Assessing Wireless Network Dependability Using Neural Networks

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Abstract
Critical infrastructures such as wireless network systems demand dependability. Dependability attributes addressed in this thesis include availability, reliability, maintainability and survivability (ARMS). This research uses computer simulation and artificial intelligence to introduce a new approach to measure dependability of wireless networks. The new approach is based on the development of a neural network, which is trained to investigate ARMS attributes of a wireless network capable of serving 100,000 subscribers. Given the reliability and maintainability of wireless infrastructure components, the resulting impact on network availability and survivability are determined. Component mean time to failure (MTTF) is used to model reliability, while mean time to restore (MTR) is used for maintainability. Here, unavailability, the complement of availability, is defined as the fraction of time the entire network system is down, while survivability is the fraction of network users who have service. Both availability and survivability can be instantaneous or averaged over some period. The simulation output is used to train the neural network, which is obtained from simulation experiments for a range of component’s MTTF and MTTR values. In turn, the NN is used to gain insights not easily apparent from simulation results. The NN also assists in estimating the number of FCC-Reportable outages of a wireless network. Lastly, a variety of reliability/maintainability growth and deterioration scenarios is analyzed with the NN. Besides focusing on questions regarding availability and survivability under reliability and maintainability growth/deterioration scenarios, this research also focuses on the relative performance of neural network modeling compared to analytical and simulation techniques.

Approved:

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Chapter 1

Introduction

1. Introduction
Earlier research has used computer simulation for estimating wireless network dependability. This work introduces a new methodology for constructing and testing a neural network model to assess wireless network dependability. This research shows how a learning environment can be created through a combination of simulation and artificial intelligence techniques.

1.1 Growing Importance of Wireless Communication
Over the past decade, wireless technology has undergone an enormous growth. Surveys have shown that a new wireless subscriber signs up every 2.5 seconds. The number of cellular and personal communication system (PCS) users in the US has passed a 100 million [1]. The growth of wireless communication in the global market is shown in the Figure 1 [2]. Along with an increasing wireless demand, there has been constant expansion of wireless capabilities technologies starting with Advanced Mobile Phone System (AMPS) to 2G, 2.5G, and 3G leading to 4G. Since 2G sets the foundation of the wireless network, this research considers 2G architectures. Current wireless technology supports 911 applications, Short Message Service (SMS), Interactive Multimedia Messaging Service (IMMS) and Wireless Application Protocol (WAP), thus making it even more popular and well accepted. To support these features and to provide continuous service with minimal call drops and call blocking, wireless carriers must focus on making the network more dependable. In short, in competitive wireless markets, a wireless carrier must pay foremost attention to dependability for attracting more subscribers and satisfying the needs of existing customers. In light of the growing importance of wireless services to society, on January 2, 2005, the Federal Communications Commission’s (FCC) put in affect a new outage reporting regulation. Now, it is mandatory for wireless carriers to report outages 30 minutes or longer that exceed 15,000 lost subscribers/hour (the product of outage duration and number of
subscribers impacted) [62]. The FCC’s new action makes it imperative for wireless carriers to place special emphasis on wireless infrastructure dependability.

![Graph showing the growth rate of wireless communications infrastructure](image)

**Figure 1: Growth Rate of Wireless Communications Infrastructure**

### 1.2 Contribution to Research

A significant amount of research has been published on network design and security management issues of wireless networks but very little has been done to explore the importance of availability, maintainability, reliability and survivability (ARMS) in wireless networks. Empirical dependability of wireless networks depends upon the number, size and duration of outages. An outage occurs because of failures that result in service disruptions to a fraction of subscribers for a certain period. The fewer the number of outages, the more dependable the network is. The three important measures of outages as specified in earlier research are frequency of outages, the number of subscribers impacted and the duration of an impact. Several metrics such as Lost Line hours, User Lost Earlangs (ULE), outage index, call blocking probability, call dropping probability, and numbers of disconnected nodes have been defined in the past for measuring the
outages [3, 4, 5, and 42]. Some research has emphasized size and duration (outage double) whereas others have laid more emphasis on size, duration and importance or type of the service lost (outage triple).

In the field of wireless networks, both analytical and simulation modeling have been used to determine the reliability of a wireless network. In other complex systems, reliability has also been modeled by neural networks (NN) like terminal networks, and cruise missile systems [6, 7]. Neural Networks have extensively been used in wireless networks for mobility prediction, and location connection management but not for determining reliability [8, 9, 10, 11, 12, 13, and 14]. This thesis deals with the use of NN to estimate the dependability of wireless networks. The data necessary to train a NN can be obtained by experimentation, analytical analysis, or simulation results. Simulation data has been successively used to train a NN in a radar tracking system, in a scheduling advisor, and for polymer resins design [15, 16, and 17]. This work also uses simulation results to train a NN.

This research uses both computer simulation and neural network modeling in order to investigate dependability of wireless networks. It also aims to assess the effectiveness of NN modeling in finding out dependability. It attempts to find new insights not easily obtainable by simulation modeling through NN sensitivity analysis and decision trees.

1.3 Scope of This Work

In this research, dependability consists of availability, reliability, maintainability and survivability (ARMS). Wireless traffic levels are also considered in this work. Various traffic profiles by the time of the day (i.e. morning, afternoon, evening and night) are taken into account while assessing the dependability of the wireless networks. In addition, wireless reliability/maintainability growth and deterioration (RG/RC/RD and MG/MC/MD) are studied for a life span of five years. Reliability and maintainability are varied to determine impact on survivability and availability. This work also assesses whether the network operators should be proactive (make the components more reliable)
or reactive (fix the components faster by maintaining an efficient staff or by keeping more spares in stock) in order to improve dependability. It incorporates the failure frequency and restoral times of various components in a wireless network such as Base stations (BS), Base station controller (BSC), Mobile Switching Center (MSC), Database (DB), BS-BSC links, BSC-MSC links. A simulation model is extended to measure dependability (ARMS) attributes. In addition, the simulation output trains a NN to measure dependability of wireless networks and explores the utility of NN sensitivity analysis and decision trees in further assessing the dependability of wireless networks.

1.4 Thesis Outline
Chapter 2 provides background information and explains the importance of ARMS in wireless network dependability. Wireless architecture, methods of improving reliability, and various modeling techniques such as analytical, simulation and NN modeling are discussed. Chapter 3 reviews the literature in the area of wireless networks and neural networks. It explores past research in the field of survivability, reliability, dependability of fault-tolerant wireless networks, and covers the use of NN in the field of reliability and wireless networks. Chapter 4 then outlines research questions. Assumptions, advantages and disadvantages of different modeling techniques are presented in chapters 5 and 6. In addition, concepts of NN are described with emphasis on NN modeling using a NN software tool (NeuroSolution). Research methodology is explained in chapter 7 while results and findings in chapter 8. Chapter 9 outlines research limitations, conclusion, and future research. Further details of the model and data analysis are provided in appendix.
Chapter 2

Background

2.1 Purpose of Research
This research aims to assess the use of NN models as a way of estimating wireless network dependability. It studies nine different scenarios of reliability/maintainability growth and deterioration to determine maximum survivability and availability. This thesis also devises a method to calculate the number of FCC-Reportable outages. Lastly, it explores the advantages and disadvantages of NN modeling over simulation modeling.

2.2 Importance of Availability, Reliability, Maintainability and Survivability (ARMS)
Dependability is defined as the trust one expects of a system in delivering its services efficiently over a predefined period. Lui describes dependability in terms of attributes, means and impairments as shown in the figure 2 [21]. Snow, et al, considered wireless network dependability as availability, reliability and survivability. Knight also includes survivability as a part of dependability [18, 19, 20, and 22]. This research takes an ARMS perspective: availability, reliability, maintainability and survivability, while integrity and confidentiality are not included in the scope of this work.

Figure 2: Dependability Tree
This study differentiates between availability and survivability. Availability implies that the system is either up or down whereas survivability indicates whether a part of the network is up or down. In addition, availability can be categorized as either instantaneous or average. Instantaneous availability is interpreted as the probability that a system is available when needed whereas average availability is represented as follows:

\[
\text{Average Availability} = \frac{\text{Mean Time to Failure (MTTF)}}{\text{Mean Time to Failure (MTTF)} + \text{Mean Time to Restore (MTR)}}
\]

Therefore, average availability tells us the expected time the entire system is up, as opposed to down. Reliability is defined as the network’s ability to perform a designated set of functions under certain conditions for a specified operational time. It is a function of mean time to failures (MTTF) [23]. Maintainability is explained as the ability to perform a successful repair action within a given time. It depends on the mean time to restore (MTR) [23]. Lastly, survivability is explained as the percentage of network users who are up. Moreover, security, an important aspect in wireless network, comprising of confidentiality, availability and integrity, is not considered here. Throughout the analysis, this research focuses on dependability as in terms of ARMS. This work primarily investigates various scenarios of reliability and maintainability growth and deterioration to determine availability and survivability as shown in Figure 3.

Figure 3: ARMS Calculation
2.3 Wireless Infrastructure

Figure 4 shows an overview of complete and integrated wireless architecture.

Figure 4: Overview of Wireless Architecture [18, 19]
A mobile agent selects a nearest base station by using appropriate modulation scheme depending upon the wireless technology deployed. A base station in a cell is connected to base station controller through a wire line mechanism, which in turn is connected to the corresponding mobile switching center. One wireless infrastructure building (WIB) block is made up of one mobile switching center (MSC), one home location register (HLR), one visitor location register (VLR), base station controllers (BSC) and multiple base stations (BS). Mobile switching centers are interconnected to enable a wireless call between users of different wireless infrastructure building block [18, 19]. An MSC sets up a connection between a mobile user and a fixed user via the Public Switching Telecommunication Network (PSTN) by Signaling System Numbering 7 (SS7) links. It also sets up a connection between two remote mobile users by establishing MSC-PSTN-MSC connection.

### 2.3.1 Wireless Infrastructure Building Architecture

Figure 5 shows the general wireless architecture of a single wireless infrastructure block (WIB), a portion of the wireless infrastructure capable of servicing 100,000 subscribers.

![Figure 5: Architecture of One WIB (2 G) [24]](image-url)
This thesis analyzes and first trains a NN for a single WIB serving 100,000 customers to assess the availability, the survivability and the number of FCC-Reportable outages. To keep the analysis simple in the beginning, only one WIB is analyzed to assess the capabilities of NN modeling, to see if the same approach can then be further extended to the entire wireless infrastructure by future researchers. The architecture is divided into three subsystems as described below [24].

The Mobile Subsystem: This subsystem consists of mobile equipment that includes the radio transceiver, digital signal processors and the Subscriber Identity Module. The SIM is a portable device in the form of a smart card that stores the subscriber’s identification number: International Mobile Subscriber Identity, the networks the subscriber is authorized to use, encryption keys and other information specific to the subscriber. The mobile equipment is uniquely determined by the International Mobile Equipment Identity. The MS is a user device and not in the scope of this work.

The Base Station Subsystem: This subsystem consists of Base Station (BS) and Base Station Controller (BSC). The Coverage area is divided into number of cells and each cell has at least one BS, which is assigned to a group of frequencies for handling MS. BSC manages multiple BS and handles radio-channel set up, access schemes and handovers. BS, BSC and BS-BSC links are included in the scope of this work.

The Network and Switching Subsystem: This subsystem provides the link between the cellular network and the public switched telecommunications networks. Its function is to handle a mobile subscriber, such as registration, authentication, location updating, and handovers and call routing to a roaming subscriber. Mobile Switching Center (MSC) is the central element of the NSS and is supported by two main databases.

- Mobile Switching Center (MSC): A MSC handles multiple BSC and controls switching of calls between MSC and PSTN, MSC and MSC and BSC and BSC.
• Home Location Register (HLR) database: HLR database contains administrative information of each subscriber registered in the area covered by its MSC. It also contains the SS7 address of the VLR associated with the mobile station.

• Visitor Location register (VLR) database: VLR database contains the selected information from HLR. It maintains information about the subscribers that are currently physically present in the region covered by its switching center.

In this work, the HLR and VLR are included as one entity (DB). In addition, this work considers the MSC, MSC-BSC links and DB.

As mentioned earlier, this research involves the analysis of a single WIB serving 100,000 customers to assess ARMS attributes of wireless networks. Due to the study of one WIB, external call handover is not analyzed, i.e. failures in other WIB’s, are also not accounted for in this thesis. It also does not include interface to either the PSTN or other WIB’s in the wireless infrastructure. Moreover, user mobility and location management are also excluded from this study.

2.4 Improving Dependability of Wireless Networks

Several architectural and structural changes can improve dependability of wireless networks. Snow, Varshney, and Malloy propose the use of sonet rings, multi-function devices, and overlay networks [18]. Survivability can also be improved by using better base stations having high signal-to-noise ratio and fewer radio link failures. The various techniques for improving dependability can be broadly categorized into four classes [21]:

1) Fault Prevention: Fault prevention techniques avoid or minimize the occurrence of faults by construction or by modifying architectural designs.
   a) Sonet rings connect the switched network with multiple base stations for the same geographic area. Such a scenario operates if there is a fiber cut or a transceiver failure, as a counter rotating ring completes the path. It is similar to dual Fiber Distributed Data Interface (FDDI) rings [18].
b) Multifunction/multimode devices provide overlapped services to ensure wireless coverage in case of network link or switch failures. This architecture increases the effective coverage area [18].

c) An overlay network enables user to select a wireless network based on availability, specified quality of service and his choices. An overlay network consists of several universal access points (UAP) connecting the user to different wireless networks. A UAP performs protocol and frequency translation as well as content adaptation [18].

d) End-to-end reliability and survivability must be ensured in the wireless network. Since a mobile user can call a fixed landline subscriber, it is imperative to ensure reliability of both wireless network and public switched telephone network. Roaming plans are made with agreements within multiple carriers and hence survivability & reliability must be ensured in each carrier’s networks. A switched network involves techniques like circuit switching, for example ATM. These networks have high degree of redundancy but access links and radio frequencies links have little or no redundancy making it a weaker part of end-to-end connections in case of a wireless network [18].

2) **Fault Tolerance:** Fault tolerance technique ensures service availability in presence of faults. Dependability can be enhanced by adding redundancy either at the component level or at the link level. Therefore, if any component or link fails, connection is still established by taking the alternative redundant route. This technique can prove to be expensive as redundant components add to the cost of the network.

3) **Fault Removal:** Fault removal technique reduces the number and seriousness of faults. Operational networks should be monitored on a continuous basis to find and document the bugs. Fault-Removal technique involves removal of bugs from software and faults from operational procedures.
4) **Fault Forecasting**: Fault forecasting technique estimates the future incidence, consequences and impact of faults. Faults and failures can be forecasted by modeling the wireless network. Simulation or analytical modeling of wireless networks help in fault estimation.

**2.5 Modeling Techniques**

Modeling is defined as the process of creating a representation of a real or abstract object with an aim to predict behavior. Fault forecasting method uses modeling techniques to estimate the working of the process and hence predicts the outcomes. This work compares three different techniques of modeling wireless networks: Analytical, Simulation and Neural Network. Extensive research has been done in the field of analytical and simulation modeling of wireless networks, but little has been done so far in the area of neural network modeling. This work assesses the NN modeling technique for wireless networks in order to answer important research questions, and to find advantages and disadvantages of NN modeling over simulation modeling.

