DEVELOPMENT OF A MULTIVARIATE HIGH- ORDER FUZZY TIME SERIES FORECASTING MODEL WITH DATA CLUSTERING FOR OPTIMUM PREDICTION AND CONTROL OF HANDOVER-BASED MOBILITY MANAGEMENT
(AIRTEL LAGOS AS CASE STUDY)

BY

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MAY, 2014

DECLARATION

I, **Sani Man-Yahaya**, hereby declare that this dissertation has been written by me and that it is a record of my research work. It has not been presented in any previous application for a higher degree. All quotations and sources of information as seen in dissertation are specifically acknowledged by means of references.

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Sani Man-Yahaya Date

CERTIFICATION

This dissertation titled "**DEVELOPMENT OF A MULTIVARIATE HIGH- ORDER FUZZY TIME SERIES FORECASTING MODEL WITH DATA CLUSTERING FOR OPTIMUM PREDICTION AND CONTROL OF HANDOVER-BASED MOBILITY MANAGEMENT (AIRTEL LAGOS AS CASE STUDY)**" by **Sani Man-Yahaya**, meets the regulations governing the award of the degree of **Doctor of Philosophy (Ph.D) in Electrical Engineering** of Ahmadu Bello University, Zaria and is approved for its contribution of knowledge and literary presentation.

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DEDICATION

I dedicate this work to the memory of my late parents. May their gentle souls rest in perfect peace, Ameen.

ACKNOWLEDGEMENT

I am grateful to Almighty Allah, the Most Beneficent, the Most Merciful, may His peace and blessings be upon the Holy Prophet, his household and all those who stood by peace till the last day. Oh! Allah, I sincerely thank you for the guidance and strength to undergo this program successfully. Oh! Allah I equally request that You bless it for me, make it a way of accepting me unto Yourself and protect me against any arrogance that may arouse from my ego as a result of this achievement, Ameen.

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MI JIYEBO SARAYIN, SOKO GA YE BE ALJANNATUL-FIRDAUSI.

I sincerely pray that this research work will contribute immensely to knowledge and development of Allah’s creations peacefully.

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ABSTRACT

The research is aimed at the development of a multivariable based high-order fuzzy time series (FTS) forecast model that will be applied for forecasting handover success rate (mobility management) in the Lagos zone of Airtel Nigeria as a case study. Multivariable FTS is based on classifying data as primary (major) and secondary (minor) as against the conventional univariate approach adopted by most FTS approaches. In order to optimize the determination of an objective interval length, the k^{th} fuzzy data clustering algorithm is adopted. In this work, 52 weeks data were collected from Airtel Lagos zone namely; handover success rate (HOSR), stand alone dedicated control channel (SDCCH), received signal strength (RSS), path loss (PLOSS) and bit error rate (BER). HOSR is termed the major data since it is the primary variable of interest whilst the rest are termed minor since they are secondary variables. 40 weeks of data are used as training data whilst 12 weeks are used as validation data. All the 40 weeks of data have been clustered in this work and the mid-value of each cluster is bounded and used in the fuzzification process (conversion of numeric values to fuzzy variables). The fuzzified data is then defuzzified and then used to forecast for week 41. The whole process is then repeated with the data length increasing each time by adding the training data of the current forecasted week to the existing training data, until forecasted results of week 41 to week 52 were obtained one after the other. The forecasted results obtained agreed with the actual data with a maximum variation of less than ±5%. The forecasting process of this type has a high computational cost in proportion to the data length and as such, a computer-based model was developed using a program written in MATLAB. The model was validated using the validation data of this work (from week 41 to week 52) and the results obtained from the developed computer-based model. To further enrich the model so as to serve as a verifiable basis of comparison and standard,

established models (Chen, Mu’azu and Jilani) were applied to the same data set and results obtained were used as additional validation. The developed model has demonstrated that it can be used to forecast HOSR using SDCCH, RSS, PLOSS and BER as attributes due to its degree of consistency with respect to the result obtained from the statistical analysis carried out. The statistical values obtained are: Average Performance Error (APE) of 0.6615%, Maximum Performance Error (MPE) of 2.4841%, Pearson’s Correlation Coefficient (PCC) of 0.9800 and Root Mean Square Error (RMSE) of 0.05012. In addition, the developed model was compared with three other FTS models, the result differences are (APE (0.0397, 0.0207 and 0.0209 respectively), MPE (3.3122, 3.9251 and 3.0111 respectively), PCC (0.0291, 0.0099 and 0.0139 respectively) and RMSE (0.001542, 0.000989 and 0.00149 respectively)) all higher than those of the developed model. Therefore, the statistical analysis and validation with other FTS models have further ascertained and confirmed the accuracy of the developed model.

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LIST OF ACRONYMS

ACE	Auxiliary Control Elements
AFER	Average Forecasting Error Rate
AGCH	Access Grant Channel
AI	Artificial Intelligence
AMPS	Advanced Mobile Phone Services
AuC	Authentication Centre
BCCH	Broadcast Control Channel
BER	Bit Error Rate
BHT	Busy Hour Traffic
BTS	Base Transceiver Station
BSC	Base Station Controller
CCR	Call Completion Ratio
CDMA	Code Division Multiple Access
CEPT	Conference of European Post and Telegraphs
CM	Communication Management
DSN	Digital Switching Network
EFR	Enhanced Full Rate
EIR	Equipment Identity Register
ETSI	European Telecommunication Standards Institute
FCC	Federal Communications Commission
FCCH	Frequency Correction Channel
FDMA	Frequency Division Multiple access

FIS	Fuzzy Inference System
FTS	Fuzzy Time Series
GMSK	Gaussian filtered Minimum Shift Keying
GOS	Grade of Service
GSM	Global System for Mobile communications
HLR	Home Location Register
HOSR	Handover Success Rate
IMEI	International Mobile Equipment Identity
IMSI	International Mobile Subscriber Identity
ISDN	Integrated Services Digital Network
ISO	International Standard Organization
ITU	International Telecommunications Union
KBS	Knowledge Based Systems
LMI	Lagos Main Land
MAP	Mobile Application Part
ME	Mobile Equipment
MM	Mobility Management
MS	Mobile Station
MSC	Mobile Switching Centre
OA	Other Areas
PCH	Paging Channel
PCM	Pulse Code Modulation
PLOSS	Path loss

POTS	Plain Old Telephone Service
PSTN	Public Switched Telephone Network
SACCH	Slow Associated Control Channel
SCH	Synchronization Channel
SDCCH	Stand-alone Dedicated Control Channel
SCM	Service Circuit Modules
SIM	Subscriber Identity Module
SMS	Short Message Services
SVM	Support Vector Machines
TCAP	Transaction Capabilities Application Part
TDMA	Time Division Multiple Access
TMN	Telecommunication Management Network
RACH	Random Access Channel
RBS	Rule Based Systems
RPE-LPC	Regular Pulse Excited – Linear Prediction Coder
RSS	Received Signal Strength
RR	Radio Resource
VI	Victoria Island
VLR	Visitor Location Register
VoIP	Voice Internet Protocol
WLAN	Wide Local Area Network
1G	First Generation
3G	Third Generation

LIST OF SYMBOLS

λ	Lambda
$\sum$	Summation
t	Time
μ	Mu
P	probability
Δ	Delta
!	Factorial
ℓ	Script ell
$\int$	Integral
$\sqrt{\ }$	Square root
ρ	Rho
ג	Small lambda
α	Alpha
U	Union
∩	Intersection

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CHAPTER ONE

INTRODUCTION

1.1 General

Cellular networks are experiencing a large scale explosion in their usage due to the wide deployment of various technologies (CDMA2000, WLAN, WCDMA, 3G, etc) and the rapid proliferation of applications and services (Smartphone, multimedia, Androids, VoIP, etc). Users are increasingly using this application gadgets on-the-go and expect always-on, high quality connectivity at all times. Mobility management is the overall information (past and present) of the mobile station activities with respect to the network. It is concerned with protocols and procedures related to roaming, identification and continuity of the established call. Mobility is the most important feature of today’s wireless networking systems and can basically be attained by handover mechanisms. Handover describes the mechanism that transfers an on-going call from one cell to another as a user moves through the coverage area of a cellular network system or a process of changing the channel (frequency, time slot, spreading code, or combination of them) associated with the current connection while a call is in progress (Qing and Dharma, 2002). The handover between wireless cells of the same type (in terms of coverage, data rate and mobility) is often referred to as horizontal handover, whereas the handover between wireless cells of different type is characterized as vertical handover.

Although, handovers are necessary for mobile devices to maintain connectivity, a recent study (Tso et al, 2010) showed that handovers generally cause short-term disruptions in application performance. Similarly, studies (Lunden et al, 2008) have shown that handovers could degrade performance of real-time applications such as voice over IP (VoIP). Moreover, some networks are prone to making handovers decisions sub-optimally (Tso, et al, 2010), incurring overhead for both applications and the infrastructure when performing unnecessary handovers. In addition, as smaller cells are deployed to meet the demands for increased capacity, the number of cell boundary crossings increase, creating chances for more handovers. Each handover requires network resources to reroute the call to the new base station. Minimizing the expected number of handovers minimizes the switching load. Another concern is delay, if handover does not occur quickly, the quality of service may degrade below an acceptable level. Minimizing delay also minimizes co-channel interference. During handover, there is a noticeable brief service interruption. As the frequency of these interruptions increases the perceived quality of service is reduced. The chances of dropping calls or blocking calls due to factors such as availability of channels increase with the number of handover attempts. All of these issues place additional challenges on the cellular network system. As the rate of handover increases, handover algorithms need to be enhanced so that the perceived quality of service does not degenerate and the cost to the cellular infrastructure does not skyrocket. Much effort is being expanded to study existing handover schemes, and to create new ones that meet these challenges.

Given the negative impact of handovers on application performance, applications could benefit from the ability to predict impeding handovers with reasonable accuracy, and modify their behavior to counter the performance degradation that accompanies handovers. Recent work (Schulman et al, 2010) has shown that mobile stations can make effective use of similar performance predictions to reduce energy consumption. Also, the network infrastructure could utilize the ability to predict conditions that are likely to require handovers to improve handover decisions and resources allocation. One of the recent methods is to control the handover of users as they move between shrinking cells, at greater speeds, and with stricter requirements on both the quality of service delivered to the user and the operational costs associated with the connection. Furthermore, to meet the growing demand for highly mobile wireless communication services, cellular system providers will continue to deploy additional cell sites and introduce increasingly complex systems, for both the radio link and the network infrastructure. As more users are supported, the ever-growing concerns regarding the limitations of switching and signalling infrastructures have been met by a diverse suite of architectural and algorithmic methods. However, predicting future handovers is challenging because they are a function of unforeseeable attributes such as user mobility and changes in the environment. All these arguments form the basis of handover forecasting by many researchers using wide range of models, techniques and algorithms based on various parameters such as received signal strength, available channels, path loss, interferences, bit error rate, deployment method, cell structures and mode, history of handover rate, etc.

The decision to initiate a handover in the network by any standard requirement depends on a number of elemental control variables, which several research approaches on handover criterion usually combined. The application of these control variables within the basic canonical approaches has been studied in the literature only for cases involving one or two variables. However, the features of mobility management in cellular networks as a natural interdependent factored phenomenon, functioning under indefinite, uncertain circumstances, condition the fuzziness of input data onto fuzzy environment.

Fuzzy logic has been used to forecast a wide range of natural phenomenon since its advent by Lotfi Zadeh. Many research works have used it and modified it; among them are Song and Chissom, (1993) who first introduced fuzzy time series to deal strictly with time series data sets using the enrolment of University of Alabama as a case study. Meaningful advances have been recorded in this area but many other issues also arisen with respect to optimizing the forecasting process.

These issues include among others:

(i) events controlled by many factors and data mining techniques, (ii) objective determination of universe of discourse and interval length, (iii) fuzzification techniques, (iv) defuzzification techniques, etc.

Most of the existing fuzzy forecasting methods based on fuzzy time series are univariate models and make use of static length of intervals, i.e., the universe of discourse is divided into a number of intervals of equal lengths. The drawback of the static length of intervals is that the historical data are roughly put into the intervals, even if the variance of the historical data is not high. Univariate models also ignored the fact that events are usually multi-factor controlled. Where data mining technique included first-order, second-order or more, comparative studies as presented by earlier studies have led to the conclusion that high-order fuzzy forecast models are among the most accurate models found in the literature (Radmehr and Gharneh, 2012).

This research work is expected to develop a multivariate forecast model that utilizes a data clustering algorithm to generate different lengths of intervals in the universe of discourse from the historical numerical data. The method does not only use the training data, but it also uses the already known testing data such that for each testing datum, data clustering algorithm uses the previously built fuzzy logical relationship to forecast. Therefore, the clustered data, current forecast and yet to be forecasted data are highly interrelated, and used simultaneously in fuzzification, fuzzy logical functions, defuzzification and forecast processes as suggested by Geva (1999a,b), Sfetsos and Siriopoulos (2004), Magalhaes et al. (2008), Shyi and Kurniawam (2011), Usman et al. (2012), Radmehr and Gharneh (2012), etc.

1.1.1 Multivariate Forecast

Multivariate forecasting is a forecasting method that takes into account a number of attributes that directly affects a particular event. This is in line with the natural law of existence that links predetermined events with identifiable factors. Literatures have indicated that for too long researchers have studied and applied fuzzy-based univariate forecasting methods. Efforts by the likes of Jilani and Burney (2008); Cheng et al (2008); Yu and Huarng (2008); Tanuwijaya and Chen (2009); Shyi (2012) and host of others in recent past have shown significant improvements in accuracy of predictions by multivariate fuzzy models over univariate ones. However, as the number of variables is increased to justify more coverage of the phenomenon so as to result in better forecast values, the computational complexity becomes a problem. Many research works like Tahseen et al (2007); Shyi and Tanuwijaya (2011); Manoj and Khola (2012); Thanachai et al (2013) etc have tried to find additional means, not only to address the complexity but to improve the existing approaches by incorporating into the multivariate model data mining techniques like high-order models, iteration models, regression models, etc.

Multivariate fuzzy forecast starts with fuzzification, which is a process of converting crisp values into fuzzy values by identifying possible uncertainties or variations in the crisp values. This is followed by identifying fuzzy relationships (which is a fuzzy set defined on the Cartesian product of crisp sets) and finally a defuzzification, that implies converting fuzzy values back into crisp ones with the earlier defined high-order.

1.1.2 High Order Analysis

High-order models are among most accurate models found in literature (Radmehr and Gharneh, 2012). High-order models are usually selected as targets for comparison and optimization. However, studies have also shown that it does not necessarily follow that the higher the order the more accurate the forecast. Currently, the highest order reported in literature with multivariate approach is third-order by (Jilani et al, 2007).

Adopting order higher than third-order can result in data becoming underutilized and resulting in the followings:

(a) the number of forecast rules (fuzzy relationships) reduces as the order increases.

(b) the combination pattern (fuzzy sets) to be matched with future pattern increases with order increments; which in turn, reduces the probability of finding equivalent pattern combination in future series data.

Other effects of the higher-order are, there is a lack of consistency between forecast rules and the data they represent; forecast accuracy is sensitive to selected interval partitions etc. In multivariate forecasting, higher orders still remain the verifiable tool for comparative analysis (Jilani et al, 2007).

1.1.3 Data Clustering

Clustering is a simple way of reducing large data set to meaningful subgroups of individuals. The division is accomplished on the basis of similarity of the individuals across a set of specified characteristics. The resulting sample is a representation of population with uncorrelated factors. There are fundamentally three main categories of clustering:

(i) Hierarchical clustering is a tree-like process appropriate for smaller data sets, (ii) Non-hierarchical clustering usually requires specification of the number of clusters a prior, and (iii) A hybrid of the two categories.

A major problem with the clustering techniques is how to deal with outliers, often caused by too many irrelevant variables. A lot of research works have tried to address this in recent literatures (Liao, 2005), (Preeti and Parag, 2008) and (Wang and Ming, 2012). However, in any data clustering techniques, the individual clusters must be;

(i) Different, (ii) Reachable, (iii) Measurable and (iv) Profitable (big enough to matter)

Lastly, two issues seem to be the primary focus of current research. The first is the selection of interval partitions (i.e. the length and number of intervals) which is replaced by clustering technique. The second is the formulation of fuzzy relationships by utilizing the successes recorded in high order techniques. Both of these factors highly influence forecast accuracy and thus are considered central to Fuzzy Time Series. It has been found that current research efforts are united by one common goal: to enhance consistency between forecast rules and the data they derive from. This implies that performance of different Fuzzy Time Series models by tradition is evaluated under known conditions. In plain words, it means that forecast rules are validated using the same old data they originate from, rather than validating them on future datasets. To make this work comparable with those of others, the same principle in the evaluation phase was followed.

High order models are highlighted in this context, because they are among most accurate models found in literature, and thus are selected as targets for comparison. The findings of this related work study has lead to the identification of the following key problems with regards to high order models:

(a) there is a lack of consistency between forecast rules and the data they represent;

(b) forecast accuracy is sensitive to selected interval partitions;

(c) data becomes underutilized as the model's order increases.

In (c), the underutilization of data manifests itself in two ways as mentioned earlier. Solving the problems (a)-(b) is the primary objective of this work.

A secondary objective is to further improve the clustering fuzzification algorithm proposed by (Chen et al, 2011). This objective is motivated by the need for an algorithm capable of generating clusters fuzzy numbers (or intervals) automatically, based on the characteristics in data.

1.2 Statement of the Problem

Lagos is the commercial capital of Nigeria and probably has the highest number of GSM users compared to any city in Nigeria. As such it also has the highest number of GSM infrastructure and services e.g. cell sites, data services, multimedia etc. It can be described as a city on the run and as such qualitative mobility of GSM services is vital. Historically, the foundation of the Airtel is the pioneer GSM service provider in Nigeria. As at 2011, the company has functional ten MSCs, over twenty BSCs and over three thousand BTSs in the Lagos zone. The company deployed macro cells and is deploying micro cells in certain areas like Victoria Island. Mobility is a key factor in wireless networks like the GSM networks. With growing demands for GSM services, like data, multimedia etc, across the world, mobility has assumed ever greater importance with respect to service quality, availability, accessibility, sustainability and affordability. At the centre of this is handover which itself depends on other factors such as Received Signal Strength, Path loss, Channels, Bit Error Rate, etc (Akhila and Suthiksh, 2009; Dimesh and Singh, 2012). Thus, in order to predict handover success rate, a forecast model that can handle interdependent variables is required that does not necessarily seek to establish the mathematical relationship between the variables. One such model is the multivariate fuzzy time series forecast model. The model is predicated on the law of nature that events do not necessarily occur in isolation but are dependent on some factors. In order to increase the accuracy of the Fuzzy Time Series model, studies have suggested adopting high-order. However, studies have also shown that orders higher than three (3) will only increase computational complexity of the process without necessarily improving forecast accuracy (Chen, 2002; Lee, 2006; Jilani et al, 2007;Aladag et al, 2008; Poulsen, 2009). To further enhance the forecasting process, an objective determination of the interval length is necessary and has been the focus of many recent studies (Huarng, 2001a; Huarng and Yu, 2006b; Tahseen et al, 2008; Mu'azu et al, 2008; Meredith et al, 2008; Muhammad et al, 2009; Tanuwijaya and Chen, 2009; Wang and Chen, 2009; Shyi and Tanuwijaya, 2001). In this work, the k^{th} fuzzy data clustering algorithm is adopted.

1.3 Significance of the Research

The research work was able to achieve contribution to knowledge by developing a designed forecasting model for GSM handovers by the use of HOSR, SDDCH, RSS, PLOSS and BER variables. The Airtel Lagos zone was used as a case study, and the results obtained were in agreement with all validation techniques used (which include the actual data, computer-based results and FTS models results).

The Airtel Lagos zone data used in the development of the designed model is an internationally recognized standard GSM data, that is the designed model developed is applicable to all similar situations (including technologies, operators and geographical locations).

1.4 Aim and Objectives

The aim of this research is to develop a multivariate high order fuzzy time series forecasting model with data clustering to forecast handover occurrence in GSM network using Airtel Lagos zone as case study.

The objectives of this research are as follows:

(i) Optimal determination of an objective interval length using the k^{th} fuzzy data clustering algorithm.

(ii) Development of a high-order multivariate fuzzy time series forecast model for forecasting handover using Airtel Lagos zone as case study.

(iii) Development of a computer-based model of the forecast model using a program to be written in MATLAB and testing with the handover data of Airtel Lagos zone. This is expected to address the computational complexities involved in the process.

(iv) Development of model validation procedure, which will be in two-folds. The first step of validation is by using the validation data of 12 weeks while the second step validation is by comparing the results obtained in (ii) and (iii).

(v) Development of a standard model that compare by comparative analysis with the established models to conclusively put forward a verifiable research work.

1.5 Research Methodology

The following methodology is adopted in research work:

i) Data Collection and Preparation: Data is collected for 52 weeks from Airtel of Lagos zone. Data is partitioned into 40 weeks of training and 12 weeks of validation. The collected data include HOSR, SDCCH, RSS, PLOSS and BER. HOSR is termed the major as it is the variable of primary interest while others are termed minor.

ii) Data Clustering using the k^{th} fuzzy clustering algorithm as follows:

a) Sort n numerical data into an ascending sequence.

b) Calculate the mean of the sorted numerical data as *d*.

c) Find the mean difference of the sorted numerical data as

$$Avg\_diff = \frac{\sum_{i=1}^{n-1}(di+1-di)}{n-1} \tag{1.1}$$

d) Find the standard deviation difference of the sorted numerical data as

$$Dev\_diff = \sqrt{\frac{\sum_{i=1}^{n-1}(di+1 - di - d)^2}{(n-1)-1}} \tag{1.2}$$

e) Calculate the maximum data distance between any two adjacent data as

Max_data_distance = 0.5 x dev_diff. or other modifications as applicable.

f) Create Clusters

g) Determine the lower and upper bounds of each created cluster

h) Find the mid values for each cluster.

These procedures were repeated for all the variables (major and minor).

iii) Development of the high-order multivariate FTS model as in the following steps.

a) Define the Universe of discourse U of the major and minor factors using the clustered data obtained from (ii).

b) Define the linguistic terms e.g. A_i represented by fuzzy sets of the major factor. Similarly, for any minor fuzzy time series, B_{jk} define its linguistic terms and represent as fuzzy sets of the minor-factors.

c) Fuzzify the historical data of the major factor as multivariate dependent. The same applies to the minor factors of the historical data to obtain fuzzy logical relationship functions.

d) Obtain the x-factors k^{th} order fuzzy logical relationships based on the fuzzified major and minor factors from the fuzzified historical data of stage (3). The minor factors here act like secondary components to the m-dimensional state vector and are used in the next stage.

e) Defuzzify the x-factor k^{th} order fuzzy logical relationship functions.

f) For x-factor k^{th} order fuzzy logical relationship, the forecasted value for a week based on history of k^{th} order is calculated. The calculated value should certify the axioms of fuzzy sets like monotonicity, boundary conditions, continuity and idempotency. The Average Forecasting Error Rate (AFER) is used as the quantitative performance criterion of the developed model.

iv) Development of a computer-based model that was tested using the clustered data obtained in (ii).

v) Model Validation: Model was validated using the 12 weeks of validation data. Results obtained from (iii) and (iv) were compared and thereafter, other established models were analyzed to determine accuracy of computer model.

1.6 Dissertation Outline

The complete dissertation write-up was structured into five chapters. Each chapter covered and addressed specific aspect of the research work which recognizes the interrelationship between the subjects and the arrangement of chapters. Chapter one titled Introduction, generally outlined the basis of the research work, statement of the problem to be addressed, aim & objectives expected at the end of the research and methodology adopted in this research. Chapter two discussed literature review of similar works and overview of fundamental concept (theoretical background of essential components of the Radio, GSM, Mobility management, Soft computing, and basics of FTS, all of which form the bases of the research work).

The actual model development and implementation were covered in chapter three. This studied the various units of the developed model which include multivariate techniques, high order incorporations and clustering algorithms. In each case, earlier approaches, current trends and developed methods were outlined.

The concluding part of the research is presented in chapter four and five. Chapter four showed results presentation, results validation and results analysis which led to the last chapter. Chapter five is conclusion which reconciled the aim of the research with the results obtained, it's significant and limitations. Recommendation for further work, references and appendix are the last components of this chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 General

The existence of the radio spectrum that allowed transmission of signals without the traditional use of wire has offered unlimited opportunities in telecommunications. Among the dividends of many researches in radio signal structures that range from radio, wireless, GSM systems etc to GPRS, PC systems etc is convenience, affordability, simplicity etc. Application of soft computing techniques to further expand these dividends by utilizing experts, reasoning, logics systems etc is the current trend in communication systems. All researches tend to combine the fundamental theories of simply radio with the basic principles of Artificial Intelligent to add value to the existing structures.

The foundation of logic which is two states was extended and advanced by Zadeh to reflect the degree of occurrence between the two states. Chissom applied Zadeh theories to solve time series problems which gave birth to fuzzy time series properties. These properties are studied, researched and applied to solve problems arising from current challenges due to user expectations, system developers, market forces and research community.

Various theoretical concepts have been reviewed in this section such as radio signal structures, soft computing techniques, fundamentals of GSM network, mobility management, fuzzy sets, fuzzy logics, fuzzification, defuzzification, fuzzy relations, fuzzy aggregation, high-order, FTS and programming language. The main purpose of this discussion has been to provide self-contained study of the underlying theoretical concepts of the forecasting model presented in the later chapters.

2.2 Overview of Fundamental Concepts

The theoretical basis of the current research work is on the Radio signal structures and Soft computing techniques in general with specific focus on mobility management and multivariate fuzzy time series respectively. The review equally established a relationship between the two, where the former is referred to as the case study and the later is the applied method.

2.2.1 Radio Signal Structures

Wireless technology is the method of delivering data from one point to another without using physical wires, and includes radio, cellular, infrared, and satellite. The discovery of electromagnetism, induction, and conduction provided the basis for developing communication techniques that manipulated the flow of electric current through the media of air and water. Guglielmo Marconi was the first person to prove that electricity traveled in waves through the air, when he was able to transmit a message beyond the horizon line. The limitations on frequency usage that hindered demand for mobile telephone service were relieved by the development of the geographically structured cellular system (Andy, 2001). Wireless communication is one of the most active areas of technological development. These developments are being driven primarily by the transformation of what has been a medium for supporting voice telephony into a medium for supporting other services such as transmission of video images, text and data etc (Wang and Poor, 2003). It is by far, one of the fastest growing technologies. The demand for connecting devices without the use of cables is increasing everywhere. In what may be referred to as market potentials of wireless systems, both vertical and horizontal markets are beginning to realize the use of wireless networks. Wireless technology are being used for business travelers needing airport and hotel access, gaming and video, for delivery services, public safety, finance, retail, and monitoring. The horizontal applications for wireless include new technology for messaging services, mapping (GPS) and location-based tracking systems, and Internet browsing.

Many authors and researchers have written extensively on technology evolution of wireless systems that included Basic principles, Access techniques, System implementations (AMPS, GSM, GPRS, EDGE, SSC, etc). Others concentrated on detail working techniques of wireless systems such as Power control, Handovers, Modulation & Coding, Diversity, etc (Mooi and Qinqing, 2006). Wireless communication systems have experienced tremendous growth in the past century. The commercial cellular systems evolved from the analog system to the digital system rapidly. Wireless technology has progressed through the first-generation (IG), the second-generation (2G), and the current third-generation (3G) systems with the fourth-generation already in certain places for new applications. The services in wireless systems have expanded from voice only to today's high-speed data, multimedia applications and wireless Internet. The key techniques in wireless communications have been exploited and the technology revolution continues its development. The future is certainly going to be driven by research works and market forces.

The cellular concept implies the use of many low-power transmitters, each specifically designed to serve only a small area (cell), thereby reducing the effect of interference between users of same channel. In general the cellular concept offers the following features to cellular architecture for efficiency (Feher, 2002; Sulaiman, 2009):

(i) Low-power transmitters and small coverage zones, (ii) Frequency reuse, (iii) Cell splitting to increase capacity, and (iv) Mobility and Central control

Cellular concept represents a very different approach to structuring a radio telephone network, as compared with the first-generation, high-power, large-coverage mobile radio system applications. Although the cellular concept offers unlimited capacity through cell splitting, it encounters practical limits which include:

(a) Escalation of popularity of cellular radio demand- capacity bottlenecks

(b) With cells becoming progressively smaller in large demanding cities, it becomes more difficult and expensive to place base stations at the best physical locations

The cellular concept practical limits results in:

(i) Radio Network Congestion, (ii) Call Drops., (iii) Handover Failures, and (iv) Interference

These problems result in subscribers being unable to place a successful call or when the call goes through, the quality is bad, and vice-versa. These are problems that could have been caused by hardware or software related issues. Software problems include data configuration, system virus and so on. Hardware problems include; antennae tilts, faulty feeders, faulty transceivers and so on (Sulaiman, 2009; Viswanathan, 2008).

The purpose of radio Network and its analysis is to increase the utilization of network resources in solving existing and potential problems. The main consideration for any mobile network is capacity, quality and coverage (Sulaiman, 2009). The main goal of radio network analysis is to create a balance between these three variables. The mobile communication network of GSM generally falls into switching part and radio part (GSM Capacity). Due to the mobility of subscribers and the complexity of radio waves in propagation, the radio part always becomes the decisive factor affecting the Quality of Service of the GSM network. The radio part is divided into two parts; signaling and traffic variables. This research work is aimed at addressing the Mobility issue by developing a multivariate fuzzy based model.

Factors that affect radio network are:

(i) Uncertainty of the radio wave propagation, (ii) Environmental Clutter, (iii) Traffic load variation with place and time, and (iv) Increase subscriber requirements

There are many parameters to determine radio network quality as developments in other areas increases and applications in new fields emerge. However, there is a minimum of three key performance indicators which includes;

(i) Channels (congestion, call drop rate, control failure rate etc), (ii) Traffic parameters and (iii) RF parameters to be monitored under radio network mobility (propagation models).

Major factors that increase the handover failure rate include; traffic congestion, weak signal strength, problems with equipment, wrong parameter settings, incomplete definition of the neigbour cell, terrain, network deployment technique, RF propagation technique deployed etc. (Viswanathan, 2008); (Godara, 2002). The area under research actually deployed macro cells in semi-urban and micro cells in heavily urban areas with high buildings. These areas were originally macro cell layout. Harmonization of the deployment technique is still in progress and is a major challenge in this research work.

2.2.2 GSM Network Structures

During the early 1980s, analog cellular telephone systems were experiencing rapid growth in Europe, particularly in Scandinavia and the United Kingdom, but also in France and Germany. Each country developed its own system, which was incompatible with everyone else's in equipment and operation. This was an undesirable situation, because not only was the mobile equipment limited to operation within national boundaries, which in a unified Europe were increasingly unimportant, but there was also a very limited market for each type of equipment, so economies of scale and the subsequent savings could not be realized. The Europeans realized this early on, and in 1982 the Conference of European Posts and Telegraphs (CEPT) formed a study group called the Groupe Special Mobile (GSM) to study and develop a pan-European public land mobile system. The proposed system had to meet certain criteria:

(i) Good subjective speech quality, (ii) Low terminal and service cost, (iii) Support for international roaming, (iv) Ability to support handheld terminals, (v) Support for range of new services and facilities, (vi) Spectral efficiency, and (vii) ISDN compatibility

In 1989, GSM responsibility was transferred to the European Telecommunication Standards Institute (ETSI), and phase I of the GSM specifications were published in 1990. Commercial service was started in mid-1991, and by 1993 there were 36 GSM networks in 22 countries. Although standardized in Europe, GSM is not only a European standard. Over 200 GSM networks (including DCS1800 and PCS1900) are operational in 110 countries around the world. In the beginning of 1994, there were 1.3 million subscribers worldwide, which had grown to more than 55 million by October 1997 and currently in billions. With North America making a delayed entry into the GSM field with a derivative of GSM called PCS1900, GSM systems exist on every continent, and the acronym GSM now aptly stands for Global System for Mobile communications. The developers of GSM chose an unproven (at the time) digital system, as opposed to the then-standard analog cellular systems like AMPS in the United States and TACS in the United Kingdom. They had faith that advancements in compression algorithms and digital signal processors would allow the fulfillment of the original criteria and the continual improvement of the system in terms of quality and cost. The over 8000 pages of GSM recommendations try to allow flexibility and competitive innovation among suppliers, but provide enough standardization to guarantee proper interworking between the components of the system. This is done by providing functional and interface descriptions for each of the functional entities defined in the system. From the beginning, the planners of GSM wanted ISDN compatibility in terms of the services offered and the control signalling used. However, radio transmission limitations, in terms of bandwidth and cost, do not allow the standard ISDN B-channel bit rate of 64 kbps to be practically achieved.

Using the ITU-T definitions, telecommunication services can be divided into bearer services, tele-services, and supplementary services. The most basic tele-service supported by GSM is telephony. As with all other communications, speech is digitally encoded and transmitted through the GSM network as a digital stream. There is also an emergency service, where the nearest emergency-service provider is notified by dialing three digits (similar to 911). A variety of data services is offered. GSM users can send and receive data, at rates up to 9600 bps, to users on Plain Old Telephone Service (POTS), ISDN, Packet Switched Public Data Networks, and Circuit Switched Public Data Networks using a variety of access methods and protocols, such as X.25 or X.32. Since GSM is a digital network, a modem is not required between the user and GSM network, although an audio modem is required inside the GSM network to interwork with POTS. Other data services include Group 3 facsimile, as described in ITU-T recommendation T.30, which is supported by use of an appropriate fax adaptor. A unique feature of GSM, not found in older analog systems, is the Short Message Service (SMS). SMS is a bidirectional service for short alphanumeric (up to 160 bytes) messages. Messages are transported in a store-and-forward fashion. For point-to-point SMS, a message can be sent to another subscriber to the service, and an acknowledgement of receipt is provided to the sender. SMS can also be used in a cell-broadcast mode, for sending messages such as traffic updates or news updates. Messages can also be stored in the SIM card for later retrieval. Supplementary services are provided on top of tele-services or bearer services. In the current (Phase I) specifications, they include several forms of call forward (such as call forwarding when the mobile subscriber is unreachable by the network), and call barring of outgoing or incoming calls, for example when roaming in another country. Many additional supplementary services will be provided in the Phase 2 specifications, such as caller identification, call waiting, multi-party conversations.

A GSM network is composed of several functional entities, whose functions and interfaces are specified. Figure 2.1 shows the layout of a generic GSM network. The GSM network can be divided into three broad parts. The Mobile Station is carried by the subscriber. The Base Station Subsystem controls the radio link with the Mobile Station. The Network Subsystem, the main part of which is the Mobile services Switching Center (MSC), performs the switching of calls between the mobile users, and between mobile and fixed network users. The MSC also handles the mobility management operations. Not shown is the Operations and

Maintenance Center, which oversees the proper operation and setup of the network. The Mobile Station and the Base Station Subsystem communicate across the Um interface, also known as the air interface or radio link. The Base Station Subsystem communicates with the Mobile services Switching Center across the A interface.

