# COST-BENEFIT ANALYSIS OF MITIGATION OF OUTAGES CAUSED BY SQUIRRELS ON THE OVERHEAD ELECTRICITY DISTRIBUTION SYSTEMS

by


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Abstract

Unpredictable power outages due to environmental factors such as lighting, wind, trees, and animals, have always been a concern for utilities because they are often unavoidable. This research aims to study squirrel-related outages by modeling past real-life outage data and provide the optimal result which would assist utilities in increasing electric system reliability. This research is a novel approach to benchmark system performance in order to identify areas and durations with higher than expected outages. The model is illustrated with seven years (2005-2011) of animal-related outage data and 14 years of weather data (1998-2011) for four cities in Kansas, used as training data to predict future outages. The past data indicates that the number of outages on any day varies with the seasons and weather conditions on that day. The prediction is based on a Bayesian Model using conditional probability table, which is calculated based on training data. Since future weather conditions are unknown and random, Monte Carlo Simulation is used with the past 14 years of weather data to create different yearly scenarios. These scenarios are then used with the models to predict expected outages. Multiple runs of Monte Carlo analysis provide a probability distribution of expected outages. Further work discusses about cost-to-benefit analysis of implementation of outage mitigation methods. The analysis is performed by considering different combinations of outage reduction and mitigation levels. In this research, eight cases of outage reduction and nine cases of mitigation levels are defined. The probability of benefit is calculated by a statistical approach for every combination. Several optimal strategies are constructed using the probability values and outage history. The outcomes are compared with each other to propose the most beneficial outage mitigation strategy. This research will immensely assist utilities in reducing the outages due to squirrels more effectively with higher benefits and therefore improve reliability of the electricity supply to consumers.

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# Dedication

I would like to dedicate my thesis to my beloved father Chandrakanth Malve.

# Acronyms

| | |
|---|---|
| MCS | Monte Carlo Simulation |
| CPT | Conditional Probability Table |
| MLE | Maximum Likelihood Estimation |
| AAE | Absolute Average Error |
| TVP | Total Vulnerable Points |
| OR | Outage Reduction |

# Chapter 1 - Introduction

This chapter introduces the research work, beginning with background research about the significance of overhead distribution system reliability. Next, the chapter provides a study of characteristics of squirrel-related outages on overhead distribution systems and outages dependence on weather conditions using historical data of weather and outages for four major cities in Kansas: Manhattan, Lawrence, Topeka, and Wichita. Monte Carlo Simulation is used to predict future outages using concepts of Bayesian model and Conditional Probability Table. Results obtained from the model are compared with observed outages to estimate the model accuracy in predicting future outages. Further research focuses on cost-to-benefit analysis for implementation of outage mitigation methods and proposes the most economical outage mitigation strategy for squirrel-related outage reduction. Objectives, scope, and importance of this research work are explained at the end of the chapter.

## Overhead Distribution System

The three major components of an electric power system are generation, transmission, and distribution. Distribution, which is categorized as primary and secondary distribution, is the part of the power system that extends from distribution substations to customer doorsteps. Depending on the type of feeders used to carry power to customers, distribution system is again divided into overhead distribution system and underground distribution system. In comparison to underground distribution systems, overhead distribution systems are more prone to outages. Outages occur regardless of time and place, causing severe impact on reliability of electric supply, affecting the industries, and hampering economic development of country. Through analysis of past history of outages, the observation was made that 80% of interruptions experienced by customers are due to outages in distribution systems [1]. Since distribution systems are located in densely populated areas with simple protection mechanisms, they are more vulnerable to outages than generation and transmission systems [2]. In the past, utilities have maintained a very high level of reliability; however, they must continue to increase their level of reliability in order to compete with recent advancements in technology. Many utilities are required to submit an annual reliability related system performance report to the utility commissions [3]. Thus, distribution system reliability is becoming a very significant component of the utility business.

## Causes of Outages in Distribution System

Various factors cause outages in distribution systems, but to achieve uniformity for comparison purposes, the IEEE Task Force has defined ten categories in benchmarking studies. However, the recommended categories do not prevent a utility from collecting additional detailed data, but the collected data must be grouped under one of the following categories [4]:

**Table 1.1 IEEE Task Force Recommended Outage Cause Categories**

| | |
|---|---|
| Equipment | Lightning |
| Planned | Power Supply |
| Public | Vegetation |
| Weather(Other than Lightning) | Wildlife |
| Unknown | Other |

Of these causes, animal outages have become a major concern for utilities due to their unpredictable nature. Animal/wildlife includes mammals, birds, reptiles, and insects or any other member of the animal kingdom. Squirrels and snakes cause outages in distribution systems by climbing up the distribution poles or transformers and creating short circuits between phase wires and ground [5]. Birds usually perch on the power lines and spread their wings, resulting in short circuits [5]. Wildlife can cause interruptions directly through contact, as with snakes, mice, ants, raccoons, squirrels, or birds, or indirectly as with nests and bird excrement. In Figure 1.1 [6], an owl perched on the lines, spread its wings and caused a short circuit fault. In Figure 1.2 [6], a squirrel climbed up the distribution pole and very possibly would have caused equipment damage.

**Figure 1.1 An Owl Caused Outage in the Distribution System [6] (With Permission of Rick Harness)**


**Figure 1.2 A Squirrel Perched on a Power Line [6] (With Permission of Rick Harness)**

Figure 1.3 shows outage percentages by different causes in the overhead distribution system in the Manhattan area in 2010 and 2011. The categories in Manhattan are different from recommended categories because of two additional causes: extreme winds and ice storms. As shown, animals caused 10% of the outages which is a significant contribution to the total outages in the system. Outages translate into millions of dollars lost due to reduced power use, man-hours paid for repair, and the cost of replacing damaged equipment**.** Thus, an efficient method to evaluate the impact of animal activities on overhead distribution lines that involves tracking the animal-related outage events, would allow utilities to gauge the effect of animal impacts on distribution reliability and to choose better operation and maintenance plans.

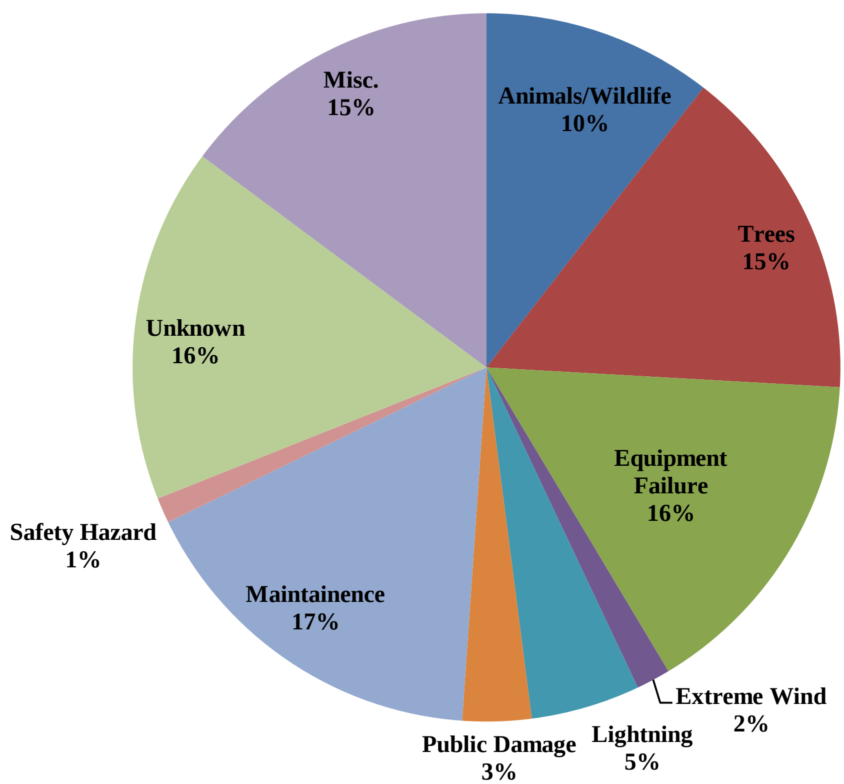



**Figure 1.3 Percentage of Outages by Different Causes in Manhattan in 2010 and 2011**

## Previous Work

In the past, Zhou, Pahwa and Yang demonstrated that the weather-related failures on overhead distribution can be modeled by the Poisson regression model and the Bayesian model [2]. The Poisson regression model determines correlation of wind and lightning with overhead feeder failures. The second method is based on one-layer Bayesian network, which uses conditional probabilities to model the causal relationship.

Later, Sahai and Pahwa did research on the weather's impact on animal-related failures in overhead distribution systems. By analyzing the historical data, it is determined that the animal-related outages are comparatively high on fair weather days. The behavioral patterns of animals in different months and their effect on animal-related outages were discovered and the 12 months are classified into three month types depending on animal activity. A one-layer Bayesian network is constructed which captures the correlation between type of month and number of fair days per week to predict animal-related outages in overhead distribution systems. The Bayesian model is applied to data of four cities in Kansas [7].

Gui, Pahwa and Das refined the models presented in [7] and have presented some additional methods to investigate the impact of weather and time of the year on the animal-related outages. Poisson regression model, neural network model, wavelet based neural network model and Bayesian model combined with Monte Carlo simulations are applied to the weekly data of four cities in Kansas. The classification of months used in Gui's research is different from Sahai's classification, as in previous work by Sahai the month type classification was only based on observation of historical data of one city, Manhattan, instead of four cities [13].

## Motivation

Distribution system reliability is crucial in order for utility companies to compete with increased power demand and the growth of technology. The present work aims to propose the optimal outage mitigation strategy with a detailed study of outages caused by animals and prediction of outages using Bayesian Network Model and Monte Carlo Simulation. By performing cost-benefit analysis, utilities can protect the distribution system effectively with exceptional benefits in terms of revenue and reliability of electric supply. Though records of outages caused by various factors were kept, the recorded data can be used to identify areas with excessive outages and control these excessive outages to achieve higher reliability of distribution systems. Various statistical methods and neural network models can be used to predict outages.

To predict animal-related outages more accurately, the effect of weather is also considered and the weather days are divided into low, medium, and high fair day levels. Similarly, recorded animal-related outages data is used to divide outages into nine outage levels. The conditional probability table is constructed using inputs, i.e., weather data and outages.

Objectives of this work are

(i) Construction of model using Bayes' theorem and Conditional Probability Table (CPT) using past data from 2005-2011.

(ii) Running Monte Carlo Simulation 10,000 times to predict future weather using past data from 1998-2011 and predict future outages using above constructed CPT.

(iii) Cost-to-benefit analysis of the implementation of outage mitigation methods and determination of the most economical outage mitigation strategy for utilities to take corrective actions in order to improve reliability of electricity supply to consumers.

# Chapter 2 - Bayesian Model Construction

Because outage occurrences are random events, they can be successfully modeled by using probabilistic methods [7]. This research uses Bayesian Model to predict future outages constructed using five-year data, from 2005-2009, referred to as training data. The developed model has been tested by comparing results with two-year outage data, from 2010-2011, known as testing data. Predictions have been conducted on a weekly, monthly, and yearly basis. Monte Carlo simulation is used to find confidence intervals for the predictions.

## Introduction to Bayesian Model

### *Bayes' Theorem*

Bayes' theorem presents the relationships of conditional probabilities and marginal probabilities of two random events. Usually the theorem is used to update the conditional probability of event A, taking account of new observations of occurrences of event B. Mathematically, Bayes' theorem is formulated by the following Equation [8]:

$$P(A|B)=\frac{P(B|A)*P(A)}{P(B)} \tag{2.1}$$

- P(A) is the prior probability or marginal probability of A. It is "prior" because no information about B is considered.
- P(A|B) is the conditional probability of A, given B. It is also called the posterior probability because it is computed after the event B has been observed.
- P(B|A) is the conditional probability of B given A.
- P(B) is the prior or marginal probability of B.

Note that B must have a non-zero prior probability in Equation 2.1.

### *Bayesian Network*

A Bayesian network is comprised of a set of variables{x1, x2… xn}, a graphical structure and a set of conditional probability tables. A Bayesian network is a directed acyclic graph, or a graph with no loops [9-11]. Each variable is represented by a node in the graph, and connection arcs are present between nodes. An arc leads a parent (casual) node to a child (influenced) node and denotes conditional dependence between the child and parent nodes. Conversely, if no connection arc is between two nodes, it indicates conditional independence. A conditional probability table, which can be computed by the prior probabilities of the parent nodes, exists for each child node.

### *Prediction by Bayesian Model*

In addition to conditional probability tables, casual relationships can also be established from the data [12]. However, the conditional probability tables are much easier to learn compared to graph topology learning [12]. Also, the conditional probability table is easier to learn with fully observed data, as compared to partially observed data in which some nodes are hidden or data is missing [12]. With fully observed data and known structure, the Maximum Likelihood Estimation (MLE) algorithm is effective [12]. For unknown graph structure, algorithms that search through model space are used [12]. MLE is a method of estimating parameters of a population such that selected values maximize the likelihood of a sample [12]. The goal of learning in this case is to find parameter values of each cumulative probability distribution, thus maximizing the likelihood of the training data [12].

A Bayesian network can be used to learn causal relationships between parents and child nodes which are captured in the conditional probability tables [9]. After graph structure and conditional probability tables are learned, a Bayesian model can be used for predictions. Given the values of parent nodes and the learned conditional probability tables, the values of the child nodes can be estimated [12]. To predict the child nodes given the status of the parent nodes, top-down reasoning is used in which the probability of an effect given the cause can be computed [12].

## Analysis of Bayesian Model

Figure 2.1 shows a one-layer discrete Bayesian network with three nodes representing the three variables: month type, fair days level, and weekly animal-related outage level [7,13]. The variables, are classified into discrete levels because with discrete variables conditional probability tables are simple to compute and easy to use. With three input states classified for month type, dividing the number of fair days per week into three different levels results in nine input states.

Classification of the input data to discrete levels, however, is at the expense of the model performance in predictions because a loss of information occurs during the classifications and all data points in each level are treated with similar priority. In order for the model to be as accurate as possible, the data must be examined carefully to get the best classification. Parent nodes should be classified in such a way that all data points with similar influences on the child nodes are grouped into the same level. Conversely, data points which have contrasting impacts on the child nodes should be grouped into different levels [7]. Also, sufficient data entries should be present for each combination of inputs because a reliable conditional probability distribution requires adequate observations in the data. On the other hand, classification of child node is required to retain as many levels as possible, with relevant number of data entries in each level [7]. The more levels that are present for the child node, the more information is available regarding the effects of parent nodes on the child node and, therefore, a sophisticated prediction of outages will be obtained.

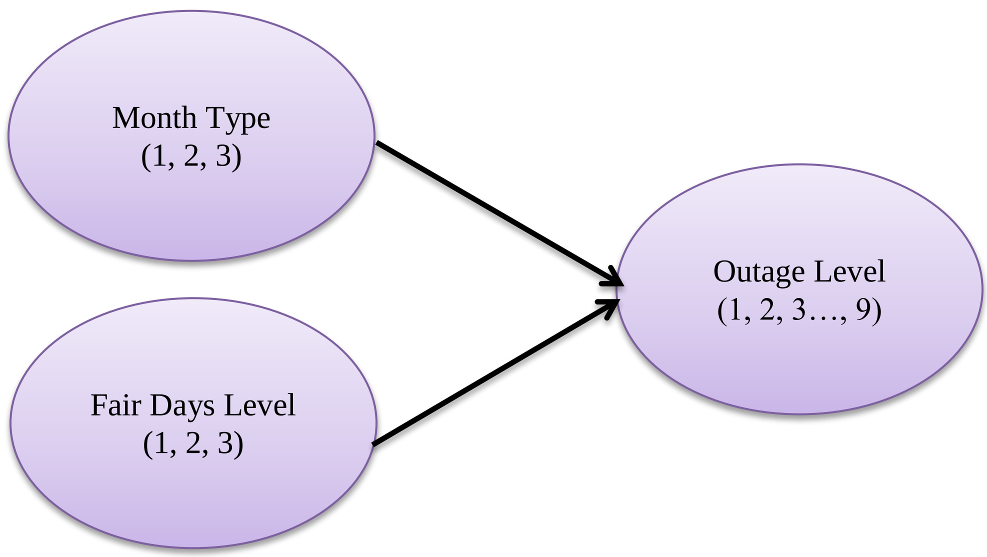



**Figure 2.1 One-layer Bayesian Model for Prediction of Squirrel-related Outages**

### *Classification of Weather Conditions*

According to previous work by Gui, Pahwa and Das, the proposed classification of 12 months into three levels based on squirrel activity is shown in Table 2.1 [13]:

**Table 2.1 Classification of Months**

| Month Type | Months | Squirrel Activity |
|---|---|---|
| 1 | January, February, March | Low |
| 2 | April, July, August, December | Moderate |
| 3 | May, June, September, October, November | High |

Squirrel activity is high for Month Type 3 because these months have more fair weather days and higher squirrel population compared to months of Month Type 1 and Month Type 2. Fair weather days are days on which temperature stays between 40 and 85 degrees Fahrenheit with no other weather activity like rain, snow, thunderstorm etc. [7]. The classification of fair day level is done by counting the number of fair days per week. For uniformity and ease of classification of data, each month is composed of exactly four weeks. Since a month can have 28, 29, 30 or 31 days, it is difficult to allocate the weeks evenly in a particular month. To make sure that all the days in a month are considered, some weeks may have eight days [7]. Therefore, the number of fair days per week can vary from zero to eight. Thus, referring to previous work [13], classification for the number of fair days per week is as follows:

**Table 2.2 Classification of Fair Weather Days per Week**

| Fair day Level | Fair weather days per week | Impact on animal caused outages |
|---|---|---|
| 1 | 0 | Low |
| 2 | 1~3 | Moderate |
| 3 | 4~7(or 8) | High |

### *Classification of Weekly Squirrel-Related Outages*

Overhead distribution feeder outage information from 2005 to 2011 for different areas in Kansas was obtained from Westar Energy. Histograms of weekly squirrel-related outages of training data from 2005 to 2009 for all the cities are shown in Figure 2.2 to 2.5. Proper classifications of outages should improve the model performance. Previous work demonstrates that classifications with nine outage levels provided the best results for almost all cities compared to other outage-level classifications [13]. Therefore, in order to maintain uniformity and simplicity, nine levels of outages are used for all cities. To construct outage levels for Wichita, every bin is made approximately of the same count of occurrences as much as possible. For instance, Wichita has a total of 240 occurrences of weekly outages varying from 1 to 65. Therefore, to obtain equal number of occurrences for every bin, which is approximately 27 (240 divided by 9), bars were grouped to sum to 27. Following this general rule, outage levels for Wichita based on Figure 2.2 are given in Table 2.3. Classifications of outage levels for other cities are given in Tables 2.4 to 2.6.

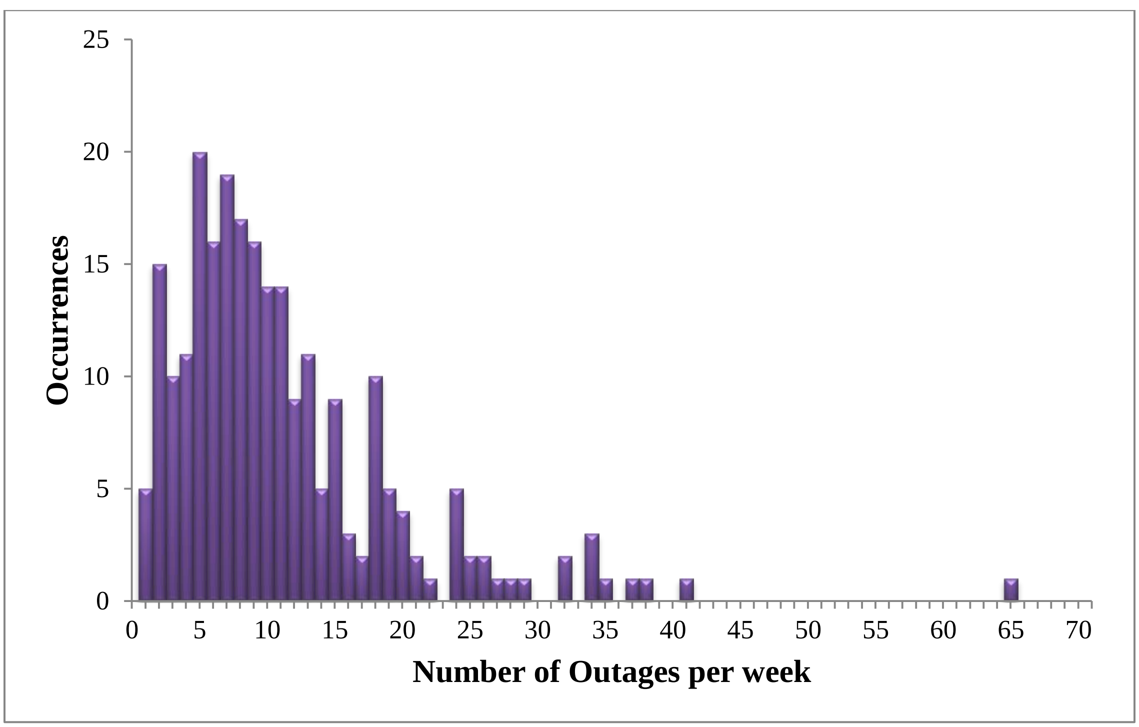



**Figure 2.2 Histogram of Weekly Squirrel-related Outages from 2005-2009 in Wichita**

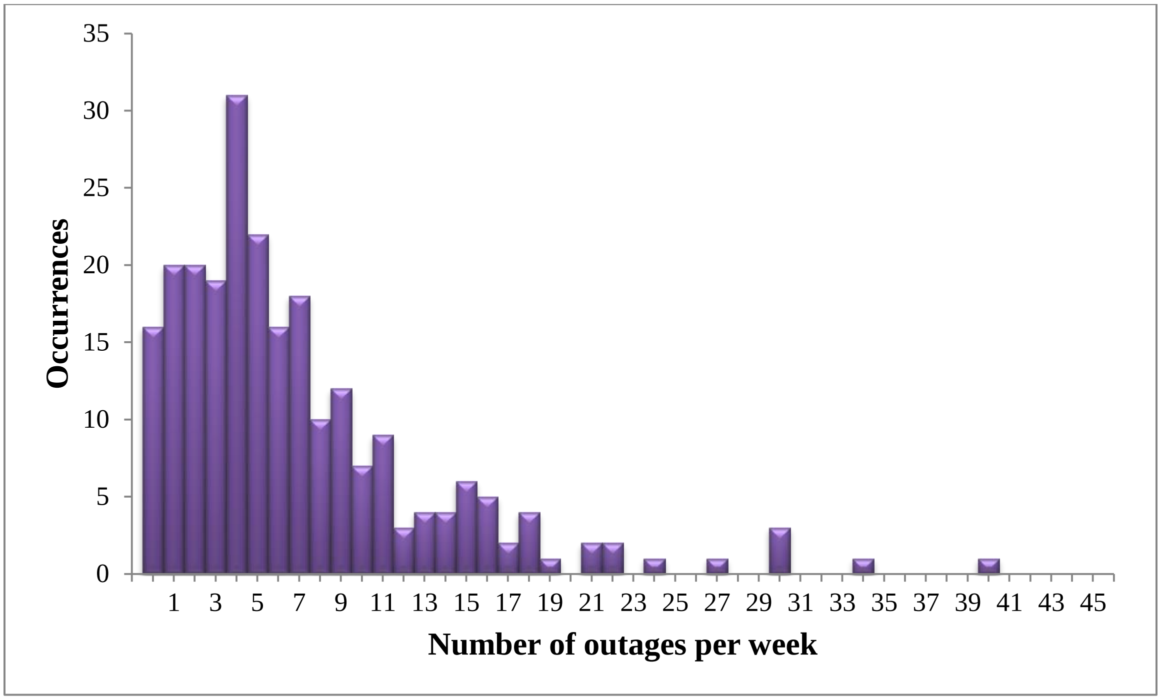



**Figure 2.3 Histogram of Weekly Squirrel-related Outages from 2005-2009 in Topeka**

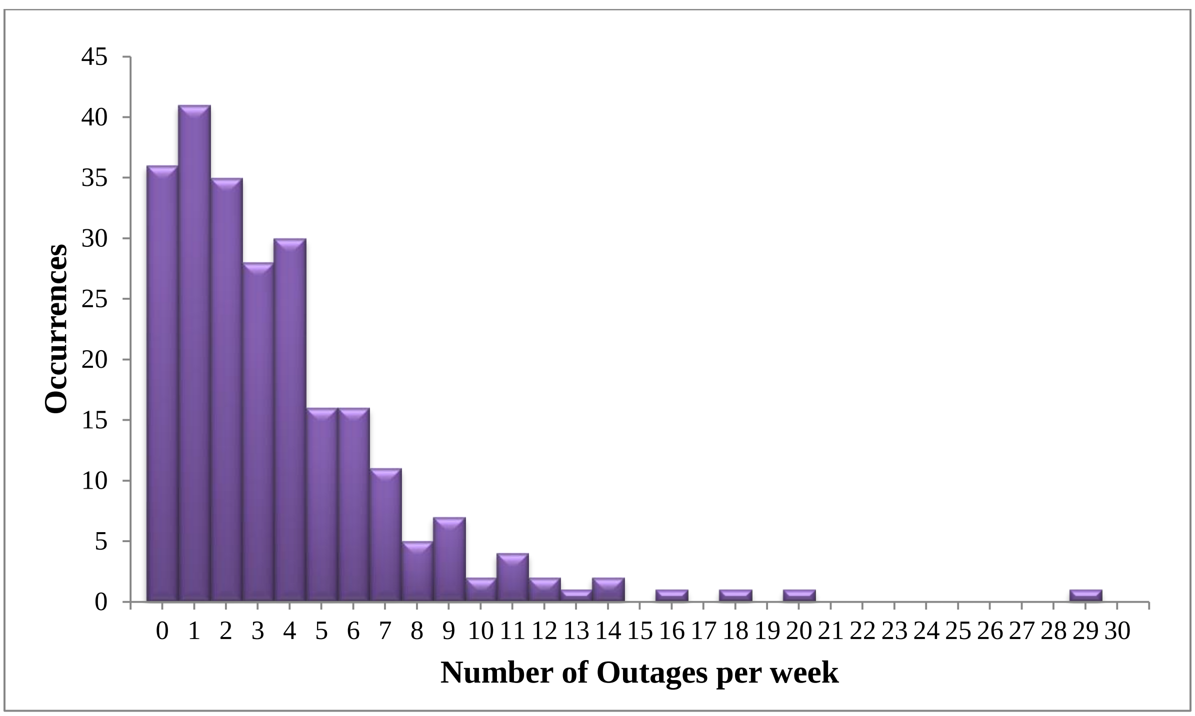



**Figure 2.4 Histogram of Weekly Squirrel -related Outages from 2005-2009 in Lawrence**

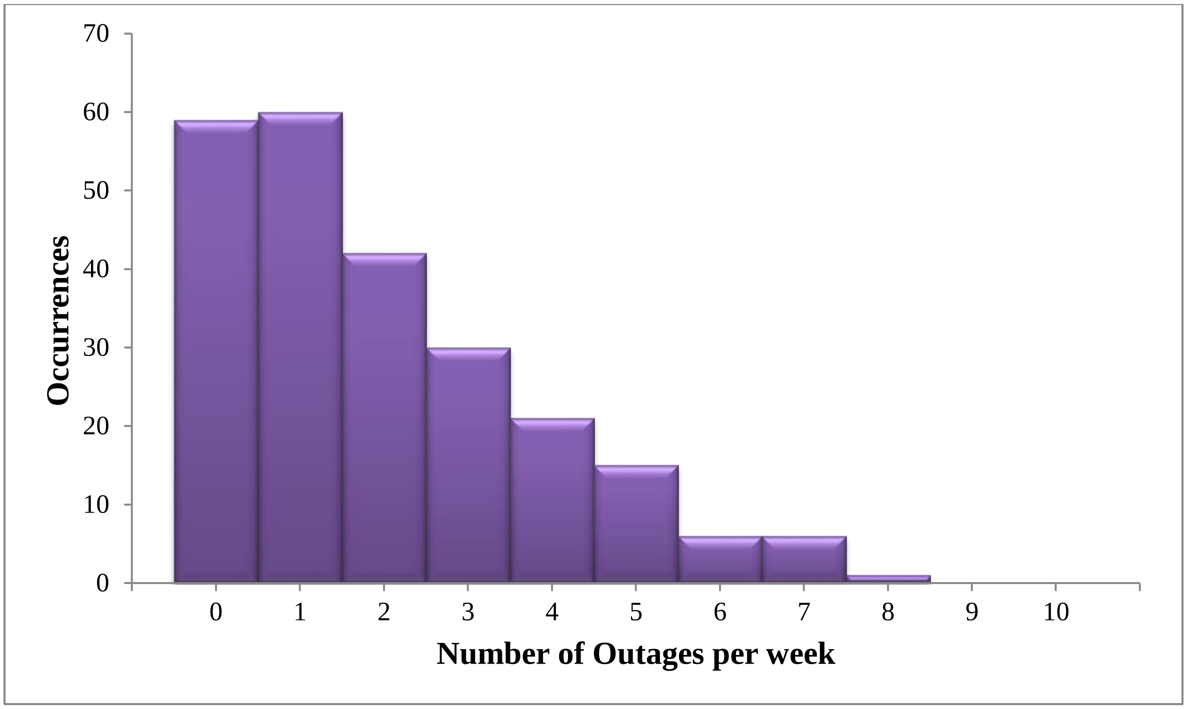



**Figure 2.5 Histogram of Weekly Squirrel-related Outages from 2005-2009 in Manhattan**

**Table 2.3 Classification of Outage Levels for Wichita**

| | Number of occurrences (weeks) | Animal Caused Outages per Week |
|---|---|---|
| Outage Level 1 | 30 | 1~3 |
| Outage Level 2 | 31 | 4 ~ 5 |
| Outage Level 3 | 35 | 6 ~ 7 |
| Outage Level 4 | 33 | 8 ~ 9 |
| Outage Level 5 | 37 | 10 ~ 12 |
| Outage Level 6 | 30 | 13 ~ 17 |
| Outage Level 7 | 21 | 18 ~ 21 |
| Outage Level 8 | 13 | 22 ~ 30 |
| Outage Level 9 | 10 | 31 ~ 65 |

**Table 2.4 Classification of Outage Levels for Topeka**

| | Number of occurrences (weeks) | Animal Caused Outages per Week |
|---|---|---|
| Outage Level 1 | 16 | 0 |
| Outage Level 2 | 40 | 1 ~ 2 |

| | | |
|---|---|---|
| Outage Level 3 | 19 | 3 |
| Outage Level 4 | 31 | 4 |
| Outage Level 5 | 38 | 5 ~ 6 |
| Outage Level 6 | 28 | 7 ~ 8 |
| Outage Level 7 | 28 | 9 ~ 11 |
| Outage Level 8 | 29 | 12 ~ 20 |
| Outage Level 9 | 11 | 21 ~ 40 |

**Table 2.5 Classification of Outage Levels for Lawrence**

| | Number of occurrences (weeks) | Animal Caused Outages per Week |
|---|---|---|
| Outage Level 1 | 36 | 0 |
| Outage Level 2 | 45 | 1 |
| Outage Level 3 | 37 | 2 |
| Outage Level 4 | 26 | 3 |
| Outage Level 5 | 31 | 4 |
| Outage Level 6 | 28 | 5 ~ 6 |
| Outage Level 7 | 18 | 7 ~ 8 |
| Outage Level 8 | 11 | 9 ~ 11 |
| Outage Level 9 | 8 | 12 ~ 29 |

**Table 2.6 Classification of Outage Levels for Manhattan**

| | Number of occurrences (weeks) | Animal Caused Outages per Week |
|---|---|---|
| Outage Level 1 | 62 | 0 |
| Outage Level 2 | 63 | 1 |
| Outage Level 3 | 42 | 2 |
| Outage Level 4 | 25 | 3 |
| Outage Level 5 | 22 | 4 |
| Outage Level 6 | 13 | 5 |
| Outage Level 7 | 9 | 6 |
| Outage Level 8 | 3 | 7 |
| Outage Level 9 | 1 | 8 |

### *Conditional Probability Table*

The conditional probability table (CPT) provides the probability of occurrence of each outage level given a month type and a level of fair weather days per week, that is,

P (Outage Level = $i$ | Month Type = $j$, Fair Weather Days per Week Level =$k$)

where $i$ = 1,…,9, $j$ =1,2,3 and $k$ = 1,2,3.

Since the graph structure is fully known, MLE is used to learn the values in the CPT with fully observed historical data. The input states are tabulated in Table 2.7 and the learned conditional probabilities are listed in Table 2.8 for Wichita. Table 2.7 shows sufficient training cases for each input state, with the exception of input state 7 because this state represents Month type 1, i.e., January, February, and March, which typically have less fair weather days. The equation used to compute conditional probabilities for input state m is:

P (Outage level = $i$ | Input state = $m$) =

Number of occurrences in outage level $i$ / Total number of occurrences in input state $m$

**Table 2.7 All Possible States and Number of Observations for Wichita**

| Input State | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Month Type | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Fair Day Level | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3 |
| Number of Occurrences | 38 | 44 | 24 | 19 | 24 | 35 | 3 | 12 | 41 |

**Table 2.8 Conditional Probability Table with Nine Input States for Wichita**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.289 | 0.289 | 0.184 | 0.158 | 0.079 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 2 | 0.205 | 0.159 | 0.250 | 0.136 | 0.182 | 0.023 | 0.023 | 0.023 | 0.000 |
| Input State 3 | 0.000 | 0.083 | 0.000 | 0.125 | 0.125 | 0.292 | 0.250 | 0.083 | 0.042 |
| Input State 4 | 0.316 | 0.158 | 0.263 | 0.105 | 0.105 | 0.053 | 0.000 | 0.000 | 0.000 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Input State 5 | 0.083 | 0.208 | 0.083 | 0.250 | 0.208 | 0.125 | 0.042 | 0.000 | 0.000 |
| Input State 6 | 0.029 | 0.086 | 0.114 | 0.029 | 0.143 | 0.200 | 0.257 | 0.057 | 0.086 |
| Input State 7 | 0.000 | 0.000 | 0.667 | 0.000 | 0.000 | 0.333 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.083 | 0.000 | 0.167 | 0.250 | 0.250 | 0.250 | 0.000 | 0.000 | 0.000 |
| Input State 9 | 0.000 | 0.000 | 0.049 | 0.146 | 0.195 | 0.171 | 0.098 | 0.195 | 0.146 |

The possible input states and conditional probability tables for other cities are shown in Table 2.9 to 2.11 and Table 2.12 to 2.14 respectively.

**Table 2.9 All Possible States and Number of Observations for Topeka**

| Input State | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Month Type | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Fair Day Level | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3 |
| Number of Occurrences | 40 | 32 | 17 | 16 | 32 | 41 | 4 | 16 | 42 |

**Table 2.10 All Possible States and Number of Observations for Lawrence**

| Input State | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Month Type | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Fair Day Level | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3 |
| Number of Occurrences | 43 | 31 | 13 | 15 | 32 | 38 | 2 | 17 | 49 |

**Table 2.11 All Possible States and Number of Observations for Manhattan**

| Input State | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Month Type | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Fair Day Level | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3 |
| Number of Occurrences | 43 | 30 | 16 | 15 | 29 | 37 | 2 | 20 | 48 |

**Table 2.12 Conditional Probability Table with Nine Input States for Topeka**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.200 | 0.300 | 0.175 | 0.175 | 0.125 | 0.025 | 0.000 | 0.000 | 0.000 |
| Input State 2 | 0.094 | 0.219 | 0.063 | 0.188 | 0.125 | 0.188 | 0.094 | 0.000 | 0.031 |
| Input State 3 | 0.000 | 0.000 | 0.118 | 0.059 | 0.118 | 0.059 | 0.353 | 0.235 | 0.059 |
| Input State 4 | 0.125 | 0.563 | 0.125 | 0.063 | 0.063 | 0.063 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.094 | 0.125 | 0.125 | 0.094 | 0.344 | 0.188 | 0.031 | 0.000 | 0.000 |
| Input State 6 | 0.000 | 0.049 | 0.000 | 0.122 | 0.146 | 0.098 | 0.171 | 0.293 | 0.122 |
| Input State 7 | 0.000 | 0.000 | 0.000 | 0.500 | 0.500 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.000 | 0.313 | 0.125 | 0.250 | 0.188 | 0.000 | 0.125 | 0.000 | 0.000 |
| Input State 9 | 0.000 | 0.024 | 0.000 | 0.048 | 0.095 | 0.214 | 0.214 | 0.310 | 0.095 |

**Table 2.13 Conditional Probability Table with Nine Input States for Lawrence**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.256 | 0.349 | 0.163 | 0.047 | 0.070 | 0.047 | 0.047 | 0.023 | 0.000 |
| Input State 2 | 0.258 | 0.226 | 0.129 | 0.161 | 0.129 | 0.097 | 0.000 | 0.000 | 0.000 |
| Input State 3 | 0.077 | 0.000 | 0.000 | 0.231 | 0.231 | 0.154 | 0.231 | 0.077 | 0.000 |
| Input State 4 | 0.267 | 0.200 | 0.267 | 0.133 | 0.067 | 0.000 | 0.000 | 0.067 | 0.000 |
| Input State 5 | 0.063 | 0.250 | 0.219 | 0.156 | 0.125 | 0.188 | 0.000 | 0.000 | 0.000 |
| Input State 6 | 0.079 | 0.053 | 0.132 | 0.053 | 0.132 | 0.237 | 0.105 | 0.184 | 0.026 |
| Input State 7 | 0.500 | 0.500 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Input State 8 | 0.176 | 0.294 | 0.353 | 0.000 | 0.118 | 0.059 | 0.000 | 0.000 | 0.000 |
| Input State 9 | 0.061 | 0.082 | 0.082 | 0.143 | 0.184 | 0.102 | 0.184 | 0.020 | 0.143 |

**Table 2.14 Conditional Probability Table with Nine Input States for Manhattan**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.349 | 0.395 | 0.093 | 0.093 | 0.047 | 0.000 | 0.000 | 0.000 | 0.023 |
| Input State 2 | 0.500 | 0.300 | 0.100 | 0.033 | 0.067 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 3 | 0.063 | 0.188 | 0.250 | 0.063 | 0.125 | 0.125 | 0.125 | 0.063 | 0.000 |
| Input State 4 | 0.333 | 0.267 | 0.200 | 0.067 | 0.133 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.172 | 0.276 | 0.310 | 0.103 | 0.069 | 0.000 | 0.069 | 0.000 | 0.000 |
| Input State 6 | 0.135 | 0.108 | 0.189 | 0.108 | 0.162 | 0.108 | 0.135 | 0.054 | 0.000 |
| Input State 7 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.350 | 0.300 | 0.100 | 0.100 | 0.150 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 9 | 0.188 | 0.208 | 0.208 | 0.188 | 0.063 | 0.146 | 0.000 | 0.000 | 0.000 |

The CPT represents the influence of month and number of fair weather days per week on the number of animal-related outages per week [7]. Zero occurrences for high outage levels in the CPT indicates that if the month type is 1 and no fair weather days occur in a week, then a very low number of animal-caused outages will takes place. In addition, other inferences can be drawn from the table similar to those of previous work [7, 13].

## *Expected Value of Outages*

Expected values of the outages can be calculated by multiplying the average value or median of each outage level to its corresponding conditional probabilities obtained from the Bayesian Model. In this research work, average values are characterized for each input state because the average values retain the distribution of outages in the same outage level and thus more accurately represent the outage levels. Average values for outage levels in the data for Wichita are tabulated in Table 2.15.

**Table 2.15 Average Values for Each Outage Level for Wichita**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Average Value | 2 | 4.5 | 6.5 | 8.5 | 11 | 15 | 19.5 | 26 | 48 |

Using Equation 2.2 [7], the expected number of squirrel-caused outages can be computed in each input state:

E (Number of Outages | Input state = *j*) =

$$\sum_{k=1}^{9} P(outage\ level = k | input\ state = j) \times Average(Outage\ level = k) \qquad (2.2)$$

where,

- E (Number of animal-caused outages | Input state = *j*) is the expected number of animal-caused outages in input state *j*, *j* = 1… 9
- P (Outage level = *k* | Input state = *j*) is the conditional probability of the occurrence of outage level *k*, given input state *j*, which can be learnt from Table 2.8.
- Average (Outage level = *k*) is the average value of the outage level *k*, *k*=1… 9. The average values can be learnt from Table 2.15.

Expected values of animal-caused outages in each input state for Bayesian models with nine input states are shown in Table 2.16 for Wichita. For clear observation of trends in the expected values, they are plotted in Figure 2.6-2.9, which illustrates the increasing trend in expected values of animal-related outages when the month type increases from 1 to 3. When the fair day level increases from 1 to 3, a similar but not-as-obvious increasing trend is observed in the expected values of outages. However, for other cities, when the fair days level increases from 2 to 3, there is a slight decrease in the expected values of outages in several cases. This is due to the fact that we are considering point estimates for outages. Also, the size of the cities can have an influence. Since Wichita is the biggest city, it gives the best results due to smoothing of the data as seen in Figure 2.6. On the other hand, observing Figures 2.8 and 2.9 shows that the results for Lawrence and Manhattan have most inconsistencies as these estimates considers only average values ignoring the actual range of outages per week.

**Table 2.16 Expected Values of Animal-related Outages for Wichita by Bayesian Model with Nine Input States**

| Outage Level | Month Type | Fair day level | Expected Number |
|---|---|---|---|
| Input State 1 | 1 | 1 | 5.29 |
| Input State 2 | 2 | 1 | 7.28 |
| Input State 3 | 3 | 1 | 16.23 |
| Input State 4 | 1 | 2 | 5.89 |
| Input State 5 | 2 | 2 | 8.75 |
| Input State 6 | 3 | 2 | 16.61 |
| Input State 7 | 1 | 3 | 9.33 |
| Input State 8 | 2 | 3 | 9.88 |
| Input State 9 | 3 | 3 | 20.27 |

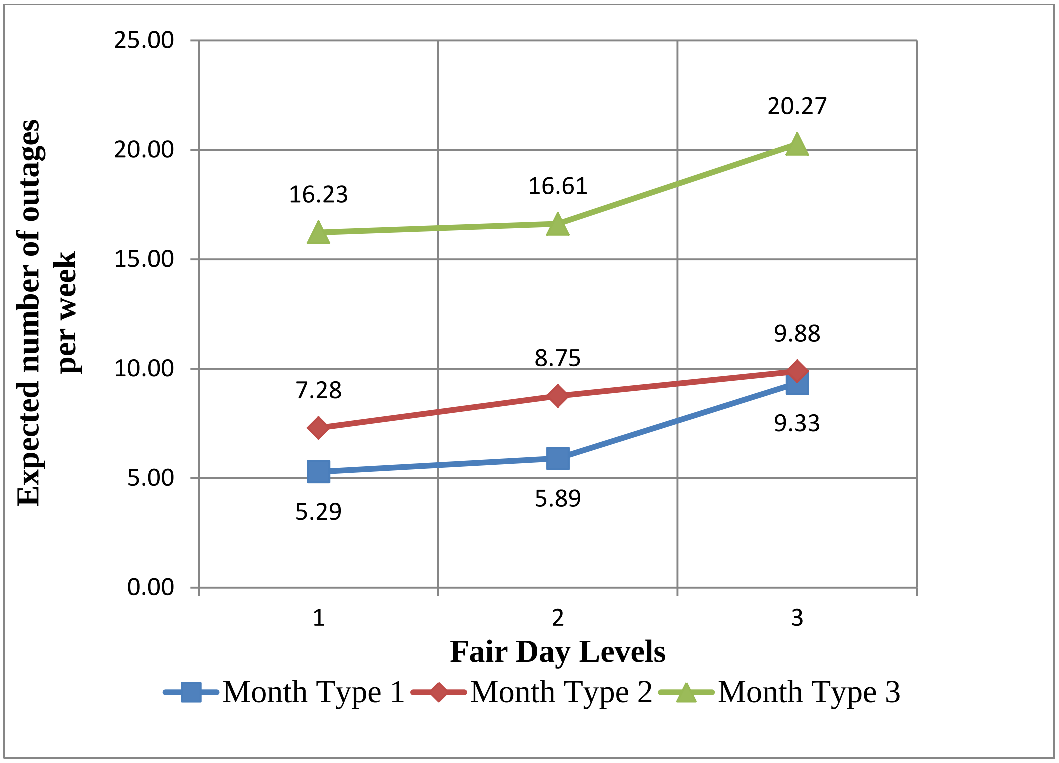



**Figure 2.6 Trends in Expected Values of Animal-related Outages for Wichita**

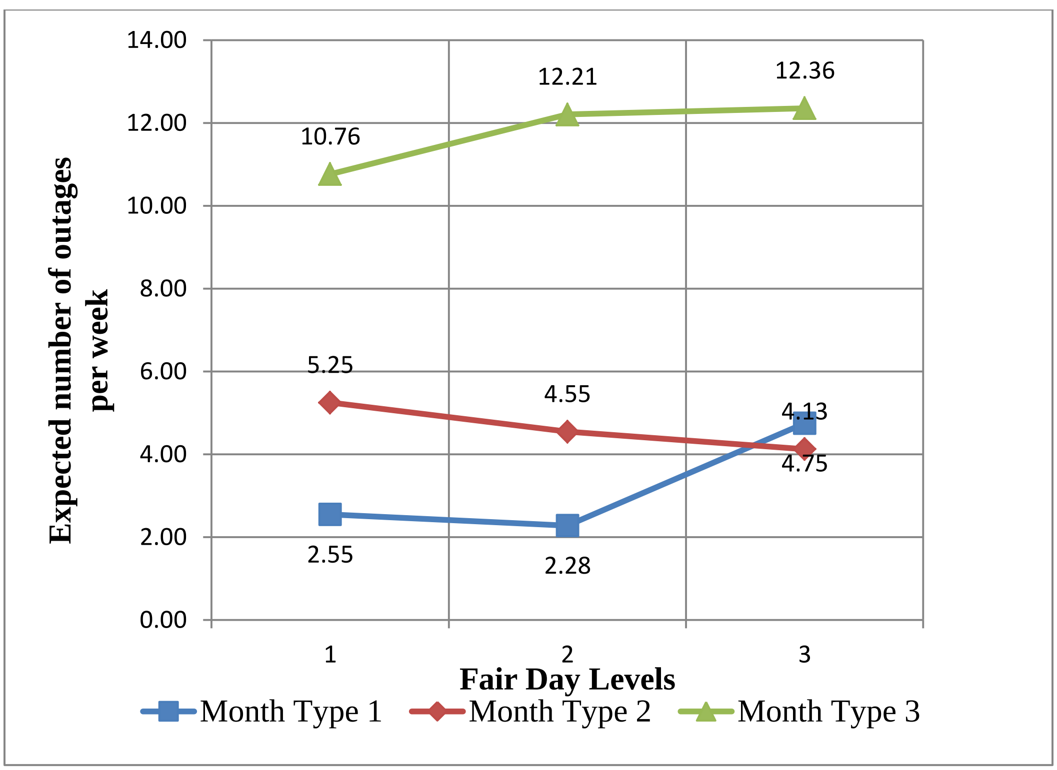



**Figure 2.7 Trends in Expected Values of Animal-related Outages for Topeka**

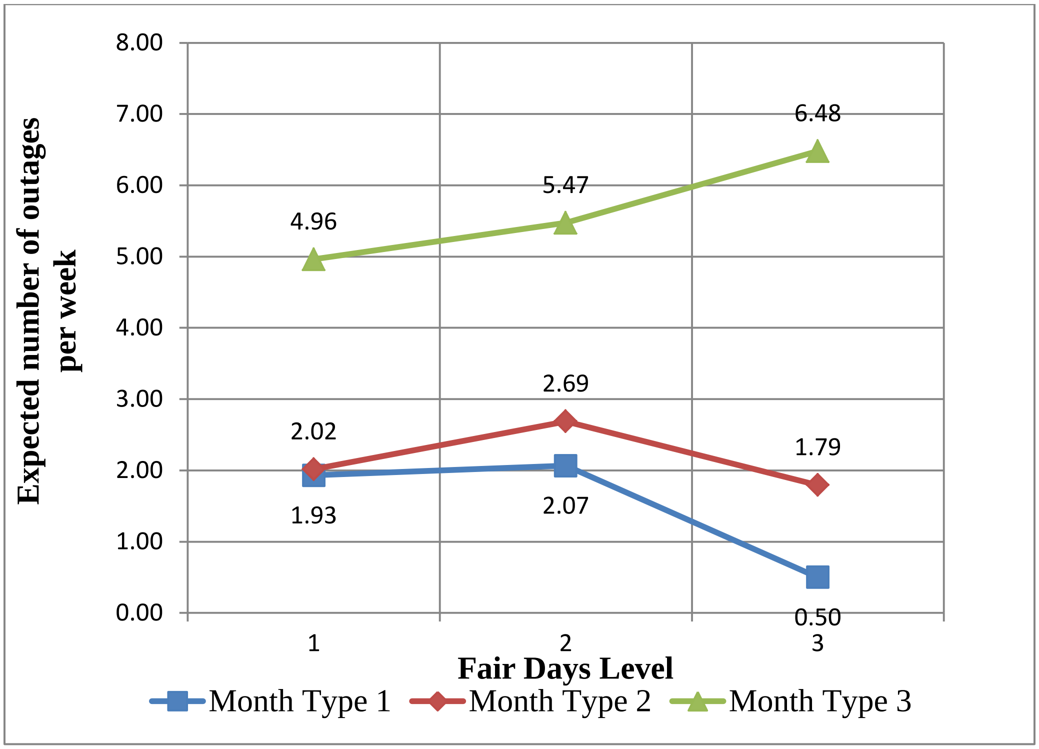



**Figure 2.8 Trends in Expected Values of Animal-related Outages for Lawrence**

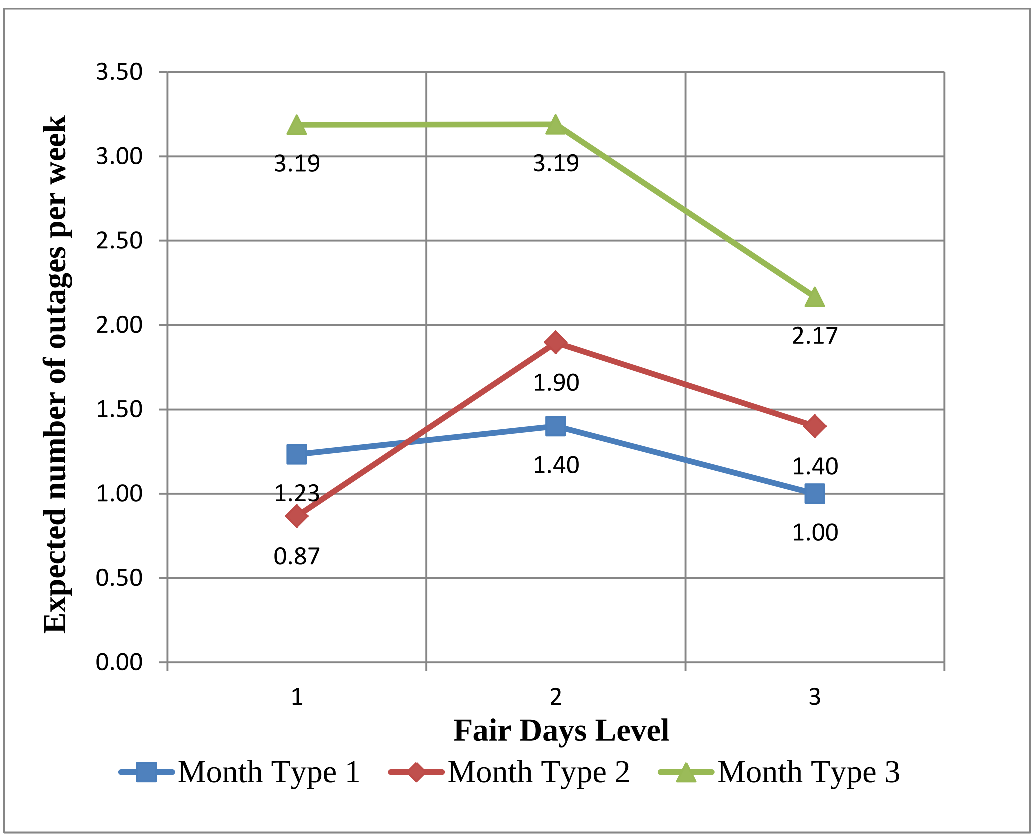



**Figure 2.9 Trends in Expected Values of Animal-related Outages for Manhattan**

The expected value in any input state is considered to be the estimated value for weeks with the same input state. A time series estimation by Bayesian model with nine input states for Wichita is shown in Figure 2.10. As shown in this figure, the model underestimates for the months in which the numbers of animal-related outages have been high, and this is mainly because of loss of information during outage classifications. The average values represent an outage level during estimations; thus, higher observed values of outages in one outage level are ignored during estimations. To overcome the above problem, the outage levels are considered as outputs instead of the numbers of outages. Outage levels can be obtained using Table 2.16 for each expected value of outages and then listed as the expected outage levels, shown in Table 2.17. The time series estimation of outage levels for Wichita is shown in Figure 2.11. Comparing Figure 2.11 to Figure 2.10, improved performance was observed when the estimates are represented as outage levels instead of number of outages.