**2.5.1 Analytical Modeling**

Analytical modeling involves the use of mathematical and statistical methods in the form of equations to simulate the process in order to predict results. Wireless networks can be modeled using analytical method to find ARMS attributes, unless the networks are too complex. These ARMS attributes can be compared with the results of simulation and NN modeling. Analytical modeling is more tractable for simpler networks but analytical methods become more difficult as a network grows as closed form solutions are difficult, if not impossible, to ascertain. For the purpose of analytic determination of wireless network’s ARMS, simple failure and repair distributions are required, which are unrealistic. However, analytical methods can be used to validate simulation models. In other words, analytical modeling has limited utility and it does not support distributions with more than one degree of freedom such as lognormal and weibull distributions, etc. Therefore, it cannot be used to model non-homogeneous process of complex systems. Olsson models mean time to failure (MTTF) as weibull distribution and mean time to
restore (MTR) as lognormal distribution for finding a reliable model for high voltage synchronous machines [26]. Over short timeframes, exponential failure models can used, even in nonhomogeneous Poisson process (NHPP) situations. However, the use of exponential repair distributions is unrealistic, but often used for analytical tractability.

In this work, the exponential distribution is chosen for MTTF due to its memoryless, Markov property and its relation to Poisson distribution. Memoryless property means that probability of occurrence of failures in the next interval is independent of failures in past intervals. Each component’s failure is independent of other component’s failure. In a homogeneous poisson process, failure inter-arrival times are independent and identically distributed according to exponential distribution \((e^{-\lambda t})\) with parameter \(\lambda\). Thus the relation of exponential distribution to Poisson distribution is stated as “if the time between failure is independent and has an exponential distribution with parameter \(\lambda\), then in a specified period of time, the number of failures follows poisson distribution of \(\lambda \ast \text{time period}\)” where \(\lambda\) represents failure rate, or the inverse of MTTF [23]. When \(\lambda\) is constant over the time period of interest, this is known as an HPP. However, if a longer period is considered for analysis, then failure rate may not remain constant and the process is assumed to be a non-homogeneous Poisson process. NHPP can be approximated by a discrete “staircase” of different HPP failure rates. This research uses the lognormal distribution to model restore time. Assumptions made in this work are listed below:

1. Reliability: Exponential Distribution for failure of components (HPP for one year)
2. Maintainability: Lognormal Distribution with standard deviation of unity for repairing components
3. All components of the same type have the same values of MTTF and MTR, and the time period is short enough that these parameters are constant.

**Derivation of Exponential Failures**

For a homogeneous process (HPP), reliability is given by:

\[
R = e^{-\lambda t}
\]

Where \(\lambda\) is the failure rate, is given by
\[ \lambda = 1 / MTTF \]

Therefore, reliability (chance of no failure in time t) in terms of mean time to failure (MTTF) is

\[ R = e^{-t/MTTF} \]

The probability of an item failing then is given by

\[ P(F) = 1 - e^{-t/MTTF} \]

If \( \lambda \) for one component is in years, the expected number of failures in one year = \( 1/\lambda \) while for N components, expected failures is equal to N * \( 1/\lambda \). Table 1 gives the range of MTTF values from the literature [19].

<table>
<thead>
<tr>
<th>Components</th>
<th>MTTF (LOW)</th>
<th>MTTF (NOMINAL)</th>
<th>MTTF (HIGH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Mobile Switching Center</td>
<td>5</td>
<td>7.5</td>
<td>10</td>
</tr>
<tr>
<td>Base Station Controller</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>MSC to BSC links</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Base Station</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>BSC to BS links</td>
<td>1</td>
<td>3</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 2 shows the expected failure numbers of all the components in a WIB using the nominal values of MTTF from Table 1. The expected failure in a WIB is given by:

\[ \text{Expected Component Failures per year} = \frac{\text{Number of Components}}{\text{Mean Time to Failure (MTTF)}} \]

For example, in a WIB, there are 50 base stations, so expected number of failures for MTTF of 2 years is 50/2 i.e. 25.
Table 2: Expected Component Failures for Nominal Components

<table>
<thead>
<tr>
<th>Component</th>
<th>Number of Components (One WIB)</th>
<th>Expected Failures (One year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Station (BS)</td>
<td>50</td>
<td>25</td>
</tr>
<tr>
<td>Base Station Controller</td>
<td>10</td>
<td>2.5</td>
</tr>
<tr>
<td>Mobile Switching Center</td>
<td>1</td>
<td>0.13</td>
</tr>
<tr>
<td>HLR/VLR</td>
<td>1</td>
<td>0.33</td>
</tr>
<tr>
<td>BS-BSC links</td>
<td>10</td>
<td>3.33</td>
</tr>
<tr>
<td>BSC-MSC links</td>
<td>5</td>
<td>1.25</td>
</tr>
</tbody>
</table>

Derivation of Expected Restoral Times

As mentioned earlier, in this research, repair time follows the lognormal distribution with two degrees of freedom (MTR and standard deviation S.D). Table 3 gives a range of restoral times for MTR values from the literature [27].

From the literature, analytical equations for lognormal distributions are given as follows:

Expected value of restore time = Mean of lognormal distribution

\[ \text{Expected value} = \log(\text{MTR}) - \log((\text{SD} \times \text{SD}) / (\text{MTR} \times \text{MTR}) + 1)/2 \]

Standard deviation = \( \sqrt{\log(\text{SD} \times \text{SD})/(\text{MTR} \times \text{MTR}) + 1}) \)

Table 3: Range of Wireless Components MTR in Hours

<table>
<thead>
<tr>
<th>Components</th>
<th>MTR (Low)</th>
<th>MTR (Nominal)</th>
<th>MTR (High)</th>
<th>Standard Deviation(hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>0.17</td>
<td>0.15</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Mobile Switching Center</td>
<td>0.17</td>
<td>0.15</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Base Station Controller</td>
<td>1</td>
<td>1.5</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>MSC to BSC links</td>
<td>1</td>
<td>4</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Base Station</td>
<td>1</td>
<td>1.5</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 3: Range of Wireless Components MTR in Hours (Contd)

| BSC to BS links | 1 | 4 | 8 | 1 |

2.5.2 Simulation Modeling
As analytical method often leads to complex equations or no closed form expressions, simulation offers an alternative. This research uses a discrete-time event simulation written in VC++. It simulates WIB behavior for one year. The inputs are MTTF, MTR and the outputs are availability, survivability and FCC-reportable outages. The analytical expectations are used to verify the simulation. Simulation results are then used to train and verify the ARMS neural networks model. The simulation method is explained further in Chapter 5 on Simulation.

2.5.3 Neural Network Modeling
As mentioned earlier, neural networks have been used extensively for location prediction and resource management in wireless environment. This research uses NN to assess wireless networks ARMS. Given reliability and maintainability, survivability and availability are calculated. NeuroSolution is used for modeling neural networks as explained in detail in Chapter 6 on Neural Networks.
Chapter 3

Literature Review

This chapter reviews the applicable wireless network and neural network literature.

3.1 Literature Survey on Wireless Networks

Here, dependability, probability distributions, and previous dependability simulation literature is reviewed.

3.1.1 Dependability - Availability, Reliability, Maintainability, And Survivability (ARMS)

Reliability is defined as the ability of a network to maintain a level of performance under given conditions for a specified period. With the tremendous growth of voice and data networks all over the world, it has become imperative for vendors, carriers and other service providers to provide ubiquitous, cheap, fast, secure and more dependable networks. As a result, pat research has emphasized reliability. Snow explains three important factors, which makes reliability tracking of complex and diverse networks challenging - unforeseen human and technical faults, rapid evolution of networks and carrier intersection of diverse networks, and ever-increasing competition [28]. He focuses on desirable network attributes and large-scale outages of voice and data networks. Deeter and Smith deal with network reliability from the cost perspective [29]. They design a minimum cost, reliable network given the network topology and sets of nodes and links. They also identify the network design problem as an NP Hard problem and suggest the Genetic Algorithm (GA) approach for solving such problems. They also provided a new approach for designing reliable networks by adding speed and volume factors along with economic considerations. Flores, Cegla, and Caceres proposed parallel asynchronous versions of promising algorithms for designing an optimal telecommunication network subject to cost and performance constraints. The other factors considered are minimum delays, maximum throughput, capacity, and the minimum number of links [30].
Communications and data networks are becoming increasingly important. Survivability is defined as the ability of a network to perform a specified function even in the case of failures or in the presence of attacks or accidents. One way to express this is by percentage of users able to use service. In a highly competitive telecommunications environment, carriers focus on building more survivable networks and therefore emphasize the use of survivability metrics in order to measure the performance of networks. Snow describes the pros and cons of a survivable metric developed by Committee T1 Telecommunications, an American National Standards Institute (ANSI) standards body [4]. He illustrated four elements of any outage – arrival time, duration, the number of subscribers impacted and the type of service affected by an outage. Hence, based on the above parameters, a generalized outage index metric was developed in 1990’s by Committee T1:

\[ I(O) = W_{Si} W_{Di} W_{Mi} \]

Where \( j = 1, \ldots, N \) are the services impacted by the outage, \( W_s = \) service weight, \( W_D = \) Duration Weight, and \( W_M = \) Magnitude Weight. In addition, the magnitude weight is multiplied by a Time Factor, where \( TF = 1.0 \) for daytime, \( TF = 0.3 \) for evening, \( TF = 0.2 \) for weekends, and \( TF = 0.1 \) for late night. The FCC influenced the survivability threshold in 1992. Any outage affecting at least 30,000 users for duration of at least 30 minutes was termed as an FCC-Reportable outage event [4]. Snow also explains two metrics to measure FCC reportable outages: Lost Line Hours and Prime Lost Line hours [5]. Later, Snow and Agarwal highlighted the drawbacks of the AND threshold and advocated the concept of PRODUCT threshold, where the product of outage size and duration is a constant. The AND threshold masks considerable communication loss and the FCC now supports some aspects of a PRODUCT threshold [31]. Snow and Thayer discuss outages with respect to signaling, transmission and power systems and examine the importance of fault-tolerant designs [32]. Moitra and Konda propose simulation modeling to track the survivability of wireless networks [33]. Zolfaghari and Kaudel describe outage in a network from a user’s perspective, focuses on outage categories and user expectations [3]. They coined the outage triple term: Unservability (U), Duration (D) and Weight (W) to describe an outage. Unservability is defined in terms of a unit of usage or the
percentage. The duration defines the time during which the unservability conditions exist in a network. The weight includes the context of geographic area, population, customer traffic patterns, in which the unservability exceeds a given threshold. In addition, outage categories are classified as catastrophic, major and minor. They posit two basic approaches to survivability analysis – probability and conditional. The probability approach seeks to find the probability of network failures, rates of repair and restoral to calculate various probabilistic measures of network availability or unservability, whereas the conditional approach is the measure of a network given failure events. Moreover, they propose two network survivability models: Random Occurrence of failure (ROF) and Given Occurrence of Failure (GOF) [3].

Knight, Strunk, and Sullivan bring out the importance of the term “survivability” with respect to dependability [22]. They believe that the terms availability and reliability are not enough to portray dependability since they do not address the needs of critical information systems, i.e. they do not include the notion of degraded service as an explicit requirement. They present a detailed summary of the significance “survivability”, especially in the sphere of critical information systems such as banking, financial services, and rail freight transportation.

### 3.1.2 Failure and Restoral Distributions
Olsson investigates the use of lognormal distribution for MTR and weibull distribution for MTTF. He states that repair time of all motors fits the lognormal distribution. Lognormal and weibull distributions fit MTR and MTTF nicely but due to the complexity of analytical equations, researchers sometimes make use of a homogeneous arrival process like exponential distribution, as it is easy for analysis. Upadhya and Srinivasan use lognormal distribution for logistic time delays and they state that either exponential or lognormal distributions can be used for MTR [34]. Electronic components consist of both the hardware and software. Lui calls such components as X-Ware components [21]. It is difficult to find the failure and restoral distributions for X-Ware components.
Selection of a distribution depends on the shape of the histogram (skewed/ symmetric/ peaked), and the plausible bounds (physical/ biological constraints). In order to fit a distribution for mean time to restore for MSC, data was collected for wire-line switches from the FCC’s ARMIS database and analyzed. Because of the skewed nature of the restoral data and the long tail associated with it, a lognormal distribution is used in this research. The selection of a lognormal distribution is also verified by using BESTFIT software that provides ranked distributions for MSC MTR. The choice of a lognormal distribution is also validated by chi-square test.

3.1.3 Survivability and Simulation
Fisher proposes simulation technology for measuring survivability of large scale networked systems. He also highlights strengths and limitations of a simulation approach [35]. This research uses simulation to measure survivability and various other attributes of a single wireless infrastructure building block as the first step in ARMS analysis.

3.1.4 Dependability Issues of Wireless Networks
Snow, Etal explain the distinction between the terms: Reliability, Availability and Survivability [18]. They describe the complete wireless infrastructure and its components and consider three major factors affecting dependability of wireless networks: MTTF MTR and the number of customers served by each in a WIB. Performance can be improved either by increasing MTTF or by lowering MTR. This work finds a relationship between reliability and maintainability to make the network more dependable. They illustrate ways to improve the reliability of various components and of the network as a whole through architectural changes such as sonnet ring, overlay network, multimode devices and end-to-end reliability.

As outage data for wireless networks is not publicly available, empirical analysis is difficult and hence in their next work, they posit various other modeling techniques to measure reliability and availability of wireless networks using analytical and Simulation approaches [19]. They also discuss reliability and survivability attributes and discusses how it can be applied to wireless networks. The differences in RS issues of a wire-line
network and a wireless network are discussed. In addition to simulation, they define nominal values for both MTTF and MTR, which have also been used in this research. They explain availability as the network’s ability to perform its functions at any given instant of time under certain conditions and have categorized it into two subparts: network availability and average-component availability. Network availability is defined as the percentage of time a user is able to access the network services, whereas component availability deals with the analysis of MTTF (how often a component fails) and MTR (how long it takes to repair). However, this work handles availability differently. Here it means either the network is totally up or down i.e., one WIB is not available if either an MSC or an HLR/VLR database is down.

Snow, et al focus on increasing the number of users, reducing call blocking, improving mobility management techniques and optimizing the performance of individual links [20]. They provide analytical expressions for effective line hours lost (ELHL) in a WIB. System availability was calculated as ELHL/Total line hour loss. Varshney and Malloy propose a novel, multilevel fault-tolerant design for the emerging wireless networks with an emphasis on availability of resources, channel allocation, dependability of wireless components and links [36]. Multilevel fault-tolerance is achieved by adding redundancy at the component, link, and block and interconnection levels. They advocate modular and scalable approach of Adaptable Building Blocks (ABB) wherein the size, number of blocks, number of components and links or the number of users can be varied. Simulation results show that increased mobility can be compensated for by developing multi-level redundancy and the performance of a wireless link is not critical in the overall availability as long as the link availability remains above a certain threshold. Malloy uses both analytical and simulation modeling of wireless networks to assess reliability, availability and survivability [27]. She analyses various network topologies: ring, star, SONET, and redundancy at item level, block level and network level. She uses analytical results to verify the simulation model. This study also uses analytical results for verification of a simulation model.
Charnsripinyo and Tipper propose an optimization model for the design of a survivable wireless access network [37]. They study the essential characteristics of a survivable wireless network. They explain the network tree topology between BS, BSC and MSC, and consider this topology weak because of the presence of only a single link between the components. Therefore, they introduce a new two-phase network design model. The first phase deals with minimizing the cost of a wireless network design and the second phase deals with making the low cost designed wireless network more survivable. The first phase is generally formulated by a mixed-integer-programming (MIP) model and solved by the branch and bound technique. They also formulate survivability strategies at the access layer radio level (where the primary concern is wireless links), at the access layer link level, transport layer (where the primary concern is component/link failure) and at the intelligent layer (where the primary concern is database HLR/VLR). Tipper and Charnsripinyo investigate the designing of minimum-cost, effective wireless network [38]. They compare different network topologies – Tree, Self-Healing and mesh in terms of cost and percentage redundancy. Tipper advocates the MIP model, which determines the network topology, dimensions of links, and optimal routes given the traffic demand and the location of base stations and MSC. This model also determines the number of base stations needed and their location in the network. Tipper and Dahlberg investigate two important survivability issues in a PCS network: User mobility and wireless channel environment [39]. A multi-layer framework for the study of survivability is proposed along with the metrics to quantify the network survivability at each layer. Strategies suggested to increase PCS network reliability are increasing component and system reliability, more efficient network design and capacity allocation, and better traffic management and restoration. Tipper and Ramaswamy study different ways of improving wireless network dependability especially in mobile commerce applications such as mobile financial applications, product location and shopping, mobile auction etc [40].