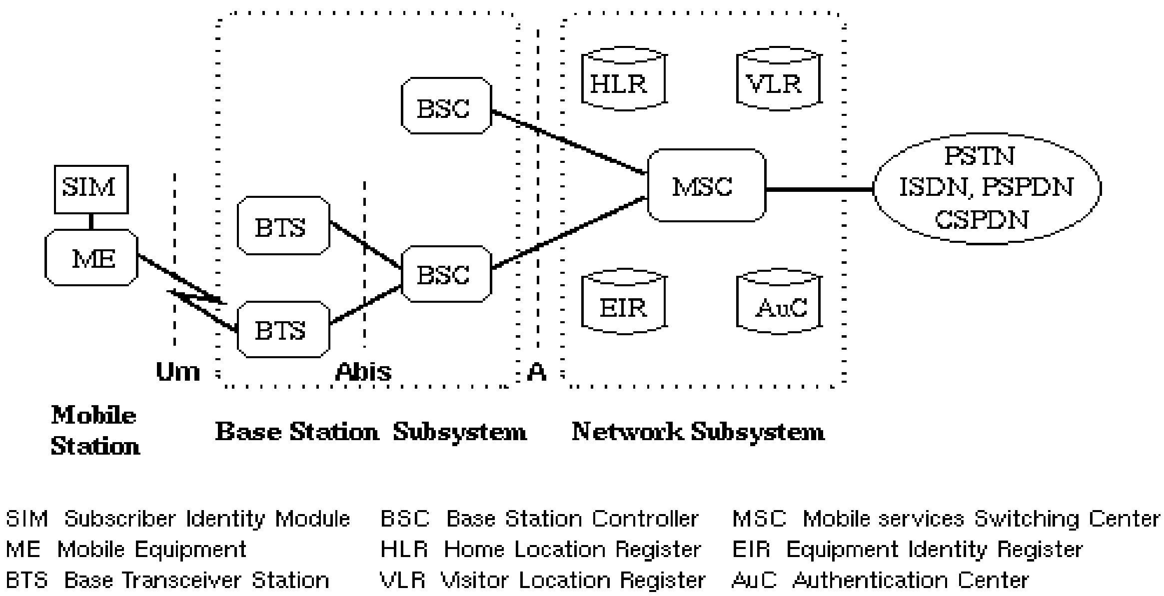


Figure 2.1: General Architecture of a GSM Network

The mobile station (MS) consists of the mobile equipment (the terminal) and a smart card called the Subscriber Identity Module (SIM). The SIM provides personal mobility, so that the user can have access to subscribed services irrespective of a specific terminal. By inserting the SIM card into another GSM terminal, the user is able to receive calls at that terminal, make calls from that terminal, and receive other subscribed services. The mobile equipment is uniquely identified by the International Mobile Equipment Identity (IMEI). The SIM card contains the International Mobile Subscriber Identity (IMSI) used to identify the subscriber to the system, a secret key for authentication, and other information. The IMEI and the IMSI are independent, thereby allowing personal mobility. The SIM card may be protected against unauthorized use by a password or personal identity number.

The Base Station Subsystem is composed of two parts, the Base Transceiver Station (BTS) and the Base Station Controller (BSC). These communicate across the standardized Abis interface, allowing (as in the rest of the system) operation between components made by different suppliers. The Base Transceiver Station houses the radio transceivers that define a cell and handles the radio-link protocols with the Mobile Station. In a large urban area, there will potentially be a large number of BTSs deployed, thus the requirements for a BTS are ruggedness, reliability, portability, and minimum cost. The Base Station Controller manages the radio resources for one or more BTSs. It handles radio-channel setup, frequency hopping, and handovers, as described below. The BSC is the connection between the mobile station and the Mobile service Switching Center (MSC).

The central component of the Network Subsystem is the Mobile services Switching Center (MSC). It acts like a normal switching node of the PSTN or ISDN, and additionally provides all the functionality needed to handle a mobile subscriber, such as registration, authentication, location updating, handovers, and call routing to a roaming subscriber. These services are provided in conjunction with several functional entities, which together form the Network Subsystem. The MSC provides the connection to the fixed networks (such as the PSTN or ISDN). Signalling between functional entities in the Network Subsystem uses Signalling System Number 7 (SS7), used for trunk signalling in ISDN and widely used in current public networks.

The Home Location Register (HLR) and Visitor Location Register (VLR), together with the MSC, provide the call-routing and roaming capabilities of GSM. The HLR contains all the administrative information of each subscriber registered in the corresponding GSM network, along with the current location of the mobile. The location of the mobile is typically in the form of the signalling address of the VLR associated with the mobile station. The actual routing procedure will be described later. There is logically one HLR per GSM network, although it may be implemented as a distributed database. The Visitor Location Register (VLR) contains selected administrative information from the HLR, necessary for call control and provision of the subscribed services, for each mobile currently located in the geographical area controlled by the VLR. Although each functional entity can be implemented as an independent unit, all manufacturers of switching equipment to date implement the VLR together with the MSC, so that the geographical area controlled by the MSC corresponds to that controlled by the VLR, thus simplifying the signalling required. Note that the MSC contains no information about particular mobile stations --- this information is stored in the location registers. The other two registers are used for authentication and security purposes. The Equipment Identity Register (EIR) is a database that contains a list of all valid mobile equipment on the network, where each mobile station is identified by its International Mobile Equipment Identity (IMEI). An IMEI is marked as invalid if it has been reported stolen or is not type approved. The Authentication Center (AuC) is a protected database that stores a copy of the secret key stored in each subscriber's SIM card, which is used for authentication and encryption over the radio channel.

The International Telecommunication Union (ITU), which manages the international allocation of radio spectrum (among many other functions), allocated the bands 890-915 MHz for the uplink (mobile station to base station) and 935-960 MHz for the downlink (base station to mobile station) for mobile networks in Europe. Since this range was already being used in the early 1980s by the analog systems of the day, the CEPT had the foresight to reserve the top 10 MHz of each band for the GSM network that was still being developed. Eventually, GSM will be allocated the entire 2x25 MHz bandwidth. Since radio spectrum is a limited resource shared by all users, a method must be devised to divide up the bandwidth among as many users as possible. The method chosen by GSM is a combination of Time- and Frequency-Division Multiple Access (TDMA/FDMA). The FDMA part involves the division by frequency of the (maximum) 25 MHz bandwidth into 124 carrier frequencies spaced 200 kHz apart. One or more carrier frequencies are assigned to each base station. Each of these carrier frequencies is then divided in time, using a TDMA scheme. The fundamental unit of time in this TDMA scheme is called a burst period and it lasts 15/26 ms (or approx. 0.577 ms). Eight burst periods are grouped into a TDMA frame (120/26 ms, or approx. 4.615 ms), which forms the basic unit for the definition of logical channels. One physical channel is one burst period per TDMA frame. Channels are defined by the number and position of their corresponding burst periods. All these definitions are cyclic, and the entire pattern repeats approximately every 3 hours. Channels can be divided into dedicated channels, which are allocated to a mobile station, and common channels, which are used by mobile stations in idle mode. A traffic channel (TCH) is used to carry speech and data traffic. Traffic channels are defined using a 26-frame multiframe, or group of 26 TDMA frames. The length of a 26-frame multiframe is 120 ms, which is how the length of a burst period is defined (120 ms divided by 26 frames divided by 8 burst periods per frame). Out of the 26 frames, 24 are used for traffic, 1 is used for the Slow Associated Control Channel (SACCH) and 1 is currently unused (see Figure 2.2). TCHs for the uplink and downlink are separated in time by 3 burst periods, so that the mobile station does not have to transmit and receive simultaneously, thus simplifying the electronics. In addition to these full-rate TCHs, there are also half-rate TCHs defined, although they are not yet implemented. Half-rate TCHs will effectively double the capacity of a system once half-rate speech coders are specified (i.e., speech coding at around 7 kbps, instead of 13 kbps). Eighth-rate TCHs are also specified, and are used for signalling. In the recommendations, they are called Stand-alone Dedicated Control Channels (SDCCH) (Sulaiman, 2009).

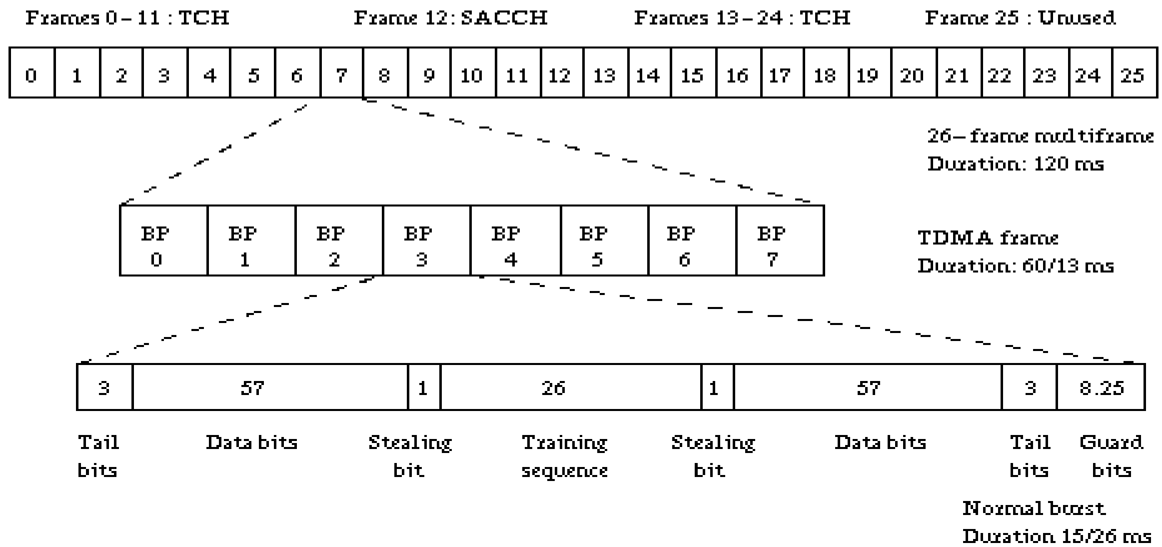


Figure 2.2: Organization of bursts, TDMA frames, and multiframes for speech and data

Common Channels can be accessed both by idle mode and dedicated mode mobiles. The common channels are used by idle mode mobiles to exchange the signalling information required to change to dedicated mode. Mobiles already in dedicated mode monitor the surrounding base stations for handover and other information. The common channels are defined within a 51-frame multiframe, so that dedicated mobiles using the 26-frame multiframe TCH structure can still monitor control channels. The common channels include:

(a) Broadcast Control Channel (BCCH) continually broadcasts, on the downlink, information including base station identity, frequency allocations, and frequency-hopping sequences.

(b) Frequency Correction Channel (FCCH) and Synchronisation Channel (SCH) is used to synchronise the mobile to the time slot structure of a cell by defining the boundaries of burst periods, and the time slot numbering. Every cell in a GSM network broadcasts exactly one FCCH and one SCH, which are by definition on time slot number 0 (within a TDMA frame).

(c) Random Access Channel (RACH) is a Slotted Aloha channel used by the mobile to request access to the network.

(d) Paging Channel (PCH) is used to alert the mobile station of an incoming call.

(e) Access Grant Channel (AGCH) is used to allocate an SDCCH to a mobile for signalling (in order to obtain a dedicated channel), following a request on the RACH.

(f) Burst Structure is of four different types of bursts used for transmission in GSM. The normal burst is used to carry data and most signalling. It has a total length of 156.25 bits, made up of two 57 bit information bits, a 26 bit training sequence used for equalization, 1 stealing bit for each information block (used for FACCH), 3 tail bits at each end, and an 8.25 bit guard sequence, as shown in Figure 2.2. The 156.25 bits are transmitted in 0.577 ms, giving a gross bit rate of 270.833 kbps.

The F burst, used on the FCCH, and the S burst, used on the SCH, have the same length as a normal burst, but a different internal structure, which differentiates them from normal bursts (thus allowing synchronization). The access burst is shorter than the normal burst, and is used only on the RACH.

GSM is a digital system, so speech which is inherently analog, has to be digitized. The method employed by ISDN, and by current telephone systems for multiplexing voice lines over high speed trunks and optical fiber lines, is Pulse Coded Modulation (PCM). The output stream from PCM is 64 kbps, too high a rate to be feasible over a radio link. The 64 kbps signal, although simple to implement, contains much redundancy. The GSM group studied several speech coding algorithms on the basis of subjective speech quality and complexity (which is related to cost, processing delay, and power consumption once implemented) before arriving at the choice of a Regular Pulse Excited -- Linear Predictive Coder (RPE--LPC) with a Long Term Predictor loop. Basically, information from previous samples, which does not change very quickly, is used to predict the current sample. The coefficients of the linear combination of the previous samples, plus an encoded form of the residual, the difference between the predicted and actual sample, represent the signal. Speech is divided into 20 millisecond samples, each of which is encoded as 260 bits, giving a total bit rate of 13 kbps. This is the so-called Full-Rate speech coding. Recently, an Enhanced Full-Rate (EFR) speech coding algorithm has been implemented by some North American GSM1900 operators. This is said to provide improved speech quality using the existing 13 kbps bit rate. Because of natural and man-made electromagnetic interference, the encoded speech or data signal transmitted over the radio interface must be protected from errors. GSM uses convolutional encoding and block interleaving to achieve this protection. The exact algorithms used differ for speech and for different data rates. Recall that the speech codec produces a 260 bit block for every 20 ms speech sample. From subjective testing, it was found that some bits of this block were more important for perceived speech quality than others. The bits are thus divided into three classes:

(i) Class Ia 50 bits - most sensitive to bit errors, (ii) Class Ib 132 bits - moderately sensitive to bit errors, and (iii) Class II 78 bits - least sensitive to bit errors

Class Ia bits have a 3 bit Cyclic Redundancy Code added for error detection. If an error is detected, the frame is judged too damaged to be comprehensible and it is discarded. It is replaced by a slightly attenuated version of the previous correctly received frame. These 53 bits, together with the 132 Class Ib bits and a 4 bit tail sequence (a total of 189 bits), are input into a 1/2 rate convolutional encoder of constraint length 4. Each input bit is encoded as two output bits, based on a combination of the previous 4 input bits. The convolutional encoder thus outputs 378 bits, to which are added the 78 remaining Class II bits, which are unprotected. Thus every 20 ms speech sample is encoded as 456 bits, giving a bit rate of 22.8 kbps. To further protect against the burst errors common to the radio interface, each sample is interleaved. The 456 bits output by the convolutional encoder are divided into 8 blocks of 57 bits, and these blocks are transmitted in eight consecutive time-slot bursts. Since each time-slot burst can carry two 57 bit blocks, each burst carries traffic from two different speech samples. Recall that each time-slot burst is transmitted at a gross bit rate of 270.833 kbps. This digital signal is modulated onto the analog carrier frequency using Gaussian-filtered Minimum Shift Keying (GMSK). GMSK was selected over other modulation schemes as a compromise between spectral efficiency, complexity of the transmitter, and limited spurious emissions. The complexity of the transmitter is related to power consumption, which should be minimized for the mobile station. The spurious radio emissions, outside of the allotted bandwidth, must be strictly controlled so as to limit adjacent channel interference, and allow for the co-existence of GSM and the older analog systems (at least for the time being).

At the 900 MHz range, radio waves bounce off everything - buildings, hills, cars, airplanes, etc. Thus many reflected signals, each with a different phase, can reach an antenna. Equalization is used to extract the desired signal from the unwanted reflections. It works by finding out how a known transmitted signal is modified by multipath fading, and constructing an inverse filter to extract the rest of the desired signal. This known signal is the 26-bit training sequence transmitted in the middle of each time-slot burst. The actual implementation of the equalizer is not specified in the GSM specifications. The mobile station already has to be frequency agile, meaning it can move between a transmit, receive mode, and monitor time slot within one TDMA frame, which normally are on different frequencies. GSM makes use of this inherent frequency agility to implement slow frequency hopping, where the mobile and BTS transmit each TDMA frame on a different carrier frequency. The frequency hopping algorithm is broadcast on the Broadcast Control Channel. Since multipath fading is dependent on carrier frequency, slow frequency hopping helps alleviate the problem. In addition, co-channel interference is in effect randomized. Minimizing co-channel interference is a goal in any cellular system, since it allows better service for a given cell size, or the use of smaller cells, thus increasing the overall capacity of the system. Discontinuous transmission (DTX) is a method that takes advantage of the fact that a person speaks less than 40 percent of the time in normal conversation , by turning the transmitter off during silence periods. An added benefit of DTX is that power is conserved at the mobile unit. The most important component of DTX is, of course, Voice Activity Detection. It must distinguish between voice and noise inputs, a task that is not as trivial as it appears, considering background noise. If a voice signal is misinterpreted as noise, the transmitter is turned off and a very annoying effect called clipping is heard at the receiving end. If, on the other hand, noise is misinterpreted as a voice signal too often, the efficiency of DTX is dramatically decreased. Another factor to consider is that when the transmitter is turned off, there is total silence heard at the receiving end, due to the digital nature of GSM. To assure the receiver that the connection is not dead, comfort noise is created at the receiving end by trying to match the characteristics of the transmitting end's background noise. Another method used to conserve power at the mobile station is discontinuous reception. The paging channel (PAGCH), used by the base station to signal an incoming call, is structured into sub-channels. Each mobile station needs to listen only to its own sub-channel. In the time between successive paging sub-channels, the mobile can go into sleep mode, when almost no power is used.

There are five classes of mobile stations defined, according to their peak transmitter power, rated at 20, 8, 5, 2, and 0.8 watts. To minimize co-channel interference and to conserve power, both the mobiles and the Base Transceiver Stations operate at the lowest power level that will maintain an acceptable signal quality. Power levels can be stepped up or down in steps of 2 dB from the peak power for the class down to a minimum of 13 dBm (20 milliwatts). The mobile station measures the signal strength or signal quality (based on the Bit Error Ratio), and passes the information to the Base Station Controller, which ultimately decides if and when the power level should be changed. Power control should be handled carefully, since there is the possibility of instability. This arises from having mobiles in co-channel cells alternatively increase their power in response to increased co-channel interference caused by the other mobile increasing its power. This is unlikely to occur in practice but it is possible.

Ensuring the transmission of voice or data of a given quality over the radio link is only part of the function of a cellular mobile network. A GSM mobile can seamlessly roam nationally and internationally, which requires that registration, authentication, call routing and location updating functions exist and are standardized in GSM networks. In addition, the fact that the geographical area covered by the network is divided into cells necessitates the implementation of a handover mechanism. These functions are performed by the Network Subsystem, mainly using the Mobile Application Part (MAP) built on top of the Signalling System No. 7 protocol.

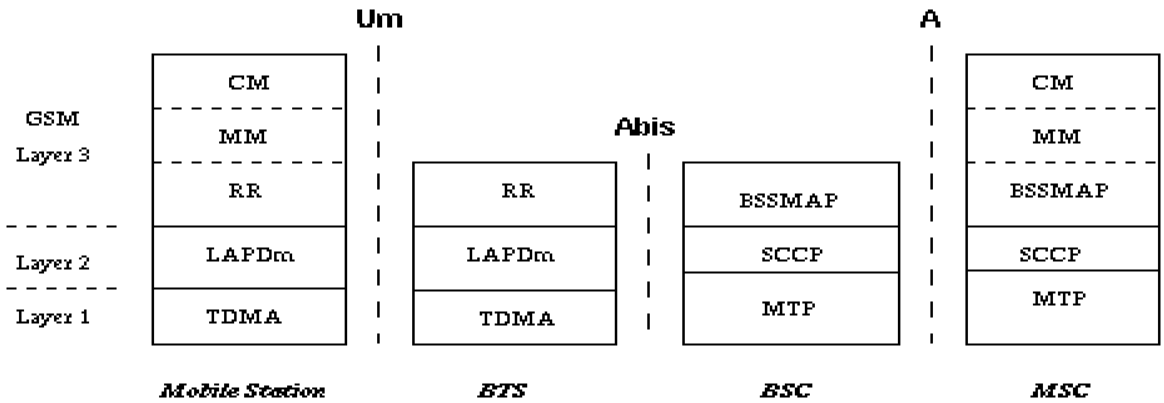


Figure 2.3: Signalling Protocol Structure in GSM

The signalling protocol in GSM is structured into three general layers , depending on the interface, as shown in Figure 2.3. Layer 1 is the physical layer, which uses the channel structures discussed above over the air interface. Layer 2 is the data link layer. Across the Um interface, the data link layer is a modified version of the LAPD protocol used in ISDN, called LAPDm. Across the A interface, the Message Transfer Part layer 2 of Signalling System Number 7 is used. Layer 3 of the GSM signalling protocol is itself divided into 3 sub-layers.

(a) Radio Resources Management: Controls the setup, maintenance, and termination of radio and fixed channels, including handovers.

(b) Mobility Management: Manages the location updating and registration procedures, as well as security and authentication.

(c) Connection Management: Handles general call control, similar to CCITT Recommendation Q.931, and manages Supplementary Services and the Short Message Service.

Signalling between the different entities in the fixed part of the network, such as between the HLR and VLR, is accomplished throught the Mobile Application Part (MAP). MAP is built on top of the Transaction Capabilities Application Part (TCAP, the top layer of Signalling System

Number 7. The specification of the MAP is quite complex, and at over 500 pages, it is one of the longest documents in the GSM recommendations.

The radio resources management (RR) layer oversees the establishment of a link, both radio and fixed, between the mobile station and the MSC. The main functional components involved are the mobile station, and the Base Station Subsystem, as well as the MSC. The RR layer is concerned with the management of an RR-session, which is the time that a mobile is in dedicated mode, as well as the configuration of radio channels including the allocation of dedicated channels. An RR-session is always initiated by a mobile station through the access procedure, either for an outgoing call, or in response to a paging message. The details of the access and paging procedures, such as when a dedicated channel is actually assigned to the mobile, and the paging sub-channel structure, are handled in the RR layer. In addition, it handles the management of radio features such as power control, discontinuous transmission and reception, and timing advance. In a cellular network, the radio and fixed links required are not permanently allocated for the duration of a call. Handover, or handoff as it is called in North America, is the switching of an on-going call to a different channel or cell. The execution and measurements required for handover form one of basic functions of the RR layer. There are four different types of handover in the GSM system, which involve transferring a call between:

(a) Channels (time slots) in the same cell

(b) Cells (Base Transceiver Stations) under the control of the same Base Station Controller (BSC),

(c) Cells under the control of different BSCs, but belonging to the same Mobile services Switching Center (MSC), and

(d) Cells under the control of different MSCs.

The first two types of handover, called internal handovers, involve only one Base Station Controller (BSC). To save signalling bandwidth, they are managed by the BSC without involving the Mobile services Switching Center (MSC), except to notify it at the completion of the handover. The last two types of handover, called external handovers, are handled by the MSCs involved. An important aspect of GSM is that the original MSC, the anchor MSC, remains responsible for most call-related functions, with the exception of subsequent inter-BSC handovers under the control of the new MSC, called the relay MSC. Handovers can be initiated by either the mobile or the MSC (as a means of traffic load balancing). During its idle time slots, the mobile scans the Broadcast Control Channel of up to 16 neighboring cells, and forms a list of the six best candidates for possible handover, based on the received signal strength. This information is passed to the BSC and MSC, at least once per second, and is used by the handover algorithm. The algorithm for when a handover decision should be taken is not specified in the GSM recommendations. There are two basic algorithms used, both closely tied in with power control. This is because the BSC usually does not know whether the poor signal quality is due to multipath fading or to the mobile having moved to another cell. This is especially true in small urban cells.

The minimum acceptable performance algorithm gives precedence to power control over handover, so that when the signal degrades beyond a certain point, the power level of the mobile is increased. If further power increases do not improve the signal, then a handover is considered. This is the simpler and more common method, but it creates 'smeared' cell boundaries when a mobile transmitting at peak power goes some distance beyond its original cell boundaries into another cell. The power budget method uses handover to try to maintain or improve a certain level of signal quality at the same or lower power level. It thus gives precedence to handover

over power control. It avoids the 'smeared' cell boundary problem and reduces co-channel interference, but it is quite complicated.

The Mobility Management layer (MM) is built on top of the RR layer, and handles the functions that arise from the mobility of the subscriber, as well as the authentication and security aspects. Location management is concerned with the procedures that enable the system to know the current location of a powered-on mobile station so that incoming call routing can be completed. A powered-on mobile is informed of an incoming call by a paging message sent over the PAGCH of a cell. One extreme would be to page every cell in the network for each call, which is obviously a waste of radio bandwidth. The other extreme would be for the mobile to notify the system, via location updating messages, of its current location at the individual cell level. This would require paging messages to be sent to exactly one cell, but would be very wasteful due to the large number of location updating messages. A compromise solution used in GSM is to group cells into location areas. Updating messages are required when moving between location areas, and mobile stations are paged in the cells of their current location area. The location updating procedures, and subsequent call routing, use the MSC and two location registers: the Home Location Register (HLR) and the Visitor Location Register (VLR). When a mobile station is switched on in a new location area, or it moves to a new location area or different operator's PLMN, it must register with the network to indicate its current location. In the normal case, a location update message is sent to the new MSC/VLR, which records the location area information, and then sends the location information to the subscriber's HLR. The information sent to the HLR is normally the SS7 address of the new VLR, although it may be a routing number. The reason a routing number is not normally assigned, even though it would reduce signalling, is that there is only a limited number of routing numbers available in the new

MSC/VLR and they are allocated on demand for incoming calls. If the subscriber is entitled to service, the HLR sends a subset of the subscriber information, needed for call control, to the new MSC/VLR, and sends a message to the old MSC/VLR to cancel the old registration.

For reliability reasons, GSM also has a periodic location updating procedure. If an HLR or MSC/VLR fails, to have each mobile register simultaneously to bring the database up to date would cause overloading. Therefore, the database is updated as location updating events occur. The enabling of periodic updating, and the time period between periodic updates, is controlled by the operator, and is a trade-off between signalling traffic and speed of recovery. If a mobile does not register after the updating time period, it is deregistered. A procedure related to location updating is the IMSI attach and detach. A detach lets the network know that the mobile station is unreachable, and avoids having to needlessly allocate channels and send paging messages. An attach is similar to a location update, and informs the system that the mobile is reachable again. The activation of IMSI attach/detach is up to the operator on an individual cell basis.

Since the radio medium can be accessed by anyone, authentication of users to prove that they are who they claim to be is a very important element of a mobile network. Authentication involves two functional entities, the SIM card in the mobile, and the Authentication Center (AuC). Each subscriber is given a secret key, one copy of which is stored in the SIM card and the other in the AuC. During authentication, the AuC generates a random number that it sends to the mobile. Both the mobile and the AuC then use the random number, in conjunction with the subscriber's secret key and a ciphering algorithm called A3, to generate a signed response (SRES) that is sent back to the AuC. If the number sent by the mobile is the same as the one calculated by the AuC, the subscriber is authenticated. The same initial random number and subscriber key are also used to compute the ciphering key using an algorithm called A8. This ciphering key, together with the TDMA frame number, use the A5 algorithm to create a 114 bit sequence that is XORed with the 114 bits of a burst (the two 57 bit blocks). Enciphering is an option for the fairly paranoid, since the signal is already coded, interleaved, and transmitted in a TDMA manner, thus providing protection from all but the most persistent and dedicated eavesdroppers. Another level of security is performed on the mobile equipment itself, as opposed to the mobile subscriber. As mentioned earlier, each GSM terminal is identified by a unique International Mobile Equipment Identity (IMEI) number. A list of IMEIs in the network is stored in the Equipment Identity Register (EIR). The status returned in response to an IMEI query to the EIR is one of the following:

(a) White-listed: The terminal is allowed to connect to the network.

(b) Grey-listed: The terminal is under observation from the network for possible problems.

(c) Black-listed: The terminal has either been reported stolen, or is not type approved (the correct type of terminal for a GSM network). The terminal is not allowed to connect to the network.

The Communication Management layer (CM) is responsible for Call Control (CC), supplementary service management, and short message service management. Each of these may be considered as a separate sub layer within the CM layer. Call control attempts to follow the ISDN procedures specified in Q.931, although routing to a roaming mobile subscriber is obviously unique to GSM. Other functions of the CC sub-layer include call establishment, selection of the type of service (including alternating between services during a call), and call release. Unlike routing in the fixed network, where a terminal is semi-permanently wired to a central office, a GSM user can roam nationally and even internationally. The directory number dialed to reach a mobile subscriber is called the Mobile Subscriber ISDN (MSISDN), which is defined by the E.164 numbering plan. This number includes a country code and a National Destination Code which identifies the subscriber's operator. The first few digits of the remaining subscriber number may identify the subscriber's HLR within the home PLMN. An incoming mobile terminating call is directed to the Gateway MSC (GMSC) function. The GMSC is basically a switch which is able to interrogate the subscriber's HLR to obtain routing information, and thus contains a table linking MSISDNs to their corresponding HLR. A simplification is to have a GSMC handle one specific PLMN. It should be noted that the GMSC function is distinct from the MSC function, but is usually implemented in an MSC. The routing information that is returned to the GMSC is the Mobile Station Roaming Number (MSRN), which is also defined by the E.164 numbering plan. MSRNs are related to the geographical numbering plan, and not assigned to subscribers, nor are they visible to subscribers. The most general routing procedure begins with the GMSC querying the called subscriber's HLR for an MSRN. The HLR typically stores only the SS7 address of the subscriber's current VLR, and does not have the MSRN (see the location updating section). The HLR must therefore query the subscriber's current VLR, which will temporarily allocate an MSRN from its pool for the call. This MSRN is returned to the HLR and back to the GMSC, which can then route the call to the new MSC. At the new MSC, the IMSI corresponding to the MSRN is looked up, and the mobile is paged in its current location area (see Figure 2.4).

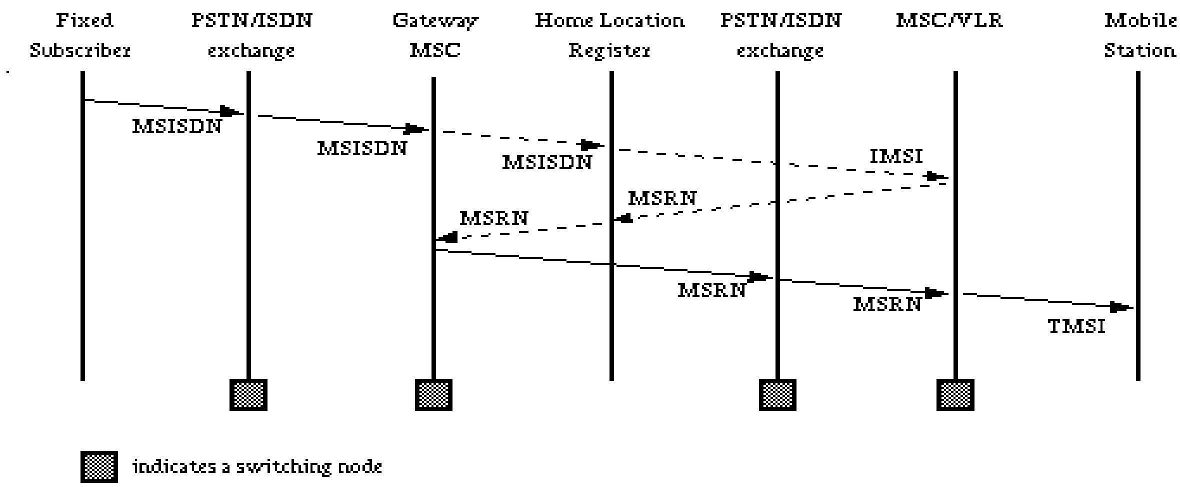


Figure 2.4: Call Routing for a Mobile Terminating Call

2.2.4 Mobility Management

Mobility is the most important feature of today's wireless networking systems (Akyildiz, et al., 1998). It can be categorized as network mobility and radio mobility. Network mobility mainly deals with mobile station location management (i.e. location updating and paging), whereas radio mobility is mainly concerned with the handover process (Vijay, 2007). If a mobile station (MS) travels across system boundaries (i.e. cell, location, MSC areas etc), the network must be able to locate the mobile station and automatically route the call to it. While at the same time, maintaining all the security mechanisms put in place to provide a level of protection against fraud to subscribers and service providers. A cellular network layout area provides wireless access and services for mobile stations within and to/from other networks. The layout area is divided into regions called location areas (LAs). Each LA is made up of one or more cells areas (see Figure 2.5). A new MS into LA must use VLR and thereafter can move freely within the given LA.

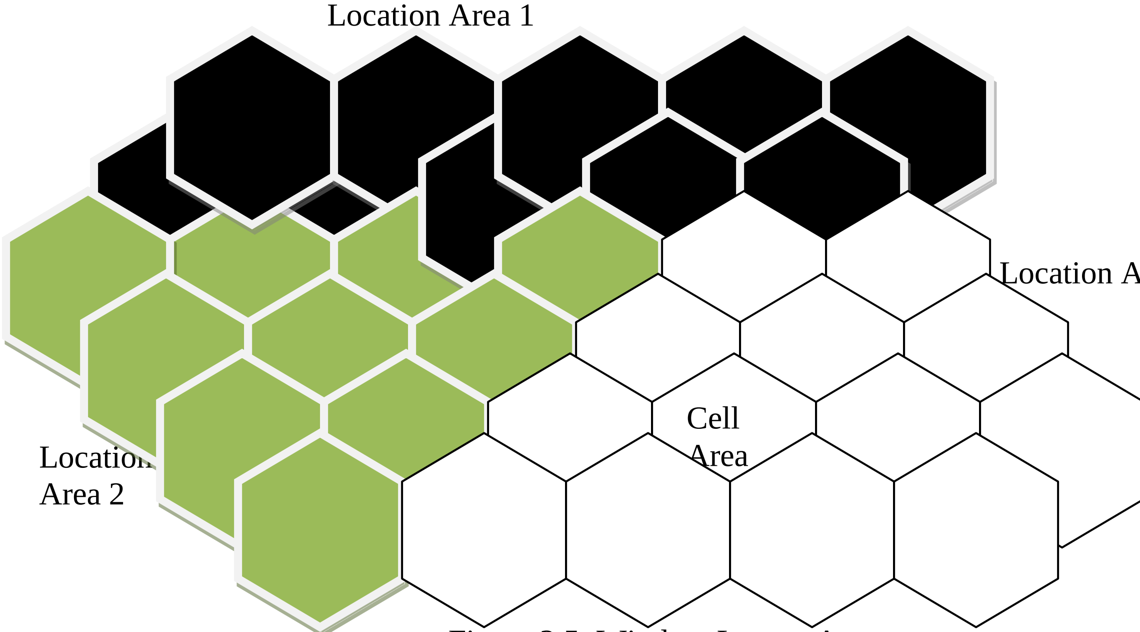


Figure 2.5: Wireless Layout Area

Mobility management deals primarily with automatic roaming, authentication, and handovers. Mobile station location management uses schemes that are based on subscribers' mobility and incoming call rate characteristics. Location Update procedures allows the network to keep track of the mobile station location to direct the incoming call. While the paging process, sends messages to all those cells where mobile station can be located. Mobility model usually describes the occurrence of procedures such as location update and handover. Among the most popular models are Fluid, Markovian, Gravity models etc each having their strengths and weakness.