**Table 2.17 Expected Outage Levels for Wichita by Bayesian Model with Nine Input States**

| Outage Level | Month Type | Fair day level | Expected Outage Level |
|---|---|---|---|
| Input State 1 | 1 | 1 | 2 |
| Input State 2 | 2 | 1 | 3 |
| Input State 3 | 3 | 1 | 6 |
| Input State 4 | 1 | 2 | 3 |
| Input State 5 | 2 | 2 | 4 |
| Input State 6 | 3 | 2 | 6 |
| Input State 7 | 1 | 3 | 4 |
| Input State 8 | 2 | 3 | 5 |
| Input State 9 | 3 | 3 | 7 |

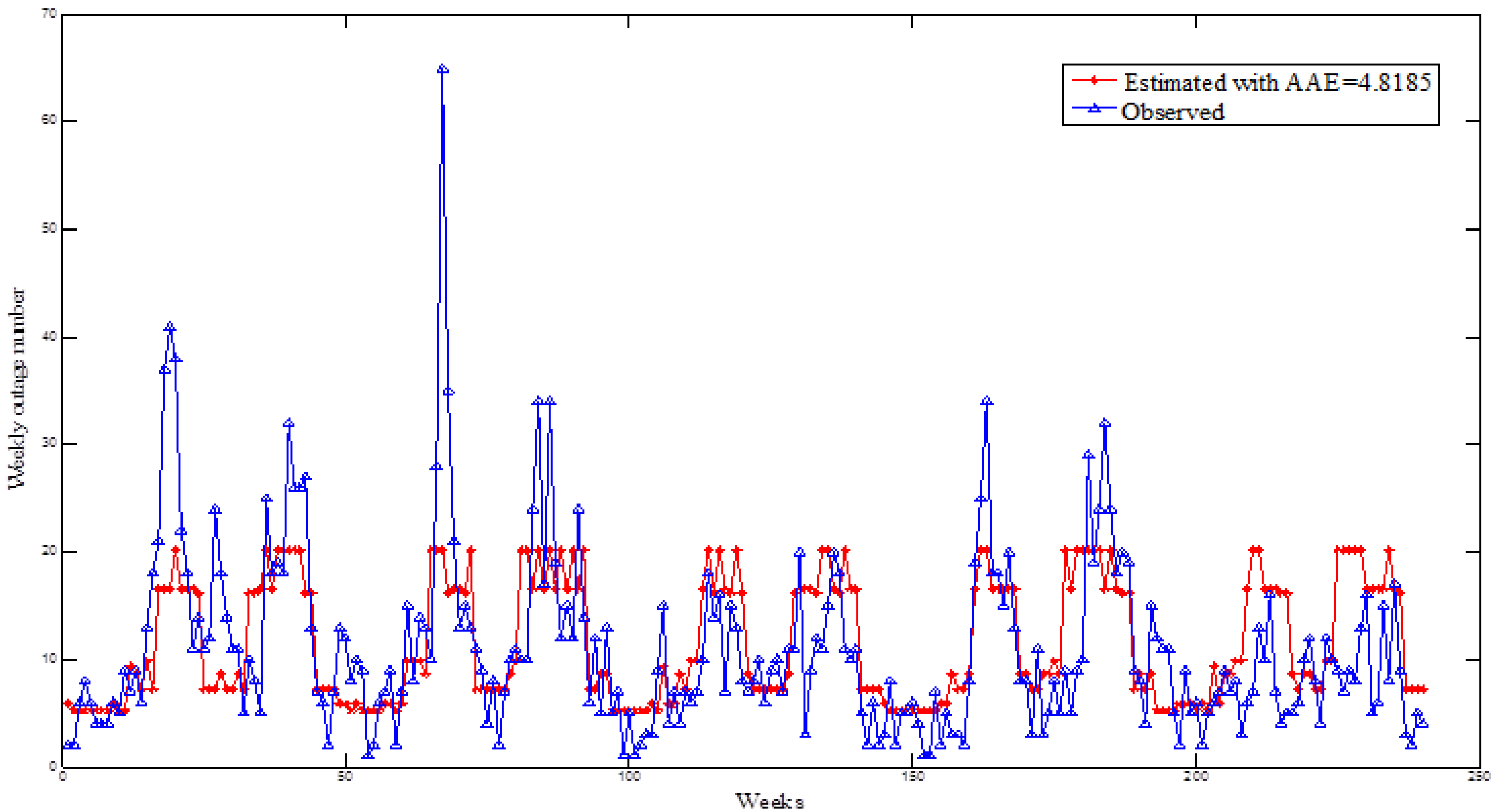



Figure 2.10 Outages Estimated and Observed by the Bayesian Model with Nine Input States for Wichita

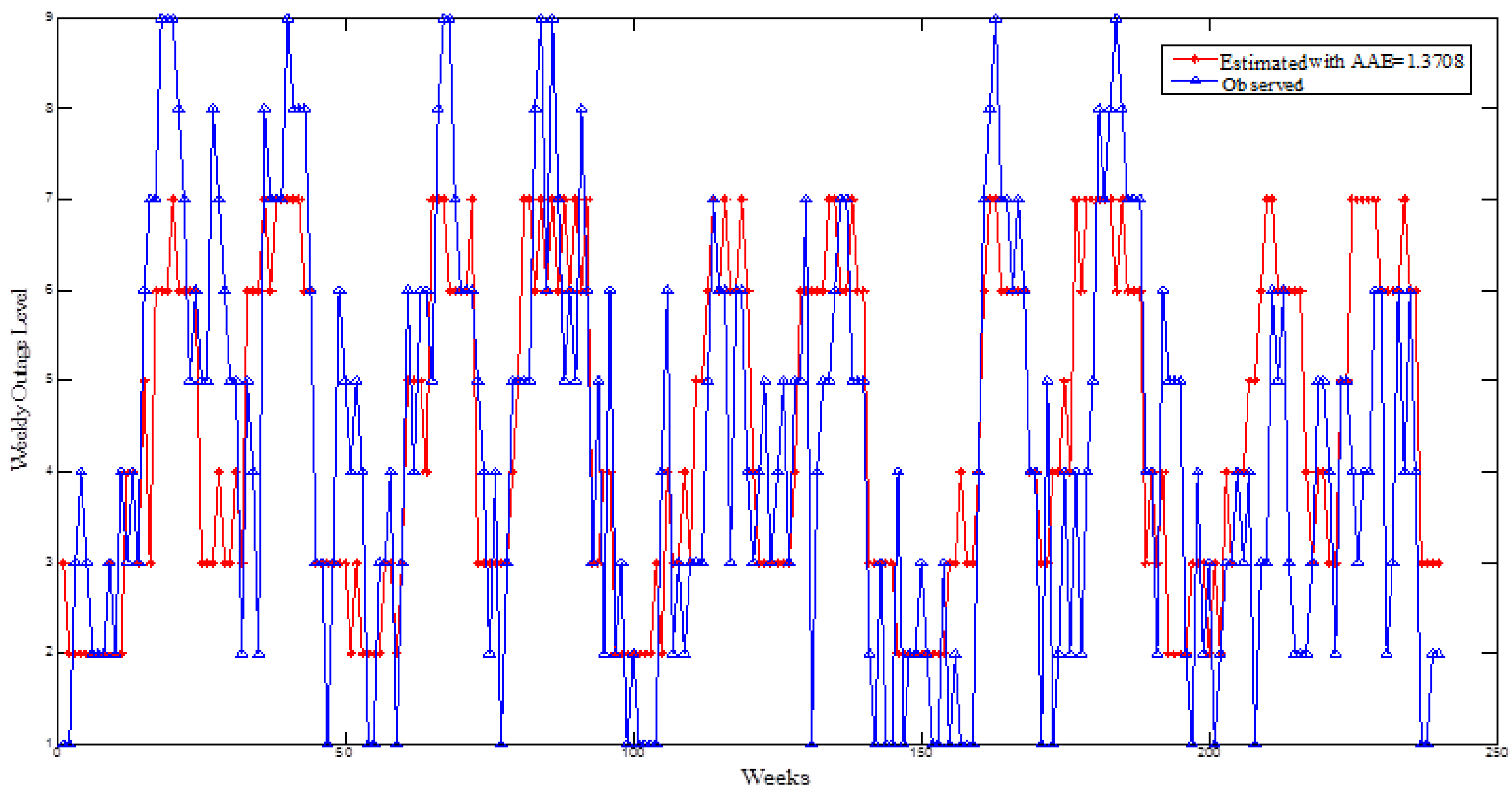



**Figure 2.11 Outage Levels Estimated and Observed by the Bayesian Model with Nine Input States for Wichita**

From Bayesian Model results, it is clear that the model performance is similar to conclusions drawn in [13]. Similar results for other cities are shown in Figure 2.11 to 2.16. The results show that using only point estimates of outages or outage level is not satisfactory.

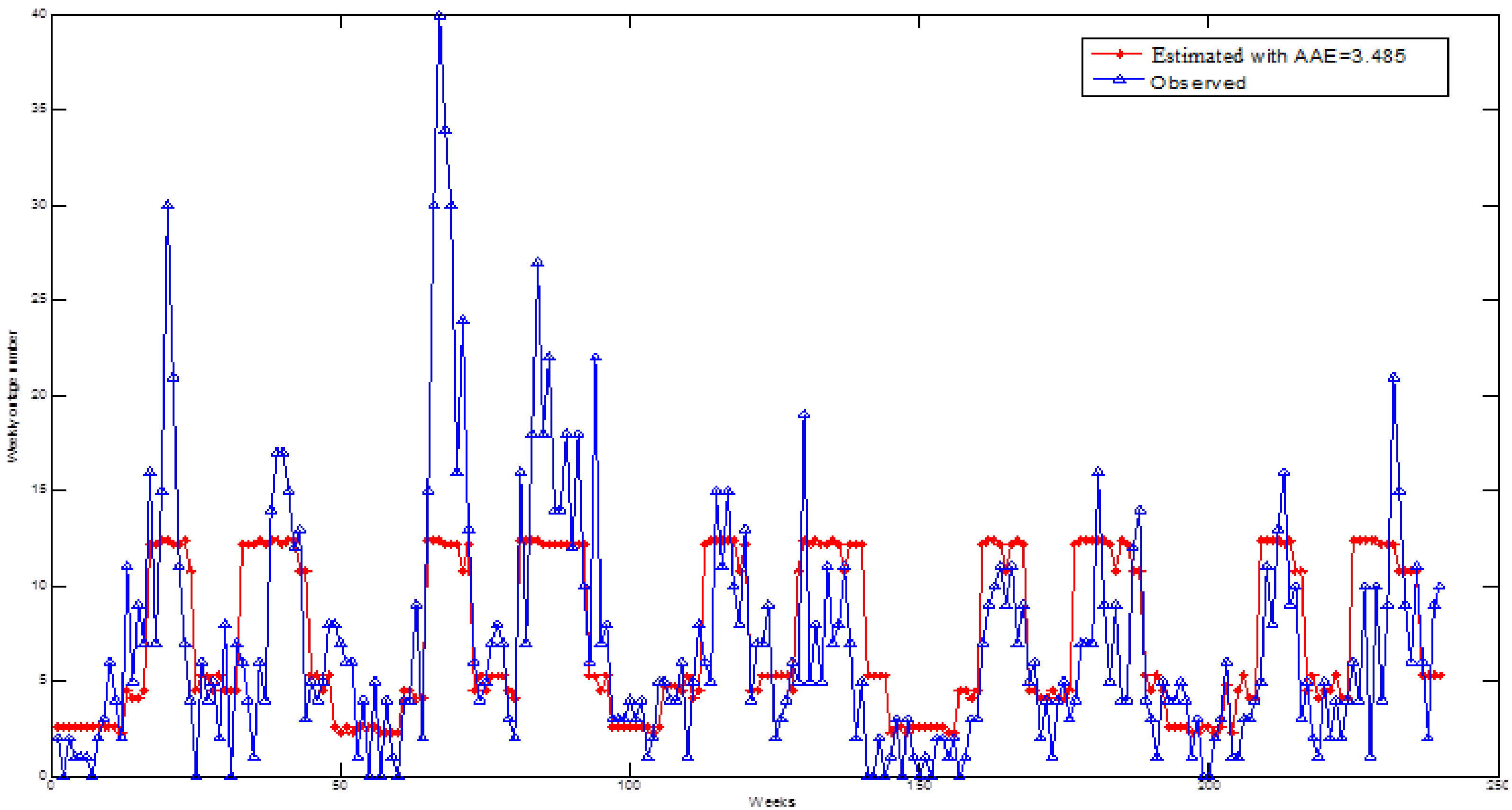



Figure 2.12  Outage Values Estimated and Observed by the Bayesian Model with Nine Input States for Topeka

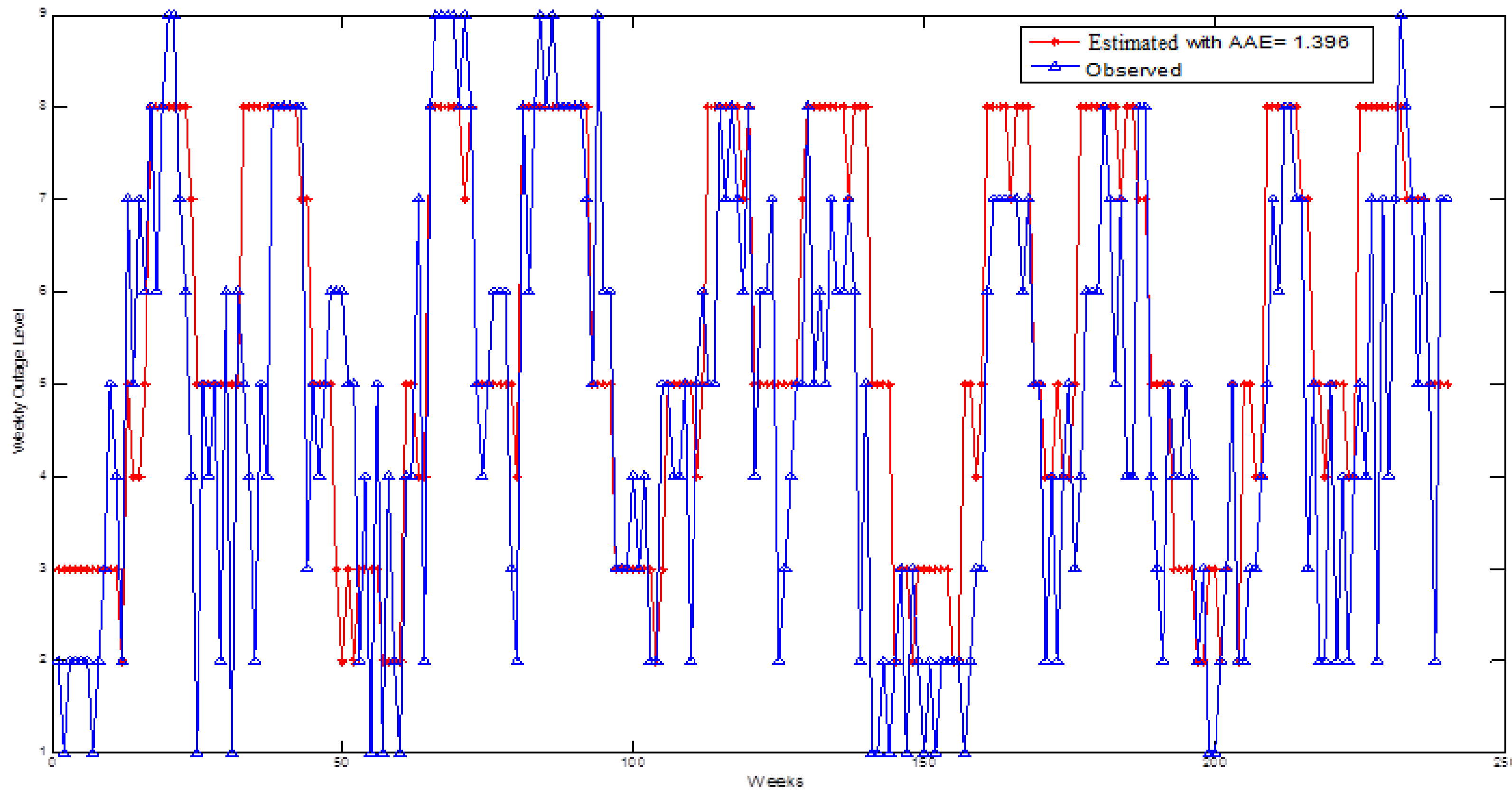



Figure 2.13 Outage Levels Estimated and Observed by the Bayesian Model with Nine Input States for Topeka

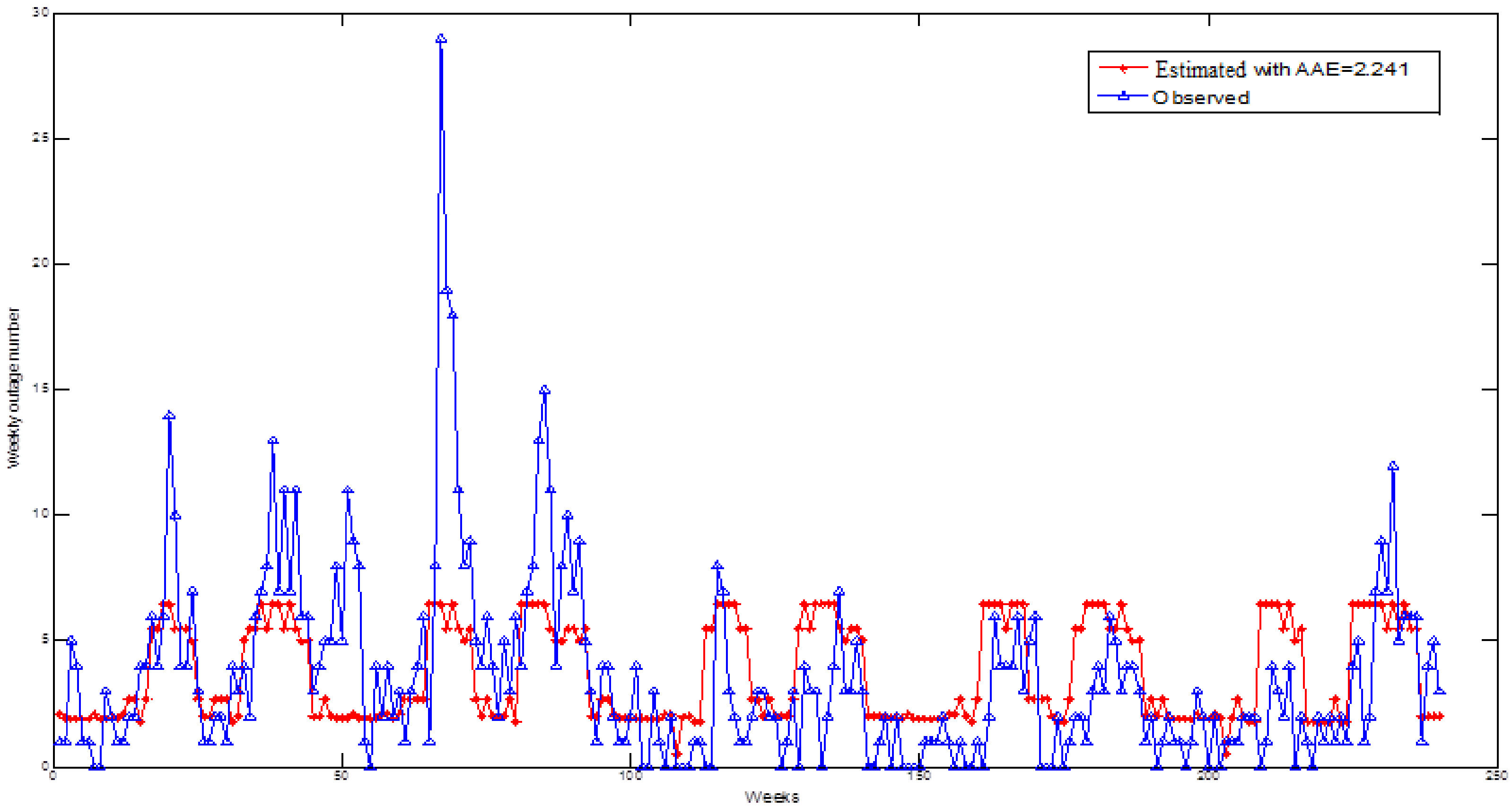



**Figure 2.14 Outage Values Estimated and Observed by the Bayesian Model with Nine Input States for Lawrence**

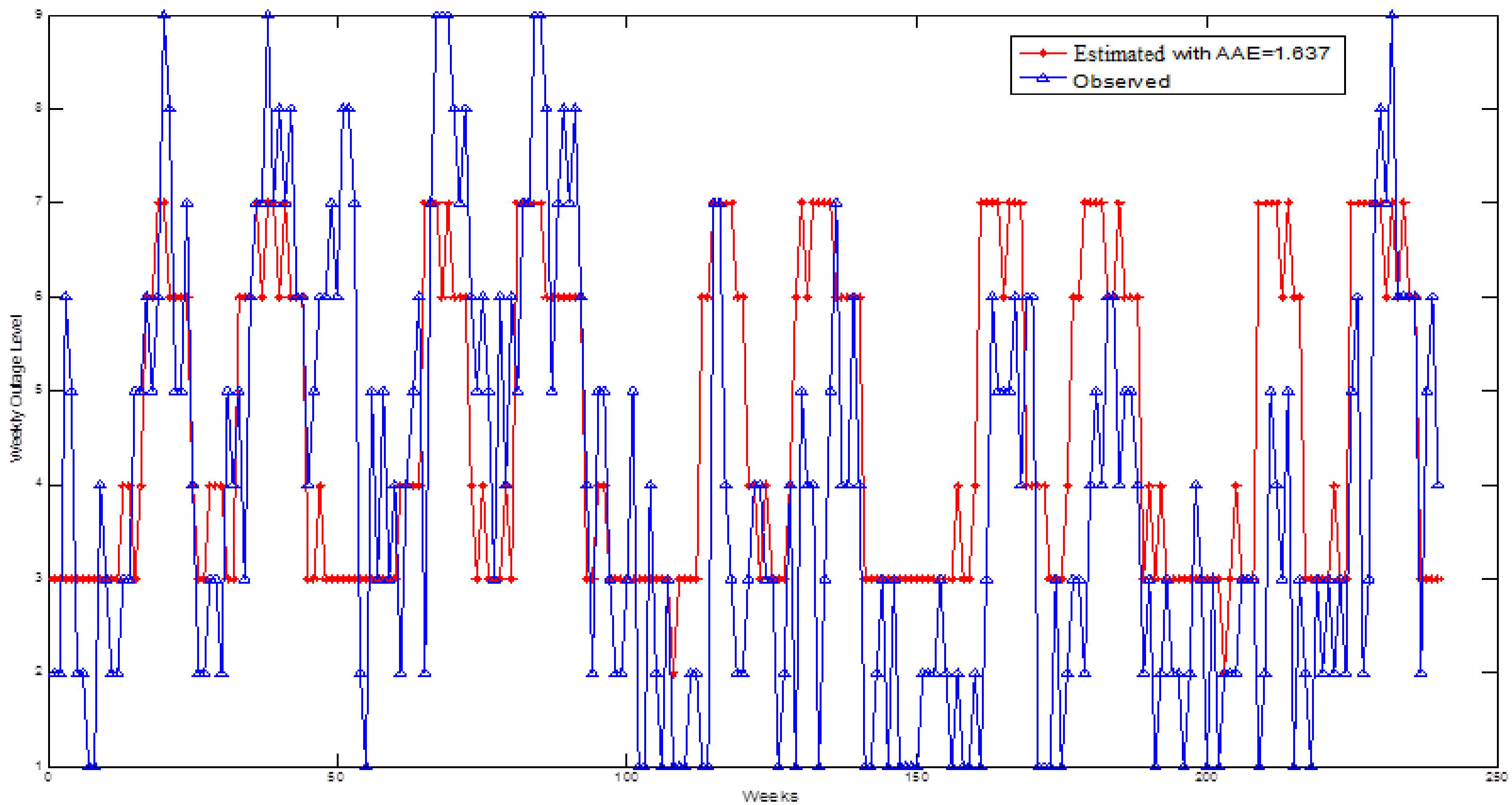



**Figure 2.15 Outage Levels Estimated and Observed by the Bayesian Model with Nine Input States for Lawrence**

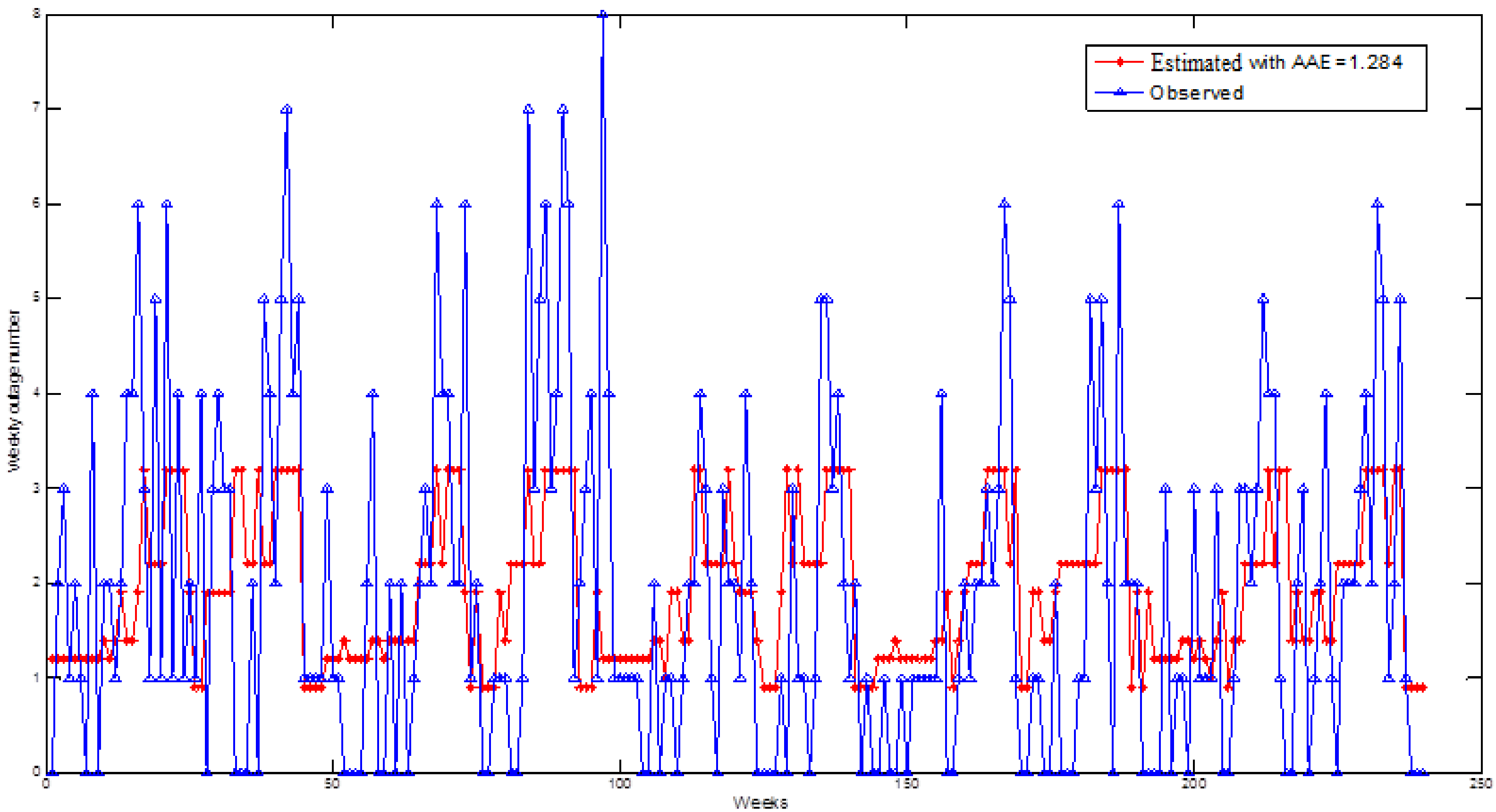



Figure 2.16 Outage Values Estimated and Observed by the Bayesian Model with Nine Input States for Manhattan

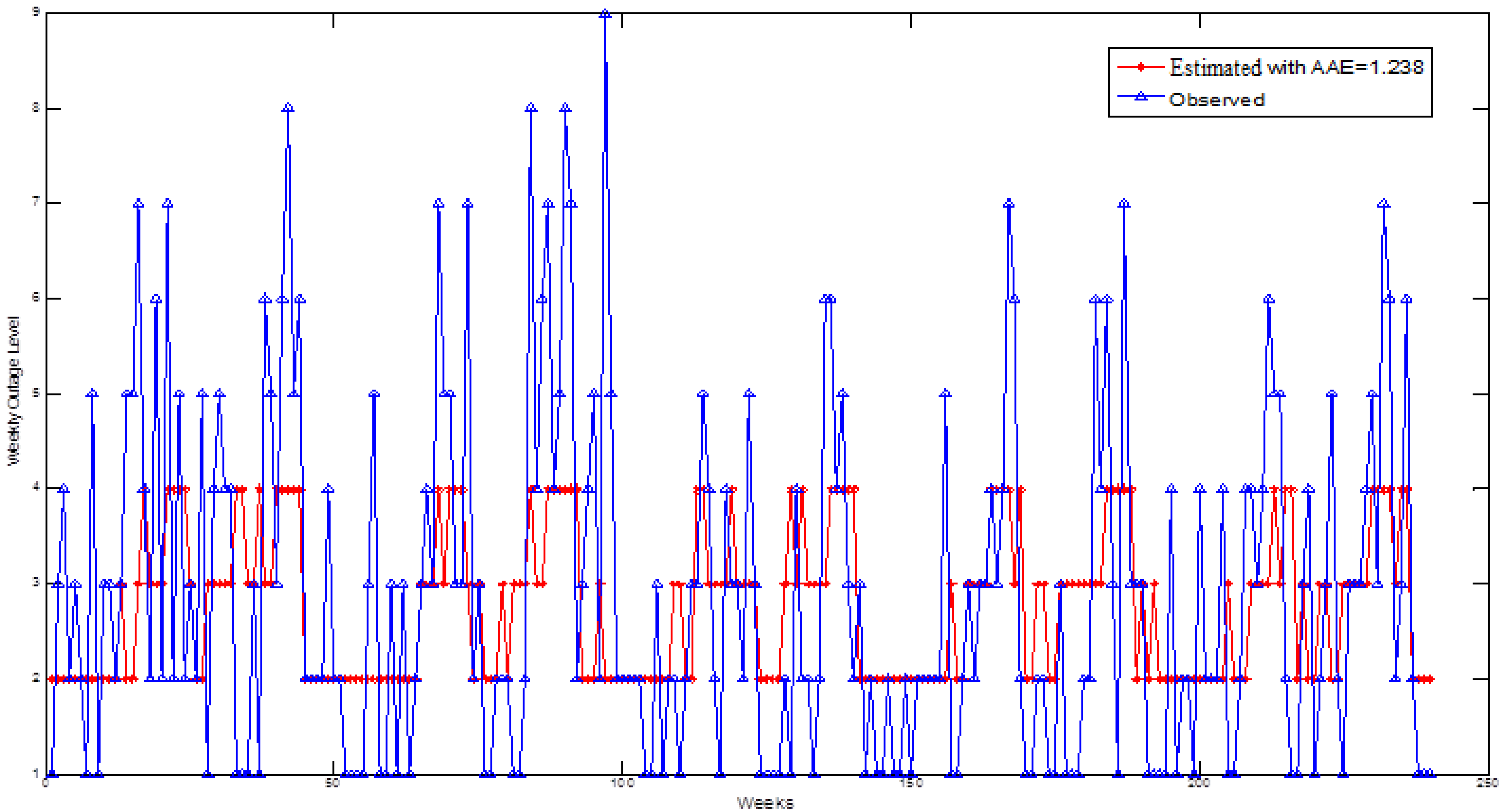



**Figure 2.17 Outage Levels Estimated and Observed by the Bayesian Model with Nine Input States for Manhattan**

# Chapter 3 - Monte Carlo Simulation

In Chapter 2, the assumption was made that the computed value of outages for each state is the expected value, which represents a point estimate for the number of outages. However, since a particular month type and particular level of fair weather days per week are composed of a number of entities, an input state represents a range of different values of factors and is only a rough classification of the effects of month and fair weather days on animal-caused outages. Thus, the model is expected to contain errors in prediction and a range of values should be found within which the observed numbers of outages are expected to lie. Monte Carlo simulation is a common method to determine the confidence intervals. Moreover, classifying input data into discrete levels causes the model prone to inaccuracies in predictions because all outages in one level are represented by an average value, causing clearly observed underestimations in predictions. Outages higher than the average in an outage level are ignored while computing average. To overcome this insufficiency, Monte Carlo simulations were utilized in order to obtain a range for predicted outages.

Monte Carlo simulation uses random numbers to resample a system and gives distributions of the output. Such methods are typically used when the computation of an exact result with a deterministic algorithm is not feasible or impossible [14]. Results of a Monte Carlo simulation are distributions of possible outcomes instead of one predicted outcome. In other words, Monte Carlo simulations give the range of possible outcomes that could occur and the likelihood of any of those occurrences. Given the same weather conditions, occurrences of animal-related outages are observed for hundreds or thousands of times instead of the limited and oftentimes insufficient training cases. Even though a Monte Carlo simulation is an approximate technique, any degree of precision can be achieved by increasing the number of iterations [15]. Monte Carlo simulations have greatly impacted many different fields of computational science, especially reliability assessment of power system [16-18].

## Algorithm

The same algorithm which was implemented in [19] was used for Monte Carlo simulations based on normalized CPT of Bayesian model with nine input states (MCS CPT9).

The algorithm outline for MCS CPT9 is provided below:

- Find the input state for a given week.
- Generate a uniform random number.
- Use roulette wheel selection with this random number to select an outage level based on CPT (not normalized by bin sizes in outage levels).
- Generate another uniform random number.
- Use roulette wheel selection with this random number to select a value of outage from each outage level. The outages follow uniform distribution within one outage level.
- Repeat the simulation 10000 times each week.

Animal-related outage data and weather data from 2005-2009 for Wichita, Topeka, Lawrence, and Manhattan have total 240 weeks. Each week has a given input state. Using the week's input state information, the algorithm generated one outage level for that week using CPT. Then, this outage level information generated outage value for that week using uniformly distributed values that assigns equal probabilities for every outage value depending on outage level. Since the simulation was repeated for 10000 iterations, 10,000 simulated sample points were obtained for each week; the expected outage is the mean of its 10,000 sample points. By totaling the sample points of four weeks in the same month in an iteration, 10,000 sample points for monthly outages were acquired, and by adding the sample points of 48 weeks in the iteration, 10,000 sample points were gathered for the yearly outages. The mean of 10,000 simulations was taken as prediction instead of using the expected value computed by Equation 2.1, thus improving the performance of Bayesian model outputs since every outage has a chance to be generated instead of representing one outage level by only the average value.

## Confidence Interval

With 10,000 sample points for every week, the confidence interval could easily be determined. The upper limit for 95% confidence is the smallest integer X such that the percentage of all numbers below X exceeds 97.5% of the 10,000 data points. The lower limits are assumed to be the largest integer, which makes the percentage of all the numbers below it smaller than 2.5%. The confidence intervals were computed based on the 10,000 aggregated monthly and yearly data points in the same way as for the weekly data. The upper limits gave a range in which the actual observed values are expected to lie given the combination of month type and the number of fair weather per week. As the amount of confidence is reduced, the range allowed for the predicted value decreases. With a lower confidence, more observed values may lie outside the predicted range of values. In this research, only the upper limits are given more attention, because they provide a benchmark for the utilities of animal-caused outages that could occur in the system. The utilities can take preventive actions based on these upper limits.

## Testing of Model Accuracy

To test if the results of Monte Carlo simulations are accurate, the histogram of input state 6 was compared with the histogram of 10,000 simulation points of the first week of May 2011 in Wichita. A comparison of Figures 3.1 and 3.2, clearly demonstrate that values generated by MCS CPT9 are in consonance with CPT values of input state 6. Therefore, the model generates the every outage value depending on CPT. However, the summation of outages for outage levels with same probability value might not be same as the outage values are generated randomly.

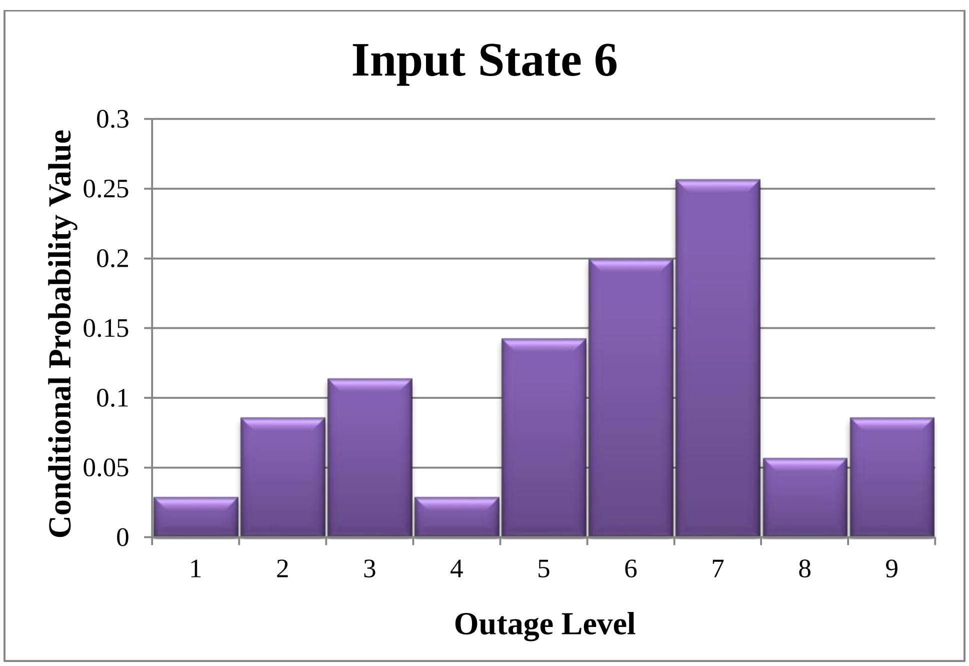



**Figure 3.1 CPT Values of Wichita for Input State 6**

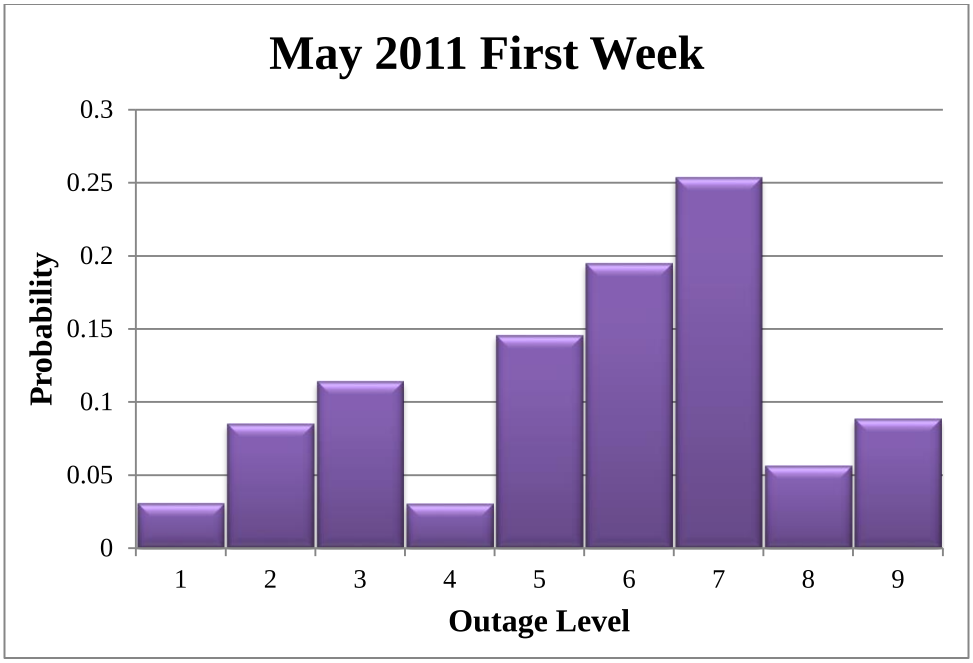



**Figure 3.2 Histogram of MCS 10,000 Points for Each Outage Level of Wichita**

Results for the weekly and monthly estimations by MCS for training data: 2005-2009 are shown in Figures 3.3-3.10 for all four cities, and for testing data: 2010-2011 are shown in Figures 3.11-3.18 for all cities. Also, the upper 95% limit for outages is shown in these figures. Observation of the weekly estimated simulation of Wichita indicates that most weeks fell below the 95% confidence interval, except Week 24, Week 44, and Week 48. In monthly estimations, January 2011 was above the confidence interval. For Topeka, nine weeks out of 96 weeks were outside the upper limit of 95% confidence interval in weekly estimations and one month was outside the upper limit for monthly estimation. For Lawrence, eight weeks were outside the upper limits and all months were below the upper limit. For Manhattan, more than ten weeks and four months were outside the upper limit for weekly and monthly estimations, respectively. Therefore, estimations are more accurate on a monthly basis since the time series evens out for bigger aggregation, resulting in a more consistent data pattern. However, in yearly estimations of all cities, excessive information was ignored and the estimations tended to flatten out over the years since weather conditions are similar from year to year.

Absolute Average Error (AAE) values are tabulated in Table 3.1. The AAE value shows closeness of estimations to the observed values.

**Table 3.1 AAE Obtained from MCS**

| City | AAE | |
|---|---|---|
| | Training data (2005-2009) | Testing data (2010-2011) |
| Wichita | 4.7414 | 8.0208 |
| Topeka | 3.4458 | 7.7917 |
| Lawrence | 2.2542 | 2.3750 |
| Manhattan | 1.2375 | 2.4479 |

From Table 3.1, the AAE values are higher for testing data as the years 2010 and 2011 had more outages than in previous years. Therefore, the CPT constructed using 2005-2009 outage data resulted in higher values of AAE for testing period than training period.