Previous work by Snow, Varshney and Malloy consider fixed size WIB. However, this work by Tipper and Ramaswamy examine the impact of the following flexibilities in the WIB architecture on dependability
• Size and number of building blocks
• Number of levels in a building block
• Number of different types of component
• Number of components of a certain type in a given level
• Size of different components in terms of number of customers supported.

Tipper discusses the effect of failures in PCS networks and survivability issues in PCS networks with emphasis on user mobility and wireless channel environment [41]. He proposes a survivable framework, which makes network failure imperceptible to the user by providing service continuity and minimizing network congestion.

Chen, Garg and Trivedi analyze the quantitative ways of measuring survivability. Survivability is equivalent to network failure duration plus failure impact on the network and it can be measured in excess packet loss [42]. They define call-blocking probability and call-dropping probability as metrics for voice networks, whereas the number of disconnected nodes and connection survivability are defined as metrics for data networks. Hiltunene and Schlichting primarily focus on building survivable networks by implementing redundancy and adaptation [43]. Redundancy is understood as inclusion of extra resources to reduce the chance of an incident affecting or disrupting the network, whereas adaptation is the ability of software to modify its behavior at runtime so that an application can also withstand adverse conditions. Clouquer and Grover compare the ring and mesh network topologies for better service path availability [44]. Their study concludes that mesh structure has significantly higher average service path availability.

### 3.1.5 Cost Management in Wireless Networks

Giles, Zander, Zetterberg, Karlsson, Sweden, Lind, Malmgren, Nilsoon discuss the cost analysis of wireless network to find key cost factors [45]. Their work examines several infrastructure cost factors such as electronic equipment cost, wiring, deployment of human and electronic resources, networking connections, etc. They advocate more cost efficient designs to combat the cost issues and lead a way for future research in the direction of cost and performance optimization. Johansson, Marker Dahl, and Zetterberg
study how high bit rate services can be provided without the addition of complex user terminals or deployment of a full coverage network with a very large number of traditional cellular base stations [46]. They advocate insertion of more intermediate access points, the relay that connects the end-user terminals to a wireless or fixed network. Cost structure of cellular systems from two perspectives of urban and rural areas is explained and the layered architecture for low cost infrastructure is described. Gabel uses software called Local Exchange Cost Optimization Model (LECOM) to study the effect of cellular services on the cost structure of a Public Switched Telephone Network (PSTN) [47]. Fente, Vicente and Cantera emphasize on optimizing the cost of transmission infrastructure required for the connection of base stations to other network elements in order to design a low cost cellular network [48]. Even though there is a need for future research in finding the cost implications for dependable wireless network, this research does not consider cost.

3.2 Literature Survey on Neural Networks

Several papers have been written explaining the basic concepts of neural network and their application. Chatterjee and Laudato explain the concepts of NN and compare it with other statistical techniques such as maximum likelihood and multiple regressions [49]. NN handles non-linear functions efficiently. NN are most useful when massive quantities of very highly dimensional data need to be modeled, without good proper modeling alternatives. This paper describes two different learning approaches: back propagation algorithm and Genetic Algorithm. However, this research uses back propagation algorithm to train a NN for assessing wireless network dependability.

3.2.1 Verification and Validation of Neural Networks

Pullum, Marjorie, Darrah and Taylor focus on the creation of the methodologies for the verification and validation (V&V) of systems using Neural Networks. They also examined the importance of practitioner assistance or guidance sheets [50]. Verification and validation of NN is very important in critical applications used for military or safety operations. Traditional verification and validation techniques for NN do not give
satisfactory results, and hence V&V techniques must be designed for the models using NN systems. Another approach is to design an adaptive NN, which can modify and learn themselves during operations. NASA Independent Verification and Validation (IV&V) develops a new software assurance methodology especially for NN. Some of the IV&V or V&V techniques are formal methods, stability analysis, run-time monitoring, testing, visualization, failures modes and effects analysis (FMEA), risk analysis, automated neural network selection and neural network design verification. This methodology offers a benefit to government and industry users of neural network topology as it can be used more widely, verified and validated more completely, and used in more trusted and dependable systems. Taylor, Darrah and Moat discuss the V&V techniques designed for NASA projects such as autonomous mission control agents and adaptive flight controllers. IV&V are also applicable to nuclear engineering projects such as safety processors and reactor controllers where traditional software assurance methods fail [51].

3.2.2 Neural Networks Applications for Reliability Assessments

Ratana, Konak and Smith estimate all network terminal reliability. All terminal reliability means that each node (computers, routers, switches or terminals) in a communication network should be able to communicate to every other node in the network [6]. This is an NP hard problem i.e. computational effort increases exponentially with network size because of the exponential growth in states. The NN model discussed in this paper consists of three inputs: network topology, the link reliability (it can be either identical or varying) and an upper bound on all terminal network reliability to calculate the exact network reliability as the output. They compare the neural networks approach with Monte Carlo simulation methods for the estimation of all terminal reliability and finally conclude that neural networks provide better economical design over that indicated by simulation techniques [6]. Though, Monte Carlo Simulation gives good enough results for the estimation of all terminal reliability, it has to be repeated several times to ensure a good estimate. Thus, the simulation method involves significant computational effort for estimating network reliability, especially for highly reliable networks where failure rates are rare. Therefore, this paper recommends the use of NN for optimization for all
topologies considered and then exactly calculate the network reliability only on the best topology. The same approach can be used in the field of wireless networks.

Michael Lyu defines the features of a reliable software system [21]. He explains the advantages of NN in developing a general-purpose reliability growth model and in identifying change/fault-prone software modules early during the development cycle. Patra proposes the use of NN to predict the long-term MTTF, software reliability, PPM (parts per million) and software failures in order to fit a reliability growth model to the system. He also compares the NN results with the results obtained from the computer aided software reliability engineering (CASRE) tool [52]. The comparison is carried out for three different models – NHPP (non-homogeneous Poisson process), S-Shaped model, and Poisson/Binomial Models to see how different software reliability growth models vary in predictive accuracies. Hoffman develops a predictive NN model that delivers the best possible 24 – month projection of cruise missile reliability using existing data sources, collection methods and software [7].

3.2.3 Neural Networks Applications in Wireless Networks

Wireless dependability depends highly on the mobility of network users. If the network is able to predict the mobility of the subscriber in advance, then it can anticipate the resource use and can take precautionary measures if required. Capka and Boutaba present a neural network system, which captures the movement of network users in a wireless environment and then predicts the future behavior of these users [8]. Vijay Kumar has done extensive research in neural network applications in mobile networks. In mobile wireless systems, to maintain the quality of service (QOS) requirements (packet loss, jitter and delay) in a specified range, traffic should be maintained in a mobile unit for both the real-time and non real-time applications. An admission Control (AC) scheme is implemented to meet certain QOS requirements. Vijay presents a linear programming resource reduction (LP-RR) principle for admission control by maintaining QOS guarantees for existing applications in order to increase the percentage of real-time and non real-time applications [10]. Neural Networks (NN) is also used to solve linear
programming problems. The reason for using neural networks is based on the consideration that it can solve non-linear equations in few microseconds. Another work by Vijay uses NN to predict the location of a mobile agent depending on its history of moving patterns [11]. A Multi-layer NN model for mobile movement prediction is designed to predict the future movement of a mobile host. For training the NN, time series data regarding the movement of mobile hosts is provided to the NN, which then predicts the future movement of a mobile host. Wireless Networks suffer from frequent disconnections due to limited bandwidth. Vijay proposes a NN based connectivity management for mobile computing environment by maintaining the status information of mobile hosts at the base station [12]. The NN are trained with the status information to provide an intelligent decision for the connectivity management. In a mobile multicast group application, when a mobile host changes its access points then multicast routes must be updated. He also proposes a NN based multicast routing algorithm, which updates the multicast routes and constructs a reliable multicast tree that connects the participants of a multicast group [13]. However, NN has been extensively used in the field of wireless networks for location updation and management but hardly any study has been done for wireless network dependability.

3.2.4 Simulation Data to Train a Neural Network

Kong, Hadzer and Mashor use a NN to track moving objects such as aircraft [15]. A tracking system generates a tracking signal mixed with additive white noise. A neural filter is designed to remove white noise from radar signals by training a NN with simulation data. Fernandes and Lona also use simulation data to train a neural network for developing polymer resins. Experiment data could not be obtained for training because it involves a large number of time consuming and costly experiments [16]. Alifantis and Robinson emphasize using both computer simulation and artificial intelligence together to solve an NP hard problem for a shop-scheduling problem. They used the output of computer simulation to train the NN [17].
3.2.5 Neural Network Decision Tree
Quingshou, Rongfang and Weiping bring forward a new architecture, Adaptive Neural Networks Decision Tree (ANNDT). ANNDT is a combination of neural networks output applied to decision tree. Experiment indicates that this ANNDT-based face recognition method can synthetically use many Neural Networks modes and feature abstraction arithmetic. It not only has recognition rapidity, accuracy, tolerance and robustness, but also meets most of the demands for developing practical face recognition systems. Another, software application developed for generating decision tree out of NN is Treepan [53].
Chapter 4
Research Questions

4. Research Questions

In this work, we examine four research questions relating to a wireless network infrastructure serving 100,000 customers. The first question deals with survivability and availability under different reliability and maintainability growth/constancy/deterioration scenarios (RG/RC/RD/MG/MC/MD). This helps network administrators decide whether to make components more reliable (proactive) or to repair them faster (reactive) in order to enhance availability and survivability. The question also deals with identifying which single component type has the most positive impact on survivability and availability. The second question studies the effect of traffic profiles on wireless dependability. The third deals with how often an FCC outage severity threshold is exceeded. The fourth and the last research question address the utility of neural network models for large-scale distributed wireless systems. In other words, this research focuses on finding out the best combinations of reliability (MTTF) and maintainability (MTR) to get the best possible values for availability and survivability. A more detailed discussion of research questions is found below.

R1: Which strategy should be followed in order to make wireless networks more dependable – Reactive (fast restoral) or Proactive (fault-tolerant provisioning)?

This research focuses on finding out whether components should be made more reliable or more easily repairable by employing a better and faster staff with spare components in stock. To address this question, nine different scenarios of reliability growth/constancy/deterioration and maintainability growth/constancy/deterioration, shown in Figure 6, are investigated.
To study the behavior of a single WIB, nine different scenarios are considered (RG/RC/RD and MG/MC/MD) i.e. change either reliability or maintainability and analyze the effect of changes in availability and survivability when:

- RM improves
- RM degrades
- R improves but M degrades
- R degrades but M improves

**R2: How often is new FCC outage reporting exceeded?**

The FCC mandates wireless carriers to report outages 30 minutes or longer that exceed 15,000 lost subscriber hours. Therefore, this research determines the number of FCC-Reportable outage events per year per 100,000 subscribers.

**R3: How well does an ARMS NN model work for wireless networks? What are the advantages and disadvantages of NN over simulation modeling?**

- Until now, wireless network have been actively modeled by simulations to measure dependability. A new approach of neural network modeling is examined in this research to further investigate ARMS.
In addition, advantages and disadvantages of NN over simulation are also investigated, such as computational savings and insights gleaned that are difficult to obtain by simulation.

R4: How perceptions of dependability vary with traffic?
Use of wireless network varies with time of the day. As we all know, many cellular calls after 9:00 p.m. are free (price is flat rate rather than usage), so the number of personal calls increases in the night. Similarly, during lunchtime, people make more calls. Therefore, we can conclude that traffic of calls vary with the time of the day. Traffic profile for weekdays is different from that of the weekend. This research analyzes wireless network dependability with an ANSI traffic profiles.

- **No Time Factors:** It implies that every subscriber in the networks is using the system all the time. It represents the potential customers affected, regardless of whether they are attempting to use the service when an outage occurs.

- **ANSI Time Factors:** It implies effective use of wireless network i.e. actual number of subscribers using the network at any given time. ANSI time factors are given below in Table 4. The number of potentially affected customers is multiplied by the time factor.

<table>
<thead>
<tr>
<th>Time Factors</th>
<th>Day (8:00am – 4:59pm) Mon. – Fri.</th>
<th>Evening (5:00pm – 10:59pm) Mon. – Fri.</th>
<th>Night (11:00pm – 7:59am)</th>
<th>Weekend (8:00am – 10:59pm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day (8:00am – 4:59pm) Mon. – Fri.</td>
<td>1</td>
<td>0.3</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Evening (5:00pm – 10:59pm) Mon. – Fri.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Night (11:00pm – 7:59am)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekend (8:00am – 10:59pm)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Chapter 5
Simulation

5. Simulation
Analytical expressions for ARMS quickly become cumbersome as wireless network size increases. Complex equations are difficult to derive and solve, therefore this research uses a simulation written in VC++ to model wireless network dependability. Since the live data is not available for wireless carriers, code in C++ was written by Raymond Lui under the supervision of Dr. Snow to model a single WIB using discrete time event simulation. Simulation version 1 was later modified by Andrew Chen for formatting output and simulation verification. Chen and Rastogi verified the Version simulation 2. Later, in simulation Version 3, two additional output fields, (availability and number of FCC-Reportable outages), were added by Rastogi so that the simulation output could be directly used to later train a neural network. The random numbers generated during simulation are checked for component reliability every five minutes. If a component fails (exponential distribution), the program calculates the repair time from a Log Normal distribution. Reliability of a component is checked by Exponential distribution ($e^{-\lambda t}$). If number falls below $(1-e^{-\lambda t})$ then the component is considered as failed. The program will not check the component again until the repair time is passed and the component is back to work. The network was checked every 5 minutes, selected because of the chance of more than one failure was five to six orders of magnitude smaller than the chance of zero and one failure.

The program also calculates the total customers affected by an outage. If a lower component in the wireless architecture hierarchy fails, the program will check if the component higher in the hierarchy has also failed (overlapping failures). If failure occurs higher in the hierarchy, then customers affected will not be double counted. The program is written in Microsoft foundation class (MFC) and runs in any win32 environment. The program generates a text file that can be directly imported to Excel.
5.1 Components in One Wireless Infrastructure Building-Block

There are six main components in a single WIB serving the 100,000 customers, as shown in Table 5.

<table>
<thead>
<tr>
<th>Components</th>
<th>Quantity in Each WIB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>1</td>
</tr>
<tr>
<td>Mobile Switching Center</td>
<td>1</td>
</tr>
<tr>
<td>Base Station Controller</td>
<td>5</td>
</tr>
<tr>
<td>MSC to BSC Links</td>
<td>5</td>
</tr>
<tr>
<td>Base Station</td>
<td>50</td>
</tr>
<tr>
<td>BSC to BS Links</td>
<td>50</td>
</tr>
</tbody>
</table>

Customers affected by each component in program are summarized in Table 6.

<table>
<thead>
<tr>
<th>Components</th>
<th>Customers Affected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>100,000</td>
</tr>
<tr>
<td>Mobile Switching Center</td>
<td>100,000</td>
</tr>
<tr>
<td>Base Station Controller</td>
<td>20,000</td>
</tr>
<tr>
<td>Links between MSC and BSC</td>
<td>20,000</td>
</tr>
<tr>
<td>Base Station</td>
<td>2,000</td>
</tr>
<tr>
<td>Links between BSC and BS</td>
<td>2,000</td>
</tr>
</tbody>
</table>

5.2 Simulation Input/Output

The simulation program for one Wireless Infrastructure Building Block (WIB) is coded in VC++. Figure 7 shows the simulation block diagram indicating simulation inputs and outputs.
5.2.1 Independent Variables

Independent variables for this simulation are listed below:

- MTTF of BS
- MTTF of BSC
- MTTF of MSC
- MTTF of BS-BSC link
- MTTF of MSC-BSC link
- MTR of BS
- MTR of BSC
- MTR of MSC
- MTR of BS-BSC link
- MTR of BSC-MSC link
- Standard deviation for MTR for each component
- Simulation period
- Time factors

5.2.2 Dependent Variables

Dependent variables are listed below.