Radio mobility can only be attained by handover mechanisms in wireless networks. As smaller cells are deployed to meet the demands for increased capacity, the number of cell boundary crossings increases, creating chances for more handovers. Each handover requires network resources to reroute the call to the new base station. Minimizing the expected number of handovers minimizes the switching load. Another concern is the delay, if handover does not occur quickly, the quality of service may degrade below an acceptable level. Minimizing delay also minimizes co-channel interference. During handover, there is a noticeable brief service interruption. As the frequency of these interruptions increases the perceived quality of service is reduced. The chances of dropping calls, blocking calls due to factors such as availability of channels increase with the number of handover attempts. All of these issues place additional challenges on the cellular network system. As the rate of handover increases, handover algorithms need to be enhanced so that the perceived quality of service does not degenerate and the cost to the cellular infrastructure does not skyrocket. Much effort is being expanded to study existing handover schemes, and to create new ones that meet these challenges.

To meet the growing demand for more mobile wireless communication services, cellular system providers will continue to deploy additional cell sites and introduce increasingly complex systems, for both the radio link and the network infrastructure. As more users are supported, the ever-growing concerns regarding the limitations of switching and signalling infrastructures have been met by a diverse suite of architectural and algorithmic methods. One of the recent methods is to control the handover of users as they move between shrinking cells, at greater speeds, and with stricter requirements on both the quality of service delivered to the user and the operational costs associated with a connection. This argument forms the basis of handover forecasting by many researchers using wide range of models, techniques and algorithms based on various parameters such as received signal strength, available channels, path loss, interferences, bit error rate, deployment method, cell structures and modes, etc (Vijay, 2007).

1. Mobility Management Structures and Protocols

Handovers are sometimes referred to as break-before-make (Hard) as in FDMA, TDMA, etc or make-before-break (Soft) as in CDMA. It can also be either internal or external handover.

Internal handover consist of two types, horizontal handover and vertical handover. The horizontal handover is a process that provides continuity of call when the MS handling the service of call is using the same technology, in other words target cell is the same radio access type of source cell, when the MS is moving from one cell to another cell. The vertical handover is a process that provides continuity of call when the MS handling the service of call is using different type of radio access technology to maintain quality of service. In the external handover, if the MS leaves a cell and no new cell can be found in the same system, then the BS can handover appropriately and equipped the MS accordingly for onward connection to a cell in another system. These intersystem handovers are highly complex because two technically dissimilar systems must be compatible with each other. Finally the connection is transferred to a BTS within another MSC.

Broadly, handovers are categorized according to the level of GSM network that is involved in the connection. For instance, changing cells within the same BTS is not complicated as the changing of the cell belonging to different MSC. There are mainly two reasons for this kind of handover. The MS moves out of the range station or the antenna of BTS respectively. Secondly the wire infrastructure of the MSC or the BSC may decide that the traffic in one cell is too high and move some to other cells with lower load. Some of these reasons establish the basis to initiate different kinds of handover which are often referred to as structures. The followings are the different kinds of handover structures in GSM network.

(a) Intra-cell BTS handover: The terms intra-cell and intra BTS handover are used both for frequency change. There is a slight difference between them but usually they are considered the same. The term intra-cell handover in not real as it deals with the frequency change of an on-going call. The frequency change occurs when the quality of the communication link degrades and the measurements of the neighboring cells are better than the current cell. In this situation, the BSC which controls the BTS serving the MS order the MSC and BTS to switch to another frequency that offers better communication link for the call. Sometime, the communication link degradation may be due to the interference because probably the neighboring cells are using the same frequencies. In such cases, it is better to try another channel to maintain communication. In the intra BTS handover, cells involved are synchronized to establish connection between the cells. Thereafter, the handover is performed by BSC. BSC equally sends acknowledgement to MSC and then requests BTS to release the resources that are no longer used. This synchronized handover saves resources and is faster than non synchronized handovers (Thomson and Manggard, 2003).

(b) Intra-BSC handover: The intra-BSC handover is performed when the MSC changes the BTS but not the BSC. The intra- BSC handover is entirely carried out by the BSC, but the MSC is notified when the handover has taken place. If the targeted cell is in a different location, then the MSC needs to perform the location updates procedure after the call. In the intra-BSC handover both synchronized and non synchronized handovers are possible. (Thomson and Manggard, 2003).

(c) Intra-MSC handover: In the intra-MSC handover when the BSC decides that handover is required but the targeted cell is controlled by a different BSC then it needs the assistance from the connected MSC of the two BSCs. In comparison to the previous handovers, the MSC is mandatory for this kind of handover. Responsibilities of the MSC do not only include processing the measurements of the BTS or the BSC but to conclude the handover. This kind of handover can be intra-MSC or Inter-MSC. In the intra-MSC handover, the targeted cell is located in a different BSC connected by the same MSC, the MSC simply contacts the targeted BSC for allocation of the required resources and informs the source BSC when they are ready. After the successful resources allocation, the MSC instruct source BSC to access the new channel and the call is transferred to the new BSC (Thomson and Manggard, 2003).

(d) Inter-MSC handover: The inter-MSC handover is performed when the two cells belonging to different MSC in the same system. In the inter-MSC handover the targeted cell is connected to a different MSC (named as MSC-B) than the one currently serving the call (named as MSC-A). When the BSC-A determines that a handover is required into another location area, it simply informs MSC-A. MSC-A then uses the network-based mobility facilities to establish traffic channel to MSC-B. It is then the duty of MSC-B to direct BSC-B to prepare BTS-B for the handover. Thereafter, the two MSCs will direct their respective BSCs to release the radio resources (Wei, 2001).

Protocols in handovers are usually centered around which part of the entire system controls the handover process. The time required to execute a handover request and the minimum measurement information required to make a request are the trade-offs associated with the various handover protocols. The current trends are to reduce the delays, decrease the information required and simplify the procedures. These protocols include network controlled handover (NCHO), mobile assisted handover (MAHO), soft handover (SHO) and mobile controlled handover (MCHO).

Network controlled handover protocol involves the network making a handover decision based on measurements of the RSSs of the MSs at a number of BSs. It is used widely in first generation analog systems (AMPS, TACS, NMT etc). The handover command is sent on a voice channel by blocking the voice with data. Conclusively, the handover process (including data transmission, channel switching, network switching etc) takes 100-200ms and produces a noticeable click in the conversation (Frech, 1998). Despite attempts by Ostling, (1995) and Rapport, (1996) to reduce the overall delay, a rapidly changing environment and a high density of users still pose a reasonable challenge to this protocol.

Mobile assisted handover protocol distributes the handover process by assigning measurements required to the MS and decision to be taken to the MSC. *TDMA*, *FDMA* based GSM and CDMA based IS-95 standards use this protocol. Although, MAHO was expected to address the delay associated with existing protocols, Mouly and Pautet, (1992) proved it to be contrarily.

Soft handover utilizes macroscopic diversity technique to establish a "make before-break" connection. In this case transmissions from a MS are received at different BSs and then used to obtain a good quality communication link to the new BS before the connection to the old BS is broken (Simmonds and Beach, 1993). The CDMA system support this function by using the GPS to provide a master clock for synchronization of all BSs in the network resulting in imperceptible delay to users (Grimlund and Gudmundson, 1991).

Mobile controlled handover put MS in control of the handover process by measuring the signal strengths from surrounding BSs and interference levels on all the channels. Once the signal strength of the servicing BS is lower than that of any other BS by a certain threshold, the MS chooses the BS with the highest signal strength and request from it for a channel with the lowest interference level to establish connection. MCHO is suitable for microcellular systems (ESCT, DECT etc) with shortest reaction time (Ostling, 1995). It is faster and less cumbersome by eliminating MSC from the handover process.

2. Mobility Management Algorithms and Attributes

Algorithms refer to different approaches in the handover decision procedures to sustain an on-going connection regardless of the mobility of the mobile station. According to Verdone (Verdone and Zanellas, 2002), all existing algorithms recognize three sequential phases, namely; measurement, initiation and resource allocation, and execution phases.

Today, all measurement of the overall link or communication quality is done by base and mobile stations. The data collected are processed and evaluated by both stations before any action can be taken. Some measured parameters may include among others, power, interference level, received signal level, Bit error rate, distance, velocity, etc. The processed measurement results or/and network variables establish need for handovers and subsequent possible initiation. The actual radio resources available and network load at a particular time determine the resource allocation phase. The execution phase depends entirely on the allocation of radio resources across the whole link. Measurement and transmission errors, processing and evaluation errors, and delays associated with all these phases are the main factors responsible for research works towards developing and adopting new and better algorithms.

Vijayan and Holtzman (1993) uses hysteresis algorithm that only initiates a handover if the signal strength of any one of the neighboring base stations is higher than a certain given hysteresis margin (typical of 6dB) of the current base station. Although satisfactory at that time, current applications shows that it actually wastes radio resources by initiating unnecessary handovers even when the current serving base station signal strength is strong enough. The likes of Shirvani et al (2000) developed an improved threshold algorithm to initiate a handover when the average signal strength of the current base station falls below a given threshold value (typical of 102dB) and the signal strength of any neighboring base station is greater than that of the current base station.

Earlier, Zhang and Holtzman (1996) actually combined hysteresis and threshold algorithms as they were and later introduced fuzzy logic by using RSS to achieve better results. Walke (2002) revealed serious setbacks with these algorithms especially in terms of ping pong effect, however, the suggestion of having higher and longer time hysteresis put forward by Markopoulos (2004) was really put into practice because of perceived increase in call drops attributed to this approach.

The need to reduce handover latency despite the continuous grow in the system capacity is the basis of researching and adopting different attributes. These attributes are used as inputs to handover algorithms. The development started from IEEE 802.11 networks to the recent bahaviourial-based mobility prediction schemes. Schemes are usually based on one or more attributes.

Behavior-based Mobility Prediction (BMP) technique has evolved and provides accurate mobility prediction by considering multifaceted user behavior: location, group, time-of-day, previous records and duration. The location-based mobility prediction is achieved by maintaining the handover history of all the MSs in the network, and then monitoring direction of movements of MSs relative to the topological placement of cells to predict their next point-of-attachment. In addition, next cell predictions are based on the frequencies of occurrences rather than signal strength. Therefore, it takes into consideration that mobility patterns are dictated by the structure of a building or a city block and the past behaviors of MSs. Moreover, the handover frequencies are treated as time-series data, thus when next cell predictions fail future predictions are recalibrated based on different groups, where each group of MSs has similar mobility patterns, time-of-day, record and duration characteristics.

Other schemes are based on the following attributes:

1. Transmitted power: The amount of power contained in the transmitted signal has direct relationship with the continuity of the established communication. It is widely used as an attribute of handover. Its proper analysis can help to reduce the power requirement, reduce interference and increase life span of batteries.

2. Distance: The likes of Hata and Nagatau, (1980); Mande, (1990) and Chia, (1991) have successfully used distance as an attribute to effect and improve handovers. Current trends towards MCHO have further established the importance of this attribute. However, the work of Liodakis and Stavroulakis, (1994) highlighted its unsuitability in a micro cellular system because it was established that the precision of the distance measurement decreases with smaller cell sizes.

3. Handover records: Anagnostou and Manos, (1994) effected handovers using attributes of total time spent, arrival time, recorded number of earlier handovers in the cell. While Lee, (1995) added the elapsed time since the last handover occurred. Most literatures have analyzed this attribute with time series techniques.

4. Received signal strength: This is an indication of power contained in the received signal. In an interference limited systems, received signal strength adequately indicates the signal quality relative to distance from the BS. It is widely used as attribute of handover in macro cells and also in microcells in conjunction with co-channel interference. Terrain and environmental factors are serious challenge to good received signal strength but typical values are about 100dB to 102dB as a threshold.

5. Traffic: Rappaport, (1993) used traffic level at certain designated period as handover attribute. This attribute is most essential if the target of handover is to ensure balanced traffic in the adjacent cells.

6. Path loss: Path attenuation is the reduction in power density of an electromagnetic wave as it propagates through space. It is a major attribute in the analysis of handovers because of its direct influence on the strength of signal. Path loss is affected by propagation, absorption, terrain contour, distance between the BS and MS, height and location of the antenna, free space etc. Exact path loss prediction in cellular system is not possible, hence there is need for many approximation methods such as Okumura-Hata, COST Hata, W.C.Y. Lee, Walfisch-Ikegami, Erceg etc. Deterministic method like Ray tracing is expected to produce more accurate and reliable prediction but less applicable because of computation complexity. The values of 100dB to 110dB at a distance of $R=2\sqrt{D^2}/\lambda$ from BS is acceptance.

7. Velocity: Holtzman and Sampath, (1995) presented a method that adaptively change the averaging interval to effect handovers for small and large cells. It was based on the estimation of mobile velocity through the maximum Doppler frequency technique. Currently this attribute is most popular with overlay systems.

8. Signal to interference ratio: this attribute directly affect voice quality system capacity, dropped call rate, reuse distance etc thus, widely used in the literature. However, it can produce ping-pong effect due to propagation conditions that may cause it to oscillate and result in bad link quality. Liodakis and Stavroulakis, 1994) and Chia, (1991) actually considered this attribute unnecessary in an interference limited environment.

9. Bit error rate: This is the number of received bits that are in error compared to the total number of bits transmitted. BER can be affected by noise, interference, distortion, bit

synchronization problem, attenuation, multipath fading etc., however, by having a strong signal strength, slow and robust modulation schemes, channel coding etc can reduce these effects. In cellular system, BER is analyzed along with SNR and tested by using bit error ratio tester. It is widely used as attribute of handover because of its relationship with signal quality.

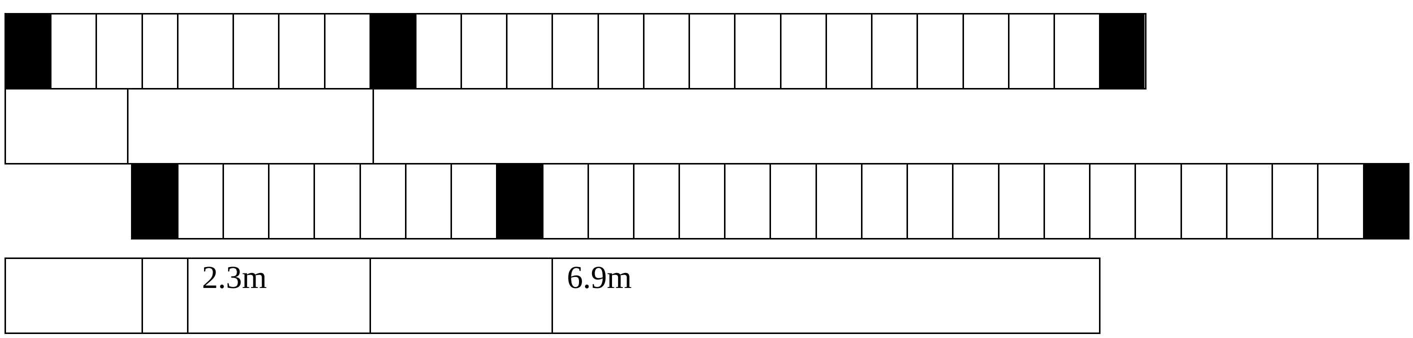
3. Mobility Management Resources and Utilization

The mobile station makes measurements which are used in triggering the handover and in the evaluation of the handover candidate cell. This makes the measurements as essential part of the handover process. The Mobile unit measures received signal strength (RSS) from each BTS in the neighborhood. The measured value of RSS (in dB) is the sum of three terms depending on the environment;

(i) path loss attenuation with respect to distance, (ii) shadow fading and (iii) fast fading.

In order to make efficient handover, these measurements should be refreshed as fast as possible. The mobile station measures the system parameter continuously and the level of the neighboring cells and sends this information to the network so that the decision for the handover is available to the network all the times. These measurement reports from the mobile station are carried on the SACCH signaling channel after every 0.48 sec but a minimum of once per second. In terms of capacity, the SACCH channel is error free which means that the measurement reporting is almost perfect. This measurement report contains parameters that define the current network connection, the radio conditions of the neighboring cells and the targeted cells to handover. In GSM one measurement message send from a mobile station to the BTS every 0.48 sec contains the signal level of up to 6 neighboring cells. However, a mobile station may pre-synchronize with more than 6 neighboring cells. In this case, the measurements corresponding to the 6 cells are taken but only the best are reported to the BTS. The measurements of the neighboring cells are more difficult because a mobile station must establish which neighboring cell it can receive and divide the measurements times among those cells it is capable of receiving.

The possible measurements times are between the transmission and reception of a burst of the traffic channel. Figure 2.6 shows time during which it is not suitable for measurements of the channel of neighboring cells. When there is discontinuity between the transmissions then the GSM measurements become inaccurate. To overcome these problems the power control and handover settings should be set more accurate (Nielsen and Wigard, 2000).



Short measurement interval long measurement interval

Figure 2.6: GSM SACCH Block

Handover represents one of the radio resource management tasks carried out by cellular networks. A couple of enhancements which can improve the performance of GSM handover algorithms to sustain an on-going call are paramount to researchers and operators. Major approaches in the literatures include the followings;

1. Conventional Handover Management, in GSM cellular networks both the mobile station and the BTS regularly measures the radio signal strength. The mobile station transmits its measurements reports continuously to the BTS. If the BTS detects a decrease in radio signal strength under a minimal level it initiates a handover request. The BTS then informs the BSC about the request, which then verifies if it is possible to transfer the call into a new adjacent cell. Actually the BSC checks whether a free channel is available in the new adjacent cell or not. In this situation, the BSC does not differentiate between the channel requests either for fresh call or handover. If a free channel is available in the new adjacent cell then handover request can be satisfied, and the mobile unit switches to a new cell. If there is no free channel in the adjacent cell then it increases the dropping probability of handover call. The drawback of this handover procedure is the fact that the handover request for channel is same as that used for fresh calls. In conventional handover, management is very problematic from the users quality of service perspective, since a user will prefer to block a fresh call rather than to be dropped in the middle of transmission (Mandjes and Tutschku, 1996).

2. Channel Carrying Handover Management allows a mobile unit to carry its current channel from one cell to another when it moves across the boundaries under specific conditions. The channel carrying management uses a linear cellular system model in which cells or BTS are arranged in linear configuration with minimum reuse distance r. Suppose N is the total number of channels available for use in the cellular system. Two cells can use the same set of channel as they are apart by distance r.

To avoid the co-channel interference an advance solution is proposed in which the distance of identical sets of channels is increased to r+1 instead of r. The distance r is the minimum reuse distance or reuse factor. Accordingly, the total number of available channels in each cell is now reduced by amount of N/r+1 where N is the total number of available channels. In a typical situation the smaller the reuse distance the more amounts of channels to be lost. The channel carrying management does not require the complex power control or global channel coordination which simplifies its implementation. Handover requests are greatly favored over new calls compared to the Conventional handover management. The main drawback of this handover procedure is that it is not suitable for metropolitan environment due to the great amount of channels lost (Li and Chong, 1996).

3. Handover Prioritization Schemes Management, different ideas and approaches are proposed to reduce the handover dropping probability. One approach to reduce the handover failure rate is to prioritize handover call over new calls. Handover prioritization schemes have a significant impact on the call dropping probability and call blocking probability. Such scheme permits high utilization of bandwidth while guaranteeing the quality of service of handover calls. Basic method of handover prioritization schemes are guard channels (GC), call admission control (CAC) and handover queuing schemes. Sometimes these schemes are combined together to obtain better results (Tripathi et al, 1998).

(i) Guard Channel Prioritization Scheme, the guard channel scheme was introduced in the 80s for mobile cellular systems. However the guard channel scheme is still used in telecommunications with the name of Cutoff Priority Schemes. Guard chaneel scheme improves the probability of successful handover by simply reserving a number of channels exclusively for handover in each cell. The remaining channels can be shared equally between handover and new calls. Guard channel is established only when the number of free channels is equal to or less than the predefined threshold. In this situation fresh calls are bypassed and only handover requests are served by the cell until all channels are occupied. The Guard channel scheme is feasible because new calls are less sensitive to delay than the handover calls (Katzela and Naghshineh, 1996).

If a cellular network is considered with C the total number of channels in a given cell, according to guard channel scheme, reserve channels for handover are C-T, where T is the predefined threshold. The guard channel will not accept any new call until the channel occupancy goes below the threshold. Suppose the arrival of new and handover calls are denoted with λ and ν respectively. The call holding and call residency for both call is exponentially distributed with $1/\mu$ and $1/\eta$ respectively. The total traffic can be calculated as

$$\rho = \frac{(\lambda + \nu)}{(\mu + \eta)} \tag{2.1}$$

Therefore according to the cell occupancy by Markov chain, it is straight forward to derive the steady state probability Pn that n channels are busy (Ghanderi and Boutaba, 2006). In fact, there is a tradeoff between minimizing probability density (Pd) and minimizing the probability that b bandwidth are available (Pb). If the number of channels is static then the admission call control fails to satisfy the specified Pd. The static channels reservation shows results of poor utilization of bandwidth (Ghanderi and Boutaba, 2006).

(ii) Call Admission Control Prioritization Scheme, the call admission control scheme refers to the task of deciding whether new call requests are admitted into the network or not. In the CAC, the arrival of new calls are estimated continuously and if they are higher than the predefined threshold level then some calls are restricted (blocked) irrespective of whether a channel is available or not to decrease the probability of handover calls. In the CAC both the new and handover calls have access to all channels. If a new call that is generated in a cell cannot find an idle channel the call is discarded immediately. There is no queue provided for the new calls to wait (Abdulova, and Aybay, 2006).

The CAC scheme can be classified into different schemes that consider the local information like (the amount of unused bandwidth in cell where the user currently resides), remote information (the amount of unused information bandwidth in the neighboring cells) or local or remote information to determine whether to accept or reject a call. CAC based on knowledge of both network and user characteristics, keeps the track of available system capacity and accommodates new call request while ensuring quality of service for all existing users. Decisions in CAC are performed in each BSC in a distributed manner and there is no central coordination. The CAC scheme can be evaluated on the basis of Efficiency, Fairness, Stability and Flexibility (Yliopisto, 2005).

(iii) Handover Queuing Prioritization Schemes, Queuing handover call prioritization scheme queues the handover calls when all the channels are occupied in the BSC. When a channel is released in the BSC, it is assigned to one of the handover call in the queue. The handover queuing scheme reduces the call dropping probability at the expense of the increased call blocking probability and decreased ratio of carried to admitted traffic since new calls are not assigned a channel until all the handover requests in the queue are served (Nishitd et al, 1998).

In the handover queuing schemes when the received signal strength of the BSC in the current cell reaches a certain defined threshold, the call is queued to be serviced by a neighboring cell. A new call request is assigned a channel if the queue is empty and if there is at least a free channel in the BSC. The call remains queued until either a channel isavailable in the new cell or the power by the base station in the current cell drops below the receiver threshold. If the call reaches the receiver threshold and no free channel is found then the call is terminated. Queuing handover is possible due to the overlap regions between the adjacent cells in which the mobile station can communicate with more than one base station. This makes provision of queuing the handover requests for certain time period equal to the time of the mobile host existence in the overlapping area (NASA, 2006).

Queuing is effective only when the handover requests arrive in groups and traffic is low. First in first out (FIFO) scheme is the most common queuing scheme where the handover requests are ordered according to their arrival. To analyze this scheme it is necessary to consider the handover procedure in more detail. By assuming the FIFO queuing strategy an infinite queue size at the base station is assumed. The handover of the mobile station depends on the system parameters such as moving speed, the direction of the mobile station and the cell size. Suppose the state ί (ί=0, 1, 2 …, ∞) of a cell as the sum of the channels being used and the number of the handover call request in the queue. Then it is clear from the Markov chain that ί is one-dimensional (Zeng and Agrawal, 2001). The equilibrium probabilities are related to each other. Then the steady state probability is found according to the Markov chain. Therefore the blocking probability for an originating call and the termination probability of the call can be calculated accordingly (Zeng and Agrawal, 2001). In the FIFO handover Prioritization scheme the probability of forced termination is decreased, however the handover call may be dropped because the handover request can only wait until the receiver threshold is reached (Zeng and Agrawal, 2001).

Some new queuing schemes like Measurement based prioritization scheme (MBSP), very early assignment (VEA), early assignment (EA) and most critical first (MCF) are proposed to improve the performance of the handover queuing scheme by modifying the queuing discipline. In the MBSP the handover calls are added to the queue and the priorities of the calls change dynamically based on the power level they have. The call with the power level close to the receiver threshold has the highest priority. This scheme produce better results than the FIFO queuing schemes. Each of these schemes has its advantages and disadvantages in term of capacity and services. The VEA for example, gives the shortest call setup but is most capacity inefficient (Nielsen and Wigard, 2000).

(iv) Cell Overlapping and Load Balancing Scheme, in order to improve the handover call prioritization scheme, it is advisable to equalize the traffic load over the cells. Traffic reason and directed retry handover make use of this principle. Traffic reason handover can be used to transfer traffic from one cell to another neighboring when they are closed to the congestion. The traffic reason handover idea is based on the neighboring cell having an overlapping service area. The overlapping service area arises naturally in GSM cellular system especially in small-cell high capacity micro cellular configurations. The small-cells are captured by subdividing a congested cell each with its own base station. The call arising in the common area (overlapping) of cells have access to channels from more than one base station. By appropriate control strategy, a cell may select the base station to establish a connection and contribute to efficient spectrum management. By subdividing a congested cell into small cells the frequency reuse distance is effectively increased which reduces the level of interference and increases the carrier interference ratio at both sides of the mobile station and base station.

Literatures have proved that the directed retry and an increase in the overlapping between cells lead to increase in the quality of service of the cellular system. A large overlapping area gives more capacity than a smaller one, but even by just having a small overlap a significant gain is achieved. The overlap of 0.1R (where R is the radius of cell) results in an overlapping area equal to 9% of the cell area that gives a gain of at least 6% whereas if the overlap is equal to 0.5R means overlapping area is 75% of the cell area then the capacity gain is boosted to 27%. The performance of this functionality is very dependent on the existing overlapping between cells since it is required that at least one neighboring cell has sufficient signal level for the mobile station to be redirected (Nielsen and Wigard, 2000).

According to the concept of cell radius when two or more adjacent cells overlap they form a set of individual regions which can be categorized into three types A, B, and C according to the number of cell they overlap. These regions can be assigned a channel from one of the three cells. The importance of the regions and areas is to perform the channel allocation scheme based on either through the region or area. The number of channels for specific region depends on the size of the regions and a specified channel can be used in that area. If the regions in one cell were summed according to their overlap then they formed a cell area. The blocking probability of the cell can be calculated from those users who are able to choose a channel from cells A, B, and C. This maintains the same lowest blocking probability and load balancing in every area (Katzis, 2005).

4. Mobility Management Performance and Evaluation

Performance is tied to quantifiable metrics. These metrics form the fundamental parameters that describe the performance aspects and by extension used to evaluate various handover models, procedures, protocols and algorithms. Common among the metrics in literatures include the followings;

1. Call Blocking Probability is the probability that a new call attempt is blocked.
2. Handover Blocking Probability is a probability that a new handover attempt is blocked.
3. Handover Probability is a probability that, while communicating with a particular cell, an ongoing call requires a handover before the call terminates. This translates into the average number of handovers per call.

4. Call Dropping Probability is the probability that a call terminates due to handover failure. This can be derived directly from the handover blocking probability and the handover probability.
5. Probability of an Unnecessary Handover is the probability that a handover is stimulated by a particular handover algorithm when the existing radio link is still adequate.
6. Rate of Handover is the number of handovers per unit time. Combined with the average call duration, it is possible to determine the average number of handover per call, and thus the handover probability.
7. Duration of Interruption is the length of time during a handover for which the mobile unit is in communication with neither BTS. This is heavily dependent on the particular network topology and the scope of the handover.
8. Delay is the distance the mobile unit moves from the point at which the handover should occur to the point at which it does.

Evaluation of the handover performance is as important as the development of handover schemes. Efforts to quantify the performance of particular approaches have become common within the literature and attempt to answer questions such as; does a user get admitted? Does a call get prematurely terminated? How many handovers are made, and are they necessary to meet the quality of service? How far into coverage area of another cell does a user drift? What is the duration of service interruption during a handover? etc is of increase. Literatures have shown that, these evaluation mechanisms can be grouped into the following mechanisms.

1. Analytical Mechanisms are usually based on the measurements made at the BSs for handovers performance evaluation. It is cost-effective and gives preliminary idea about the performance of some handover algorithms. However, it is valid only under specified constraints because such

measurements are not very useful since they cannot characterize small-area performance. Typical analytical models include the level crossing model that uses the difference between the RSSs from two BSs modeled as Poisson processes for stationery/non-stationery signal strength measurements, linear model, cell coverage model, prioritized model, micro/macrocell overlay model, microcell model etc. The results of all these models are sufficient for determining the averaging interval and hysteresis level, the effect of handovers techniques on cell coverage and reverse link capacity, the call termination probability, the probability of the new call blocking and handovers call forced termination, etc.

2. Simulation Mechanisms approach allows incorporation of many features of a cellular system and a cellular environment into the evaluation framework. It is the most commonly used handover evaluation scheme because it provides a common test bed for comparison of different handover algorithms, and gives an insight into the behavior of the system. Software simulation provides fast, easy, and cost-effective evaluation. Several simulation models suitable for evaluation of different types of handover algorithms under different deployment scenarios have been proposed and used in the literatures. Typical examples of such simulation models usually consist of one or more of the following components; the cell model, propagation model, traffic model, mobility model etc.

3. Emulation Mechanisms uses a software simulator consisting of a number of handover algorithms to process measured variables (e.g. RSS and BER). Actual propagation measurements-based simulation has the advantage of giving better insight into the behavior of the radio channels and more accurate data. The main disadvantages are that this scheme requires periodic measurement efforts and is not suitable for comparison of different handover algorithms on the same conditions. Major works on emulation mechanism include the followings: measured

data using 1700MHz for urban environment, 950MHz for indoor environment and Digital Cellular System for switching channels subsystems.

5. Mobility Management Development, Challenges and Future

The history of mobility development is as old as the existence of GSM networks because of mobility requirements. Researchers have achieved tremendous improvements in handover structures, protocols, resources, management, attributes, algorithms, performances and evaluation techniques. All these sub-titles have become major research units considering the trends toward MCHO, replacement of macro cells by microcells, and migration of technology through and toward higher generations with additional complex features. Users, equipment and service providers, together with research community will continue to develop and adopt new findings to maintain the current developmental efforts in all aspect of handover to ensure higher quality of service in mobility management.

To actualize an effective and efficient handover poses many challenges due to cell dynamics (cell size, topography, propagation, traffic, mobility, etc), striking a good balance between power requirements and tolerable delay, and resources utilization can be a herculean task. Included among such challenges are:

1. Cellular structure: Different cellular structures, layouts and radii of cells place remarkable constraints on handover algorithms and attributes (Polini, 1996 and Ransom, 1995). Pockets of microcells now coexist with macro cells to cover designated services (microcells cover hot spots, high traffic areas while macro cells cover low traffic areas, high speed users, overflow traffic etc). As the number of MSs to be handled by the existing infrastructure increases with continuous deployment of additional microcells, the number of handovers per call would

definitely increase. Attributes will change faster requiring more processing facilities within shortest possible time (Munoz-Rodriguez et al, 1992).

2. Propagation factors: Physical environment have direct effect on radio propagation (environmental factors can result in lower RSS at locations closer to BS than those further). Propagation characteristics of microcells are different from those of macro cells (Grimlund and Gudmundson, 1991). This is a continuous primary influencing factor in planning and deployment stages.

3. Mobility: High speed result in degradation of communication quality. The today user bahaviour, network evolution and deployment all point to fast handover mechanisms.

4. Traffic: Capacity availability is related to installed infrastructure while capacity carried is a function of time and space. Cell sizes, channel allocation and cell load balancing techniques should be adequate for even traffic distribution.

5. System limitations: Certain factors like power control, channel allocation, handovers, etc is been decentralized to enhance cellular systems performance. Similar factors are equally been considered for the same purpose, the concern here is the interplay between these factors and the cumulative effects on the entire system.

6. Topographical conditions: Chia, (1991) concluded that the performance of handovers depend on the signal profile in a particular region. Signal profile components are characterized by the terrain and a lot of physical developments in our community keep changing these terrains. It is not easy to implement designs and plans on dynamic terrain.

In summary, the future of a good mobility should address certain fundamental objectives to avoid other side effects on the entire cellular system.

1. Handover should be fast to avoid service degradation, co-channel interference and network delay.
2. Handover should be successful to avoid call drops and user's dissatisfaction.
3. Handover should be reliable to avoid network congestions and unnecessary infrastructure engagement.
4. Handover should respect the cellular layout to avoid ping pong effect, congestion and call dropping.
5. Handover should result in improved quality of service as the reverse is usually the case before handovers.

According to Kanai and Furuya, (1988); Frech and Mesquida, (1989); Mende, (1990); Anagnostou, (1994) a good handover should maximize QoS and capacity by providing high communication quality and retainability, ensure proper cell borders and load balancing at the same time maintaining low signal interference with little or no system delay.

2.2.4 Soft Computing Techniques

Artificial Intelligence (AI) is a system that acts and thinks (like humans) rationally (Deshpande, 2008). AI systems can understand a natural language or perceive and comprehend a visual scene, and is a system that performs feats that require human type of intelligence. Artificial Intelligence can be summed up as the study of how to make computers do things which, at the moment, people do better (Rich and Knigh, 1999). Some of the task domains of AI include: Mundane tasks, Formal tasks and Expert tasks (Rich and Knigh, 1999). The research work will focus on expert tasks domain which offers gateway to injection of Artificial Intelligence to engineering (design, fault finding, planning, optimization etc), scientific and financial analysis, and medical diagnosis.

AI technique is a method that exploits knowledge that should be represented in such a way that:

(i) The knowledge captures generalizations, (ii) It can be understood by people who must provide for it, (iii) It can easily be modified to correct errors and to reflect changes, (iv) It must have some degree of independence between problems and problem solving techniques, and (v) It can be used to help overcome its sheer bulk by helping to narrow the range of possibilities that must be considered (Rich and Knigh, 1999; Patternson, 2004).