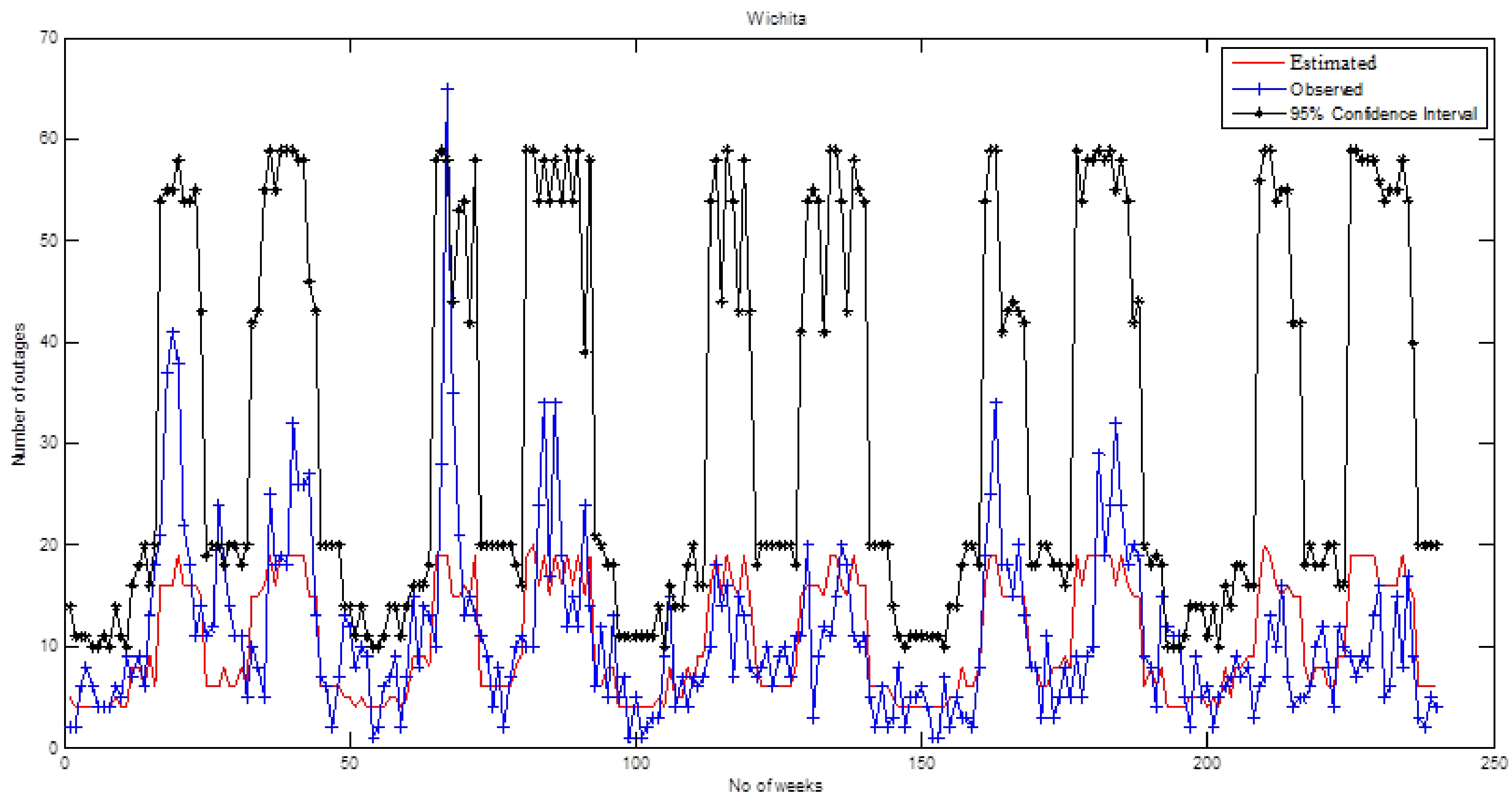



**Figure 3.3 Weekly Estimation and 95% Confidence Limit by MCS for Wichita**

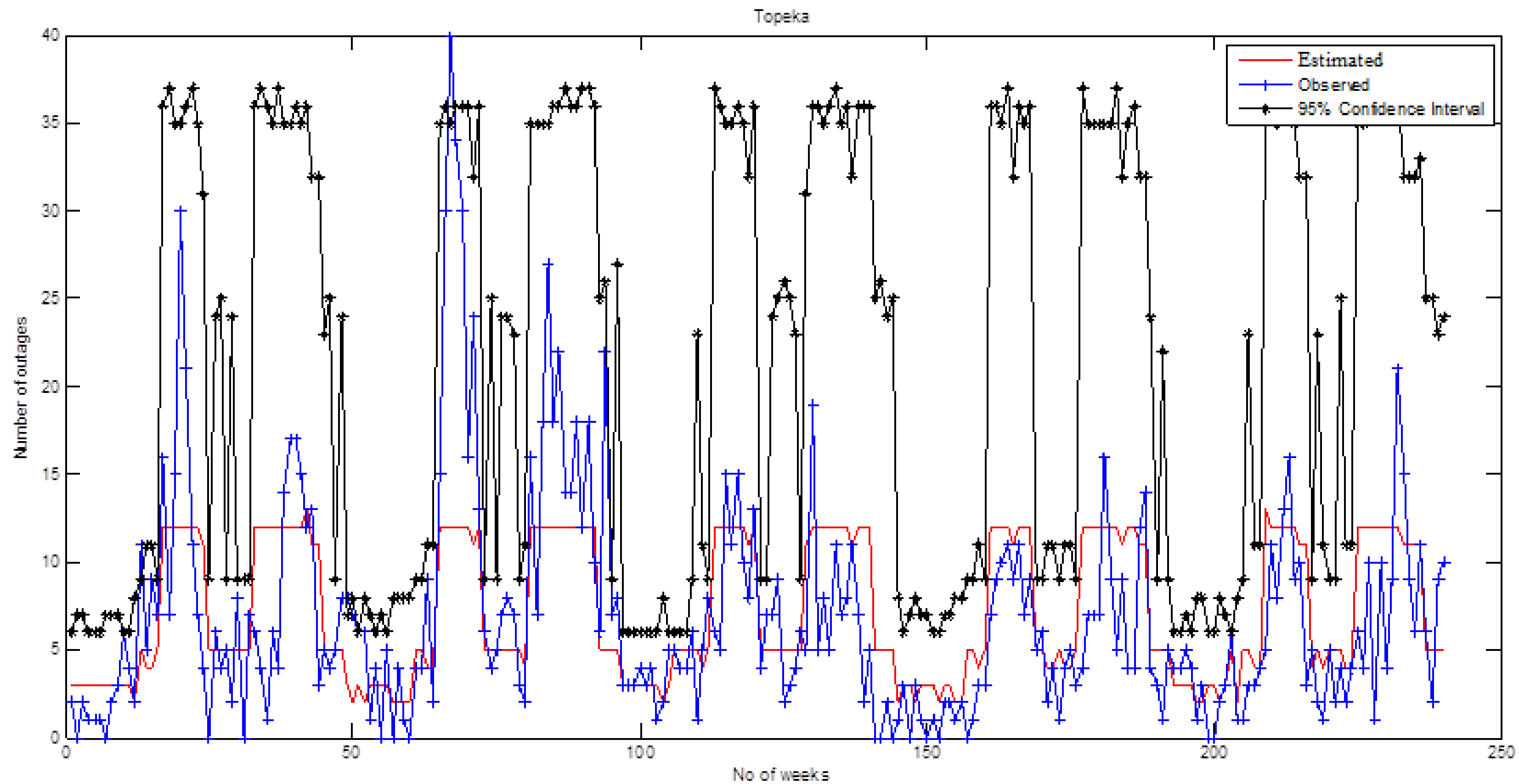



**Figure 3.4 Weekly Estimation and 95% Confidence Limit by MCS for Topeka**

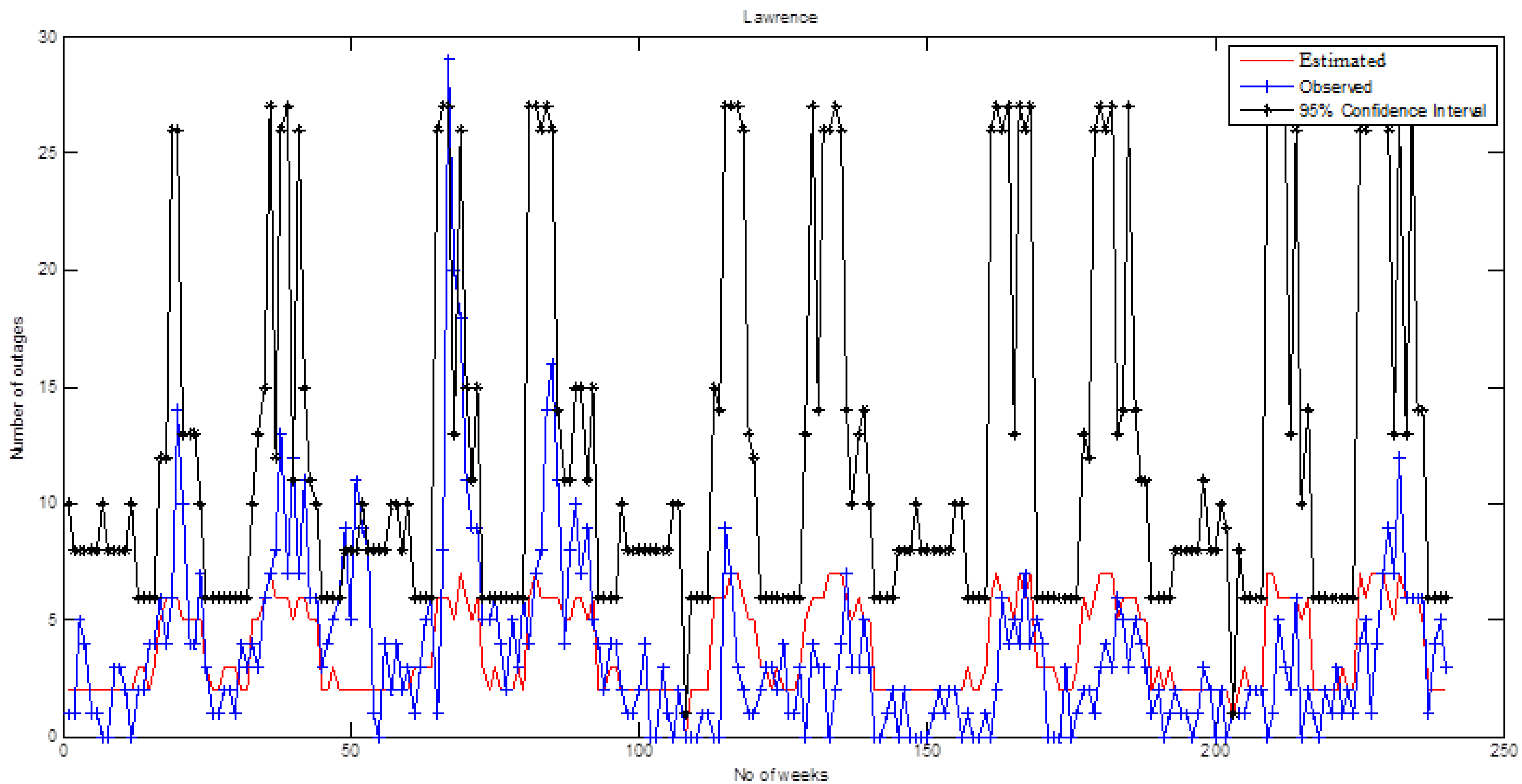



Figure 3.5 Weekly Estimation and 95% Confidence Limit by MCS for Lawrence

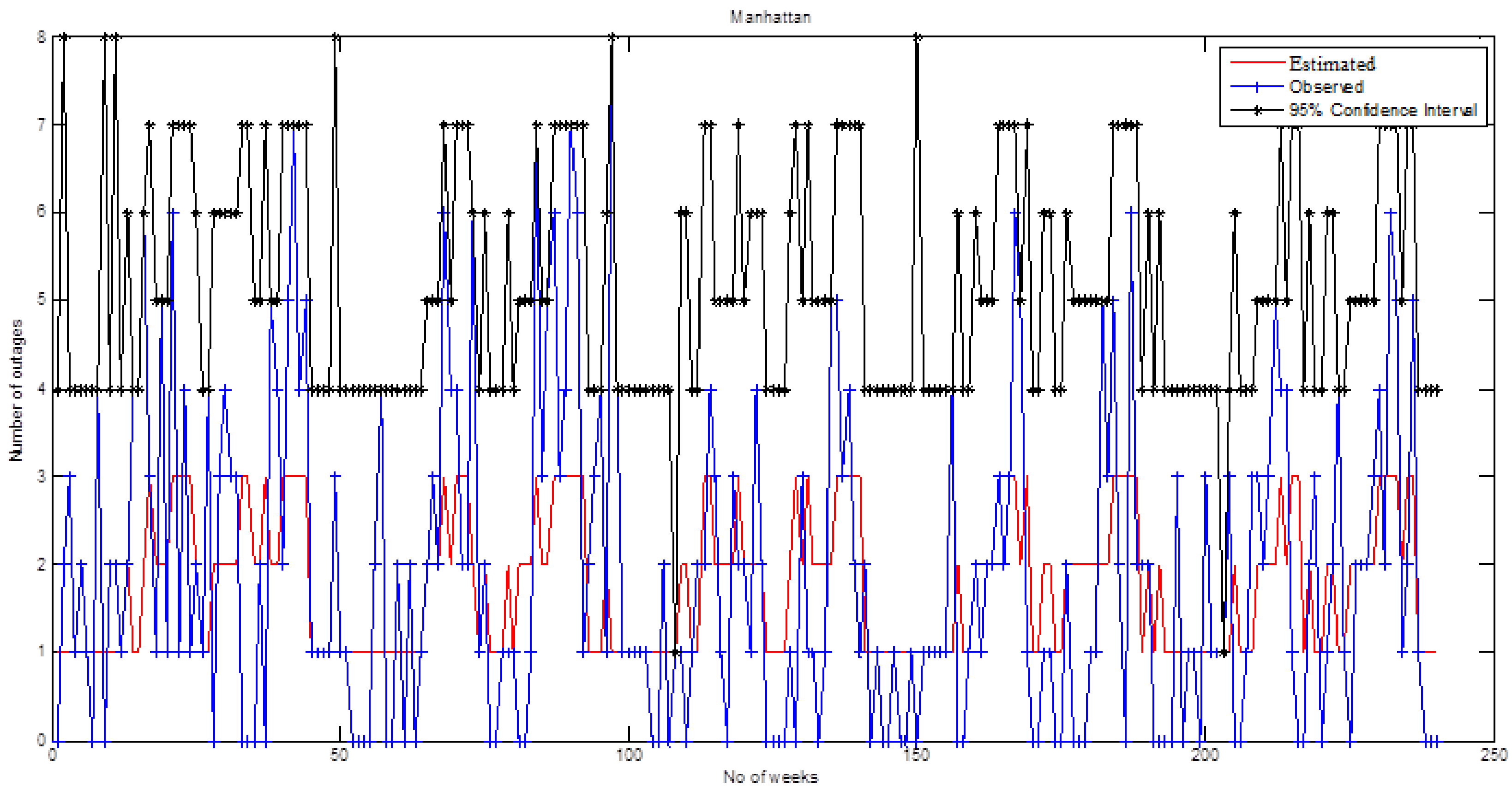



Figure 3.6  Weekly Estimaion and 95% Confidence Limit by MCS for Manhattan

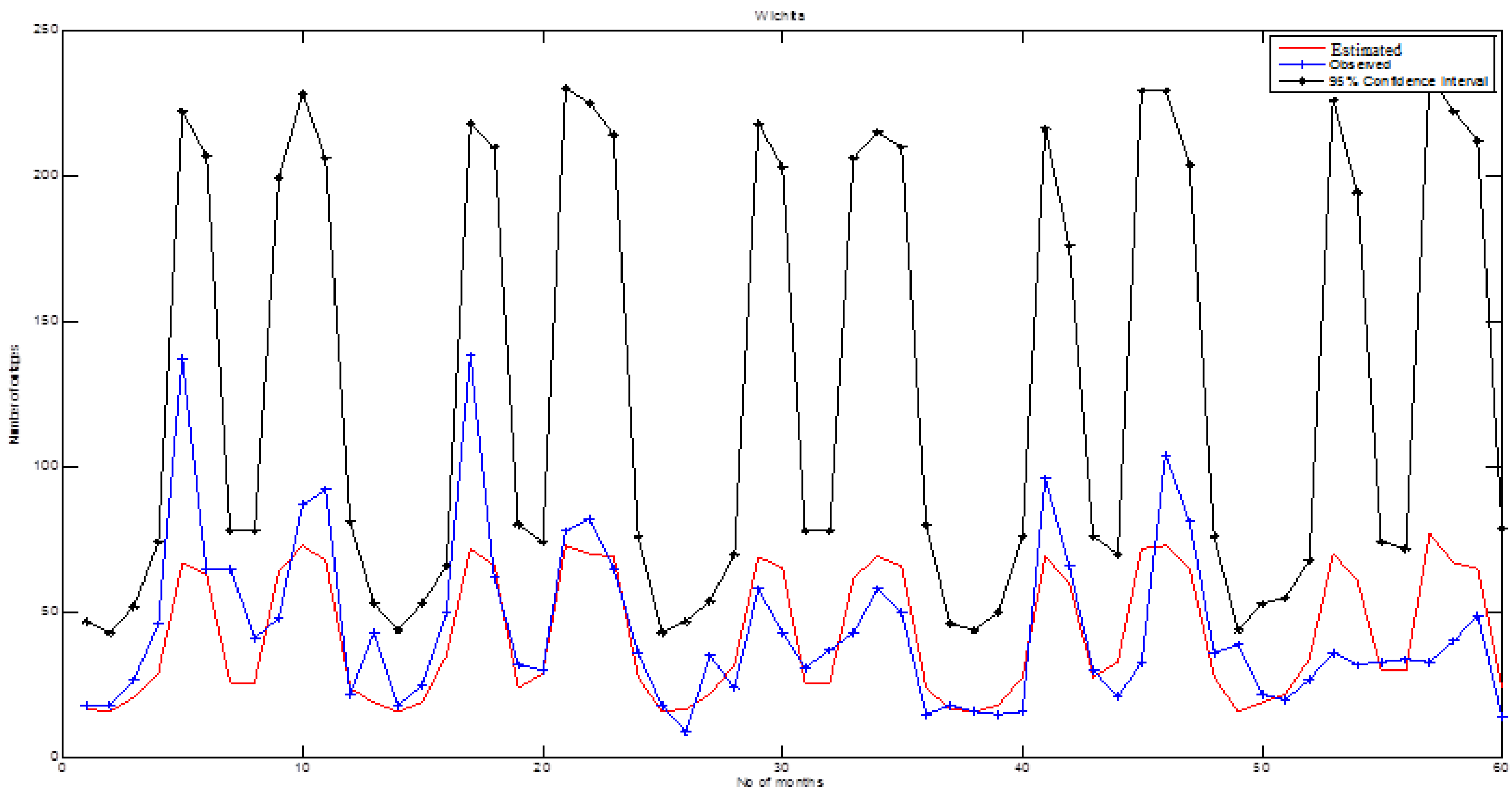



**Figure 3.7 Monthly Estimation and 95% Confidence Limit by MCS for Wichita**

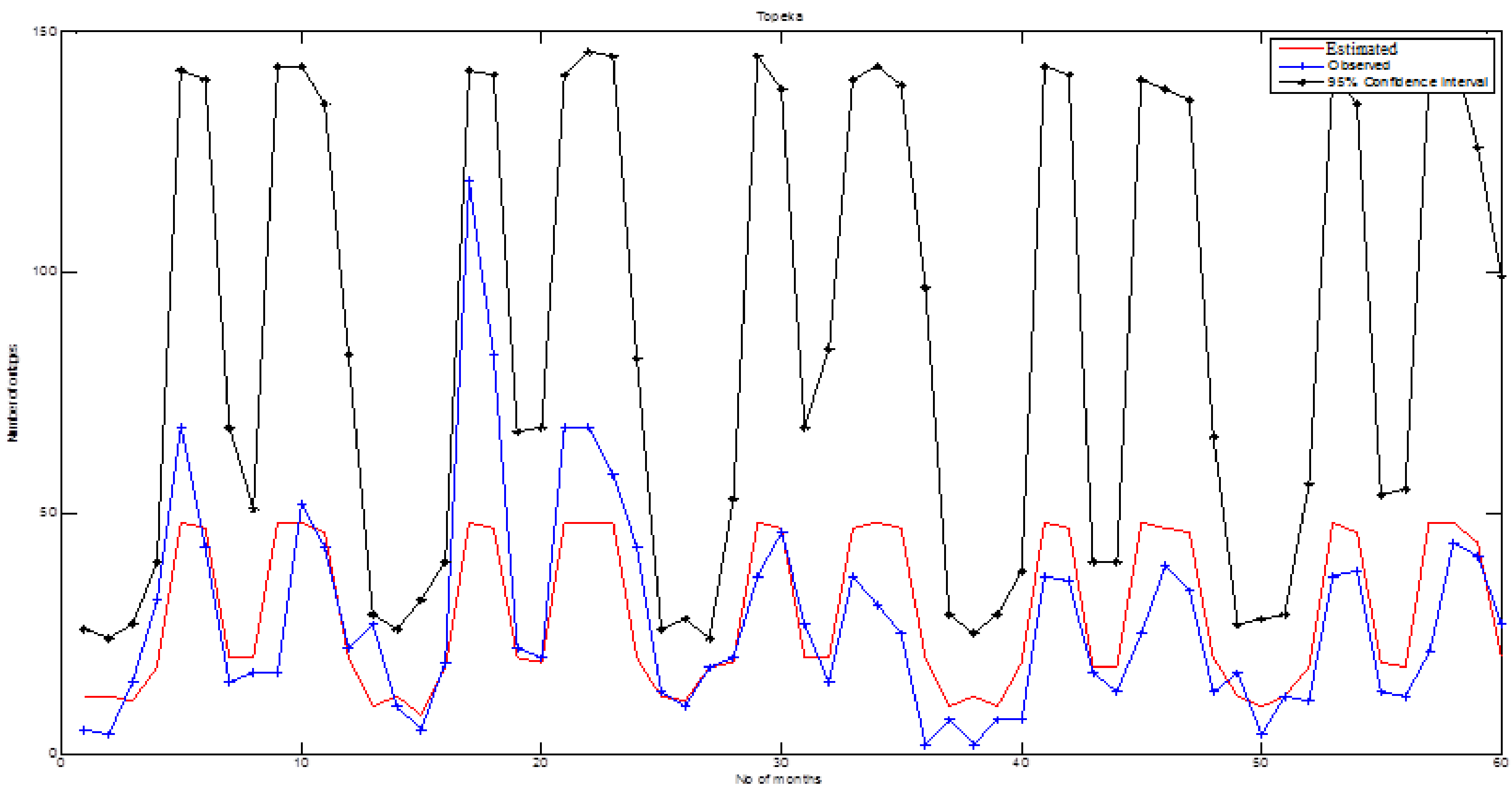



**Figure 3.8 Monthly Estimation and 95% Confidence Limit by MCS for Topeka**

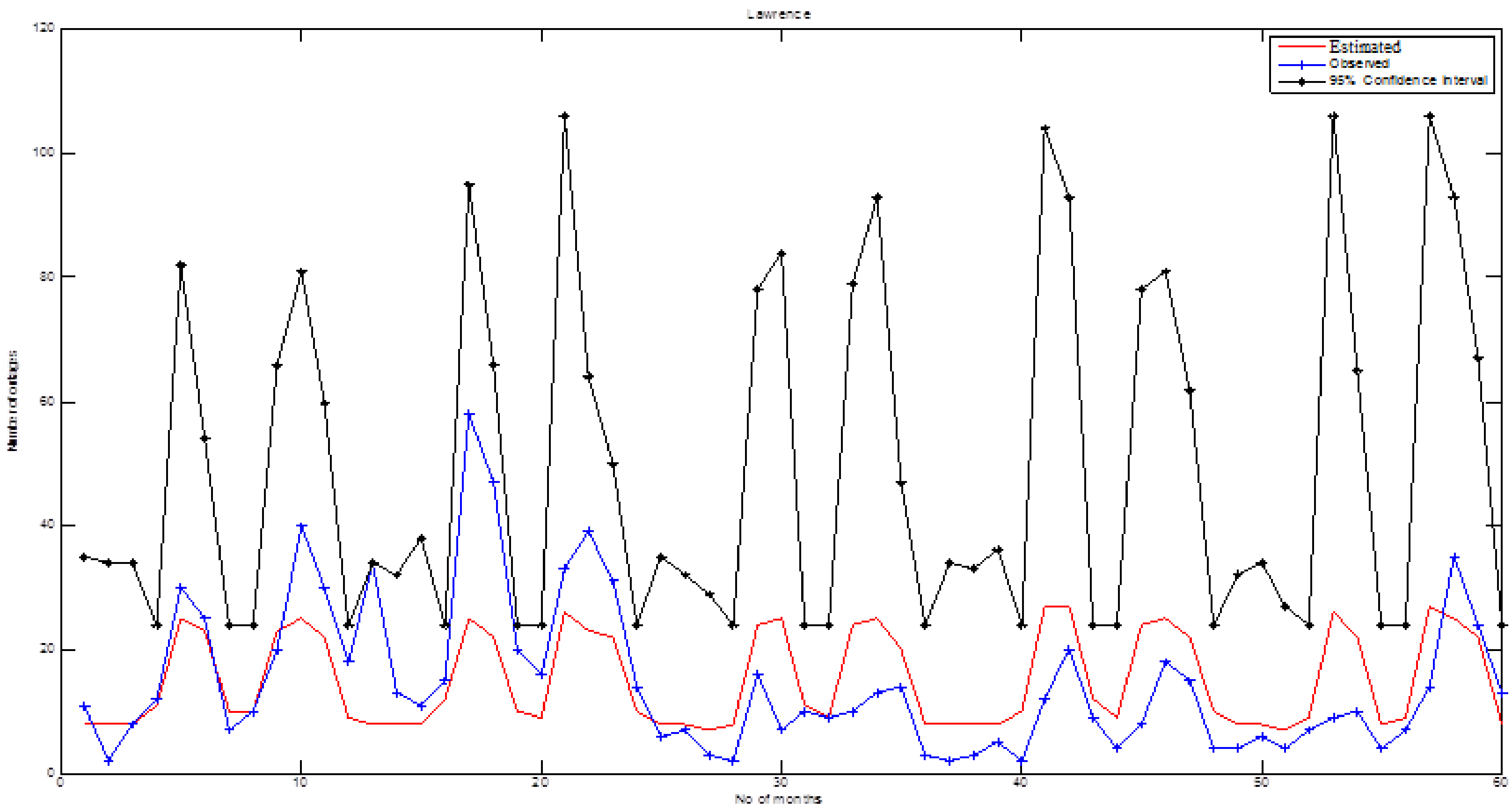



Figure 3.9 Monthly Estimation and 95% Confidence Limit by MCS for Lawrence

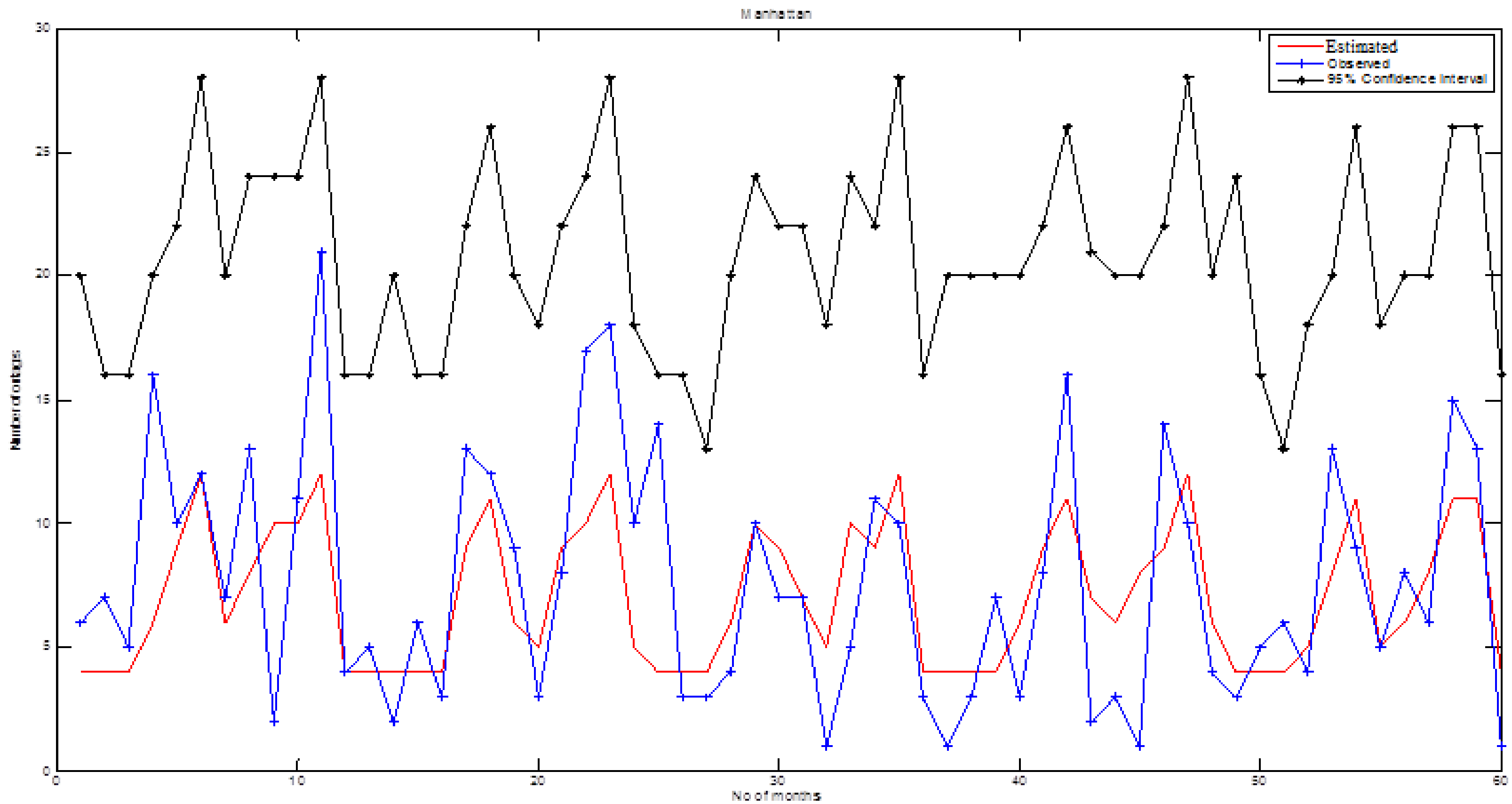



Figure 3.10 Monthly Estimation and 95% Confidence Limit by MCS for Manhattan

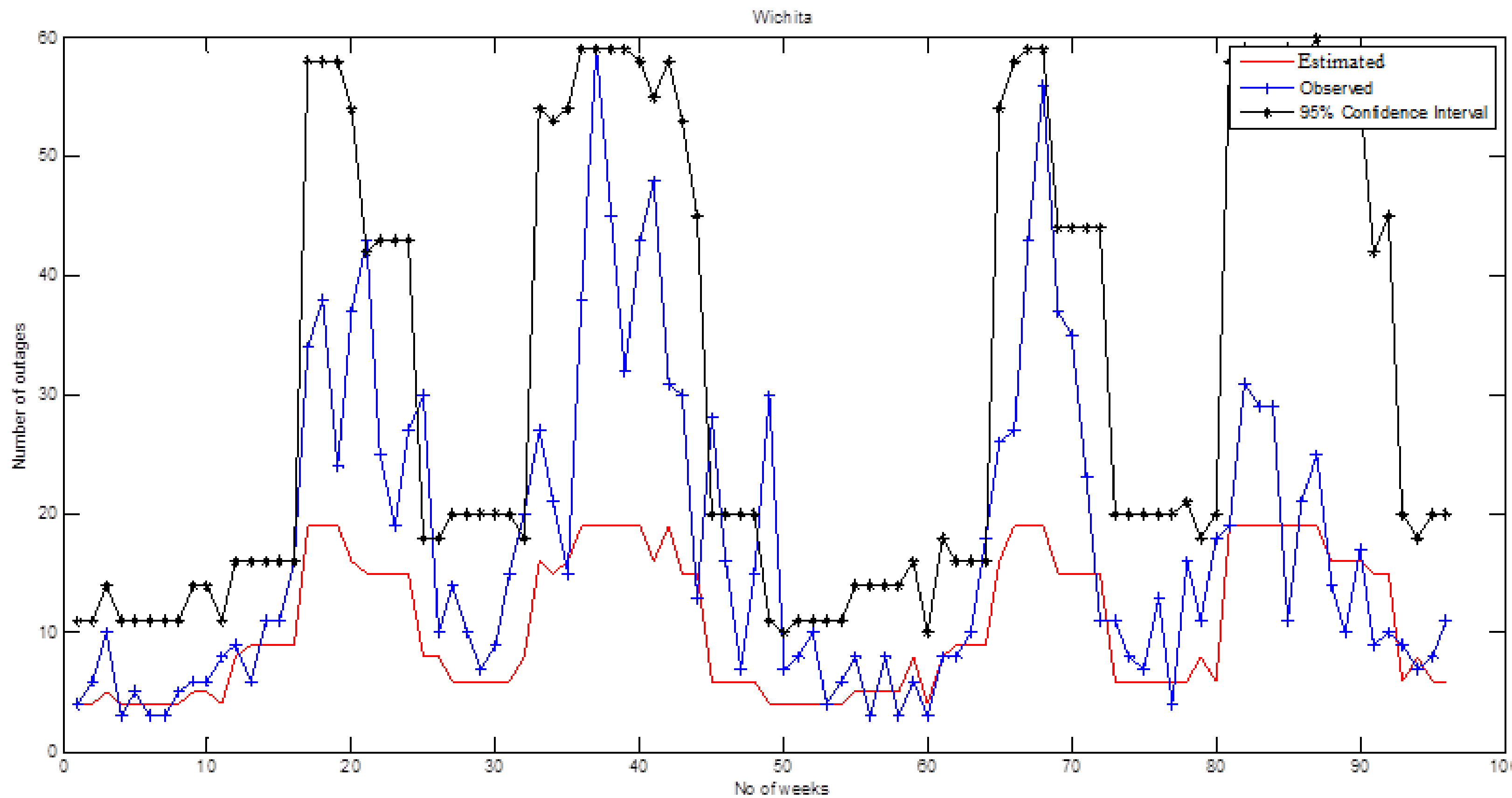



**Figure 3.11 Weekly Estimation and 95% Confidence Limit by MCS for Wichita**

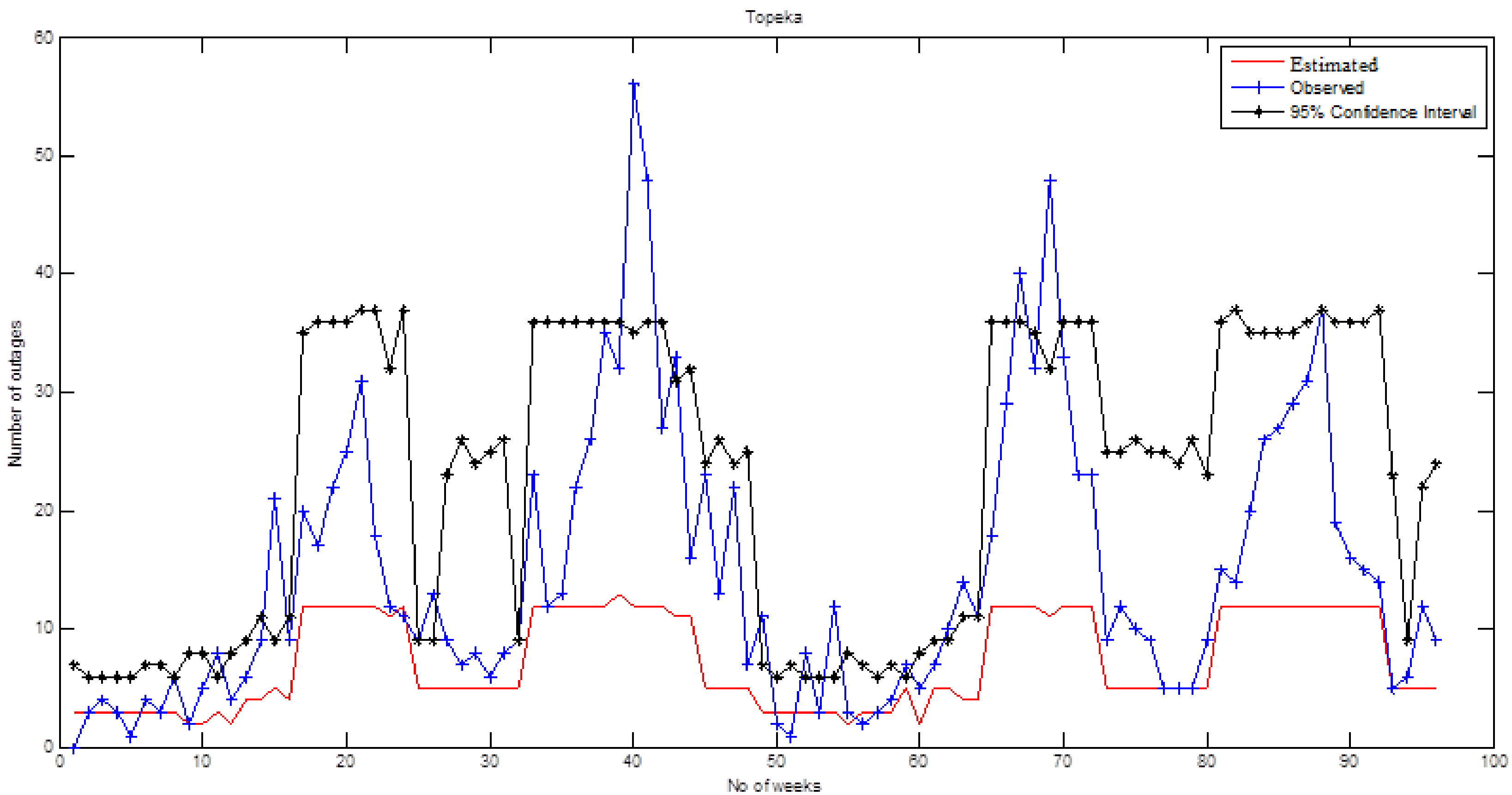



**Figure 3.12 Weekly Estimation and 95% Confidence Limit by MCS for Topeka**

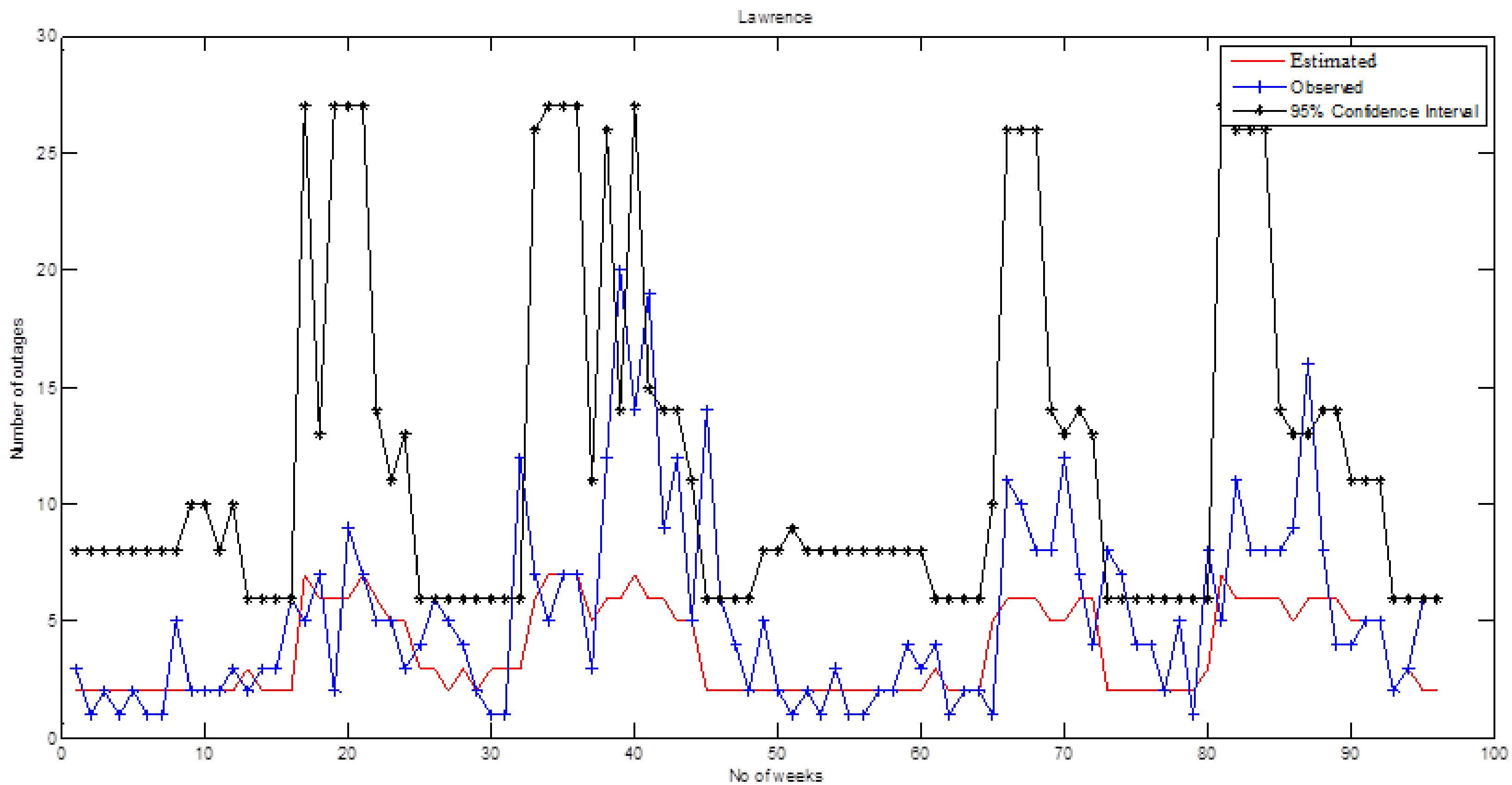



**Figure 3.13 Weekly Estimation and 95% Confidence Limit by MCS for Lawrence**

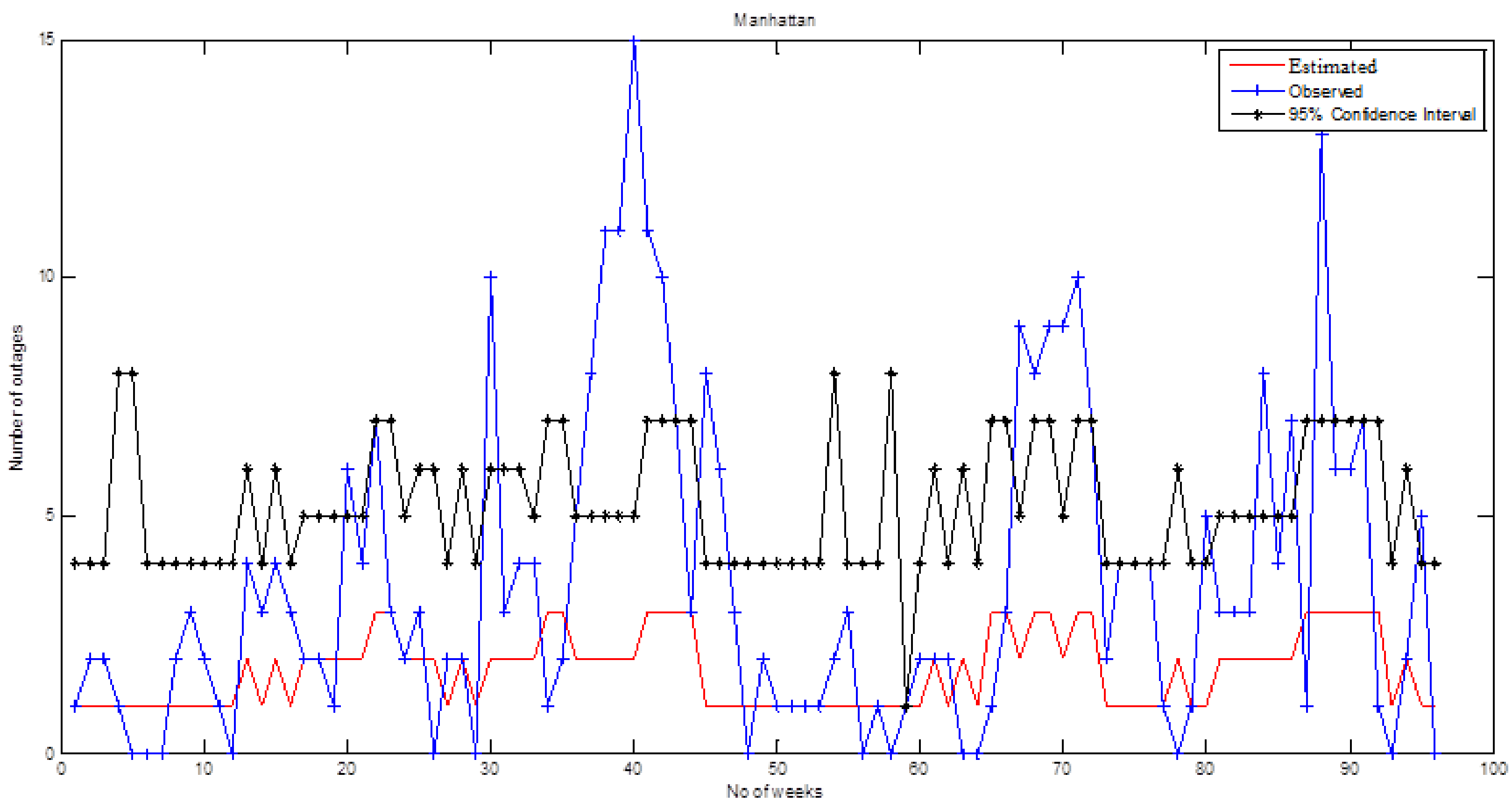



**Figure 3.14 Weekly Estimation and 95% Confidence Limit by MCS for Manhattan**

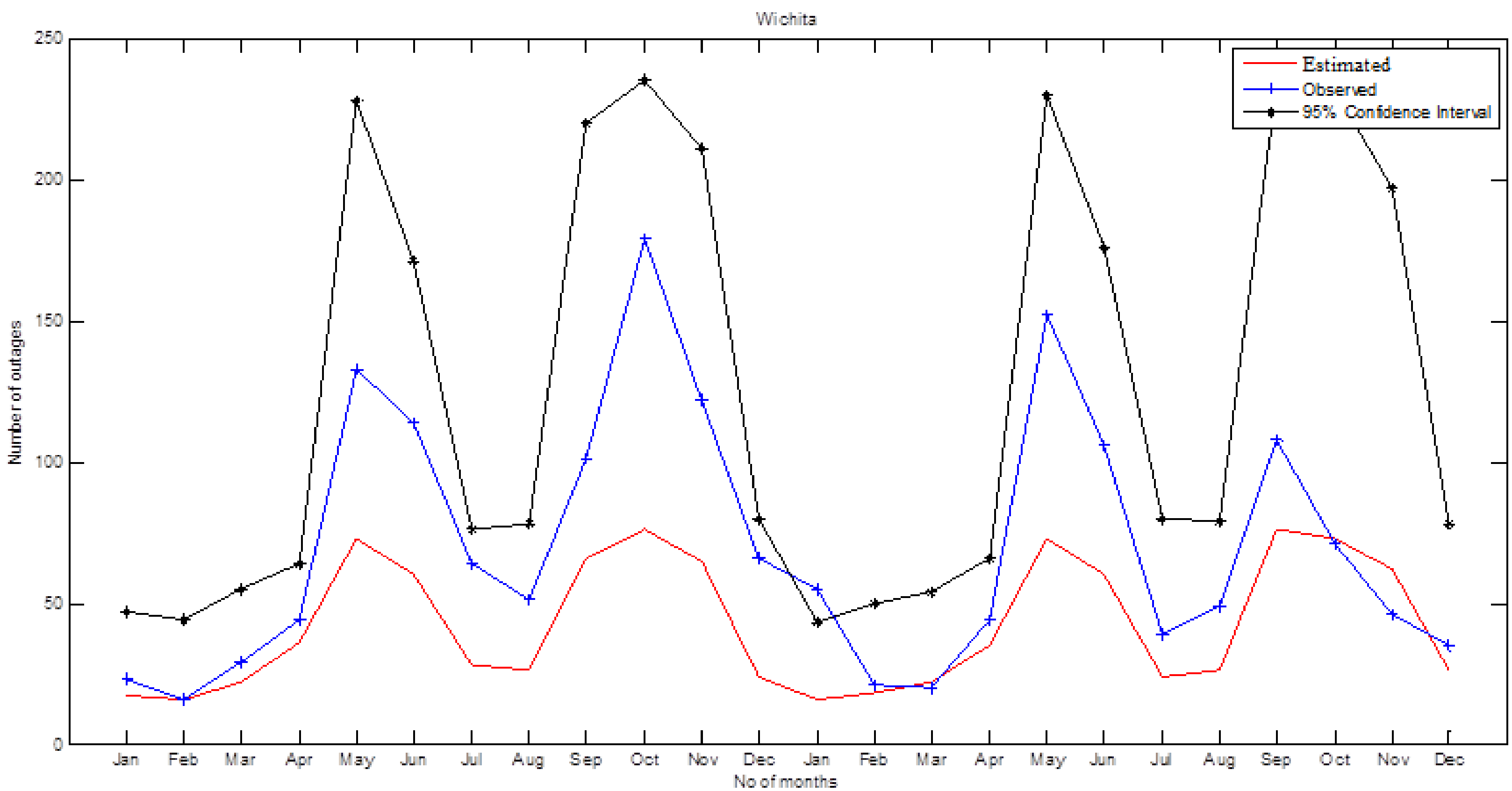



**Figure 3.15 Monthly Estimation and 95% Confidence Limit by MCS for Wichita**

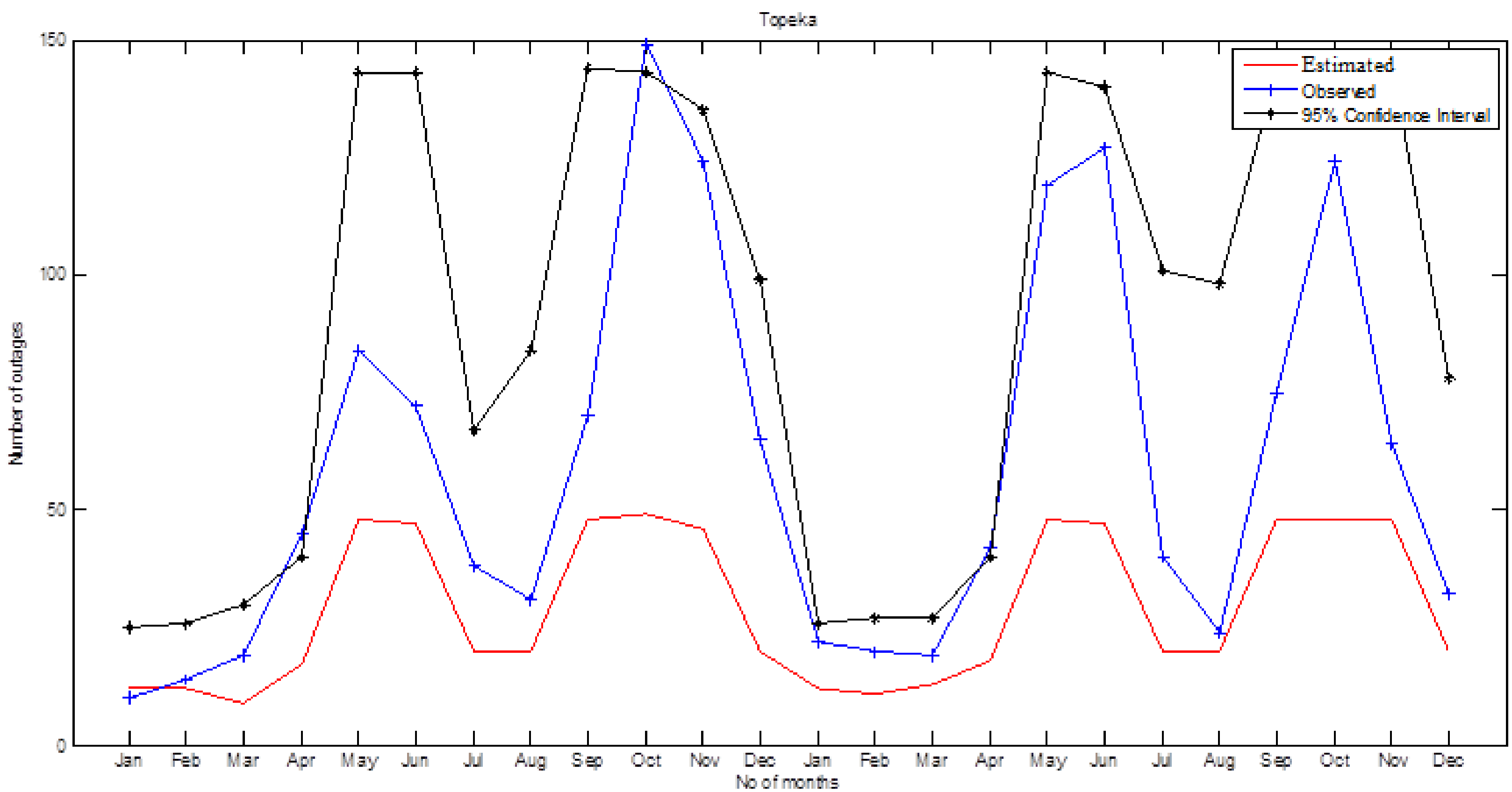



**Figure 3.16 Monthly Estimation and 95% Confidence Limit by MCS for Topeka**

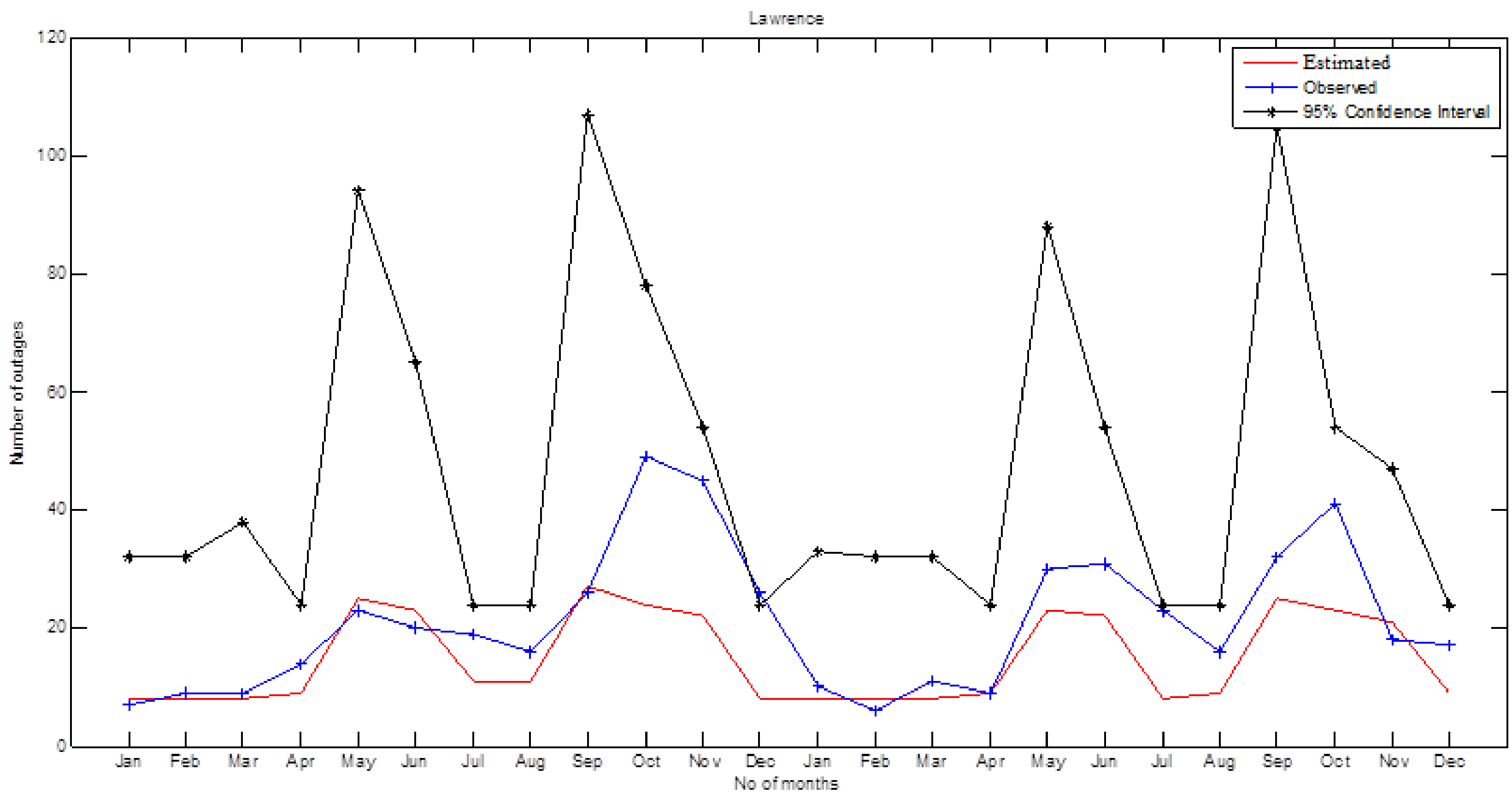



**Figure 3.17 Monthly Estimation and 95% Confidence Limit by MCS for Lawrence**

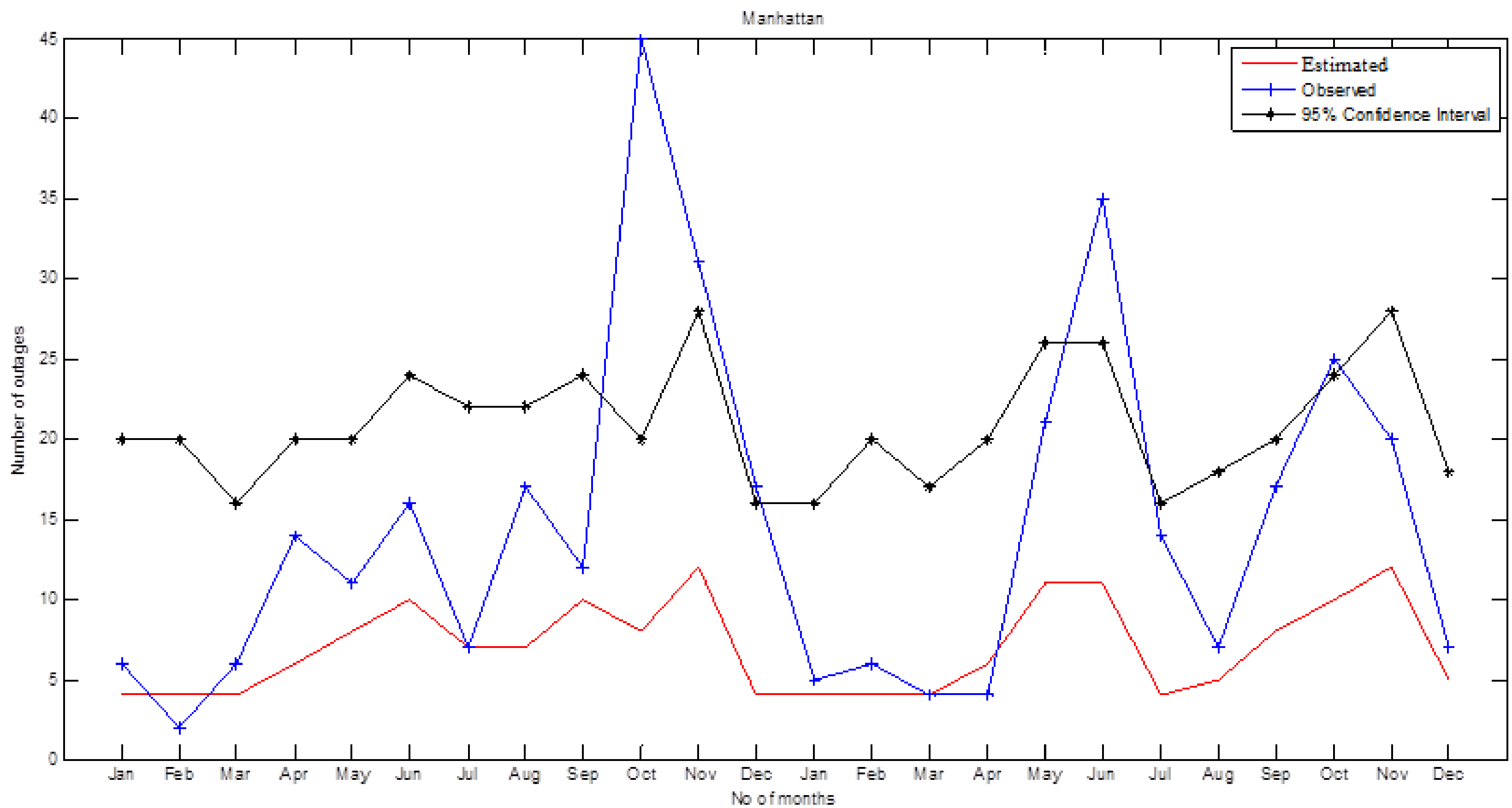



**Figure 3.18 Monthly Estimation and 95% Confidence Limit by MCS for Manhattan**

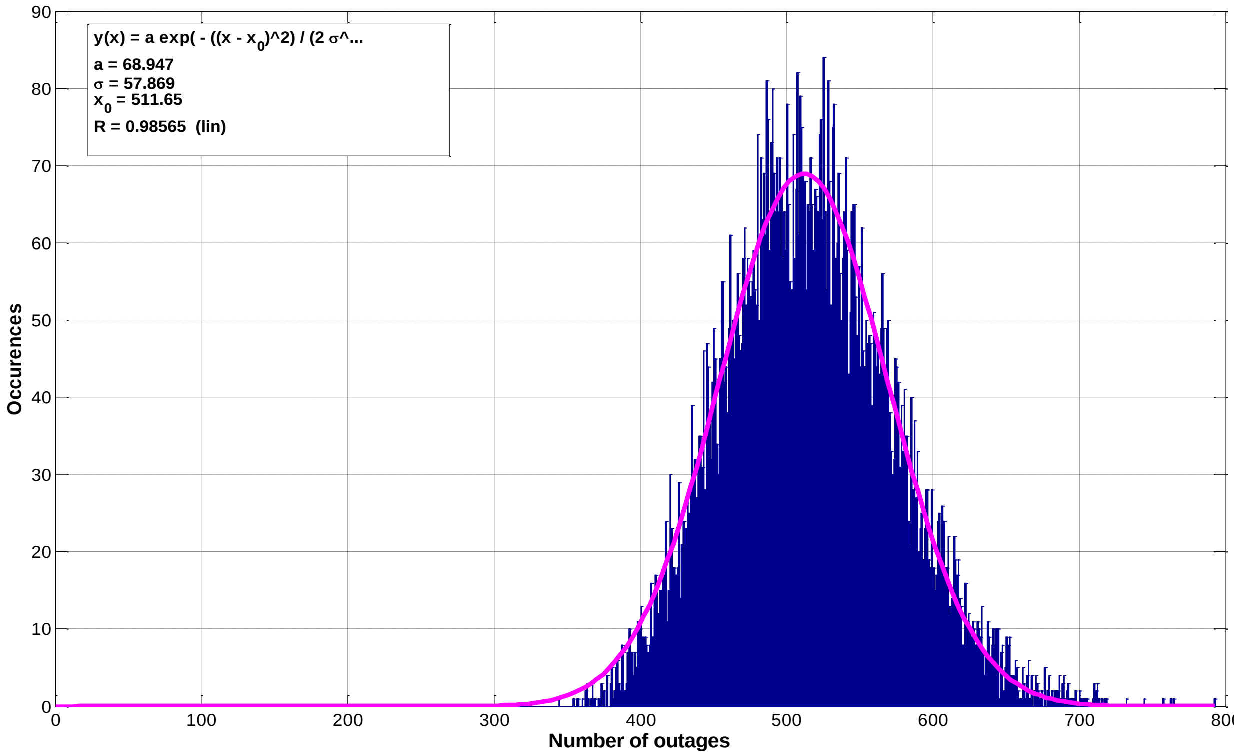



**Figure 3.19 Histogram of Estimated Outages in year 2010 for Wichita**

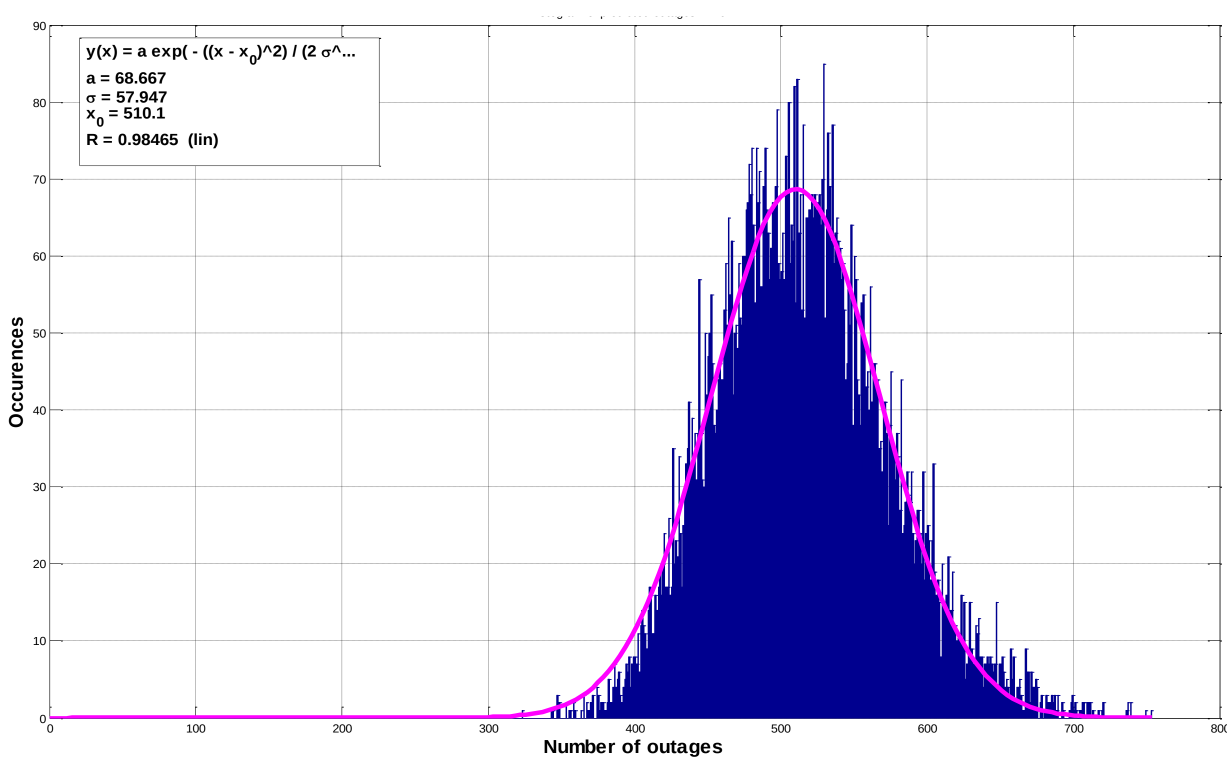



**Figure 3.20 Histogram of Estimated Outages in year 2011 for Wichita**

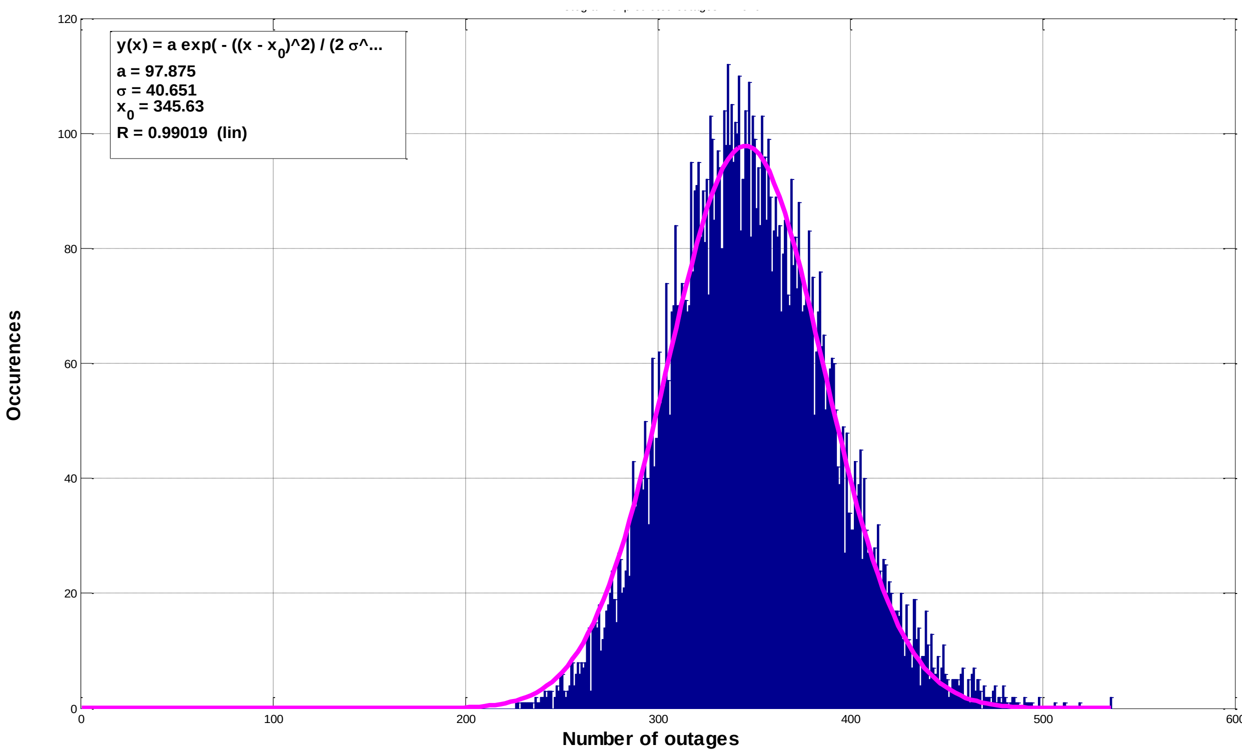



**Figure 3.21 Histogram of Estimated Outages in year 2010 for Topeka**

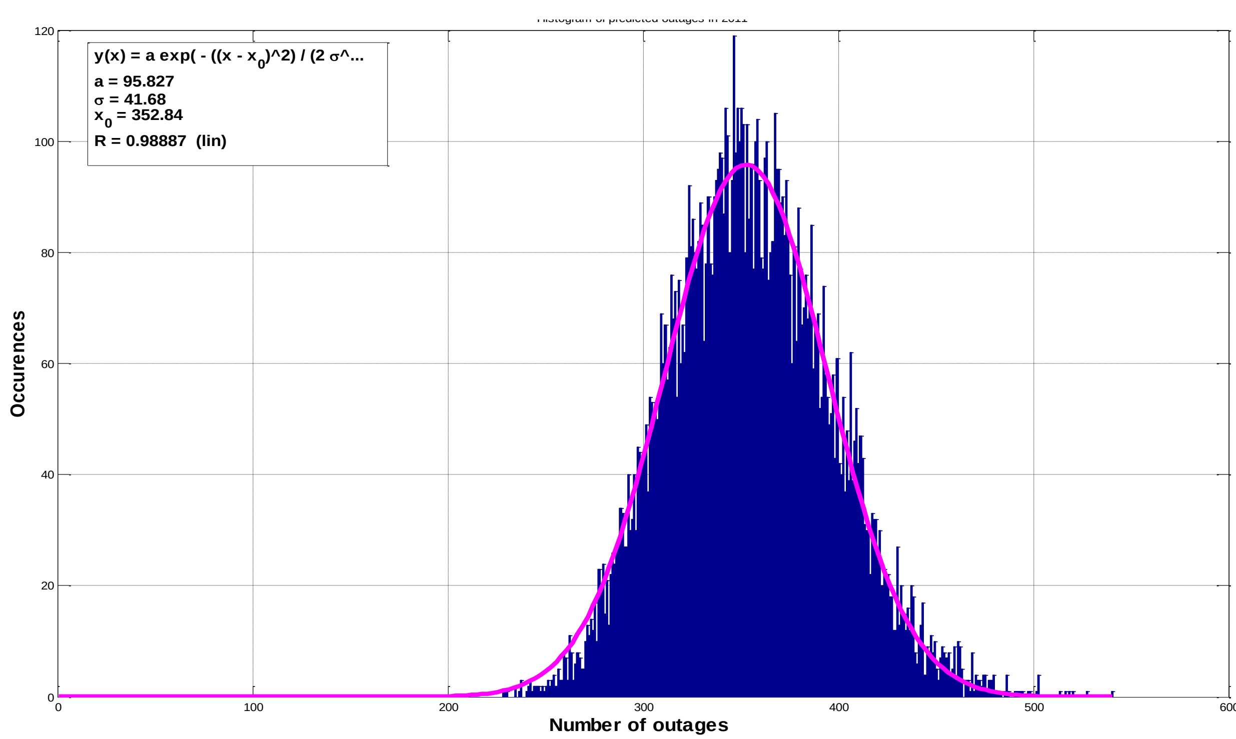



**Figure 3.22 Histogram of Estimated Outages in year 2011 for Topeka**

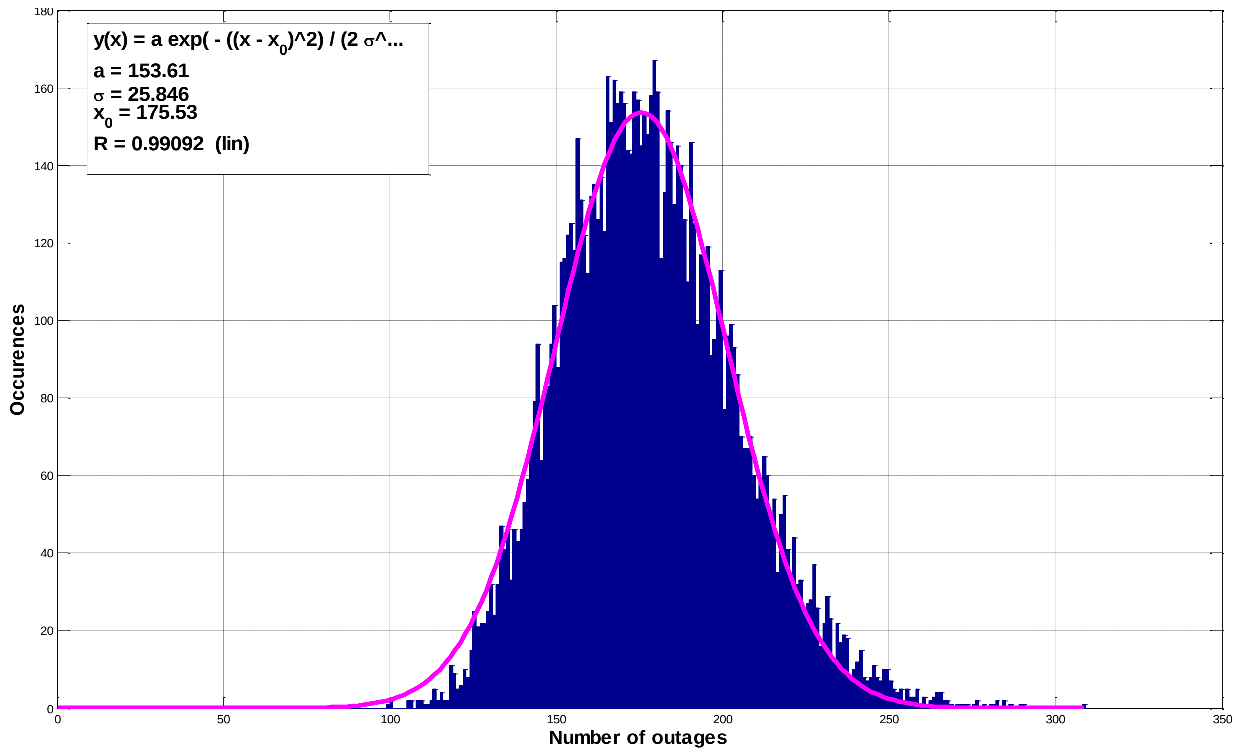



**Figure 3.23 Histogram of Estimated Outages in year 2010 for Lawrence**

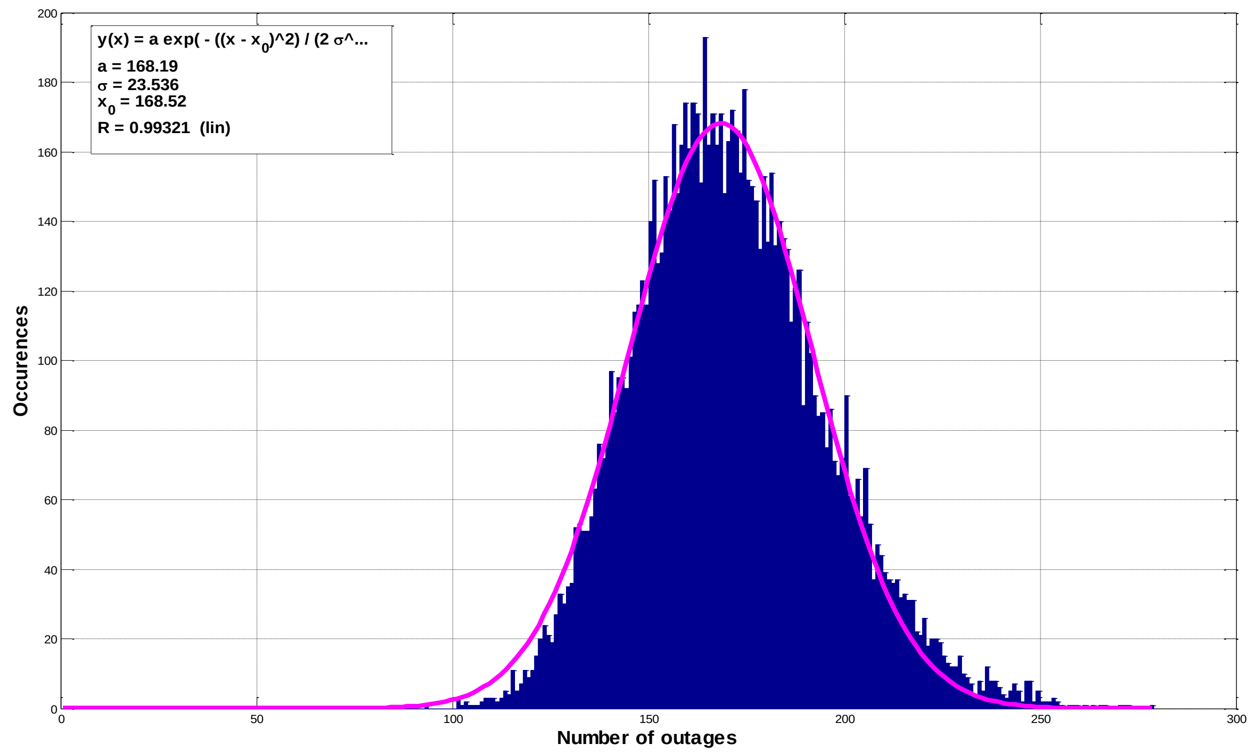



**Figure 3.24 Histogram of Estimated Outages in year 2011 for Lawrence**

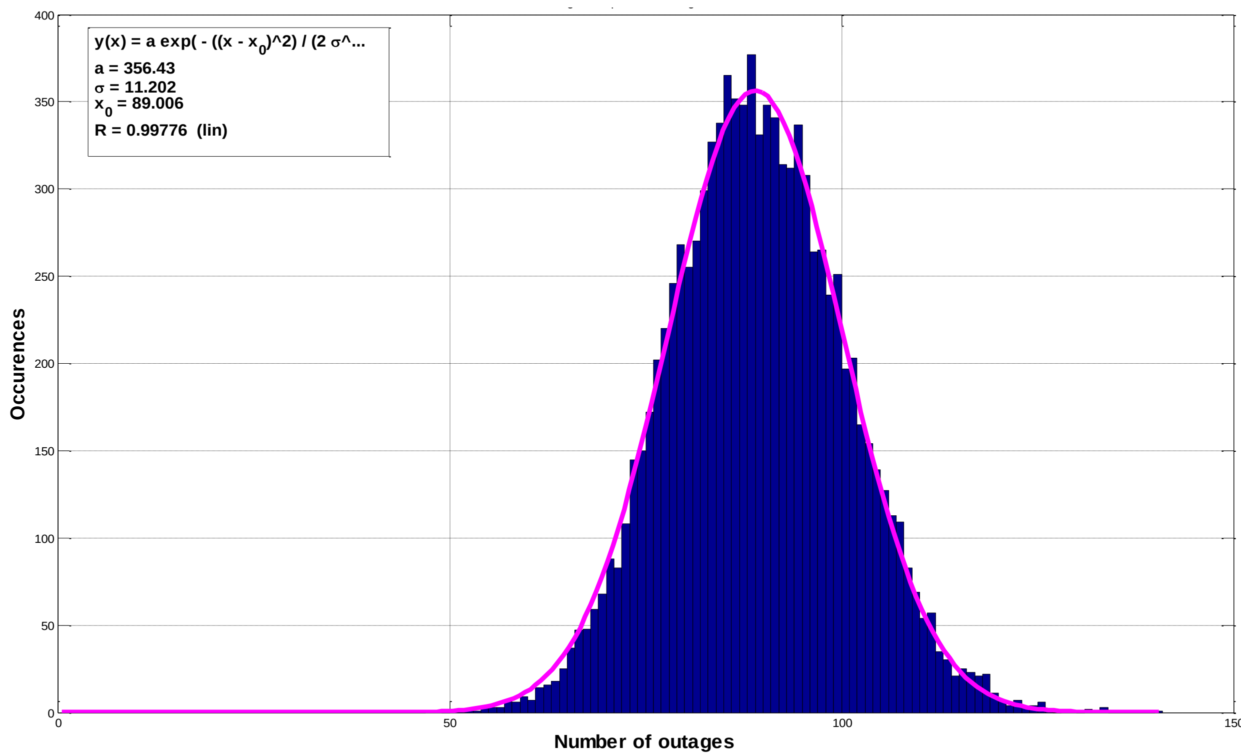



**Figure 3.25 Histogram of Estimated Outages in year 2010 for Manhattan**

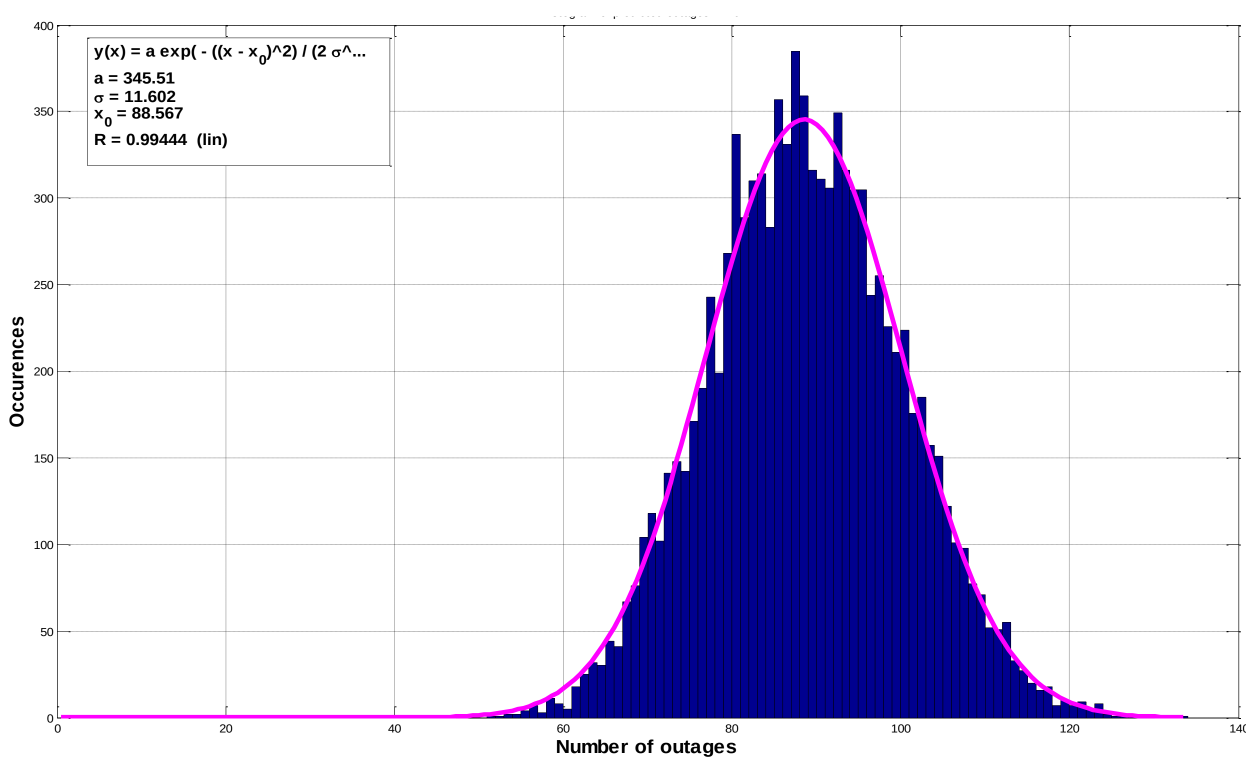



**Figure 3.26 Histogram of Estimated Outages in year 2011 for Manhattan**

By observing Figures 3.19-3.26, it is found that the animal-related estimated outages in 2010 and 2011 are almost in the same range for all cities. The observed outages and its 95% confidence intervals for years 2010 and 2011 are given in Table 3.2. From Table 3.2, it is seen that the observed outages are below the upper limit of 95% confidence interval, which implies that the Bayesian network model is able to capture the time-based pattern in animal-related outages.

**Table 3.2 95% Confidence Intervals by MCS and Observed Outages for Different Cities for years 2010 and 2011**

| City | Year | Mean | Lower 95% | Upper 95% | Observed Outages |
|---|---|---|---|---|---|
| Wichita | 2010 | 515.50 | 79 | 1518 | 944 |
| | 2011 | 517.92 | 88 | 1518 | 744 |
| Topeka | 2010 | 348.70 | 48 | 1075 | 721 |
| | 2011 | 355.82 | 55 | 1110 | 708 |
| Lawrence | 2010 | 178.94 | 0 | 590 | 261 |
| | 2011 | 171.79 | 0 | 545 | 243 |
| Manhattan | 2010 | 89.90 | 0 | 252 | 184 |
| | 2011 | 89.19 | 1 | 249 | 165 |

Tables 3.2-3.5 show the mean and sigma (standard deviation) obtained from 10,000 Monte-Carlo Simulations points and by fitting Gaussian curves to the histogram of 10,000 simulation points. These values do not have significant difference. Therefore for cost-benefit analysis in Chapter 5, the distributions based on the Gaussian fit are used.

**Table 3.3 Comparison of Mean and Standard Deviation Values from MCS and Gaussian Fits to Estimated data of Wichita for Years 2005-2011**

| Year | MCS | | Gaussian Fit | |
|---|---|---|---|---|
| | Mean | Sigma | Mean | Sigma |
| 2005 | 500.19 | 57.41 | 494.87 | 57.33 |