- Survivability
• Availability
• Number of BS failing, and duration of each outage
• Number of BSC failing, and duration of each outage
• Number of MSC failing, and duration of each outage
• Number of BS-BSC link failing, and duration of each outage
• Number of BSC-MSC link failing, and duration of each outage
• Number of FCC-Reportable outages
• Component failure profile for one year

5.3 Simulation Assumption
The following assumptions have been made in the simulation regarding components
1) Times to failure from an exponential distribution and a homogeneous Poisson Process for simulation period of one year
2) Times to restore from lognormal distributions
3) Standard deviation for the lognormal repair distributions are “1”
4) MTTF and MTR of like components the same
5) Impact of other WIB’s on the chosen WIB is not considered
6) All MTTF and MTR are invariant for one year.
7) Architecture of WIB is fixed in terms of configuration, components and subscribers.

5.4 Simulation Pseudo Chart
Simulation process is divided into parts. The first part as depicted in figure 8 deals with coding and programming logic of the simulation whereas the second part as shown in figure 9 involves the validation and verification of the code.

5.4.1 Simulation Modeling
A simulation is written to determine survivability, availability and FCC-reportable outages from the two inputs: reliability and maintainability. Figure 8 shows the pseudo chart for simulation.
Select Reliability and Maintainability by choosing the values of MTTF and MTR for each component

Check for each component failures every 5 minutes

If the component has failed,
a) Calculate customers impacted
b) Calculate repair time
c) component is not checked again until repair time is over

To find the the total number of customers impacted, check for the component above the failed component
a) if the above component is failed, then customers impacted below component are not added to total customers impacted
b) if above component is not failed, then add the subscribers of the failed component to total customers impacted

Calculate Outputs:
Availability in minutes (MSC or DB is down)
Survivability in Prime Lost Line Hours (PLLH)
FCC-Reportable Outages

Figure 8: Pseudo Chart for Simulation Modeling

5.4.2 Verification and Validation of the Model

Simulation output was validated by chi-square test and Best Fit as shown in Figure 9. The two parts of the validating process for this program are
1. Validating the numbers of failure (down number) for each components
2. Validating restore time of each component
5.4.3 Verification of Component Failures

Chi-square is used as the principal verification technique to validate the number of failures. Analytical modeling gives the expected number of failures, which is then compared with the simulation down numbers. The hypothesis chosen is “Predicted Value (produced by simulation) should be equal to the expected number of failure”.

The simulation was run for each component with different values of reliability and maintainability. The chi-square test is then implemented to either reject or accept the hypothesis. If chi-square value of the failures in one year is less than the chi-square value at the significance of 95% with (n-1) degree of freedom where n is the number of times that the program is run, then the hypothesis is accepted else it is rejected. The actual chi-square result is calculated and is shown together with expected chi-square value at the end of the validate output (Chapter 9 on Results). The same test is repeated for all components 50 times.

The result supports the hypothesis that the down numbers given by the simulation supports the Number of Components/MTTF relation. Therefore, it can be successfully concluded that the simulation was validated for down numbers and it provides convincing results.
5.4.4 Verification of Restore Time
Simulation based on previous research made an assumption of lognormal distribution for restore time. Best fit is used to validate this assumption of using a lognormal distribution having two degrees of freedom. Simulation was run 20 to 100 times and restore time was calculated for each failed component. Best fit was then used to fit a distribution for calculated restore time and it was found that lognormal distribution fits the restore time with a very high degree of confidence. Data was also collected from ARMIS in an FCC database for local switch outages with 20,000 to 100,000 lines to determine an empirically based restore time distribution. Local switches in the wireline network are very similar to MSC switches in a wireless infrastructure. This was verified for years 1998, 1999, 2000, 2002 and 2003. Year 2001 was eliminated because September 11 attack caused big failures of some big switches. The reason for choosing higher capacity switches is that small switches normally have very long restore time because of their low priorities, which seems not true for the MSC in a mobile system. The results show that years 2000 and 2002 of five years fit in a lognormal distribution very well whereas the other three years fit in the normal distribution well.

The Chi-square test was also used for validating MTR. Actual restore time was calculated for each failing component. Expected value of restore time can be found out by finding the mean of all the restore time. Hypothesis chosen is “Actual restore time is equal to expected restore time.” The Chi-square test for deviation from the expected values was also carried out. The Ch-square tests were satisfactory for the range of means and the standard deviation used in this research. The conclusion of the restore time distribution is that it complies with lognormal distribution, which validates MTR.

5.5 Strength and Limitations of Simulation
Simulation offers advantages over both analytical and NN modeling, which are listed below.

1) Simulation logic accounts for overlapping or joint failures while calculating the number of subscribers affected.
2) An estimation of FCC reportable outages can be determined which is of great importance to wireless carriers in the new FCC regulation.

3) Reliability growth/deterioration processes can be simulated by running the simulation year by year with different growth/deterioration values for each run.

4) Simulation behavior is immaterial to the size of the network. It is more flexible and readily adapts to the size of the network if it is changed. Simulation handles and accommodates complex distributions like lognormal and hence depicts more realistic situations as compared to exponential repair which is often used because of mathematical tractability.

Even though simulation has been extensively used for both software and hardware reliability growth modeling, there is one major drawback associated with simulation modeling. As compared to NN modeling, simulation modeling takes more time to generate the desired output. Once trained, NN output is almost instantaneous.
Chapter 6

Neural Networks

6. Neural Networks

In the field of wireless networks, a neural network (NN) has generally been used for location and resource management for prediction of mobile mobility. This research studies the use of NN in the field of reliability and discusses how a NN can be combined with computer simulation to give a new model for wireless networks. Before exploring the answers for the above questions, the basic concepts of NN are explained below.

6.1 Concept of Artificial Intelligence

All software either follow knowledge based systems or computational intelligence techniques. Knowledge based systems imply symbolic representations of knowledge in words and symbols. These symbols are combined to form rules, facts, relations or other forms of knowledge representation. Because of explicit representation of knowledge, it is readily understood and read by human beings. These symbolic techniques contrast with numerical techniques such as genetic algorithms and neural networks. In numerical techniques, also called as computational intelligence or soft computing the knowledge, is represented by numbers, which are later adjusted as the system improves its accuracy. A neural network is one of the categories under computational intelligence as shown in figure 10 [57].

Figure 10: Artificial Intelligence [57]
6.1.1 Analogy with Brain

The human brain contains around 10 billion neurons. A neuron only fires if its input signal exceeds a certain amount (the threshold) in a short time period. A neuron has a cell body (soma, where the cell nucleus is located), a branching input structure (the dendrites) and a branching output structure (the axon). Each of these has perhaps 10,000 connections on an average to other neurons, both incoming (via dendrites) and outgoing (via axons) [63].

6.1.2 Computer and Neural Network

A computer can perform functions such as mathematical operations more quickly and precisely whereas neural network (NN) can recognize faces and complex images in a more precise, efficient and faster manner than a computer. The reason behind this is that the computer works alone with one processor whereas NN works with billions of neurons with a high degree of interconnection [63].

6.2 Definition of Neural Network

A neural network consists of processing neurons, also called as nodes or perceptron and information flow channels between neurons. Each node in a neural network can have more than one input and each of it has a weight associated to it. The node performs a simple computation on its input values, which are single integers or real numbers, to produce a single numerical value as its output. This output can act as an input to any other node in the next layer or it can be a part of the output from the network as a whole. Figure 11 illustrates the schematic representation of a neuron whereas Figure 12 illustrates the complete neural network [63].

6.2.1 Schematic Representation of a Neuron

Each neuron has weighted inputs from other neurons and maintains a particular threshold value. The input signals form a weighted sum and if the activation level exceeds the threshold the neuron “fires”. Each hidden or output neuron has weighted input connections from each of the units in the preceding layer. The unit performs a weighted
sum of its inputs, and subtracts its threshold value, to give its activation level. Activation level is passed through an activation function to determine output.

![Figure 11: Schematic Representation of a Neuron [63]](image1)

![Figure 12: Schematic Representation of the Complete Neural Network [63]](image2)

In short, the neural network is a non-linear model wherein both the model inputs and outputs are numeric. Figure 13 shows a general diagram for NN black box.

![Figure 13: NN Black Box](image3)
6.2.2 Network Topology

There are two types of neural networks regarding dataflow and training: Rummelhart-type and Hopfield networks. The Rummelhart Network deals with data flowing in one direction whereas Hopfield Network has multidimensional data flow. The Hopfield Networks do not show neuron layers. All neurons are linked between themselves. These networks are typically used for studies about the optimization of connections. This kind of neural network can be trained with or without supervision; the purpose of its training is the minimization of its energy, leading to independent behavior. Other networks in NN are Hamming Network, Adaptive Resonance Theory (ART), Kohonen self-organizing networks and radial basis function networks. This research uses Rummelhart network topology where data flows from inner (input) layers to outer (output) layers.

In a single layer feed forward perceptron, the neuron is organized in layers such that each neuron is totally connected to the neurons in the layers above and below, but not to the neurons in the same layer. These networks are also called feed forward networks where the direction of data flow is always “forward,” i.e., toward the output. A Multiple level Perceptron (MLP) operates by feeding data forward along the interconnections from the input layer, through the hidden layer, to the output layer. With the exception of the nodes in the input layer, the inputs to a node are the outputs from each node in the previous layer. At each node apart from those in the input layer, the data are weighed, summed, added to the bias, and then passed through the transfer function. In this work, a MLP is used to model wireless networks. In recurrent feedback model, there is a feedback output to the input. Time lag feed forward is very similar to multiple layer feed forward except the insertion of memory registers to add time lags to the inputs.

6.2.3 Learning

A Neural Network can be trained by two forms of learning: supervised and unsupervised learning. Supervised learning needs an external teacher, which directs each output unit towards a desired response for an input signal. It aims at minimizing the difference between the actual and the desired output by adjusting the weights with this calculated
difference. Most of the NN application use least square method (LSM) for error convergence in supervised learning. This research also uses supervised learning with low mean square error (MSE) for training a NN. In other terms, Supervised-learning is off-line learning where the learning and operation phases are different. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning. Unsupervised learning does not require an external teacher and is based only upon local information. It is also referred to as self-organization i.e. it self-organizes data presented to the network and detects their emergent collective properties. It falls under the category of online learning where a NN learns and operates at the same time. Paradigms of unsupervised learning include Hebbian learning and competitive learning.

6.2.4 Transfer Function
Transfer function falls under three categories: linear (ramp), threshold, tanh and sigmoid. For linear units, the output activity is proportional to the total weighted output. For threshold units, the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value. For sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neuron than do linear or threshold units, but all three must be considered rough approximations. This research uses tanh function for training NN.

6.2.5 Learning Algorithm
The backpropagation algorithm consists of two phases: the forward phase where the activations are propagated from the input to the output layer, and the backward phase, where the error between the observed actual and the requested nominal value in the output layer is propagated backwards in order to modify the weights and bias values. In backward propagation, the neuron in the output layer calculates an error between its actual value from the forward phase and the expected nominal target value. The calculated error is propagated backward to the previous layer. The neuron in the hidden layer also calculates an error that is propagated backwards again to its previous layer. To
minimize the error, the weights of the projective edges of neuron and the bias values in the receptive layer are changed.

6.2.6 Training

During the training step, real data (input and output) are continuously presented to the network. One complete set of input and output data is called epoch whereas one individual set of input and output data is called an exemplar. It periodically compares real data with results calculated by the neuron network. The difference between real and calculated results (i.e., the error) is processed through a relatively complicated mathematical procedure, which adjusts the value of the synapse weights in order to minimize this error as explained in figure 14. This is an important feature of the neural networks; their knowledge is stored in their synapse weights. The duration of the training step must not be excessively short to allow the network to fully extract the relationships between variables. Neither can this step be very long; in this case, the neural network will simply memorize the real data delivered to it, forgetting the relationships between them. So, it is advisable to break away approximately 25% of the available data in a subset and use only the remaining 75% for training the neural network. The 15% of training data can be assigned for cross validation for verification of NN. The training step must be interrupted periodically and the network tested using the 25% subset, checking the precision of the calculated results with real data. When the precision of the neural network stabilizes, it is time to consider the neural network as fully trained and it can be exposed to the test data (25%).

Figure 14: Training of NN
6.2.7 Verification of NN

Trained neural network can be verified by the following methods:

- **Cross validation**: Out of an epoch, 15% of the data is used for cross validation. Once the NN is trained with 60% of the data, cross validation is done wherein just the inputs are provided to NN and outputs are compared with desired values.

- **Learning Curve**: A learning curve is plotted between mean squared error (MSE) and training time (Epoch number) while training a NN. Depending upon the nature of the learning curve, following points can be inferred.
  1. Rising Learning Curve: Bad training
  2. Decreasing learning Curve: Good training
  3. Oscillating Learning Curve: Bad training

- **MSE and R^2**: As mentioned earlier, a Mean Squared Error is used for training the network. A low value of MSE indicates good training of NN. It represents the square of error between the actual and the desired output. Coefficient of regression can also be calculated for verifying NN. A higher value of the coefficient of regression implies a better training of NN.

6.3 Applications

A NN can be used to solve almost any problem, which has a historical data, and if there is a need to create a model for that data. Four major applications of neural network are function approximation, time series prediction, classification and data mining. Signal Analysis and processing, process control, robotics, data classification, pattern recognition, image analysis, speech analysis, stock market forecasting, analysis for loan or credit solicitations and oriented marketing are some of the upfront areas where NN is being used highly. This research aims at finding the utility of NN in the field of wireless networks especially to assess ARMS attributes.

6.4 NeuroSolution

Several softwares like Stuttgart Neural network Simulator (SNNS), NeuroForecaster GENETICA, Perception etc. are available for Neural Network modeling. This work uses
NeuroSolution for Excel for NN modeling to evaluate the performance of wireless networks.

6.5 Pseudo -Chart for NN Modeling

Figure 15 shows the NN black box used in this research with thirteen inputs and nine outputs.

In NN modeling, the first step is the division of data into three parts: 65% of data for training, 15% for cross-validation and 20% for testing a NN. After division of simulation results, train data is fed to NN for the learning and training process. Once NN is trained, it is verified by cross validation. Testing of NN gives results about the availability, reliability, maintainability and survivability of wireless networks. Sensitivity analysis can be carried out to find out the sensitive independent variables to the dependent variables and then a decision tree can be created by using the software TREEPAN. The pseudo chart for NN modeling is shown in figure 16.
6.6 Strengths and Limitations

In Neural Network, there is no need to select the most important independent variable in dataset, as it automatically selects them. The synapses associated with irrelevant variables readily show negligible weight values. There is no need to propose a model as required in multiple regression, NN learns and adapts to the best model. NN is robust, immune to noise, makes it very useful for industrial applications. As compared to simulation, it is fast. There is a significant reduction in data analysis tasks/time. In addition, it adds some more insights such as decision trees, and sensitivity analysis. NN solves difficult process problems that cannot be solved quickly or accurately with conventional methods. Because of the following features, NN is gaining a considerable recognition in industries

- Learns from past experiences, improving results as time passes
- Predicts based on current situation
- Extracts rules for interactions in complex environments
- Offers solutions to problems that can not be described in words where standard algorithms and models fail
Chapter 7
Research Methodology

7. Research Methodology
This research follows a chronological order of steps, shown below:

- Analytical modeling
- Simulation modeling
- Verification of simulation model
- Neural Network modeling
- Verification of neural model
- Application of NN model to measure wireless network dependability
- Generation of a decision tree

Table 7 gives a list of tools used in executing the methodology.

