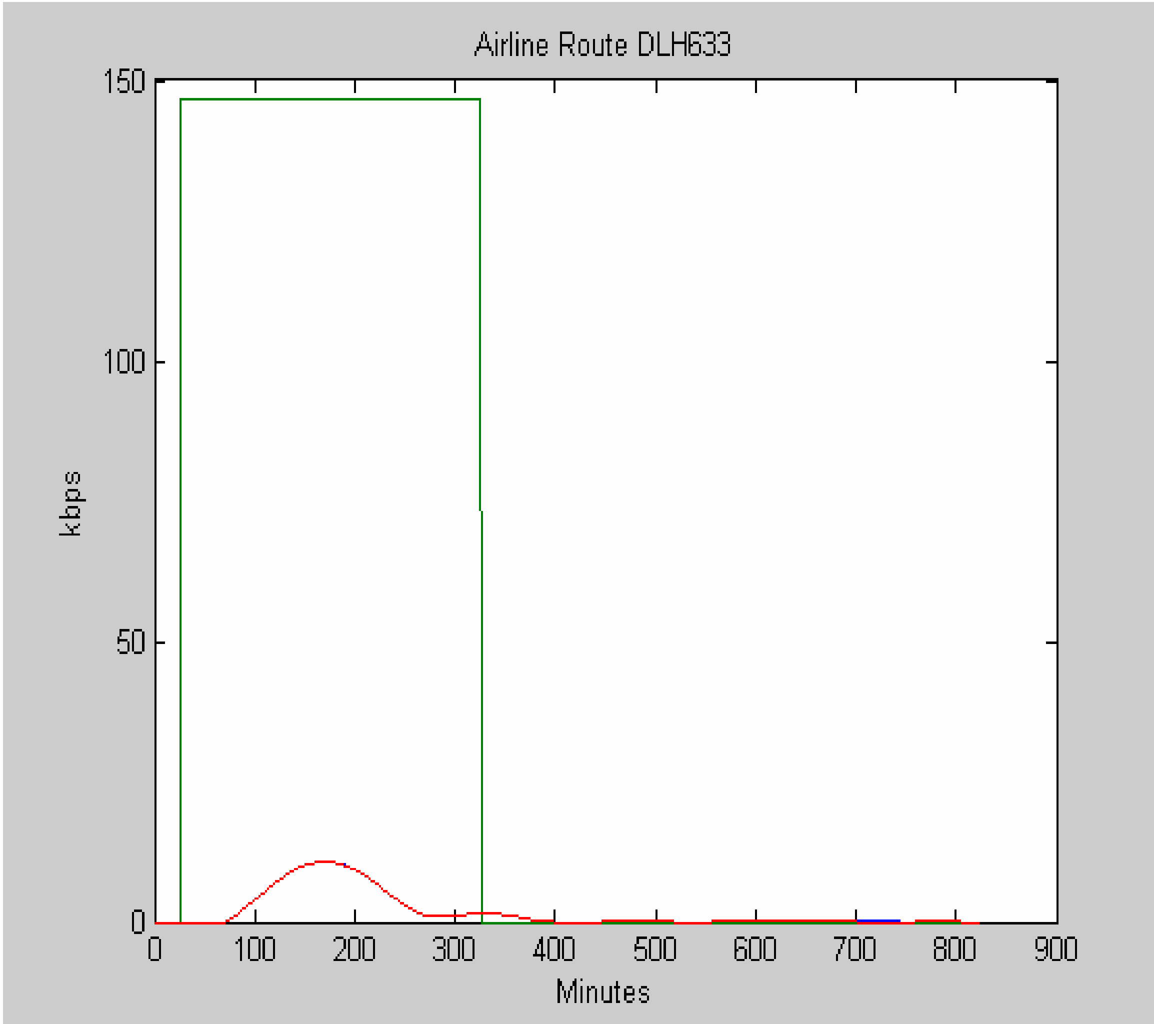
800
900
Minutes



Airline Route DLH633
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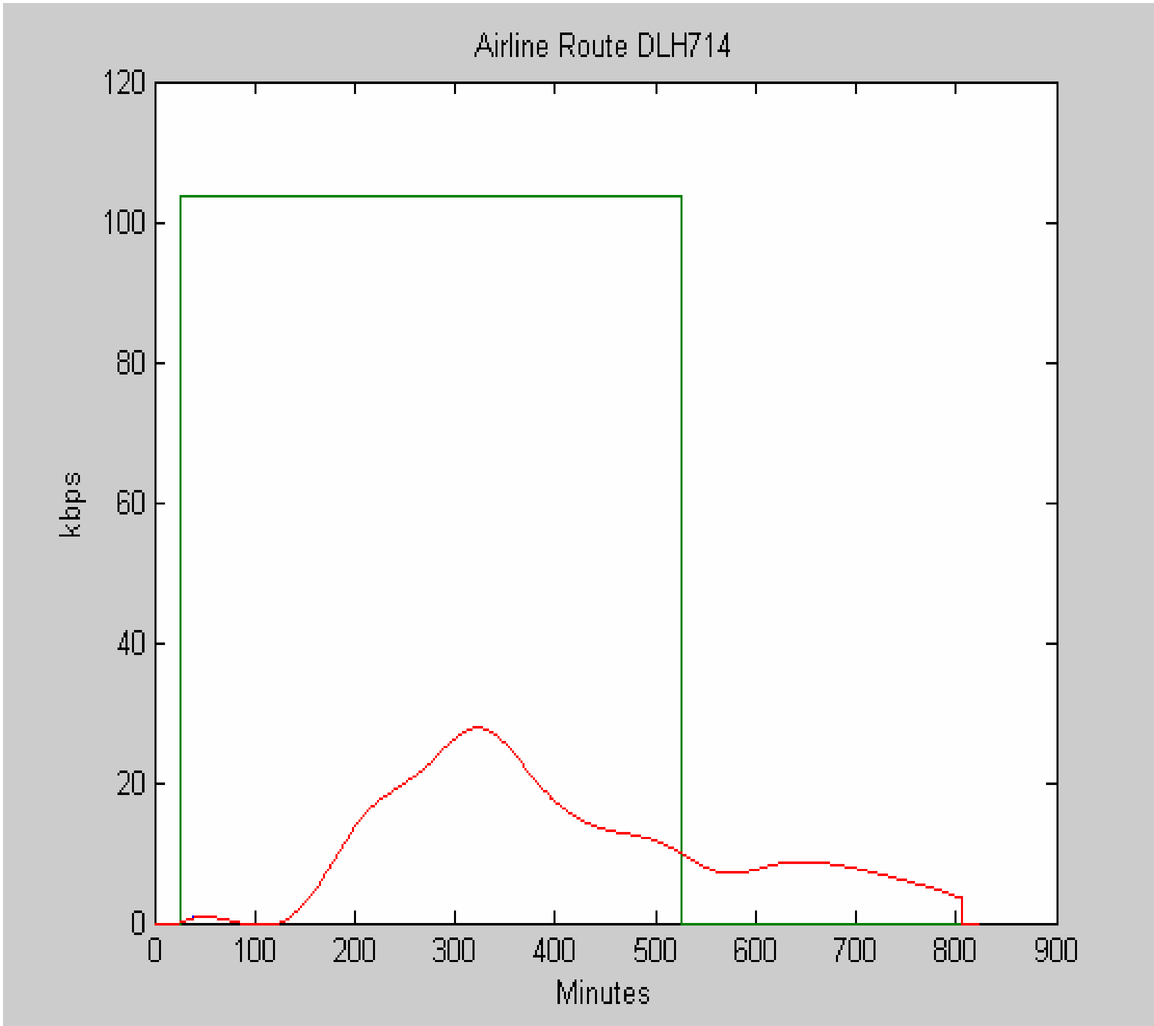
900


Airline Route DLH714
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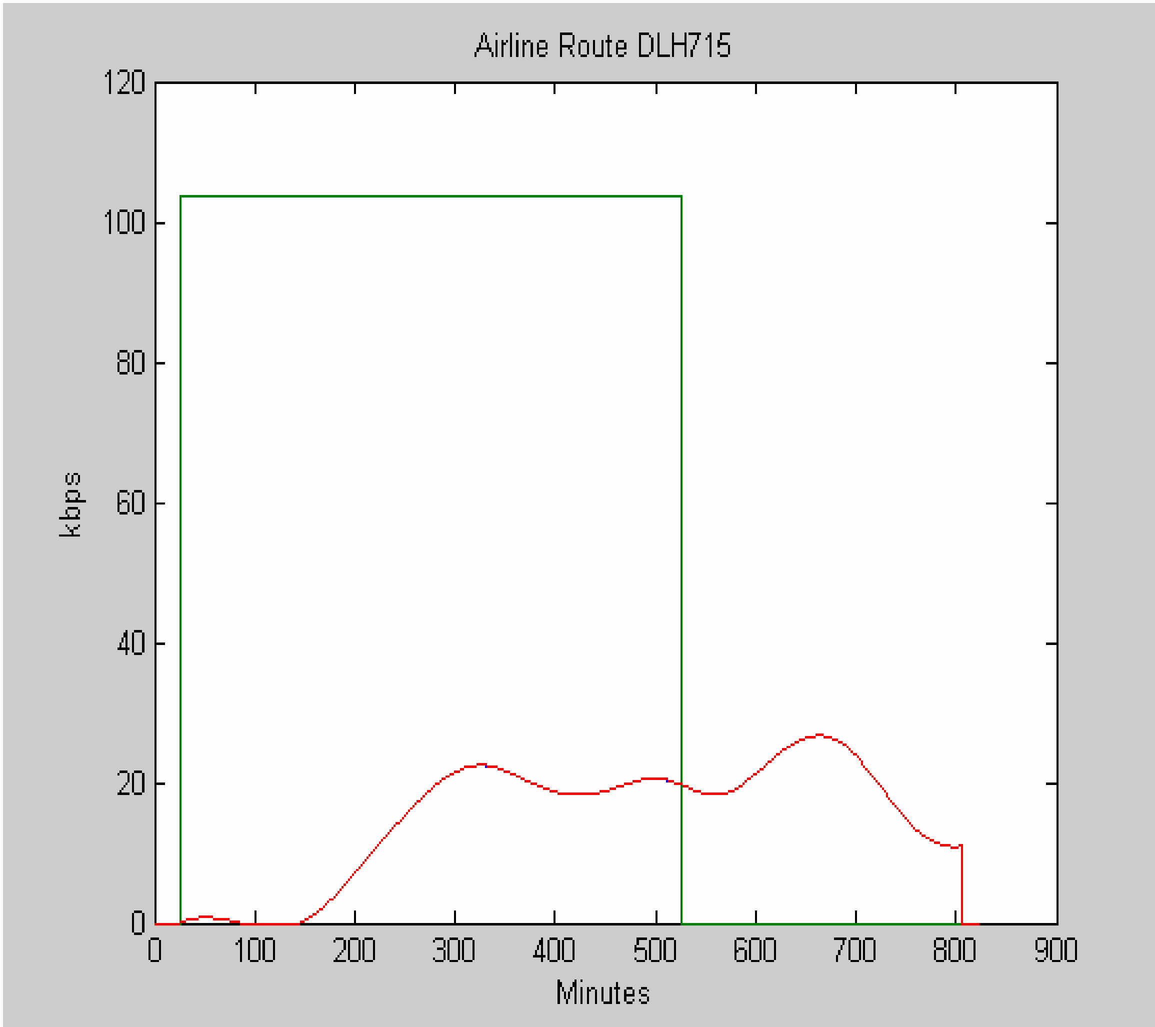
900
Minutes



Airline Route DLH715
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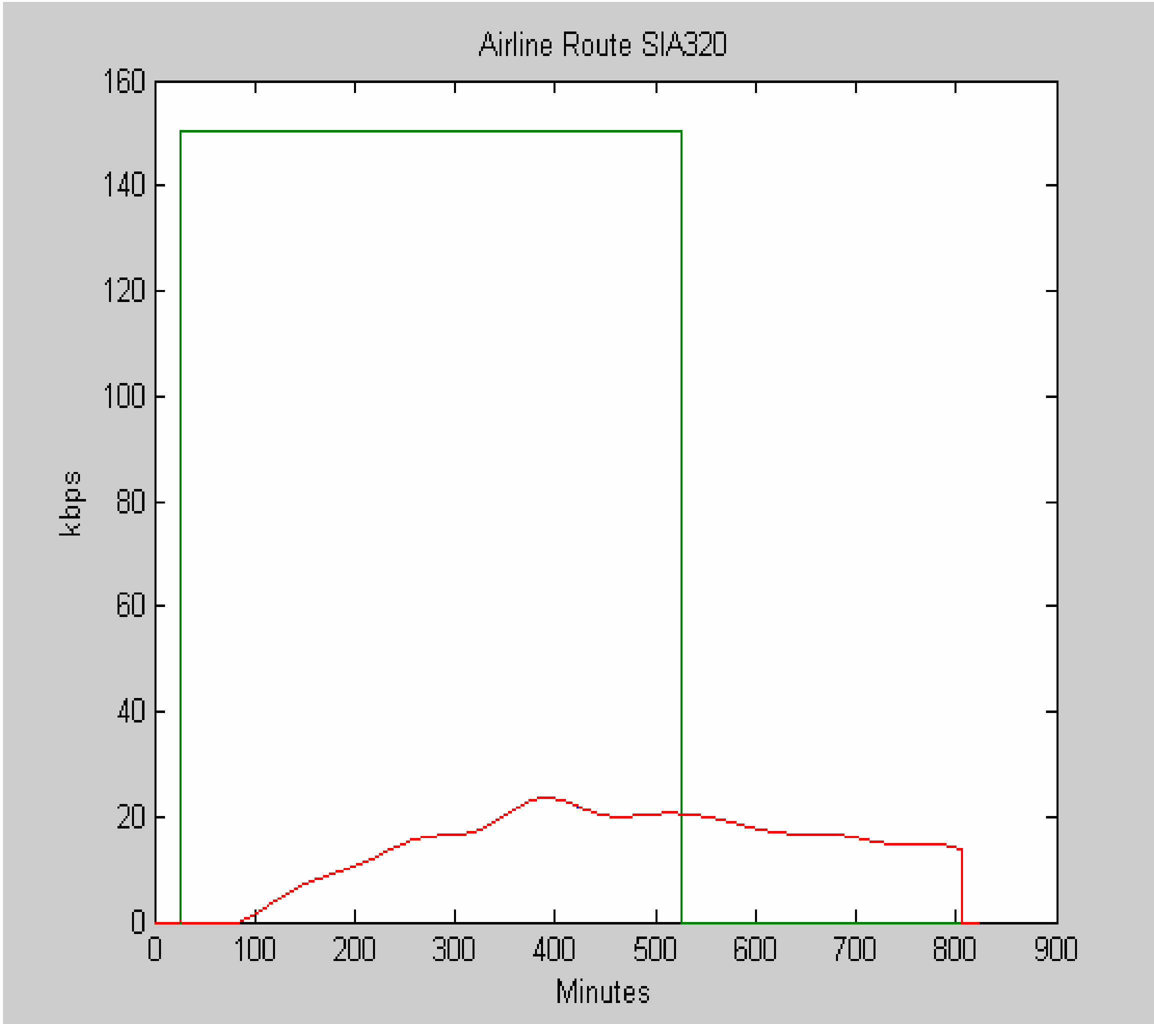
Airline Route SIA320
kbps
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100
80
60
40
20
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200
300