| 2006 | 521.90 | 59.95 | 516.66 | 59.58 |
| 2007 | 498.78 | 56.43 | 492.97 | 55.40 |
| 2008 | 512.51 | 57.13 | 506.92 | 55.70 |
| 2009 | 516.62 | 59.05 | 511.65 | 57.95 |
| 2010 | 515.58 | 58.02 | 511.65 | 57.87 |
| 2011 | 517.19 | 58.08 | 512.25 | 57.42 |

**Table 3.4 Comparison of Mean and Standard Deviation Values from MCS and Gaussian Fits to Estimated data of Topeka for Years 2005-2011**

| Year | MCS | | Gaussian Fit | |
|---|---|---|---|---|
| | Mean | Sigma | Mean | Sigma |
| 2005 | 347.19 | 39.56 | 343.81 | 39.66 |
| 2006 | 348.78 | 41.38 | 345.52 | 41.67 |
| 2007 | 357.42 | 40.46 | 353.69 | 40.23 |
| 2008 | 341.61 | 37.50 | 339.03 | 37.64 |
| 2009 | 344.38 | 37.97 | 340.56 | 37.67 |
| 2010 | 348.66 | 41.27 | 344.98 | 41.09 |
| 2011 | 354.99 | 41.82 | 350.95 | 41.37 |

**Table 3.5 Comparison of Mean and Standard Deviation Values from MCS and Gaussian Fits to Estimated data of Lawrence for Years 2005-2011**

| Year | MCS | | Gaussian Fit | |
|---|---|---|---|---|
| | Mean | Sigma | Mean | Sigma |
| 2005 | 174.77 | 23.62 | 172.07 | 23.20 |
| 2006 | 178.89 | 25.96 | 175.24 | 25.15 |
| 2007 | 174.95 | 25.81 | 171.81 | 25.27 |
| 2008 | 182.41 | 27.42 | 179.4 | 26.96 |
| 2009 | 176.18 | 27.70 | 172.71 | 27.17 |
| 2010 | 178.42 | 25.99 | 175.55 | 25.65 |
| 2011 | 171.62 | 24.24 | 168.75 | 23.71 |

**Table 3.6 Comparison of Mean and Standard Deviation Values from MCS and Gaussian Fits to Estimated data of Manhattan for Years 2005-2011**

| Year | MCS | | Gaussian Fit | |
|---|---|---|---|---|
| | Mean | Sigma | Mean | Sigma |
| 2005 | 94.88 | 11.54 | 94.11 | 11.56 |
| 2006 | 90.70 | 11.27 | 89.83 | 11.28 |

| | | | | |
|---|---|---|---|---|
| 2007 | 90.18 | 11.36 | 89.26 | 11.43 |
| 2008 | 92.97 | 11.36 | 92.08 | 11.43 |
| 2009 | 89.55 | 11.14 | 88.85 | 11.30 |
| 2010 | 89.90 | 11.20 | 89.07 | 11.16 |
| 2011 | 89.39 | 11.23 | 88.63 | 11.20 |

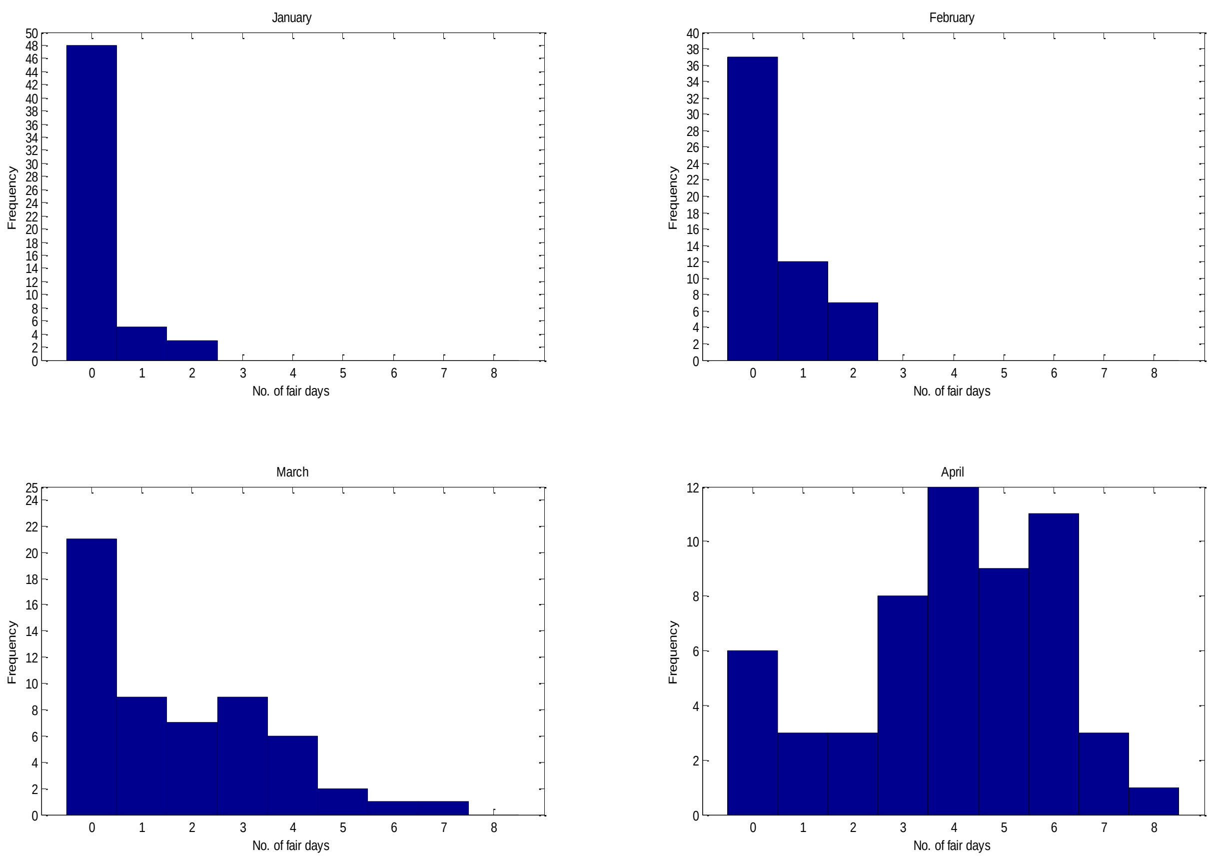
# Chapter 4 - Prediction of Outages in The Future

To predict future outages using past data, the same model was used that was discussed in Chapter 3. However, since outages due to squirrel are known to be dependent on weather, future weather must also be predicted. The prediction for future weather was obtained by running Monte Carlo simulations 10,000 times based on the weather history.

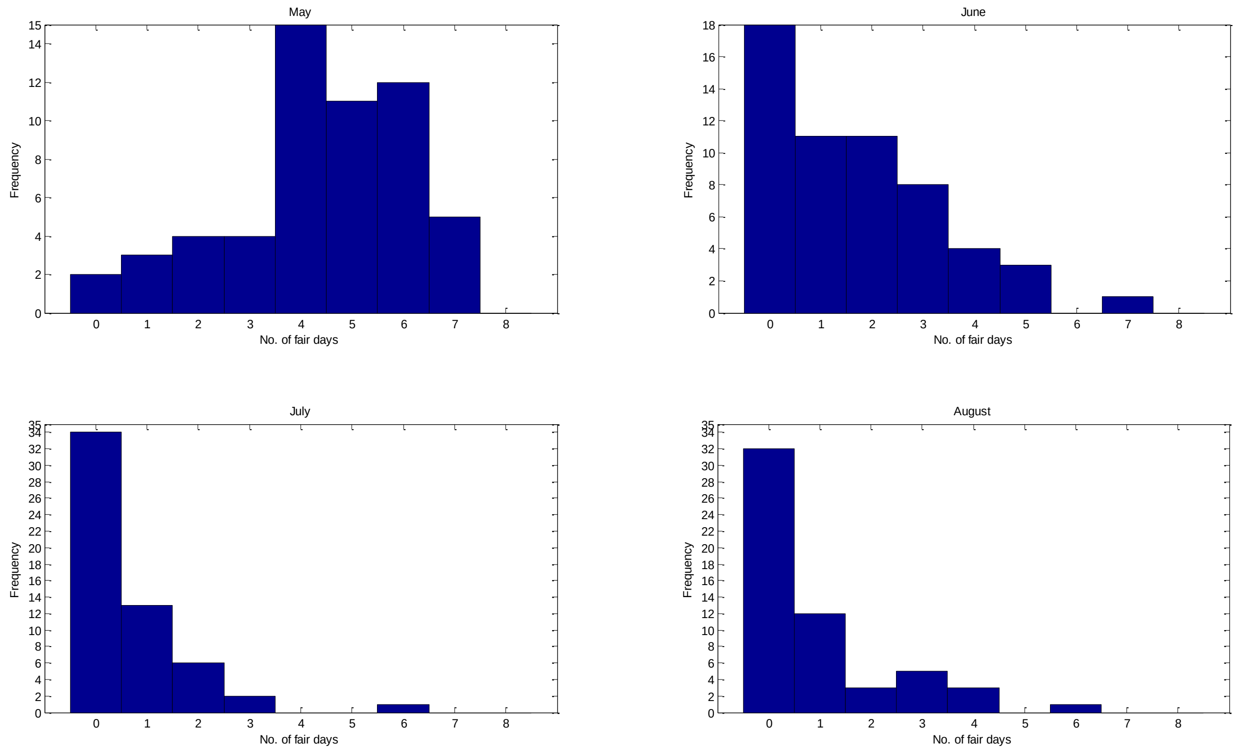
## Prediction of Future Weather

Prediction of weather data was performed by using the past 14 years of data, from 1998-2011. For every month, the number of fair days in each week were calculated and a histogram of number of fair days per month was plotted for the four cities as shown in Figures 4.1-4.4.

**(a)**



**(b)**




**(c)**

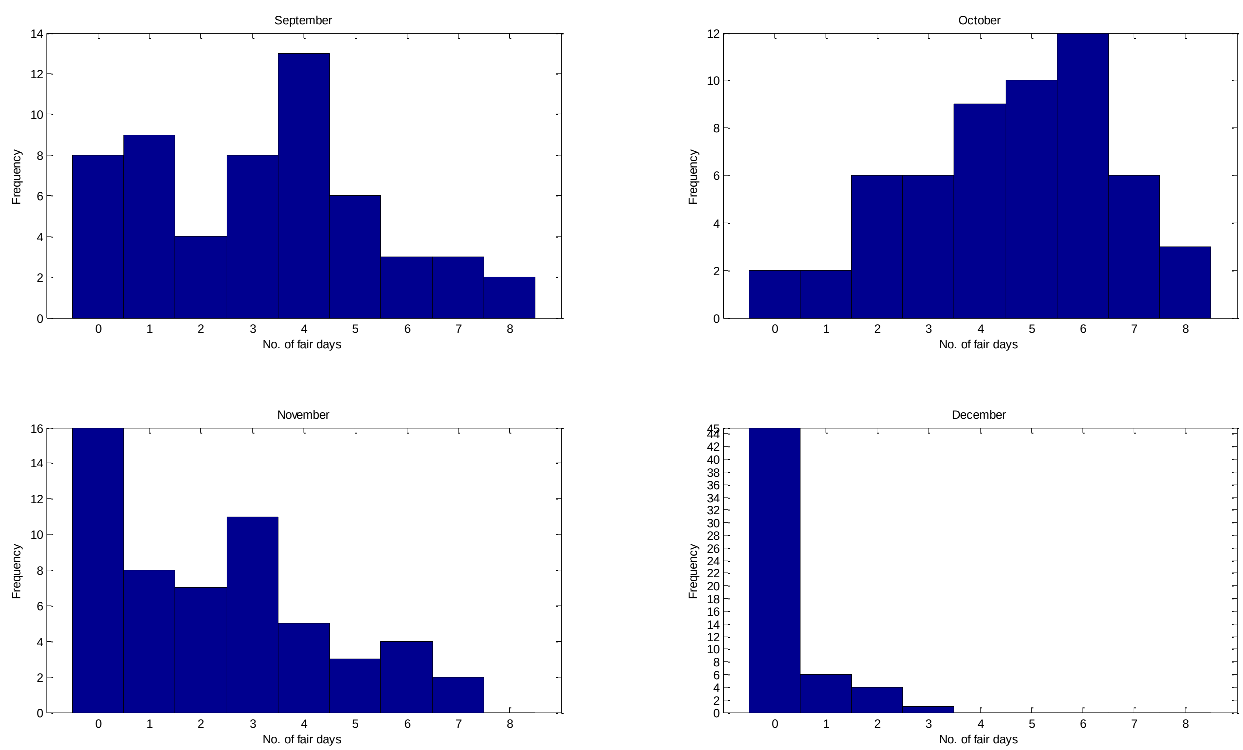
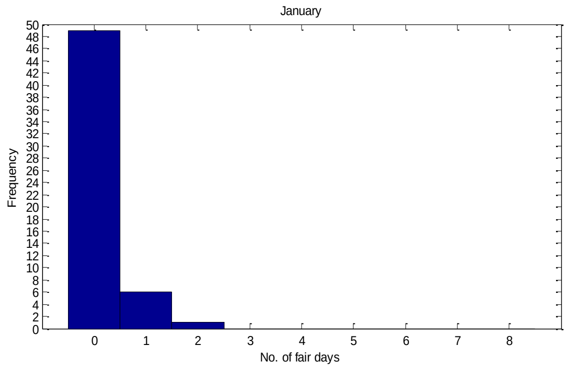
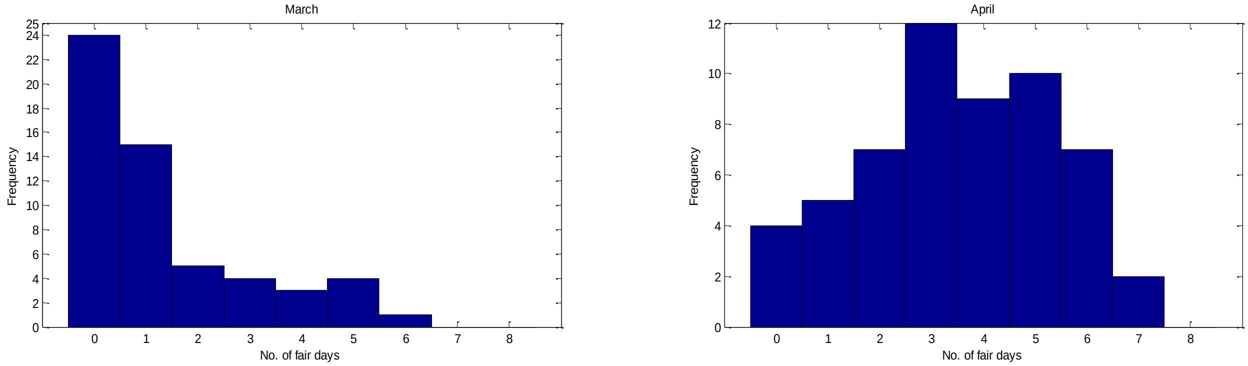



**Figure 4.1 (a)-(c) Histogram Showing Number of Fair Days for Wichita from 1998-2011**

**(a)**


January
February
March
April
Frequency
No. of fair days

**(b)**


May
June
July
August
Frequency
No. of fair days

**(c)**

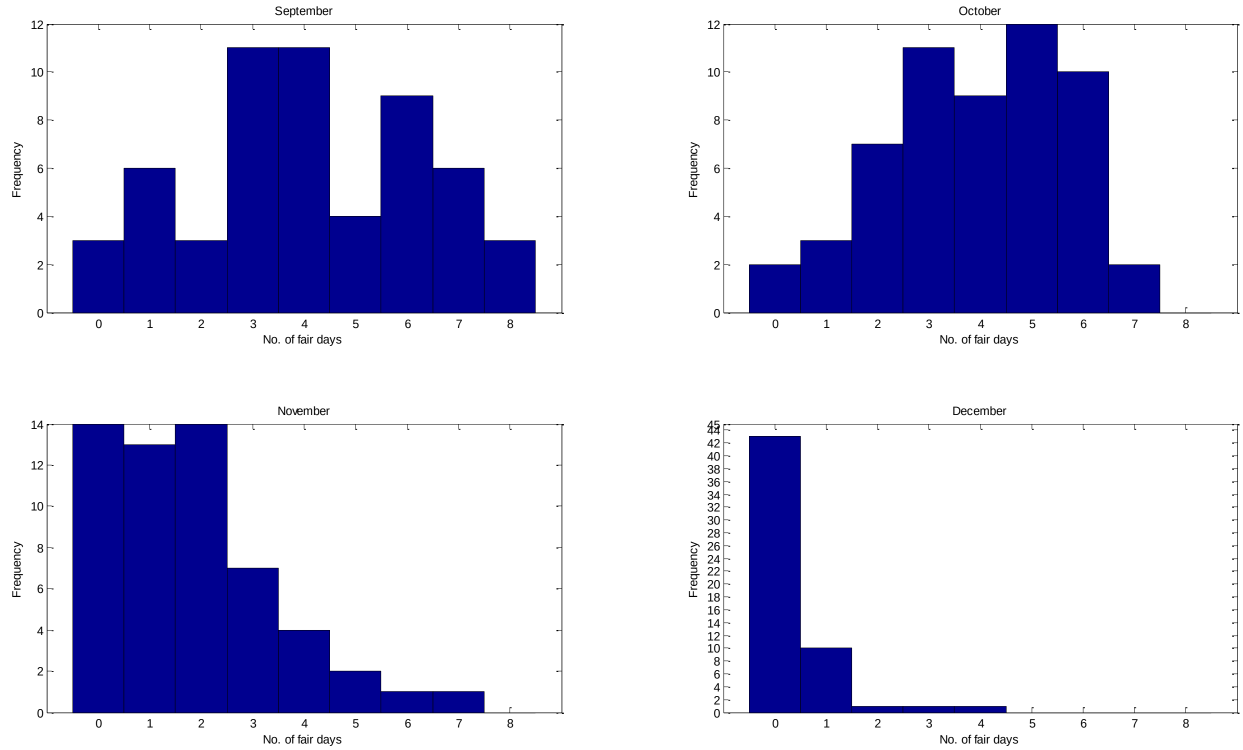
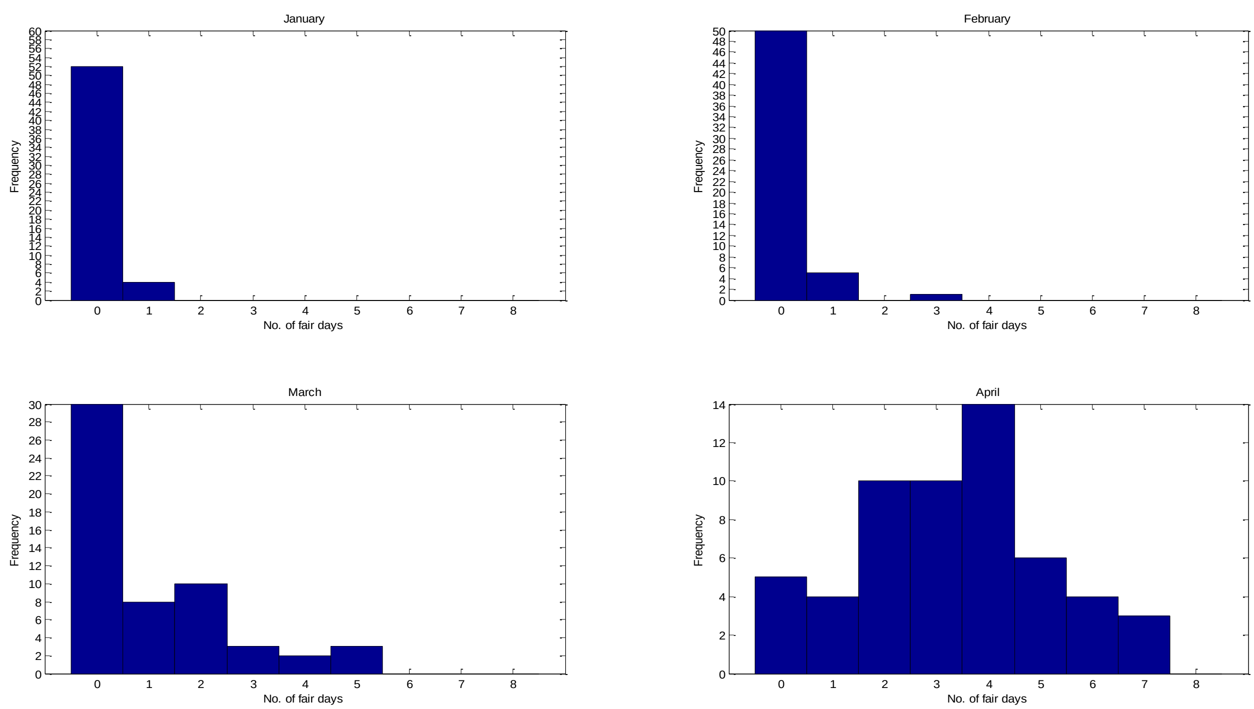
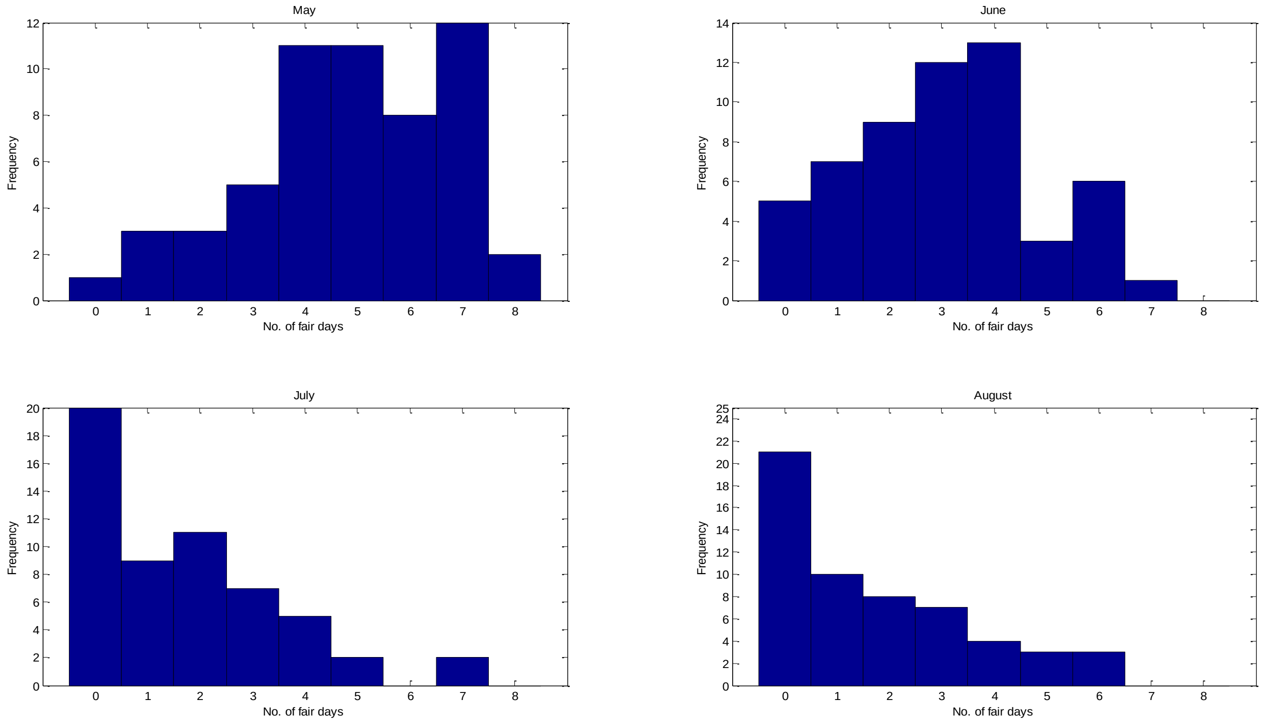



**Figure 4.2 (a)-(c) Histogram Showing Number of Fair Days for Topeka from 1998-2011**

**(a)**



**(b)**




**(c)**

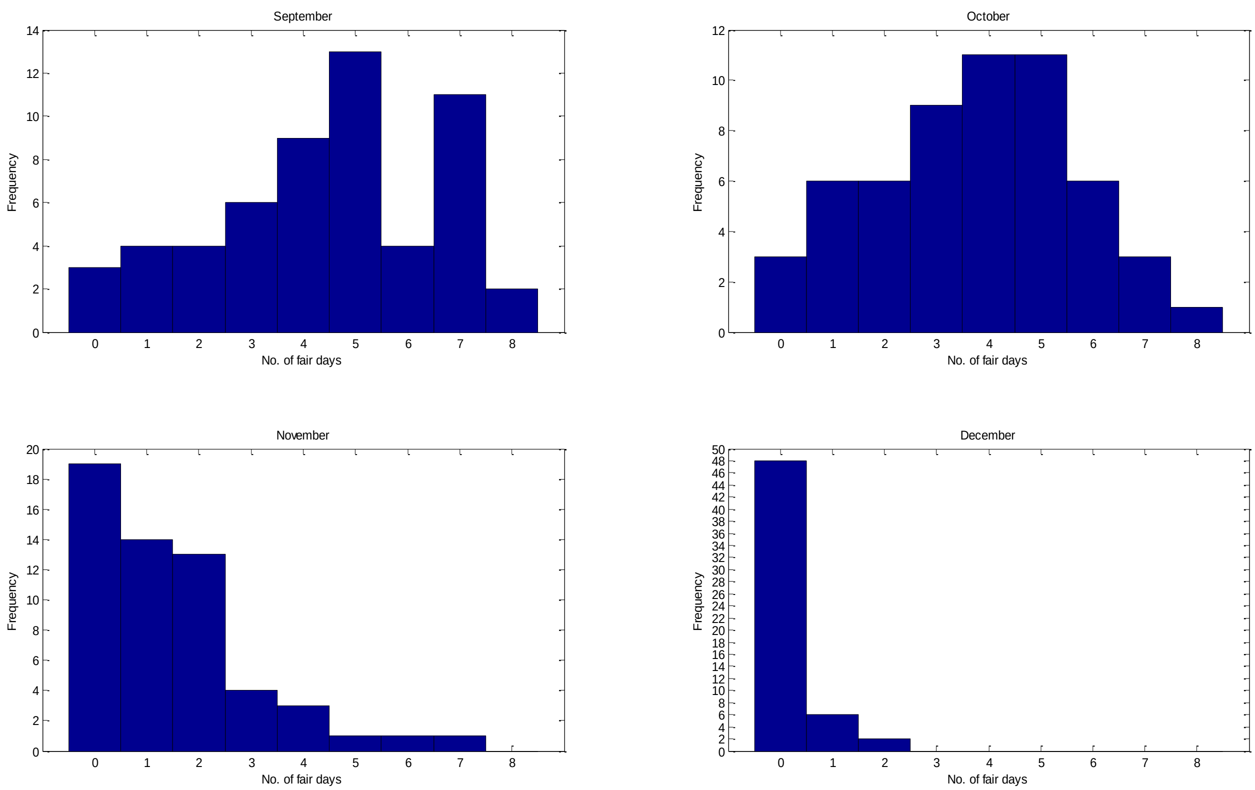
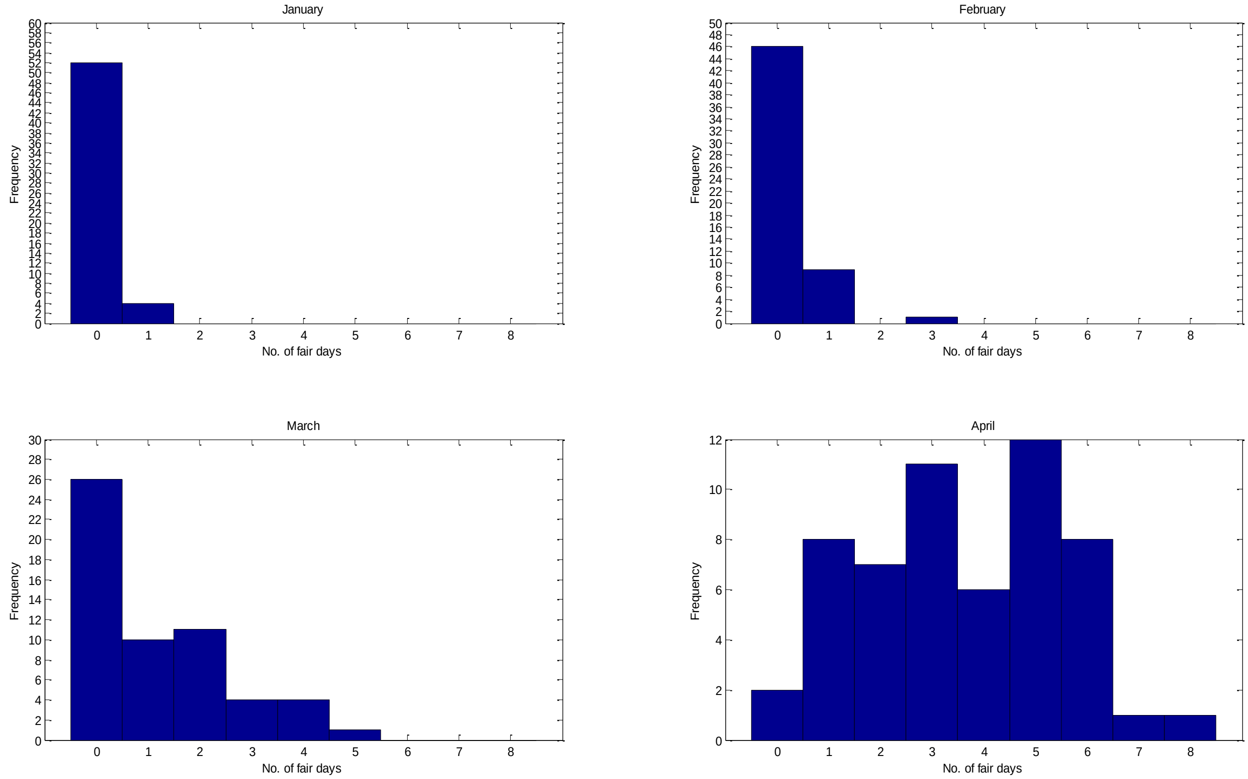
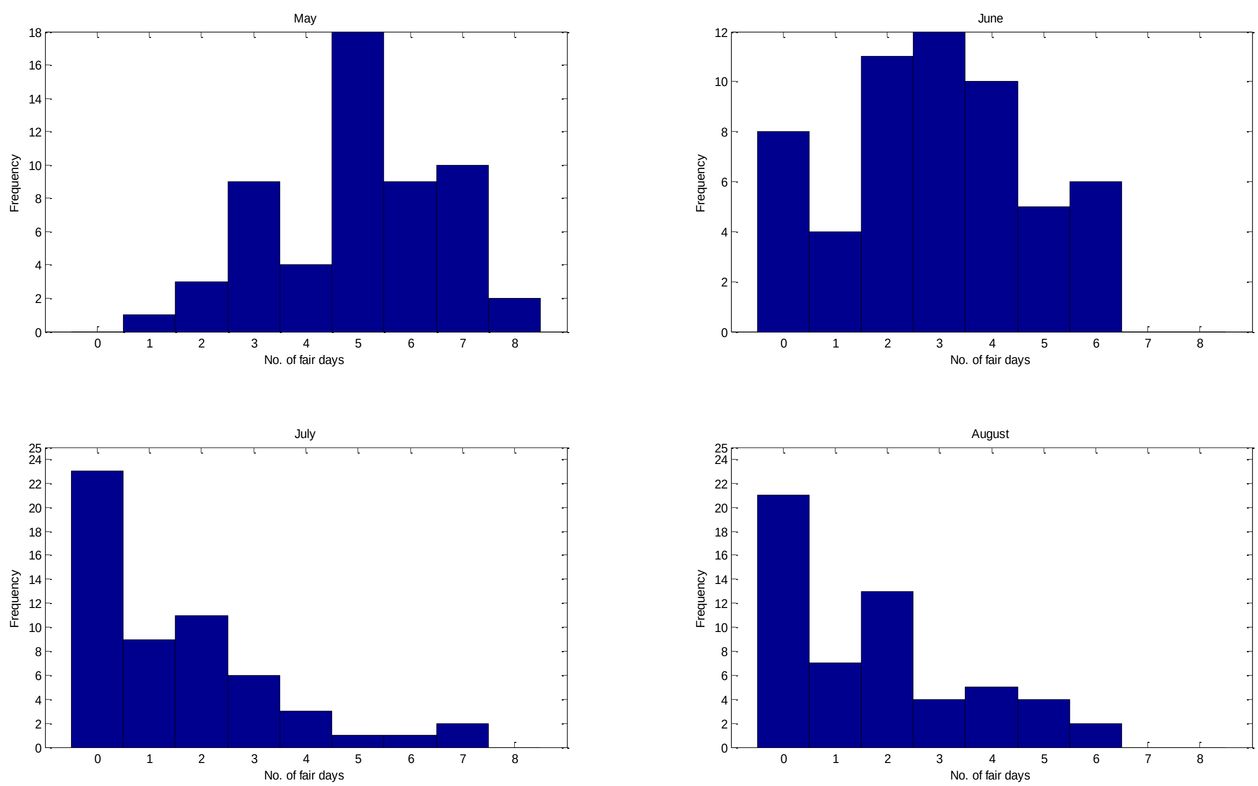



**Figure 4.3 (a)-(c) Histogram Showing Number of Fair Days for Lawrence from 1998-2011**

**(a)**


January
February
March
April
Frequency
No. of fair days

**(b)**


May
June
July
August
Frequency
No. of fair days

**(c)**

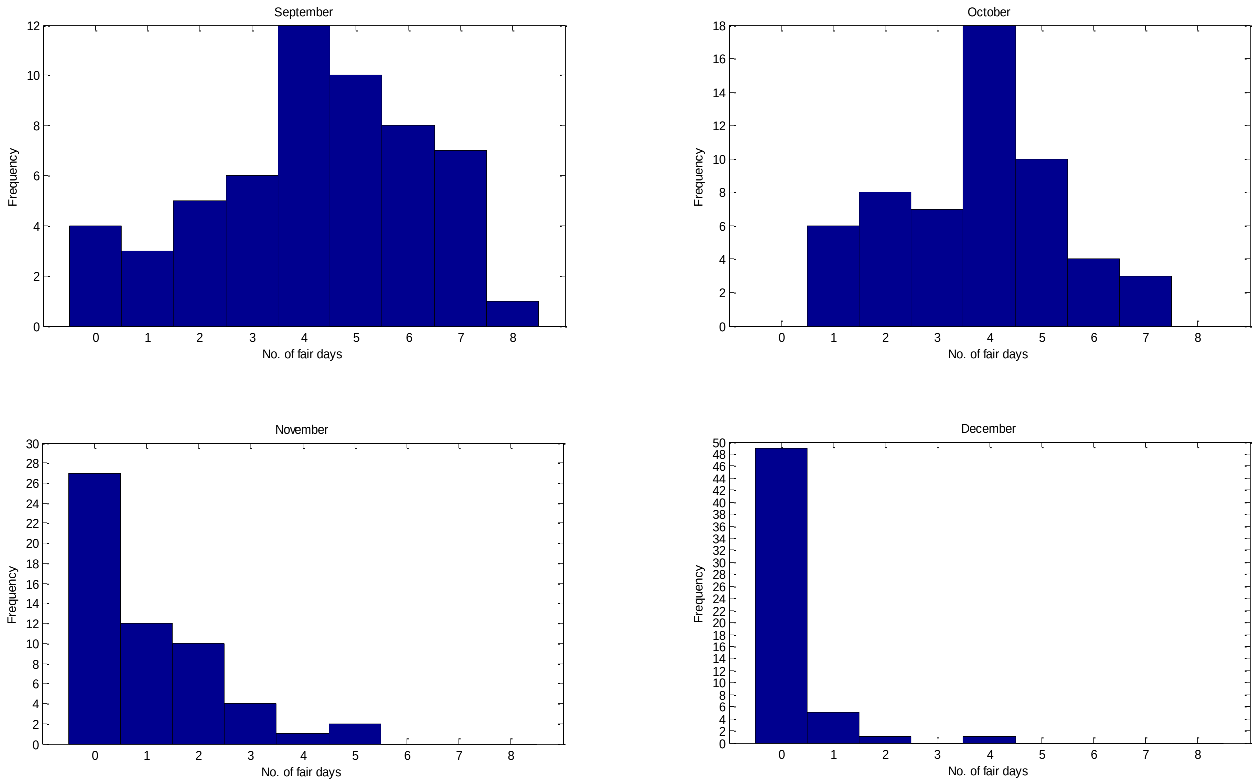



**Figure 4.4 (a)-(c) Histogram Showing Number of Fair Days for Manhattan from 1998-2011**

As observed from the histogram plots, the number of fair days was greater for month type 3: May, June, September, October, and November, followed by month type 2: April, July, August, and December. Also, the weather pattern for all the four cities is very similar. Using this 14 year weather data from 1998-2011, the probability values are calculated by dividing the number of fair days per month by 56, as for each month we have 56 (14 years×4 weeks) data points. The probability tables for four cities are shown in Table 4.1- 4.4. Monte Carlo simulations combined with these probability tables were performed to predict future weather. This predicted weather data was used to predict outages for an unknown year in the future.