<table>
<thead>
<tr>
<th>Tools</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>VC++</td>
<td>Simulation coding</td>
</tr>
<tr>
<td>Best Fit</td>
<td>Verification of simulation results</td>
</tr>
<tr>
<td>NeuroSolution</td>
<td>Generation and training of NN</td>
</tr>
<tr>
<td>Treepan</td>
<td>Generation of decision trees</td>
</tr>
<tr>
<td>MS Excel</td>
<td>NN executions</td>
</tr>
</tbody>
</table>

The first step in the methodology consists of constructing and verifying a discrete time event simulation model for the wireless system. Next, the simulation results are used to train and validate the neural network. Once trained, the neural network is used to investigate (1) a wide range of RG/RC/RD/MG/MC/MD and traffic scenarios, (2) the number of times the outage severity threshold is exceeded over time, and (3) perform
sensitivity analysis to determine the component type to make more reliable and maintainable, in order to maximize survivability and availability. In this work, RG/RD is modeled as a non-homogeneous Poisson process. Additionally MTR distribution is modeled as lognormal, with different means to approximate MG/MD.

A more detailed depiction of the methodology is seen in figure 19. The methodology is explained by the steps enumerated below.

**STEP 1:** Generating analytical results.
**STEP 2:** Creating a discrete-time event simulation
**STEP 3:** Verification of MTTF by chi-square and analytical results
**STEP 4:** Verification of MTR by chi-square and Best Fit.
**STEP 5:** Simulation runs to get data for training NN
**STEP 6:** Training NN by using NeuroSolution
**STEP 7:** Verification /Cross Validation of NN
**STEP 8:** Validation of NN by checking MSE values and simulation results
**STEP 9:** Use of sensitivity analysis to see how the dependability changes
**STEP 10:** Use of TREPAN to evolve decision tree for wireless network
**STEP 11:** Plotting of reliability and maintainability graphs

For NHPP component failure approximation, simulation or NN is run for each year for five years with 10% change (decrease or increase) per year in component reliability, as shown in figure 17.

![Figure 17: Reliability Growth/Consistency/Deterioration](image_url)
For maintainability approximation, MTR is changed each year by 10% for five years, as shown in figure 18. The standard deviation is kept constant as unity and mean is varied to change the maintainability.

Figure 18: Maintainability Growth/Consistency/Deterioration

STEP 12: Plot survivability and availability graphs
Reliability and maintainability are used to investigate survivability and availability. Nine different scenarios of RG/RC/RD and MG/MC/MD are studied.

- Plot survivability graph for RG with MG/MC/MD
- Plot survivability graph for RC with MG/MC/MD
- Plot survivability graph for RD with MG/MC/MD
- Plot availability graph for RG with MG/MC/MD
- Plot availability graph for RC with MG/MC/MD
- Plot availability graph for RD with MG/MC/MD

STEP 13: Plotting of FCC reportable outages

- Plot FCC reportable outages graph for RG with MG/MC/MD
- Plot FCC reportable outages graph for RC with MG/MC/MD
- Plot FCC reportable outages graph for RD with MG/MC/MD
Figure 19: Research Methodology
Chapter 8

Results and Findings

8.1 Simulation Results

As mentioned earlier in the chapter 5 on simulation, simulation results for a single run were verified by chi-square, analytical results and Bestfit. Next the simulation was modified for 50 repetitions for the same set of input MTTF and MTR values for the six components. The modified simulation results were again tested by chi-square.

8.1.1 Verification of Simulation

Chi-square tests were used to verify the simulation for MTTF and MTR. The expected values were compared to the simulation output for 50 runs. The verification results are summarized in the tables 8 and 9 below.

<table>
<thead>
<tr>
<th>Component</th>
<th>Chi-Square for MTTF</th>
<th>Chi-Square at 0.05 level significance</th>
<th>Hypothesis (MTTF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Station</td>
<td>60.72</td>
<td>66.34 (49 df)</td>
<td>Accept</td>
</tr>
<tr>
<td>Base Station Controller</td>
<td>42.50</td>
<td>66.34 (49 df)</td>
<td>Accept</td>
</tr>
<tr>
<td>BS-BSC Links</td>
<td>47.13</td>
<td>66.34 (49 df)</td>
<td>Accept</td>
</tr>
<tr>
<td>MSC</td>
<td>50.67</td>
<td>66.34 (49 df)</td>
<td>Accept</td>
</tr>
<tr>
<td>MSC-BSC Links</td>
<td>39.70</td>
<td>66.34 (49 df)</td>
<td>Accept</td>
</tr>
<tr>
<td>Database</td>
<td>37.67</td>
<td>66.34 (49 df)</td>
<td>Accept</td>
</tr>
</tbody>
</table>

Table 8: Chi-Square for MTTF

<table>
<thead>
<tr>
<th>Component</th>
<th>Chi-Square for MTR</th>
<th>Chi-Square for S.D</th>
<th>Chi-Square value at 0.05 level significance</th>
<th>Hypothesis (MTR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Station</td>
<td>100.19</td>
<td>101.19</td>
<td>124.34 (100 df)</td>
<td>Accept</td>
</tr>
<tr>
<td>Base Station Controller</td>
<td>30.74</td>
<td>31.23</td>
<td>80.23 (61df)</td>
<td>Accept</td>
</tr>
<tr>
<td>BS-BSC Links</td>
<td>16.74</td>
<td>62.70</td>
<td>124.34 (100 df)</td>
<td>Accept</td>
</tr>
</tbody>
</table>

Table 9: Chi-Square for MTR
Table 9: Chi-Square for MTR (Contd)

<table>
<thead>
<tr>
<th>Output</th>
<th>Description</th>
<th>DF</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSC</td>
<td>0.95</td>
<td>0.05</td>
<td>14.10 (7 df)</td>
</tr>
<tr>
<td>MSC-BSC Links</td>
<td>12.19</td>
<td>0.05</td>
<td>81.38 (62 df)</td>
</tr>
<tr>
<td>Database</td>
<td>7.03</td>
<td>0.05</td>
<td>23.7 (14 df)</td>
</tr>
</tbody>
</table>

8.2 Neural Network Results

Software NeuroSolution is used to create the neural network model for nine different outputs and sensitivity analysis is performed. Several steps follow to arrive at the previously mentioned neural network results.

STEP 1: Fitting a Neural Network

STEP 2: Verification of Neural Networks

STEP 3: Study of NN for Survivability, Availability and FCC-Reportable Outages

8.2.1 Fitting a Neural Network

A Neural Network is created by using the nine simulation outputs listed in table 10.

Table 10: NN Outputs

<table>
<thead>
<tr>
<th>Output</th>
<th>Description</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSDOWN</td>
<td>No. of BS failing/year</td>
<td>Verification of NN</td>
</tr>
<tr>
<td>BSCDOWN</td>
<td>No. of BSC failing/year</td>
<td>Verification of NN</td>
</tr>
<tr>
<td>BSCBSDOWN</td>
<td>No. of BSCBS links failing/year</td>
<td>Verification of NN</td>
</tr>
<tr>
<td>MSCDOWN</td>
<td>No. of MSC failing/year</td>
<td>Verification of NN</td>
</tr>
<tr>
<td>MSCBSCDOWN</td>
<td>No. of MSCBSC links failing/year</td>
<td>Verification of NN</td>
</tr>
<tr>
<td>DBDOWN</td>
<td>No. of DB failing/year</td>
<td>Verification of NN</td>
</tr>
<tr>
<td>FCC-Reportable Outages</td>
<td>No. of outages to be reported to FCC</td>
<td>Dependability Assessment</td>
</tr>
<tr>
<td>Survivability (Lost Line Hour)</td>
<td>No. of customers times down time</td>
<td>Dependability Assessment</td>
</tr>
<tr>
<td>Availability (WIB Downtime)</td>
<td>Total time entire WIB is down</td>
<td>Dependability Assessment</td>
</tr>
</tbody>
</table>
This work uses models developed for the first six outputs for verifying a neural network and weighing the applicability of a neural network for modeling wireless networks. The availability and survivability outputs, if represented in series of many nines, vary only in last 5-7 significant digits. It is difficult to train a NN with little variation in the training data. Hence, to overcome this problem, WIB downtime and lost line hours are used as proxies for availability and survivability, respectively. This is further explained below in detail. The rest of the models are used to study the nine different scenarios of reliability growth and deterioration for FCC-Reportable outages, Survivability and Availability. A neural network model was chosen based on the following selection criteria.

- Selection of architecture
- Selection of transfer function
- Selection of the number of exemplars

### 8.2.1.1 Selection of Architecture and Transfer Function

Different models such as multilayer perceptron (MLP) and generalized feed forward were examined. MLP provided the best results. Similarly, various transfer functions such as Tanh Axon, Sigmoid Axon, LinearTanhAxon, Sigmoid Tanh Axon, out of which Tanh Axon gives the best results. This is supported by modeling survivability with different transfer functions and comparing the correlation results (summarized below in table 11).

<table>
<thead>
<tr>
<th>Survivability Model</th>
<th>R Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tanh Axon</td>
<td>0.97</td>
</tr>
<tr>
<td>Linear Sigmoid Axon</td>
<td>0.966</td>
</tr>
<tr>
<td>Linear Tanh Axon</td>
<td>0.958</td>
</tr>
<tr>
<td>Sigmoid Axon</td>
<td>0.93</td>
</tr>
</tbody>
</table>

### 8.2.1.2 Selection of the Number of Exemplar

Once a NN is created, the next important step is to train it. Training results depend upon the quantity and quality of the available training data. A neural network model for
survivability was trained with 170, 370 and lastly with 670 exemplars. It is observed that after certain number of runs, the NN does not give a better model. Table 12 shows that increasing exemplars beyond 370 does not have any profound impact on the regression value. Therefore, this research uses 370 exemplars to train a NN.

Table 12: Selection of the Number of Exemplar

<table>
<thead>
<tr>
<th>Survivability Model</th>
<th>R Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>170 Exemplars</td>
<td>0.93</td>
</tr>
<tr>
<td>370 Exemplars</td>
<td>0.97</td>
</tr>
<tr>
<td>670 Exemplars</td>
<td>0.97</td>
</tr>
</tbody>
</table>

8.2.2 Verification of NN models

Applicability of NN modeling to wireless networks is estimated by checking the regression value of the models designed for nine outputs. NN models are verified by the sensitivity analysis of six outputs: BSDOWN, BSCDOWN, BSCBSDOWN, MSCBSCDOWN, MSCDOWN and DBDOWN. Table 13 represents the characteristics of the respective models.

Table 13: Verification of NN Models

<table>
<thead>
<tr>
<th>Component</th>
<th>R Value</th>
<th>Results of Sensitivity Analysis</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSDOWN</td>
<td>0.99</td>
<td>MTTFBS</td>
<td>Excellent Model</td>
</tr>
<tr>
<td>BSCDOWN</td>
<td>0.71</td>
<td>MTTFBSC MTRDB</td>
<td>Good Model</td>
</tr>
<tr>
<td>BSCBSDOWN</td>
<td>0.99</td>
<td>MTTFBSCBS</td>
<td>Excellent Model</td>
</tr>
<tr>
<td>MSCBSCDOWN</td>
<td>0.71</td>
<td>(1) MTTFMSCBSC (2) MTRBSC (3) MTTFBSC (4) MTRMSC</td>
<td>Good Model</td>
</tr>
</tbody>
</table>
Table 13: Verification of NN Models (Contd)

<table>
<thead>
<tr>
<th>MSCDOWN</th>
<th>0.5</th>
<th>(1) MTRMSC</th>
<th>(2) MTTFMSC</th>
<th>(3) Model also shows some other less significant variables like MTTFBS, MTTFMSCBSC, MTRBS, MTRBSC and MTRDB</th>
<th>Marginal Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBDOWN</td>
<td>0.64</td>
<td>MTRDB</td>
<td>(1) MTTFDB</td>
<td>(2) MTRBSC(small) (3) MTRMSC(small)</td>
<td>Good Model</td>
</tr>
</tbody>
</table>

8.2.2.1 Verification of NN Model for BSDOWN

The trained NN is tested for the test exemplars. Figure 20 shows the relation between the NN and simulation outputs, for BSDOWN. The Y-axis gives the number of BS down as estimated by the neural network whereas. The X-axis shows the number of base stations down as given by the simulation.

Figure 20: Simulation Vs Neural Network Outputs for BSDOWN
The solid line in the figure 21 shows the simulation output for different exemplars, whereas the dotted line gives the NN output for the same set of test exemplars. It is seen the neural network output tracks simulation results very closely. This indicates that the NN model estimates the number of base stations down well.

Figure 21: Neural Network Output Vs Exemplars for BSDOWN

Sensitivity analysis of BSDOWN is shown in figure 22. As expected, it is clearly seen that MTTFBS affects the BSDOWN the most. With an increase in MTTF, the number of base stations failing in a year decreases. This relation is depicted in the figure 23, which validates this NN model for BSDOWN.

Figure 22: Sensitivity Analysis of BSDOWN
The expected relationship between BSDOWN and MTTFBS is shown below and is a hyperbola:

\[ \text{Expected Down Number} = \frac{\text{Number of Base Stations}}{\text{MTTF}} \]

With the number of Base Stations as 50 and MTTF as 2 years, expected down number is calculated as 25. This tallies with figure 23 for MTTF of 2 years and hence it can be concluded that NN model works well for BSDOWN in the range used in later investigations.

![Figure 23: BSDOWN Vs MTTFBS](image)

8.2.2.2 Verification of NN Model for BSCDOWN

The same tests are conducted for BSCDOWN. The trained NN is tested for the test exemplars. Figure 24 shows the relation between actual and desired outputs. The X-axis shows the number of base station controller down as given by the simulation whereas the Y-axis gives the number of BSC down as estimated by the neural network.
The solid line in figure 25 shows the simulation output for different exemplars, whereas dotted line gives the NN output for the same set of test exemplars.
Sensitivity analysis of BSCDOWN is shown in figure 26. It is clearly seen that MTTFBSC affects the BSCDOWN the most. The graph shows that as MTTFBSC increases, the number of BSC failing in a year decreases. This validates the NN model for BSCDOWN.

![Figure 26: Sensitivity Analysis of BSCDOWN](image)

Similar to BSDOWN, this curve can also be verified by checking the expected down number for BSC for MTTFBSCBS = 4 years. Figure 27 gives the down number of 1.2 as opposed to the analytical value of 1.25.

![Figure 27: BSCDOWN Vs MTTFBSC](image)
8.2.2.3 Verification of NN Model for BSCBSDOWN

BSCBSDOWN is also verified as BSDOWN and BSCDOWN. The trained NN is tested for the test exemplars. The figure 28 shows the relation between actual and desired outputs. The X-axis shows the number of BSCBS links down as given by the simulation whereas the Y-axis gives the number of BSCBS links down as estimated by the neural network.

![Figure 28: Simulation Vs Neural Network Outputs for BSCBSDOWN](image)

The solid line in figure 29 shows the simulation output for different exemplars, whereas dotted line gives the output from the neural network for the same set of test exemplars.

![Figure 29: Neural Network Output Vs Exemplars for BSCBSDOWN](image)
Sensitivity analysis of BSCBSDOWN is shown in figure 30. It is clearly seen that BSCBSDOWN is affected mainly by the MTTFBSCBS. The inverse relation between MTTFBSCBS and BSCBSDOWN is depicted in figure 31, which validates this NN model for BSCBSDOWN.

![Figure 30: Sensitivity Analysis of BSCBSDOWN](image)

![Figure 31: BSCBSDOWN Vs MTTFBSCBSDOWN](image)

Similar analysis for MSCDOWN, MSCBSDOWN and DBDOWN verifies NN modeling for wireless networks.
8.2.3 Study of NN Models for Survivability, Availability and FCC-Reportable Outages

As mentioned in the step 3, NN model is finally used to study nine different reliability/maintainability growth and deterioration scenarios. Table 14 gives the regression and sensitivity analysis of FCC-Reportable outages, prime lost line hours and WIB downtime.