The AI technique offers a class that attempts to model human performance within AI tasks; they do things that are not trivial for the computer. Modeling human performance in AI fashion is motivation to:

(i) Test psychological theories of human performance, (ii) Enable computers to understand human reasoning, (iii) Enable humans to understand computer reasoning, and (iv) Exploit knowledge from humans (Rich and Knigh, 1999; Patternson, 2004).

The last motivation is probably the most pervasive of the four. It motivated several early systems that attempted to produce intelligent behavior by imitating people at the level of individual neurons. The solid goal of AI is to construct a working program using languages that have been designed to support symbolic rather than primarily numeric computation by utilizing Expert, Reasoning and Logic systems.

1. Expert System

This is a Knowledge-based system (KBS) that uses the non-deductive inference for its analysis (Patternson, 2004). Non-deductive inferences include:

(i) Adductive inference (causal fact), (ii) Inductive inference (assumption), (iii) Analogical inference (experimental), and (iv) Rule-based systems (IF…..THEN).

2. Reasoning System

This is an extension of established past or present to tell the future (Deshpande, 2008). It basically includes:

(a) Monotonic as a method of reasoning under conditions of certain, complete, unchanging, and consistent facts. It assumes that sufficient amount of reliable knowledge (facts, rules, etc) are available with which to deduce confident conclusions (Patternson, 2004). This form of reasoning suffers from several limitations:

    (i) It is limited in expressive power, (ii) Inability to express uncertain, imprecise, hypothetical or vague knowledge, and (iii) Available inference methods inefficient.

(b) Non-Monotonic that deals with Monotonic and additions of uncertain, incomplete, changing facts and knowledge. It also deals with symbolic reasoning under uncertainty. It offers several advantages:

    (i) Knowledge base can be extended to allow inferences to be made on the basis of lack of knowledge, (ii) Allows knowledge base to be updated properly when a new fact is added to the system or when an old one is removed, and (iii) Knowledge can be used to help resolve conflicts when there are several inconsistent monotonic inferences that could be drawn (Rich and Knigh, 1999) (Patternson, 2004).

The non-monotonic reasoning is an extension that accommodates different forms of uncertainty and non-monotony. There are different non-monotonic reasoning methods, which includes;

(i) Truth Maintenance Systems (maintain consistency of the basis), (ii) Default Reasoning (avoid the need to explicitly store all facts), (iii) Closed World Assumption (all facts are known to prove situation), and (iv) Predicate Completion and Circumscription (limits default assumptions).

Knowledge-base system and Reasoning all fall under the traditional logics in dealing with certainty, uncertainty, completeness and incompleteness knowledge. Traditional logics have limitations:

(i) Interpretation of results as either true or false only, (ii) Only one type of expression modality, and (iii) Lack of intensive and extensive axioms to express the meanings and relations of concepts such as possibility, necessity, obligations, known truth, etc (Patternso, 2004; Deshpande, 2008). With these limitations, they fail to effectively represent vague or fuzzy concept.

3. Logics

Logic is a science of critical reasoning. Many concepts which can be verbalized can be translated into symbolic representations which closely approximate the meaning of these concepts. These symbolic structures can then be manipulated in programs to deduce various facts, to carry out a form of automated reasoning. It includes:

(a) Modal logics that were invented to extend the expressive power of traditional logics, to add the ability to express the necessity and possibility of prepositions, to help capture and represent additional subjective mood concepts (supposition, desire). Consequently result may be true or false in some degrees (measurement between 0 and 1) (Patternson, 2004; Deshpande, 2008);

(b) Temporal logics that uses modal operators in relation to concepts of time, such as past, present, future, proceeds, succeeds, etc. Various schemes have been proposed for the management of temporarily changing worlds including other modal operators, time and date tokens. This problem has taken on increased importance and a number of solutions have been offered. Still much work remains to be done to find comprehensive solutions. A combination of Modal logics and Temporal logics is Fuzzy logic system (Rich and Knigh, 1999; Patternson, 2004).

(c) Fuzzy logic is a logical system, which is an extension of multi-valued logic. Fuzzy logic is almost synonymous with the theory of fuzzy sets, a theory in which membership is a matter of degree. Another basic concept in fuzzy logic is that of a fuzzy if-then rule or, simply, fuzzy rule, and fuzzy reasoning. Fuzzy logic has machinery for dealing with fuzzy consequents and/or fuzzy antecedents. This machinery is provided by what is called the calculus of fuzzy rules. Its basic structure consists of three components:

(i) Rule base that contains the fuzzy rules, (ii) Membership Functions used as the reasoning mechanism, which acts on the set of rules, and (iii) Data Base that defines the membership function (Patternson, 2004; Mu'azu, 2006).

Fuzzy logic systems are very useful in two general contexts:

(i) In situations involving highly complex systems whose behaviors are not well understood, and

(ii) In situations where an approximate, but fast, solution is warranted.

The fuzzy-set framework is numerical and multidimensional. The AI framework is symbolic and one-dimensional, with usually only bivalent expert rules or prepositions allowed. Both frameworks can encode structured knowledge in linguistic form, but the fuzzy approach translates the structured knowledge into a flexible numerical framework and processes it. The numerical framework also allows fuzzy systems to adaptively infer and modify, with statistical techniques, directly from problem-domain sample data (Patternson, 2004; Mu'azu, 2006). A fuzzy set defines a point in a set. A fuzzy system defines a mapping between points. A fuzzy system S maps families of fuzzy sets to families of fuzzy sets, thus

$$\boldsymbol{S}: \boldsymbol{I}^{n1}\boldsymbol{x} \ldots . \boldsymbol{x}\boldsymbol{I}^{nr} \rightarrow \boldsymbol{I}^{p1}\boldsymbol{x} \ldots . \boldsymbol{x}\boldsymbol{I}^{pr} \qquad (2.2)$$

Where;

$\boldsymbol{I}^{n}$houses all the fuzzy subsets of the domain space or input universe discourse with n-dimensions; and

$\boldsymbol{I}^{p}$ houses all the fuzzy subsets of the range space, or output of universe of discourse.

Membership function defines the degree to which the value of a variable belongs to the universe of discourse (universal set) with ranges between 0 and 1. A fuzzy $\boldsymbol{A}$ in $\boldsymbol{X}$, is defined as:

$$\boldsymbol{\mu_A}(\boldsymbol{x}) \in [\boldsymbol{0}, \boldsymbol{1}] \qquad (2.3)$$

The symbol $\boldsymbol{\mu_A}(\boldsymbol{x})$ is the degree of membership of element x in fuzzy set A, Therefore, $\boldsymbol{\mu_A}(\boldsymbol{x})$ is a value on the unit interval that measures the degree to which element $\boldsymbol{X}$ belongs to fuzzy set $\boldsymbol{A}$.

Fuzzy systems theory is similar to other engineering theories, because almost all of them characterize the real world in an approximate manner. A fuzzy logic system accepts imprecise data and vague statements such as low, medium, high and provides decisions, as shown in Figure 2.7.

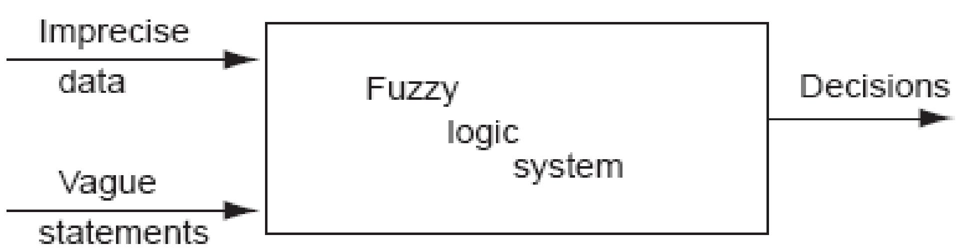


Figure. 2.7: Fuzzy Logic System- Courtesy Matlab 2008a (CM8a)

Fuzzy sets provide means to model the uncertainty associated with vagueness, imprecision, and lack of information regarding a problem. The uncertainty is found to arise from ignorance, from chance and randomness, due to lack of knowledge, from vagueness (unclear), like the fuzziness existing in our natural language.

For instance, consider two fuzzy sets A and B on the universe X. For a given element x of the universe X, exist the basic operators. They are unions, intersection, subset and complement and are defined for A and B on X (Mu'azu, 2006; Dadone, 2001) as shown in Figure 2.8.

Containment or subset:

$$\forall \boldsymbol{x} \in \boldsymbol{X}: \boldsymbol{\mu_A}(\boldsymbol{A}) \leq \boldsymbol{\mu_B}(\boldsymbol{B}) \qquad (2.4)$$

Union:

$$\boldsymbol{\mu_{A \cup B}}(\boldsymbol{x}) = \boldsymbol{\mu_A}(\boldsymbol{x})\ \boldsymbol{V}\ \boldsymbol{\mu_B}(\boldsymbol{x}) \qquad (2.5)$$

Intersection:

$$\boldsymbol{\mu_{A \cap B}}(\boldsymbol{x}) = \boldsymbol{\mu_A}(\boldsymbol{x})\ \boldsymbol{\Lambda}\ \boldsymbol{\mu_B}(\boldsymbol{x}) \qquad (2.6)$$

Complement:

$$\boldsymbol{\mu_{-A}}(\boldsymbol{x}) = \boldsymbol{1} - \boldsymbol{\mu_A}(\boldsymbol{x}) \qquad (2.7)$$

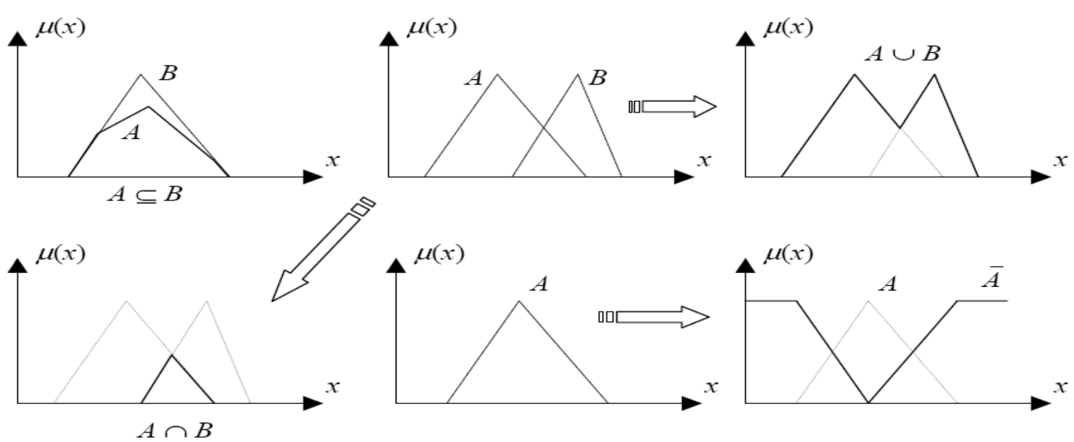


Figure 2.8: Graphical Representation of Containment, Union, Intersection, and Compliment-Courtesy Matlab 2008a

Hedges are operators that are created independently to modify fuzzy values. These operations are provided in an effort to maintain close ties to natural language and to allow for generation of fuzzy statements through mathematical calculations (Ojala, 1995). Typical hedges include:

$$\boldsymbol{'very'}\text{: } \boldsymbol{\mu('very'A) = \mu(A)^{2}}$$

$$\boldsymbol{'somewhat'}\text{: } \boldsymbol{\mu('somewhat'A) = \mu(A)^{0.5}}$$

$$\boldsymbol{'extremely'}\text{: } \boldsymbol{\mu('extremely'A) = \mu(A)^{3}} \qquad (2.8)$$

Fuzzy reasoning is usually performed using if-then rules. The fuzzy rules define the connection between input and output fuzzy (linguistic) variables. The rule consists of two parts: an antecedent and a consequence part. A typical rule which describes this simple fact is shown in equation (2.9).

$$\textbf{IF}\ \underbrace{\text{input1 is } \textit{small}\ \textbf{AND}\ \text{input2 is } \textit{negative big}}_{\text{antecedent part}}\ \textbf{THEN}\ \underbrace{\text{output is } \textit{zero}.}_{\text{consequence part}} \qquad (2.9)$$

In equation (2.9), input1, input2 and output are called fuzzy variables, and small, negative big and zero as linguistic variables. **AND** is a connective operation and it aggregates the results within the premise part. The other common connectives are union **OR** and complement **NOT** (Ojala, 1995).

The fuzzy inference system (FIS) performs fuzzy reasoning. The basic FIS is composed of five functional blocks, as depicted in Figure 2.9

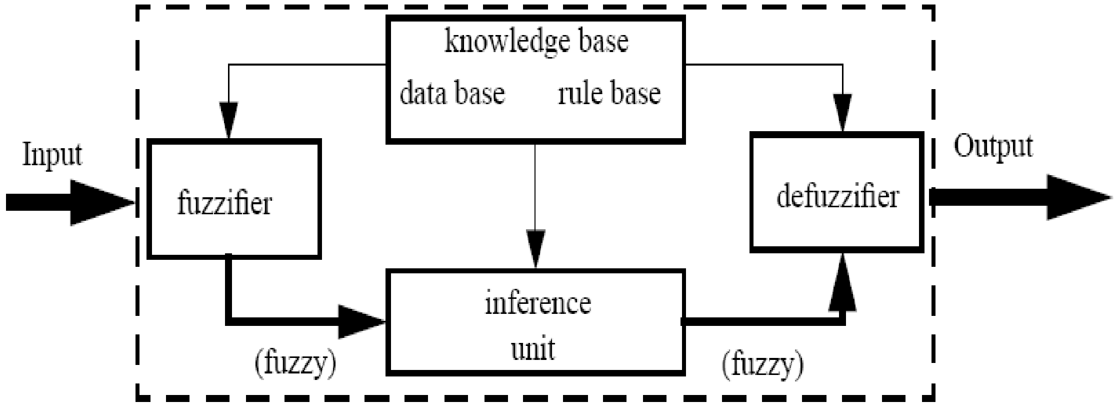
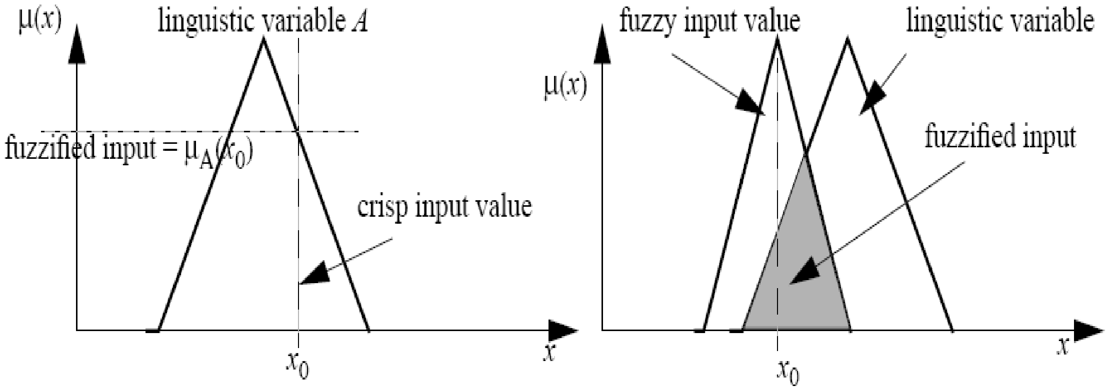


Figure 2.9: Structure of the Fuzzy Logic Inference System.

The knowledge base consists of the data base and the rule base. The fuzzy sets are defined in the data base and fuzzy rules in the rule base. The decision-making unit executes fuzzy reasoning rules taking fuzzified inputs of fuzzy inference system as inputs and delivering the fuzzy result to the defuzzifier, which produces the output of the fuzzy inference system. The operation of the FIS is illustrated in Figure 2.9. First, crisp inputs *x* and *y* are fed into a fuzzy inference system. In the second stage, they are fuzzified. After that, the fuzzified inputs are combined according to the fuzzy rules in the knowledge base. Finally, the results of all rules are combined and defuzzified. In the following, each stage is described in more detail (Ojala, 1995).

In the fuzzification stage the crisp input values are transformed to fuzzy values. If the input has a crisp value, the matching against the membership function of linguistic variable is shown in Figure 2.10(a). If the input contains noise, it can be modeled by using a fuzzy input value. In this case the fuzzy output is the intersection of fuzzy input and the linguistic variable membership functions as shown in Figure 2.10(b). However, the crisp input value fuzzification is mostly used because of its simplicity.



(a) (b)

Figure 2.10: Fuzzification of a crisp input (a) (on the left) and a fuzzy input (b) (on the right)

Fuzzifiers are generally divided into singleton and non-singleton ones. A singleton fuzzifier maps an object to the singleton fuzzy set centered at the object itself (i.e., with support and core being the set containing only the given object). A non-singleton fuzzifier, maps an object to a fuzzy set generally centered at the object itself (i.e., the core of the fuzzy set contains the object) and with support containing the object but being a set bigger than only the object itself. A non-singleton fuzzifier maps an object into a non-singleton fuzzy set generally centered at the object itself. Typically, the use of a singleton fuzzifier is very common. Non-singleton fuzzifiers are also used, especially in the presence of noisy measurements. Indeed, in this case the input crisp value is affected by some uncertainty, thus, the corresponding input fuzzy set can reflect this uncertainty by allowing non-zero membership values around the (noisy) measurement. Therefore, when a non-singleton fuzzifier is used, the width of the corresponding fuzzy set is generally proportional to the amount of noise affecting the measurement. Figure 2.11 shows an example of singleton and non-singleton fuzzification (Ojala, 1995).

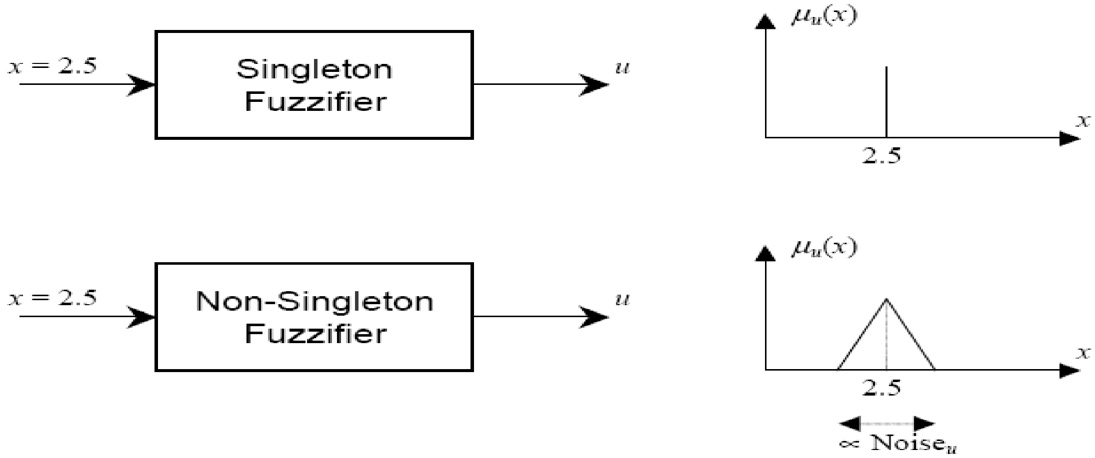


Figure 2.11: Singleton and Non-singleton Fuzzifiers

The decision making unit (Inference) performs the inference operations on the fuzzy rules. The fuzzy values within a fuzzy rule are aggregated with connective operators like intersection (AND), union (OR) and complement (NOT). Due to the use of the multi-valued logic, the connective operators for fuzzy logic differ from the ones used in the Boolean logic. They have membership values which are combined by operators. The firing strengths of the fuzzy rules are computed by employing above operators. The operation of the intersection is shown in Figure 2.10(b). The final output fuzzy sets are obtained either by scaling (Max-Dot method) or by cutting (Max-Min) according to the firing strength of the fuzzy rules. If the output fuzzy sets are singletons, they are not handled by the firing strengths in this stage.

In the defuzzification stage, the outputs of the fuzzy rules are combined to a crisp output value. Several defuzzification strategies have been suggested (Mu’azu, 2006; Ojala, 1995). The most common method is the center of area defuzzification strategy, illustrated in Figure 2.11. Assuming a discrete universe of discount, the crisp output *Z* is produced by searching the center of gravity of consequence fuzzy sets according to the equation depicted

$$\boldsymbol{Z = \sum_{i=0}^{m} \frac{\mu_c(z_i) z_i}{\mu_i(z_i)}} \qquad (2.10)$$

Where $\boldsymbol{m}$ is the number of quantization levels of the output,

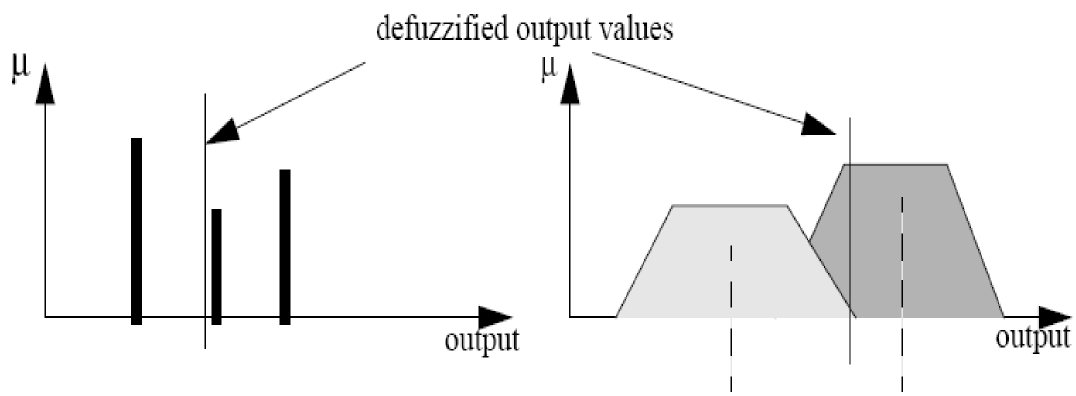
$\boldsymbol{z_i}$ is the amounts of output at the quantization level $\mathbf{i}$,

$\boldsymbol{\mu_i}(\boldsymbol{z_i})$ that represents its membership value in C.

If only singletons are used as the consequences of fuzzy rules, the natural defuzzification method is the weighted average. It can be considered as a special case of center of area defuzzification method. The weighted average method combines the consequences of the fuzzy rules to the output of the inference system *z* according to

$$\boldsymbol{Z} = \sum_{\boldsymbol{i=0}}^{\boldsymbol{n}} \frac{\boldsymbol{\mu_i z_i}}{\boldsymbol{\mu_i}} \tag{2.11}$$

where $\boldsymbol{n}$ is number of fuzzy rules, $\boldsymbol{\mu_i}$ is the firing strength of the rule, and $\boldsymbol{z_i}$ is the output value of the i^{th} singleton.



(a) (b)

Figure 2.12: Defuzzification Methods.

In Figure 2.12 (a), depicted are three fuzzy rules which have singleton output fire. The output is computed by using weighted average strategy. In Figure 2.12 (b) two fuzzy rules fires are shown. The crisp output is the center of the area (Mu'azu, 2006; Ojala, 1995).

The fuzzy logic systems models are classified into Mamdani and Takagi-Sugeno types,

(a) Mamdani is a set of linguistic control rules obtained from experienced human operators, utilizing the **if-then rules**, whose antecedents and consequents utilizes the fuzzy values. An instance is

$$\boldsymbol{If}\ pressure\ is\ high, \boldsymbol{then}\ volume\ is\ small$$

Where pressure and volume are linguistic variables, high and small are linguistic values or terms that are characterized by membership functions.

(b) Takagi-Sugeno uses systematic approach to generate fuzzy rules from an input-output data set. In a Takagi-Sugeno fuzzy logic system, the consequent of each rule is not a fuzzy set but it is a local model of the system (function) to be controlled (approximated). Thus the Ith rule of a Takagi-Sugeno fuzzy logic system has the form:

$$R^{(I)}: \boldsymbol{If}\ \boldsymbol{\mu_1}\ is\ A_{1k}(1,1)\ and\ \boldsymbol{\mu_2}\ is\ A_{2k}(2,1)\ and\ ....$$

$$\boldsymbol{\mu_n}\ is\ A_{nk}(n,1),$$

$$\boldsymbol{then}\ y = \boldsymbol{g_1}(\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots \boldsymbol{x_n}) \qquad (2.12)$$

The idea of this approach is to fit enough local models g_l to adequately describe the system while the fuzzy inference provides for some smooth interpolation between models. These local models are generally linear; thus the Ith rule of a Takagi-Sugeno fuzzy logic system becomes:

$$R^{(I)}: \boldsymbol{If}\ \boldsymbol{\mu_1}\ is\ A_{1k}(1,1)\ and\ \boldsymbol{\mu_2}\ is\ A_{2k}(2,1)\ and\ ....$$

$$\boldsymbol{\mu_n}\ is\ A_{nk}(n,1),$$

$$\boldsymbol{then}\ y = \boldsymbol{p_{01}x_1} + \boldsymbol{p_{02}}\ \boldsymbol{x_2} +\ \boldsymbol{p_{03}}\ \boldsymbol{x_3} + \cdots \boldsymbol{p_{n1}x_n}) \qquad (2.13)$$

If a precise solution is required without much bother to interpretability, then the Takagi-Sugeno model system is used otherwise mamdani model is used.

2.2.5 Fuzzy Time Series

Fuzzy sets theory and fuzzy logic were introduced as a means of representing, manipulating, and utilizing data and information that possesses non-statistical uncertainty, which is lexical or linguistic uncertainty (Gorzalczany, 2002). The motivation, therefore, for fuzzy set theory is mainly to provide a formal, powerful and quantitative framework to cope with the vagueness of human knowledge as it is expressed by means of natural languages (Lee at al, 2001).

A fuzzy set A in the universe of discourse U is characterized by a membership function:

$$\mu_A : U \rightarrow [0,1] \qquad 2.14$$

This associates with each element u of U a number $\mu(u)$ in the interval [0,1] that represents the grade of membership of u in A.

The fuzzy set A of U = $u_1, u_2, u_3, \ldots\ldots, u_n$ will be denoted by :

$$A = \sum_{i=1}^{n} \frac{\mu(ui)}{ui} \qquad 2.15$$

The construction of a fuzzy set, therefore, depends on two things; the identification of a suitable universe of discourse and the specification of an appropriate membership function. However, the specification of the membership function may vary, for the same concept, from person to person but certainly not subject to arbitral assignment. The fuzzy logic is an extension to fuzzy set theory that applies logic operators (AND, OR, NOT) (Tome, 2005).

Time series represents a consecutive series of observations taken over equal time intervals and lies at the root of exploring such real processes as in natural and applied sciences among others (Hsu et al, 2003). The application of Fuzzy Logic sets to time series analysis gave rise to Fuzzy Time Series.

A number of approaches have been developed for time series forecasting (Lee et al, 2001). Among them is ARMA models and Box-Jenkins model building (Huarng, 2001). But of recent years, many researchers used fuzzy time series to handle prediction problems. Song and Chissom (Yu, 2005) presented the concept of fuzzy time series based on the concepts of fuzzy set theory to forecast the historical enrollments of the University of Alabama. Huarg (Yu, 2005) presented the definition of two kinds of intervals of discourse to forecast the TAIFEX. Chen (Versaci and Morabito, 2003) presented a method for forecasting based on high-order fuzzy time series. Lee (Chen and Hsu, 2004) presented a method for temperature prediction based on two-factor high-order fuzzy time series. Lee (Huarng, 2001) presented handling of forecasting problems using two-factor high order fuzzy time series for TAIFEX and daily temperature in Taipei, Taiwan. All this techniques are therefore, mere forecasting tool where time series exist to properly plan and implement policies in every society.

Let U be the universe of discourse, where $U = \{u_1, u_2, u_3, \ldots, u_n\}$ and let A be a fuzzy set in the universe of discourse defined as:

$$A = f_A(u_1)/u_1 + f_A(u_2)/u_2 + \ldots\ldots + f_A(u_n)/u_n \,, \qquad (2.16)$$

where f_A is the membership function of A, $f_A : U \rightarrow [0,1]$

$f_A(u_i)$ indicates the grade of membership of u_i in the fuzzy set A, such that

$f_A(u_i)\ \varepsilon\ [0,1]$ and $1 \leq i \leq n$.

Let X(t) (t = ….,0,1,2,3,…) be the universe of discourse and be a subset of R, and let fuzzy set $f_i(t)(i = 1,2,3,\ldots)$ be defined in X(t).

Let F(t) be a collection of $f_i(t)(i = 1,2,3,\ldots)$. Then F(t) is called a **fuzzy time series** of X(t) (t = …,0,1,2,3,…).

If F(t) is caused by $F(t-1) \rightarrow F(t)$, then this relationship can be represented by:

$$F(t) = F(t-1) \circ R(t, t-1). \qquad (2.17)$$

where the symbol "o" denotes the max-min composition operator;

R(t, t-1) is a fuzzy relation between F(t) and F(t-1) and is called the **first-order model** of F(t).

Let F(t) be a fuzzy time series and let R(t, t-1) be a first-order model of F(t).

If R(t, t-1) = R(t-1, t-2) for any time t, then F(t) is called **time-invariant fuzzy time series**.

If R(t, t-1) is dependent on time t, that is R(t, t-1) may be different from R(t-1, t-2) for a time t, then F(t) is called a **time-variant fuzzy time series** (Chen, 2002) and (Lee et al, 2006).

Research works have revealed that the fundamental concepts of FTS as they originally were conceived in pioneering publications of Song/Chissom (Song and Chissom, 1993; 1994) and Chen (Chen, 1996; 2002) have not changed. However, various researchers have added improvements referred to as definitions to the basic principles.

Definition 1: Fuzzy Time Series

Let Y(t) (t = ….., 0,1,2,….,), a subset of real numbers, be the universe of discourse on which fuzzy sets $f_i(t)$ (i = 1,2,….) are defined. If F(t) is a collection of $f_i(t)$ (i = 1,2,….), then F(t) is called a fuzzy time series on Y(t) (t = ….,0,1,2,….).

Definition 2: Fuzzy Relations

If there exists a fuzzy relationship R(t-1,t), such that F(t) = F(t-1) x R(t-1,t), where *x* represents an operator, then F(t) is said to be caused by F(t-1). The relationship between F(t) and F(t-1) is denoted by F(t-1)→F(t).

Definition 3: N-Order Fuzzy Relations

Let F(t) be a fuzzy time series. If F(t) is caused by F(t-1), F(t-2),……,F(t-n), then this fuzzy relationship is represented by F(t-n),……., F(t-2), F(t-1) → F(t), and is called an n-order fuzzy time series. The n-order concept was first introduced by Chen (Chen, 2002). N-order based FTS models are referred to as high order models.

Definition 4: Time-Invariant Fuzzy Time Series

Suppose F(t) is caused by F(t-1) only and is denoted by F(t-1) → F(t), then there is a fuzzy relationship between F(t) and F(t-1) which is expressed as the equation; F(t) = F(t-1) *x* R(t-1,t). The relation R is referred to as a first order model of F(t). If R(t-1,t) is independent of time, t that is, for different times t_1 and t_2, $R(t_1,t_1-1) = R(t_2,t_2-1)$, then F(t) is called a time-invariant fuzzy time series. Otherwise it is called a time-variant fuzzy time series.

Definition 5: Fuzzy Logical Relationship Group (FLRG)

Relationships with the same fuzzy set on the left hand side can be further grouped into a relationship group. Relationship groups are also referred to as fuzzy logical relationship groups or FLRG's in short. Suppose there are relationships such that

$A_i \rightarrow A_{j1}$; $A_i \rightarrow A_{j2}$;…………..; $A_i \rightarrow A_{jn}$., then these fuzzy sets be grouped into a relationship group as $Ai \rightarrow A_{j1}$; A_{j2} ; …………..; A_{jn}

The same fuzzy set cannot appear more than once on the right hand side or the relationship group as introduced by Chen (Chen, 1996). The foundation of the current research includes the multivariate, high-order and data clustering techniques.

1. Multivariate Analysis Techniques

The procedure is defined in steps as follows:

Step one:

Apply the clustering algorithm to generate intervals from the training data, for all the main variable and minor variables. Assume that the universe of discourse of the main variable is clustered into n intervals u_1, u_2, ... and u_n, and assume that the universe of discourse of the j^{th} minor variables are clustered into m_j intervals v_{j1}, v_{j2}, ... and v_{jmj}., etc.

Step two:

1. Define the linguistic terms A_1, A_2, ... and A_n represented by fuzzy sets of the main variable, using the following:

$$A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + \ldots + 0/u_{n-1} + 0/u_n,$$

$$A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + \ldots + 0/u_{n-1} + 0/u_n,$$

$$A_3 = 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + \ldots + 0/u_{n-1} + 0/u_n, \quad (2.18)$$

. .

$$A_n = 0/u_1 + 0/u_2 + 0/u_3 + 0/u_4 + \ldots + 0.5/u_{n-1} + 1/u_n,$$

where A_1, A_2,….and A_n are the linguistic terms of the main variable.

2. Define the linguistic terms represented by fuzzy sets of the j^{th} minor variables, using the following:

$$B_{j,1} = 1/v_{j,1} + 0.5/v_{j,2} + 0/v_{j,3} + 0/v_{j,4} + \ldots + 0/v_{j,mj-1} + 0/v_{j,mj},$$

$$B_{j,2} = 0.5/v_{j,1} + 1/v_{j,2} + 0.5/v_{j,3} + 0/v_{j,4} + \ldots + 0/v_{j,mj-1} + 0/v_{j,mj},$$

$$B_{j,3} = 0/v_{j,1} + 0.5/v_{j,2} + 1/v_{j,3} + 0.5/v_{j,4} + \ldots + 0/v_{j,mj-1} + 0/v_{j,mj}, \quad (2.19)$$

.

$$B_{j,mj} = 0/v_{j,1} + 0/v_{j,2} + 0/v_{j,3} + 0/v_{j,4} + \ldots + 0.5/v_{j,mj-1} + 1/v_{j,mj},$$

where $B_{j,1}$, $B_{j,2}$,….and $B_{j,mj}$ are the linguistic terms of the j^{th} minor variables and m_j is the number of intervals in the universe of discourse of the j^{th} minor variables.

Step three:

Fuzzify each datum into a fuzzy set. If the datum of the main variable belongs to the interval u_i then the datum of the main variable is fuzzified into A_i, where $1 \leq i \leq n$. If the datum of the j^{th} minor variables belongs to interval $v_{j,k}$, then the datum of the j^{th} minor variables is fuzzified into $B_{j,k}$, where $1 \leq k \leq m_j$.

Step four:

Construct fuzzy logical relationships based on the fuzzified major variable and the fuzzified minor variables. Then, group the fuzzy logical relationships into fuzzy logical relationship groups based on the current state of the fuzzy logical relationships, where the fuzzy logical relationships having the same current state are grouped into the same fuzzy logical relationship group.