**Table 4.1 Probability Table of 1998-2011 Weather Data for Wichita**

| No. of Fairdays | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| January | 0.86 | 0.09 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| February | 0.66 | 0.21 | 0.13 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| March | 0.38 | 0.16 | 0.13 | 0.16 | 0.11 | 0.04 | 0.02 | 0.02 | 0.00 |
| April | 0.11 | 0.05 | 0.05 | 0.14 | 0.21 | 0.16 | 0.20 | 0.05 | 0.02 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| May | 0.04 | 0.05 | 0.07 | 0.07 | 0.27 | 0.20 | 0.21 | 0.09 | 0.00 |
| June | 0.32 | 0.20 | 0.20 | 0.14 | 0.07 | 0.05 | 0.00 | 0.02 | 0.00 |
| July | 0.61 | 0.23 | 0.11 | 0.04 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 |
| August | 0.57 | 0.21 | 0.05 | 0.09 | 0.05 | 0.00 | 0.02 | 0.00 | 0.00 |
| September | 0.14 | 0.16 | 0.07 | 0.14 | 0.23 | 0.11 | 0.05 | 0.05 | 0.04 |
| October | 0.04 | 0.04 | 0.11 | 0.11 | 0.16 | 0.18 | 0.21 | 0.11 | 0.05 |
| November | 0.29 | 0.14 | 0.13 | 0.20 | 0.09 | 0.05 | 0.07 | 0.04 | 0.00 |
| December | 0.80 | 0.11 | 0.07 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 4.2 Probability Table of 1998-2011 Weather Data for Topeka**

| No. of Fairdays | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| January | 0.88 | 0.11 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| February | 0.77 | 0.20 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| March | 0.43 | 0.27 | 0.09 | 0.07 | 0.05 | 0.07 | 0.02 | 0.00 | 0.00 |
| April | 0.07 | 0.09 | 0.13 | 0.21 | 0.16 | 0.18 | 0.13 | 0.04 | 0.00 |
| May | 0.00 | 0.02 | 0.11 | 0.13 | 0.23 | 0.23 | 0.20 | 0.05 | 0.04 |
| June | 0.18 | 0.13 | 0.25 | 0.18 | 0.09 | 0.14 | 0.04 | 0.00 | 0.00 |
| July | 0.39 | 0.20 | 0.14 | 0.18 | 0.02 | 0.04 | 0.02 | 0.00 | 0.02 |
| August | 0.46 | 0.16 | 0.13 | 0.11 | 0.07 | 0.04 | 0.04 | 0.00 | 0.00 |
| September | 0.05 | 0.11 | 0.05 | 0.20 | 0.20 | 0.07 | 0.16 | 0.11 | 0.05 |
| October | 0.04 | 0.05 | 0.13 | 0.20 | 0.16 | 0.21 | 0.18 | 0.04 | 0.00 |
| November | 0.25 | 0.23 | 0.25 | 0.13 | 0.07 | 0.04 | 0.02 | 0.02 | 0.00 |
| December | 0.77 | 0.18 | 0.02 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 4.3 Probability Table of 1998-2011 Weather Data for Lawrence**

| No. of Fairdays | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| January | 0.93 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| February | 0.89 | 0.09 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| March | 0.54 | 0.14 | 0.18 | 0.05 | 0.04 | 0.05 | 0.00 | 0.00 | 0.00 |
| April | 0.09 | 0.07 | 0.18 | 0.18 | 0.25 | 0.11 | 0.07 | 0.05 | 0.00 |
| May | 0.02 | 0.05 | 0.05 | 0.09 | 0.20 | 0.20 | 0.14 | 0.21 | 0.04 |
| June | 0.09 | 0.13 | 0.16 | 0.21 | 0.23 | 0.05 | 0.11 | 0.02 | 0.00 |
| July | 0.36 | 0.16 | 0.20 | 0.13 | 0.09 | 0.04 | 0.00 | 0.04 | 0.00 |
| August | 0.38 | 0.18 | 0.14 | 0.13 | 0.07 | 0.05 | 0.05 | 0.00 | 0.00 |
| September | 0.05 | 0.07 | 0.07 | 0.11 | 0.16 | 0.23 | 0.07 | 0.20 | 0.04 |
| October | 0.05 | 0.11 | 0.11 | 0.16 | 0.20 | 0.20 | 0.11 | 0.05 | 0.02 |
| November | 0.34 | 0.25 | 0.23 | 0.07 | 0.05 | 0.02 | 0.02 | 0.02 | 0.00 |
| December | 0.86 | 0.11 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 4.4 Probability Table of 1998-2011 Weather Data for Manhattan**

| No. of Fairdays | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| January | 0.93 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| February | 0.82 | 0.16 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| March | 0.46 | 0.18 | 0.20 | 0.07 | 0.07 | 0.02 | 0.00 | 0.00 | 0.00 |
| April | 0.04 | 0.14 | 0.13 | 0.20 | 0.11 | 0.21 | 0.14 | 0.02 | 0.02 |
| May | 0.00 | 0.02 | 0.05 | 0.16 | 0.07 | 0.32 | 0.16 | 0.18 | 0.04 |
| June | 0.14 | 0.07 | 0.20 | 0.21 | 0.18 | 0.09 | 0.11 | 0.00 | 0.00 |
| July | 0.41 | 0.16 | 0.20 | 0.11 | 0.05 | 0.02 | 0.02 | 0.04 | 0.00 |
| August | 0.38 | 0.13 | 0.23 | 0.07 | 0.09 | 0.07 | 0.04 | 0.00 | 0.00 |
| September | 0.07 | 0.05 | 0.09 | 0.11 | 0.21 | 0.18 | 0.14 | 0.13 | 0.02 |
| October | 0.00 | 0.11 | 0.14 | 0.13 | 0.32 | 0.18 | 0.07 | 0.05 | 0.00 |
| November | 0.48 | 0.21 | 0.18 | 0.07 | 0.02 | 0.04 | 0.00 | 0.00 | 0.00 |
| December | 0.88 | 0.09 | 0.02 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 |

## Prediction of Future Outages

In order to predict outages for an unknown year in the future, seven years of outage data, from 2005-2011, were utilized. A new CPT was constructed with these data for each city as shown in Table 4.5-4.8, and the same method discussed in Chapter 3 was followed for the prediction of outages, except for weather data. The predicted weather data was used as input for this model.

**Table 4.5 CPT for Wichita Using 2005-2011 Outage Data**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.283 | 0.283 | 0.189 | 0.151 | 0.075 | 0.000 | 0.000 | 0.019 | 0.000 |
| Input State 2 | 0.143 | 0.127 | 0.222 | 0.159 | 0.175 | 0.111 | 0.032 | 0.032 | 0.000 |
| Input State 3 | 0.000 | 0.069 | 0.000 | 0.138 | 0.172 | 0.207 | 0.138 | 0.138 | 0.138 |
| Input State 4 | 0.308 | 0.115 | 0.269 | 0.154 | 0.115 | 0.038 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.067 | 0.167 | 0.100 | 0.233 | 0.233 | 0.100 | 0.067 | 0.033 | 0.000 |
| Input State 6 | 0.020 | 0.059 | 0.078 | 0.020 | 0.118 | 0.235 | 0.255 | 0.118 | 0.098 |
| Input State 7 | 0.000 | 0.000 | 0.600 | 0.200 | 0.000 | 0.200 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.053 | 0.000 | 0.158 | 0.211 | 0.316 | 0.211 | 0.053 | 0.000 | 0.000 |
| Input State 9 | 0.000 | 0.000 | 0.033 | 0.100 | 0.150 | 0.117 | 0.100 | 0.217 | 0.283 |

**Table 4.6 CPT for Topeka Using 2005-2011 Outage Data**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.155 | 0.276 | 0.379 | 0.103 | 0.069 | 0.017 | 0.000 | 0.000 | 0.000 |
| Input State 2 | 0.058 | 0.135 | 0.154 | 0.269 | 0.269 | 0.058 | 0.058 | 0.000 | 0.000 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Input State 3 | 0.000 | 0.000 | 0.143 | 0.095 | 0.333 | 0.286 | 0.095 | 0.048 | 0.000 |
| Input State 4 | 0.095 | 0.476 | 0.238 | 0.190 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.075 | 0.100 | 0.175 | 0.450 | 0.150 | 0.025 | 0.025 | 0.000 | 0.000 |
| Input State 6 | 0.000 | 0.031 | 0.077 | 0.138 | 0.138 | 0.338 | 0.231 | 0.046 | 0.000 |
| Input State 7 | 0.000 | 0.000 | 0.400 | 0.600 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.000 | 0.250 | 0.300 | 0.150 | 0.250 | 0.050 | 0.000 | 0.000 | 0.000 |
| Input State 9 | 0.000 | 0.019 | 0.037 | 0.204 | 0.204 | 0.296 | 0.204 | 0.019 | 0.019 |

**Table 4.7 CPT for Lawrence Using 2005-2011 Outage Data**

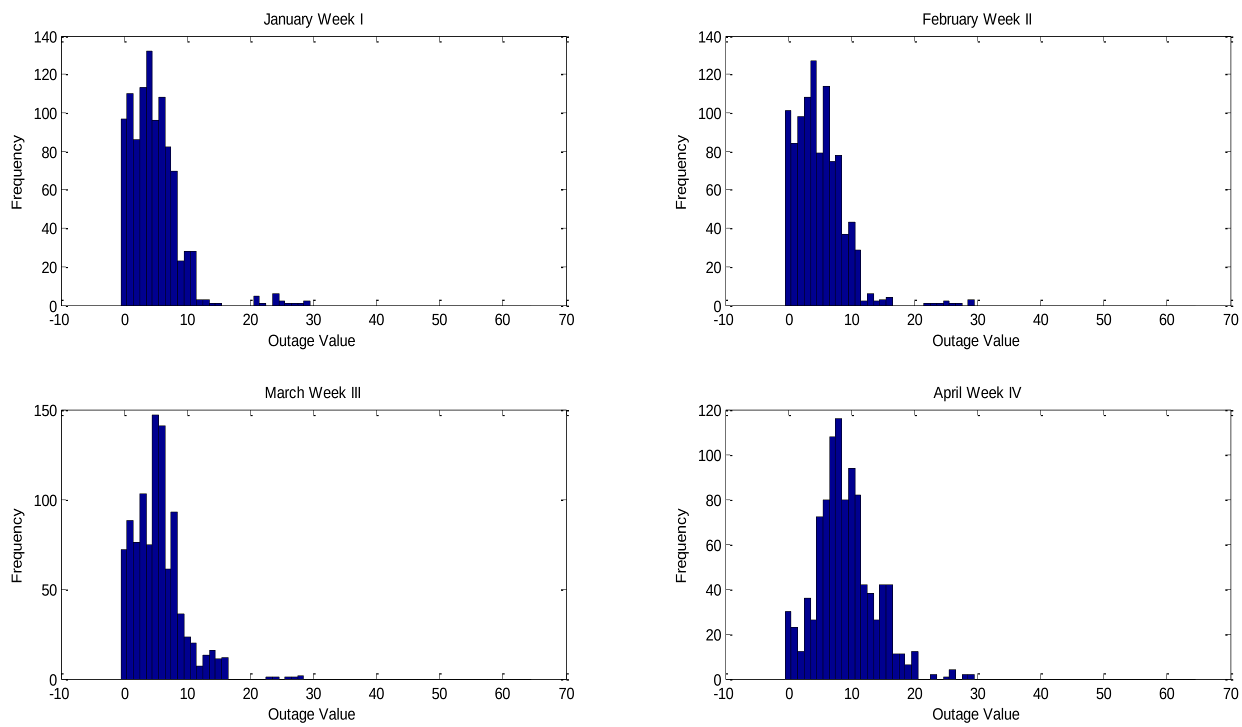
| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.172 | 0.359 | 0.219 | 0.078 | 0.063 | 0.063 | 0.031 | 0.016 | 0.000 |
| Input State 2 | 0.170 | 0.170 | 0.170 | 0.106 | 0.149 | 0.170 | 0.043 | 0.000 | 0.021 |
| Input State 3 | 0.050 | 0.050 | 0.000 | 0.200 | 0.200 | 0.300 | 0.150 | 0.050 | 0.000 |
| Input State 4 | 0.222 | 0.167 | 0.333 | 0.167 | 0.056 | 0.000 | 0.000 | 0.056 | 0.000 |
| Input State 5 | 0.048 | 0.238 | 0.190 | 0.143 | 0.167 | 0.167 | 0.024 | 0.000 | 0.024 |
| Input State 6 | 0.056 | 0.037 | 0.093 | 0.056 | 0.130 | 0.185 | 0.167 | 0.167 | 0.111 |
| Input State 7 | 0.500 | 0.500 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.130 | 0.261 | 0.348 | 0.087 | 0.087 | 0.087 | 0.000 | 0.000 | 0.000 |
| Input State 9 | 0.045 | 0.061 | 0.076 | 0.106 | 0.136 | 0.121 | 0.242 | 0.076 | 0.136 |

**Table 4.8 CPT for Manhattan Using 2005-2011 Outage Data**

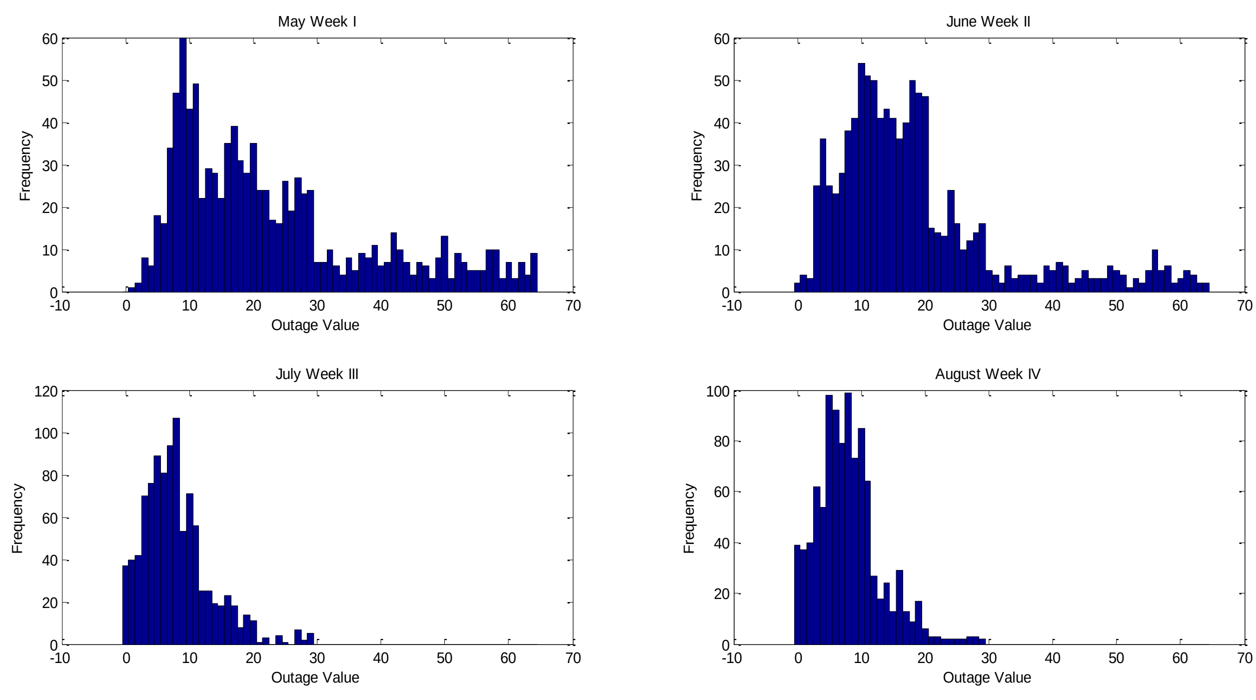
| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.323 | 0.403 | 0.161 | 0.065 | 0.032 | 0.000 | 0.016 | 0.000 | 0.000 |
| Input State 2 | 0.413 | 0.239 | 0.109 | 0.043 | 0.109 | 0.065 | 0.022 | 0.000 | 0.000 |
| Input State 3 | 0.045 | 0.182 | 0.182 | 0.136 | 0.091 | 0.227 | 0.136 | 0.000 | 0.000 |
| Input State 4 | 0.316 | 0.211 | 0.211 | 0.158 | 0.105 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.195 | 0.195 | 0.293 | 0.122 | 0.122 | 0.049 | 0.000 | 0.024 | 0.000 |
| Input State 6 | 0.098 | 0.137 | 0.157 | 0.098 | 0.118 | 0.196 | 0.118 | 0.059 | 0.020 |
| Input State 7 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.333 | 0.250 | 0.125 | 0.167 | 0.125 | 0.000 | 0.000 | 0.000 | 0.000 |
| Input State 9 | 0.132 | 0.162 | 0.191 | 0.176 | 0.088 | 0.132 | 0.074 | 0.029 | 0.015 |

Predictions were carried out on weekly, monthly, and yearly basis for four cities. Examples of results for Wichita are shown in Figures 4.5-4.7. Results for yearly prediction for other cities are shown in Figure 4.8-4.10. Weekly and monthly predictions of other cities are included in Appendix A. As demonstrated, normal distribution fits the yearly predictions histogram and the parameters of normal distribution for each city are tabulated in Table 4.9. Both mean and standard deviation for all the cities are slightly higher than those found for 2005 to 2011 shown in Tables 3.3-3.6. This could be due to the fact that 14 years of weather data was used for the future prediction whereas the outages are based only on seven years of data.

**(a)**




**(b)**



**(c)**

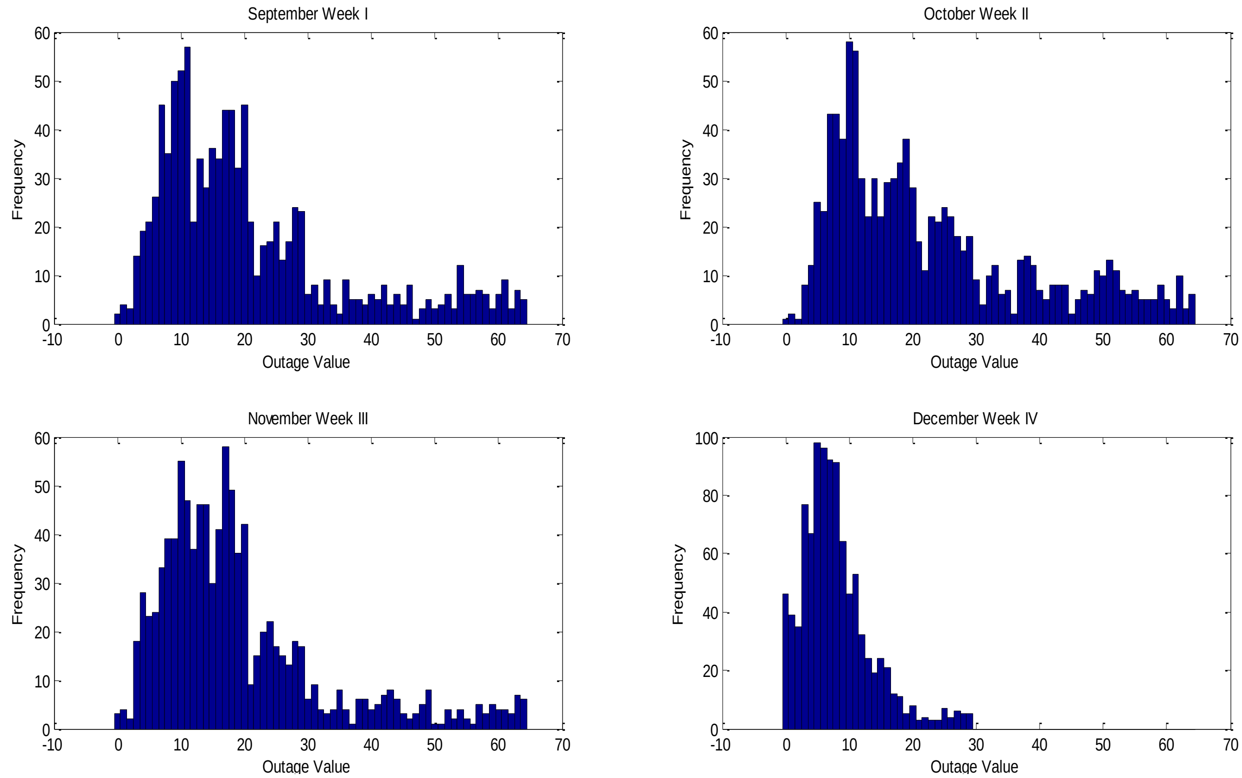
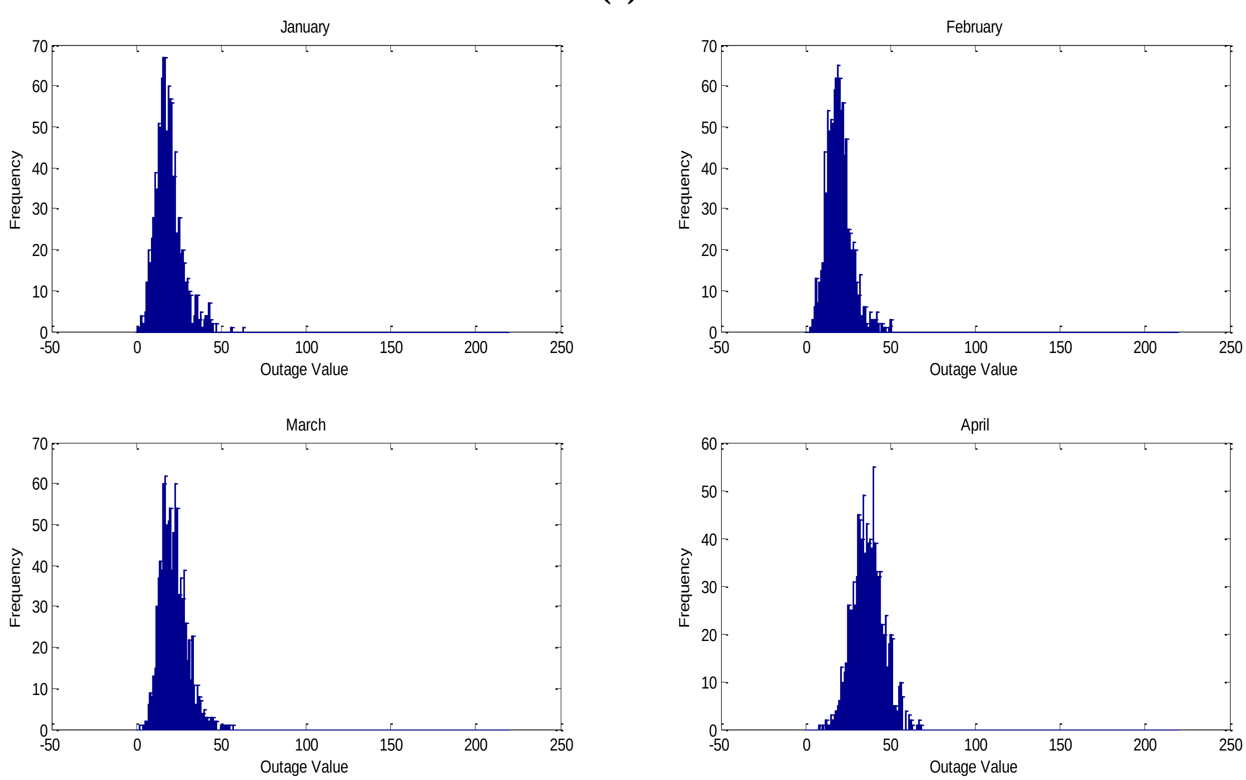
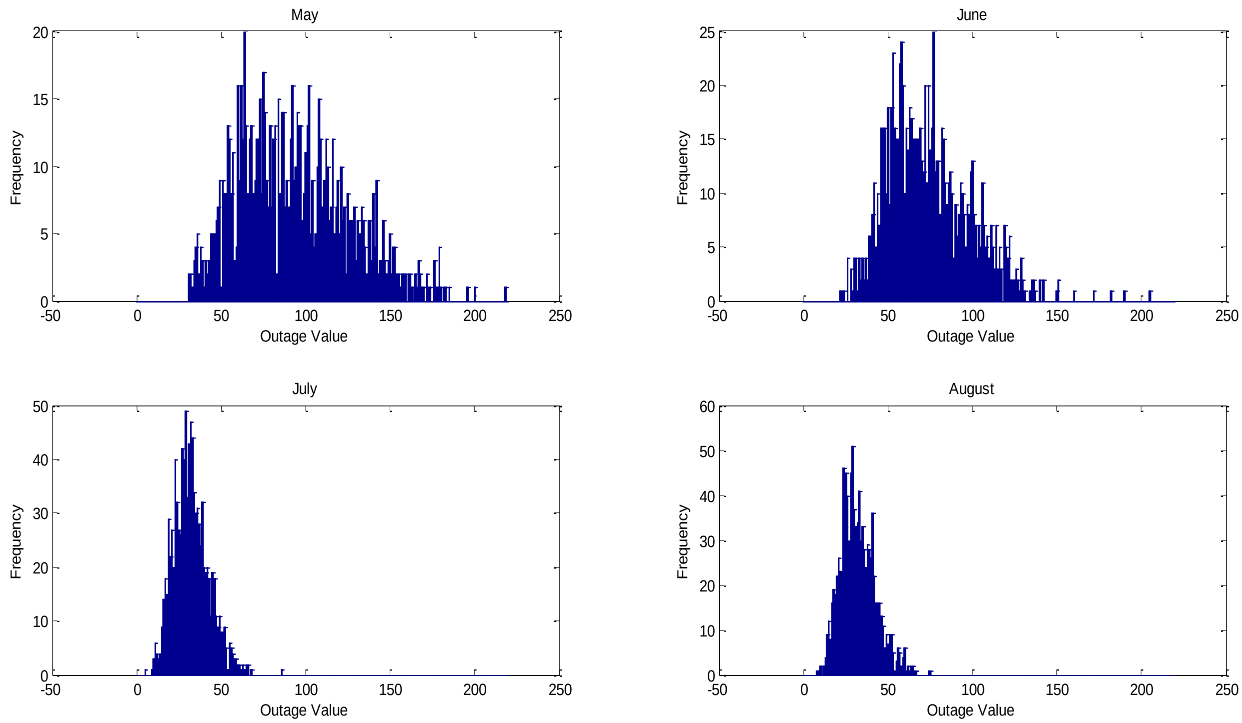



**Figure 4.5 (a)-(c) Wichita Weekly Predictions by MCS**

**(a)**



**(b)**




**(c)**

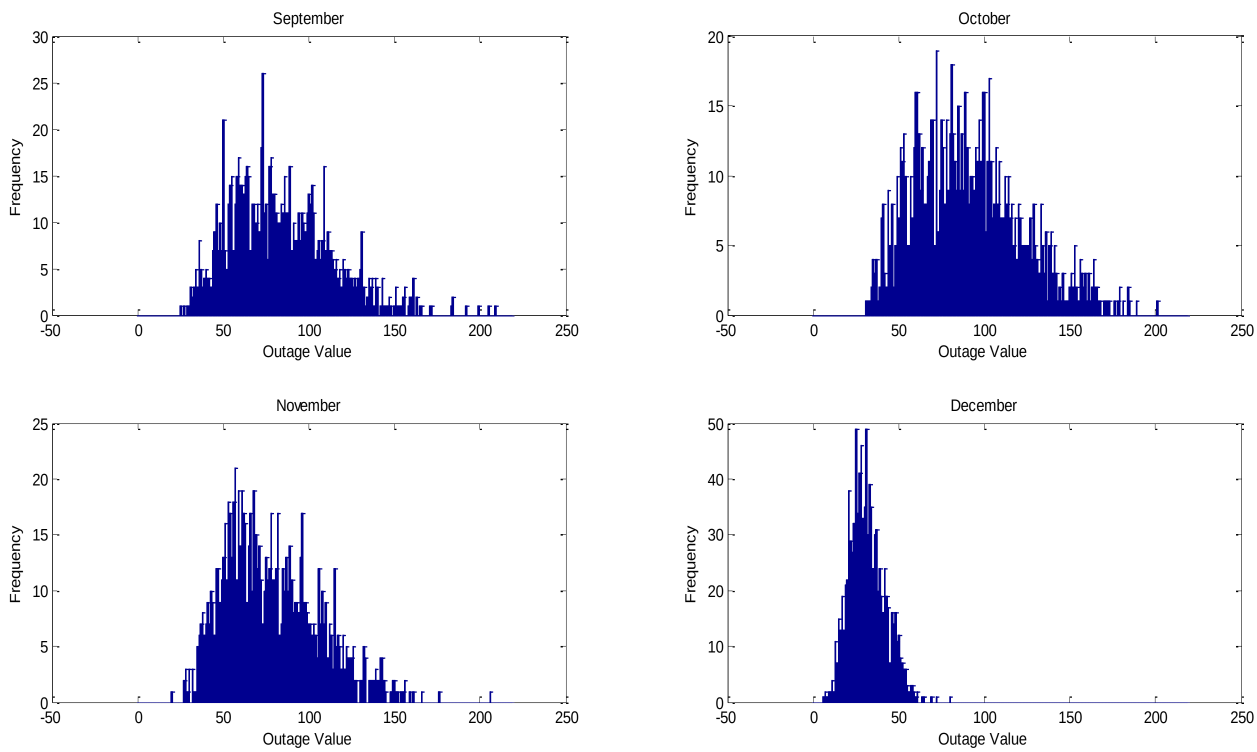



**Figure 4.6 (a)-(c) Wichita Monthly Predictions by MCS**

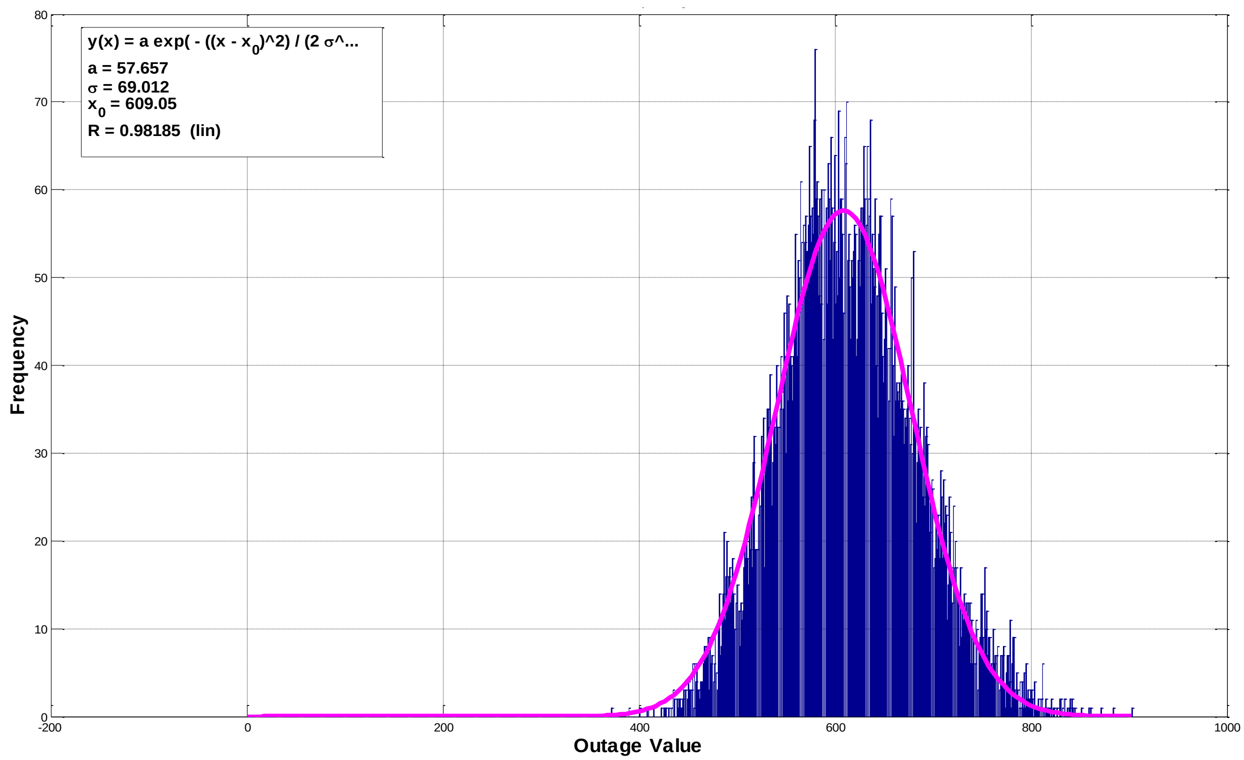



**Figure 4.7 Wichita Yearly Predictions by MCS**

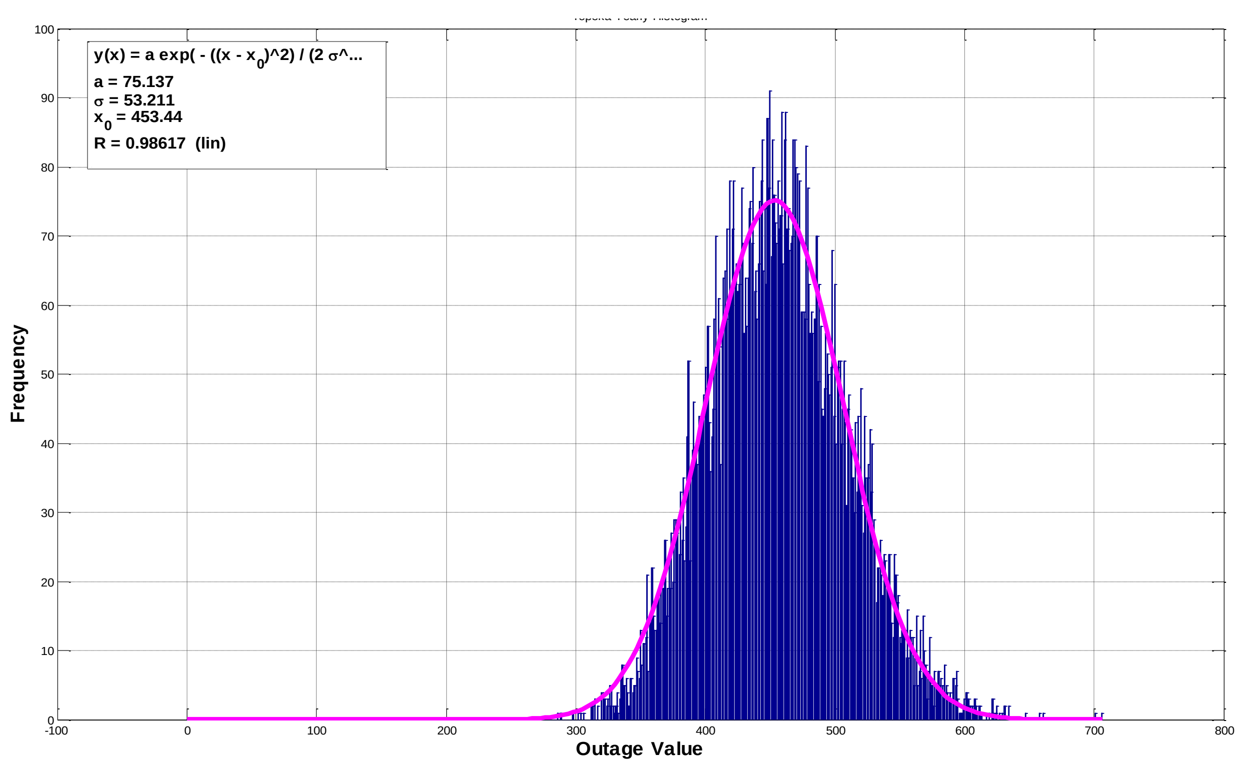



**Figure 4.8 Topeka Yearly Predictions by MCS**

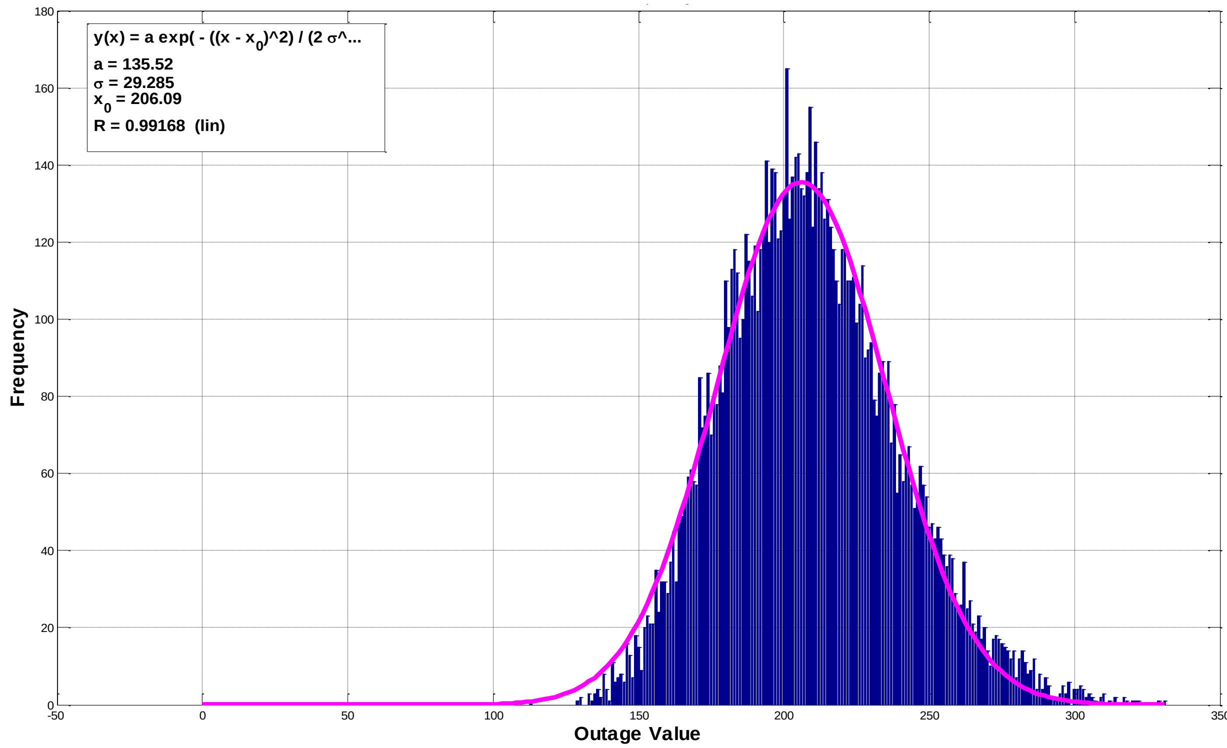



**Figure 4.9 Lawrence Yearly Predictions by MCS**

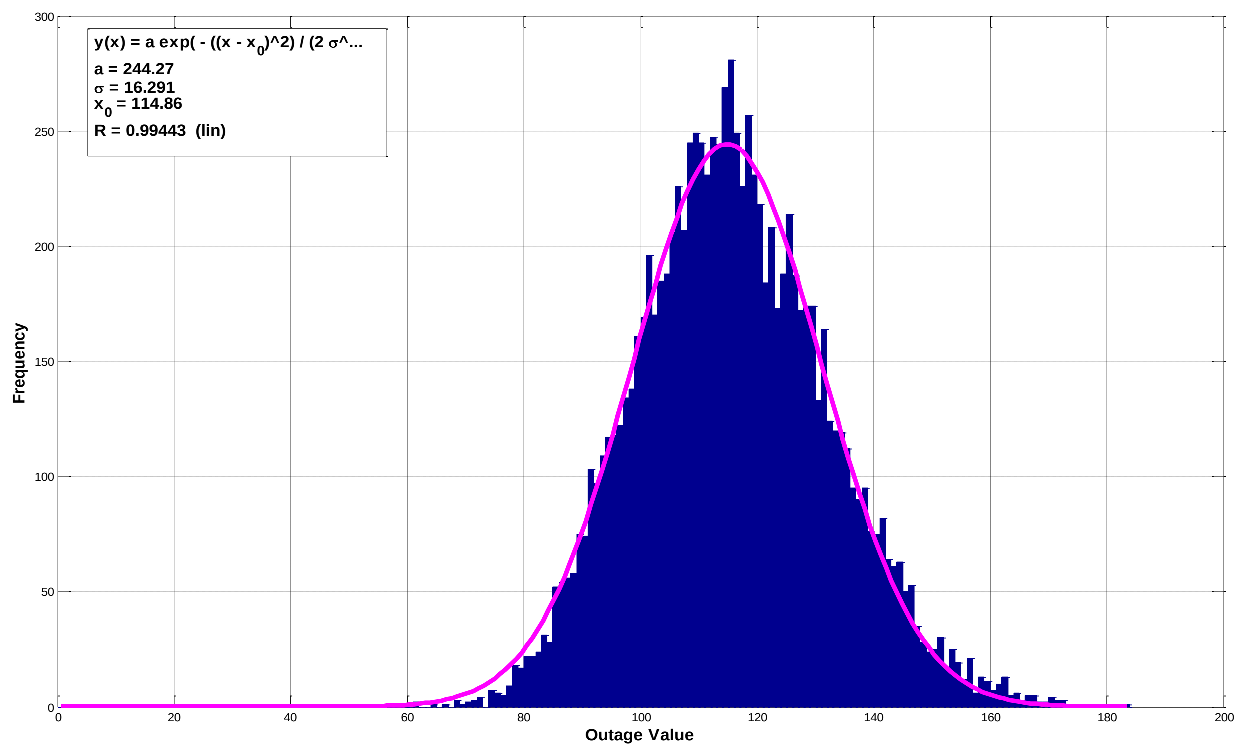



**Figure 4.10 Manhattan Yearly Predictions by MCS**

**Table 4.9 Parameters of Normal Distribution for Yearly Predicted Outages**

| City | Mean | Standard Deviation |
|---|---|---|
| Wichita | 609.05 | 69.01 |
| Topeka | 453.44 | 53.21 |
| Lawrence | 206.09 | 29.29 |
| Manhattan | 114.86 | 16.29 |

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# Chapter 5 - Cost-Benefit Analysis of Outage Mitigation

In this chapter, costs which utilities incur after installation of animal guards at vulnerable points are discussed, including the calculation of savings obtained for outage reductions. Real-time data was used to perform all calculations in order to maintain credibility of results. This analysis was conducted for Wichita, Topeka, Lawrence, and Manhattan since outage mitigation strategies vary by city size.

## Installation of Squirrel Guards

Conventional methods which are implemented to prevent animals from reaching out to vulnerable points include tree trimming, installing animal guards on devices such as transformers and fuses, using chemical repellants or ultrasonic units [21]. Additionally, appropriate measures in initial construction stage include reviewing construction design standards and making sure the devices are not mounted in such a way that they facilitate animal contacts [21]. A variety of squirrel guards, commonly called Critter Guards, are currently available on the market. According to data provided by a utility in Kansas:

| | |
|---|---|
| Cost of installation (including animal guard cost) | = \$77 per animal guard |
| Annual Cost of replacing of damaged animal guards | = 4% of total installation cost |
| Crew wage on a weekday | = \$95/hr. |
| Crew wage on a weekday: 6 pm-6 am shift, and weekend | = \$143/hr. |
| Average time taken by crew to respond to an outage (excluding duration of outage) | = 30 minutes per outage |

In order to determine the total installation cost of animal guards, the knowledge of total vulnerable points is required. These vulnerable points are the devices on overhead distribution, such as transformers, fuses, cutouts, switches, reclosers, etc., which must be protected from animals that can cause outages. Table 5.1 shows the number of vulnerable points in the distribution systems of Wichita, Topeka, Lawrence, and Manhattan as provided by the utility.

**Table 5.1 Vulnerable Points in Four Cities in Kansas**

| City | Total Number of Vulnerable Points |
|---|---|
| Wichita | 8646 |
| Topeka | 4250 |
| Lawrence | 3837 |
| Manhattan | 3871 |

Since most of the animal outages take place on the single-phase laterals, devices on three-phase lines were not counted. The number of vulnerable points increases with the size of the cities. However, Manhattan has larger number of vulnerable points compared to its size.

The total investment which a utility would incur for installing animal guards at all the points for Wichita, Topeka, Lawrence, and Manhattan are calculated using the given data and shown in Table 5.2.

**Table 5.2 Total Investment for Installing Animal Guards**

| City | Total Investment |
|---|---|
| Wichita | \$868,289.46 |
| Topeka | \$426,813.58 |
| Lawrence | \$385,337.34 |
| Manhattan | \$388,751.85 |

For the cost-benefit analysis, the initial investment is converted to an annual cost-per-year with time duration of 20 years and a discount rate of 10%. The Present Worth Factor for these values is given by Equation 5.1.

$$\textbf{Present Worth Factor} = \frac{(\mathbf{1}+\boldsymbol{d})^{\boldsymbol{N}}-\mathbf{1}}{\boldsymbol{d}\times(\mathbf{1}+\boldsymbol{d})^{\boldsymbol{N}}} \qquad 5.1$$

$$\textbf{Cost - per - year} = \frac{Initial\ Investment}{Present\ Worth\ Factor} \qquad 5.2$$

In order to propose optimal outage mitigation strategy, different percent of vulnerable points starting from 20% were considered. They were increased by 10% in each step. Cost-per-year for all four cities are given in the Table 5.3. For example, if the utility plans to install animal guards on 20% of vulnerable points in Wichita, which equals to 1729 devices, the cost-per-year incurred by the utility with a 10% discount rate is \$20,964.70/yr for a period of 20 years.