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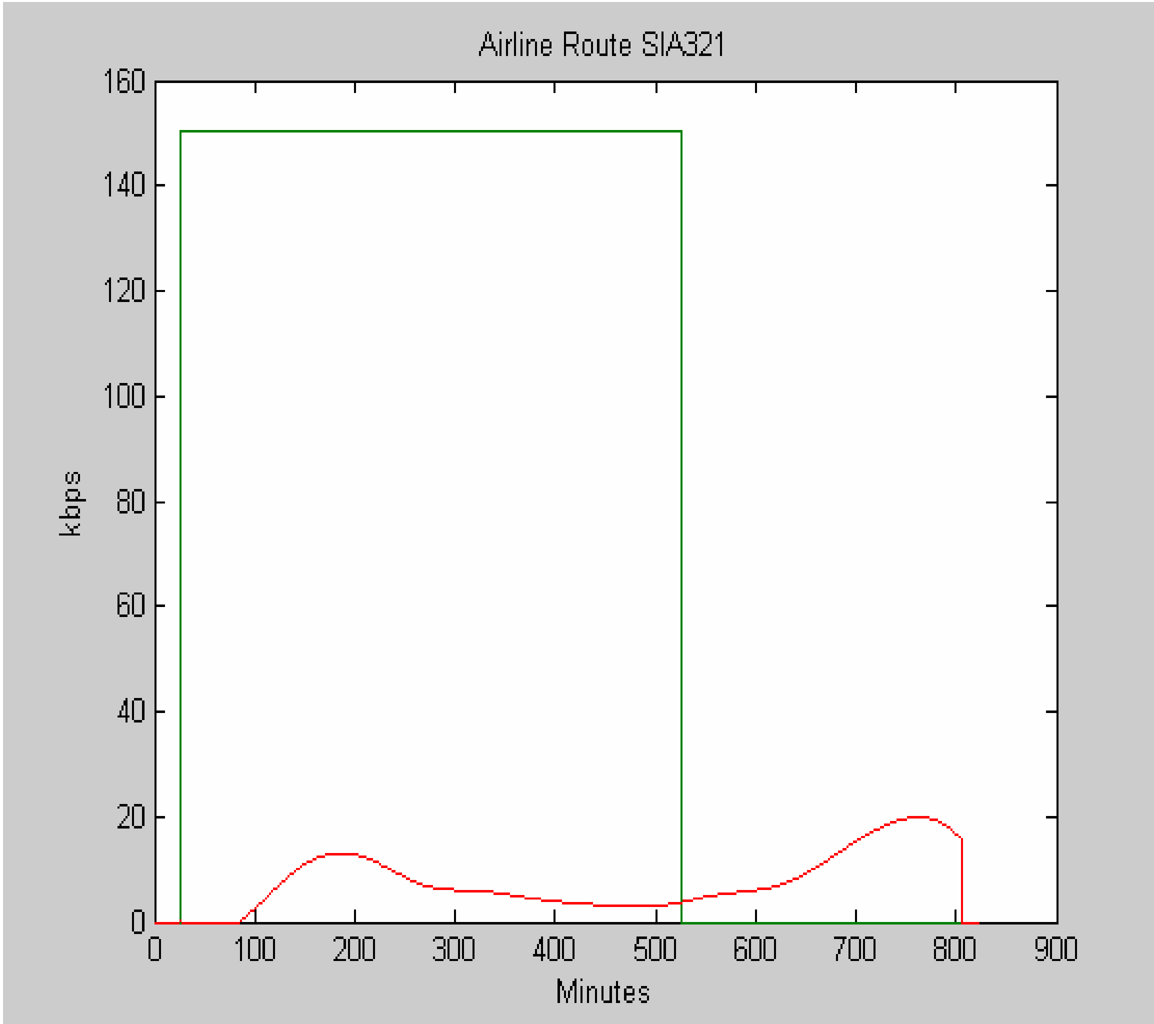
500
600
700
800
900


Airline Route SIA321
kbps
Minutes
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80
100
120
140
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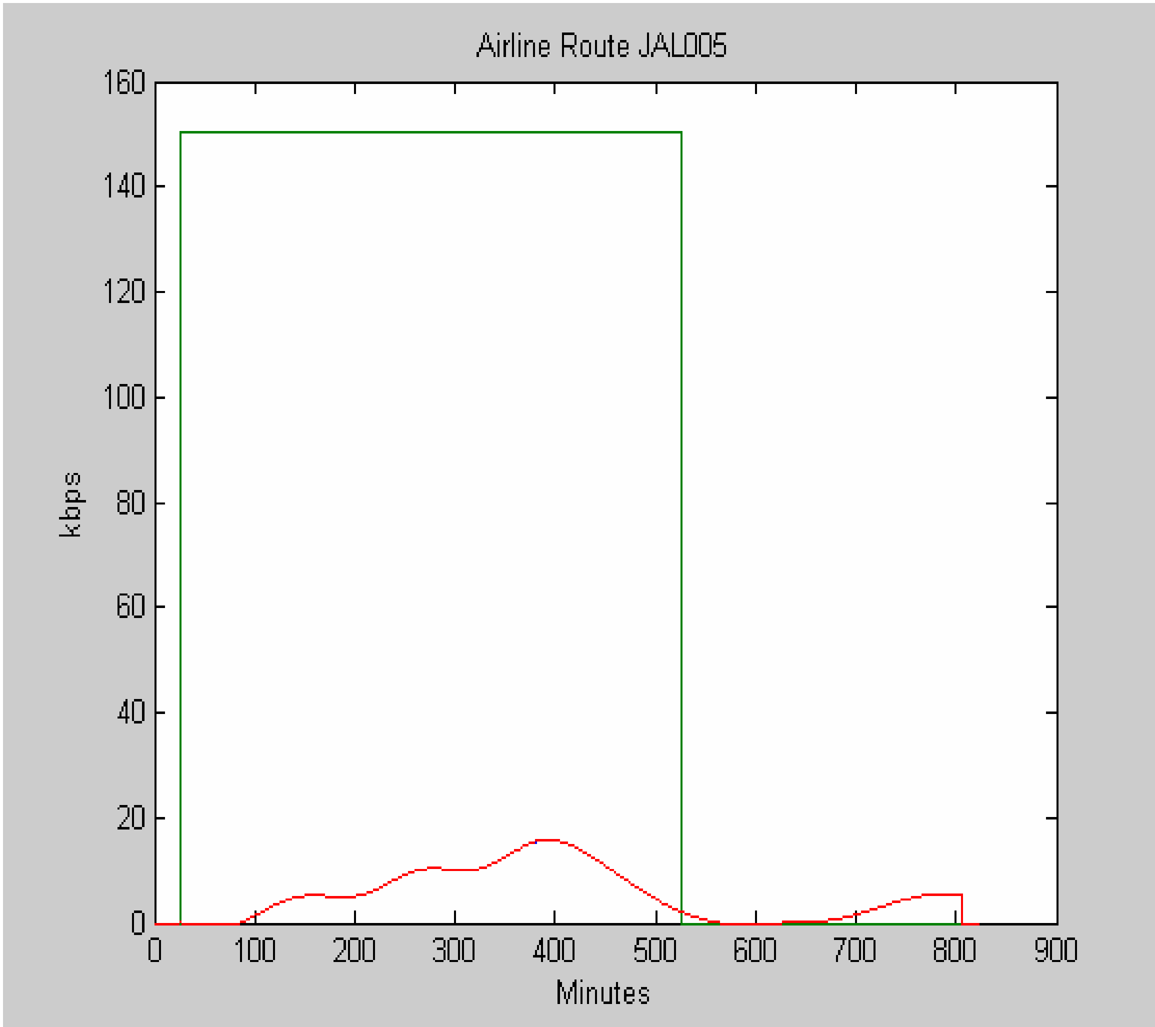
200
300
400
500
600
700
800
900


Airline Route JAL005
kbps
Minutes
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60
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200
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800
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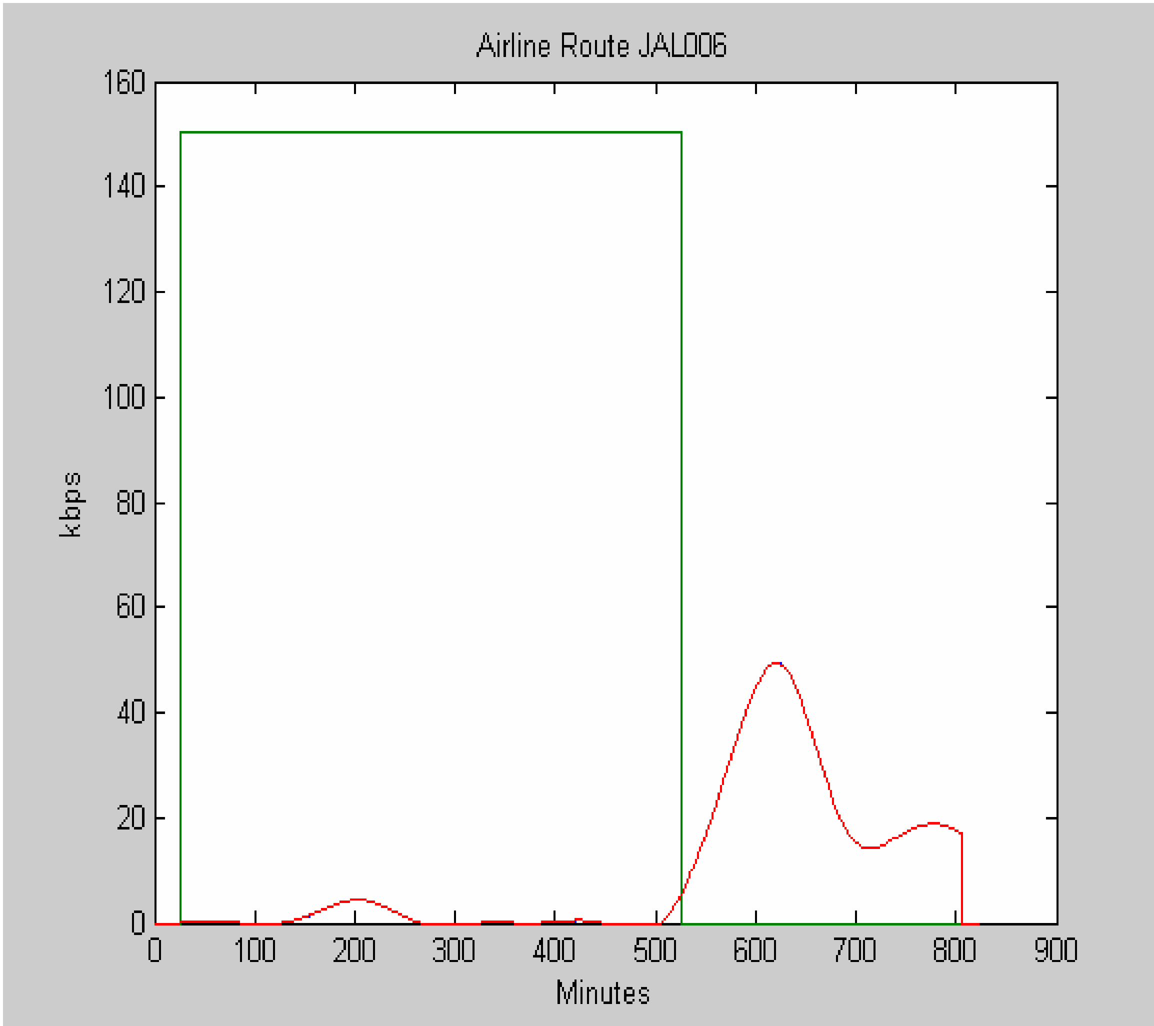