For example, if four minor variables are used as follows:

If $F(t-1) = A_i, B_{1,k}, B_{2,k}, B_{3,k}, B_{4,k}$ and $F(t) = A_q$, where

A_i, = the fuzzified value of the main variable

$B_{1,k}$, = the fuzzified value of the first minor variable

$B_{2,k}$, = the fuzzified value of the second minor variable

$B_{3,k}$, = the fuzzified value of the third minor variable

$B_{4,k}$ = the fuzzified value of the fourth minor variable at time t-1, respectively,

A_q is the fuzzified value of the major variable at the time t,

then the fuzzy logical relationship between F(t-1) and F(t) can be represented by:

$A_i, B_{1,k}, B_{2,k}, B_{3,k}, B_{4,k} \rightarrow A_q$, where:

"$A_i, B_{1,k}, B_{2,k}, B_{3,k}, B_{4,k}$" is called the current state

"A_q" is called the next state of the fuzzy logical relationship.

Step five:

Obtain the m-factors kth-order fuzzy logical relationships based on the fuzzified major and minor variables from the fuzzified historical data obtained in the earlier step. If the fuzzified historical data of the major variable of i^{th} week is X_i, then construct the m-factors kth-order fuzzy logical relationships,

$(X_{j-k}; Y_{2j-k} \ldots Y_{m-1,j-k}) \ldots (X_{j-2}; Y_{2,j-2} \ldots Y_{m-1,j-2}), (X_{j-1}; Y_{1j-1}, Y_{2,j-1} \ldots Y_{m-1,j-1}), \rightarrow X_j$

where j>k, X_{j-k} shows the k-step dependence of j^{th} value of the major variable X_j, Y_i, j-k, i = 1……..,m-1,j = 1….,k.

Then, divide the derived fuzzy logical relationships into fuzzy logical relationship groups based on the current states of the fuzzy logical relationships. The minor variables act like a minor component to the m-dimensional state vector and is applied to the chosen order.

Calculate the forecasted output at time t for the testing datum by the following rules:

Rule1:- If the fuzzified value of the major variable, the fuzzified value of the first minor variable, the fuzzified value of the second minor variable,…., and the fuzzified value of the p^{th} minor variable at time t-1 are A_i,$B_{1,k}$, ….., and $B_{p,k}$, respectively, and there is only one fuzzy logical relationship in the fuzzy logical relationship group, given by:

$$A_i, B_{1,k},\ldots, B_{p,k} \rightarrow A_q, \tag{2.20}$$

then the forecasted value at time t is equal to

$$0.5 \times (m_q + S(t-1)) \tag{2.21}$$

where m_q is the midpoint of the interval u_q, the maximum membership value of A_q occurs at interval u_q, and S(t-1) is the actual value at time t-1.

Rule2:- If the fuzzified value of the major variable, the fuzzified value of the first minor variable, the fuzzified value of the second minor variable,…….., and fuzzified value of the p^{th} minor variable at time t-1 are A_i,$B_{1,k}$, ….., and $B_{p,k}$, respectively, and there is a fuzzy logical relationship in the fuzzy logical relationship group, given by:

$$A_i, B_{1,k},\ldots, B_{p,k} \rightarrow A_{q1},A_{q2},\ldots,A_{qr},$$

then the forecasted value at time t is calculated as follows:

$$0.5 \times \left(\frac{m_{q1} + m_{q2} + \ldots + m_{qr}}{r} + S(t-1)\right) \tag{2.22}$$

where m_{q1}, m_{q2},……, and m_{qr} are the midpoint of the interval u_{q1}, u_{q2},…., and u_{qr}, respectively, the maximum membership value of A_{q1},A_{q2},….., and A_{qr} occurs at interval u_{q1}, u_{q2},….., and u_{qr}, respectively, and S(t-1) is the actual value at time t-1.

Rule3:- If the fuzzified value of the major variable, the fuzzified value of the first minor variable, the fuzzified value of the second minor variable,…., and the fuzzified value of the p^{th} minor variable at time t-1 are A_i,$B_{1,k}$, ….., and $B_{p,k}$, respectively, and there is a fuzzy logical relationship in the fuzzy logical relationship group, shown as follows:

A_i, $B_{1,k}$,….., $B_{p,k}$ → #, where the symbol "#" denotes an unknown value, then the forecasted value at time t is equal to

$$0.5 \times (m_i + S(t-1)) \qquad (2.23)$$

where m_i is the midpoint of the interval u_i, the maximum membership value of A_i occurs at interval u_i, and S(t-1) is the actual value at time t-1.

The forecasting formulae (rule1 to rule3) fulfills the axioms of fuzzy sets like monotonicity, boundary conditions, continuity and idempotency.

Step six:

If there is another testing datum of the major factor, then put the actual values of the last forecasting (both the major variable and the minor variables) into the existing training data set and go to step one, to forecast another testing datum. Otherwise stop.

2. High Order Techniques and Analysis

For instance, the multi-factors k^{th}-order fuzzy logical relationships based on the fuzzified major and minor variables from the fuzzified historical data can be obtained**.** If the fuzzified historical data of the major-factor of i^{th} day is X_i , then, the constructed multi-factors k^{th}-order fuzzy logical relationships is,

$(X_{j-k}\ ;\ Y_{2,j-k}\ \ldots\ldots\ldots\ Y_{m-1,j-k}),\ldots\ldots..\ (X_{j-2};\ Y_{2,j-2}\ldots\ldots\ldots\ldots Y_{m-1,j-2}),$

$$(X_{j-1};\ Y_{2,j-1}\ldots\ldots..Y_{m-1,j-1}),\rightarrow X_j \qquad (2.24)$$

where $j>k$. X_{j-k} shows the k-step dependence of j^{th} value of main factor X_j ,$Y_{i,\,j-k}$, $I = 1,...,m-1$, $j = 1,...,k$.

Then, divide the derived fuzzy logical relationships into fuzzy logical relationship groups based on the current states of the fuzzy logical relationships. The minor factors acts like a minor component to the multi-dimensional state vector and is used as follows.

For multi-factor k^{th} order fuzzy logical relationship, the forecasted value of day j based on history of third order is calculated as follows:

$$t_j = \frac{\sum_{j-1}^{j+1} w}{\frac{w_{j-1}}{a_{j-1}} + \frac{w_j}{a_j} + \frac{w_{j+1}}{a_{j+1}}} \qquad (2.25)$$

Where a_{l-1}, a_l and a_{l+1} are the midpoints of the intervals l 1, l u u − and l 1 u + respectively.

3. Clustering Methods

Data are called static if all their feature values do not change with time, or change negligibly. The bulk of clustering analyses has been performed on static data. Most, if not all, clustering programs developed as an independent program or as part of a large suite of data analysis or data mining software to date work only with static data. Han and Kamber (Han and Kamber, 2001) classified clustering methods developed for handing various static data into five major categories: partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model-based methods.

A partitioning method constructs k partitions of the data, where each partition represents a cluster containing at least one object and $k \leq n$. The partition is crisp if each object belongs to exactly one cluster, or fuzzy if one object is allowed to be in more than one cluster to a different degree. Two renowned heuristic methods for crisp partitions are the *k-means* algorithm, where each cluster is represented by the mean value of the objects in the cluster and the *k-medoids* algorithm, where each cluster is represented by the most centrally located object in a cluster. Two counterparts for fuzzy partitions are the *fuzzy c-means* algorithm and the *fuzzy c-medoids* algorithm (Krishnapuran et al, 2001). These heuristic algorithms work well for finding spherical-shaped clusters and small to medium data sets. To find clusters with non-spherical or other complex shapes, specially designed algorithms such as Gustafson–Kessel and adaptive fuzzy clustering algorithms or density-based methods to be introduced in the sequel are needed. Most genetic clustering methods implement the spirit of partitioning methods, especially the *k-means* algorithm, the *k-medoids* algorithm, and the *fuzzy c means* algorithm.

A hierarchical clustering method works by grouping data objects into a tree of clusters. There are generally two types of hierarchical clustering methods: agglomerative and divisive. Agglomerative methods start by placing each object in its own cluster and then merge clusters into larger clusters, until all objects are in a single cluster or until certain termination conditions such as the desired number of clusters are satisfied. Divisive methods do just the opposite. A pure hierarchical clustering method suffers from its inability to perform adjustment once a merged or split decision has been executed. For improving the clustering quality of hierarchical methods, there is a trend to integrate hierarchical clustering with other clustering techniques. Both Chameleon (Chameleon et al, 1999) and Cure et al, 1998) perform careful analysis of object “linkages” at each hierarchical partitioning whereas Birch (Birch, 1996) uses iterative relocation to refine the results obtained by hierarchical agglomeration.

The general idea of density-based methods such as DBSCAN (Ester et al, 1996) is to continue growing a cluster as long as the density (number of objects or data points) in the "neighborhood" exceeds some threshold. Rather than producing a clustering explicitly, Optics (Optics et al, 1999) computed an augmented cluster ordering for automatic and interactive cluster analysis. The ordering contains information that is equivalent to density-based clustering obtained from a wide range of parameter settings, thus overcoming the difficulty of selecting parameter values.

Grid-based methods quantize the object space into a finite number of cells that form a grid structure on which all of the operations for clustering are performed. A typical example of the grid-based approach is Sting (Sting et al, 1997), which uses several levels of rectangular cells corresponding to different levels of resolution. Statistical information regarding the attributes in each cell are pre-computed and stored. A query process usually starts at a relatively high level of the hierarchical structure. For each cell in the current layer, the confidence interval is computed reflecting the cell's relevance to the given query. Irrelevant cells are removed from further consideration. The query process continues to the next lower level for the relevant cells until the bottom layer is reached.

Model-based methods assume a model for each of the clusters and attempt to best fit the data to the assumed model. There are two major approaches of model-based methods: statistical approach and neural network approach. An example of statistical approach is AutoClass (Cheseeman and Stutz, 1996), which uses Bayesian statistical analysis to estimate the number of clusters. Two prominent methods of the neural network approach to clustering are competitive learning, including ART (Carpenter and Grossberg, 1987) and self-organizing feature maps (Kohomen, 1990).

Unlike static data, the time series of a feature comprise values changed with time. Time series data are of interest because of its pervasiveness in various areas ranging from science, engineering, business, finance, economic, health care, to government. Given a set of unlabeled time series, it is often desirable to determine groups of similar time series. These unlabeled time series could be monitoring data collected during different periods from a particular process or from more than one process. The process could be natural, biological, business, or engineered. Works devoting to the cluster analysis of time series are relatively scant compared with those focusing on static data. However, there seems to be a trend of increased activity. Just like static data clustering, time series clustering requires a clustering algorithm or procedure to form clusters given a set of unlabeled data objects and the choice of clustering algorithm depends both on the type of data available and on the particular purpose and application. As far as time series data are concerned, distinctions can be made as to whether the data are discrete-valued or real-valued, uniformly or non-uniformly sampled, univariate or multivariate, and whether data series are of equal or unequal length. Non-uniformly sampled data must be converted into uniformed data before clustering operations can be performed. This can be achieved by a wide range of methods, from simple down sampling based on the roughest sampling interval to a sophisticated modeling and estimation approach.

Various algorithms have been developed to cluster different types of time series data. Putting their differences aside, it is far to say that in spirit they all try to modify the existing algorithms for clustering static data in such a way that time series data can be handled or to convert time series data into the form of static data so that the existing algorithms for clustering static data can be directly used. The former approach usually works directly with raw time series data, thus called raw-data-based approach, and the major modification lies in replacing the distance and similarity measure for static data with an appropriate one for time series. The latter approach first converts a raw time series data either into a feature vector of lower dimension or a number of model parameters, and then applies a conventional clustering algorithm to the extracted feature vectors or model parameters, thus called feature- and model-based approach, respectively.

Three of the five major categories of clustering methods for static data, specifically partitioning methods, hierarchical methods, and model-based methods, have been utilized directly or modified for time series clustering. Depending upon whether the data are discrete-valued or real-valued and whether time series are of equal or unequal length, a particular measure might be more appropriate than another. Most clustering algorithms and procedures are iterative in nature. Such algorithms and procedures rely on a criterion to determine when a good clustering is obtained in order to stop the iterative process.

Clustering algorithms and procedures involve some general purpose clustering algorithms and procedures that have been employed in the previous time series clustering studies. While relocation clustering procedure that appears to attract the attention of recent researchers has the following three steps:

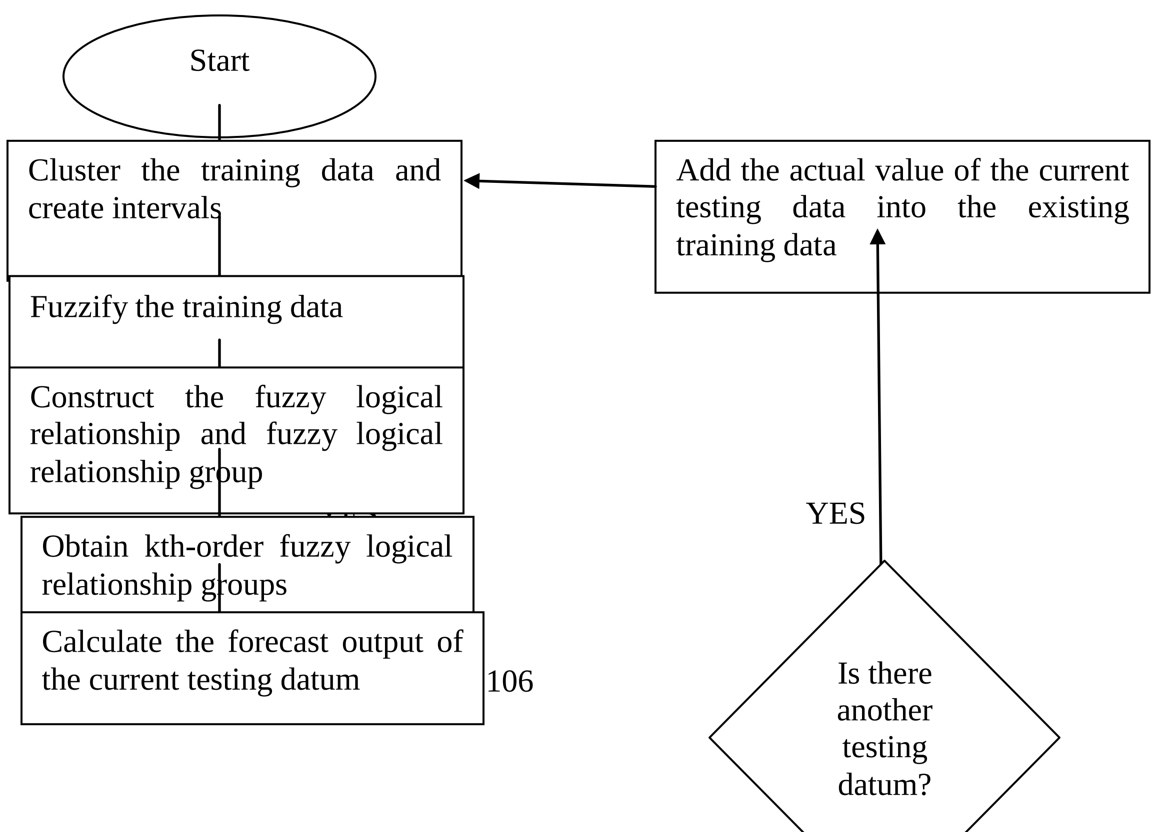
Step 1: Start with an initial clustering, denoted by *C*, having the prescribed *k* number of clusters.

Step 2: For each time point compute the dissimilarity matrix and store all resultant matrices computed for all time points for the calculation of trajectory similarity.

Step 3: Find a clustering *C'* such that *C'* is better than *C* in terms of the *generalized Ward criterion function*. The clustering *C'* is obtained from *C* by relocating one member

The process adopted in this research work which is derived from the basis of the result of earlier research works was outlined as follows:

The data set is divided into training data set and testing data set. The training data d_1 to d_n is clustered based on the algorithm to forecast d_{n+1}, where d_{n+1} is the first datum of the testing data set. This result is then added to the previously clustered data to form d_1 to d_{n+1} data. This is now re-clustered and used to forecast d_{n+2}. This process is repeated until a clustered data set equal to the size of the sample data is obtained together with the forecast values. The flowchart of this process is illustrated in Figure 2.13 and Figure 2.14 which show an algorithmic description of the process.



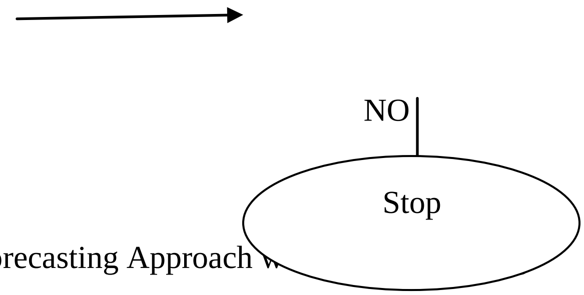
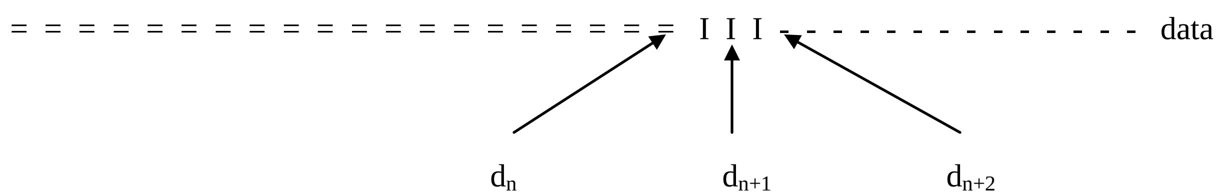
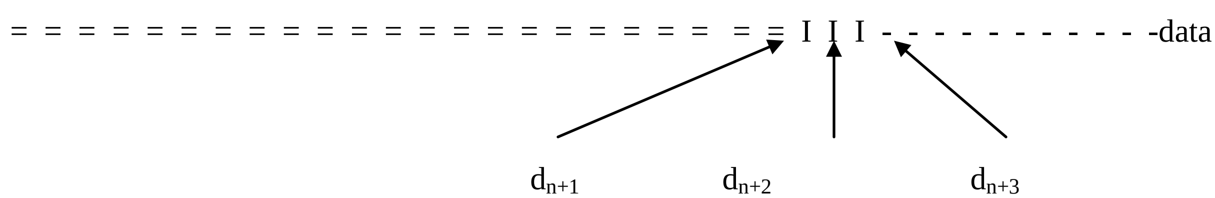


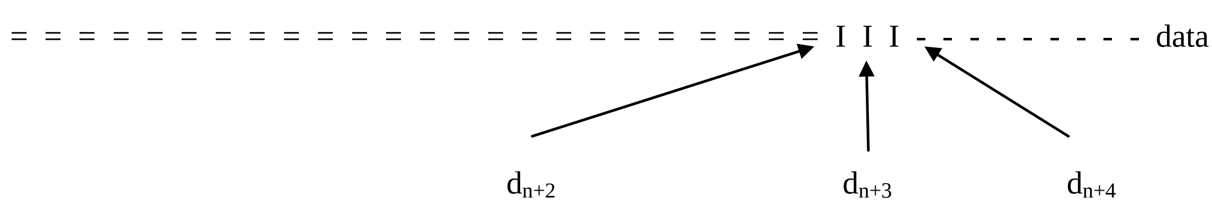
Figure 2.13: Flowchart of the Multivariate Forecasting Approach w



(a) Forecast for d_{n+1}



(b) Forecast for d_{n+2}



(c) Forecast for d_{n+3}

Key:
= = = = = Clustered
I I I I I I Current forecast
\- - - - - - To be clustered

Figure 2.14: Clustering based Technique for Fuzzy Time Series Forecast.

A simple data clustering algorithm used in this research is as follows:

Step one: sort n numerical data into an ascending sequence. Assume that the ascending sequence of the data is shown as follows;

d_1, d_2, d_3, ………, d_i, …………., d_n

where d_1 is the smallest datum among the n numerical data, d_n is the largest datum among the n numerical data, and $1 \leq i \leq n$. Based on the ascending data sequence calculate the average difference *avg_diff* between any two adjacent data and calculate the standard deviation *dev_diff* of the difference between any two adjacent data, shown as follows:

$$avg\_diff \quad = \quad \frac{\sum_{i=1}^{n-1}(di+1-di)}{n-1} \tag{2.26}$$

$$dev\_diff \quad = \quad \sqrt{\frac{\sum_{i=1}^{n-1}(di+1-di-d)^2}{(n-1)-1}} \tag{2.27}$$

where d denotes the mean of the data d_1, d_2, d_3, ………, d_i, …………., and d_n.

Step two: Create a new cluster for the first datum, i.e. the smallest datum, and let the cluster to be the current cluster. Calculate the maximum distance *max_data_distance* between any two adjacent data using *dev_diff*, shown as follows:

$$max\_data\_distance \quad = \quad 0.5 \text{ x } dev\_diff \tag{2.28}$$

Based on the value of *max_data_distance*, determine whether the following datum can be put into the current cluster or whether a new cluster has to be created:

Consider the following:

$\ldots\ldots, \{\ldots., d_i\}, d_{i+1}, d_{i+2}, \ldots\ldots, d_n$ where $1 \leq i \leq n$.

If $d_{i+1} - d_i <$ *max_data_distance,* then put d_{i+1} into the current cluster in which d_i belongs. Otherwise, create a new cluster for d_{i+1} and let the new cluster in which d_{i+1} belongs be the current cluster.

Where the differences between the data is small (i.e. If $d_{i+1} - d_i <$ *max_data_distance*, is true for all the data set), then find the mean value of the maximum and minimum difference value and use it to calculate the maximum data distance to create the clusters.

$$max\_data\_distance = 0.5 \times \text{Avg\_diff} \quad (2.29)$$

Otherwise subtract the minimum value difference between any data in the data set from the maximum value different between any data in the data set and divide by two, use the result to calculate maximum data distance to avoid many clusters.

$$max\_data\_distance = 0.5 \times (\text{maximum value diff} - \text{minimum value diff}) \quad (2.30)$$

Repeatedly perform the above process, until all the data have been clustered.

Step three: Assume that there are two adjacent clusters, i.e. $cluster_i$ and $cluster_j$, where d_{in} is the last datum in $cluster_i$ and d_{j1} is the first datum in $cluster_j$, shown as follows:

……., $\{d_{i1},……..,d_{in}\}$, $\{d_{j1},……..,d_{jm}\}$,…………

Then, the border between the two adjacent clusters i.e. $cluster_i$ and $cluster_j$, can be determined as follows:

$$cluster\_uBound_i = \frac{din + dj1}{2} \quad (2.31)$$

$$cluster\_lBound_j = cluster\_uBound_i \quad (2.32)$$

where $cluster\_uBound_i$ is the upper bound of $cluster_i$ and $cluster\_lBound_j$ is the lower bound of $cluster_j$. Because there is no previous cluster before the first cluster and there is no next cluster after the last cluster, the lower bound of the first cluster and the upper bound of the last cluster can be calculated, shown as follows:

$$cluster\_uBound_n = d_n + max\_data\_distance, \quad (2.33)$$

$$cluster\_lBound_1 \quad = \quad d_1 - max\_data\_distance, \qquad (2.34)$$

where d_1 is the first datum in the first cluster and d_n is the last datum in the last cluster. The clusters themselves correspond to intervals, where the upper bound and the lower bound of an interval are taken from the upper bound and the lower bound of a cluster. From the upper bound and the lower bound of an interval, the middle value mid_value_i of the ith interval $interval_i$ can be calculated, shown as follows:

$$mid\_value \quad = \quad \frac{(\mathrm{interval}_{\mathrm{lBoundi}} + \mathrm{interval\_uBoundi})}{2} \qquad (2.35)$$

where interval_$lBound_i$ and $interval\_uBound_i$ denotes the lower bound and the upper bound of $interval_i$, respectively.

2.3 Review of Similar Works

It is important to note that there can hardly be any singular event that is not directly or indirectly controlled by a number of factors. Although, the traditional forecasting methods usually operate on a factor to predict future occurrences within the forecasting process due to so many reasons, but, if multiple factors are considered, with higher complexity then it is possible to have better forecasting results.

The work of so many researchers have shown that in real world, one event can be affected by many factors at varying degrees. Any holistic approach of prediction or forecasting of such event should be able to consider these multiple factors. However, the statistics, chaos, Support Vector Machines (SVM) forecasting methods usually do not use more than one factor within the forecasting process.

In recent years, other methods based on fuzzy time series have been presented for forecasting different phenomena in general (Aladag, 2008; Basaran, 2008; Egrioglu, 2008; Yolcu, 2008; Uslu, 2008; Chen, 1996, 2002; Chen and Chung, 2006; Cheng et al, 2008a, 2008b, 2008c, 2009; Chen and Hsu, 2004; Chen and Hwang, 2000; Huarng, 2001a, 2001b; Huarng and Yu, 2005, 2006a, 2006b; Huarng, Yu, and Hsu, 2007; Hwang et al, 1998; Jilani and Burney, 2008; Kuo et al., 2009; Lee et al, 2006a, 2006b, 2009; Sullivan and Woodall, 1994; Tanuwijaya and Chen, 2009; Wang and Chen, 2009; Yu, 2005; Yu and Huarng, 2008) to make predictions in many areas, such as forecasting stock price, university enrollments, the weather, etc. The current trend within the FTS research community is the optimization of the existing techniques with focus on interval length (Huarng, (2001a); Huarng and Yu, (2006b); Tahseen et al., (2008); Mu'azu et al., (2008); Meredith et al,. (2008); Sun et al., (2008); Muhammad et al., (2009); Chen and Tanuwijaya, (2009), Wang and Chen, (2009), Shyi and Tanuwujaya, (2011)), high-order (Chen and Hwang, (2000); Chen, (2002); Hsu and Chen, (2004); Melike, (2004); Lee, (2006); Cheng and Chung, (2006); Aladag et al., (2008); Poulsen, (2009)), data clustering (Geva, (1999a; 1999b); Sfesos and Siriopoulos, (2004); Shyi and Kurniawan, (2011); Usman et al., (2012)), univariate (Ming-Tao et al., (2005); Cheng et al., (2006); Tiffany et al., (2009); Yi-Chang et al., (2009)' Chang et al., (2010), Eleruja et al., (2012); Usman, (2012)), multivariable (Abbasov et al., (2003); Huarng and Yu, (2007); Tahseen et al., (2007); Feng et al., (2008); Huarng and Yu, (2008); Shyi and Tanuwijaya, (2011)), among others. However, specific research works of the followings have direct relationship with this research.

Ghosh, (1998) pioneered the use of fuzzy logic in telecommunication systems and networks. The work reviewed the current research efforts in fuzzy logic based approaches and possible applications to queuing, buffer management, distributed access control, load management, routing, call acceptance, policing, congestion mitigation, bandwidth allocation, channel assignment, network management, mobility management and quantitative performance evaluation in networks. The work succeeded in opening up new challenges in network analyses, helping other researchers realize the full potential of fuzzy logic in telecommunications networks and suggested application of optimization techniques in the areas highlighted in the work. The work been a pioneer work, however did not deal with any specifics rather it dealt with general outlines.

Lin and Lin, (2000) used FTS for the first time to forecast seasonal requirements in Telecommunication. The approach was not only fundamental but among the early ones. However, it was purely univariate-based and data analyses in FTS were still at a primitive stage. The work finally suggested better data mining approaches that will allow multi-factor models to be developed and applied in the telecommunication sub-sector.

Toril, (2003) was the first to introduce FTS into handover forecasting by using an automatic optimization algorithm which maximized the overall traffic carried in the network by equalizing long-term blocking effects to optimize handovers forecast. The work is univariate based and lacked any advance data mining technique, and as such only a significant improvement in homogeneous handover parameter settings was achieved. The work concluded by recommending the use of data mining techniques to ensure multivariate-based approach.

Akhila and Suthiksh, (2009) used received signal level and received signal quality to forecast, and analyze handovers in GSM network. The work was limited in that it was purely univariate-based and dedicated large portions to analysis rather than using optimization techniques to enhance forecast. Accordingly, a multiple parameter based approach was, however, suggested to improve the forecast.

Jianmin, (2009) used Takagi-Sugeno fuzzy model and SVM to forecast mobile communication traffic based on historical data collected from mobile networks. The emphasis of the work was on ways of handling the noisy and chaotic nature of the data. The work specifically addressed unusual occurrences in mobility management of the networks. The approach was strictly univariate-based and specifically recommended other fuzzy models that are multivariate based.

Paris and Constantinious, (2011) used dynamic neuro-fuzzy network to forecast outgoing telephone traffic of large organizations. It utilized real world telecommunication data with elements of dynamism related properties. The work introduced neuro-fuzzy concept and tried to compare its findings with the real data. The shortcomings as identified in the work included; lack of specialization, the results obtained were not targeted at any problem and recommended studies specifically, into handover based on the dynamism of the networks.

Manoj and Khola, (2012) used fuzzy logic to make handover decisions by utilizing three input parameters, of predicted received signal strength, bandwidth and users preferences. The calculated and simulated results of the handover decision algorithm showed possibility of achieving accurate handover decisions but the entire work lacked comparative analysis to justify the claim of improved performance of the networks.

Dinesh and Singh, (2012) used path loss and received signal strength to analyze handovers in GSM network. The received signal strength from the two base stations was calculated and plotted with respect to distance. The different path loss models were used and then the received signal strength was calculated to determine the model that can be adopted to minimize the number of handovers. The use of multiple parameters, a case study that reflected current cell structure deployment, environmental representation of complex structures, computer-based model was suggested for further work.

Weetit et al., (2013) presented the behavior-based mobility prediction scheme to eliminate the scanning overhead incurred in IEEE 802.11 networks by considering not only location information but also group, time-of-day, and duration characteristics of mobile users. Although, the simulation studies on a campus network showed an improvement in prediction accuracy and reduction in average handover delay down, the major limitations of the work included over simplicity of the chosen variables, lack of verifiable relationship between the variables and the static nature of the case study that hardly compared to practical cases. The work suggested that the scheme should be tested on cellular networks along with a computer-based model.

Thanachai et al., (2013) used adaptive modular fuzzy-based handover decision system to forecast by including relatively large number of decision parameters that are quality-of-service related. The results obtained were quite impressive and showed a reasonable improvement on the accuracy of predictions. However, due to increase computational complexity and long algorithm execution time, which affects real-time applications, this approach is not cost effective.

Umar et al, (2013) studied predictability of handovers based on attributes that reflect recent mobility history, such as, past handover rate, size of the active set, active set update rate and signal strength variations. Although, it was shown that it is possible to predict impeding handovers with almost 80% accuracy compared to 53% in the earlier works, the chosen variables by recent development in cellular industry are not physically isolated rather are highly interwoven and interdependent. The work concluded with the suggestion for further studies using other attributes and development of computer-based models.

This research work is to develop a soft computational based Multivariate High Order Fuzzy Time Series Forecasting with interval length defined using Data Clustering Model, thus, taking advantage of their various strengths. This is based on the findings from the critique on earlier research works and useful suggestions from prominent research works like that of Chen's method (1996), Huarng et al.'s method (2007), the conventional regression methods (Yu and Huarng, 2008), the neural-network models (Yu and Huarng, 2008), the neural-networks fuzzy time series models (Yu and Huarng, 2008) and the neural-networks fuzzy time series models with substitutes (Yu and Huarng, 2008) for forecasting the Taiwan exchange (TAIEX).

To the best of my knowledge, there is no existing work that actually incorporates multivariate, high-order with data clustering or similarly, application to mobility management in GSM networks. It is in line with the suggestions from researchers that further research work be carried out in this relatively new area in order to verify claims, produce standards and allows soft computing techniques for data processing that is the motivation for this work.

CHAPTER THREE

METHODOLOGY

3.1 General

In the literature, many fuzzy time series forecasting methods are based on first-order fuzzy time series model, high-order fuzzy time series model, univariate fuzzy time series, bivariate fuzzy time series model, and multivariate fuzzy time series model. Some of these methods are due to Chen, (2002), Aladag et al., (2009), and Egrioglu et al., (2009). Generally, fuzzy time series methods are based on three stages. These are fuzzification, determination of fuzzy relation, and defuzzification. In recent literatures, the fuzzy time series methods are improved by employing various artificial intelligence techniques in these three stages. The genetic algorithms, particle swarm optimization, and fuzzy c-means methods, intuition method, aggregation, neural networks, etc are used in the fuzzification stage. Feed-forward neural networks, max-min membership principle, centroid method, weighted average method, mean-max membership, etc are used in determining fuzzy relation and in the defuzzification stage.

Largely, the focus of current FTS research has been on the establishment of fuzzy relationships and interval partitions. Early studies, in particular, were entirely devoted to the former issue such as Song and Chissom, (1993;1994); Chen, (1996); Hwang et al, (1998); Sullivan and Woodall, (1994). Other more recent studies dealing with the relationship aspect can also be found, like Tsaur et al, (2005) and Sing, (2007).

More recently, interval partitions have received a considerable amount of attention in current studies. A major reason for this paradigm shift is the need for formalized approaches to interval partitioning. In early studies, intervals were assumed to be subjectively defined by the user, in the same manner as shown in the example provided of Chen's model Chen, (1996), in Section 3.2. Huarng, (2001), was probably the first researcher to focus on the interval partition aspect. In Huarng, (2001), proposed the distribution- and average-based length approaches to determine the lengths of intervals. Furthermore, the study conducted by Huarng, (2001), was the first to investigate the influence of interval lengths on forecast results. Other examples of formalized approaches to interval partitioning can be found in Cheng et al, (2006); Huarng and Yu, (2006); and Wang et al, (2008).

A common factor shared by the models published in Cheng, (2006); Huarng and Yu, (2006); Huarng, (2001); and Cheng et al, (2008), is that interval lengths are determined independently of forecast accuracy. In contrast, Chen and Chung, (2006) applied a somewhat different strategy where they exploit genetic algorithm (GA) to tune interval lengths in order to improve forecast accuracy. A similar study is published by Kuo et al in Pan, et al (2009), where particle swarm optimization (PSO) is exploited in an analogous manner. The studies published in Chen and Chung, (2006) and Pan et al, (2009) are highlighted in this project because they have presented the best results currently published in literature. Both of these models will be used as targets for comparison with the respect to the high order model presented in later chapters.

Other studies can also be found which both deal with the fuzzy relationship aspect and the interval partition aspect, such as the ones presented in Li and Cheng, (2007); Huarng and Yu, (2004); and Yu, (2004). The current study belongs to this latter category of projects, as it sets out to develop new and hopefully better ways of creating interval partitions and relational computations.

The approach is to implement the designed and developed model to predict the handovers as outlined in section 2.2.5. Thereafter, the validation model of developed computer program will be applied to the same section by using the same data set in addition to the application of established FTS models.