**Table 5.3 Cost-per-year Values for Four Cities**

| Mitigation Level | % of TVP | Wichita ($/yr.) | Topeka ($/yr.) | Lawrence ($/yr.) | Manhattan ($/yr.) |
|---|---|---|---|---|---|
| 1 | 20% | $20,964.70 | $10,305.34 | $9,303.90 | $9,386.34 |
| 2 | 30% | $31,447.04 | $15,458.01 | $13,955.85 | $14,079.52 |
| 3 | 40% | $41,929.39 | $20,610.68 | $18,607.80 | $18,772.69 |
| 4 | 50% | $52,411.74 | $25,763.35 | $23,259.76 | $23,465.86 |
| 5 | 60% | $62,894.09 | $30,916.02 | $27,911.71 | $28,159.03 |
| 6 | 70% | $73,376.43 | $36,068.68 | $32,563.66 | $32,852.21 |
| 7 | 80% | $83,858.78 | $41,221.35 | $37,215.61 | $37,545.38 |
| 8 | 90% | $94,341.13 | $46,374.02 | $41,867.56 | $42,238.55 |
| 9 | 100% | $104,823.48 | $51,526.69 | $46,519.51 | $46,931.72 |

## Outage Reduction

Installations of animal guards are expected to reduce squirrel-related outages by as much as 80% [20]. Thus eight cases of outage reduction from 10 % outage reduction to 80% outage reduction in increments of 10% are considered in this research. In this section, new CPTs are constructed for different cases of outage reduction using the original CPT discussed in Chapter 4. For example, using the original CPT of Wichita given in Table 4.1, the new CPT for 10% outage reduction was calculated by multiplying all values for all outage levels in the original CPT by 0.9, except for outage level 1. Since the sum of probability is always 1, probability values for outage level 1 will be the difference of one and the summation of other probability values of outage level 2 to outage level 9 for every corresponding input state. Similarly, to construct a CPT for 20% outage reduction, all values for all outage levels in the original CPT are multiplied by 0.8, except for outage level 1, and the same steps are followed to obtain values of outage level 1. It is understood that X% outage reduction implies that new outage levels will be (100-X) % of the original outage levels. Therefore, for 2005-2011 outage data, the outage levels were formed. In the originally selected outage levels, outage level 1 has zero outages except for Wichita. Outage levels using 2005-2011 outage data for four cities is shown in Table 5.4. The CPT of Wichita for 10% outage reduction is given in Table 5.5. CPT for other cases are shown in Appendix B. Using similar procedure, CPT for other cities were obtained.

**Table 5.4 Outage Levels Using 2005-2011 Outage Data**

| Outage levels | Wichita (Animal outages per week) | Topeka (Animal outages per week) | Lawrence (Animal outages per week) | Manhattan (Animal outages per week) |
|---|---|---|---|---|
| Outage level 1 | 1~3 | 0 | 0 | 0 |
| Outage level 2 | 4~5 | 1~2 | 1 | 1 |
| Outage level 3 | 6~7 | 3~4 | 2 | 2 |
| Outage level 4 | 8~9 | 5~7 | 3 | 3 |
| Outage level 5 | 10~12 | 8~11 | 4 | 4 |
| Outage level 6 | 13~17 | 12~20 | 5~6 | 5~6 |
| Outage level 7 | 18~21 | 21~35 | 7~8 | 7~9 |
| Outage level 8 | 22~30 | 36~50 | 9~11 | 10~12 |
| Outage level 9 | 31~65 | 51~56 | 12~29 | 13~15 |

**Table 5.5 CPT of Wichita for 10% Outage Reduction Case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.355 | 0.255 | 0.170 | 0.136 | 0.068 | 0.000 | 0.000 | 0.017 | 0.000 |
| Input State 2 | 0.229 | 0.114 | 0.200 | 0.143 | 0.157 | 0.100 | 0.029 | 0.029 | 0.000 |
| Input State 3 | 0.100 | 0.062 | 0.000 | 0.124 | 0.155 | 0.186 | 0.124 | 0.124 | 0.124 |
| Input State 4 | 0.377 | 0.104 | 0.242 | 0.138 | 0.104 | 0.035 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.160 | 0.150 | 0.090 | 0.210 | 0.210 | 0.090 | 0.060 | 0.030 | 0.000 |
| Input State 6 | 0.118 | 0.053 | 0.071 | 0.018 | 0.106 | 0.212 | 0.229 | 0.106 | 0.088 |
| Input State 7 | 0.100 | 0.000 | 0.540 | 0.180 | 0.000 | 0.180 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.147 | 0.000 | 0.142 | 0.189 | 0.284 | 0.189 | 0.047 | 0.000 | 0.000 |
| Input State 9 | 0.100 | 0.000 | 0.030 | 0.090 | 0.135 | 0.105 | 0.090 | 0.195 | 0.255 |

As the percentage of outage reduction increases, the probability values for outage level 1 increase for all nine input states. Using the new CPTs, outage values per year are predicted for four cities using the Bayesian model and running Monte-Carlo simulation 10,000 times. For example, the yearly predictions of outages for eight cases for Wichita and Manhattan are shown in Figures 5.1 to 5.16 and the data is fitted to normal distribution with appropriate mean and sigma values. The yearly outage predictions for Topeka and Lawrence are given in Appendix C.

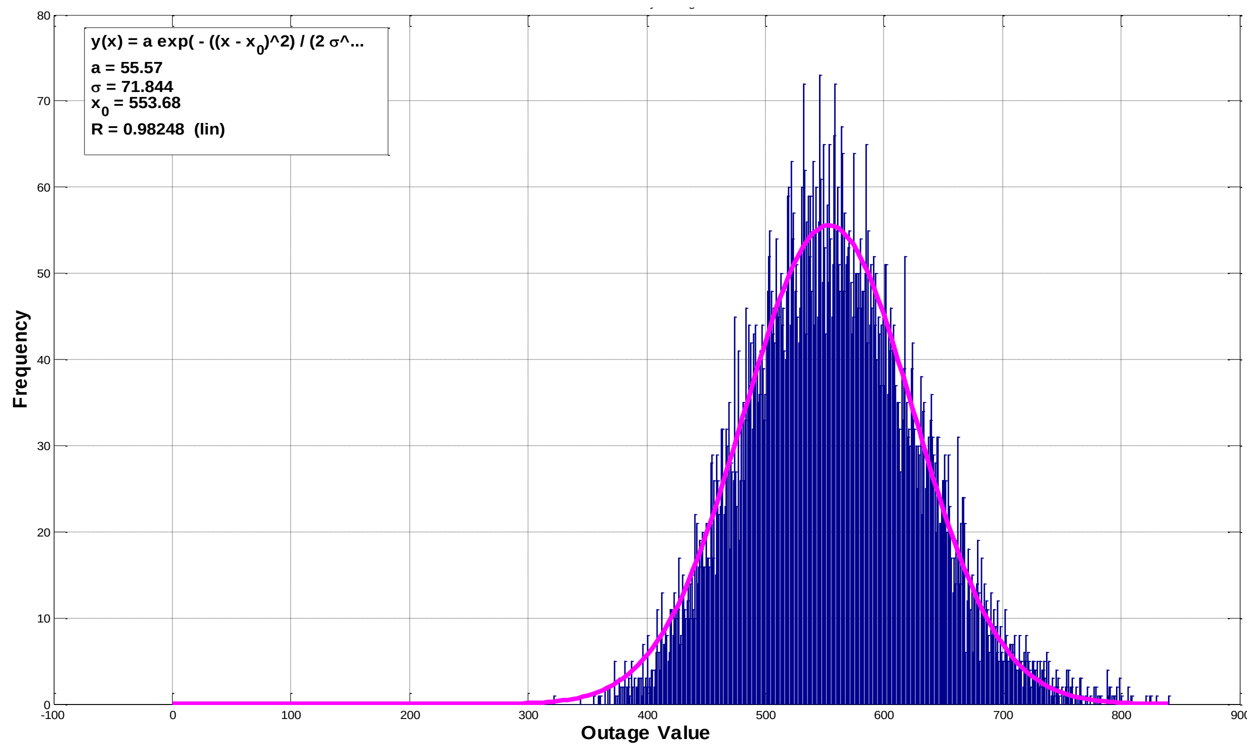


**Figure 5.1 Wichita Yearly Outages with 10% Outage Reduction**

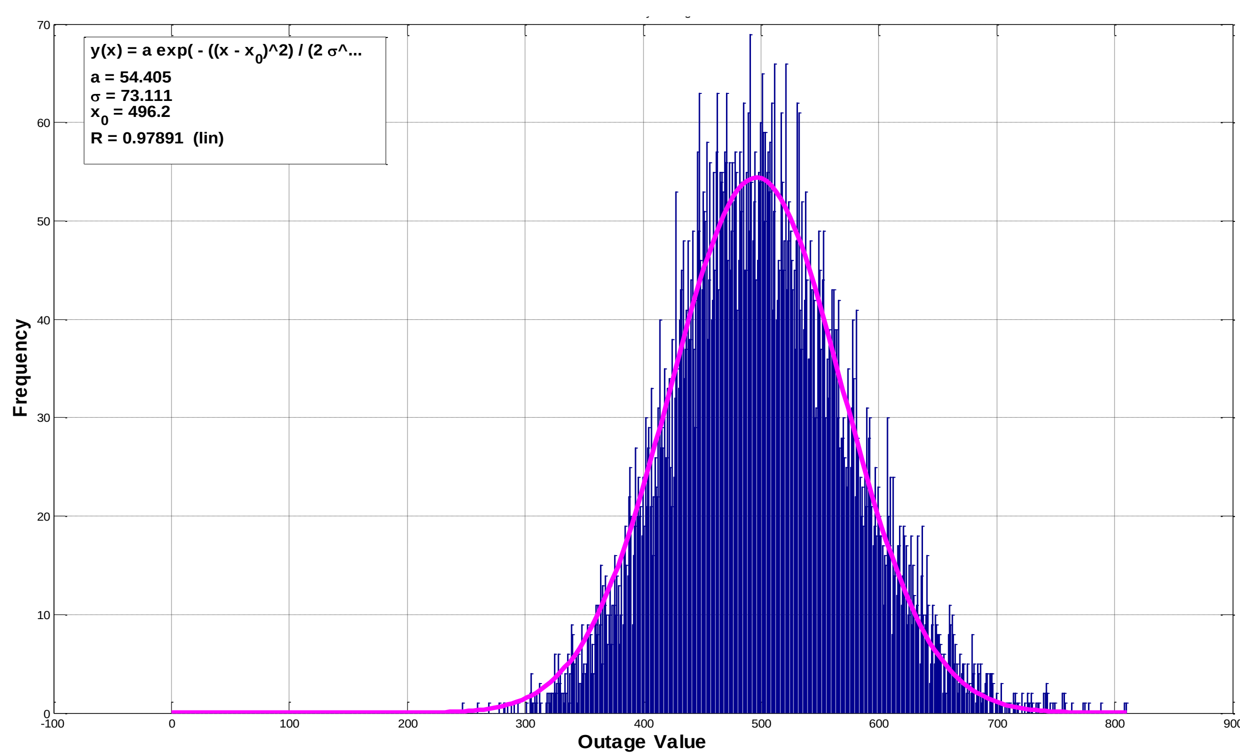


**Figure 5.2 Wichita Yearly Outages with 20% Outage Reduction**

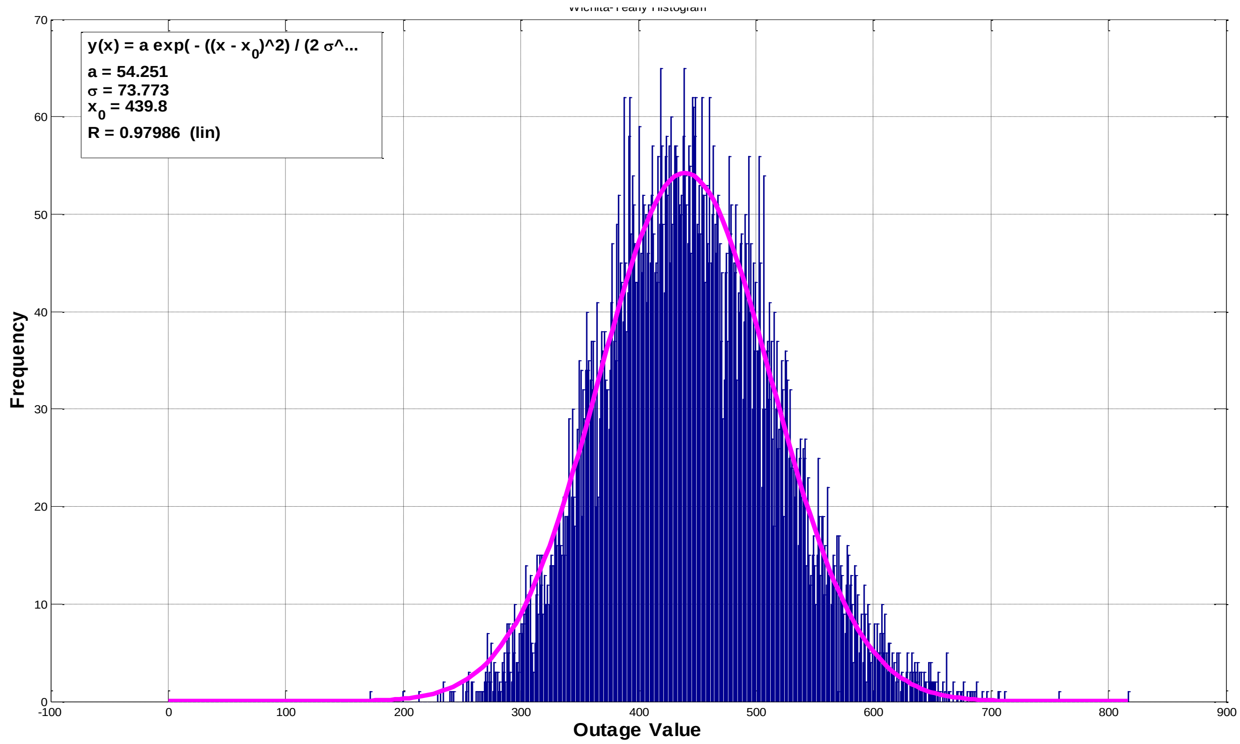


**Figure 5.3 Wichita Yearly Outages with 30% Outage Reduction**

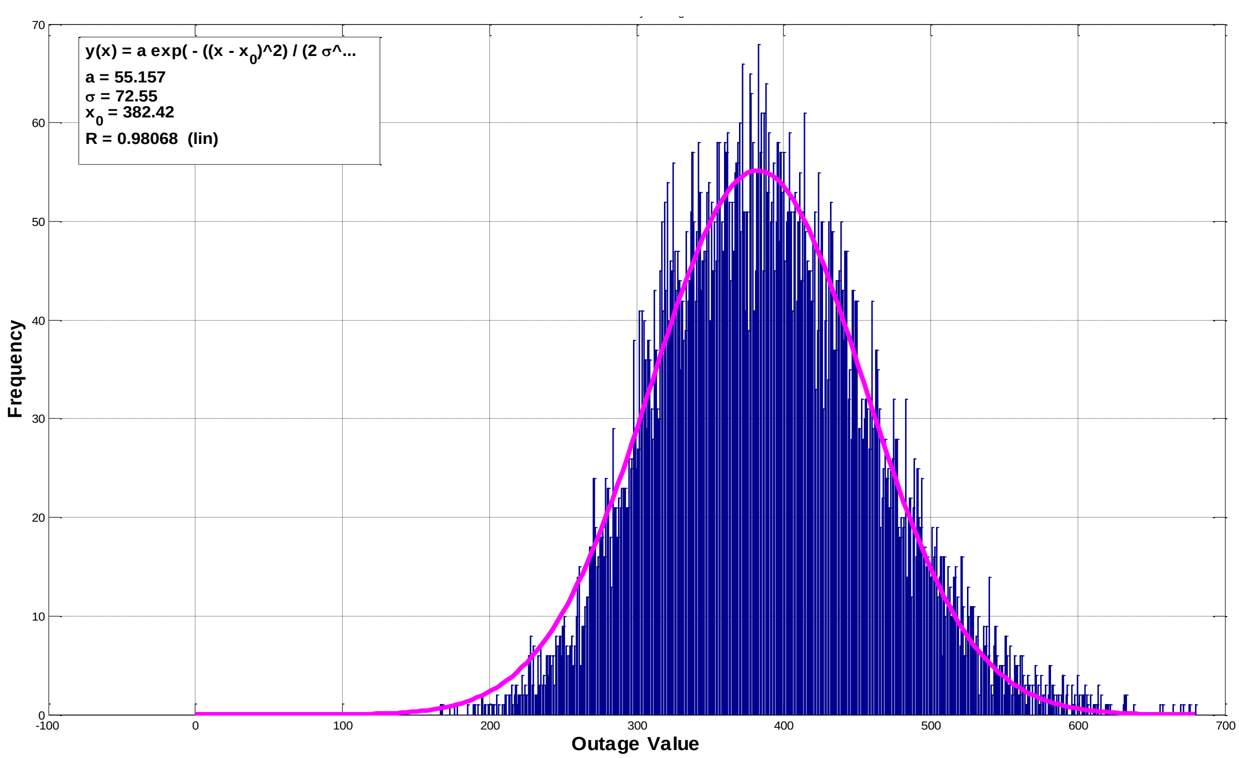


**Figure 5.4 Wichita Yearly Outages with 40% Outage Reduction**

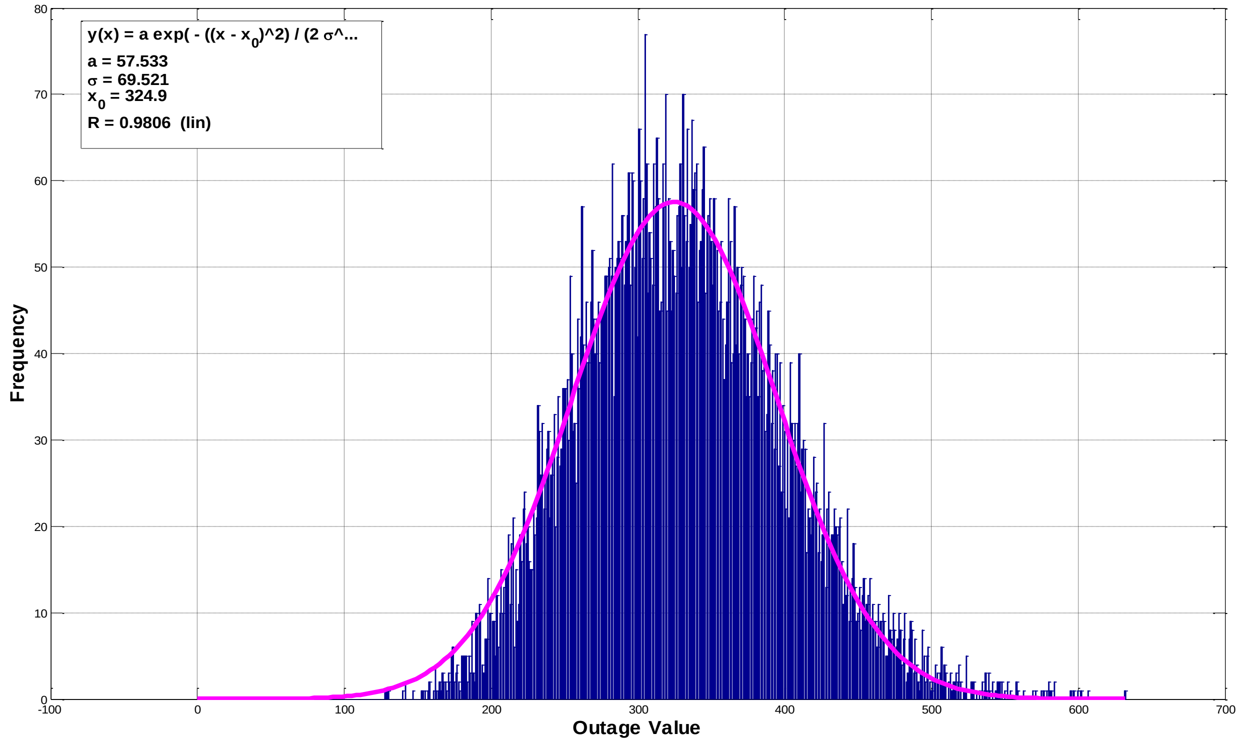


**Figure 5.5 Wichita Yearly Outages with 50% Outage Reduction**

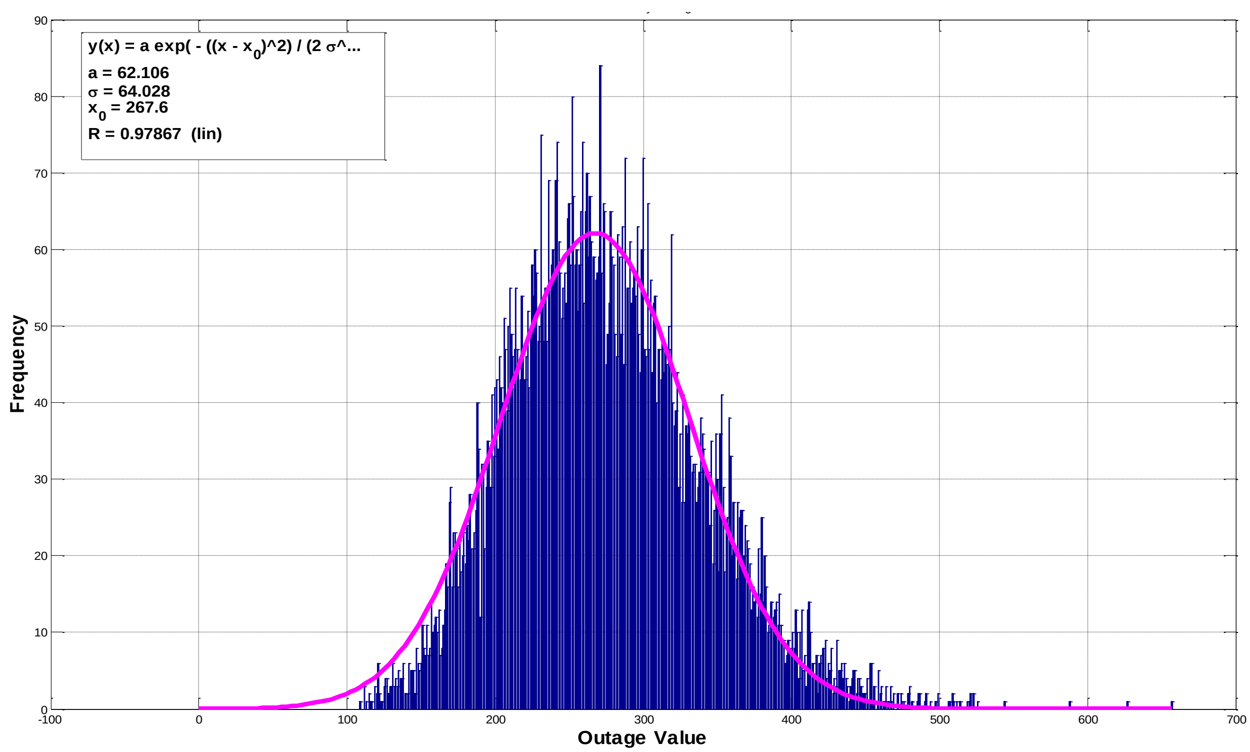


**Figure 5.6 Wichita Yearly Outages with 60% Outage Reduction**

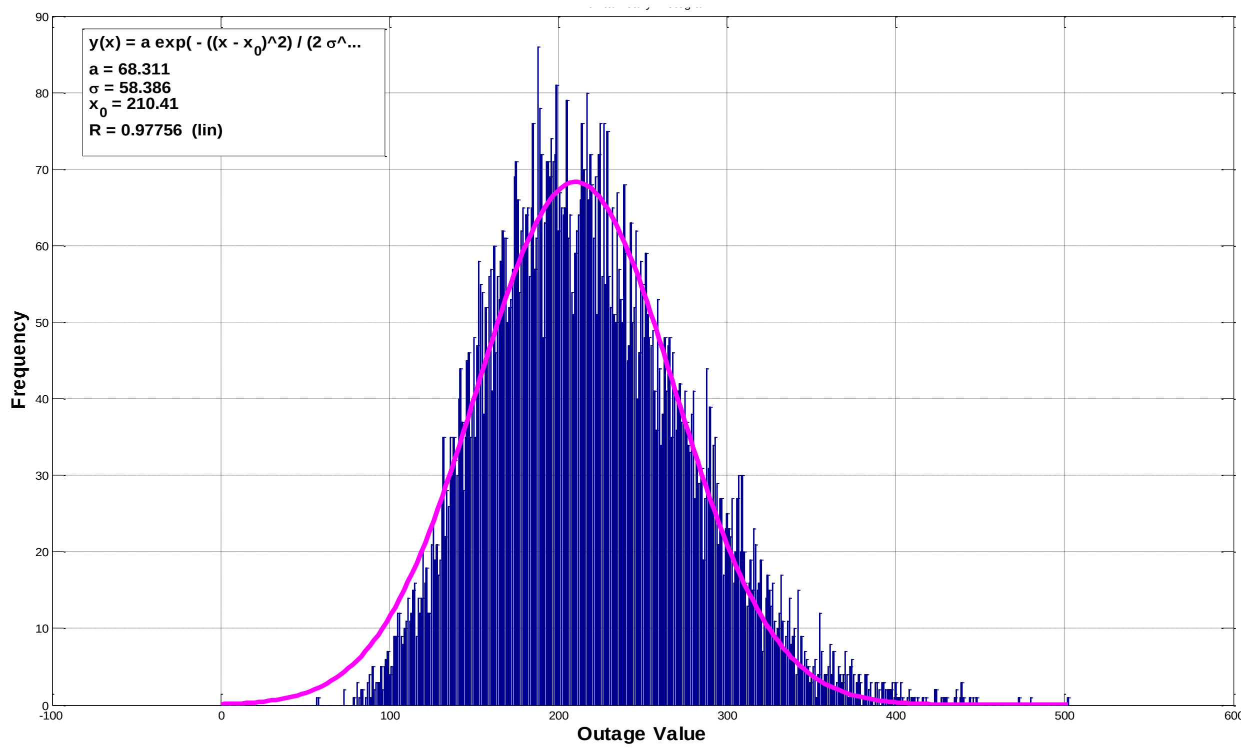


**Figure 5.7 Wichita Yearly Outages with 70% Outage Reduction**

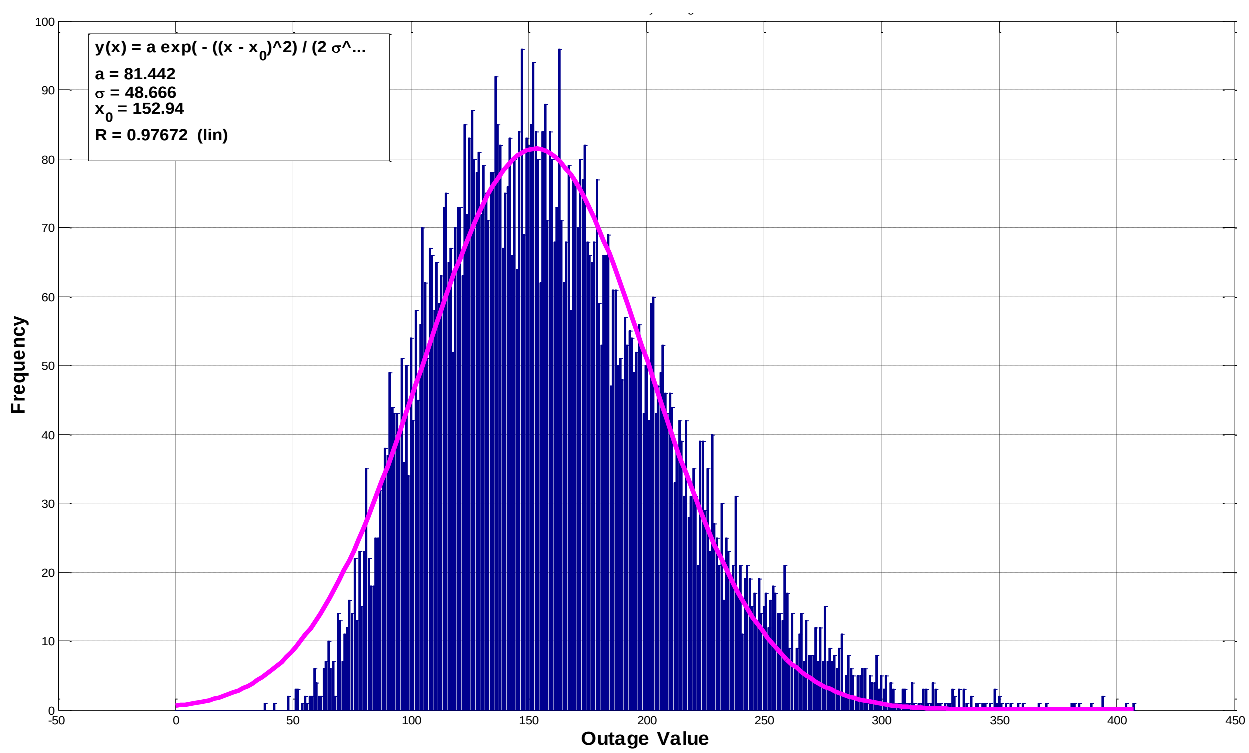


**Figure 5.8 Wichita Yearly Outages with 80% Outage Reduction**

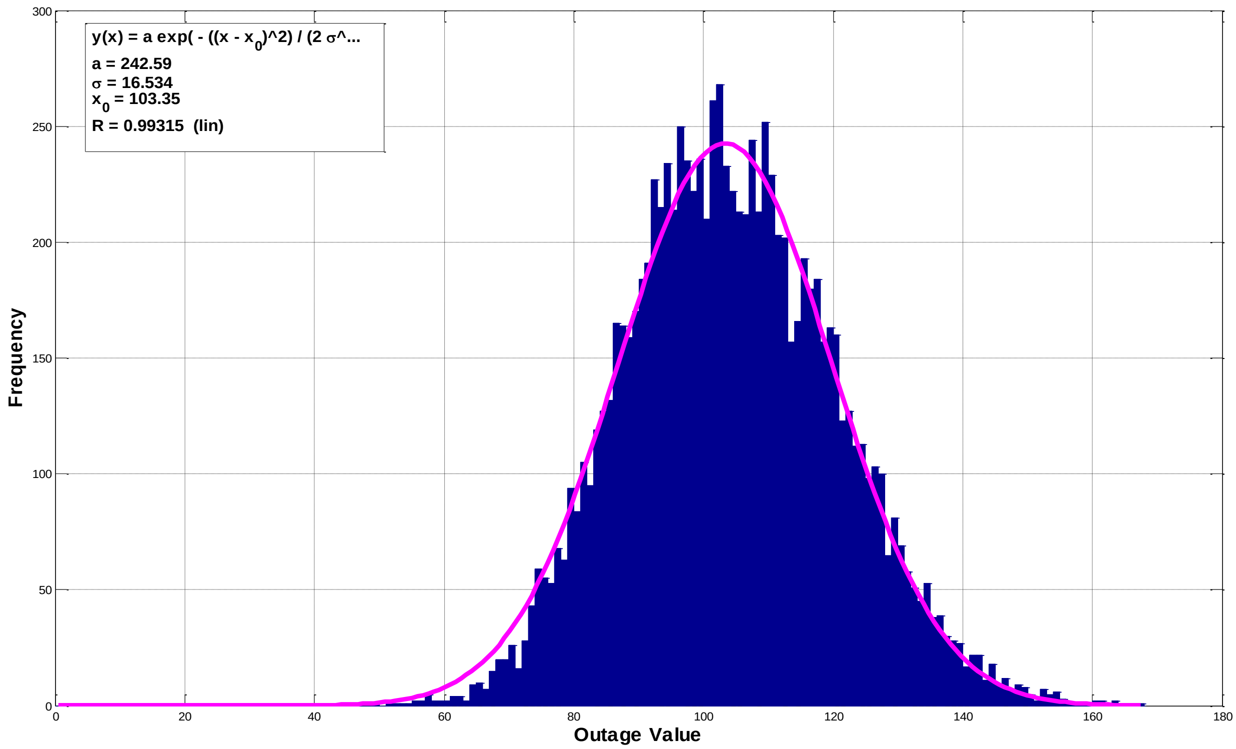


**Figure 5.9 Manhattan Yearly Outages with 10% Outage Reduction**

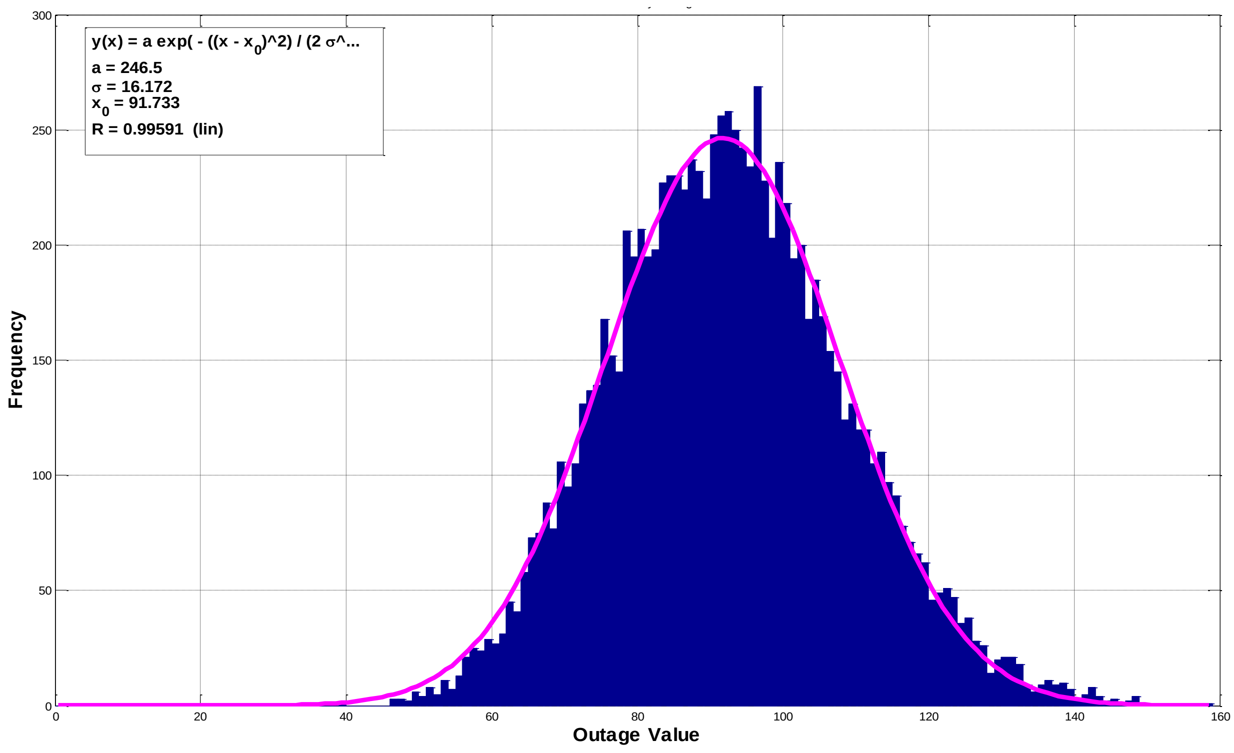


**Figure 5.10 Manhattan Yearly Outages with 20% Outage Reduction**

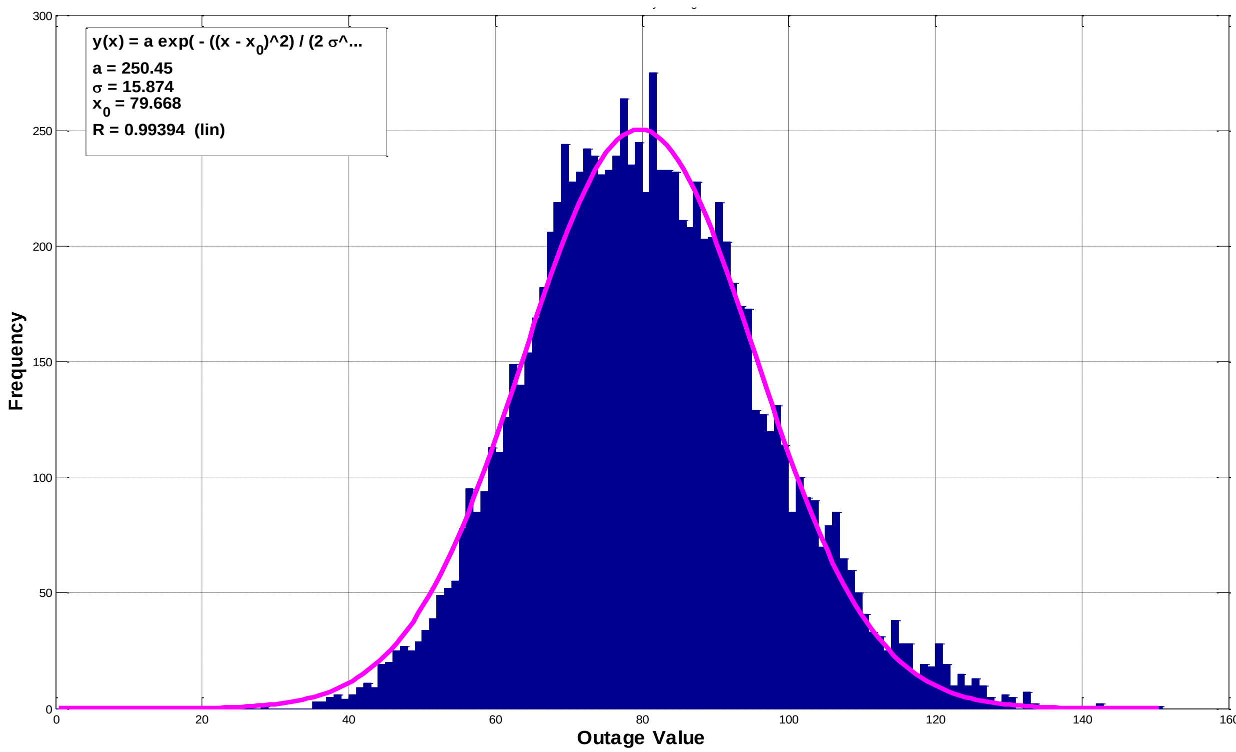


**Figure 5.11 Manhattan Yearly Outages with 30% Outage Reduction**

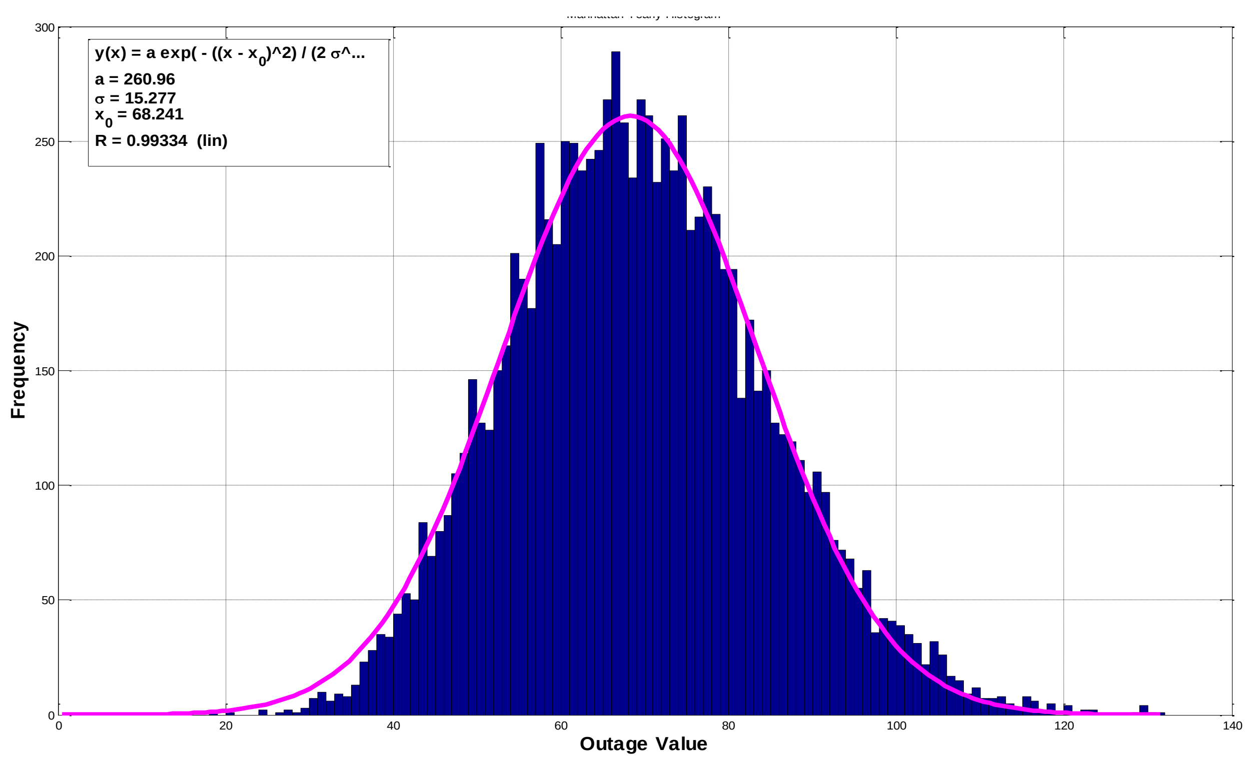


**Figure 5.12 Manhattan Yearly Outages with 40% Outage Reduction**

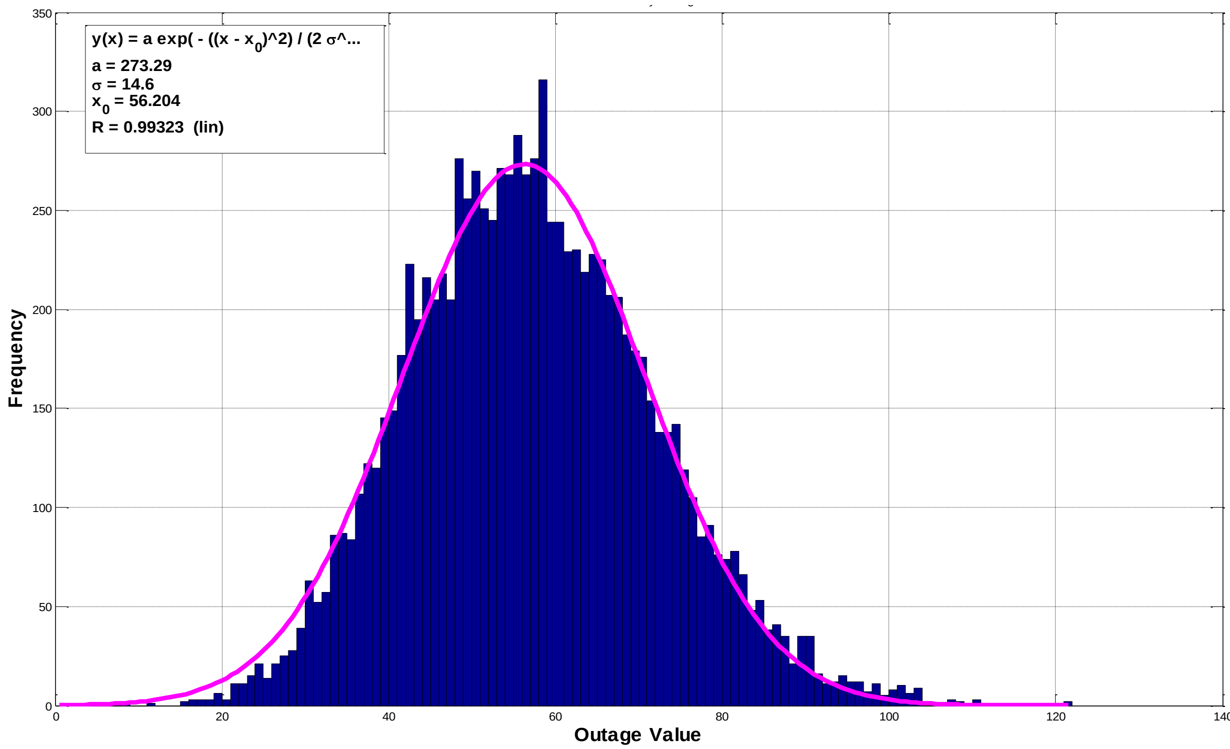


**Figure 5.13 Manhattan Yearly Outages with 50% Outage Reduction**

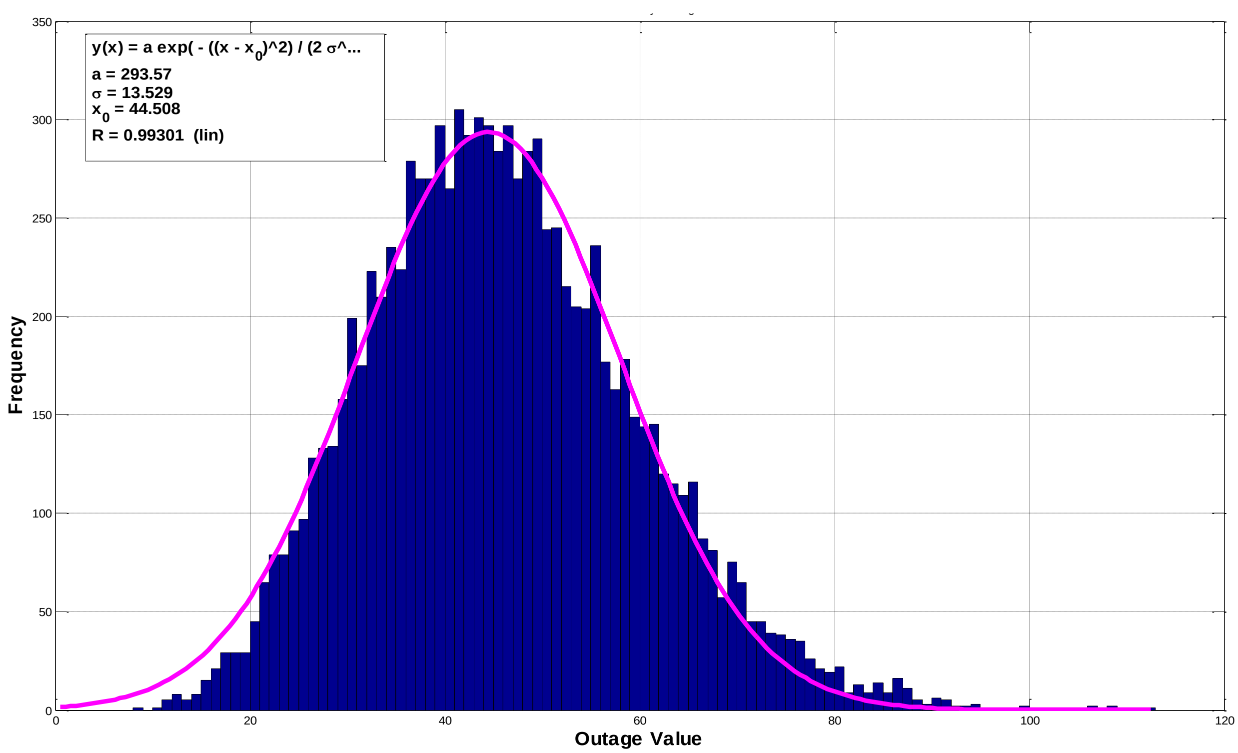


**Figure 5.14 Manhattan Yearly Outages with 60% Outage Reduction**

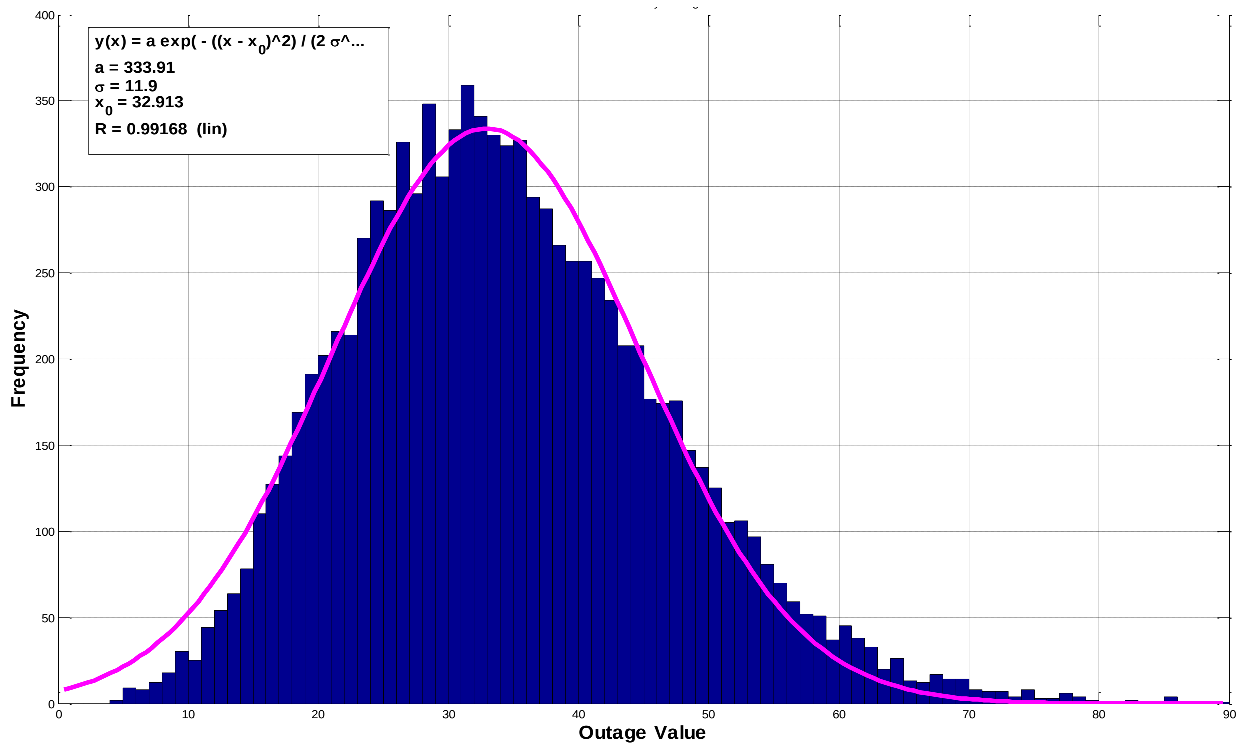


**Figure 5.15 Manhattan Yearly Outages with 70% Outage Reduction**

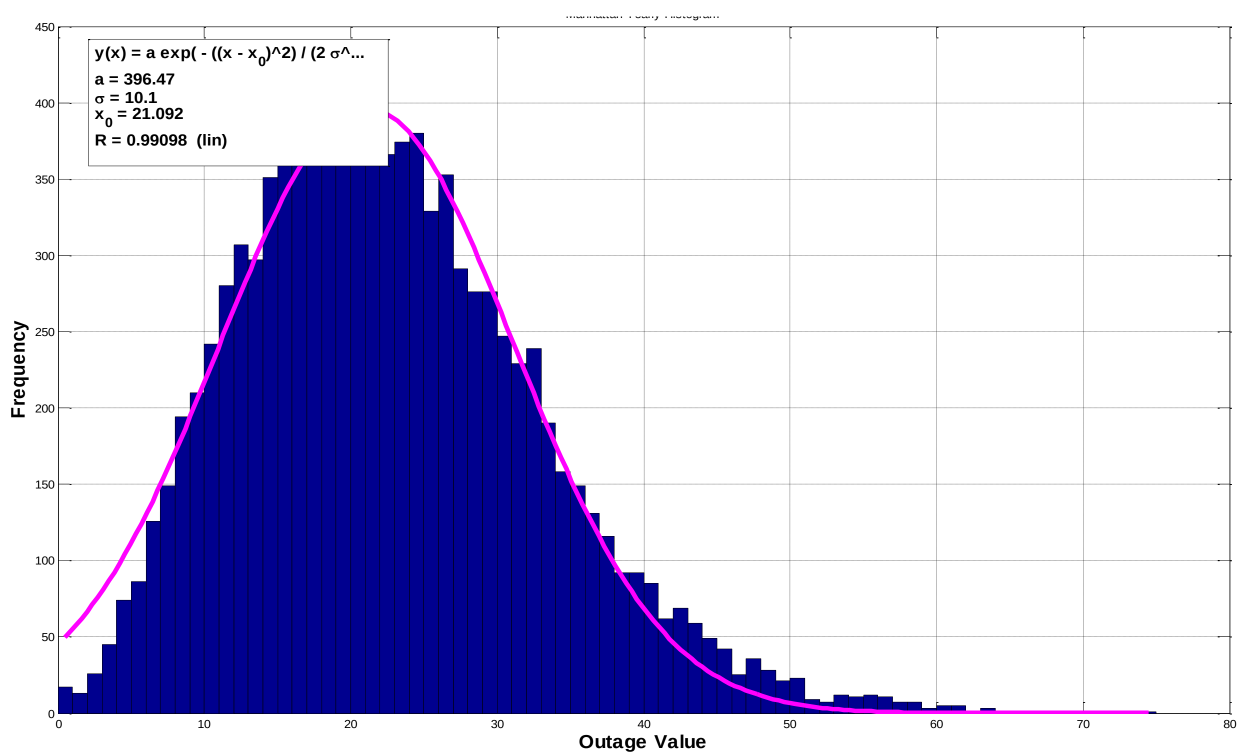


**Figure 5.16 Manhattan Yearly Outages with 80% Outage Reduction**

The above figures show that the mean value of outages decreases with increased outage reduction. The significance of fitting normal curve to yearly predicted outage data is discussed in the following section. The mean and sigma parameters of normal distribution for eight cases of outage reduction for four cities are tabulated in Tables 5.13-5.16.