Airline Route JAL006
kbps
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80
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40
20
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700
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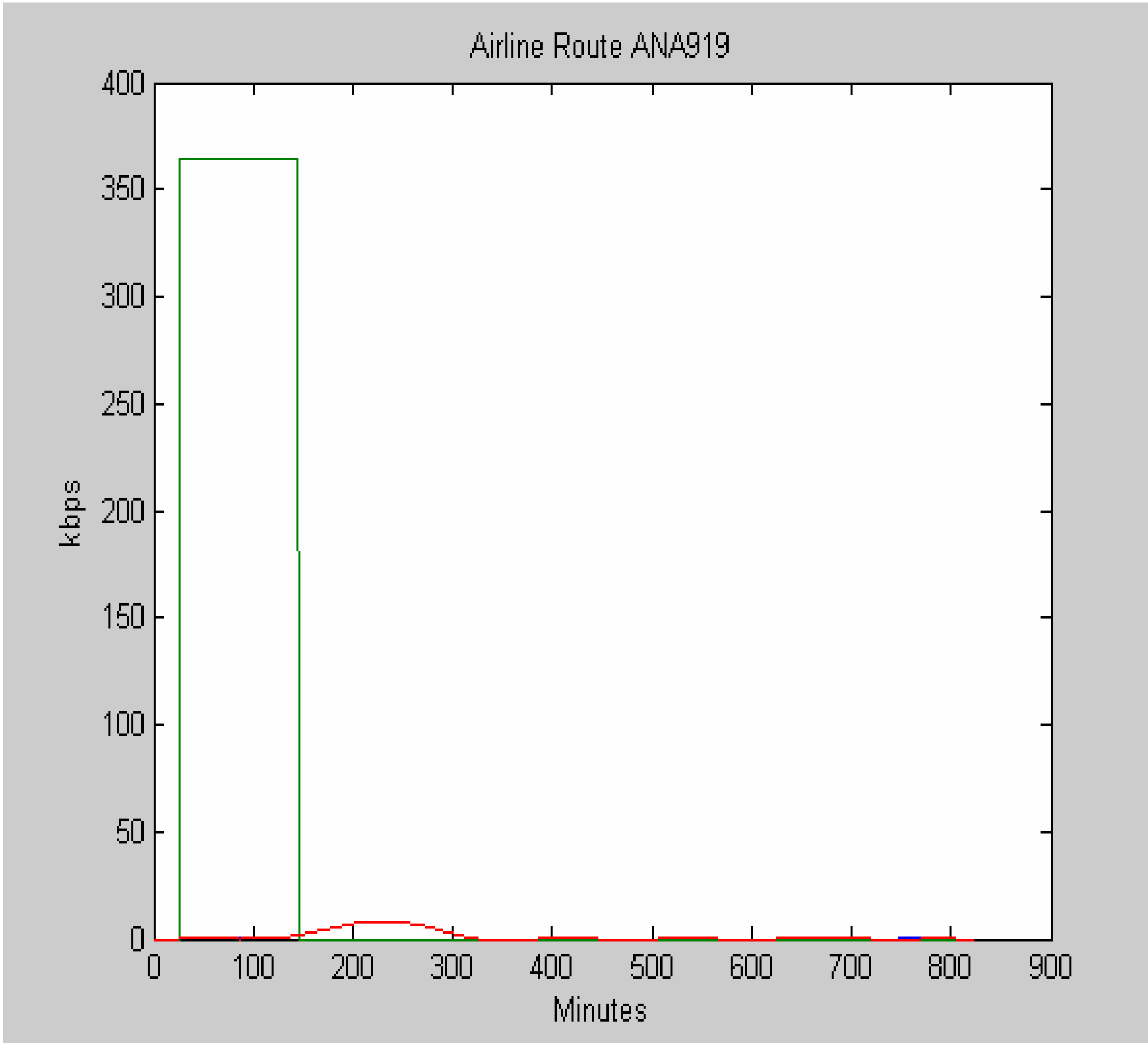
Airline Route ANA919
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250
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150
100
50
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kbps
0
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200
300
400