3.2 Data Collection and Preparation Methods

To study the propagation characteristics of Airtel Radio signals, two distinct set of approaches were chosen. The first approach covered the entire Lagos zone. The objective was to study attenuation of received signal strength as the receiver was moved away from BSC. The second approach was restricted to Victoria Island which has a number of high buildings. The objective was to study the multipath propagation and shadowing effects of these buildings on the transmitted signal from the BSC.

Statistical data of the seventeen active BSC that make up the Airtel Nigeria Lagos region network are obtained from the Airtel Regional Switching Center at Lagos. Data were gathered and collected at Operation and Maintenance Centre (OMC) with aid of software tools, which include; Intelligent Manager (Imanager), Fast Access to Contents, Trends and Statistics (FACTS), and OPTIMA. Drive tests were equally conducted to obtain certain data.

Data obtained from the network include Handover success rate (HOSR), Call set-up success rate (CSSR), Call drop rate (CDR), SDCCH congestion ratio (SDCCH), and TCH available (TCH). Measurement was conducted to obtain Received Signal Strength (RSS). Data regarding path loss (PL) was measured and predicted using Hata model, while Bit error rate (BER) and Shadow were supplied by technical staff through measurement. See Table 3.1.

Intelligent Manager (Imanager): Imanager software is vendor specific application software. It provides a way to indicate statistical data of calls, to assist operations, maintenance and network optimization personnel in spotting network problems. Software input includes configuration of data management terminal, traffic statistical results and commissioning engineering data recorded in BSC traffic statistical terminal. Data output of the software is in diagrams and tables along with failure spotting. In addition, the output also supports flexible report forms. Interfaces could be either graphical user interface or command line interface.

Fast Access to Contents, Trends And Statistics (Facts): Another data gathering tool used is Fast Access to Contents, Trends and Statistics (FACTS). It is server based with ability of combining both engineering and other data types to generate reports of various kinds. This is strictly network based, which implies no direct access for outsider.

Optima: Is a network performance management and monitoring software that logs and stores network parameters, enabling a complete understanding of the current and past performance of the network. By accessing and analyzing invaluable performance data, it is possible to identify and respond quickly to change.

3.3 Development of the Model

The multivariate high order fuzzy time series with data clustering was applied to forecast the HOSR for the year 2011, where the HOSR is called the main variable, the SDCCH, RSS, PLOSS and BER are called the minor variables. The data of the whole year is separated into two parts, where the data of the first forty weeks are used as the training data set, whereas the data of the last twelve weeks is used as the testing data set.

The weekly data of the HOSR as the major variable and the weekly data of the SDCCH, the RSS, the PLOSS and the BER as the minor variables were used. The HOSR of the year 2011 was used for the research work, where the major variable was used as the basis. Table 3.1 shows the prepared data collected from Airtel Lagos Zone on weekly basis while Table 3.2 indicates data of the five variables of interest, namely; HOSR as the main variable and SDCCH, RSS, PLOSS, BER as the minor variables for 52 weeks.

Table 3.1: AIRTEL Data – From January to December 2011 on Weekly Basis

HOSR	**CSSR**	**CDR**	**SDCCH**	**TCH**	**RSS**	**PLOSS**	**BER**	*WEEK*
94.67	90	0.7	95	98	-76.1	134.5	0.5	*1*
95.87	93	0.8	98	98	-75.1	133.0	0.4	*2*
91.20	96	0.7	96	97	-76.4	134.0	0.5	*3*
93.24	98	0.6	94	98	-76.2	134.1	0.5	*4*
94.36	97	0.7	97	96	-75.9	133.5	0.4	*5*
94.23	94	0.8	95	98	-77.1	135.1	0.6	*6*
95.10	93	0.8	93	97	-76.5	134.9	0.5	*7*
92.89	95	0.6	97	98	-76.0	133.4	0.4	*8*
93.45	94	0.7	95	98	-75.8	133.3	0.4	*9*
92.79	92	0.7	95	98	-76.4	134.2	0.5	*10*
94.37	94	0.7	96	97	-74.9	133.4	0.4	*11*
95.38	95	0.7	94	96	-77.1	135.3	0.6	*12*
93.29	96	0.7	96	96	-76.5	134.2	0.5	*13*

94.56	93	0.8	95	97	-76.9	135.8	0.6	*14*
91.45	95	0.8	94	97	-76.4	134.7	0.5	*15*
94.35	98	0.6	97	98	-76.7	134.5	0.5	*16*
93.36	90	0.8	95	98	-76.3	134.3	0.5	*17*
94.39	94	0.8	94	98	-75.4	133.2	0.4	*18*
92.23	93	0.7	96	97	-77.0	135.6	0.6	*19*
94.59	96	0.7	97	96	-76.9	135.8	0.6	*20*
95.20	97	0.7	95	97	-76.3	134.0	0.5	*21*
93.39	94	0.6	94	97	-77.4	135.3	0.6	*22*
93.89	95	0.7	97	96	-76.4	134.3	0.5	*23*
93.90	96	0.7	95	98	-77.0	134.0	0.5	*24*
94.32	97	0.8	94	97	-76.3	134.4	0.5	*25*
94.59	94	0.6	96	98	-76.2	134.3	0.5	*26*
93.65	95	0.6	97	98	-75.4	133.9	0.4	*27*
93.96	93	0.8	96	98	-75.9	134.3	0.5	*28*
92.78	96	0.8	93	97	-77.3	135.8	0.6	*29*
93.11	94	0.8	96	96	-77.6	135.5	0.6	*30*
93.78	96	0.8	98	97	-76.5	134.8	0.5	*31*
92.45	93	0.6	96	97	-76.8	134.3	0.5	*32*
92.13	96	0.7	94	97	-76.4	134.8	0.5	*33*
94.39	95	0.7	93	97	-75.7	133.9	0.4	*34*
93.22	93	0.7	96	98	-76.2	133.9	0.5	*35*
93.59	92	0.8	96	96	-76.1	134.6	0.5	*36*
93.41	95	0.7	95	97	-77.5	135.8	0.6	*37*
94.38	94	0.7	96	96	-77.6	135.2	0.6	*38*
95.03	96	0.7	97	97	-76.8	134.2	0.5	*39*
92.11	97	0.8	98	96	-76.2	134.1	0.5	*40*
94.37	95	0.7	95	98	-76.6	134.5	0.5	*41*
93.88	96	0.7	96	98	-77.9	135.8	0.6	*42*
94.30	95	0.7	94	98	-75.4	133.1	0.4	*43*
94.45	96	0.8	95	97	-76.5	134.3	0.5	*44*
94.67	94	0.8	95	96	-76.8	134.7	0.5	*45*
95.09	93	0.8	96	97	-76.7	134.6	0.5	*46*
93.90	96	0.8	97	98	-77.0	135.9	0.6	*47*
92.99	94	0.8	95	97	-76.1	135.0	0.5	*48*
93.89	95	0.6	96	98	-75.9	134.0	0.4	*49*
95.30	96	0.8	97	98	-77.8	135.6	0.6	*50*
93.86	95	0.8	98	97	-77.3	135.8	0.6	*51*
94.18	97	0.8	95	96	-76.4	134.7	0.5	*52*

Table 3.2: Data of Major and Minor Variables – From January to December 2011

HOSR	SDCCH	RSS	PLOSS	BER	*WEEK*
94.67	95	-76.1	134.5	0.5	*1*
95.87	98	-75.1	133.0	0.4	*2*
91.20	96	-76.4	134.0	0.5	*3*
93.24	94	-76.2	134.1	0.5	*4*
94.36	97	-75.9	133.5	0.4	*5*
94.23	95	-77.1	135.1	0.6	*6*
95.10	93	-76.5	134.9	0.5	*7*
92.89	97	-76.0	133.4	0.4	*8*
93.45	95	-75.8	133.3	0.4	*9*
92.79	95	-76.4	134.2	0.5	*10*
94.37	96	-74.9	133.4	0.4	*11*
95.38	94	-77.1	135.3	0.6	*12*

93.29	96	-76.5	134.2	0.5	*13*
94.56	95	-76.9	135.8	0.6	*14*
91.45	94	-76.4	134.7	0.5	*15*
94.35	97	-76.7	134.5	0.5	*16*
93.36	95	-76.3	134.3	0.5	*17*
94.39	94	-75.4	133.2	0.4	*18*
92.23	96	-77.0	135.6	0.6	*19*
94.59	97	-76.9	135.8	0.6	*20*
95.20	95	-76.3	134.0	0.5	*21*
93.39	94	-77.4	135.3	0.6	*22*
93.89	97	-76.4	134.3	0.5	*23*
93.90	95	-77.0	134.0	0.5	*24*
94.32	94	-76.3	134.4	0.5	*25*
94.59	96	-76.2	134.3	0.5	*26*
93.65	97	-75.4	133.9	0.4	*27*
93.96	96	-75.9	134.3	0.5	*28*
92.78	93	-77.3	135.8	0.6	*29*
93.11	96	-77.6	135.5	0.6	*30*
93.78	98	-76.5	134.8	0.5	*31*
92.45	96	-76.8	134.3	0.5	*32*
92.13	94	-76.4	134.8	0.5	*33*
94.39	93	-75.7	133.9	0.4	*34*
93.22	96	-76.2	133.9	0.5	*35*
93.59	96	-76.1	134.6	0.5	*36*
93.41	95	-77.5	135.8	0.6	*37*
94.38	96	-77.6	135.2	0.6	*38*
95.03	97	-76.8	134.2	0.5	*39*
92.11	98	-76.2	134.1	0.5	*40*
94.37	95	-76.6	134.5	0.5	*41*
93.88	96	-77.9	135.8	0.6	*42*
94.30	94	-75.4	133.1	0.4	*43*
94.45	95	-76.5	134.3	0.5	*44*
94.67	95	-76.8	134.7	0.5	*45*
95.09	96	-76.7	134.6	0.5	*46*
93.90	97	-77.0	135.9	0.6	*47*
92.99	95	-76.1	135.0	0.5	*48*
93.89	96	-75.9	134.0	0.4	*49*
95.30	97	-77.8	135.6	0.6	*50*
93.86	98	-77.3	135.8	0.6	*51*
94.18	95	-76.4	134.7	0.5	*52*

For instance, for the first week (week1), the data of the HOSR, SDCCH, RSS, PLOSS and BER are 94.67, 95, -76.1, 134.5 and 0.5 respectively. Table 3.3 shows the training data of the HOSR, the SDCCH, the RSS, the PLOSS and the BER of the year 2011 from week1 to week40.

Table 3.3: Data of Major and Minor Variables – From Week1 to Week 40

HOSR	SDCCH	RSS	PLOSS	BER	*WEEK*
94.67	95	-76.1	134.5	0.5	*1*

95.87	98	-75.1	133.0	0.4	*2*
91.20	96	-76.4	134.0	0.5	*3*
93.24	94	-76.2	134.1	0.5	*4*
94.36	97	-75.9	133.5	0.4	*5*
94.23	95	-77.1	135.1	0.6	*6*
95.10	93	-76.5	134.9	0.5	*7*
92.89	97	-76.0	133.4	0.4	*8*
93.45	95	-75.8	133.3	0.4	*9*
92.79	95	-76.4	134.2	0.5	*10*
94.37	96	-74.9	133.4	0.4	*11*
95.38	94	-77.1	135.3	0.6	*12*
93.29	96	-76.5	134.2	0.5	*13*
94.56	95	-76.9	135.8	0.6	*14*
91.45	94	-76.4	134.7	0.5	*15*
94.35	97	-76.7	134.5	0.5	*16*
93.36	95	-76.3	134.3	0.5	*17*
94.39	94	-75.4	133.2	0.4	*18*
92.23	96	-77.0	135.6	0.6	*19*
94.59	97	-76.9	135.8	0.6	*20*
95.20	95	-76.3	134.0	0.5	*21*
93.39	94	-77.4	135.3	0.6	*22*
93.89	97	-76.4	134.3	0.5	*23*
93.90	95	-77.0	134.0	0.5	*24*
94.32	94	-76.3	134.4	0.5	*25*
94.59	96	-76.2	134.3	0.5	*26*
93.65	97	-75.4	133.9	0.4	*27*
93.96	96	-75.9	134.3	0.5	*28*
92.78	93	-77.3	135.8	0.6	*29*
93.11	96	-77.6	135.5	0.6	*30*
93.78	98	-76.5	134.8	0.5	*31*
92.45	96	-76.8	134.3	0.5	*32*
92.13	94	-76.4	134.8	0.5	*33*
94.39	93	-75.7	133.9	0.4	*34*
93.22	96	-76.2	133.9	0.5	*35*
93.59	96	-76.1	134.6	0.5	*36*
93.41	95	-77.5	135.8	0.6	*37*
94.38	96	-77.6	135.2	0.6	*38*
95.03	97	-76.8	134.2	0.5	*39*
92.11	98	-76.2	134.1	0.5	*40*

Step One:

The data clustering technique was applied to generate intervals from the training data for each data set (i.e. HOSR, SDCCH, RSS, PLOSS and BER), respectively as follows:

1. The training data of the HOSR, the SDCCH, the RSS, the PLOSS and the BER as shown in Table 3.3 were sorted in an ascending sequence and presented as Table 3.4.

Table 3.4: Sorted Data – From Week1 to Week40 of Major and Minor Variables

HOSR	SDCCH	RSS	PLOSS	BER
91.20	93	-77.6	133.0	0.4
91.45	93	-77.6	133.2	0.4
92.11	93	-77.5	133.3	0.4
92.13	94	-77.4	133.4	0.4
92.23	94	-77.3	133.4	0.4
92.45	94	-77.1	133.5	0.4
92.78	94	-77.1	133.9	0.4
92.79	94	-77.0	133.9	0.4
92.89	94	-77.0	133.9	0.5
93.11	94	-76.9	134.0	0.5
93.22	95	-76.9	134.0	0.5
93.24	95	-76.8	134.0	0.5
93.29	95	-76.8	134.1	0.5
93.36	95	-76.7	134.1	0.5
93.39	95	-76.5	134.2	0.5
93.41	95	-76.5	134.2	0.5
93.45	95	-76.5	134.2	0.5
93.59	95	-76.4	134.3	0.5
93.65	95	-76.4	134.3	0.5
93.78	96	-76.4	134.3	0.5
93.89	96	-76.4	134.3	0.5
93.90	96	-76.4	134.3	0.5
93.96	96	-76.3	134.4	0.5
94.23	96	-76.3	134.5	0.5
94.32	96	-76.3	134.5	0.5
94.35	96	-76.2	134.6	0.5
94.36	96	-76.2	134.7	0.5
94.37	96	-76.2	134.8	0.5
94.38	96	-76.2	134.8	0.5
94.39	96	-76.1	134.9	0.5
94.39	97	-76.1	135.1	0.6
94.56	97	-76.0	135.2	0.6
94.59	97	-75.9	135.3	0.6
94.59	97	-75.9	135.3	0.6
94.67	97	-75.8	135.5	0.6
95.03	97	-75.7	135.6	0.6
95.10	97	-75.4	135.8	0.6
95.20	98	-75.4	135.8	0.6
95.38	98	-75.1	135.8	0.6
95.87	98	-74.9	135.8	0.6

Then, the mean value denoted as d, the mean difference value denoted as Avg_diff between any two adjacent data and the standard deviation difference value denoted as dev_diff of the difference between any two adjacent data of the training data of the HOSR were calculated as follows using Table 3.5:

Table 3.5: Summation Process of HOSR Training Data Set for Week1 to Week40

Iteration	Current Datum	Datum	d_{i+1} - d_i	$(d_{i+1} - d_i - d)^2$
1	91.20	91.45	0.25	8737.80931
2	91.45	92.11	0.66	8661.32689
3	92.11	92.13	0.02	8780.86129
4	92.13	92.23	0.10	8765.87469
5	92.23	92.45	0.22	8743.41879
6	92.45	92.78	0.33	8722.85951
7	92.78	92.79	0.01	8782.73551
8	92.79	92.89	0.10	8765.87469
9	92.89	93.11	0.22	8743.41879
10	93.11	93.22	0.11	8764.00226
11	93.22	93.24	0.02	8780.86129
12	93.24	93.29	0.05	8775.23981
13	93.29	93.36	0.12	8762.13004
14	93.36	93.39	0.03	8778.98726
15	93.39	93.41	0.02	8780.86129
16	93.41	93.45	0.04	8777.11344
17	93.45	93.59	0.14	8758.38619
18	93.59	93.65	0.06	8773.36639
19	93.65	93.78	0.13	8760.25801
20	93.78	93.89	0.11	8764.00226
21	93.89	93.90	0.01	8782.73551
22	93.90	93.96	0.60	8672.49844
23	93.96	94.23	0.27	8734.07066
24	94.23	94.32	0.09	8767.74731
25	94.32	94.35	0.03	8778.98726
26	94.35	94.36	0.01	8782.73551
27	94.36	94.37	0.01	8782.73551
28	94.37	94.38	0.01	8782.73551
29	94.38	94.39	0.01	8782.73551
30	94.39	94.39	0.00	8784.60994
31	94.39	94.56	0.17	8752.77191
32	94.56	94.59	0.03	8778.98726
33	94.59	94.59	0.00	8784.60994
34	94.59	94.67	0.08	8769.62014
35	94.67	95.03	0.36	8717.25664
36	95.03	95.10	0.07	8771.49316
37	95.10	95.20	0.10	8765.87469
38	95.20	95.38	0.18	8750.90089
39	95.38	95.87	0.49	8692.99831
40	95.87			
SUM:	3749.05		5.26	341615.5

a) The mean = $\frac{\sum_{i=1}^{n} d_i}{n}$

$$= \frac{91.20+91.45+92.11+92.11+92.23+\ldots\ldots+95.38+95.87}{40}$$

$$= \frac{3749.05}{40}$$

= 93.72625

From equations (2.26) mean difference value is calculated as follows:

$$Avg\_diff = \frac{\sum_{i=1}^{n-1}(di+1-di)}{n-1}$$

$$= \frac{5.26}{40-1}$$

= 0.13487

Also, from equation (2.27), the standard deviation difference value is calculated as follows:

$$Dev\_diff = \sqrt{\frac{\sum_{i=1}^{n-1}(di+1-di-d)^2}{(n-1)-1}}$$

$$= \sqrt{\frac{341615.5}{(40-1)-1}}$$

= 94.81499

2. The value of maximum data distance denoted as max_data_distance for the data of the HOSR is calculated using equation (2.28) as follows:

   max_data_distance = 0.5 x *dev_diff*

   = 0.5 x 94.81499

   = 47.40749

Recall the following conditions in equations (2.28), (2.29) and (2.30). Based on the calculated value of the max_data_distance, the first condition is not applicable.

The second condition is applied as follows:

max_data_distance = 0.5 x Avg_*diff*

= 0.5 x 0.13487

= 0.067435

The third condition is used if the second condition will result in many clusters that may have no significant difference between them. Again, the maximum data distance is calculated as follows to create the clusters.

max_data_distance = 0.5 x (maximum value difference - minimum value difference)

= 0.5 x (0.66 – 0.00)

= 0.3300

To achieve a better result, the second and third conditions were combined and used together as maximum data distance which is then used to create clusters of HOSR as indicated in Table 3.6.

Table 3.6: Clustering Process of HOSR Training Data set for Week1 to Week40

Iteration	Current Cluster	Datum	Remark
1	91.20	91.45	Create a new cluster
2	91.45	92.11	Create a new cluster
3	92.11	92.13	Insert into the current cluster
4	92.13	92.23	,,
5	92.23	92.45	Create a new cluster
6	92.45	92.78	Create a new cluster
7	92.78	92.79	Insert into the current cluster
8	92.79	92.89	,,
9	92.89	93.11	Create a new cluster

10	93.11	93.22	Create a new cluster
11	93.22	93.24	Insert into the current cluster
12	93.24	93.29	,,
13	93.29	93.36	Create a new cluster
14	93.36	93.39	Insert into the current cluster
15	93.39	93.41	,,
16	93.41	93.45	,,
17	93.45	93.59	Create a new cluster
18	93.59	93.65	Insert into the current cluster
19	93.65	93.78	Create a new cluster
20	93.78	93.89	Create a new cluster
21	93.89	93.90	Insert into the current cluster
22	93.90	93.96	Create a new cluster
23	93.96	94.23	Create a new cluster
24	94.23	94.32	Insert into the current cluster
25	94.32	94.35	,,
26	94.35	94.36	,,
27	94.36	94.37	,,
28	94.37	94.38	,,
29	94.38	94.39	,,
30	94.39	94.39	,,
31	94.39	94.56	Create a new cluster
32	94.56	94.59	Insert into the current cluster
33	94.59	94.59	,,
34	94.59	94.67	,,
35	94.67	95.03	Create a new cluster
36	95.03	95.10	Insert into the current cluster
37	95.10	95.20	,,
38	95.20	95.38	Create a new cluster
39	95.38	95.87	Create a new cluster
40	95.87		

3. After all the training data sets of HOSR are clustered, the lower bound and upper bound of each cluster is calculated using equations (2.29) and (2.30) respectively as follows:

   For example, from Table 3.6 the last data of cluster 2 is 92.11 and the last data of cluster 3 is 92.45. Therefore, from equation (2.31):

$$cluster\_uBound_i \quad = \quad \frac{din + dj1}{2}$$

Upper bound of cluster 2 = $\frac{92.11 + 92.45}{2}$

= 92.28

Also, from equation (2.32):

cluster_lBound$_j$ = *cluster_uBound*$_i$

upper bound of cluster 2 = lower bound of cluster 3

This process is repeated for cluster 2 to cluster 15 as indicated in Table 3.7.

For the lower bound of the first cluster and the upper bound of the last cluster of HOSR training data set, equations (2.33) and (2.34) were used to calculate them respectively as follows:

cluster_uBound$_n$ = d_n + *max_data_distance*,

Upper band of cluster 16 = 95.87 + 0.33

= 96.2

cluster_lBound$_1$ = d_1 – *max_data_distance*,

Lower bound of cluster 1 = 91.45 – 0.33

= 91.12

Also, equation (2.35) is used to calculate the middle value of each cluster as follows:

For example the mid value of cluster 10:

mid_value = $\frac{(\text{interval}_{\text{lBoundi}} + \text{interval\_uBoundi})}{2}$

mid value of cluster 10 = $\frac{(93.835 + 93.925)}{2}$

= 93.88

This is repeated for all clusters from cluster 1 to cluster 16 as indicated in Table 3.7.

Table 3.7: Interval Generation Process of the HOSR Training Data Set from Week1 to Week40

Clusters	Data	Lower bound	Upper bound	Middle value

Cluster1	91.45	91.120	91.780	91.4500
Cluster2	92.11	91.780	92.280	92.0300
Cluster3	92.45	92.280	92.615	92.4475
Cluster4	92.78	92.615	92.945	92.7800
Cluster5	93.11	92.945	93.165	93.0550
Cluster6	93.22	93.165	93.290	93.2275
Cluster7	93.36	93.290	93.475	93.3825
Cluster8	93.59	93.475	93.685	93.5800
Cluster9	93.78	93.685	93.835	93.7600
Cluster10	93.89	93.835	93.925	93.8800
Cluster11	93.96	93.925	94.095	94.0100
Cluster12	94.23	94.095	94.395	94.2450
Cluster13	94.56	94.395	94.795	94.5950
Cluster14	95.03	94.795	95.205	95.0000
Cluster15	95.38	95.205	95.625	95.4150
Cluster16	95.87	95.625	96.200	95.9125

These clusters are treated as intervals, which mean that these clusters correspond to intervals. Therefore, the lower bound and the upper bound of a cluster are also the lower bound and the upper bound of an interval, respectively. The interval generation process of the HOSR gave rise to Table 3.7. For instance, from Table 3.7, cluster1 represents the first interval of the HOSR data, which is symbolized as u_1, where its lower bound and upper are as shown in Table 3.7.

This process (step one) is repeated for all the minor variables with the results indicated in the Tables 3.8 to 3.19.

Table 3.8: Summation Process of SDCCH Training Data Set for Week1 to Week40

Iteration	Current Datum	Datum	$d_{i+1} - d_i$	$(d_{i+1} - d_i - d)^2$
1	93	93	0	9125.025625
2	93	93	0	9125.025625
3	93	94	1	8934.975625
4	94	94	0	9125.025625
5	94	94	0	9125.025625
6	94	94	0	9125.025625
7	94	94	0	9125.025625
8	94	94	0	9125.025625
9	94	94	0	9125.025625
10	94	95	1	8934.975625

11	95	95	0	9125.025625
12	95	95	0	9125.025625
13	95	95	0	9125.025625
14	95	95	0	9125.025625
15	95	95	0	9125.025625
16	95	95	0	9125.025625
17	95	95	0	9125.025625
18	95	95	0	9125.025625
19	95	96	1	8934.975625
20	96	96	0	9125.025625
21	96	96	0	9125.025625
22	96	96	0	9125.025625
23	96	96	0	9125.025625
24	96	96	0	9125.025625
25	96	96	0	9125.025625
26	96	96	0	9125.025625
27	96	96	0	9125.025625
28	96	96	0	9125.025625
29	96	96	0	9125.025625
30	96	97	1	8934.975625
31	97	97	0	9125.025625
32	97	97	0	9125.025625
33	97	97	0	9125.025625
34	97	97	0	9125.025625
35	97	97	0	9125.025625
36	97	97	0	9125.025625
37	97	98	1	8934.975625
38	98	98	0	9125.025625
39	98	98	0	9125.025625
40	98			
SUM	3821		5	354925.7

Table 3.9: Summation Process of RSS Training Data Set for Week1 to Week40

Iteration	Current Datum	Datum	$d_{i+1} - d_i$	$(d_{i+1} - d_i - d)^2$
1	-77.6	-77.6	0	5841.5449
2	-77.6	-77.5	0.1	5856.8409
3	-77.5	-77.4	0.1	5856.8409
4	-77.4	-77.3	0.1	5856.8409
5	-77.3	-77.1	0.2	5872.1569
6	-77.1	-77.1	0	5841.5449
7	-77.1	-77.0	0.1	5856.8409
8	-77.0	-77.0	0	5841.5449
9	-77.0	-76.9	0.1	5856.8409
10	-76.9	-76.9	0	5841.5449
11	-76.9	-76.8	0.1	5856.8409
12	-76.8	-76.8	0	5841.5449
13	-76.8	-76.7	0.1	5856.8409
14	-76.7	-76.5	0.2	5872.1569
15	-76.5	-76.5	0	5841.5449

16	-76.5	-76.5	0	5841.5449
17	-76.5	-76.4	0.1	5856.8409
18	-76.4	-76.4	0	5841.5449
19	-76.4	-76.4	0	5841.5449
20	-76.4	-76.4	0	5841.5449
21	-76.4	-76.4	0	5841.5449
22	-76.4	-76.3	0.1	5856.8409
23	-76.3	-76.3	0	5841.5449
24	-76.3	-76.3	0	5841.5449
25	-76.3	-76.2	0.1	5856.8409
26	-76.2	-76.2	0	5841.5449
27	-76.2	-76.2	0	5841.5449
28	-76.2	-76.2	0	5841.5449
29	-76.2	-76.1	0.1	5856.8409
30	-76.1	-76.1	0	5841.5449
31	-76.1	-76.0	0.1	5856.8409
32	-76.0	-75.9	0.1	5856.8409
33	-75.9	-75.9	0	5841.5449
34	-75.9	-75.8	0.1	5856.8409
35	-75.8	-75.7	0.1	5856.8409
36	-75.7	-75.4	0.3	5887.4929
37	-75.4	-75.4	0	5841.5449
38	-75.4	-75.1	0.3	5887.4929
39	-75.1	-74.9	0.1	5856.8409
40	-74.9			
SUM	-3057.2		2.6	228218.1

Table 3.10: Summation Process of PLOSS Training Data Set for Week1 to Week40

Iteration	Current Datum	Datum	$d_{i+1} - d_i$	$(d_{i+1} - d_i - d)^2$
1	133.0	133.2	0.2	18024.405025
2	133.2	133.3	0.1	18051.266025
3	133.3	133.4	0.1	18051.266025
4	133.4	133.4	0	18078.147025
5	133.4	133.5	0.1	18051.266025
6	133.5	133.9	0.4	17970.743025
7	133.9	133.9	0	18078.147025
8	133.9	133.9	0	18078.147025
9	133.9	134.0	0.1	18051.266025
10	134.0	134.0	0	18078.147025
11	134.0	134.0	0	18078.147025
12	134.0	134.1	0.1	18051.266025
13	134.1	134.1	0	18078.147025
14	134.1	134.2	0.1	18051.266025
15	134.2	134.2	0	18078.147025
16	134.2	134.2	0	18078.147025
17	134.2	134.3	0.1	18051.266025
18	134.3	134.3	0	18078.147025
19	134.3	134.3	0	18078.147025
20	134.3	134.3	0	18078.147025

21	134.3	134.3	0	18078.147025
22	134.3	134.4	0.1	18051.266025
23	134.4	134.5	0.1	18051.266025
24	134.5	134.5	0	18078.147025
25	134.5	134.6	0.1	18051.266025
26	134.6	134.7	0.1	18051.266025
27	134.7	134.8	0.1	18051.266025
28	134.8	134.8	0	18078.147025
29	134.8	134.9	0.1	18051.266025
30	134.9	135.1	0.2	18024.405025
31	135.1	135.2	0.1	18051.266025
32	135.2	135.3	0.1	18051.266025
33	135.3	135.3	0	18078.147025
34	135.3	135.5	0.2	18024.405025
35	135.5	135.6	0.1	18051.266025
36	135.6	135.8	0.2	18024.405025
37	135.8	135.8	0	18078.147025
38	135.8	135.8	0	18078.147025
39	135.8	135.8	0	18078.147025
40	135.8			
SUM	5378.2		2.8	704295.3

Table 3.11: Summation Process of BER Training Data Set from Week1 to Week40

Iteration	Current Datum	Datum	$d_{i+1} - d_i$	$(d_{i+1} - d_i - d)^2$
1	0.4	0.4	0	0.255025
2	0.4	0.4	0	0.255025
3	0.4	0.4	0	0.255025
4	0.4	0.4	0	0.255025
5	0.4	0.4	0	0.255025
6	0.4	0.4	0	0.255025
7	0.4	0.4	0	0.255025
8	0.4, 0.5	0.4	0	0.255025
9	0.5	0.5	0.1	0.164025
10	0.5	0.5	0	0.255025
11	0.5	0.5	0	0.255025
12	0.5	0.5	0	0.255025
13	0.5	0.5	0	0.255025
14	0.5	0.5	0	0.255025
15	0.5	0.5	0	0.255025
16	0.5	0.5	0	0.255025
17	0.5	0.5	0	0.255025
18	0.5	0.5	0	0.255025
19	0.5	0.5	0	0.255025
20	0.5	0.5	0	0.255025
21	0.5	0.5	0	0.255025
22	0.5	0.5	0	0.255025
23	0.5	0.5	0	0.255025
24	0.5	0.5	0	0.255025
25	0.5	0.5	0	0.255025

26	0.5	0.5	0	0.255025
27	0.5	0.5	0	0.255025
28	0.5	0.5	0	0.255025
29	0.5	0.5	0	0.255025
30	0.5, 0.6	0.5	0	0.255025
31	0.6	0.6	0.1	0.164025
32	0.6	0.6	0	0.255025
33	0.6	0.6	0	0.255025
34	0.6	0.6	0	0.255025
35	0.6	0.6	0	0.255025
36	0.6	0.6	0	0.255025
37	0.6	0.6	0	0.255025
38	0.6	0.6	0	0.255025
39	0.6	0.6	0	0.255025
40	0.6			
SUM	20.2		0.2	9.763975

Table 3.12: Clustering Process of SDCCH Training Data Set for Week1 to Week40

Iteration	Current Cluster	Datum	Remark
1	93	93	Create a new cluster
2	93	93	Insert into the current cluster
3	93	94	Create a new cluster
4	94	94	Insert into the current cluster
5	94	94	,,
6	94	94	,,
7	94	94	,,
8	94	94	,,
9	94	94	,,
10	94	95	Create a new cluster
11	95	95	Insert into the current cluster
12	95	95	,,
13	95	95	,,
14	95	95	,,
15	95	95	,,
16	95	95	,,
17	95	95	,,
18	95	95	,,
19	95	96	Create a new cluster
20	96	96	Insert into the current cluster
21	96	96	,,
22	96	96	,,

23	96	96	,,
24	96	96	,,
25	96	96	,,
26	96	96	,,
27	96	96	,,
28	96	96	,,
29	96	96	,,
30	96	97	Create a new cluster
31	97	97	Insert into the current cluster
32	97	97	,,
33	97	97	,,
34	97	97	,,
35	97	97	,,
36	97	97	,,
37	97	98	Create a new cluster
38	98	98	Insert into the current cluster
39	98	98	,,
40	98		

Table 3.13: Clustering Process of RSS Training Data Set for Week1 to Week40

Iteration	Current Cluster	Datum	Remark
1	-77.6	-77.6	Create a new cluster
2	-77.6	-77.5	Create a new cluster
3	-77.5	-77.4	Create a new cluster
4	-77.4	-77.3	Create a new cluster
5	-77.3	-77.1	Create a new cluster
6	-77.1	-77.1	Insert into the current cluster
7	-77.1	-77.0	Create a new cluster
8	-77.0	-77.0	Insert into the current cluster
9	-77.0	-76.9	Create a new cluster
10	-76.9	-76.9	Insert into the current cluster
11	-76.9	-76.8	Create a new cluster
12	-76.8	-76.8	Insert into the current cluster
13	-76.8	-76.7	Create a new cluster
14	-76.7	-76.5	Create a new cluster
15	-76.5	-76.5	Insert into the current cluster
16	-76.5	-76.5	,,
17	-76.5	-76.4	Create a new cluster
18	-76.4	-76.4	Insert into the current cluster
19	-76.4	-76.4	,,
20	-76.4	-76.4	,,
21	-76.4	-76.4	,,
22	-76.4	-76.3	Create a new cluster
23	-76.3	-76.3	Insert into the current cluster
24	-76.3	-76.3	,,
25	-76.3	-76.2	Create a new cluster
26	-76.2	-76.2	Insert into the current cluster
27	-76.2	-76.2	,,

28	-76.2	-76.2	,,
29	-76.2	-76.1	Create a new cluster
30	-76.1	-76.1	Insert into the current cluster
31	-76.1	-76.0	Create a new cluster
32	-76.0	-75.9	Create a new cluster
33	-75.9	-75.9	Insert into the current cluster
34	-75.9	-75.8	Create a new cluster
35	-75.8	-75.7	Create a new cluster
36	-75.7	-75.4	Create a new cluster
37	-75.4	-75.4	Insert into the current cluster
38	-75.4	-75.1	Create a new cluster
39	-75.1	-74.9	Create a new cluster
40	-74.9		