**Table 5.6 Normal Distribution Parameters for Wichita**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 0% | 609.5 | 70.277 |
| 10% | 551.15 | 72.562 |
| 20% | 496.23 | 73.758 |
| 30% | 439.45 | 72.553 |
| 40% | 382.03 | 71.594 |
| 50% | 324.89 | 68.334 |
| 60% | 267.44 | 63.58 |
| 70% | 209.92 | 57.468 |
| 80% | 151.87 | 48.515 |

**Table 5.7 Normal Distribution Parameters for Topeka**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 0% | 454.1 | 53.004 |
| 10% | 408.07 | 54.428 |
| 20% | 362.28 | 56.754 |
| 30% | 314.77 | 55.792 |
| 40% | 269.33 | 54.712 |
| 50% | 223.08 | 52.545 |
| 60% | 178.47 | 49.341 |
| 70% | 131.23 | 44.06 |
| 80% | 84.821 | 37.24 |

**Table 5.8 Normal Distribution Parameters for Lawrence**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 0% | 206.73 | 29.377 |
| 10% | 184.45 | 29.533 |
| 20% | 165.07 | 29.407 |
| 30% | 143.15 | 29.203 |
| 40% | 122.04 | 27.828 |

| | | |
|---|---|---|
| 50% | 101.59 | 26.731 |
| 60% | 79.864 | 24.254 |
| 70% | 59.581 | 21.782 |
| 80% | 37.939 | 18.113 |

**Table 5.9 Normal Distribution Parameters for Manhattan**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 0% | 115.3 | 16.319 |
| 10% | 104.19 | 16.326 |
| 20% | 91.916 | 16.177 |
| 30% | 80.52 | 15.813 |
| 40% | 68.519 | 15.249 |
| 50% | 56.886 | 14.756 |
| 60% | 45.049 | 13.178 |
| 70% | 33.477 | 11.868 |
| 80% | 21.424 | 10.009 |

Similar to Wichita, the mean of outage value decreases for every 10% increase in outage reduction for Topeka, Lawrence, and Manhattan as seen in Table 5.14 to 5.16.

## Calculation of Savings

The two primary savings through which utilities are effectively benefitted with decreased squirrel outages on overhead distribution system are:

1. Crew Cost
2. Customer Minutes of Interruption (CMI) Cost

As outages decrease, the requirement of crew to respond to an outage also decreases and comparatively less usage of company vehicles is required for transportation to fix outages. When an outage occurs, the utility loses revenues related to consumption that would have taken place and the utility bears the cost to fix the outage [22]. According to a comprehensive study carried out by Duke Power Company in cooperation with Electric Power Research Institute, residential customer interruption costs for utilities range from $0 to $64 per customer hour of outage [23]. In this thesis, the cost of customer interruption is considered to be $30 per customer hour.

The total cost which utility spends on outages is calculated as the summation of crew cost and CMI cost. These values are calculated on a per outage basis using outage data provided by the utility. Crew cost is calculated using Equation 5.3

$$\text{Crew cost} = (\text{Duration of Outage} + \text{Crew travel time}) \times \text{Crew Wage} \qquad 5.3$$

In the above equation, the values of duration of every outage are provided by the utility with outage data. Crew travel time is the average time taken by a crew to respond to the outage, which is 30mins per outage. It is assumed that the difference between the time when the utility knows that an outage has occurred and the time of outage occurrence is very small. Crew cost is for crew wages, which is $95/hr for weekdays from 6 am-6 pm and $143/hr for 6 pm to 6 am on weekdays and weekend.

Similarly, CMI cost is computed based on the total CMI for each interruption.

$$\text{CMI cost} = \text{CMI} \times \text{Cost of customer interruption} \qquad 5.4$$

Thus, the total cost is calculated in $/outage and the plots for all four cities are shown in Figures 5.9 to 5.12. Log-normal distribution seems to fit well for these plots. Table 5.10 shows the parameters of the log-normal distribution for all cities.

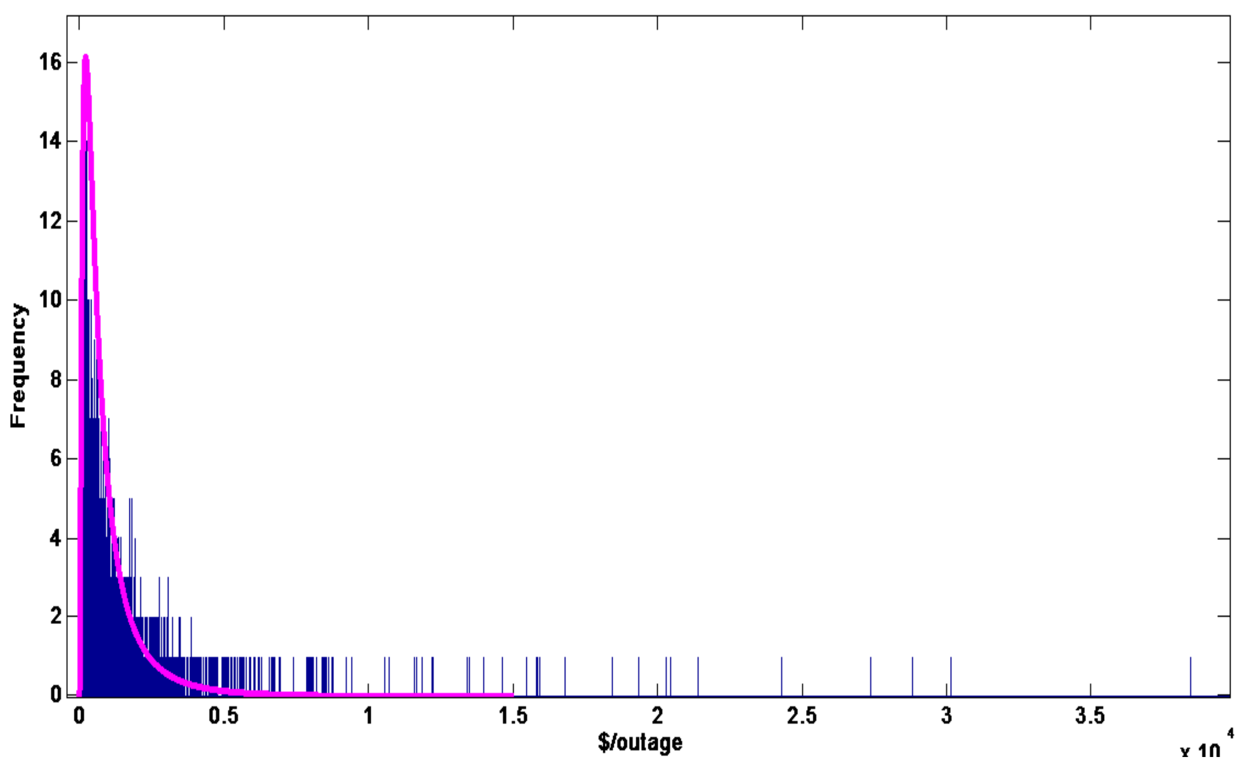


**Figure 5.17 Histogram of Total Cost of Outages for Wichita**

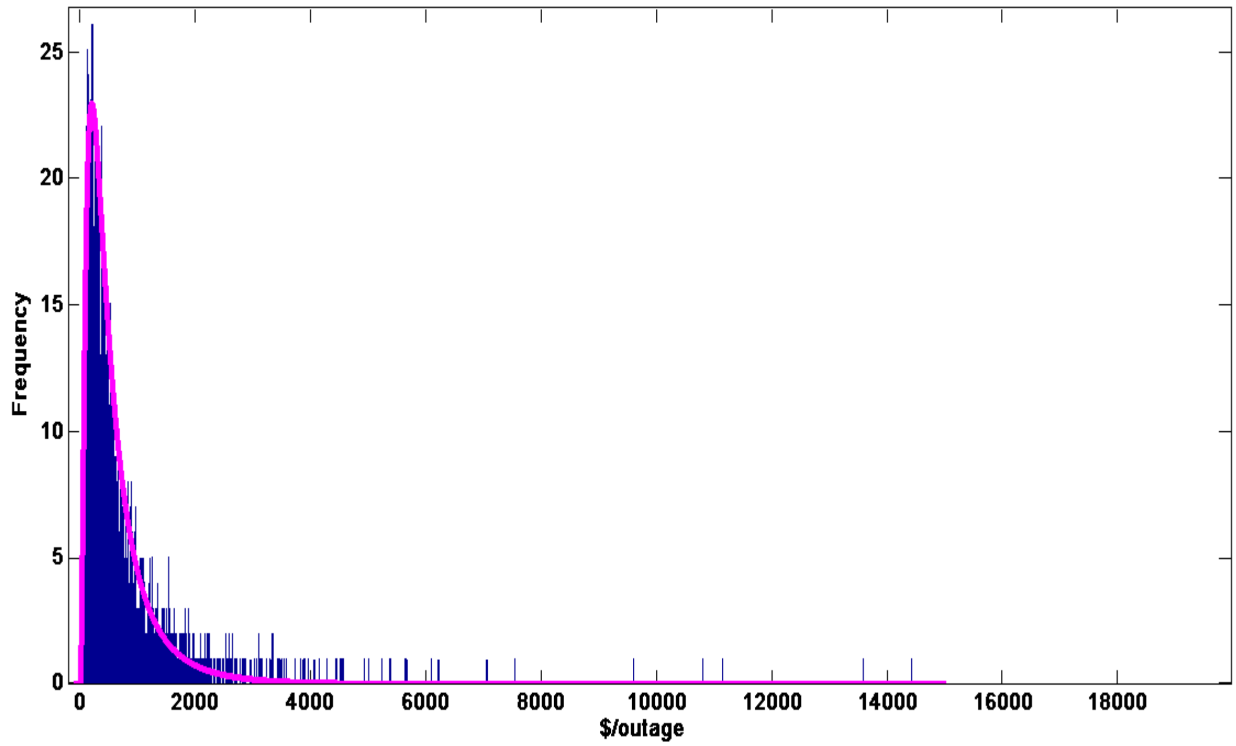


**Figure 5.18 Histogram of Total Cost of Outages for Topeka**

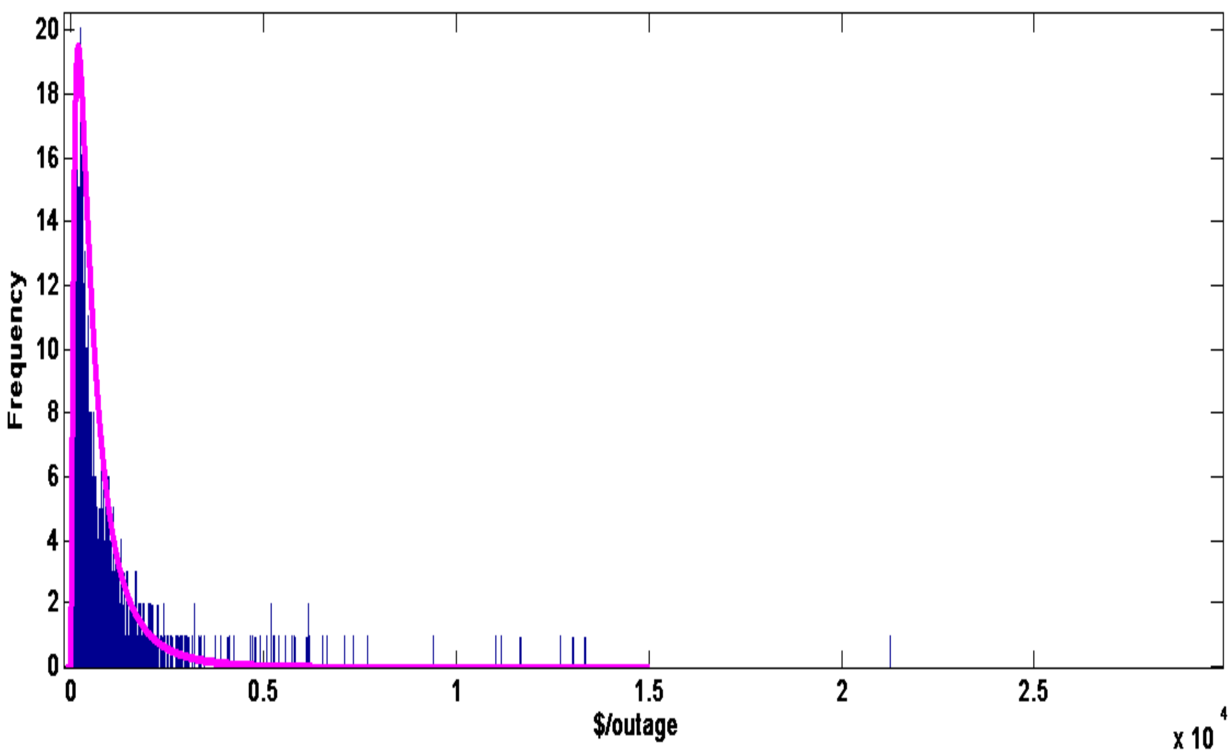


**Figure 5.19 Histogram of Total Cost of Outages for Lawrence**

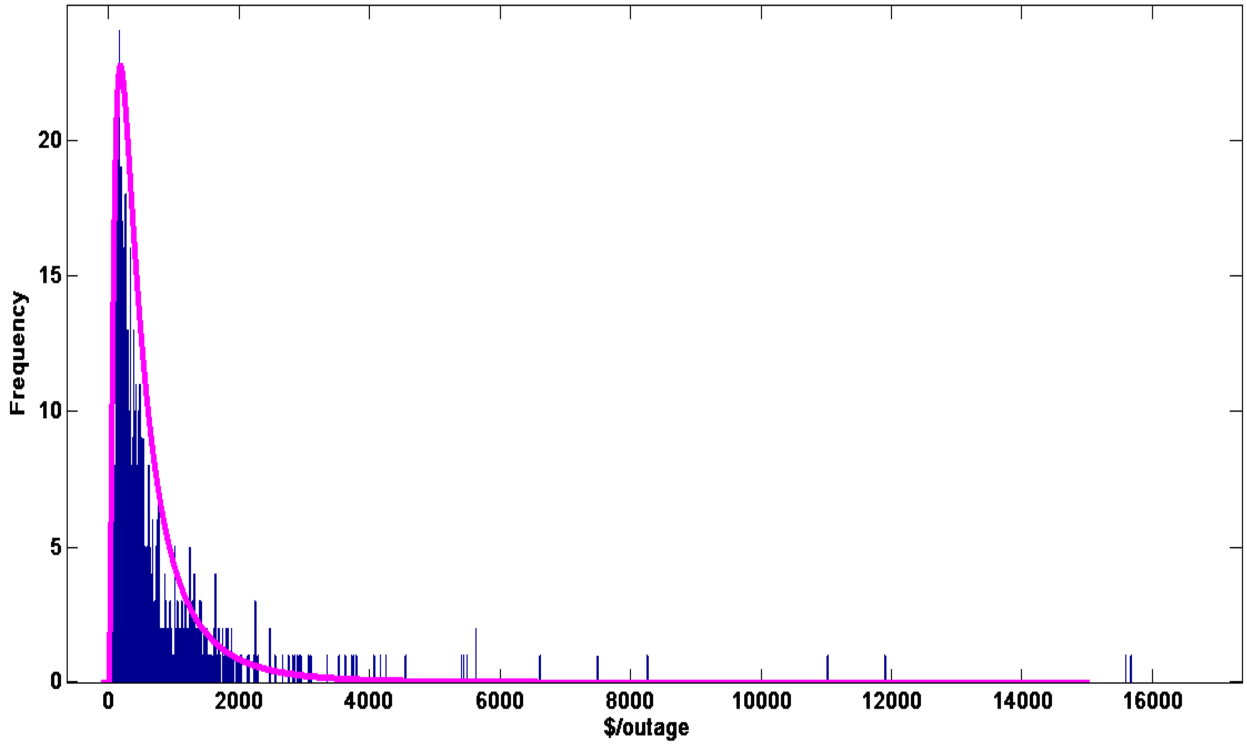


**Figure 5.20 Histogram of Total Cost of Outages for Manhattan**

**Table 5.10 Log-normal Distribution Parameters for Four Cities**

| Parameters | Wichita | Topeka | Lawrence | Manhattan |
|---|---|---|---|---|
| Scale Parameter ($\sigma$) | 6.4246 | 6.0950 | 6.2423 | 6.0854 |
| Location Parameter ($\mu$) | 1.0163 | 0.8584 | 0.9432 | 0.9312 |

### *Savings from Outage Reduction*

Savings can be calculated by multiplying the number of reduced outages per year and the total cost per outage. The reduction in outages is obtained by the difference of two normally distributed variables, "Outage data predicted with no reduction ($\mu_1$, $\sigma_1$)" and "Outage data predicted with X% reduction ($\mu_2$, $\sigma_2$)" where X=10, 20, 30...80. Therefore, the new parameters are $\mu_{1-2}=\mu_1-\mu_2$ and $\sigma^2_{1-2}=\sigma^2_1+\sigma^2_2$ [24]. Parameters of normal distribution curves for eight cases of reduced outages of four cities are shown in Tables 5.11-5.14.

**Table 5.11 Normal Distribution Parameters for Wichita**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 10% | 58.35 | 101.015 |
| 20% | 113.27 | 101.878 |
| 30% | 170.05 | 101.009 |
| 40% | 227.47 | 100.322 |
| 50% | 284.61 | 98.022 |
| 60% | 342.06 | 94.769 |
| 70% | 399.58 | 90.782 |
| 80% | 457.63 | 85.396 |

**Table 5.12 Normal Distribution Parameters for Topeka**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 10% | 46.03 | 75.973 |
| 20% | 91.82 | 77.656 |
| 30% | 139.33 | 76.956 |
| 40% | 184.77 | 76.176 |
| 50% | 231.02 | 74.635 |
| 60% | 275.63 | 72.415 |
| 70% | 322.87 | 68.925 |
| 80% | 369.279 | 64.778 |

**Table 5.13 Normal Distribution Parameters for Lawrence**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 10% | 22.28 | 41.656 |
| 20% | 41.66 | 41.567 |
| 30% | 63.58 | 41.422 |
| 40% | 84.69 | 40.465 |
| 50% | 105.14 | 39.718 |
| 60% | 126.866 | 38.095 |
| 70% | 147.149 | 36.571 |
| 80% | 168.791 | 34.512 |

**Table 5.14 Normal Distribution Parameters for Manhattan**

| Outage Reduction (%) | Mean | Sigma |
|---|---|---|
| 10% | 11.11 | 23.084 |
| 20% | 23.384 | 22.978 |

| | | |
|---|---|---|
| 30% | 34.78 | 22.724 |
| 40% | 46.781 | 22.335 |
| 50% | 58.414 | 22.001 |
| 60% | 70.251 | 20.975 |
| 70% | 81.823 | 20.178 |
| 80% | 93.876 | 19.144 |

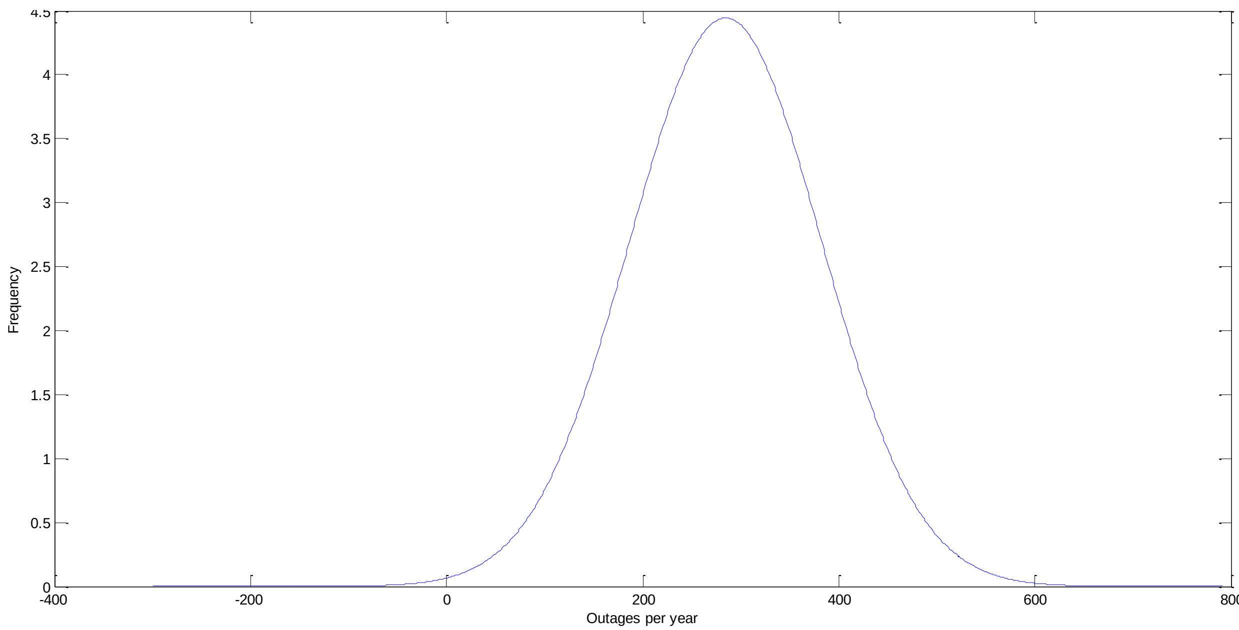


**Figure 5.21 Normal Distribution Curve of 50% reduced outages for Wichita with normal parameters Mean μ = 284.61 and Standard Deviation σ = 98.022**

The double numerical integration of product of probability density functions (PDFs) of reduction in outages and total outage cost gives cumulative density function (CDF) of savings. Using the CDF of savings, the probability values of savings greater than the cost of installation of animal guards are obtained. These probability values will help utilities decide on percentage of vulnerable points for installation of animal guards.

Initial attempts were made to find a closed form for double integration of product of log-normal and normal distribution mathematically, rather than using MATLAB. Applying the fundamental ideas found in [25], a step-by-step procedure is explained below.

For mathematical convenience, let parameters of log-normal be referred to as ($\mu_{LN}$, $\sigma_{LN}$) and normal as ($\mu_N$, $\sigma_N$).

Let Z=XY, where Z represents the savings, given in \$/yr.

X represents the total cost per outage, given in \$/outage.

Y represents the number of reduced outages per year, given in outage/yr.

Therefore, F(x) represents log-normal distribution where $x \in (0, +\infty)$

F(y) represents normal distribution where $y \in (-\infty, +\infty)$

To obtain $P(Z \geq$ Cost of installing squirrel guards$)$ = Probability of having benefit.

The cumulative distribution function (CDF) of a random variable Z is defined by [25],

$$F_Z(z) = P(Z \leq z) \qquad 5.2$$

In this research, "z" represents the cost of installing squirrel guards and $P(Z > z) = 1 - P(Z \leq z)$.

Using Equation 5.5,

$$F_Z(z) = P(Z \leq z) = P(XY \leq z) = P((X,Y) \in A_z),$$

where $A_z := \{(x, y): xy \leq z\}$ is partitioned into two disjoint regions, $A_z = A_z^+ \cup A_z^-$,

$$A_z^+ := \{(x, y): y \leq z/x \text{ and } x > 0\} \text{ and } A_z^- := \{(x, y): y \geq z/x \text{ and } x < 0\}$$

$$\text{Therefore, } F_Z(z) = P((X,Y) \in A_z^+) + P((X,Y) \in A_z^-)$$

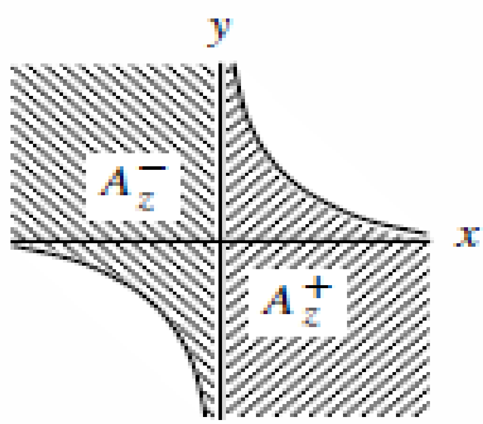


**Figure 5.22 The curve is y=z/x and Shaded Regions Represent $A_z^+$ and $A_z^-$, Respectively [25].**

In this research, $x \in (0, +\infty)$ and $y \in (-\infty, +\infty)$; therefore, the final expression to find probability for Z is $F_Z(z) = P((X,Y) \in A_z^+)$

$$P((X,Y) \in Az+) = \int_{\mathbf{0}}^{\infty} [\int_{-\infty}^{\boldsymbol{z/x}} \boldsymbol{f(x,y)dy}]\boldsymbol{dx} \qquad 5.3$$

Since F(x) and F(y) are independent, f(x,y)=f(x).f(y)

Therefore,

$$F_Z(z) = \int_0^{\infty} [\int_{-\infty}^{z/x} f(x).f(y)dy]dx$$

$$F_Z(z) = \int_0^{\infty} f(x)[\int_{-\infty}^{z/x} f(y)dy]dx$$

$$F_Z(z) = \int_0^{\infty} f(x) \times\ CDF\ of\ f(y)\ dx$$

$$F_Z(z) = \int_0^{\infty} f(x) \times\ (0.5 + 0.5erf(\frac{\frac{z}{x} - \mu N}{\sqrt{2} \times \sigma N}))dx$$

$$F_Z(z) = \int_0^{\infty} \frac{1}{x \times \sigma LN \sqrt{2\pi}} \times \exp\{\frac{-(lnx - \mu LN)^2}{2\sigma LN^2}\} \times (0.5 + 0.5erf(\frac{\frac{z}{x} - \mu N}{\sqrt{2} \times \sigma N}))dx$$

After several substitutions, the final equation obtained for CDF of Net Savings is:

$$F_Z(z) = P(Z \leq z) = 0.5 + \frac{\mathbf{1}}{\sqrt{\mathbf{8}\boldsymbol{\pi}}\ \boldsymbol{\sigma LN}} \int_{-\infty}^{\infty} \boldsymbol{exp}\{\frac{-(\boldsymbol{t} - \mu \boldsymbol{LN})^{\mathbf{2}}}{(\mathbf{2} \times \boldsymbol{\sigma LN^2})}\} \times \boldsymbol{erf}(\frac{\boldsymbol{ze^{-t}} - \boldsymbol{\mu N}}{\sqrt{\mathbf{2}} \times \boldsymbol{\sigma N}})\boldsymbol{dt} \qquad 5.4$$

At this point, finding closed form solution for $F_Z(z)$ becomes difficult because of the error function in Equation 5.7. Hence, MATLAB was used at this step to perform numerical integration of function $F_Z(z)$ by substituting values of z. Results are shown in Figures 5.23 and 5.24.

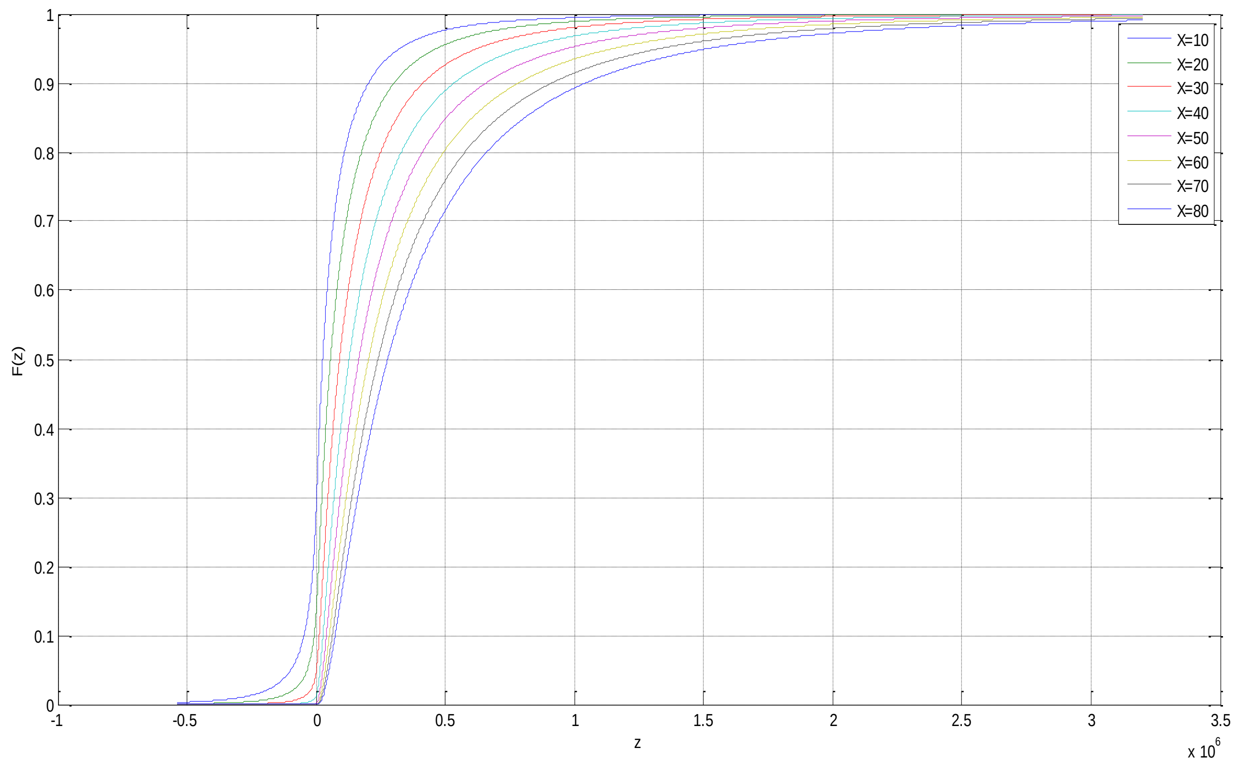


**Figure 5.23 $F_Z(z)$ Plot for X% Reduced Outages for Wichita**

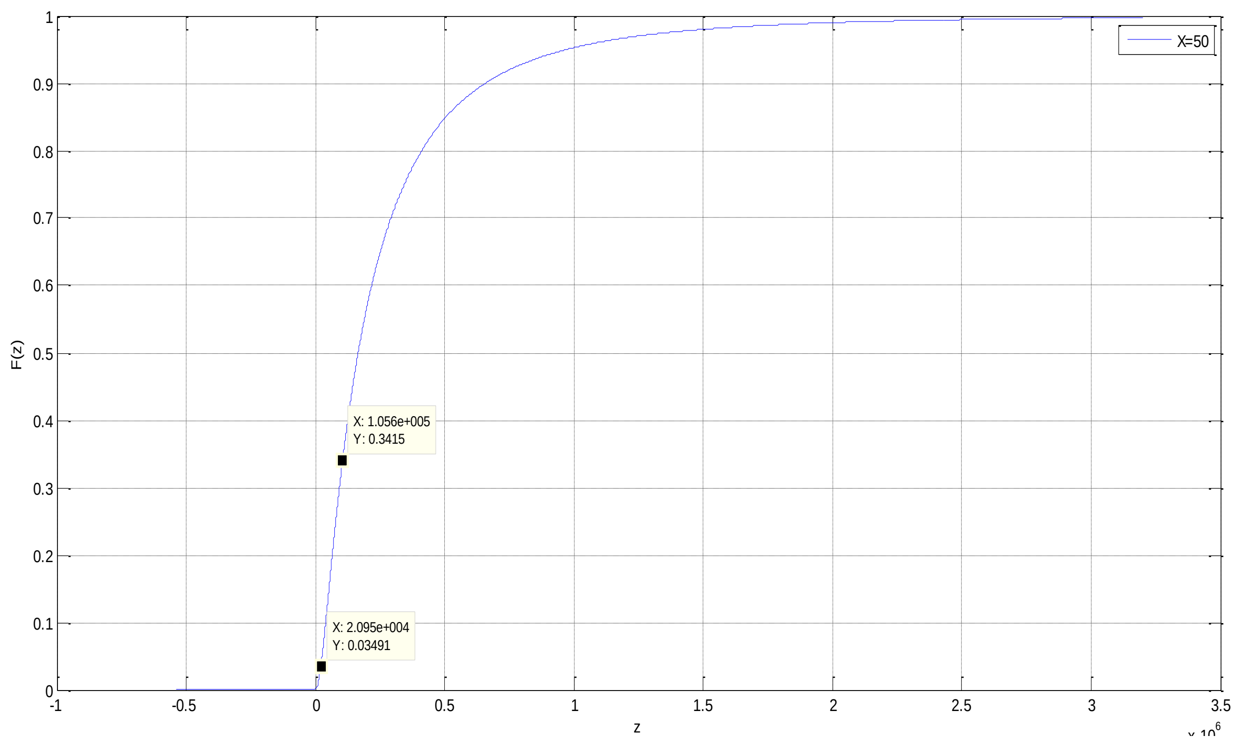


**Figure 5.24 $F_Z(z)$ Plot for 50% Reduced Outages for Wichita**

After obtaining the CDFs of $F_Z(z)$ for all eight cases of reduced outages, the probability values of savings greater than the cost of installing guards can easily be determined. Considering Wichita as an example, the cost of protecting 20% of all devices is \$20,964.70/yr. and the cost to protect all devices is \$104,823.48 /yr. As shown in Figure 5.16, $P(Z \leq z)$ at z =20,964.70 and z =104,823.48 are 0.03491 and 0.3415, respectively.

Therefore,

P(savings > 20,964.70) = 1-0.03491=0.96509

P(savings > 104,823.48) =1-0.3415= 0.6585

This implies that a 96.509% probability exists of benefit greater than zero if 20% of the vulnerable points are protected, which results in outage reduction of 50%. Similarly, there is 65.85% probability of benefit greater than zero if all locations are protected with 50% outage reduction.

Figure 5.25 shows probability values for all eight cases of outage reduction at nine levels of animal guard installations for Wichita, where mitigation level 1 represents cost for 20% of devices and mitigation level 9 represents cost for 100%, or all devices. The figure demonstrates that as the cost increases probability values decrease and as the outage reduction increases probability value increase. Hence, higher probability values are obtained when the cost is less and outage reduction is high.

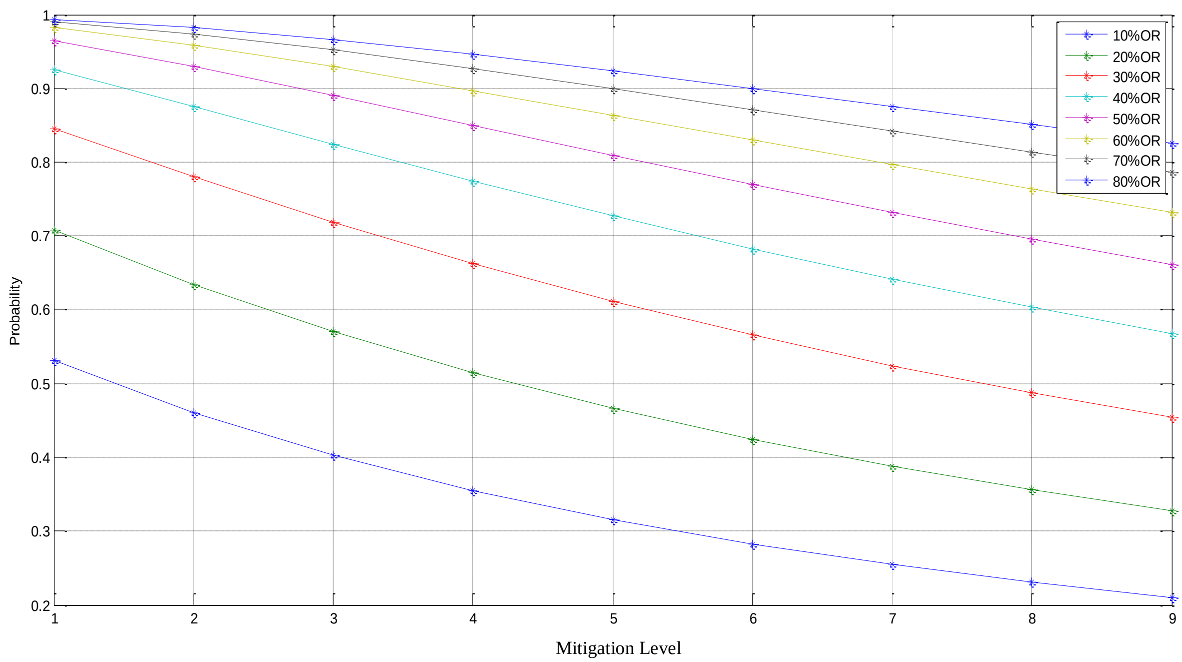


**Figure 5.25 Probability Graph for Wichita at Different Mitigation Levels**

The probability results for Manhattan are shown in Figures 5.26-5.28, demonstrating identical behavior except that probability values decrease more rapidly for higher costs, as shown in Figure 5.28.

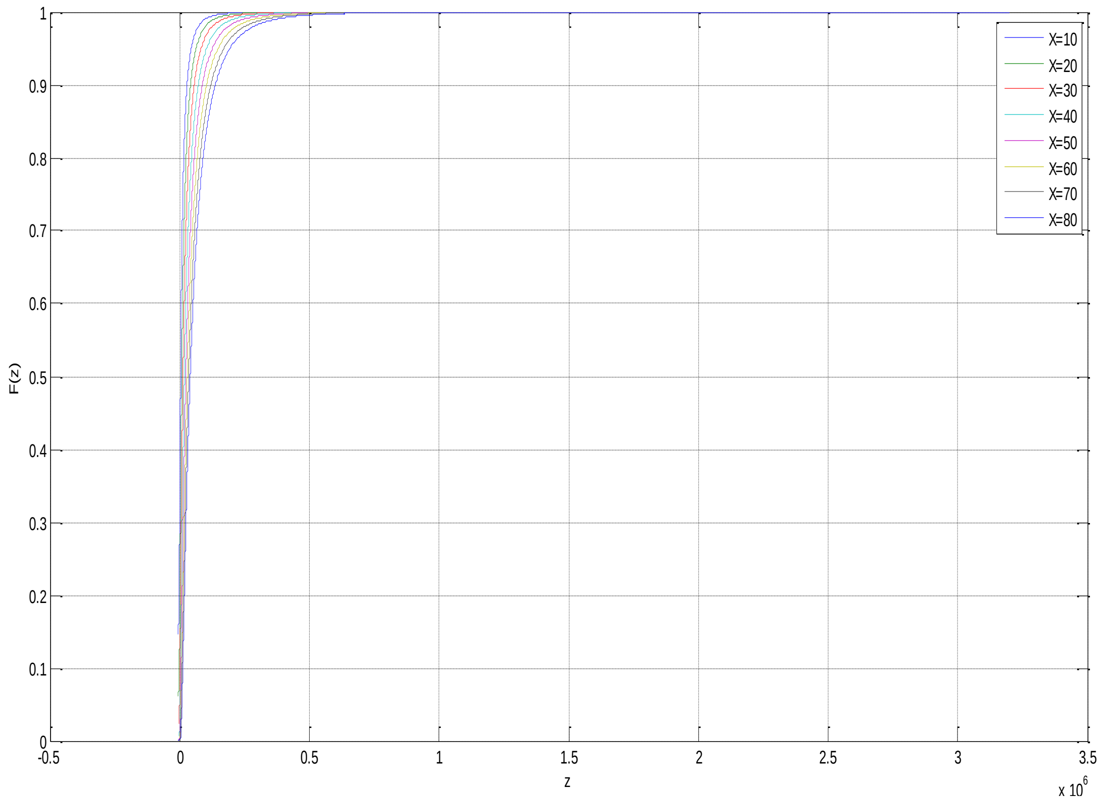


**Figure 5.26 $F_Z(z)$ Plot for X% Reduced Outages for Manhattan**

Using Figure 5.27, for Manhattan, it is found that the probability of benefit greater than zero profit is 81.36% when 20% of the locations are protected and 25.45% when all the locations are protected for 50% reduction in outages

**Table 5.15 Comparison of Probabilities of Benefit >0 with 50% Outage Reduction**

| City | Mitigation Level 1 | Mitigation Level 9 |
|---|---|---|
| Wichita | 96.51% | 81.36% |
| Manhattan | 65.85% | 25.45% |

From Table 5.15, it is observed that Manhattan has lower probabilities compared to Wichita for 50% outage reduction in both cities. This is because the total vulnerable points are high in proportion to the city size for Manhattan. Therefore, higher investment in animal guards is needed, which decreases the probability of getting positive benefit. However, detailed study based on these probability plots provides the best mitigation level as discussed in next section. The probability plots for Topeka and Lawrence are shown in Figure 5.29-5.32.

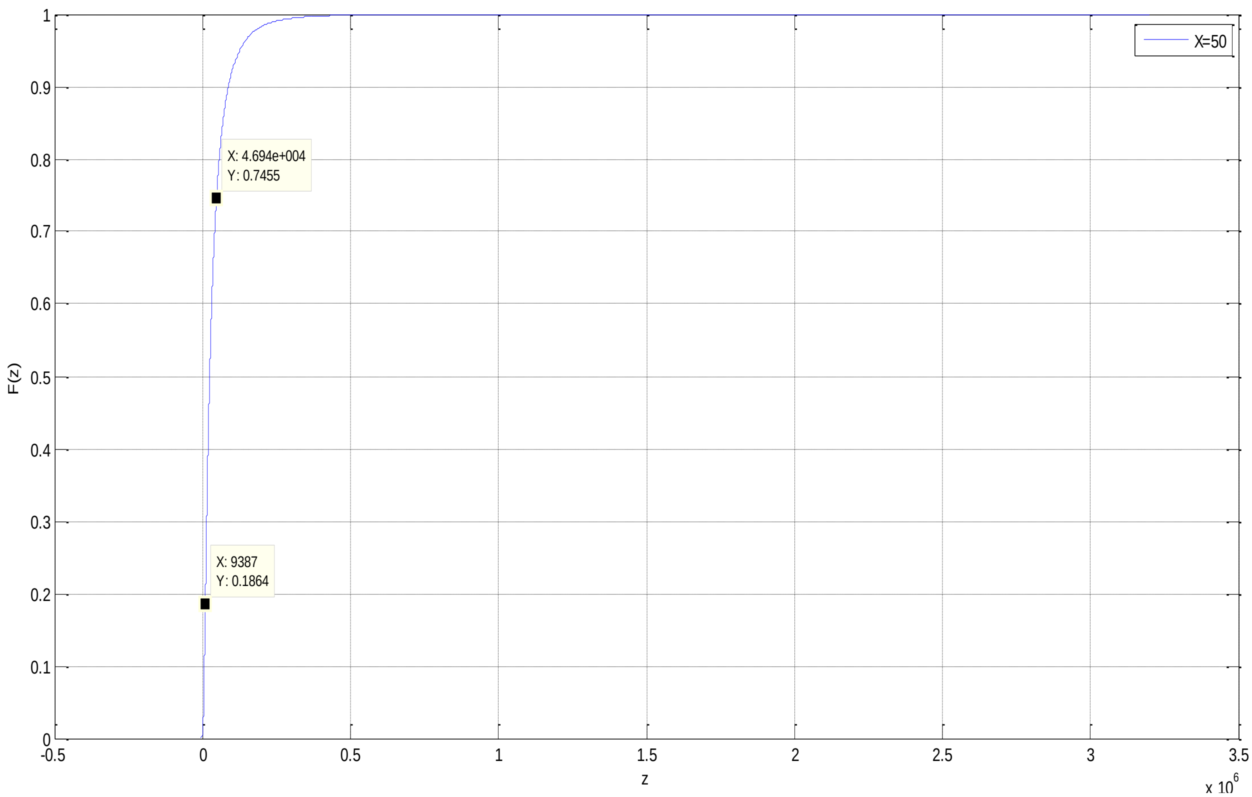


**Figure 5.27 $F_Z(z)$ Plot for 50% Reduced Outages for Manhattan**

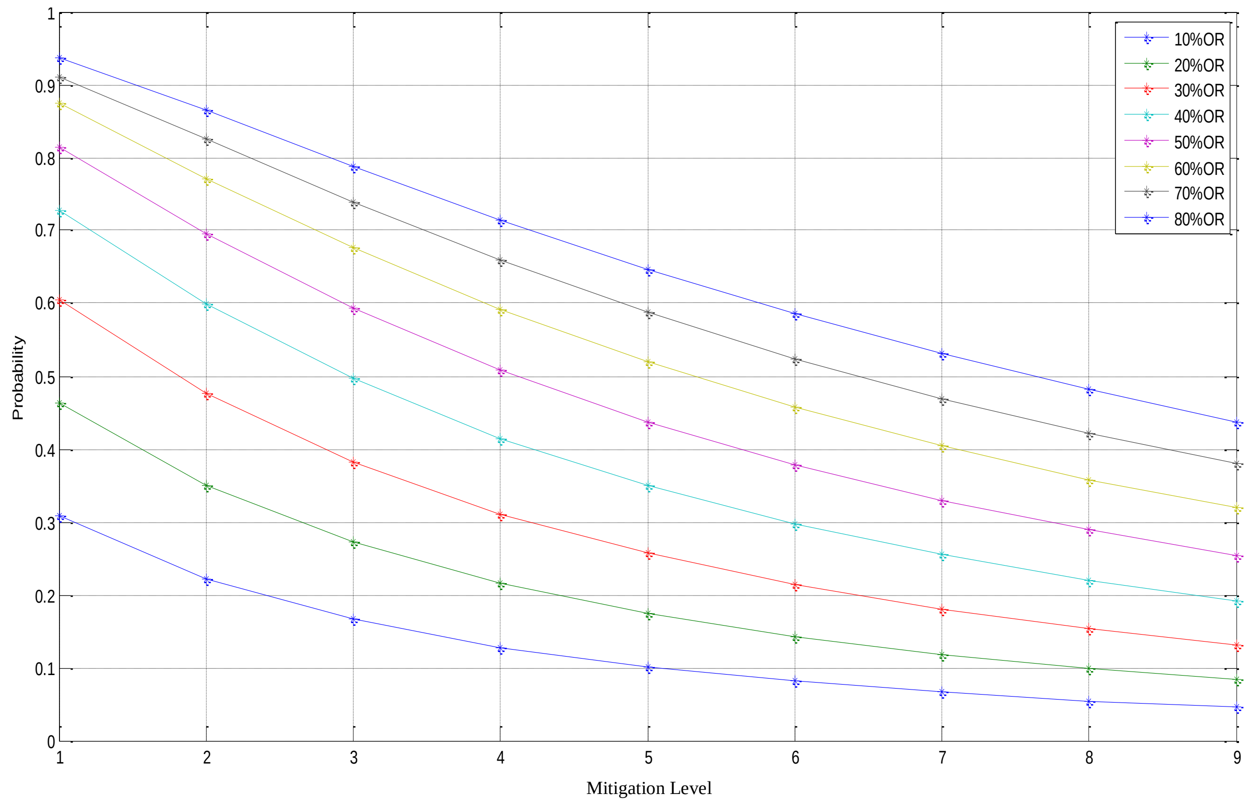


**Figure 5.28 Probability Graph for Manhattan at Different Mitigation Level**

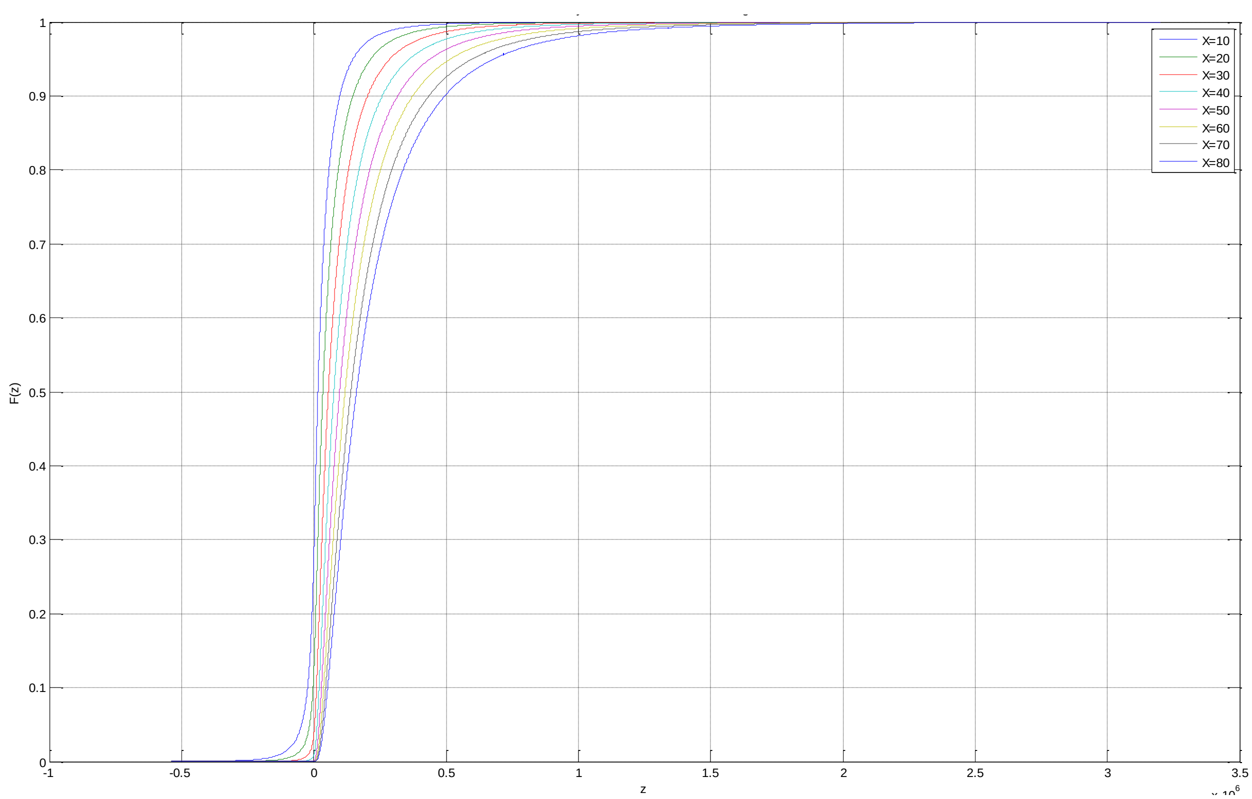


**Figure 5.29 $F_Z(z)$ Plot for X% Reduced Outages for Topeka**

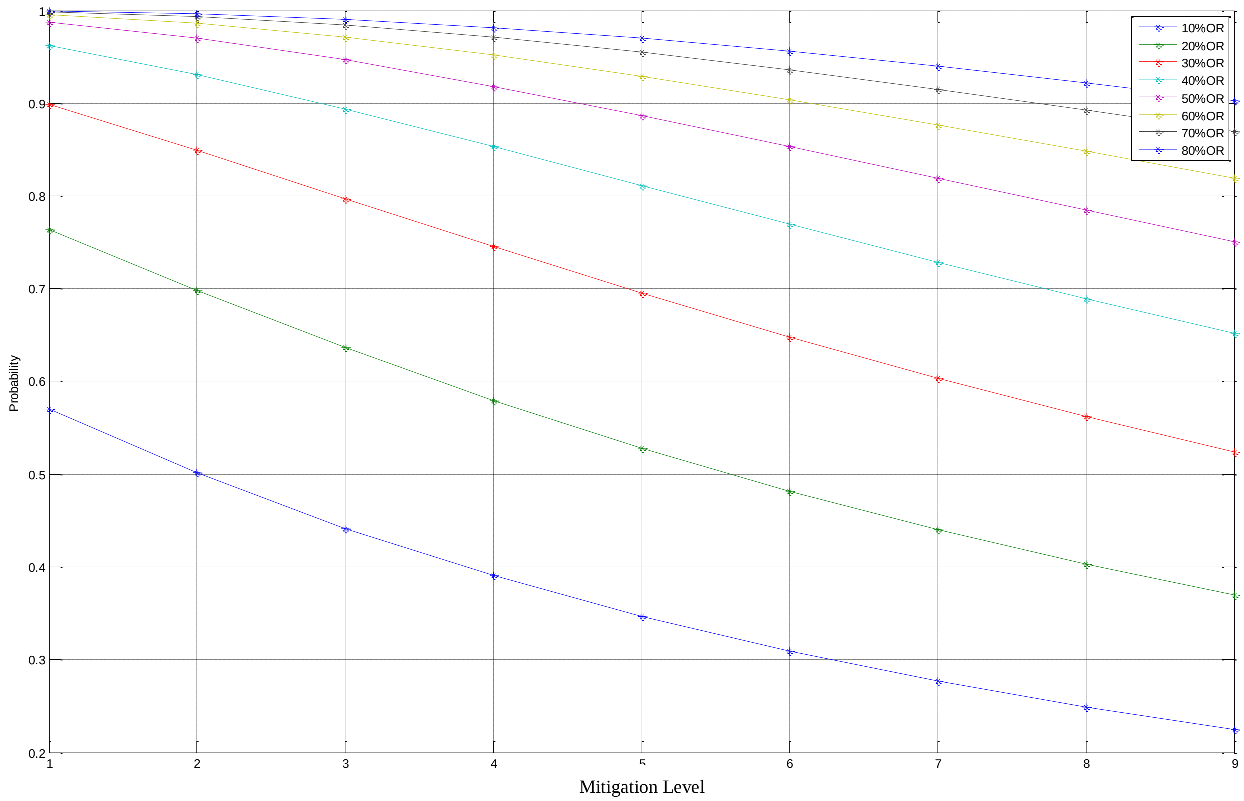


**Figure 5.30 Probability Graph for Topeka at Different Mitigation Level**

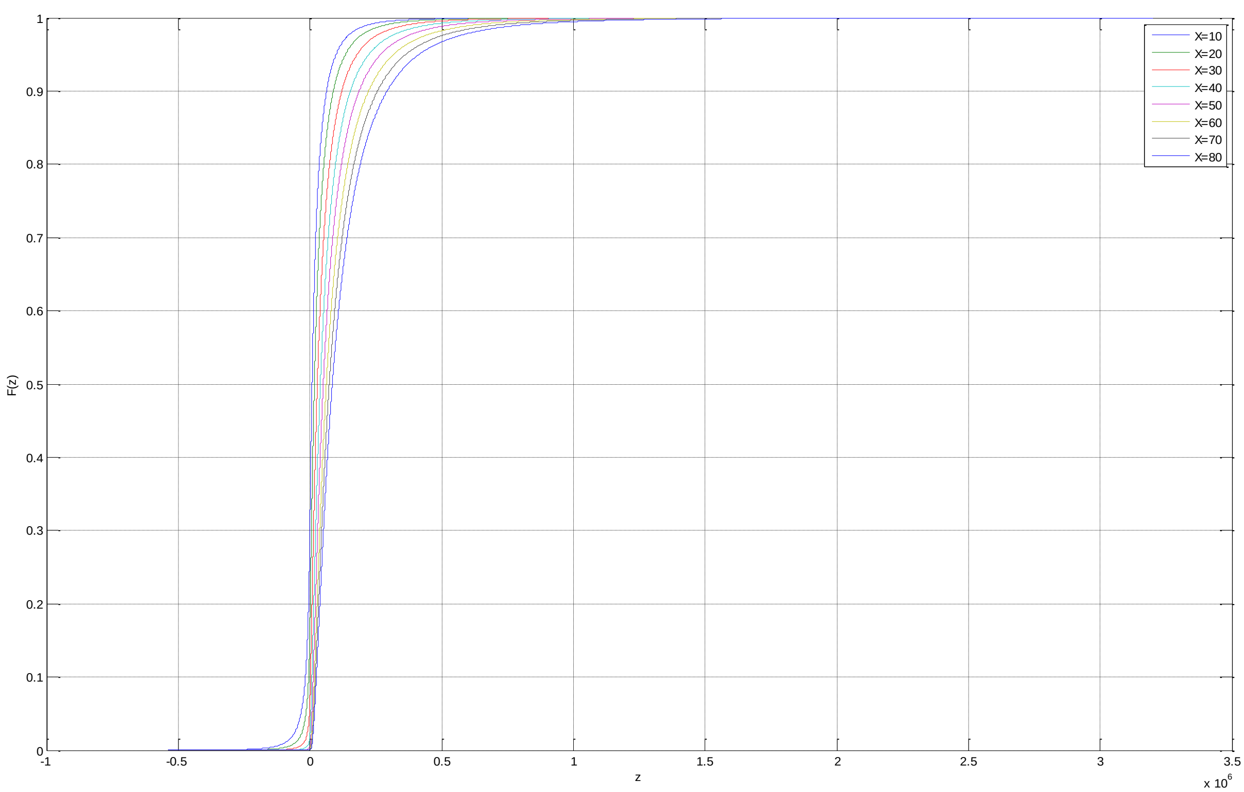


**Figure 5.31 $F_Z(z)$ Plot for X% Reduced Outages for Lawrence**

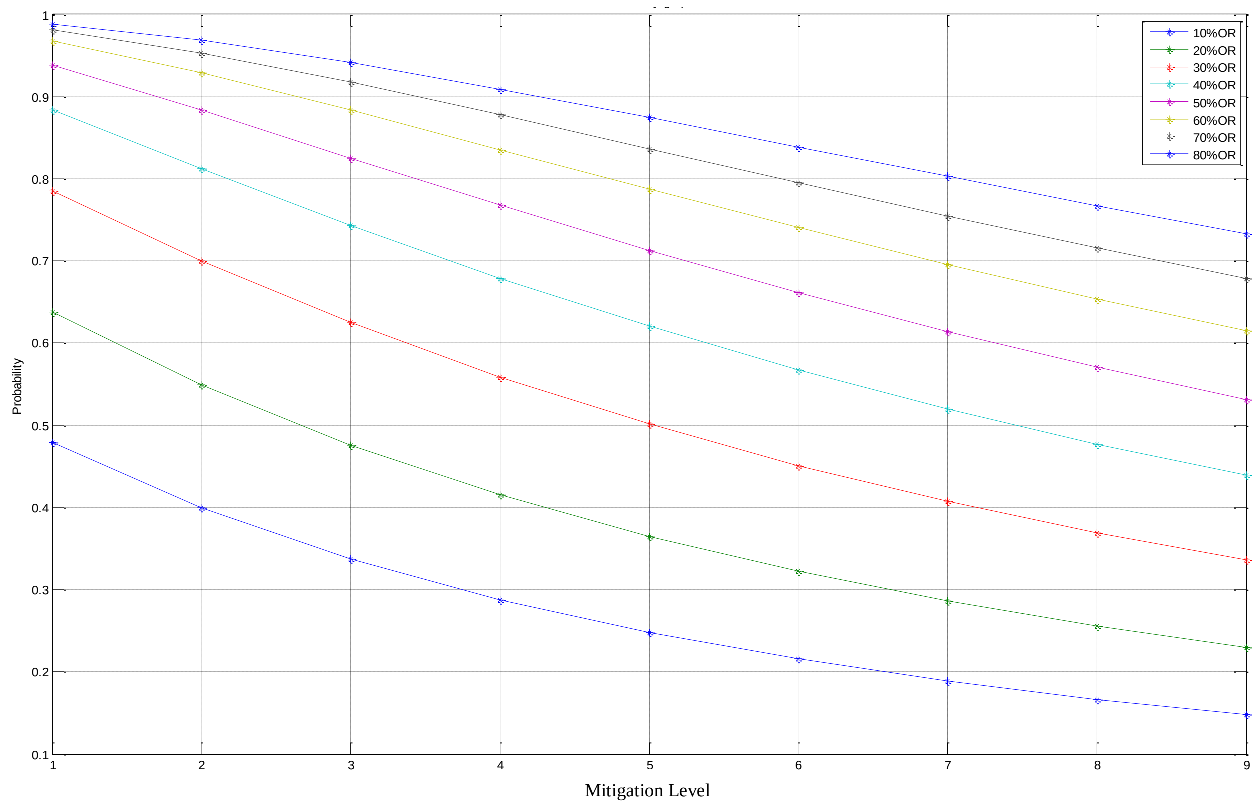


**Figure 5.32 Probability Graph for Lawrence at Different Mitigation Level**

## Outage Mitigation Strategy

In this section, a detailed study of probability plots is carried out to decide which combination of protecting devices and outage reduction results in greater benefit.