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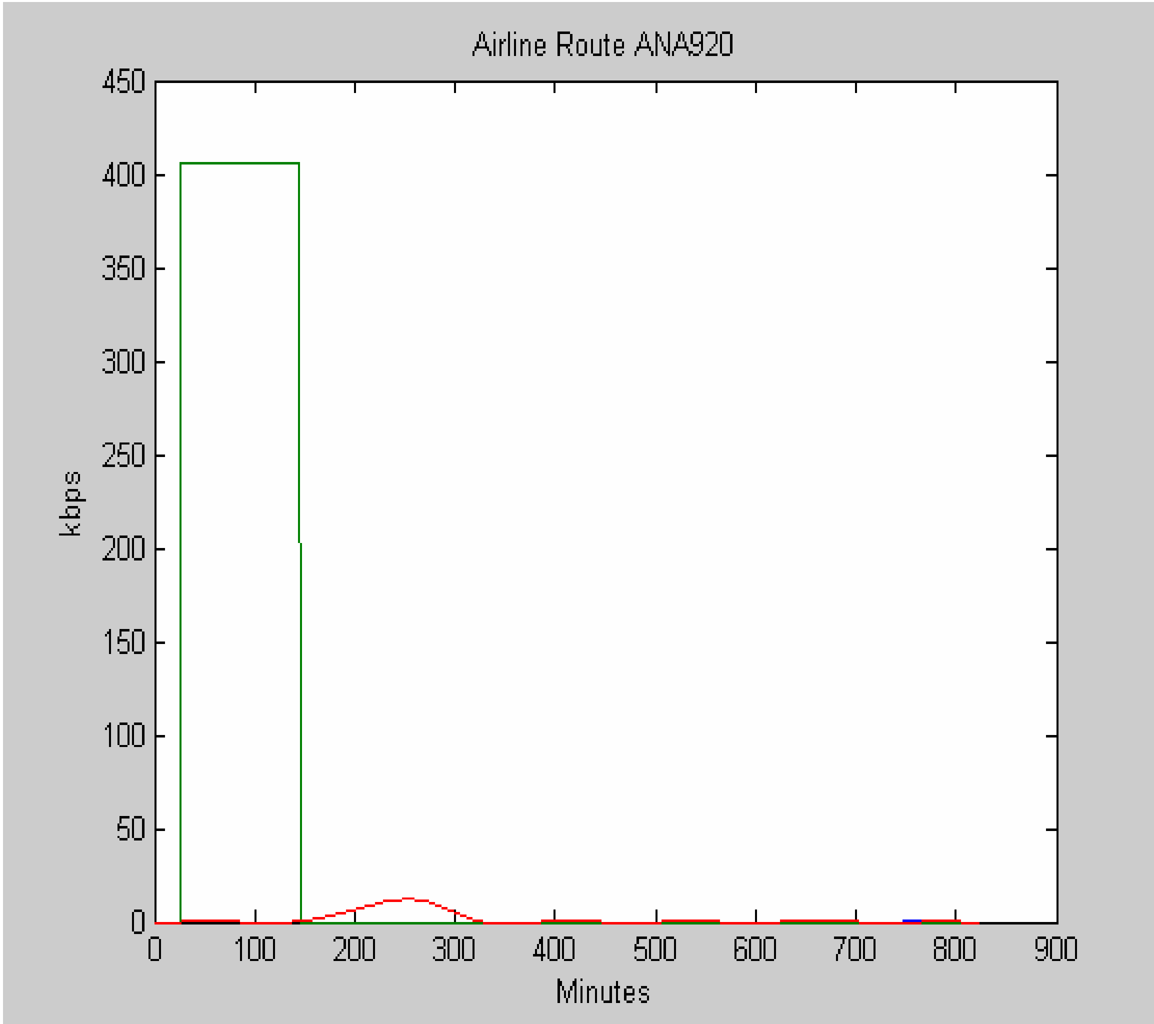
600
700
800
900
Minutes


Airline Route ANA920
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100
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kbps
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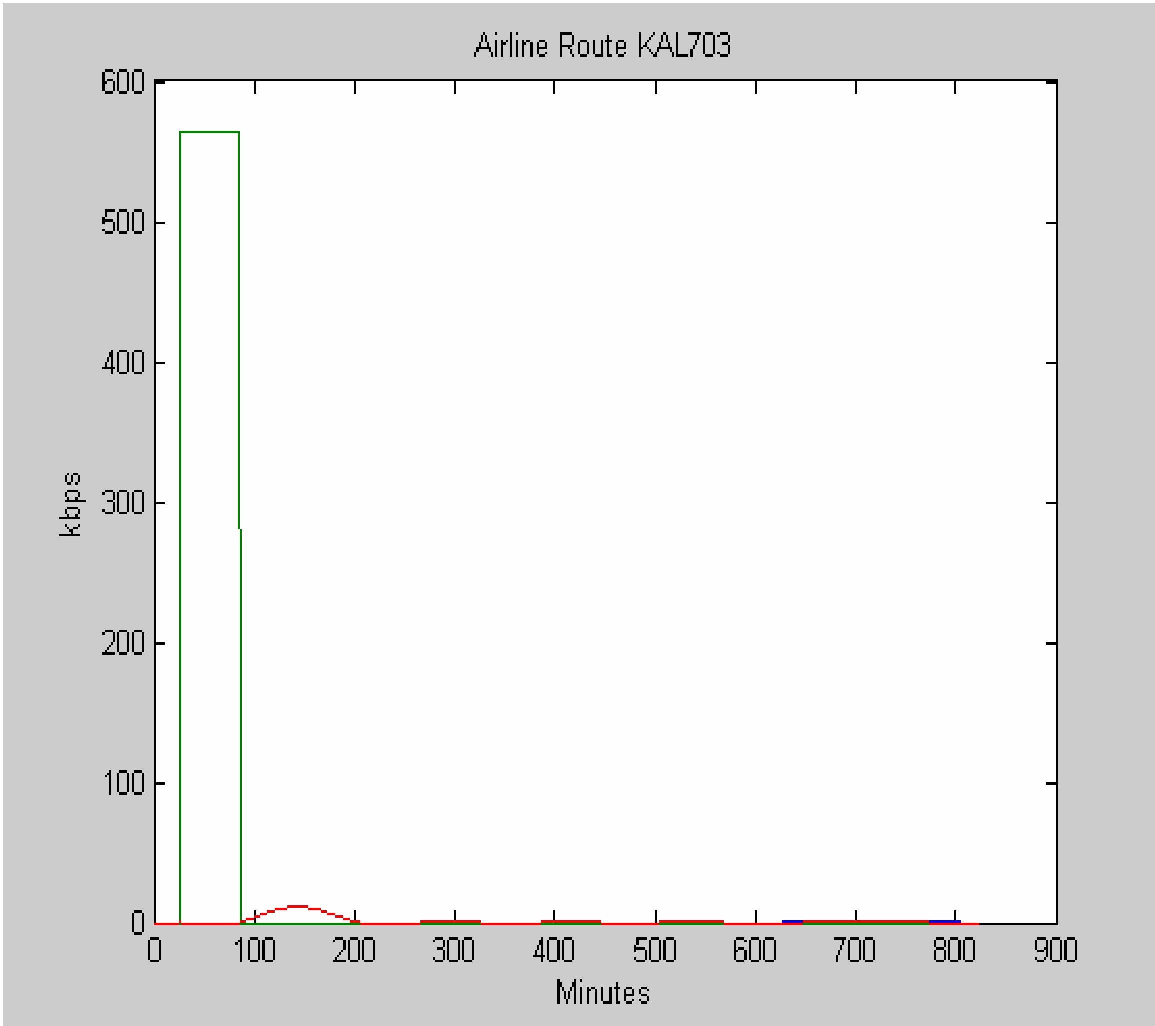
700
800
900
Minutes


Airline Route KAL703
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200
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kbps
0
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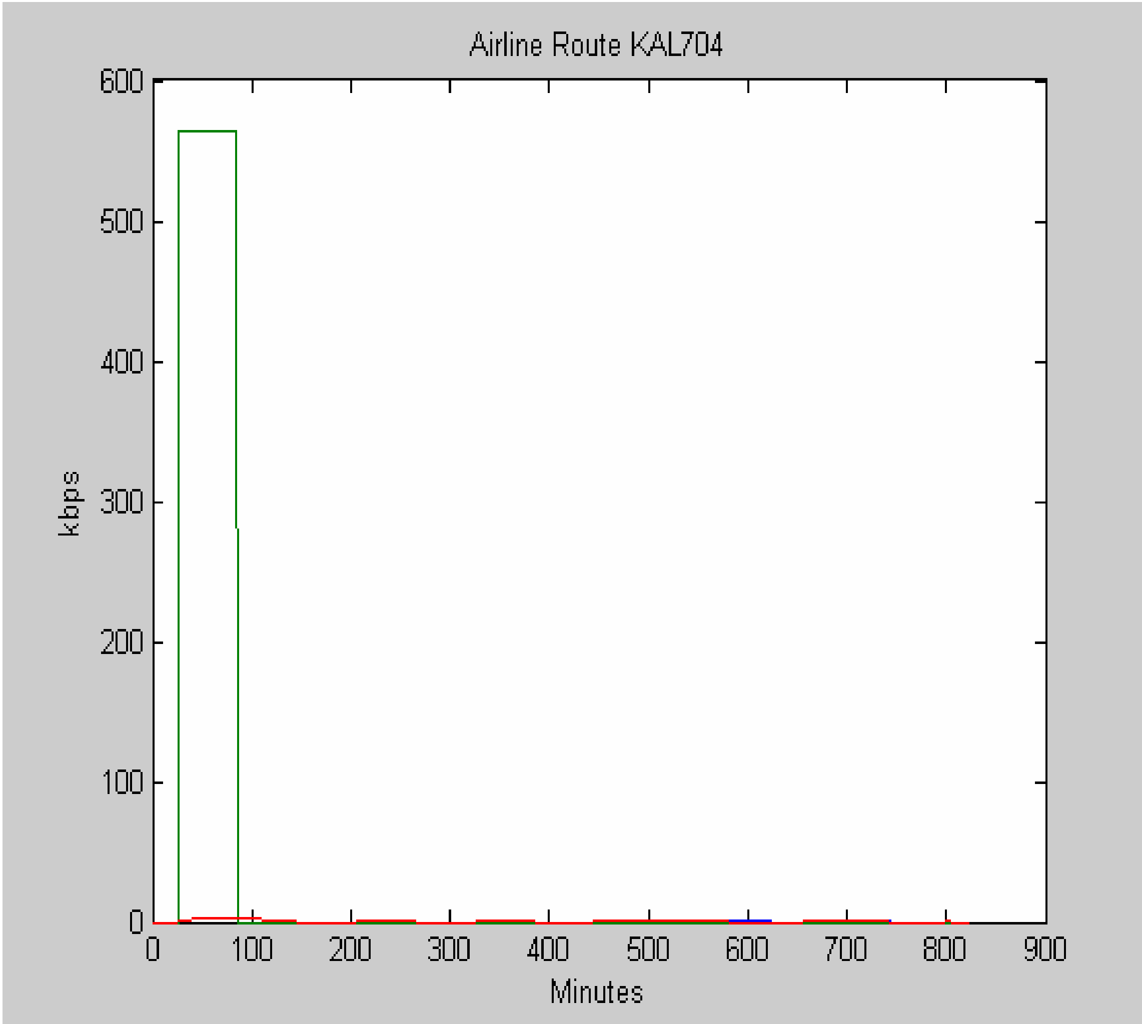
900
Minutes



Airline Route KAL704
kbps
Minutes