Table 3.14: Clustering Process of PLOSS Training Data Set for Week1 to Week40

Iteration	Current Cluster	Datum	Remark
1	133.0	133.2	Create a new cluster
2	133.2	133.3	Create a new cluster
3	133.3	133.4	Create a new cluster
4	133.4	133.4	Insert into the new cluster
5	133.4	133.5	Create a new cluster
6	133.5	133.9	Insert into the current cluster
7	133.9	133.9	,,
8	133.9	133.9	Create a new cluster
9	133.9	134.0	Insert into the current cluster
10	134.0	134.0	,,
11	134.0	134.0	,,
12	134.0	134.1	Create a new cluster
13	134.1	134.1	Insert into the current cluster
14	134.1	134.2	Create a new cluster
15	134.2	134.2	Insert into the current cluster
16	134.2	134.2	,,
17	134.2	134.3	Create a new cluster
18	134.3	134.3	Insert into the current cluster
19	134.3	134.3	,,
20	134.3	134.3	,,
21	134.3	134.3	,,
22	134.3	134.4	Create a new cluster
23	134.4	134.5	Create a new cluster
24	134.5	134.5	Insert into the current cluster
25	134.5	134.6	Create a new cluster
26	134.6	134.7	Create a new cluster
27	134.7	134.8	Create a new cluster
28	134.8	134.8	Insert into the current cluster
29	134.8	134.9	Create a new cluster
30	134.9	135.1	Create a new cluster
31	135.1	135.2	Create a new cluster
32	135.2	135.3	Create a new cluster

33	135.3	135.3	Insert into the current cluster
34	135.3	135.5	Create a new cluster
35	135.5	135.6	Create a new cluster
36	135.6	135.8	Create a new cluster
37	135.8	135.8	Insert into the current cluster
38	135.8	135.8	,,
39	135.8	135.8	,,
40	135.8		

Table 3.15: Clustering Process of BER Training Data Set from Week1 to Week40

Iteration	Current Cluster	Datum	Remark
1	0.4	0.4	Create a new cluster
2	0.4	0.4	Insert into the current cluster
3	0.4	0.4	,,
4	0.4	0.4	,,
5	0.4	0.4	,,
6	0.4	0.4	,,
7	0.4	0.4	,,
8	0.4, 0.5	0.4	,,
9	0.5	0.5	create a new cluster
10	0.5	0.5	Insert into the current cluster
11	0.5	0.5	,,
12	0.5	0.5	,,
13	0.5	0.5	,,
14	0.5	0.5	,,
15	0.5	0.5	,,
16	0.5	0.5	,,
17	0.5	0.5	,,
18	0.5	0.5	,,
19	0.5	0.5	,,
20	0.5	0.5	,,
21	0.5	0.5	,,
22	0.5	0.5	,,
23	0.5	0.5	,,
24	0.5	0.5	,,
25	0.5	0.5	,,
26	0.5	0.5	,,
27	0.5	0.5	,,
28	0.5	0.5	,,
29	0.5	0.5	,,
30	0.5, 0.6	0.5	,,
31	0.6	0.6	Create a new cluster
32	0.6	0.6	Insert into the current cluster
33	0.6	0.6	,,
34	0.6	0.6	,,
35	0.6	0.6	,,
36	0.6	0.6	,,
37	0.6	0.6	,,

38	0.6	0.6		,,
39	0.6	0.6		,,
40	0.6			

Table 3.16: Interval Generation Process of the SDCCH Training Data Set from Week1 to Week40

Clusters	Data	Lower bound	Upper bound	Middle value
Cluster1	93	92.5	93.5	93
Cluster2	94	93.5	94.5	94
Cluster3	95	94.5	95.5	95
Cluster4	96	95.5	96.5	96
Cluster5	97	96.5	97.5	97
Cluster6	98	97.5	98.5	98

Table 3.17: Interval Generation Process of the RSS Training Data Set from Week1 to Week40

Clusters	Data	Lower bound	Upper bound	Middle value
Cluster1	-77.6	-77.75	-77.55	-77.650
Cluster2	-77.5	-77.55	-77.45	-77.500
Cluster3	-77.4	-77.45	-77.35	-77.400
Cluster4	-77.3	-77.35	-77.20	-77.275
Cluster5	-77.1	-77.2	-77.05	-77.125
Cluster6	-77.0	-77.05	-76.95	77.000
Cluster7	-76.9	-76.95	-76.85	-76.900
Cluster8	-76.8	-76.85	-76.75	-76.800
Cluster9	-76.7	-76.75	-76.60	-76.700
Cluster10	-76.5	-76.60	-76.45	-76.525
Cluster11	-76.4	-76.45	-76.35	-76.400
Cluster12	-76.3	-76.35	-76.25	-76.300
Cluster13	-76.2	-76.25	-76.15	-76.200
Cluster14	-76.1	-76.15	-76.05	-76.100
Cluster15	-76.0	-76.05	-75.95	-76.000
Cluster16	-75.9	-75.95	-75.85	-75.900
Cluster17	-75.8	-75.85	-75.75	-75.800
Cluster18	-75.7	-75.75	-75.55	-75.650
Cluster19	-75.4	-75.55	-75.25	-75.400
Cluster20	-75.1	-75.25	-75.00	-75.125
Cluster21	-74.9	-75.00	-74.75	74.850

Table 3.18: Interval Generation Process of the PLOSS Training Data Set from Week1 to Week40

Clusters	Data	Lower bound	Upper bound	Middle value
Cluster1	133.2	133.1	133.25	133.175
Cluster2	133.3	133.25	133.35	133.300
Cluster3	133.4	133.35	133.45	133.400
Cluster4	133.5	133.45	133.70	133.575
Cluster5	133.9	133.70	134.00	133.850
Cluster6	134.1	134.00	134.15	134.075
Cluster7	134.2	134.15	134.25	134.200
Cluster8	134.3	134.25	134.35	134.300
Cluster9	134.4	134.35	134.45	134.400
Cluster10	134.5	134.45	134.55	134.500
Cluster11	134.6	134.55	134.65	134.600
Cluster12	134.7	134.65	134.75	134.700
Cluster13	134.8	134.75	134.85	134.800

Cluster14	134.9	134.85	134.95	134.900
Cluster15	135.1	134.95	135.15	135.050
cluster16	135.2	135.15	135.25	135.200
Cluster17	135.3	135.25	135.40	135.325
Cluster18	135.5	135.40	135.55	135.475
Cluster19	135.6	135.55	135.70	135.625
Cluster20	135.8	135.70	135.90	135.800

Table 3.19: Interval Generation Process of the BER Training Data Set from Week1 to Week40

Clusters	Data	Lower bound	Upper bound	Middle value
Cluster1	0.4	0.27152	0.45000	0.36076
Cluster2	0.5	0.45000	0.55000	0.50000
Cluster3	0.6	0.55000	0.72848	0.63924

The data clustering algorithm is used to generate different lengths of intervals in the universe of discourse of major and minor variables. This approach uses the pattern of the data themselves to be put into intervals rather than roughly putting them into intervals of static length. The results of Table 3.7 and 3.16 to 3.19 clearly show a pattern that reflects the interval lengths of the training numerical data.

Step Two:

The generated intervals of Table 3.7 are applied to define the linguistic terms from the training data for the data set of HOSR as follows:

$A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + \ldots\ldots + 0/u_{15} + 0/u_{16}$

$A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + \ldots\ldots + 0/u_{15} + 0/u_{16}$,

$A_3 = 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + \ldots\ldots + 0/u_{15} + 0/u_{16}$,

- - -

- - - .

$A_{16} = 0/u_1 + 0/u_2 + 0/u_3 + 0/u_4 + \ldots\ldots + 0.5/u_{15} + 1/u_{16}$,

where A_1, A_2,….and A_{16} are the linguistic terms of the HOSR.

But,

u_1 = 91.4500, u_2 = 92.0300, u_3 = 92.4475, u_4 = 92.7800, u_5 = 93.0550, u_6 = 93.2275, u_7 = 93.3825, u_8 = 93.5800, u_9 = 93.7600, u_{10} = 93.8800, u_{11} = 94.0100, u_{12} = 94.2450, u_{13} = 94.5950,

u_{14} = 95.0000, u_{15} = 95.4150 and u_{16} = 95.9125 are the actual values of u_i (where i = 1 to 16) for the HOSR as in Table 3.7.

For example:

A_1 = 1/91.4500 + 0.5/92.0300 + 0/92.4475 + 0/92.7800 + ... + 0/95.4150 + 0/95.9125

= 0.016368

A_2 = 0.5/91.4500 + 1/92.0300 + 0.5/92.4475 + 0/92.7800 + ... + 0/95.4150 + 0/95.9125,

= 0.02721

A_3 = 0/91.4500 + 0.5/92.0300 + 1/92.4475 + 0.5/92.7800 + ... + 0/95.4150 + 0/95.9125,

= 0.02899

- - .- -

- - - - .

A_{16} = 0/91.4500 + 0/92.0300 + 0/92.4475 + 0/92.7800 + ... + 0.5/95.4150 + 1/95.9125,

= 0.01567

Step one and step two are repeated for all the minor variables, for instance based on Table 3.12, the linguistic terms represented by fuzzy sets of the SDCCH minor variable are defined as follows:

$B_{1,1} = 1/v_{1,1} + 0.5/v_{1,2} + 0/v_{1,3} + 0/v_{1,4} + \ldots + 0/v_{1,5} + 0/v_{1,6}$

$B_{1,2} = 0.5/v_{1,1} + 1/v_{1,2} + 0.5/v_{1,3} + 0/v_{1,4} + \ldots + 0/v_{1,5} + 0/v_{1,6}$

$B_{1,3} = 0/v_{1,1} + 0.5/v_{1,2} + 1/v_{1,3} + 0.5/v_{1,4} + \ldots + 0/v_{1,5} + 0/v_{1,6}$

- - -

- - -

$B_{1,6} = 0/v_{1,1} + 0/v_{1,2} + 0/v_{1,3} + 0/v_{1,4} + \ldots + 0.5/v_{1,5} + 1/v_{1,6}$

where $B_{1,1}$, $B_{1,2}$,….and $B_{1,6}$ are the linguistic terms of the SDCCH.

Based on Table 3.13, the linguistic terms represented by fuzzy sets of the RSS minor variable is defined as follows:

$B_{2,1} = 1/v_{2,1} + 0.5/v_{2,2} + 0/v_{2,3} + 0/v_{2,4} + \ldots\ldots + 0/v_{2,20} + 0/v_{2,21}$

$B_{2,2} = 0.5/v_{2,1} + 1/v_{2,2} + 0.5/v_{2,3} + 0/v_{2,4} + \ldots\ldots + 0/v_{2,20} + 0/v_{2,21}$

$B_{2,3} = 0/v_{2,1} + 0.5/v_{2,2} + 1/v_{2,3} + 0.5/v_{2,4} + \ldots\ldots + 0/v_{2,20} + 0/v_{2,21}$

- - -

- - -

$B_{2,21} = 0/v_{2,1} + 0/v_{2,2} + 0/v_{2,3} + 0/v_{2,4} + \ldots\ldots + 0.5/v_{2,20} + 1/v_{2,21}$

where $B_{2,1}$, $B_{2,2}$,….and $B_{2,21}$ are the linguistic terms of the RSS.

Based on Table 3.14, the linguistic terms represented by fuzzy sets of the PLOSS minor variable defined as follows:

$B_{3,1} = 1/v_{3,1} + 0.5/v_{3,2} + 0/v_{3,3} + 0/v_{3,4} + \ldots\ldots + 0/v_{3,19} + 0/v_{3,20}$

$B_{3,2} = 0.5/v_{3,1} + 1/v_{3,2} + 0.5/v_{3,3} + 0/v_{3,4} + \ldots\ldots + 0/v_{3,19} + 0/v_{3,20}$

$B_{3,3} = 0/v_{3,1} + 0.5/v_{3,2} + 1/v_{3,3} + 0.5/v_{3,4} + \ldots\ldots + 0/v_{3,19} + 0/v_{3,20}$

- - -

- - -

$B_{3,20} = 0/v_{3,1} + 0/v_{3,2} + 0/v_{3,3} + 0/v_{3,4} + \ldots\ldots + 0.5/v_{3,19} + 1/v_{3,20}$

where $B_{3,1}$, $B_{3,2}$,….and $B_{3,20}$ are the linguistic terms of the PLOSS.

Based on Table 3.15, the linguistic terms represented by fuzzy sets of the BER minor variable is defined as follows:

$B_{4,1} = 1/v_{4,1} + 0.5/v_{4,2} + 0/v_{4,3} + 0/v_{4,4} + \ldots\ldots + 0/v_{4,2} + 0/v_{4,3}$

$B_{4,2} = 0.5/v_{4,1} + 1/v_{4,2} + 0.5/v_{4,3} + 0/v_{4,4} + \ldots\ldots + 0/v_{4,2} + 0/v_{4,3}$

$B_{4,3} = 0/v_{4,1} + 0.5/v_{4,2} + 1/v_{4,3} + 0.5/v_{4,4} + \ldots\ldots + 0/v_{42} + 0/v_{4,3}$

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$B_{4,3} = 0/v_{4,1} + 0/v_{4,2} + 0/v_{4,3} + 0/v_{4,4} + \ldots\ldots + 0.5/v_{4,2} + 1/v_{4,3}$

where $B_{4,1}$, $B_{4,2}$,….and $B_{4,3}$ are the linguistic terms of the BER.

Step Three:

This process involves fuzzification of each datum into a fuzzy set. For instance, if the value of the major variable belongs to u_i, where $1 \leq i \leq n$, then it is fuzzified into A_i, if the datum of the jth minor variable belongs to $v_{j,k}$, where $1 \leq k \leq m_j$, then the datum of the jth minor variable is fuzzified into $B_{j,k}$.

Table 3.20: Fuzzified Data of Major and Minor Variables – From Week1 to Week 40

HOSR	**Fuzzified HOSR**	**SDCCH**	**Fuzzified SDCCH**	**RSS**	**Fuzzified RSS**	**PLOSS**	**Fuzzified PLOSS**	**BER**	**Fuzzified BER**	***WEEK***
94.67	$\mathbf{A_3}$	95	$B_{1,3}$	-76.1	$B_{2,14}$	134.5	$B_{3,10}$	0.5	$B_{4,2}$	*1*
95.87	$\mathbf{A_{16}}$	98	$B_{1,6}$	-75.1	$B_{2,20}$	133.0	$B_{3,1}$	0.4	$B_{4,1}$	*2*
91.20	$\mathbf{A_1}$	96	$B_{1,4}$	-76.4	$B_{2,11}$	134.0	$B_{3,5}$	0.5	$B_{4,2}$	*3*
93.24	$\mathbf{A_6}$	94	$B_{1,2}$	-76.2	$B_{2,13}$	134.1	$B_{3,6}$	0.5	$B_{4,2}$	*4*
94.36	$\mathbf{A_{12}}$	97	$B_{1,5}$	-75.9	$B_{2,16}$	133.5	$B_{3,4}$	0.4	$B_{4,1}$	*5*
94.23	$\mathbf{A_{12}}$	95	$B_{1,3}$	-77.1	$B_{2,5}$	135.1	$B_{3,15}$	0.6	$B_{4,3}$	*6*
95.10	$\mathbf{A_{14}}$	93	$B_{1,1}$	-76.5	$B_{2,10}$	134.9	$B_{3,14}$	0.5	$B_{4,2}$	*7*
92.89	$\mathbf{A_4}$	97	$B_{1,5}$	-76.0	$B_{2,15}$	133.4	$B_{3,3}$	0.4	$B_{4,1}$	*8*
93.45	$\mathbf{A_7}$	95	$B_{1,3}$	-75.8	$B_{2,17}$	133.3	$B_{3,2}$	0.4	$B_{4,1}$	*9*
92.79	$\mathbf{A_4}$	95	$B_{1,3}$	-76.4	$B_{2,11}$	134.2	$B_{3,7}$	0.5	$B_{4,2}$	*10*
94.37	$\mathbf{A_{12}}$	96	$B_{1,4}$	-74.9	$B_{2,21}$	133.4	$B_{3,9}$	0.4	$B_{4,1}$	*11*
95.38	$\mathbf{A_{15}}$	94	$B_{1,2}$	-77.1	$B_{2,5}$	135.3	$B_{3,17}$	0.6	$B_{4,3}$	*12*
93.29	$\mathbf{A_6}$	96	$B_{1,4}$	-76.5	$B_{2,10}$	134.2	$B_{3,7}$	0.5	$B_{4,2}$	*13*
94.56	$\mathbf{A_{13}}$	95	$B_{1,3}$	-76.9	$B_{2,7}$	135.8	$B_{3,20}$	0.6	$B_{4,3}$	*14*
91.45	$\mathbf{A_1}$	94	$B_{1,2}$	-76.4	$B_{2,11}$	134.7	$B_{3,12}$	0.5	$B_{4,2}$	*15*
94.35	$\mathbf{A_{12}}$	97	$B_{1,5}$	-76.7	$B_{2,9}$	134.5	$B_{3,10}$	0.5	$B_{4,2}$	*16*

93.36	A_{7}	95	$B_{1,3}$	-76.3	$B_{2,12}$	134.3	$B_{3,8}$	0.5	$B_{4,2}$	*17*
94.39	A_{12}	94	$B_{1,2}$	-75.4	$B_{2,19}$	133.2	$B_{3,1}$	0.4	$B_{4,1}$	*18*
92.23	A_{2}	96	$B_{1,4}$	-77.0	$B_{2,6}$	135.6	$B_{3,19}$	0.6	$B_{4,3}$	*19*
94.59	A_{13}	97	$B_{1,5}$	-76.9	$B_{2,7}$	135.8	$B_{3,20}$	0.6	$B_{4,3}$	*20*
95.20	A_{14}	95	$B_{1,3}$	-76.3	$B_{2,12}$	134.0	$B_{3,5}$	0.5	$B_{4,2}$	*21*
93.39	A_{7}	94	$B_{1,2}$	-77.4	$B_{2,3}$	135.3	$B_{3,17}$	0.6	$B_{4,3}$	*22*
93.89	A_{10}	97	$B_{1,5}$	-76.4	$B_{2,11}$	134.3	$B_{3,8}$	0.5	$B_{4,2}$	*23*
93.90	A_{10}	95	$B_{1,3}$	-77.0	$B_{2,6}$	134.0	$B_{3,5}$	0.5	$B_{4,2}$	*24*
94.32	A_{12}	94	$B_{1,2}$	-76.3	$B_{2,12}$	134.4	$B_{3,9}$	0.5	$B_{4,2}$	*25*
94.59	A_{13}	96	$B_{1,4}$	-76.2	$B_{2,13}$	134.3	$B_{3,8}$	0.5	$B_{4,2}$	*26*
93.65	A_{8}	97	$B_{1,5}$	-75.4	$B_{2,19}$	133.9	$B_{3,5}$	0.4	$B_{4,1}$	*27*
93.96	A_{11}	96	$B_{1,4}$	-75.9	$B_{2,16}$	134.3	$B_{3,8}$	0.5	$B_{4,2}$	*28*
92.78	A_{4}	93	$B_{1,1}$	-77.3	$B_{2,4}$	135.8	$B_{3,20}$	0.6	$B_{4,3}$	*29*
93.11	A_{5}	96	$B_{1,4}$	-77.6	$B_{2,1}$	135.5	$B_{3,18}$	0.6	$B_{4,3}$	*30*
93.78	A_{9}	98	$B_{1,6}$	-76.5	$B_{2,10}$	134.8	$B_{3,13}$	0.5	$B_{4,2}$	*31*
92.45	A_{3}	96	$B_{1,4}$	-76.8	$B_{2,8}$	134.3	$B_{3,8}$	0.5	$B_{4,2}$	*32*
92.13	A_{2}	94	$B_{1,2}$	-76.4	$B_{2,11}$	134.8	$B_{3,13}$	0.5	$B_{4,2}$	*33*
94.39	A_{12}	93	$B_{1,1}$	-75.7	$B_{2,18}$	133.9	$B_{3,5}$	0.4	$B_{4,1}$	*34*
93.22	A_{6}	96	$B_{1,4}$	-76.2	$B_{2,13}$	133.9	$B_{3,5}$	0.5	$B_{4,2}$	*35*
93.59	A_{8}	96	$B_{1,4}$	-76.1	$B_{2,14}$	134.6	$B_{3,11}$	0.5	$B_{4,2}$	*36*
93.41	A_{7}	95	$B_{1,3}$	-77.5	$B_{2,2}$	135.8	$B_{3,20}$	0.6	$B_{4,3}$	*37*
94.38	A_{12}	96	$B_{1,4}$	-77.6	$B_{2,1}$	135.2	$B_{3,16}$	0.6	$B_{4,3}$	*38*
95.03	A_{14}	97	$B_{1,5}$	-76.8	$B_{2,8}$	134.2	$B_{3,7}$	0.5	$B_{4,2}$	*39*
92.11	A_{2}	98	$B_{1,6}$	-76.2	$B_{2,13}$	134.1	$B_{3,6}$	0.5	$B_{4,2}$	*40*

Step Four:

The fuzzy logical relationships based on the fuzzified major variable and the fuzzified minor variables were constructed and use to forecast.

Table 3.21: Fuzzy Logical Relationship of Major and Minor Variables – from Week1 to Week 40

Fuzzified HOSR	Fuzzified SDCCH	Fuzzified RSS	Fuzzified PLOSS	Fuzzified BER	*WEEK*
A_{3}	$B_{1,3}$	$B_{2,14}$	$B_{3,10}$	$B_{4,2}$	*1*
A_{16}	$B_{1,6}$	$B_{2,20}$	$B_{3,1}$	$B_{4,1}$	*2*
A_{1}	$B_{1,4}$	$B_{2,11}$	$B_{3,5}$	$B_{4,2}$	*3*
A_{6}	$B_{1,2}$	$B_{2,13}$	$B_{3,6}$	$B_{4,2}$	*4*
A_{12}	$B_{1,5}$	$B_{2,16}$	$B_{3,4}$	$B_{4,1}$	*5*
A_{12}	$B_{1,3}$	$B_{2,5}$	$B_{3,15}$	$B_{4,3}$	*6*
A_{14}	$B_{1,1}$	$B_{2,10}$	$B_{3,14}$	$B_{4,2}$	*7*
A_{4}	$B_{1,5}$	$B_{2,15}$	$B_{3,3}$	$B_{4,1}$	*8*
A_{7}	$B_{1,3}$	$B_{2,17}$	$B_{3,2}$	$B_{4,1}$	*9*
A_{4}	$B_{1,3}$	$B_{2,11}$	$B_{3,7}$	$B_{4,2}$	*10*
A_{12}	$B_{1,4}$	$B_{2,21}$	$B_{3,9}$	$B_{4,1}$	*11*
A_{15}	$B_{1,2}$	$B_{2,5}$	$B_{3,17}$	$B_{4,3}$	*12*
A_{6}	$B_{1,4}$	$B_{2,10}$	$B_{3,7}$	$B_{4,2}$	*13*
A_{13}	$B_{1,3}$	$B_{2,7}$	$B_{3,20}$	$B_{4,3}$	*14*

$\mathbf{A_1}$	$B_{1,2}$	$B_{2,11}$	$B_{3,12}$	$B_{4,2}$	*15*
$\mathbf{A_{12}}$	$B_{1,5}$	$B_{2,9}$	$B_{3,10}$	$B_{4,2}$	*16*
$\mathbf{A_7}$	$B_{1,3}$	$B_{2,12}$	$B_{3,8}$	$B_{4,2}$	*17*
$\mathbf{A_{12}}$	$B_{1,2}$	$B_{2,19}$	$B_{3,1}$	$B_{4,1}$	*18*
$\mathbf{A_2}$	$B_{1,4}$	$B_{2,6}$	$B_{3,19}$	$B_{4,3}$	*19*
$\mathbf{A_{13}}$	$B_{1,5}$	$B_{2,7}$	$B_{3,20}$	$B_{4,3}$	*20*
$\mathbf{A_{14}}$	$B_{1,3}$	$B_{2,12}$	$B_{3,5}$	$B_{4,2}$	*21*
$\mathbf{A_7}$	$B_{1,2}$	$B_{2,3}$	$B_{3,17}$	$B_{4,3}$	*22*
$\mathbf{A_{10}}$	$B_{1,5}$	$B_{2,11}$	$B_{3,8}$	$B_{4,2}$	*23*
$\mathbf{A_{10}}$	$B_{1,3}$	$B_{2,6}$	$B_{3,5}$	$B_{4,2}$	*24*
$\mathbf{A_{12}}$	$B_{1,2}$	$B_{2,12}$	$B_{3,9}$	$B_{4,2}$	*25*
$\mathbf{A_{13}}$	$B_{1,4}$	$B_{2,13}$	$B_{3,8}$	$B_{4,2}$	*26*
$\mathbf{A_8}$	$B_{1,5}$	$B_{2,19}$	$B_{3,5}$	$B_{4,1}$	*27*
$\mathbf{A_{11}}$	$B_{1,4}$	$B_{2,16}$	$B_{3,8}$	$B_{4,2}$	*28*
$\mathbf{A_4}$	$B_{1,1}$	$B_{2,4}$	$B_{3,20}$	$B_{4,3}$	*29*
$\mathbf{A_5}$	$B_{1,4}$	$B_{2,1}$	$B_{3,18}$	$B_{4,3}$	*30*
$\mathbf{A_9}$	$B_{1,6}$	$B_{2,10}$	$B_{3,13}$	$B_{4,2}$	*31*
$\mathbf{A_3}$	$B_{1,4}$	$B_{2,8}$	$B_{3,8}$	$B_{4,2}$	*32*
$\mathbf{A_2}$	$B_{1,2}$	$B_{2,11}$	$B_{3,13}$	$B_{4,2}$	*33*
$\mathbf{A_{12}}$	$B_{1,1}$	$B_{2,18}$	$B_{3,5}$	$B_{4,1}$	*34*
$\mathbf{A_6}$	$B_{1,4}$	$B_{2,13}$	$B_{3,5}$	$B_{4,2}$	*35*
$\mathbf{A_8}$	$B_{1,4}$	$B_{2,14}$	$B_{3,11}$	$B_{4,2}$	*36*
$\mathbf{A_7}$	$B_{1,3}$	$B_{2,2}$	$B_{3,20}$	$B_{4,3}$	*37*
$\mathbf{A_{12}}$	$B_{1,4}$	$B_{2,1}$	$B_{3,16}$	$B_{4,3}$	*38*
$\mathbf{A_{14}}$	$B_{1,5}$	$B_{2,8}$	$B_{3,7}$	$B_{4,2}$	*39*
$\mathbf{A_2}$	$B_{1,6}$	$B_{2,13}$	$B_{3,6}$	$B_{4,2}$	*40*

Step Five:

Table 3.21 shows the fuzzy logical relationships obtained from Table 3.20 for each testing data from week 1 to week 40, and up to week 52, step1 to step 5 are repeatedly done. Now, to forecast for week 41, the previous record from Table 3.21 of week 40 are 92.11 (A_2), 98 ($B_{1,6}$), -76.2 ($B_{2,13}$), 134.1 ($B_{3,6}$), and 0.5 ($B_{4,2}$) respectively. A look at Table 3.21 does not indicate any fuzzy logical relationship whose current state is “A_2, $B_{1,6}$, $B_{2,13}$, $B_{3,6}$, $B_{4,2}$”. Then option 3 of equation (2.16) is applicable to forecast the HOSR of week 41 as follows:

$$0.5 \times m_2 + S(\text{week } 40) = 0.5 \times (92.03 + 92.11)$$

$$= 0.5 \times 184.14$$

$$= \quad 92.07$$

where m_2 denotes the middle value of the interval corresponding to cluster2 shown in Table 3.7 and cluster2 corresponding to the 2^{nd} interval.

Then applying equation (2.25)

$$week\ 41 = \frac{92.11+94.37+93.88}{\frac{92.11}{92.03}+\frac{94.37}{92.2450}+\frac{93.88}{93.76}}$$

$$= \frac{280.36}{3.025}$$

$$= 92.68$$

Therefore, the forecast for week 41 $= 0.5(92.07 + 92.68)$

$$= 92.37$$

Step Six:

To forecast the HOSR of week 42, where the data of the HOSR, the SDCCH, the RSS, the PLOSS and the BER on week 41 are 94.37, 95, -76.6, 134.5 and 0.5, respectively, these data were added into the existing training data and redo steps 1 to 5 to forecast the HOSR of week 42. The entire procedure was repeated for weeks 43, 44, 45, … 52 respectively.

3.4 Validation Model

The validation is in threefold, first is the development of a computer program using MATLAB facility to implement section 3.2, second is to apply the procedures of existing FTS models to the same data set and finally to compare all results with the actual data obtained as in Table 3.1.

The computer-based model was designed using MATLAB facility. The approach was to produce soft computing software to handle multivariate high order fuzzy time series forecast with data clustering. The model comprised of algorithm, flowchart and program.

1. Algorithm, is the logical solution to the problem which started with the initialization of variables and ended with the forecasted values. The algorithm was designed in modular form to handle each of the Data clustering, the Fuzzification/ Defuzzification and High-Ordering/Forecasting so as to conform to modular design structure.

(a) Data Clustering Algorithm

This is a logical description of the solution. It must have a beginning and an end such that in-between, a complete solution to the problem must exist.

(i) BEGIN

(ii) Initialize all the variables as one major and all others minor.

(iii) Sort the n numerical data set in an ascending order for major and minor variables respectively.

(iv) Calculate the mean of the major and minor variables respectively.

(v) Calculate the Average difference between any two adjacent data of the major and minor variables respectively.

(vi) Calculate the Standard deviation of the difference between any two adjacent data of the major and minor variables respectively.

(vii) Calculate the maximum data distance between any two adjacent data of the major and minor variables respectively (use Average difference, Standard deviation and/or the Difference between the extreme value differences as the case may be).

(viii) Create the Clusters as Intervals for the major and minor variables respectively.

(ix) Calculate the Lower and Upper bounds for all the Intervals of the major and minor variables respectively.

(x) From the Lower and Upper bounds of each of the Intervals, calculate the Mid-value as Universe of discourse for all the Intervals of the major and minor variables respectively.

(xi) STOP.

(b) Fuzzification and Defuzzification

(i) BEGIN

(ii) Initialize the Universe of discourse of the major and minor variables respectively.

(iii) Calculate the linguistic terms for the major and minor variables respectively.

(iv) Fuzzify each datum into a fuzzy set of the major and minor variables respectively.

(v) Formulate Fuzzy logical relationships and create the Fuzzy logical relationship groups based on the current-state of each Fuzzy logical relationship to establish the next-state.

(vi) STOP.

(c) High-Ordering ad Forecasting

(i) BEGIN

(ii) From the Fuzzy logical relationship groups, establish the next-state from the current-state (use rules 1 to 3).

(iii) Construct m-factor K^{th} order Fuzzy logical relationship (5-factor 3^{rd} order).

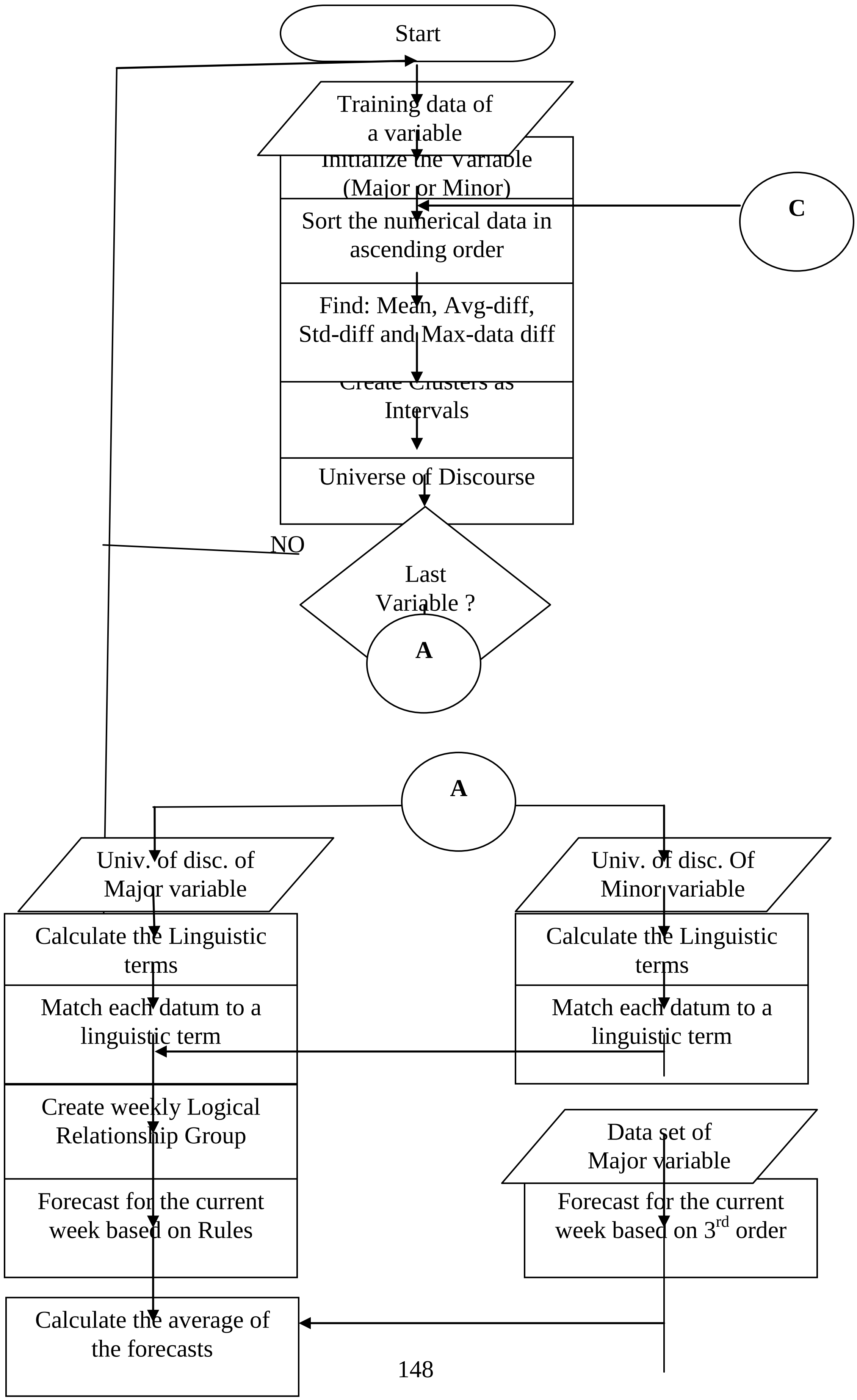
(iv) Calculate the average of results in (ii) and (iii).

(v) STOP

2. Flowchart, actually depicts the pictorial view of the algorithm. Figure 3.1 represent the flowchart of Data clustering, Fuzzification/Defuzzification and High-ordering/Forecasting.

3. Program coding of the algorithm ad flow chart is in the attached as Appendix I.

The result of the computer-based model was used as an additional validation tool to showcase the soft computing approach.