<table>
<thead>
<tr>
<th>Component</th>
<th>R Value</th>
<th>Sensitivity</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCC-Reportable Outages</td>
<td>0.99</td>
<td>MTTFBS</td>
<td>Excellent Model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTTRBSCBS</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTTFBSBS</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTTRBS</td>
<td></td>
</tr>
<tr>
<td>Lost Line hours (Proxy for Survivability)</td>
<td>0.97</td>
<td>MTTFBS</td>
<td>Excellent Model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTRBSCBS</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTRMSCBS</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTRMSCBS</td>
<td></td>
</tr>
<tr>
<td>WIB Downtime (Proxy for Availability)</td>
<td>0.64</td>
<td>MTRDB</td>
<td>Marginal Model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTRMSC</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTTDB</td>
<td></td>
</tr>
</tbody>
</table>

8.2.3.1 Use of NN for Analyzing FCC-Reportable Outages

The trained NN is tested for the test exemplars. The figure 32 below shows the relation between actual and desired outputs. The X-axis shows the number of FCC-Reportable outages as given by the simulation whereas the Y-axis gives the number of FCC-Reportable outages as estimated by the neural network.
The solid line in the figure 33 below shows the simulation output for different exemplars, whereas dotted line gives the output from the neural network for the same set of test exemplars. It can be seen that simulation and NN output completely overlaps, verifying the model for reportable outages.

Sensitivity analysis of FCC-Reportable outages is shown in figure 34. It indicates that FCC-Reportable outages depends highly on the MTTF values of BSCBS links and MTR values of BSCBS links. Other factors leading to outages often are MTTF and MTR
values of BS. Since there are 50 base stations and BSCBS links in a WIB, and the fact that they have comparatively lower values of MTTF and higher MTR values, their tendency to break and stay down is more. The FCC demands wireless carriers to report an outage of 30 minutes or longer if it exceeds 15,000 lost line hours. Even though BS or BSCBS failures affect 2000 customers, they are multiplied by 8 for the calculation of the impacted customers (as required by the new FCC regulation), leading to 16,000 customers per BS and BSCBS link. Therefore, if any of the two above-mentioned components is down around an hour, it leads to a reportable outage.

![Figure 34: Sensitivity Analysis of FCC-Reportable Outages](image)

The Relation between FCC-Reportable outages and MTTFBSCBS is given by the figure 35, while the relation between FCC-Reportable outages and MTR is shown in figure 36.

### 8.2.3.2 Use of NN for analyzing Survivability

As survivability is a series of nines, it is difficult to train a neural network with a data having low variation (variation in the last 5-7 significant digits) and hence to solve this problem, lost line hours is used for training instead of survivability. Finally, survivability is calculated as:
Survivability = \frac{\text{TotalLostLineHours} - \text{LostLineHours}}{\text{TotalLostLineHours}}

Where \( \text{TotalLostLineHours} = 365 \times 24 \times 100,000 \)

The NN trained for lost line hours is tested for the test exemplars. Figure 37 shows the relation between the actual and desired outputs. The X-axis shows the lost line hours as given by the simulation whereas the Y-axis gives the lost line hours as estimated by the neural network.
The solid line in the figure 38 shows the simulation output for different exemplars, whereas dotted line gives the NN output for the same set of test exemplars. An overlapping of the two outputs verifies the model for survivability.
Sensitivity analysis of survivability in figure 39 demonstrates three factors: MTTFBSCBS, MTRBSCBS and MTRMSCBSC. This is because the probabilities of BS, BSCBS and MSCBS failures are more as compared to DB and MSC. Hence, their impact on lost line hours is more as compared to DB and MSC failures.

Figure 39: Sensitivity Analysis of Survivability

Figure 40 shows the relation between survivability and MTTFBSCBS and figure 41 shows the relation between survivability and MTRBSCBS.
8.2.3.3 Use of NN for Analyzing Availability

As in the case of survivability, availability is also represented in the form of WIB down time to overcome the problem of consecutive nine’s. Unavailability, the complementary of availability is given by

\[ \text{Unavailability} = \frac{\text{WIB Down Time}}{\text{Total Time}} \]

where \( \text{Total Time} = 365 \times 24 \times 60 \) minutes. Figure 42 shows the relation between actual and desired outputs. X-axis shows the WIB down time as given by the simulation whereas the Y-axis gives the WIB down time as estimated by the neural network.
The solid line in figure 43 shows the simulation output for different exemplars, whereas dotted line gives the output from the neural network for the same set of test exemplars. NN and simulation do not overlap to a higher extent indicating the marginal NN model for availability.

Sensitivity analysis of availability in figure 44 demonstrates three important factors: MTRDB, MTRMSC and MTTFDB. This research involves the analysis of a single WIB, wherein an entire network is said to be unavailable when either MSC is down or DB is down. Therefore, sensitivity analysis highlights that unavailability largely depends on the duration for which either MSC or DB is down, which in turn depends on the MTTF and MTR values of DB and MSC.
Figure 45 explains the relation between WIB down time and MTRDB whereas figure 46 shows the relation between WIB down and MTRMSC.

**Figure 45: Availability Vs MTRDB**

**Figure 46: Availability Vs MTRMSC**

### 8.2.4 Creation of Excel NN Models

After NN models is verified, in order to study different scenarios and answer the research questions, especially the research question 1 and the research question 2, the neural network is represented as an excel spreadsheet. The layout of an excel NN model is shown for FCC-Reportable outages in appendix B. The excel model facilitates fast computing and easy study of different growth and deterioration scenarios.
8.2.5 Generation of Decision Trees

One of the biggest advantages of using a NN model, apart from sensitivity analysis tool, is an extraction of a decision tree. TREPAN software is used for extracting decision trees for survivability, availability and FCC-Reportable outages. Sensitivity analysis gives the list of variables affecting the outputs but decision tree also gives the values associated with the significant variables and branches into different paths depending upon the threshold values at the nodes.

8.2.5.1 Decision Tree for FCC-Reportable Outages

A decision tree for FCC-Reportable outages can be used to answer the research question 3 regarding the frequency of wireless outages. Figure 47 shows the decision tree for FCC-Reportable Outages and Table 15 shows the classification for FCC-reportable outages used to generate the decision tree.

![Decision Tree for FCC-Reportable Outages](image_url)

Figure 47: Decision Tree for FCC-Reportable Outages
Table 15: Classification of FCC-Reportable Outages

<table>
<thead>
<tr>
<th>Range of Outages</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below 10</td>
<td>Very Good</td>
</tr>
<tr>
<td>10-20</td>
<td>Good</td>
</tr>
<tr>
<td>20-30</td>
<td>Okay</td>
</tr>
<tr>
<td>30-40</td>
<td>Poor</td>
</tr>
<tr>
<td>Above 40</td>
<td>Very Poor</td>
</tr>
</tbody>
</table>

8.2.5.2 Decision Tree for Survivability

A decision tree is also generated for lost line hours (survivability) by classifying it into eleven different categories. Table 16 shows the eleven classifications and Figure 48 shows the decision tree generated out of survivability NN model.

Table 16: Classification for Survivability

<table>
<thead>
<tr>
<th>Survivability Ranges (Lost Line Hours)</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below 50K</td>
<td>CL1</td>
</tr>
<tr>
<td>50K-100K</td>
<td>CL3</td>
</tr>
<tr>
<td>100K-150K</td>
<td>CL4</td>
</tr>
<tr>
<td>150K-200K</td>
<td>CL5</td>
</tr>
<tr>
<td>200K-250K</td>
<td>CL6</td>
</tr>
<tr>
<td>250K-300K</td>
<td>CL7</td>
</tr>
<tr>
<td>300K-350K</td>
<td>CL8</td>
</tr>
<tr>
<td>350K-400K</td>
<td>CL9</td>
</tr>
<tr>
<td>400K-450K</td>
<td>CL10</td>
</tr>
<tr>
<td>Above 450K</td>
<td>CL11</td>
</tr>
</tbody>
</table>
8.2.5.3 Decision Tree for Availability

A decision tree is lastly generated for WIB downtime (availability) by classifying it into five different categories. Table 17 shows the five classifications and Figure 49 shows the
decision tree generated out of availability NN model. By looking at the graph, it is seen that the model never predicted a value higher than 40, so it does not predict class B or VB. This is probably because of low R-value that a decision tree does not have any branches for class B and Class VB.

Table 17: Classification for Availability

<table>
<thead>
<tr>
<th>Availability Ranges (WIB Down Time)</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below 10</td>
<td>Very Good</td>
</tr>
<tr>
<td>10-20</td>
<td>Good</td>
</tr>
<tr>
<td>20-30</td>
<td>Okay</td>
</tr>
<tr>
<td>30-40</td>
<td>Poor</td>
</tr>
<tr>
<td>Above 50</td>
<td>Very Poor</td>
</tr>
</tbody>
</table>

Figure 49: Decision Tree for WIB Downtime
8.3 Addressing Research Questions

R1: Which strategy should be followed in order to make wireless networks more dependable – Reactive (restore faster) and Proactive (fault-tolerant)?

Once the NN is trained, an excel file is created with the weights of a trained NN. This question is answered by studying different scenarios of reliability growth and deterioration along with the maintainability growth and deterioration. This is achieved by varying reliability or maintainability by 10% per year for a span of five years to study the change in average survivability, average FCC reportable outages and average availability. Compounded, a 10% increase per year corresponds to a 61% increase by the fifth year. Similarly, compounding a 10% decrease per year results in 40.95% decrease by the fifth year. The compounded impact of 10% change per year for reliability and maintainability growth and deterioration is shown in table 18.

<table>
<thead>
<tr>
<th>Years</th>
<th>Compounded Growth (%)</th>
<th>Compounded Deterioration (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>21</td>
<td>19</td>
</tr>
<tr>
<td>3</td>
<td>33.1</td>
<td>27.1</td>
</tr>
<tr>
<td>4</td>
<td>46.4</td>
<td>34.4</td>
</tr>
<tr>
<td>5</td>
<td>61.1</td>
<td>40.1</td>
</tr>
</tbody>
</table>

8.3.1 Study of FCC-Reportable Outages with Time Factor

Applying the time factor accounts for variation in traffic over different times of day and day of week. A NN model for outages is tested with nine different scenarios of reliability and maintainability growth and deterioration. The nominal value of FCC-Reportable outages is obtained with the nominal values of MTTF and MTR of six components with no growth or deterioration. This is calculated as 11.55 as shown in the table 19 in the RC/MC column.
Table 19: Reliability/Maintainability Growth and Deterioration (FCC-Reportables)

<table>
<thead>
<tr>
<th>Year</th>
<th>RG/MD</th>
<th>RG/MG</th>
<th>RD/MG</th>
<th>RD/MD</th>
<th>RG/MC</th>
<th>RD/MC</th>
<th>RC/MD</th>
<th>RC/MG</th>
<th>RC/MC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11.52</td>
<td>9.77</td>
<td>11.70</td>
<td>14.17</td>
<td>10.58</td>
<td>12.90</td>
<td>12.64</td>
<td>10.55</td>
<td>11.55</td>
</tr>
<tr>
<td>4</td>
<td>11.52</td>
<td>8.14</td>
<td>12.92</td>
<td>26.37</td>
<td>8.77</td>
<td>18.71</td>
<td>17.01</td>
<td>8.76</td>
<td>11.55</td>
</tr>
<tr>
<td>5</td>
<td>11.36</td>
<td>8.05</td>
<td>13.54</td>
<td>31.86</td>
<td>8.50</td>
<td>21.03</td>
<td>18.92</td>
<td>8.45</td>
<td>11.55</td>
</tr>
</tbody>
</table>

RG/RC/RD and MG/MC/MD scenarios are categorized into three subclasses with increasing, constant and decreasing scenarios as shown in the table 20.

Table 20: Trends in FCC-Reportable Outages

<table>
<thead>
<tr>
<th>Constant Outages</th>
<th>Increasing Outages</th>
<th>Decreasing Outages</th>
</tr>
</thead>
<tbody>
<tr>
<td>RC/MC</td>
<td>RD/MD</td>
<td>RG/MG</td>
</tr>
<tr>
<td>RG/MD</td>
<td>RD/MD</td>
<td>RG/MC</td>
</tr>
<tr>
<td></td>
<td>RD/MG</td>
<td>RC/MG</td>
</tr>
<tr>
<td></td>
<td>RD/MC</td>
<td></td>
</tr>
<tr>
<td></td>
<td>RC/MD</td>
<td></td>
</tr>
</tbody>
</table>
Figure 50: FCC-Reportable Outages Reliability/Maintainability Scenarios

Figure 51: Reliability Growth for FCC-Reportable Outages
For constant reliability in figure 52, it is observed that curve RC/MD has a larger slope as compared to RC/MG. This implies that maintainability deterioration has a higher impact on the number of FCC-reportable outages as compared to maintainability growth.
For reliability deterioration in the figure 53, it is seen that RD/MG and RC/MC do not coincide as in the case of RC/MC and RG/MD and it can be concluded that reliability deterioration cannot be compensated by maintainability growth. However, if both reliability and maintainability are degraded then it leads to a sharp increase in the number of FCC-reportable outages.

Scenarios are also tabulated for the values at the end of year 1 and year 5 as shown in the tables 21 and 22 respectively. The year 1 values are close to the nominal value of 11.55 but by year 5 larger values result. It is also seen that the diagonal of the year 1 scenarios is almost the same but for the fifth year; RD/MG value is higher than the other two values showing that reliability deterioration is not compensated by maintainability growth.

### Table 21: FCC-Reportable Outages after Year 1

<table>
<thead>
<tr>
<th>Year 1</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>9.77</td>
<td>10.58</td>
<td>11.52</td>
</tr>
<tr>
<td>RC</td>
<td>10.55</td>
<td>11.55</td>
<td>12.64</td>
</tr>
<tr>
<td>RD</td>
<td>11.70</td>
<td>12.90</td>
<td>14.17</td>
</tr>
</tbody>
</table>

The elements for year five in table 22 shows that number of FCC-Reportable Outages is minimal for RG/MG and is greatest for RD/MD. In addition, the FCC-Reportable outages increase across the row and along the column, showing that deterioration is more dominant than improvement for survivability.