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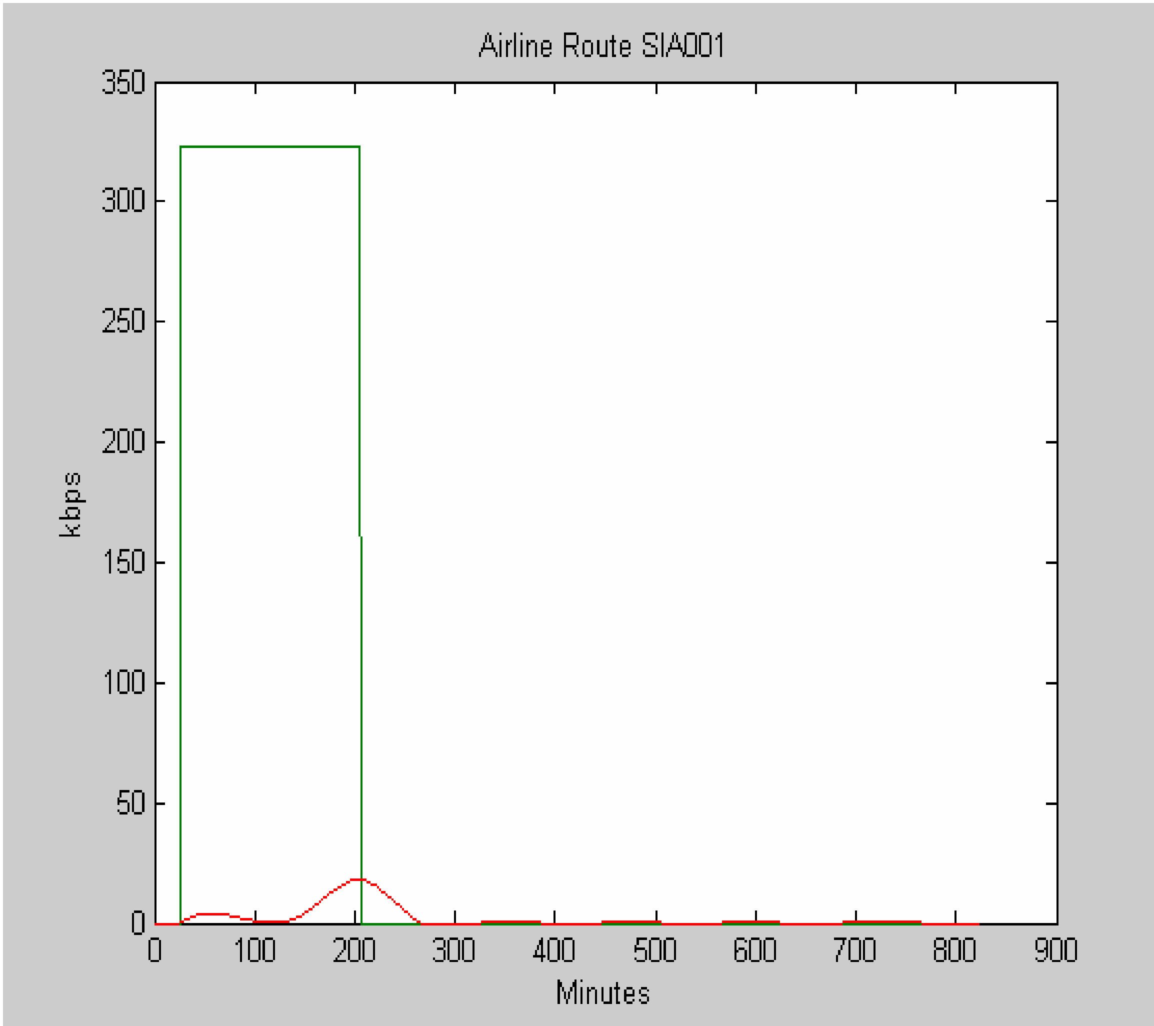
600
700
800
900


Airline Route SIA001
kbps
Minutes
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100
200
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400
500
600
700
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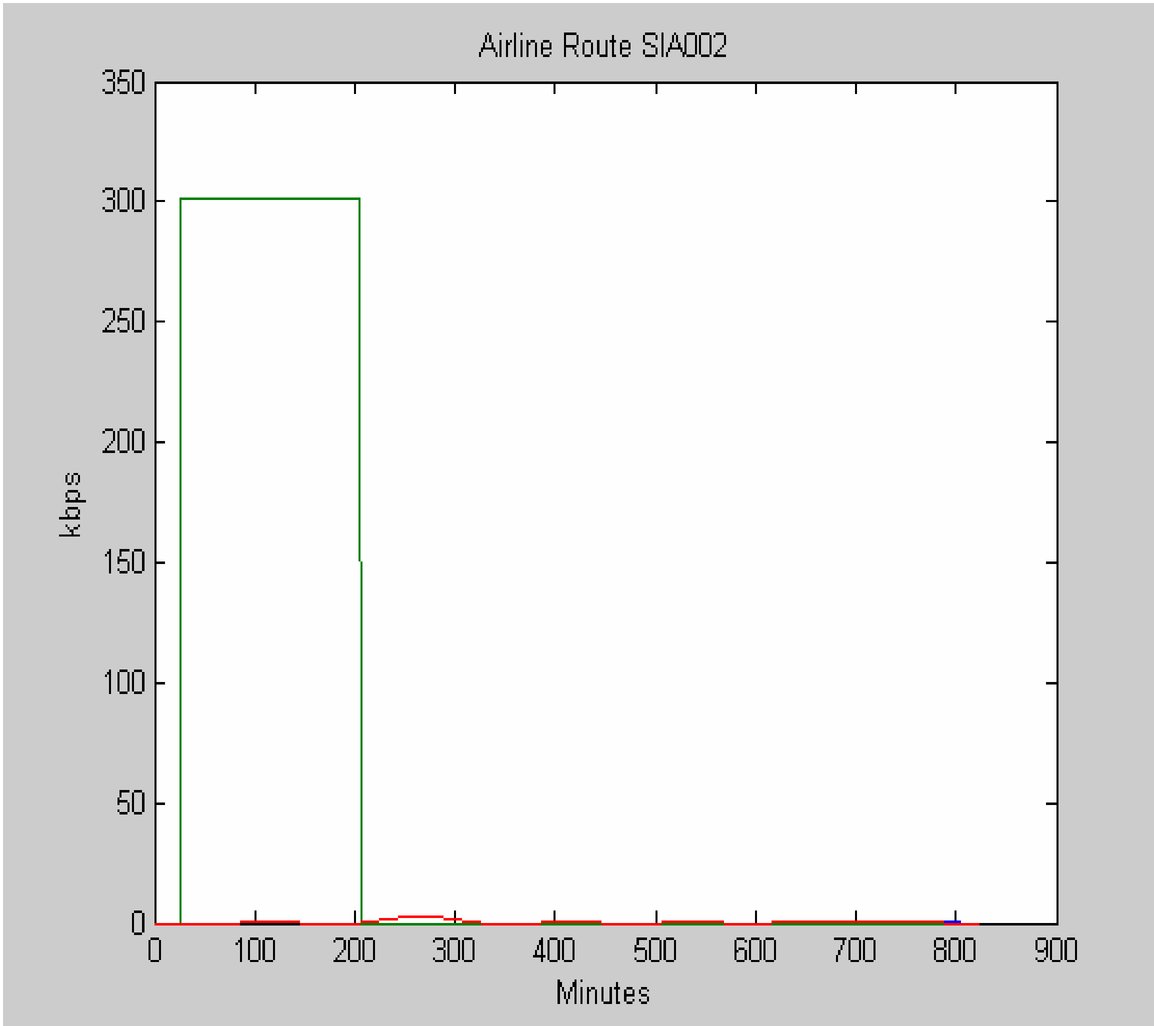
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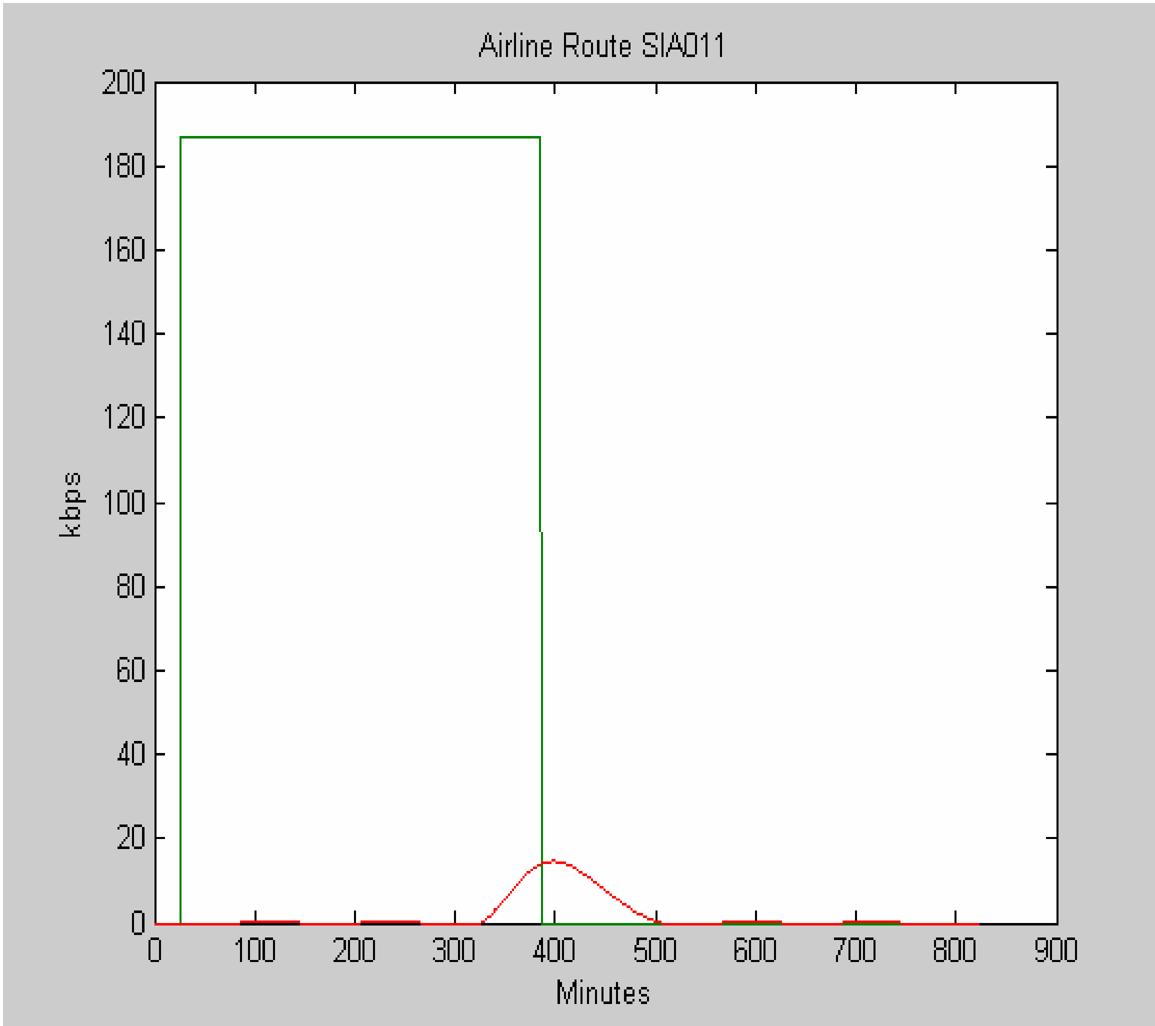
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kbps
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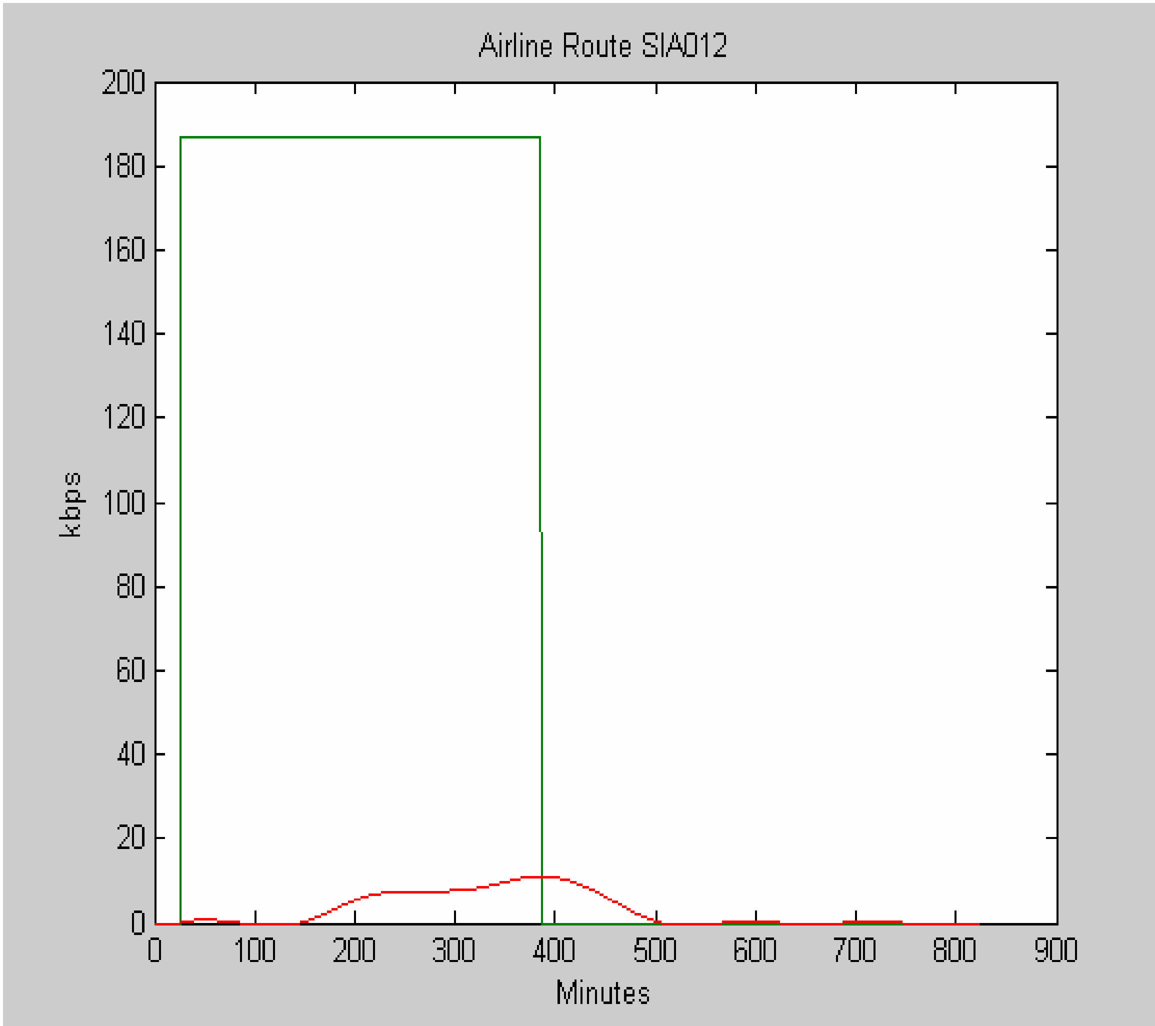