Start
Training data of a variable
Initialize the Variable (Major or Minor)
C
Sort the numerical data in ascending order
Find: Mean, Avg-diff, Std-diff and Max-data diff
Create Clusters as Intervals
Universe of Discourse
NO
Last Variable ?
A
A
Univ. of disc. of Major variable
Univ. of disc. Of Minor variable
Calculate the Linguistic terms
Calculate the Linguistic terms
Match each datum to a linguistic term
Match each datum to a linguistic term
Create weekly Logical Relationship Group
Data set of Major variable
Forecast for the current week based on Rules
Forecast for the current week based on 3rd order
Calculate the average of the forecasts

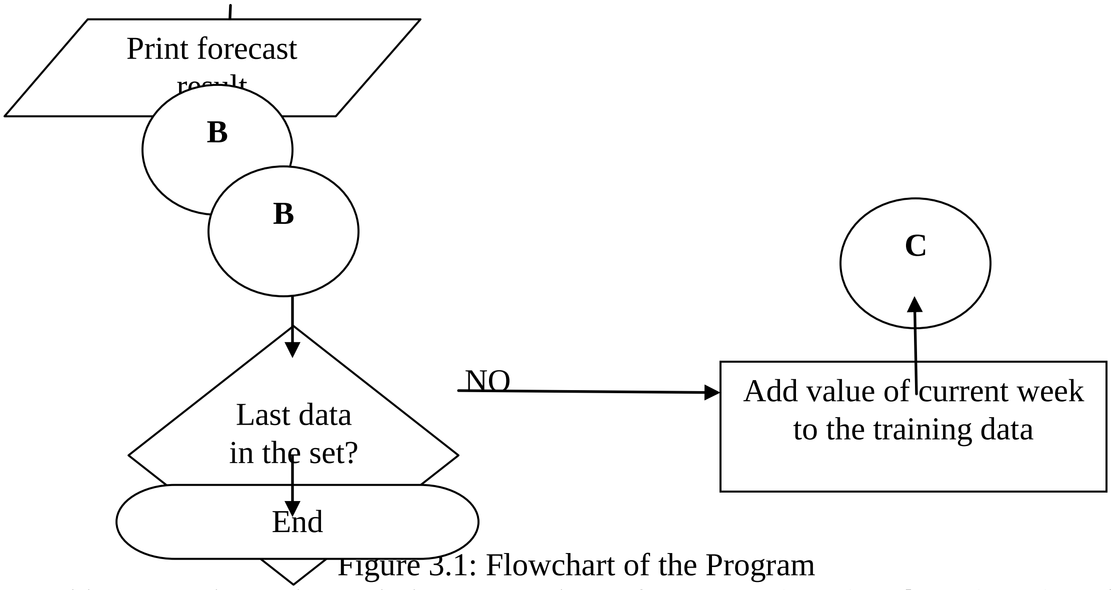


Figure 3.1: Flowchart of the Program

This research work used the approaches of Mu'azu (2005), Jilani (2007) and Chen (2011). In their separate approaches, each work reveal a distinct relationship with the current work, namely; from Univariable/Multivariable, Single order/Higher order to Interval length/Data clustering. All the results of the three works were used as validation materials.

Mu'azu's work was a modified univariable approach with interval length that was based on earlier conclusions that preferred old number intervals. The approach was used in the development of the forecast model using the fuzzy time series techniques to forecast for the handovers. Jilani's research work presented an extended method for handling forecasting problems based on m-factor high-order fuzzy time series. The theoretical and practical step of the method was used in the development of the forecast model using the fuzzy time series techniques to forecast handovers. Chen's method started with data clustering technique by avoiding the use of interval length and thereafter, applied multivariable procedures. To avoid mathematical complications, due to numerous derivations the method adopted first order approach. The procedure of the work was used in the development of the forecast model using the fuzzy time series techniques to forecast for the handovers. For the detailed descriptions of these methods, see Mua’zu, (2006), Jilani et al, (2007) and Chen et al, (2011).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 General

The result obtained from application of chapter three is presented for all the models, analyzed using statistical tests along with validation charts and actual data. Thereafter, these results were discussed to reveal their significance. Contribution to knowledge and improvement offered by this research over existing works were analyzed.

4.2 Results Presentation

The Fuzzy Time Series models considered have five distinct results namely; Developed model, Computer-Based (CB) model, Mua’zu model, Chen model and Jilani model. All the models forecasted HOSR based on their respective principles. The result is presented in Table 4.1.

Table 4.1: Results of all the Models

Actual HOSR	**Developed Model**	**CB Model**	**Mua'zu Model**	**Chen Model**	**Jilani Model**	**Week number**
94.37	92.37	93.0	93.8	92.07	92.5	41
93.88	94.5	93.6	96.2	95.01	94.9	42
94.3	94.9	94.0	92.5	90.5	97.7	43
94.45	95.01	94.8	91.6	90.9	93.5	44
94.67	94.72	94.2	93.2	92.05	91.8	45
95.09	94.6	94.9	95.6	97.02	90.02	46
93.9	94.0	93.6	94.7	96.9	95.0	47
92.99	93.6	93.2	97.5	94.6	88.02	48
93.89	94.2	93.9	89.1	96.5	91.5	49
95.3	96.4	96.2	91.9	98.02	98.1	50
93.86	94.8	94.0	90.3	95.0	90.5	51

94.18	95.3	94.3	87.6	91.6	96.6	52

4.3 Results Analysis

The result of each model is compared with the actual HOSR using statistical tools. The statistical values obtained are the basis of the validation of the developed model.

1. Pearson's Correlation Coefficient focuses on comparing the data sequences, in order to establish the degree of interdependency of the corresponding pair of points of the variables. A value between 0 and 1 (Correl(X,Y)) is calculated as:

$$\boldsymbol{C(X,Y)} = \frac{\sum\ (\boldsymbol{x_1}(\mathbf{n})\ \mathbf{x_2}(\mathbf{n}))}{\sqrt{\sum(\mathbf{x_1}(\mathbf{n}))^2 \sum(\mathbf{x_2}(\mathbf{n}))^2}} \tag{4.1}$$

Where, $x_1(n) = (x - x')$ (4.2)

$x_2(n) = (y - y')$ (4.3)

Using equations (4.1), (4.2) and (4.3) and Table 4.1, the statistical values obtained are:

$C(X,Y)_{Developed} = 0.9800$

$C(X,Y)_{CB} = 0.9911$

$C(X,Y)_{Mua'zu} = 0.9509$

$C(X,Y)_{Chen} = 0.9701$

$C(X,Y)_{Jilani} = 0.9661$

2. Root Mean Square Error (RMSE) is quantitative technique used to determine the performance function of the model. It is calculated as:

$$\mathbf{MSE} = \sum_{\mathbf{i=1}}^{n} \frac{[(\mathbf{HOSR_{Actual}} - \mathbf{HOSR_{Model}})]}{\mathbf{n}} \quad (4.4)$$

$$\boldsymbol{RMSE} = \sqrt{\boldsymbol{MSE}} \quad (4.5)$$

Where MSE is the Mean Square Error and n is the number of weeks for validation of the model.

Using equations (4.4) and (4.5) and Table 4.1, the statistical values obtained are:

$RMSE_{Developed}$ = 0.005012

$RMSE_{CB}$ = 0.004908

$RMSE_{Mua'zu}$ = 0.006554

$RMSE_{Chen}$ = 0.006001

$RMSE_{Jilani}$ = 0.006502

3. Validation analysis is to evaluate and compare the HOSR of the developed model with the actual data and in turn to validation models. The Maximum Performance Error (MPE) and Average Performance Error (APE) were calculated from:

$$MPE = \frac{\text{Max}\left(\left|\text{Forecast Value} - \text{Actual Value}\right|\right)}{\text{Max (Actual Value)}} \text{ x } 100\% \quad (4.6)$$

$$APE = \frac{\sum\frac{(\text{Forecast Value} - \text{Actual Value})}{\text{Actual Value}}}{\text{n}} \text{ x } 100\% \quad (4.7)$$

Using equation (4.6) and Table 4.1, the statistical values obtained are:

$MPE_{Developed}$ = 2.4841%

MPE_{CB} = 3.4520%

$MPE_{Mua'zu}$ = 5.7963%

MPE_{Chen} = 5.4092%

MPE_{Jilani} = 5.4952%

Using equation (4.7) and Table 4.1, the statistical values obtained are:

$APE_{Developed}$ = 0.6615%

APE_{CB} = 0.5011%

$APE_{Mua'zu}$ = 0.7012%

APE_{Chen} = 0.6822%

APE_{Jilani} = 0.6905%

The plots of Figures 4.1 to 4.6 show a comparison of Developed Model, Validation models and the Actual Handover Success Rate.

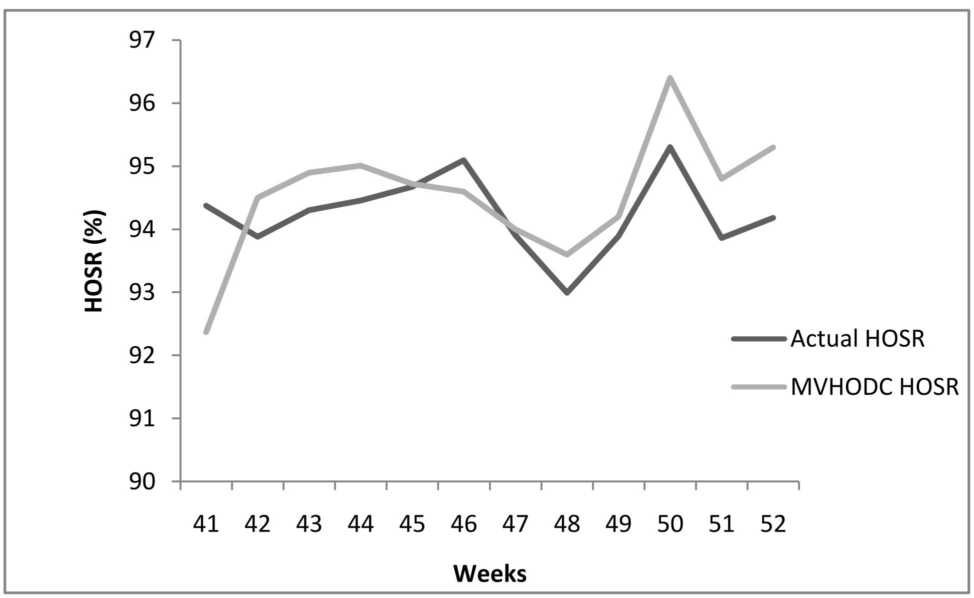


Figure 4.1: Developed Model and Actual Handover Success Rate

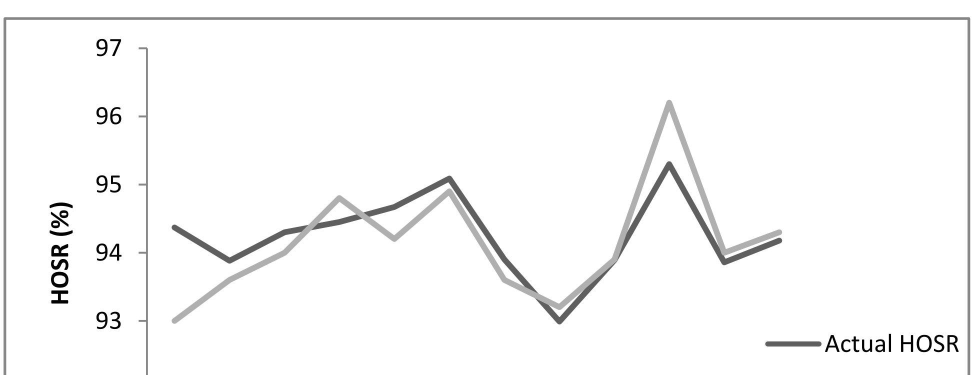


Figure 4.2: Computer-based Model and Actual Handover Success Rate

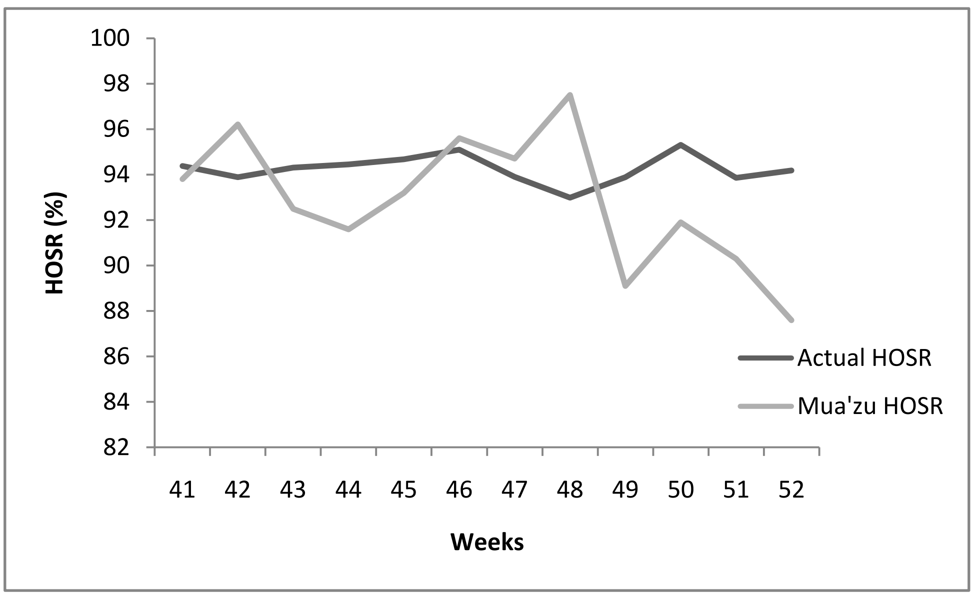


Figure 4.3: Mu’azu Model and Actual Handover Success Rate

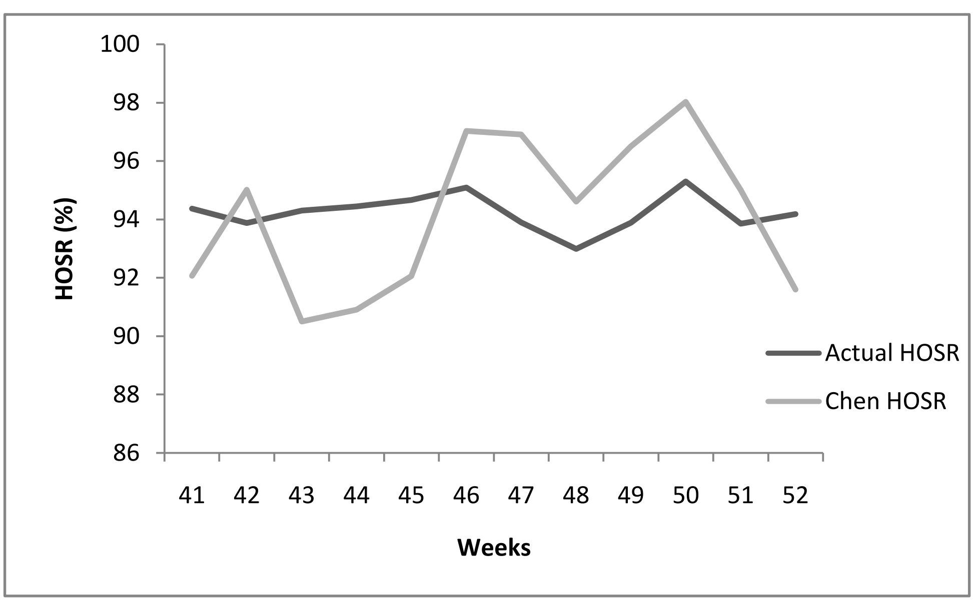


Figure 4.4: Chen model and Actual Handover Success Rate

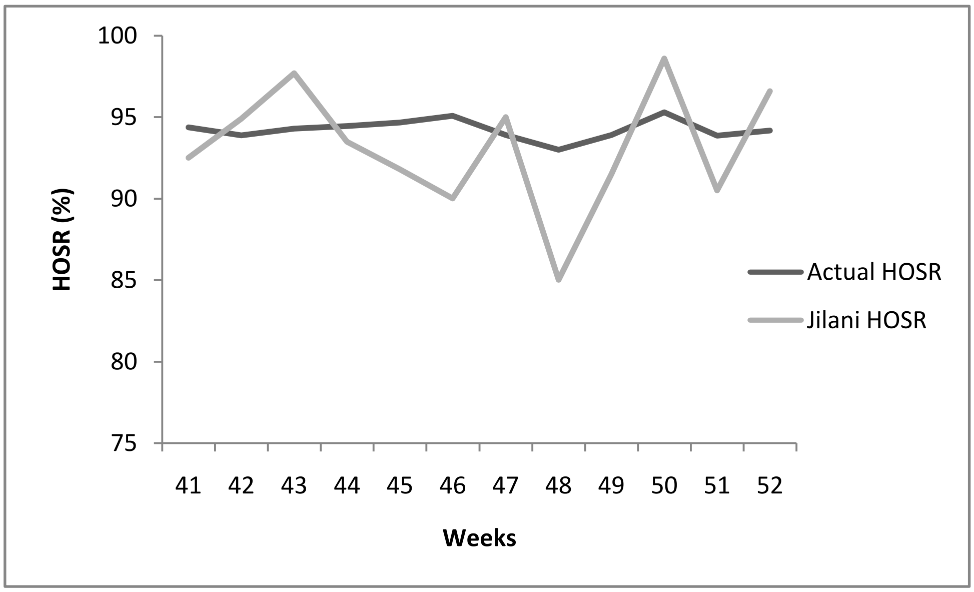


Figure 4.5: Jilani Model and Actual Handover Success Rate

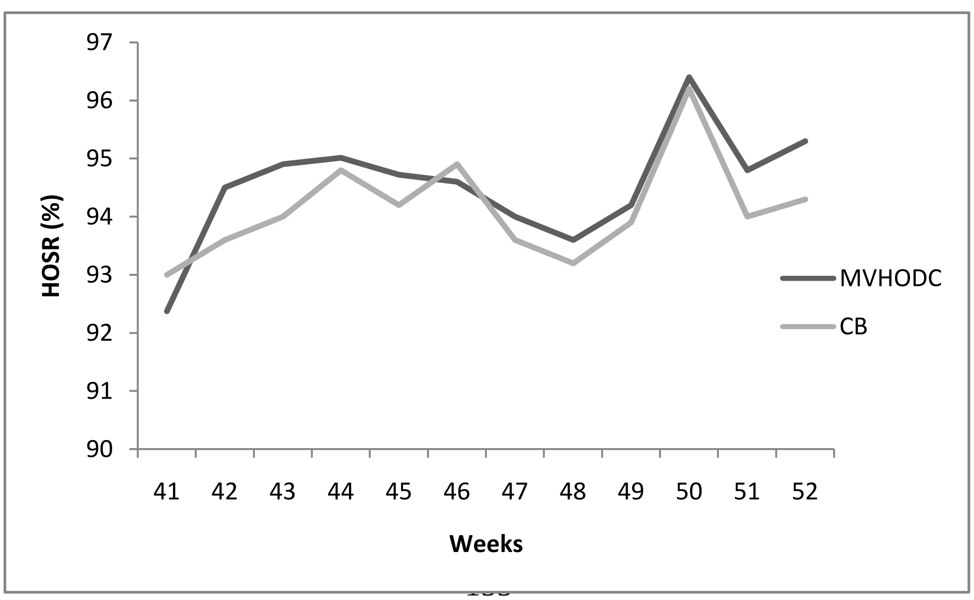


Figure 4.6: Developed Model and Computer-Based Model

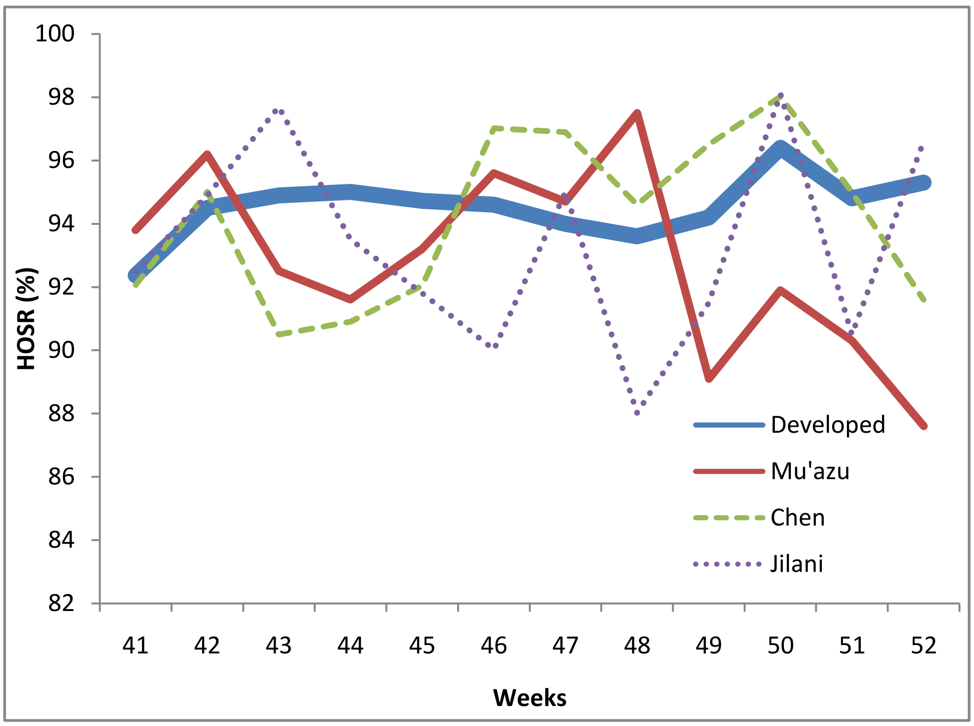
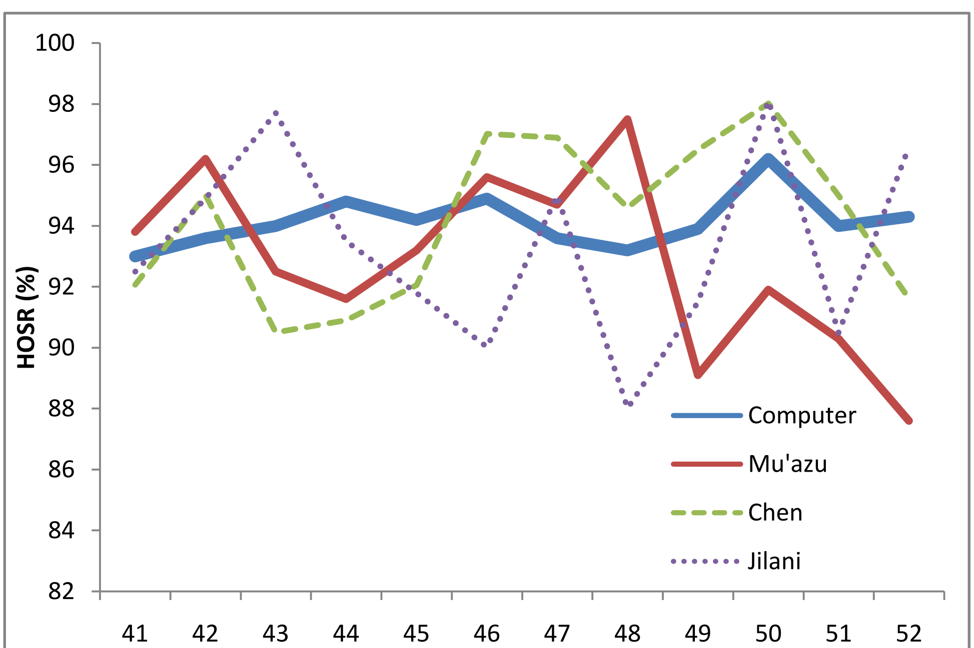


Figure 4.7: Developed, Mu’azu, Chen and Jilani



4.4 Results Discussion

From the results obtained in Table 4.1, values calculated from the quantitative analysis carried out and the validation models, the developed model is of high accuracy. The values of Pearson's correlation coefficient indicate high level of correlation of the two sets of data, and the developed model meet the requirement for forecasting.

The values of Average percentage error, Maximum percentage error and Root mean square error are low and indicate high level of performance and efficiency. The validation analysis results of Computer-based and FTS models have furthermore confirmed the accuracy of the developed model in dealing with uncertain and nonlinear nature of the data in fuzzy time series environment.

Figures 4.1 to 4.8 are graphical representations of each model for the obtained data. Figure 4.1 shows a relatively comparative linear trend with the obtained data that showed significant differences in weeks 41, 50 and 52. However, weeks 42, 45 and 47 indicated almost exact values with the obtained data probably, because this model incorporated multivariate high-order with data clustering. Figure 4.2 follows completely the linear trend of the obtained data with little or minimum variations in weeks 41, 45 and 50. This model actually eliminated most arithmetic errors during the computation in Figure 4.1. Figure 4.3 indicated considerable variations with the obtained data in almost all the weeks with the exception of weeks 41, 46 and

48. The model is a modified univariate-based approach. Figure 4.4 showed certain differences in virtually all the weeks with the exception of weeks 42, 45 and 51. The model is although multivariate with data clustering but without high-order. Figure 4.5 is relatively in line with the obtained data that indicated minor variations in weeks 47, 49 and 51. Although, the model is multivariate with high-order, the training data were partitioned arbitrary into interval lengths. Figure 4.6 compares the developed model with the computer-based model that used multivariate high-order with data clustering. From Figures 4.1 and 4.2, it is clear that the developed model suffers from many arithmetic computational errors.

Although, the developed model has improved the earlier FTS models considered, computerization of the processes of computation that actually involved repeated procedures as indicated in Figure 4.2 results in better forecast. The accuracy of the forecasted results is better when the developed model is computerized as indicated in Figures 4.1, 4.2, 4.6, 4.7 and 4.8.

4.5 Contribution to Knowledge

The primary aim and objective of this research work have been achieved. A verifiable and optimized technique to model and perform forecast of the handovers of GSM network has been implemented. The main contributions to knowledge from the research work are as follows:

(i) Development of a verifiable and optimized technique to model and perform forecast of the handovers of GSM network has been implemented.

(ii) The developed forecasting model has been used to model and perform prediction of the handovers of the GSM networks in the Lagos zone of the Airtel in Nigeria. This technique is efficient, reliable and verifiable. The RMSE and APE are both less than **1%**. The Pearson's correlation values are between **0.9** and **1.0**.

(iii) In addition, the developed model was compared with three other FTS models of Mua'zu (2005), Jilani (2007) and Chen (2011), the result difference are (APE (**0.0397, 0.0207 and 0.0209** respectively), MPE (**3.3122, 3.9251 and 3.0111** respectively), PCC (**0.0291, 0.0099 and 0.0139** respectively) and RMSE (**0.001542, 0.000989 and 0.00149** respectively)) all the values are higher than those of the developed model.

(iv) The computer-based model developed in this research has addressed the fundamental problem of complexity and computational cost associated with every form of multivariate FTS with data clustering. The results in Table 4.1 and Figures 4.2 ad 4.8 clearly indicated the superiority of the model.

(v) With clear identification of elemental control variables, the developed model can be used in other related areas like demands, number of calls, QoS, load etc forecasts.

(vi) In their separate works Akhila and Suthiksh (2009) used two related variables, Jianmin (2009) adopted a method based on the historical data collected from mobile network, Manoj and Khola (2012) extended earlier works to include three dissimilar variables, Weetit et al (2013) introduced bahaviour of the mobile user, Thanachai et al (2013) suggested the use of the most recent mobility history variables. It is sufficient to state that the designed model can be applied to produce optimized solutions of those problems highlighted in the works of these earlier researchers.

4.6 Improvement offered by the developed model as Compared to the existing research works.

Toril been the first recorded researcher in 2003 to introduce FTS into mobility management forecasting was able, by using an automatic optimization algorithm which maximized the overall traffic carried in the network that equalizes long-term blocking effects, to optimize handovers forecast. The work is univariate based and lacked any advance data mining technique, and as such only a significant improvement in homogeneous handover parameter settings was achieved. The multivariate-based approach and advanced data clustering technique adopted in this current research work have significantly showed desired improvement.

Manoj and Khola, (2012) used fuzzy logic to make mobility management decisions by utilizing three input parameters, of predicted received signal strength, bandwidth and users preferences. The calculated and simulated results of the handover decision algorithm forecasted showed possibility of making accurate handover decisions but the entire work lacked comparative analysis to justify the claim of improved performance of the networks. The validation approach in the current research work that included computer based model and the existing FTS models (Mua'zu, Chen and Jilani) have provided basis for various comparative analysis.

In the research work of Thanachai et al., (2013) that used adaptive modular fuzzy-based mobility management decision system to forecast handovers by including relatively large number of decision parameters that are quality-of-service related. The results obtained were quite impressive and showed a reasonable improvement on the accuracy of predictions. However, due to increase computational complexity and long algorithm execution time, which affects real-time applications, this approach is not cost effective. The computer based model included in this current research work is a significant improvement that will certainly add value to their work.

Conclusively, in this research work contrary to the others, the number of intervals, the interval length, and the degree of memberships are not arbitrarily determined (subjective decisions) in the fuzzification stage, so the approach is more systematic than the others. The multivariate high-order structure in which membership degrees are taken into account to define fuzzy relations overcomes a lot of encountered problems in the real life where a forecasting method must be set to reveal fuzzy relations between FTS and some other FTS. Membership values of observations are employed when fuzzy relations are defined. Therefore, information loss is prevented and this is also an evidence of the transparent nature of computation involved in this work.

CHAPTER FIVE

CONCLUSION AND SUGGESTIONS FOR FURTHER WORK

5.1 General

The Development of a Multivariate High-order Fuzzy Time Series Forecasting Model with Data Clustering was undertaken and applied to mobility management using Airtel Lagos zone as case study. The results obtained showed significant contributions to knowledge within the bounds of certain limitations. Conclusions were drawn from the results obtained in accordance with the aim and objectives of the research. Notable areas of further work to improve the results and significance of this research work were highlighted.

5.2 Limitations

In multivariate forecasting, the degrees of influence of the individual secondary variables are naturally important. Although, the newest of this field, relatively few research works available and developing characteristics of multivariate forecasting have play-down on this issue, it is certainly going to be a contesting factor as more research works are carried out in many application fields.

Data clustering techniques are prone to outliers caused by too many irrelevant variables. It is often difficult to eliminate if not to reduce this in all the chosen variables so as to establish the definition of a cluster (as been different, reachable, measurable and profitable).

Identification of a particular suitable order in the high order models is a serious concern because highest possible orders do not necessarily yield the desired accuracy in all situations. Clearly, higher orders require additional computational cost and the results usually obtained are data dependent.

5.3 Conclusions

The basis and fundamental importance of mobility management is outlined to stress the need for its developments with respect to current trends in other technologies. The designed and developed model is presented and the validated models of computer-based model along with the earlier implemented models of Mu'azu, Chen and Jilani models were implemented.

Fuzzy Time Series technique was applied in this research work to develop a Multivariate High-Order forecast model with Data Clustering. The developed model was applied to forecast handovers as a mobility management issue. The results were obtained and validated.

The developed model is compared with the validation model of validation data of 12 weeks, Computer-based model and existing FTS models and (Mua'zu, Chen and Jilani) to explore the behavior of the developed model. The four statistical tests of Maximum Percentage Error, Average Percentage Error, Root Mean Square Error and Pearson's Correlation Coefficient were applied to the developed and validation models so as to establish a common basis of comparison and reference. All results further ascertained and confirmed the accuracy of the developed model.

The Airtel Data used in developing the Multivariate High-Order Fuzzy Time Series Forecasting Model with Data Clustering is a universally standard GSM Data, which implies that the developed model can be applied to other GSM operators, especially operators that uses the GSM900 and GSM1800.

The developed Multivariate High-Order Fuzzy Time Series Forecasting Model with Data Clustering has demonstrated that it can be used to model Handover Success Rate using past record of handover success rate, stand alone dedicated control channel, received signal strength, path loss and bit error rate due to its degree of consistency with respect to the validation models and result obtained from the statistical analysis. The statistical values are APE = **0.6615%**, MPE = **2.4841%**, RMSE = **0.05012** and C(X,Y) = **0.9800** which compared favourably with the existing models. Analytically and experimentally the results obtained from the validation models clearly showed that, the developed model has outperformed those other FTS models (Mu'azu (2005), Jilani (2007) and Chen (2011)), by the result differences as (APE (**0.0397, 0.0207 and 0.0209** respectively), MPE (**3.3122, 3.9251 and 3.0111** respectively), PCC (**0.0291, 0.0099 and 0.0139** respectively) and RMSE (**0.001542, 0.000989 and 0.00149** respectively)) all higher than values for the developed model.

5.4 Suggestions for Further work

The followings are suggested as possible means of improving this research:

(i) The developed model can be further enhanced by incorporating Behaviour-based mobility prediction variables (Location information, Group, Time-of-day, duration characteristics of the mobile users) in addition to network variables as against for, example, the use of the scanning overhead incurred in IEEE 802.11 networks that uses only location information that are network-based to predict handovers.

(ii) A study into detail impacts of individual minor variables on the major variable so as to open-up and discover new findings to facilitate self-tuning of the fuzzy data mining techniques in real-time enabling the handover decisions to respond to changes in user preferences.

(iii) A further investigation and possible development of an axiom of standard that focuses on how mobile applications might use this ability to predict handovers to enhance user performance or throughput and what kind of benefits would network providers get if they utilize such information provided by this and similar research work.

(iv) An expanded research work on the model needs to be extended to capture designated areas (like Abuja due to fast developments, further North due to vast geographical land mass) and Nigeria in general, because of the deregulation and interrelationship between network services providers to minimize delays and improve infrastructural utilization.

(v) The method of approach in developing the forecasted developed model can also be adapted to areas such as data communication networks (SMS, INTERNET, dedicated transactions etc), transmission related issues (which may include attenuation, shadowing, Rayleigh fading, time dispersion and alignment among others) as they affect network coverage and capacity and Power Systems (load demand, load consumption etc) in order to produce forecast models for areas like packet switching growth and power system demand respectively. The Power system sector has been deregulated in Nigeria and it is expected that with forecast model that can project growth in both the short and long terms, efficiency and proper planning can be enhanced.

(vi) Development of forecasting model that will address the next generation Wireless Cellular Network (WCN) networks such as High Speed Downlink Packet Access (HSDPA), High Speed Uplink Packet Access (HSUPA), and Worldwide Interoperability for Microwave Access (WiMAX). This is to enhance customer satisfaction, stimulate growth that results in higher profits for manufacturers and services providers, and finally advance the intellectual ability of the research community.

(vii) Further Development to enhance and standardized the developed computer-based model so as to accommodate forecasting problems of other related areas that may not necessary be in the boundary of the case study of this research work. This will certainly reduce the computational cost associated generally with forecast studies and furthermore reduce the gap between short and long term forecasting.

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APPENDICES

Appendix I: Program List