### Table 22: FCC-Reportable Outages after Year 5

<table>
<thead>
<tr>
<th>Year 5</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>8.05</td>
<td>8.50</td>
<td>11.36</td>
</tr>
</tbody>
</table>
Table 22: FCC-Reportable Outages after Year 5 (Contd)

<table>
<thead>
<tr>
<th>RC</th>
<th>8.45</th>
<th>11.55</th>
<th>18.92</th>
</tr>
</thead>
<tbody>
<tr>
<td>RD</td>
<td>13.54</td>
<td>21.03</td>
<td>31.86</td>
</tr>
</tbody>
</table>

Table 23: Normalized FCC-Reportable after Year 5

<table>
<thead>
<tr>
<th>Year 5</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>0.7</td>
<td>0.74</td>
<td>0.98</td>
</tr>
<tr>
<td>RC</td>
<td>0.73</td>
<td>1.00</td>
<td>1.64</td>
</tr>
<tr>
<td>RD</td>
<td>1.17</td>
<td>1.82</td>
<td>2.76</td>
</tr>
</tbody>
</table>

8.3.2 Study of Survivability with Time Factor

A NN model for survivability is tested for nine different scenarios of reliability and maintainability growth and deterioration. The nominal value of survivability is obtained with the nominal values of MTTF and MTR of six components (RC/MC) and is calculated as 133,794 as shown in table 24. Survivability in terms of fraction of lost line hours (LLH) available to users is shown in the table 25(A) and 25(B):

Table 24: Reliability/Maintainability Growth and Deterioration (LLH)

<table>
<thead>
<tr>
<th>Years</th>
<th>RC/MC</th>
<th>RG/MD</th>
<th>RD/MG</th>
<th>RG/MG</th>
<th>RD/MD</th>
<th>RD/MC</th>
<th>RG/MC</th>
<th>RC/MG</th>
<th>RC/MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>133794</td>
<td>131306</td>
<td>138262</td>
<td>114627</td>
<td>166722</td>
<td>151595</td>
<td>122109</td>
<td>123920</td>
<td>145627</td>
</tr>
<tr>
<td>2</td>
<td>133794</td>
<td>129996</td>
<td>144641</td>
<td>104075</td>
<td>211343</td>
<td>174605</td>
<td>113792</td>
<td>117223</td>
<td>159693</td>
</tr>
<tr>
<td>3</td>
<td>133794</td>
<td>129461</td>
<td>161758</td>
<td>98068</td>
<td>258469</td>
<td>201363</td>
<td>107842</td>
<td>112992</td>
<td>175422</td>
</tr>
<tr>
<td>4</td>
<td>133794</td>
<td>129311</td>
<td>161758</td>
<td>94621</td>
<td>302105</td>
<td>229192</td>
<td>103399</td>
<td>110492</td>
<td>193424</td>
</tr>
<tr>
<td>5</td>
<td>133794</td>
<td>129281</td>
<td>171178</td>
<td>92792</td>
<td>337587</td>
<td>255424</td>
<td>99896</td>
<td>109154</td>
<td>216044</td>
</tr>
</tbody>
</table>
Table 25(A): Nines Representation of Survivability

<table>
<thead>
<tr>
<th>Year</th>
<th>RC/MC</th>
<th>RG/MD</th>
<th>RD/MG</th>
<th>RG/MG</th>
<th>RD/MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.999847</td>
<td>0.999850</td>
<td>0.999842</td>
<td>0.999979</td>
<td>0.999970</td>
</tr>
<tr>
<td>2</td>
<td>0.999847</td>
<td>0.999852</td>
<td>0.999835</td>
<td>0.999981</td>
<td>0.999963</td>
</tr>
<tr>
<td>3</td>
<td>0.999847</td>
<td>0.999852</td>
<td>0.999826</td>
<td>0.999982</td>
<td>0.999954</td>
</tr>
<tr>
<td>4</td>
<td>0.999847</td>
<td>0.999852</td>
<td>0.999815</td>
<td>0.999983</td>
<td>0.999945</td>
</tr>
<tr>
<td>5</td>
<td>0.999847</td>
<td>0.999852</td>
<td>0.999805</td>
<td>0.999983</td>
<td>0.999936</td>
</tr>
</tbody>
</table>

Table 25(B): Nines Representation of Survivability

<table>
<thead>
<tr>
<th>Year</th>
<th>RD/MC</th>
<th>RG/MC</th>
<th>RC/MG</th>
<th>RC/MC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.999827</td>
<td>0.999861</td>
<td>0.999859</td>
<td>0.999834</td>
</tr>
<tr>
<td>2</td>
<td>0.999801</td>
<td>0.999870</td>
<td>0.999866</td>
<td>0.999818</td>
</tr>
<tr>
<td>3</td>
<td>0.999770</td>
<td>0.999877</td>
<td>0.999871</td>
<td>0.999800</td>
</tr>
<tr>
<td>4</td>
<td>0.999738</td>
<td>0.999882</td>
<td>0.999874</td>
<td>0.999779</td>
</tr>
<tr>
<td>5</td>
<td>0.999708</td>
<td>0.999886</td>
<td>0.999875</td>
<td>0.999753</td>
</tr>
</tbody>
</table>

RG/RC/RD and MG/MC/MD scenarios are categorized into three subclasses with increasing, constant and decreasing scenarios as shown in table 26.

Table 26: Trends in LLH

<table>
<thead>
<tr>
<th>Constant LLH</th>
<th>Increasing LLH</th>
<th>Decreasing LLH</th>
</tr>
</thead>
<tbody>
<tr>
<td>RC/MC</td>
<td>RD/MD</td>
<td>RG/MG</td>
</tr>
<tr>
<td>RG/MD</td>
<td>RD/MD</td>
<td>RG/MD</td>
</tr>
<tr>
<td></td>
<td>RD/MC</td>
<td>RC/MC</td>
</tr>
<tr>
<td></td>
<td>RC/MD</td>
<td>RC/MG</td>
</tr>
</tbody>
</table>

A single graph with nine different scenarios is plotted as shown in figure 54. The three graphs of reliability growth, reliability constancy and reliability deterioration are plotted to study the different scenarios. For reliability growth as shown in figure 55, it is observed that scenarios RG/MD and RC/MC are parallel and near to each other. This
implies that maintainability deterioration can be compensated by reliability improvement. It is also seen that curves RG/MG and RG/MC are also parallel and near to each other. This indicates that maintainability growth beyond the nominal value does not have any profound impact on survivability.

Figure 54: Survivability Reliability/Maintainability Scenarios

For constant reliability as shown in figure 56, it is observed that curve RC/MD has a larger slope as compared to RC/MG. This implies that maintainability deterioration has a higher impact on survivability as compared to maintainability improvement.

Figure 55: Reliability Growth for Survivability
For reliability deterioration as shown in figure 57, it is observed that scenarios RD/MG and RC/MC do not run parallel and not very close as in the case of RC/MC and RG/MD and therefore, it can be concluded that reliability deterioration cannot be compensated by maintainability growth. However, if both reliability and maintainability are degraded then it leads to a sharp decrease in survivability.
Scenarios are also tabulated for the values at the end of year 1 and year 5 as shown in the tables 27 and 28 respectively. The values for year 1 are close to the nominal value of 133,794 but year 5 shows larger differences in the values of different scenarios. It is also seen that the diagonal of the year 1 scenarios is almost the same, but for the fifth year RD/MG, values are higher than the other two values. This shows that reliability deterioration is not compensated by maintainability growth.

Table 27: Lost Line Hours after Year 1

<table>
<thead>
<tr>
<th>Year 1</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>114,627</td>
<td>122,109</td>
<td>131,306</td>
</tr>
<tr>
<td>RC</td>
<td>123,920</td>
<td>133,794</td>
<td>145,627</td>
</tr>
<tr>
<td>RD</td>
<td>138,262</td>
<td>151,595</td>
<td>166,722</td>
</tr>
</tbody>
</table>

Year five shows that survivability is minimal for RG/MG and is greatest for RD/MD. In addition, survivability increases across the row and along the column, showing that deterioration is more dominant than improvement for survivability. It is also observed that RC/MD ranges from $[145,627, 216,044]$ whereas RD/MC ranges from $[151,595, 255,424]$. This shows that reliability deterioration has a higher impact on survivability than maintainability deterioration. Table 29 depicts lost line hours normalized to the nominal, at the end of 5 years.

Table 28: Lost Line Hours after Year 5

<table>
<thead>
<tr>
<th>Year 5</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>92,792</td>
<td>99,896</td>
<td>129,281</td>
</tr>
<tr>
<td>RC</td>
<td>109,154</td>
<td>133,794</td>
<td>216,044</td>
</tr>
<tr>
<td>RD</td>
<td>171,178</td>
<td>255,424</td>
<td>337,587</td>
</tr>
</tbody>
</table>
Table 29: Normalized Lost Line Hours after Year 5

<table>
<thead>
<tr>
<th>Year 5</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>0.69</td>
<td>0.75</td>
<td>0.97</td>
</tr>
<tr>
<td>RC</td>
<td>0.82</td>
<td>1</td>
<td>1.61</td>
</tr>
<tr>
<td>RD</td>
<td>1.28</td>
<td>1.91</td>
<td>2.52</td>
</tr>
</tbody>
</table>

8.3.3 Study of Availability with Time Factor

A NN model for availability is tested for nine different scenarios of reliability and maintainability growth and deterioration. The nominal value of availability is obtained with the nominal values of MTTF and MTR (RC/MC) for six components and is calculated as 13.02 minutes as shown in 30. Availability in terms of WIB downtime is shown in the table below:

Table 30: Reliability/Maintainability Growth and Deterioration (WIB Downtime)

<table>
<thead>
<tr>
<th>Year</th>
<th>RC/MC</th>
<th>RG/MD</th>
<th>RD/MG</th>
<th>RG/MG</th>
<th>RD/MD</th>
<th>RG/MC</th>
<th>RC/MG</th>
<th>RC/MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13.02</td>
<td>13.64</td>
<td>12.74</td>
<td>11.17</td>
<td>15.71</td>
<td>14.14</td>
<td>12.33</td>
<td>11.76</td>
</tr>
<tr>
<td>2</td>
<td>13.02</td>
<td>14.59</td>
<td>12.82</td>
<td>10.00</td>
<td>19.40</td>
<td>15.63</td>
<td>11.91</td>
<td>10.77</td>
</tr>
<tr>
<td>3</td>
<td>13.02</td>
<td>15.77</td>
<td>13.21</td>
<td>9.30</td>
<td>23.94</td>
<td>17.47</td>
<td>11.77</td>
<td>10.00</td>
</tr>
<tr>
<td>5</td>
<td>13.02</td>
<td>17.94</td>
<td>14.64</td>
<td>8.82</td>
<td>33.63</td>
<td>21.90</td>
<td>11.99</td>
<td>8.90</td>
</tr>
</tbody>
</table>

Table 31(A): Nines Representation of Availability

<table>
<thead>
<tr>
<th>Year</th>
<th>RC/MC</th>
<th>RG/MD</th>
<th>RD/MG</th>
<th>RG/MG</th>
<th>RD/MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.999975</td>
<td>0.999974</td>
<td>0.999976</td>
<td>0.999979</td>
<td>0.999970</td>
</tr>
<tr>
<td>2</td>
<td>0.999975</td>
<td>0.999972</td>
<td>0.999976</td>
<td>0.999981</td>
<td>0.999963</td>
</tr>
<tr>
<td>3</td>
<td>0.999975</td>
<td>0.99997</td>
<td>0.999976</td>
<td>0.999982</td>
<td>0.999954</td>
</tr>
<tr>
<td>4</td>
<td>0.999975</td>
<td>0.999968</td>
<td>0.999974</td>
<td>0.999983</td>
<td>0.999945</td>
</tr>
<tr>
<td>5</td>
<td>0.999975</td>
<td>0.999966</td>
<td>0.999972</td>
<td>0.999983</td>
<td>0.999936</td>
</tr>
</tbody>
</table>
RG/RC/RD and MG/MC/MD scenarios are categorized into three subclasses with increasing, constant and decreasing scenarios as shown in table 32.

### Table 31(B): Nines Representation of Availability

<table>
<thead>
<tr>
<th>Year</th>
<th>RD/MC</th>
<th>RG/MC</th>
<th>RC/MG</th>
<th>RC/MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.999973</td>
<td>0.999977</td>
<td>0.999978</td>
<td>0.999973</td>
</tr>
<tr>
<td>2</td>
<td>0.99997</td>
<td>0.999977</td>
<td>0.99998</td>
<td>0.999969</td>
</tr>
<tr>
<td>3</td>
<td>0.999967</td>
<td>0.999978</td>
<td>0.999981</td>
<td>0.999965</td>
</tr>
<tr>
<td>4</td>
<td>0.999963</td>
<td>0.999978</td>
<td>0.999982</td>
<td>0.999961</td>
</tr>
<tr>
<td>5</td>
<td>0.999958</td>
<td>0.999977</td>
<td>0.999983</td>
<td>0.999956</td>
</tr>
</tbody>
</table>

A single graph with nine different scenarios is plotted as shown in figure 58. The three graphs of reliability growth, reliability constancy and reliability deterioration are plotted to study the different scenarios. For reliability growth as shown in figure 59, it is observed that scenarios RG/MD moves away from the scenario RC/MC. This implies that maintainability deterioration cannot be compensated by reliability improvement.
For constant reliability as shown in figure 60, it is observed that curve RC/MD has a larger slope as compared to RC/MG. This implies that maintainability deterioration has a higher impact on survivability as compared to maintainability improvement.
Figure 60: Reliability Constancy for Availability

For reliability deterioration as shown in figure 61, it is observed that scenarios RD/MG and RC/MC almost overlap, unlike the relation with the scenarios RG/MD and RC/MC, showing that reliability deterioration can be compensated by maintainability growth. However, if both reliability and maintainability are degraded then it leads to a sharp decrease in availability.

Figure 61: Reliability Deterioration for Availability
Scenarios are also tabulated for the values at the end of year 1 and year 5 as shown in the tables 33 and 34 respectively. The values year 1 has values close to the nominal value of 13.02 but the grid for year 5 shows larger changes in the values of different scenarios. It is also seen that the diagonal of the year 1 scenarios is almost the same, but for the fifth year the RG/MD value is higher than the other two values in a diagonal. This shows that maintainability deterioration is not compensated by reliability growth. Table 36 shows the normalized WIB downtime after year 5, compared to nominal.

Table 33: WIB Downtime after Year 1

<table>
<thead>
<tr>
<th>Year 1</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>11.17</td>
<td>12.33</td>
<td>13.64</td>
</tr>
<tr>
<td>RC</td>
<td>11.76</td>
<td>13.02</td>
<td>14.45</td>
</tr>
<tr>
<td>RD</td>
<td>12.74</td>
<td>14.14</td>
<td>15.71</td>
</tr>
</tbody>
</table>

Table 34: WIB Downtime after Year 5

<table>
<thead>
<tr>
<th>Year 5</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>8.82</td>
<td>11.99</td>
<td>17.94</td>
</tr>
<tr>
<td>RC</td>
<td>8.90</td>
<td>13.02</td>
<td>23.22</td>
</tr>
<tr>
<td>RD</td>
<td>14.64</td>
<td>21.90</td>
<td>33.63</td>
</tr>
</tbody>
</table>

Table 35: Normalized WIB Downtime after Year 5

<table>
<thead>
<tr>
<th>Year 5</th>
<th>MG</th>
<th>MC</th>
<th>MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>0.68</td>
<td>0.92</td>
<td>1.38</td>
</tr>
<tr>
<td>RC</td>
<td>0.68</td>
<td>1</td>
<td>1.78</td>
</tr>
<tr>
<td>RD</td>
<td>1.12</td>
<td>1.68</td>
<td>2.56</td>
</tr>
</tbody>
</table>
8.3.4 Study of Survivability without Time Factor
Survivability is plotted without time for nine different scenarios of reliability and maintainability scenarios as shown in table 36.

Table 36: Lost Line Hours without Time Factors

<table>
<thead>
<tr>
<th>Year</th>
<th>RG/MD</th>
<th>RD/MD</th>
<th>RG/MG</th>
<th>RD/MD</th>
<th>RD/MC</th>
<th>RG/MC</th>
<th>RC/MG</th>
<th>RC/MC</th>
<th>RC/MD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>322646</td>
<td>352203</td>
<td>277443</td>
<td>434865</td>
<td>388394</td>
<td>295433</td>
<td>300496</td>
<td>325773</td>
<td>362742</td>
</tr>
<tr>
<td>2</td>
<td>334816</td>
<td>398152</td>
<td>266951</td>
<td>560621</td>
<td>469108</td>
<td>283890</td>
<td>286733</td>
<td>325773</td>
<td>412576</td>
</tr>
<tr>
<td>3</td>
<td>356084</td>
<td>446315</td>
<td>256660</td>
<td>639585</td>
<td>535050</td>
<td>284031</td>
<td>277317</td>
<td>325773</td>
<td>465821</td>
</tr>
<tr>
<td>4</td>
<td>380220</td>
<td>482624</td>
<td>256665</td>
<td>684812</td>
<td>574982</td>
<td>290282</td>
<td>272777</td>
<td>325773</td>
<td>511897</td>
</tr>
<tr>
<td>5</td>
<td>399855</td>
<td>506061</td>
<td>257711</td>
<td>715760</td>
<td>597266</td>
<td>298485</td>
<td>269582</td>
<td>325773</td>
<td>547159</td>
</tr>
</tbody>
</table>

The figures 62, 63 and 64 show the variation in survivability with and without time factors for extreme scenarios: RG/MG, RC/MC and RD/MD. It is seen that for all the three scenarios, lost line hour curves without and with time factors run parallel to each other, indicating that application of time factor leads to different perceptions of survivability.