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VITA

Douglas Keith Swift was born in Muskogee, Oklahoma in January 1955. He graduated from Tulsa Central High School in May 1973. He went to college at the United States Air Force Academy (USAFA) in Colorado Springs, Colorado. He graduated from USAFA in June 1977 with a BS in Astronautical Engineering and received a commission as an officer in the United States Air Force. He served in the Air Force for five years and was stationed at Los Angeles Air Force Station where he was assigned to the GPS (Global Positioning System) satellite program as an astronautical engineer. While there he met and married his wife, Jacquelyn Rucker, in August 1979. In June 1982 he started work as an engineer at the Military Aircraft Division of the Boeing Company in Wichita, Kansas, where he worked for five years in the Flight Controls Technical Staff. In December 1989 he transferred to the Space and Missiles Division of the Boeing Company in Kent, Washington, where he has worked five years on the Launch Systems Integration (LSI) Program, five years on the Inertial Upper Stage (IUS) program, five years on the Sea Launch (SL) program, three years on the Connexion by Boeing (CBB) program, and is now working in the Puget Sound Systems Engineering Functional Group. While in the Air Force he attended graduate school and studied Modern Control Theory at the University of Southern California (USC) in Los Angeles, California. In December 1981 he received a MS degree in Electrical Engineering from USC. In recent years, while working at the Boeing Company, he attended graduate school and studied Systems Engineering and Network-Centric Systems at the University of Missouri – Rolla (UMR), Rolla, Missouri. In December 2007 he completed his PhD in Systems Engineering from UMR.