Figure 62: Survivability for RG/MG
8.3.5 Study of Availability without Time Factor

Availability is plotted without time factors for nine different scenarios of reliability and maintainability scenarios as shown in table 37.
Table 37: Availability without Time Factors

<table>
<thead>
<tr>
<th>Year</th>
<th>RG/MD</th>
<th>RD/MG</th>
<th>RG/MG</th>
<th>RD/MD</th>
<th>RD/MC</th>
<th>RG/MC</th>
<th>RC/MG</th>
<th>RC/MD</th>
<th>RC/MC</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>15.69</td>
<td>12.09</td>
<td>12.92</td>
<td>15.34</td>
<td>13.01</td>
<td>13.71</td>
<td>12.47</td>
<td>15.43</td>
<td>13.30</td>
</tr>
<tr>
<td>3</td>
<td>17.75</td>
<td>11.76</td>
<td>13.03</td>
<td>17.60</td>
<td>12.91</td>
<td>13.98</td>
<td>12.30</td>
<td>17.50</td>
<td>13.30</td>
</tr>
<tr>
<td>4</td>
<td>20.54</td>
<td>11.51</td>
<td>13.23</td>
<td>20.76</td>
<td>12.84</td>
<td>14.30</td>
<td>12.21</td>
<td>20.43</td>
<td>13.30</td>
</tr>
<tr>
<td>5</td>
<td>23.92</td>
<td>11.33</td>
<td>13.51</td>
<td>24.25</td>
<td>13.10</td>
<td>14.64</td>
<td>12.16</td>
<td>23.94</td>
<td>13.30</td>
</tr>
</tbody>
</table>

The figures 64, 65 and 66 show the variation in availability with and without time factors for extreme scenarios: RG/MG, RC/MC and RD/MD. It is observed that application of time factor do affect availability perceptions but since the NN model for availability is marginal, these results need some more investigation (especially the RG/MG scenario).

Figure 65: Availability for RG/MG
Figure 66: Availability for RC/MC

Figure 67: Availability for RD/MD
Chapter 9
Conclusion

The results obtained from the study of reliability/maintainability growth and deterioration scenarios are summarized below.

- The reliability and maintainability deterioration below the nominal values affects wireless network dependability more as compared to the reliability and maintainability growth above the nominal values. In fact, reliability and maintainability growth above the nominal values does not improve ARMS performance much. Therefore a cost/performance ratio plays an important role in deciding R/M improvement.

- The scenario RG/MG gives the lowest value for FCC-Reportable outages, lost line hours and WIB downtime (high survivability and availability). The scenario RD/MD gives the highest values for FCC-Reportable outages, lost line hours and WIB downtime (low survivability and availability).

- For FCC-Reportable outages and survivability, reliability deterioration below the nominal values cannot be compensated by maintainability growth, whereas maintainability deterioration can be compensated by reliability growth.

- For availability, reliability deterioration below the nominal values can be compensated by maintainability growth, whereas maintainability deterioration cannot be compensated by reliability growth.

- By comparing scenarios RG/MC and RC/MG for the availability scenarios, we find that reliability growth (RG/MC) still leads to little change over time whereas maintainability growth (RC/MG) increases availability and hence it can be
inferred that it is beneficial to make MSC and DB more maintainable as compared to reliable.

- The number of FCC-Reportable outages and lost line hours is more for potential customers as compared to actual customers, whereas availability remains more or less the same with or without time factors.

**Research Question 1**

R1: Which strategy should be followed in order to make wireless networks more dependable – Reactive (restore faster) and Proactive (fault-tolerant)?

For better wireless network dependability, results indicate that for components DB and MSC a reactive strategy is best (lower MTR values), whereas for other components such as Base Station, Base Station Controller, Base Station and Base Station Controller Links, Base Station Controller and Mobile Switching Controller Links, a proactive strategy is best (higher MTTF values).

**Research Question 2**

R2: How often is new FCC outage reporting threshold exceeded?

With the help of a NN model, a wireless carrier can find out the expected number of FCC-reportable outages for a given set of component’s MTTF and MTR values. Moreover, sensitivity analysis for FCC-Reportable outages gives a list of sensitive independent variables, so that a wireless carrier could keep the rest of the variables at their nominal values and vary the sensitive variables to get a minimal number of FCC-Reportable outages. In addition, a decision tree gives insight as to how these twelve inputs affect the reportable outages. However, this research does not consider cost.
Research Question 3
R3: How well does NN model work for wireless networks? What are the advantages and disadvantages of NN over simulation modeling?

NN results indicate neural networks can be used to examine a wide range of reliability, maintainability, and traffic scenarios to investigate wireless network survivability, availability, and number of FCC-Reportable outages. The first part of this research question can be answered from the results of BSDOWN, BSCDOWN, MSCDOWN, BSCBSCDOWN, and MSCBSCDOWN. It is also seen that NN model gives good results for components that fail more often, because of either low MTTF or large numbers of components in the infrastructure. For example, base station, links, and base station controller failures can be accurately and efficiently modeled. However, MSC and database failures could not be figured out to a higher degree of accuracy as they are very less in number and their failure rate is comparatively low. FCC-Reportable Outages and Survivability depend mostly on components such as BS, BSC, BSCBSC links and MSCBSC links and little on MSC and DB; hence, they can be nicely modeled using neural networks. Availability depends only on DB and MSC whose failure rats are relatively low. Therefore, in this instance, availability could be marginally modeled using NN.

The second part of the question refers to the advantages and disadvantages of NN modeling over simulation. Once trained, neural network takes less time whereas simulation needs more computational effort. In addition, NN easily provides some very useful insights such as Sensitivity Analysis, and Decision Tree.

The number of simulation runs to gain the same insights as provided by NN modeling is much more than that required training the neural network. Sensitivity analysis finds out the independent variables that affect the output the most, i.e. a small variation in an input variable producing a larger impact on the output. With this utility available in NeuroSolution, the NN model takes a fraction of seconds to generate the sensitivity chart and table. It also provides twelve different graphs for each input to show its impact on the output. An equation or a trend line can be easily fitted to the graph and hence an
analytical equation can be generated for input and output parameters. One might wonder as to how many runs of a simulation would be required to perform sensitive analysis. For this study, there are 13 input parameters and 3 outputs. For a single output, to study the impact of a single input parameter, other input parameters are kept constant at the nominal values. Suppose, a single input needs at least 20 values to for one output. Since, there are 13 inputs and 20 simulation runs per input, atleast 260 runs are required to do the sensitivity analysis of one output. However, this research focuses on three outputs; therefore, three times 260 simulations runs equaling to 780 runs are required. Hence, it can be concluded that NN modeling saves computational time over simulation modeling.

A NN model can be represented in an excel spreadsheet as shown in appendix B. In an excel spreadsheet, output is represented as the summation of weighted inputs, generated by NN modeling. Therefore, an output can be generated very quickly for any set of input parameters where as in simulation modeling, a simulation program needs to be run for each set of inputs. Excel NN model also supports solver. Solver could be used to implement reverse engineering by studying how the sensitive variables vary with respect to each other for an optimum output.

Lastly, decision trees provide a conditional tree structure of all the sensitive variables with associated deciding thresholds. For example, in case of reportable outages, just by looking at the decision tree, a wireless carrier could find out the threshold values of all the sensitive variables to keep the reportable outages either below 20 or below 40 for example.

Although NN offers many advantages over simulation, it is found out that some difficulty is encountered for rare events. For example, this research could only generate a marginally efficient NN model for availability as both the DB and MSC rarely fail. The maximum regression that could be achieved by NN modeling for availability was an r of 0.71 ($r^2$ about 0.5), whereas for the other two outputs (survivability and FCC-Reportable), and r of 0.98 ($r^2$ about 0.96) was achieved.
Research Question 4

R4: How does the perception of dependability vary with the level of traffic?

Perceptions of survivability are greatly affected by assuming all customers are affected rather than those estimated to be actually using the network.
Chapter 10
Research Limitations and Future Research

10.1 Research Limitations

This research analyzes only one wireless infrastructure building block (WIB) and does not include the entire wireless network integrated with PSTN. It models 2G to 2.5G wireless infrastructures and may not be applicable for 3G and 4G architectures. This work considers a fixed size WIB with fixed network topology. Component failures are assumed independent. Modeling is done without time factors (some affected) and with ANSI time factors (all affected). Wireless signaling outside one WIB is not considered i.e. failures outside the WIB is not taken into account. Optimization is done without the consideration of reliability and maintainability cost functions; hence economic considerations are not examined. Simulation and neural network modeling is carried over a period of one year, assuming constant reliability and maintainability.

As mentioned earlier, this research involves the analysis of a single WIB serving 100,000 customers to assess ARMS attributes of wireless networks. Due to the study of one WIB, external call handover is not analyzed i.e. failures in other WIB’s are also not studied in the research. It also does not include interface to either PSTN or other WIB’s. In addition, user mobility and location management are not covered in this research. Wireless links between user and BS are not excluded from this research.

In spite of these limitations, NN shows great promise in the modeling of wireless survivability, in the form of nines (0.9999xxx) and survivability exceeding thresholds (FCC-Reportable outages).
10.2 Future Research

Simulation can be further extended an entire wireless architecture and investigate time factors, type of traffic affected, various reliability and maintainability growth, constancy and deterioration. Simulation modeling can be further extended for different network topologies such as WIB star and WIB rings to evaluate the performance for different network topologies. Cost functions can be developed and simulation can be designed for an optimal set of dependability and cost of WIB. This analysis can be further applied for 3G and 4G wireless technology. Effectiveness of neural network modeling can be evaluated for an entire PCS architecture and different network topologies and variable sized WIBs. Reverse engineering can be carried out for neural networks to find the optimal set of inputs (component MTTF and MTR values). NN modeling can also be implemented with empirical data, provided by wireless carriers for more accurate perspectives of ARMS.
References:


Appendix A

Verification of MTTF and MTR of BS by chi-square test results

<table>
<thead>
<tr>
<th>No.</th>
<th>Component</th>
<th>Down No.</th>
<th>Average</th>
<th>AveMTR</th>
<th>CumuMTR</th>
<th>Chisquare</th>
<th>ExpectCS</th>
<th>DeviCS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Base Station</td>
<td>25</td>
<td>25.00</td>
<td>0.86</td>
<td>0.86</td>
<td>10.06</td>
<td>36.40</td>
<td>10.00</td>
</tr>
<tr>
<td>2</td>
<td>Base Station</td>
<td>32</td>
<td>28.50</td>
<td>0.85</td>
<td>0.86</td>
<td>12.19</td>
<td>44.99</td>
<td>11.82</td>
</tr>
<tr>
<td>3</td>
<td>Base Station</td>
<td>30</td>
<td>29.00</td>
<td>1.17</td>
<td>0.96</td>
<td>*85.14</td>
<td>42.60</td>
<td>*87.19</td>
</tr>
<tr>
<td>4</td>
<td>Base Station</td>
<td>31</td>
<td>29.50</td>
<td>0.83</td>
<td>0.93</td>
<td>17.37</td>
<td>43.80</td>
<td>17.02</td>
</tr>
<tr>
<td>5</td>
<td>Base Station</td>
<td>18</td>
<td>27.20</td>
<td>0.72</td>
<td>0.90</td>
<td>4.57</td>
<td>27.60</td>
<td>3.36</td>
</tr>
<tr>
<td>6</td>
<td>Base Station</td>
<td>22</td>
<td>26.33</td>
<td>0.77</td>
<td>0.88</td>
<td>5.49</td>
<td>32.70</td>
<td>4.57</td>
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<tr>
<td>7</td>
<td>Base Station</td>
<td>24</td>
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<td>0.77</td>
<td>0.87</td>
<td>6.54</td>
<td>35.20</td>
<td>5.47</td>
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<td>Base Station</td>
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<td>26.00</td>
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<td>0.86</td>
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<td>37.70</td>
<td>15.78</td>
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<tr>
<td>9</td>
<td>Base Station</td>
<td>22</td>
<td>25.56</td>
<td>0.71</td>
<td>0.84</td>
<td>7.61</td>
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<td>6.05</td>
</tr>
<tr>
<td>10</td>
<td>Base Station</td>
<td>20</td>
<td>25.00</td>
<td>0.98</td>
<td>0.85</td>
<td>5.43</td>
<td>30.10</td>
<td>5.71</td>
</tr>
</tbody>
</table>

The chi-square of all down numbers in this validation is: 8.16
The chi-square value at 0.05 level of significance with df 9 is: 16.90
The chi-square value for first 101 mtr in this validation is: 117.18
The chi-square of total deviation for first 101 mtr in this validation is: 117.95
The chi-square value at 0.05 level of significance with df 100 is: 124.34

Verification of MTTF and MTR of MSC by chi-square test results

<table>
<thead>
<tr>
<th>MTTF [years]: 7.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTTR [hours]: 0.166667</td>
</tr>
</tbody>
</table>

Validate for 1 years
Check components every 5 minutes
Total run the validation for 10 times
MSC: 1

<table>
<thead>
<tr>
<th>No.</th>
<th>Component</th>
<th>Down NO.</th>
<th>Average</th>
<th>AveMTR</th>
<th>CumuMTR</th>
<th>Chisquare</th>
<th>ExpectCS</th>
<th>DeviCS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MSC</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>MSC</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>MSC</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>MSC</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>MSC</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>MSC</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>7</td>
<td>MSC</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>8</td>
<td>MSC</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>9</td>
<td>MSC</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>10</td>
<td>MSC</td>
<td>1</td>
<td>0.10</td>
<td>0.02</td>
<td>0.02</td>
<td>0.13</td>
<td>3.84</td>
<td>0.00</td>
</tr>
</tbody>
</table>

The chi-square of all down numbers in this validation is: 6.83
The chi-square value at 0.05 level of significance with df 9 is: 16.90
The chi-square value for total mtr in this validation is: 0.13
The chi-square of total deviation for total mtr in this validation is: 0.00
The chi-square value at 0.05 level of significance with df 0 is: 3.84

Similarly, other components such as BSC, BSCBS links, MSCBSC links and DB are also verified.
APPENDIX B

A part of an excel spreadsheet for FCC-reportable outages model is shown below. Any change in reliability/maintainability on FCC-reportable outages can be studied by changing twelve inputs.

<table>
<thead>
<tr>
<th>Input Data</th>
<th>Amplitude</th>
<th>Offset</th>
<th>Normalized</th>
<th>Skip</th>
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</thead>
<tbody>
<tr>
<td>MTTFBS</td>
<td>1.180980</td>
<td>0.9075645208</td>
<td>1.8075644970</td>
<td>-0.735748949</td>
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<tr>
<td>MTTFBSC</td>
<td>2.361960</td>
<td>0.9075646400</td>
<td>3.6226937771</td>
<td>-1.479062400</td>
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<tr>
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<td>MTTFMSCBSC</td>
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<tr>
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<td>1.771470</td>
<td>0.9075645208</td>
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<tr>
<td>MTRBS</td>
<td>0.59049</td>
<td>1.8305146694</td>
<td>2.7305145264</td>
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</tr>
<tr>
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<td>1.8305146694</td>
<td>2.7305145264</td>
<td>-1.649613919</td>
</tr>
<tr>
<td>MTRBSCBS</td>
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<tr>
<td>MTRMSC</td>
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<table>
<thead>
<tr>
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<td>Outages</td>
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</tbody>
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