### *Wichita*

The probability values of Wichita, obtained from Figure 5.17, for all cases are tabulated in Table 5.22, thus forming an 8-by-9 matrix in which the rows represent various cases of outage reduction (OR) and the columns represent different levels of mitigation from protecting 20% of total vulnerable points (TVP) to protecting 100%, or all locations.

**Table 5.16 Probability Values of Wichita for Different Levels of Mitigation**

| TVP%→ OR%↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 53.09 | 46.01 | 40.27 | 35.54 | 31.61 | 28.29 | 25.47 | 23.05 | 20.95 |
| 20 | 70.85 | 63.46 | 57.04 | 51.48 | 46.66 | 42.48 | 38.82 | 35.6 | 32.75 |
| 30 | 84.51 | 78 | 71.87 | 66.25 | 61.16 | 56.58 | 52.45 | 48.73 | 45.37 |
| 40 | 92.54 | 87.58 | 82.45 | 77.46 | 72.72 | 68.28 | 64.16 | 60.35 | 56.82 |
| 50 | 96.51 | 93.03 | 89.09 | 84.99 | 80.91 | 76.94 | 73.14 | 69.52 | 66.11 |
| 60 | 98.23 | 95.87 | 92.95 | 89.72 | 86.36 | 82.98 | 79.64 | 76.39 | 73.24 |
| 70 | 98.98 | 97.36 | 95.19 | 92.67 | 89.95 | 87.11 | 84.24 | 81.39 | 78.58 |
| 80 | 99.36 | 98.21 | 96.58 | 94.61 | 92.39 | 90.03 | 87.59 | 85.11 | 82.63 |

The probabilities of benefit greater than zero ranges from a minimum value of 20.95% to a maximum value of 99.36%. To propose the best mitigation level, probability values greater than 90% are considered as acceptable. Further, a pre-defined set of combinations of vulnerable points and outages are considered for all cities to derive the optimal combination which promises higher benefits from outage reduction. Table 5.17 shows these values. This is an example but in real-life situation utilities can obtain this information from detailed examination of the outage data.

**Table 5.17 Pre-defined Combinations of Vulnerable Points and Outages**

| Vulnerable Points (%) | Outages (%) |
|---|---|
| 20 | 50 |
| 40 | 60 |
| 60 | 70 |
| 80 | 80 |

It is assumed that installation of animal guards at the number of points shown in Table 5.17 will result in respective outage reduction. Hence, the probability for different mitigation levels can be obtained as shown in Table 5.18.

**Table 5.18 Outage Mitigation Strategy for Wichita**

| Mitigation Level | Vulnerable Points Protected (%) | Outage Reduction (%) | Probability of Benefit>0 (%) |
|---|---|---|---|
| 1 | 20 | 50 | 96.51 |
| 3 | 40 | 60 | 92.95 |
| 5 | 60 | 70 | 89.95 |
| 7 | 80 | 80 | 87.59 |

From Table 5.18, it is clear that by installing animal guards on 20% most vulnerable devices of all locations will result in 96.51% probability of benefit greater than zero with 50% outage reduction. This combination seems more attractive to utility by considering the fact that it has highest probability compared to others. However, if the utility desires for more reduction in outages then they shouldn’t be having any concerns for implementing mitigation level 3 or mitigation level 5 as the probabilities are also greater than or equal to 90%. Mitigation level 7 is not desirable because it has probability less than 90%. To determine exact optimal combination the expected values of benefit are computed.

The expected benefit is found using mean values of reduced outages, total cost, and cost of installation of squirrel guards.

$$\begin{aligned}\text{Expected Benefit (\$/yr.)} &= E[XY-z] \\ &= E[XY] - E[z] \\ &= E[X] \times E[Y] - z\end{aligned} \qquad 5.5$$

$E[z] = z$ = Cost of installation of squirrel guards

$E[X]$ = Expected value (mean) of log-normal distribution=$e^{\mu+\frac{\sigma^2}{2}}$ [26]

$E[Y]$ = Expected value (mean) of normal distribution which varies with outage reduction case, as given in Table 5.11 for Wichita.

Expected benefit values are calculated using Equation 5.8 and tabulated in Table 5.19 for various combinations forming an 8-by-9 matrix.

**Table 5.19 Expected Benefit of Wichita for Different Levels of Mitigation**

| TVP%→ OR% ↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 39359.69 | 28877.35 | 18395 | 7912.649 | -2569.7 | -13052 | -23534.4 | -34016.7 | -44499.1 |
| 20 | 96138.02 | 85655.68 | 75173.33 | 64690.98 | 54208.63 | 43726.29 | 33243.94 | 22761.59 | 12279.22 |
| 30 | 154839.3 | 144356.9 | 133874.6 | 123392.2 | 112909.9 | 102427.6 | 91945.2 | 81462.85 | 70980.48 |
| 40 | 214202.2 | 203719.9 | 193237.5 | 182755.2 | 172272.8 | 161790.5 | 151308.1 | 140825.8 | 130343.4 |
| 50 | 273275.6 | 262793.3 | 252311 | 241828.6 | 231346.3 | 220863.9 | 210381.6 | 199899.2 | 189416.8 |
| 60 | 332669.6 | 322187.2 | 311704.9 | 301222.5 | 290740.2 | 280257.9 | 269775.5 | 259293.2 | 248810.8 |
| 70 | 392135.9 | 381653.5 | 371171.2 | 360688.8 | 350206.5 | 339724.2 | 329241.8 | 318759.5 | 308277.1 |
| 80 | 452150.1 | 441667.8 | 431185.4 | 420703.1 | 410220.7 | 399738.4 | 389256 | 378773.7 | 368291.3 |

Table 5.16 and Table 5.19 show that there is 96.51% probability of obtaining $273275.6/yr. as benefit with 50% outage reduction by protecting 20% of all locations in Wichita. The expected values of benefit for other mitigation levels are given in Table 5.20.

**Table 5.20 Expected Values of Benefit for Wichita**

| Mitigation Level | Vulnerable Points Protected (%) | Outage Reduction (%) | Expected Benefit ($/yr.) |
|---|---|---|---|
| 1 | 20 | 50 | 273275.6 |
| 3 | 40 | 60 | 311704.9 |
| 5 | 60 | 70 | 350206.5 |
| 7 | 80 | 80 | 389256.0 |

By observing Table 5.18 and Table 5.20, mitigation level 5 implies there is 89.95% probability of expected benefit 350206.5$/yr with 70% outage reduction, if 60% of all vulnerable points are protected. So, this is the optimal combination as the other combinations either has lower expected benefit or lower probability values comparatively. By implementing this mitigation level, the utility can expect a vast improvement in reliability of electricity to customers. A similar study is performed for other cities and the results are discussed in following sections.

### *Topeka*

The probability values of Topeka for all cases are given in Table 5.21 and the computed expected benefit values are given in Table 5.22. In case of Topeka, the probabilities of having benefit greater than zero ranges from a minimum value 22.45% to maximum value 99.91%. Again, 90% is considered as the acceptable probability to propose the best mitigation level.

**Table 5.21 Probability Values of Topeka for Different Levels of Mitigation**

| TVP%→ OR%↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 57.07 | 50.14 | 44.17 | 39.06 | 34.68 | 30.93 | 27.69 | 24.89 | 22.45 |
| 20 | 76.38 | 69.84 | 63.64 | 57.95 | 52.81 | 48.19 | 44.05 | 40.35 | 37.02 |
| 30 | 89.86 | 84.93 | 79.71 | 74.51 | 69.50 | 64.77 | 60.34 | 56.23 | 52.43 |
| 40 | 96.24 | 93.13 | 89.39 | 85.32 | 81.13 | 76.94 | 72.86 | 68.93 | 65.17 |
| 50 | 98.77 | 97.06 | 94.67 | 91.81 | 88.64 | 85.30 | 81.89 | 78.47 | 75.10 |
| 60 | 99.56 | 98.63 | 97.14 | 95.19 | 92.89 | 90.33 | 87.61 | 84.79 | 81.93 |
| 70 | 99.82 | 99.31 | 98.41 | 97.11 | 95.49 | 93.60 | 91.51 | 89.27 | 86.93 |
| 80 | 99.91 | 99.61 | 99.03 | 98.15 | 96.99 | 95.58 | 93.97 | 92.20 | 90.30 |

**Table 5.22 Expected Benefit of Topeka for Different Levels of Protection**

| TVP%→ OR% ↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 19211.58 | 14058.91 | 8906.242 | 3753.572 | -1399.1 | -6551.76 | -11704.4 | -16857.1 | -22009.8 |
| 20 | 48574.6 | 43421.93 | 38269.26 | 33116.59 | 27963.92 | 22811.26 | 17658.59 | 12505.92 | 7353.252 |
| 30 | 79040.58 | 73887.91 | 68735.24 | 63582.57 | 58429.9 | 53277.24 | 48124.57 | 42971.9 | 37819.23 |
| 40 | 108179.2 | 103026.5 | 97873.82 | 92721.15 | 87568.48 | 82415.82 | 77263.15 | 72110.48 | 66957.81 |
| 50 | 137837.2 | 132684.5 | 127531.8 | 122379.1 | 117226.5 | 112073.8 | 106921.1 | 101768.5 | 96615.81 |
| 60 | 166443.5 | 161290.8 | 156138.2 | 150985.5 | 145832.8 | 140680.2 | 135527.5 | 130374.8 | 125222.2 |
| 70 | 196736.3 | 191583.7 | 186431 | 181278.3 | 176125.7 | 170973 | 165820.3 | 160667.7 | 155515 |
| 80 | 226496.3 | 221343.6 | 216191 | 211038.3 | 205885.6 | 200733 | 195580.3 | 190427.6 | 185274.9 |

**Table 5.23 Probability Values and Expected Benefit for Defined Outage Mitigation Strategy**

| Mitigation Level | Vulnerable Points Protected (%) | Outage Reduction (%) | Probability of benefit >0 (%) | Expected Benefit ($/yr.) |
|---|---|---|---|---|
| 1 | 20 | 50 | 98.77 | 137837.2 |
| 3 | 40 | 60 | 97.14 | 156138.2 |
| 5 | 60 | 70 | 95.49 | 176125.7 |
| 7 | 80 | 80 | 93.97 | 195580.3 |

From Table 5.23, the optimal combination is mitigation level 7 as there is 93.97% probability for obtaining highest expected benefit 195580.3$/yr with 80% outage reduction if the utility protects 80% of all vulnerable points. There is also possibility for opting mitigation level 5 as optimal combination as it gives second highest expected benefit 176125.7$/yr with a high probability value 95.49% , if the utility decides to compromise with outage reduction.

### *Lawrence*

The probability values and the computed expected benefit values of Lawrence are given in Table 5.24 and Table 5.25 respectively. For Lawrence, the probabilities of benefit greater than zero ranges from a minimum value 14.79% to maximum value 98.86%. Again 90% probability is considered as acceptable value to propose the best mitigation level.

**Table 5.24 Probability Values of Lawrence for Different Levels of Protection**

| TVP%→<br>OR% ↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 47.90 | 39.93 | 33.71 | 28.78 | 24.81 | 21.58 | 18.91 | 16.68 | 14.79 |
| 20 | 63.75 | 54.94 | 47.63 | 41.57 | 36.52 | 32.27 | 28.69 | 25.63 | 23.00 |
| 30 | 78.47 | 70.07 | 62.52 | 55.90 | 50.13 | 45.12 | 40.75 | 36.94 | 33.58 |
| 40 | 88.34 | 81.27 | 74.34 | 67.90 | 62.03 | 56.74 | 51.99 | 47.74 | 43.92 |
| 50 | 93.80 | 88.36 | 82.53 | 76.77 | 71.29 | 66.17 | 61.43 | 57.08 | 53.10 |
| 60 | 96.82 | 92.94 | 88.37 | 83.55 | 78.73 | 74.06 | 69.61 | 65.41 | 61.47 |
| 70 | 98.14 | 95.34 | 91.78 | 87.81 | 83.67 | 79.53 | 75.48 | 71.57 | 67.84 |
| 80 | 98.86 | 96.86 | 94.13 | 90.92 | 87.46 | 83.88 | 80.29 | 76.75 | 73.30 |

**Table 5.25 Expected Benefit of Lawrence for Different Levels of Protection**

| TVP%→<br>OR% ↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 8564.727 | 3912.777 | -739.173 | -5391.13 | -10043.1 | -14695 | -19347 | -23998.9 | -28650.9 |
| 20 | 24107.54 | 19455.59 | 14803.64 | 10151.68 | 5499.735 | 847.785 | -3804.17 | -8456.12 | -13108.1 |
| 30 | 41687.45 | 37035.5 | 32383.55 | 27731.59 | 23079.64 | 18427.69 | 13775.74 | 9123.791 | 4471.841 |
| 40 | 58617.73 | 53965.78 | 49313.83 | 44661.87 | 40009.92 | 35357.97 | 30706.02 | 26054.07 | 21402.12 |
| 50 | 75018.7 | 70366.75 | 65714.8 | 61062.84 | 56410.89 | 51758.94 | 47106.99 | 42455.04 | 37803.09 |
| 60 | 92443.01 | 87791.06 | 83139.11 | 78487.15 | 73835.2 | 69183.25 | 64531.3 | 59879.35 | 55227.4 |
| 70 | 108710 | 104058.1 | 99406.14 | 94754.18 | 90102.23 | 85450.28 | 80798.33 | 76146.38 | 71494.43 |
| 80 | 126067 | 121415 | 116763.1 | 112111.1 | 107459.2 | 102807.2 | 98155.28 | 93503.33 | 88851.38 |

**Table 5.26 Probability Values and Expected Benefit for Defined Outage Mitigation Strategy**

| Mitigation Level | Vulnerable Points Protected (%) | Outage Reduction (%) | Probability of benefit >0 (%) | Expected Benefit ($/yr.) |
|---|---|---|---|---|
| 1 | 20 | 50 | 93.80 | 75018.70 |
| 3 | 40 | 60 | 88.37 | 83139.11 |
| 5 | 60 | 70 | 83.67 | 90102.23 |
| 7 | 80 | 80 | 80.29 | 98155.28 |

From Table 5.26, mitigation level 1 is the only option with probability higher than 90% giving expected benefit 75018.70$/yr with 50% outage reduction, if the utility protects 20% of the vulnerable points.

### *Manhattan*

The probability values and the computed expected benefit values of Manhattan are given in Table 5.27 and Table 5.28 respectively. For Manhattan, the probabilities of benefit greater than zero ranges from a minimum value of 4.57% to a maximum value of 93.62%. To propose the best mitigation level, probability values greater than 90% are considered as acceptable. As observed in Table 5.27, the probabilities are very low compared to other cities, since the total number of vulnerable points is not in proportion to the size of the city. This suggests that investment in installing animal guards is high, which leads to decrease in probability of getting benefit.

**Table 5.27 Probability Values of Manhattan for Different Levels of Protection**

| TVP%→<br>OR% ↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 30.81 | 22.21 | 16.63 | 12.82 | 10.10 | 8.12 | 6.62 | 5.47 | 4.57 |
| 20 | 46.39 | 35.07 | 27.21 | 21.58 | 17.42 | 14.27 | 11.85 | 9.94 | 8.42 |
| 30 | 60.44 | 47.70 | 38.23 | 31.12 | 25.67 | 21.43 | 18.07 | 15.38 | 13.20 |
| 40 | 72.74 | 59.92 | 49.64 | 41.49 | 35.00 | 29.78 | 25.54 | 22.06 | 19.18 |
| 50 | 81.36 | 69.56 | 59.35 | 50.83 | 43.76 | 37.90 | 33.02 | 28.92 | 25.46 |
| 60 | 87.41 | 77.16 | 67.59 | 59.17 | 51.91 | 45.69 | 40.38 | 35.82 | 31.91 |
| 70 | 91.11 | 82.46 | 73.82 | 65.85 | 58.72 | 52.45 | 46.95 | 42.15 | 37.94 |
| 80 | 93.62 | 86.45 | 78.84 | 71.49 | 64.70 | 58.56 | 53.05 | 48.13 | 43.76 |

**Table 5.28 Expected Benefit of Manhattan for Different Levels of Protection**

| TVP%→<br>OR% ↓ | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|
| 10 | -1854.87 | -6548.05 | -11241.2 | -15934.4 | -20627.6 | -25320.7 | -30013.9 | -34707.1 | -39400.3 |
| 20 | 6465.674 | 1772.494 | -2920.68 | -7613.85 | -12307 | -17000.2 | -21693.4 | -26386.5 | -31079.7 |
| 30 | 14191.02 | 9497.842 | 4804.672 | 111.502 | -4581.67 | -9274.85 | -13968 | -18661.2 | -23354.4 |
| 40 | 22326.5 | 17633.32 | 12940.15 | 8246.98 | 3553.81 | -1139.37 | -5832.54 | -10525.7 | -15218.9 |
| 50 | 30212.51 | 25519.33 | 20826.16 | 16132.99 | 11439.82 | 6746.641 | 2053.471 | -2639.7 | -7332.87 |
| 60 | 38236.81 | 33543.63 | 28850.46 | 24157.29 | 19464.12 | 14770.94 | 10077.77 | 5384.603 | 691.4329 |
| 70 | 46081.47 | 41388.29 | 36695.12 | 32001.95 | 27308.78 | 22615.6 | 17922.43 | 13229.26 | 8536.092 |
| 80 | 54252.2 | 49559.02 | 44865.85 | 40172.68 | 35479.51 | 30786.33 | 26093.16 | 21399.99 | 16706.82 |

The first negative element in Table 5.28 implies that there is 30.81% probability of obtaining benefit, but the expected value of benefit is -$1854.87, which implies a loss. Other negative values also imply the same. Therefore, these cases must be avoided while making decisions regarding outage mitigation.

**Table 5.29 Probability Values and Expected Benefit for Outage Mitigation Strategy**

| Mitigation Level | Vulnerable Points Protected (%) | Outage Reduction (%) | Probability of benefit >0 (%) | Expected Benefit ($/yr.) |
|---|---|---|---|---|
| 1 | 20 | 50 | 81.36 | 30212.51 |
| 3 | 40 | 60 | 67.59 | 28850.46 |
| 5 | 60 | 70 | 58.72 | 27308.78 |
| 7 | 80 | 80 | 53.05 | 26093.16 |

From Table 5.29, it is observed that none of the strategies have probability higher than 90%. Therefore, installation of animal guards is not recommended. However, if utility desires, mitigation level 1 can be implemented which promises 81.36% probability to get expected benefit of 30212.51$/yr with 50% outage reduction, if 20% of the vulnerable points are protected.

Analyzing different strategies will give different solutions to utilities. However, additional information about number of outages at each vulnerable point would help utility to obtain more appropriate combination.

# Chapter 6 - Conclusions and Future Work

## Conclusions

Study of future weather and corresponding squirrel-outages will help utilities face unpredictable events more effectively. A Bayesian model combined with Monte Carlo Simulation was used in this research to predict outages in the future based on weather and outage history. The results were used in a probabilistic cost-benefit analysis to evaluate outage mitigation strategies, which is a significant and novel contribution of this research.

By predicting future outage, utilities have an opportunity to prevent overhead distribution system outages due to squirrels by taking appropriate corrective measures. Corrective measures include regular tree trimming, use of repellants, and installations of animal guards, etc. However, in this research, only installing animal guards on vulnerable points is considered. The model performance is judged by testing data of four cities in Kansas: Wichita, Topeka, Lawrence, and Manhattan. Wichita and Topeka are large cities in terms of population and area, and Lawrence and Manhattan are comparatively smaller. Outage data was aggregated on a weekly basis to even out randomness in the daily data. Thus, simulations of all cities were able to retain patterns in the time series of weekly data.

Various combinations of input states and outage levels in the Bayesian model successfully captured probabilistic relationships between them in the CPT. Confidence intervals of the estimates were found by running Monte Carlo simulations 10,000 times. The weekly estimated results indicated that most observed values are within the upper limits of 95% confidence of the predicted values for every city, confirming that the model is reliable.

The future weather must be predicted first to predict future outages. To accomplish that a probability table is constructed using past 14 years of weather data from 1998-2011 for each city, which is combined with Monte Carlo Simulations to predict future weather. This predicted future weather is used to predict future outages and the outage prediction is carried out on weekly, monthly and yearly basis for each city. The CPT used in prediction of future outages is constructed using 2005-2011 outage data, which is later used in cost-benefit analysis to generate outage reduction cases.

Cost-benefit analysis considers cost of installing animal guards and benefit due to reduction in outages. They can be used for implementing the best outage mitigation strategy. In this research, probability values of benefit greater than zero are determined for all four cities using a statistical approach. Different combinations of outage reduction cases and mitigation levels are studied in detail to propose optimal mitigation plan. It is found that Wichita has the highest probability of getting expected benefit greater than zero with 70% reduction in outages. Topeka, the second the largest city considered in this research, promises 93.97% probability of benefit greater than zero with 80% outage reduction. For Lawrence, the analysis shows that there is 93.80% probability of benefit greater than zero with 50% reduction in outages. As the total vulnerable points are not in proportion with size of Manhattan, the methodology used in this research didn't recommend installation of animal guards. However, the utility can still choose an outage mitigation level with acceptable probability value, but may face risk of having a loss.

Utilities spend large amounts of money to improve system reliability and diligently strive to maintain an excellent relationship with customers with the goal of providing uninterrupted power supply. However, due to lack of proper analysis or inevitable natural disasters, there is always a risk of harming their system's credibility. The novel approach proposed in this research will assist utilities to keep themselves ahead in order to significantly reduce the number of outages and in providing continuous electricity to their customers. Because this analysis was performed using real-life cost values and with consideration of different cases of outage reduction and mitigation levels, a high possibility exists to rapidly and effectively improve system reliability.

## Future Work

The data used in outage mitigation strategies provided only general information on the total outages for a complete distribution network and weather conditions for an entire city. In order to select the best outage mitigation strategy, analysis based on detailed data indicating the exact location of vulnerable points with high occurrence of outages is required.

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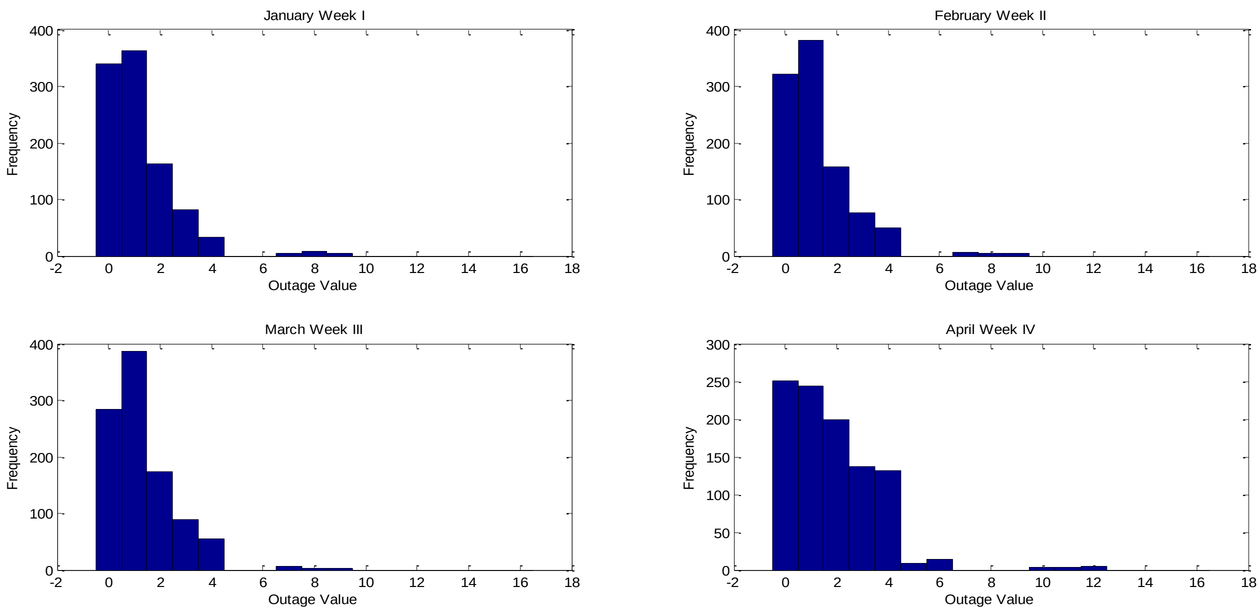
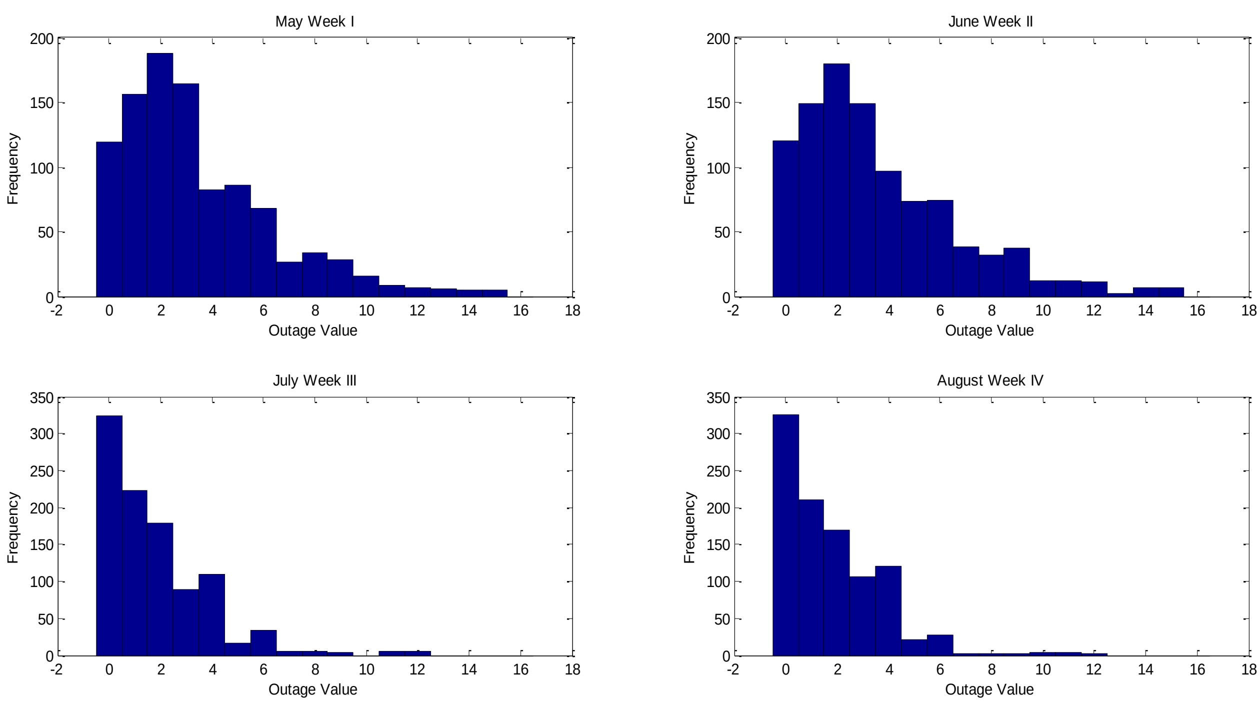
# Appendix A - Weekly and Monthly Outage Predictions for Other Cities

**(a)**




**(b)**



**(c)**

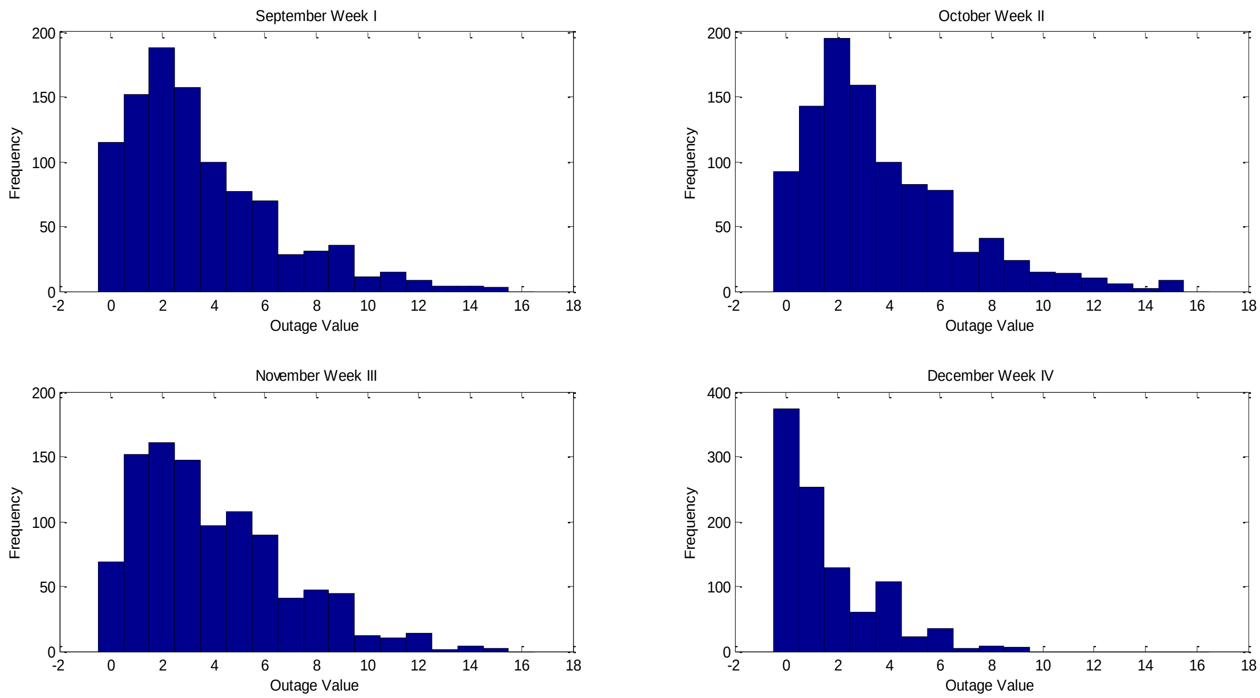
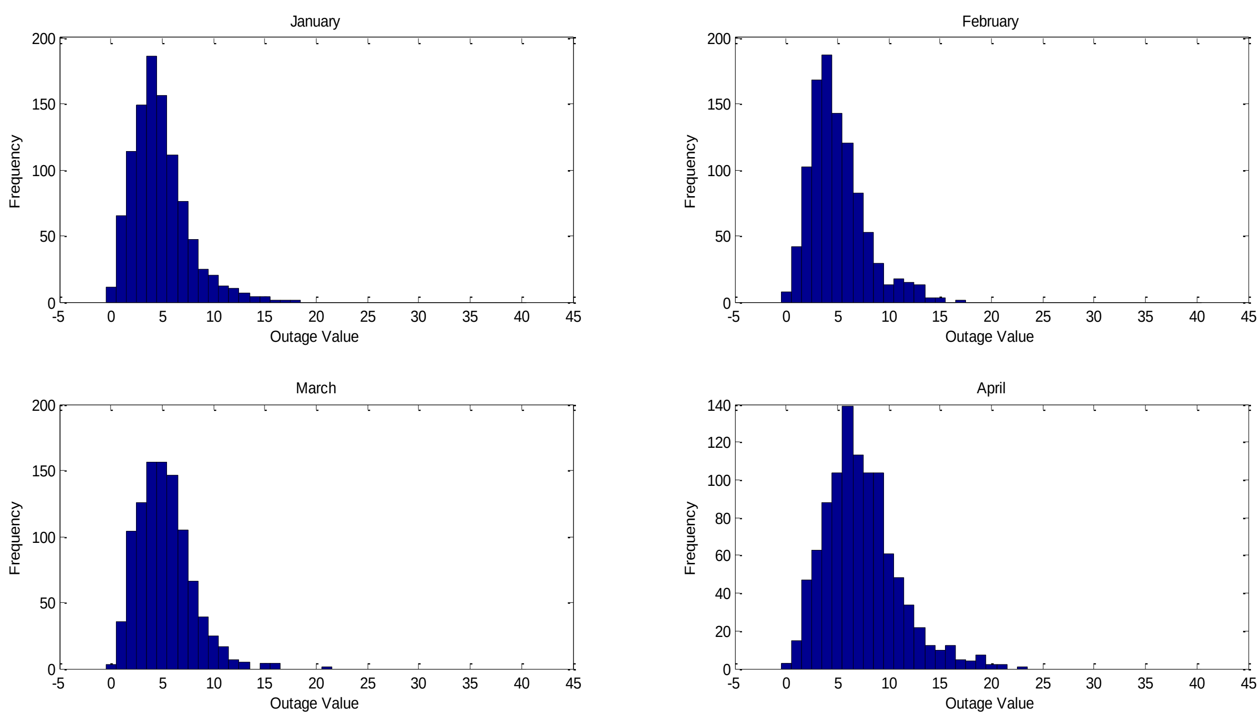
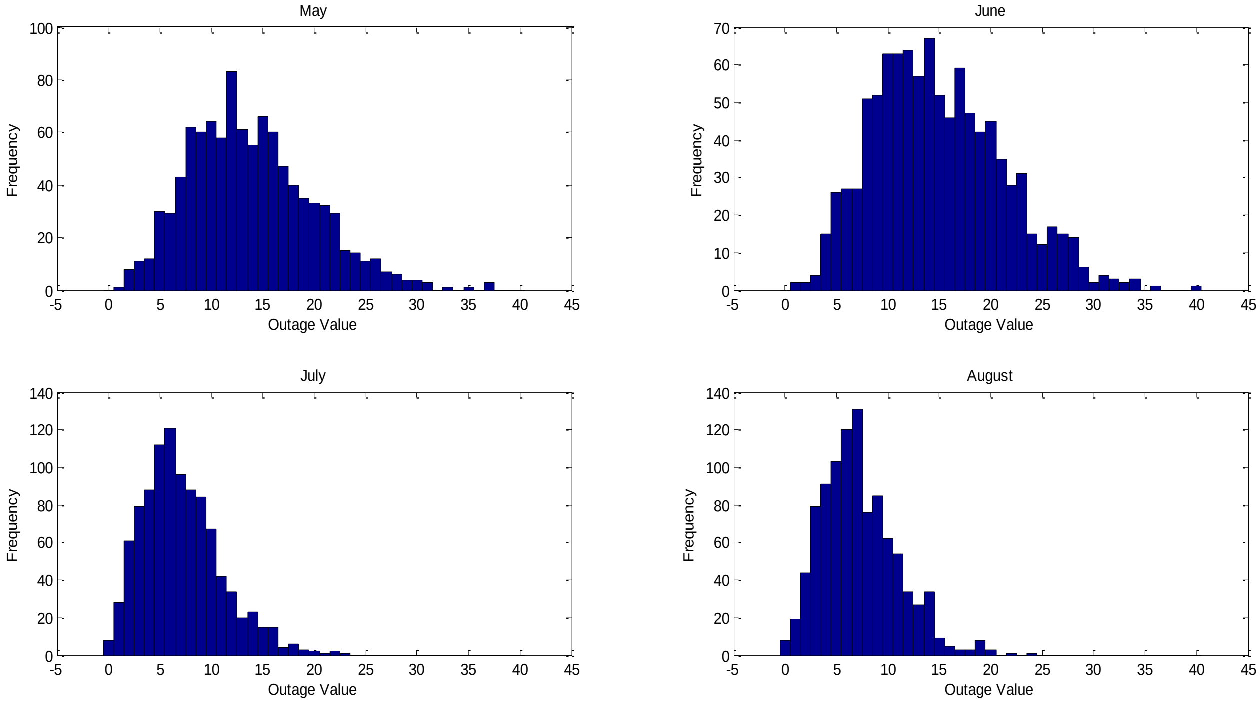



**Figure 6.1 (a)-(c) Manhattan Weekly Predictions by MCS**

**(a)**



**(b)**




**(c)**

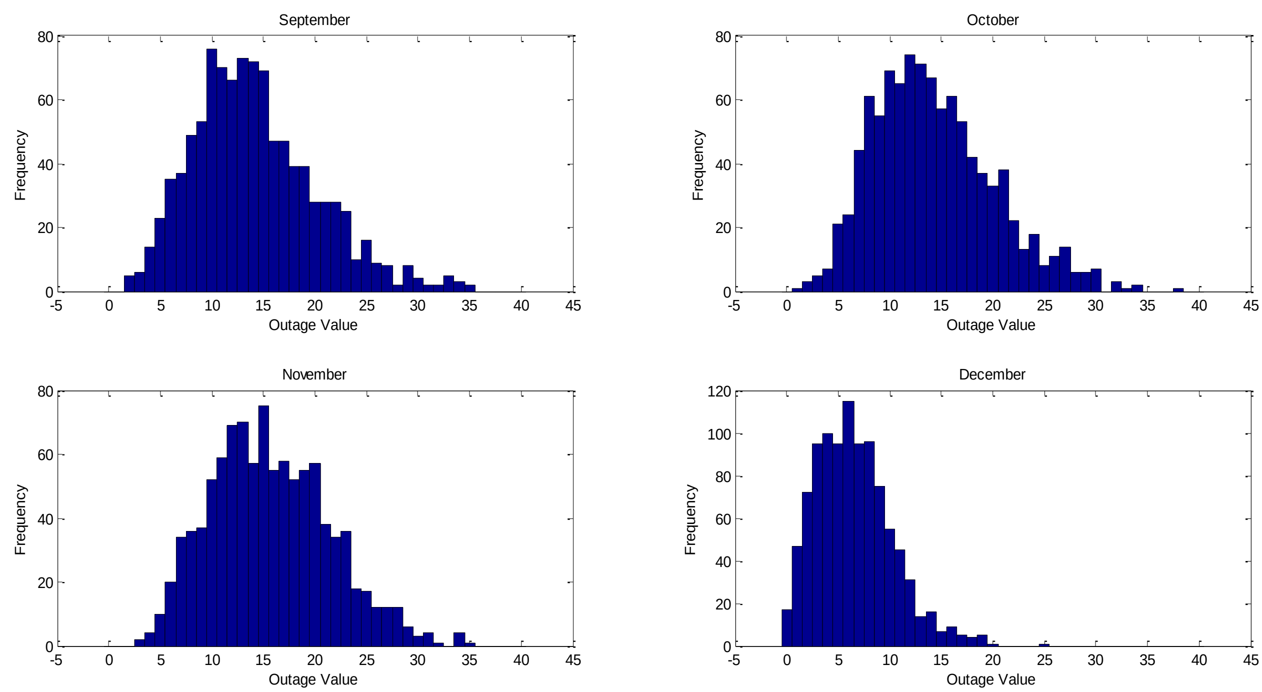
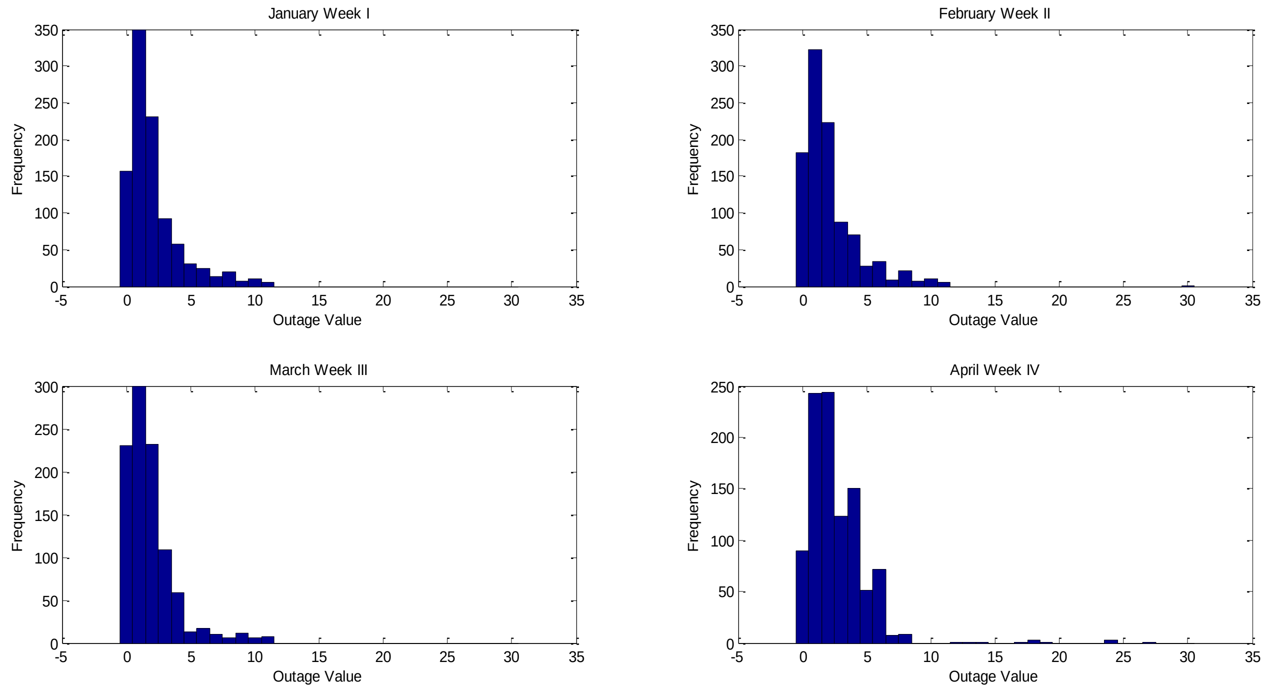
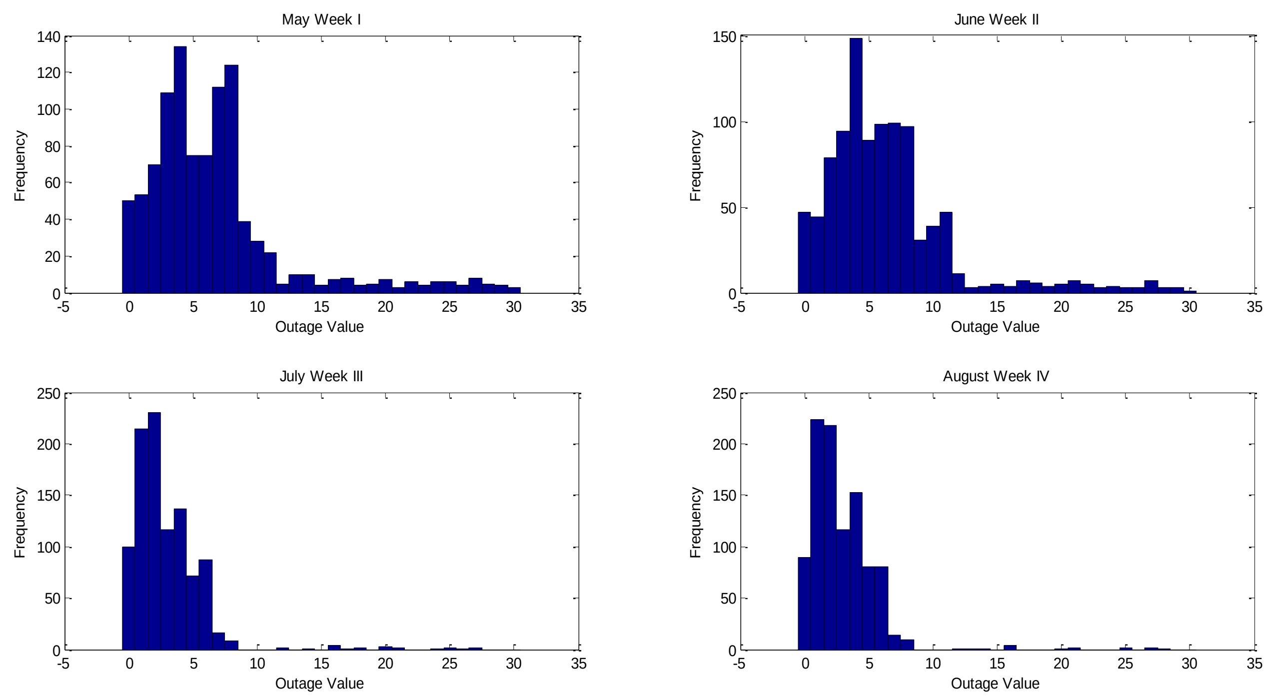



**Figure 6.2 (a)-(c) Manhattan Monthly Predictions by MCS**

**(a)**


January Week I
February Week II
March Week III
April Week IV
Frequency
Outage Value

**(b)**


May Week I
June Week II
July Week III
August Week IV
Frequency
Outage Value

**(c)**

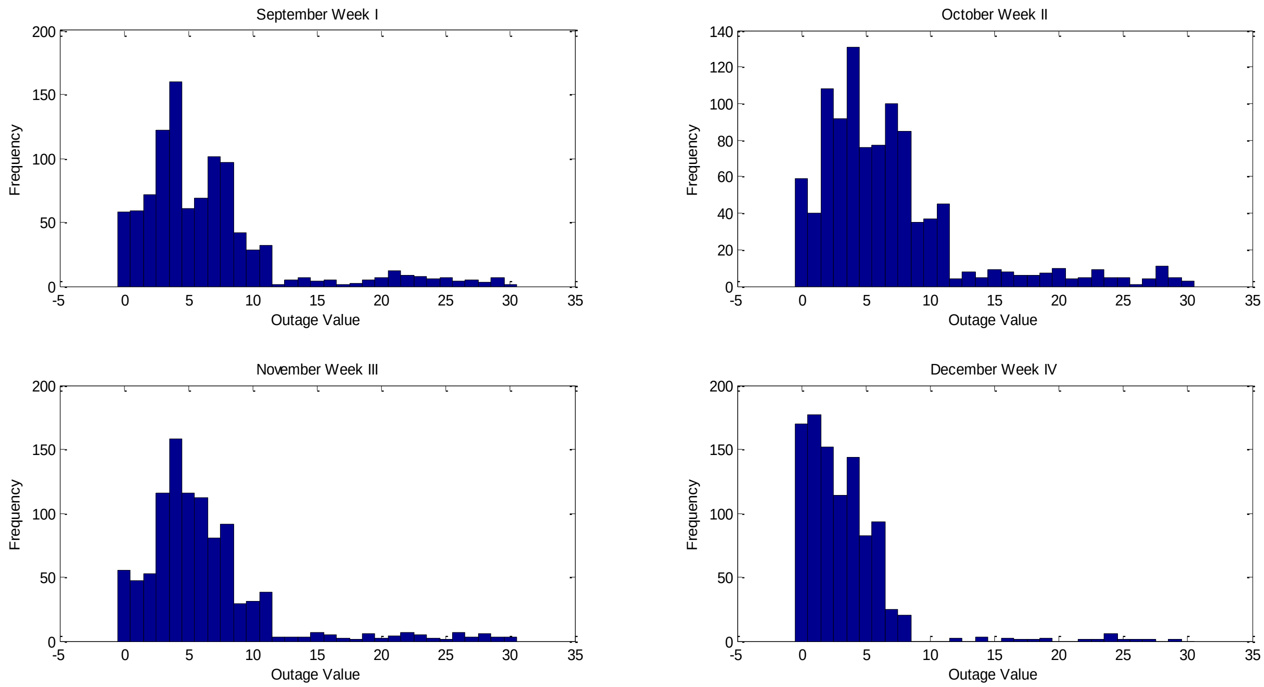
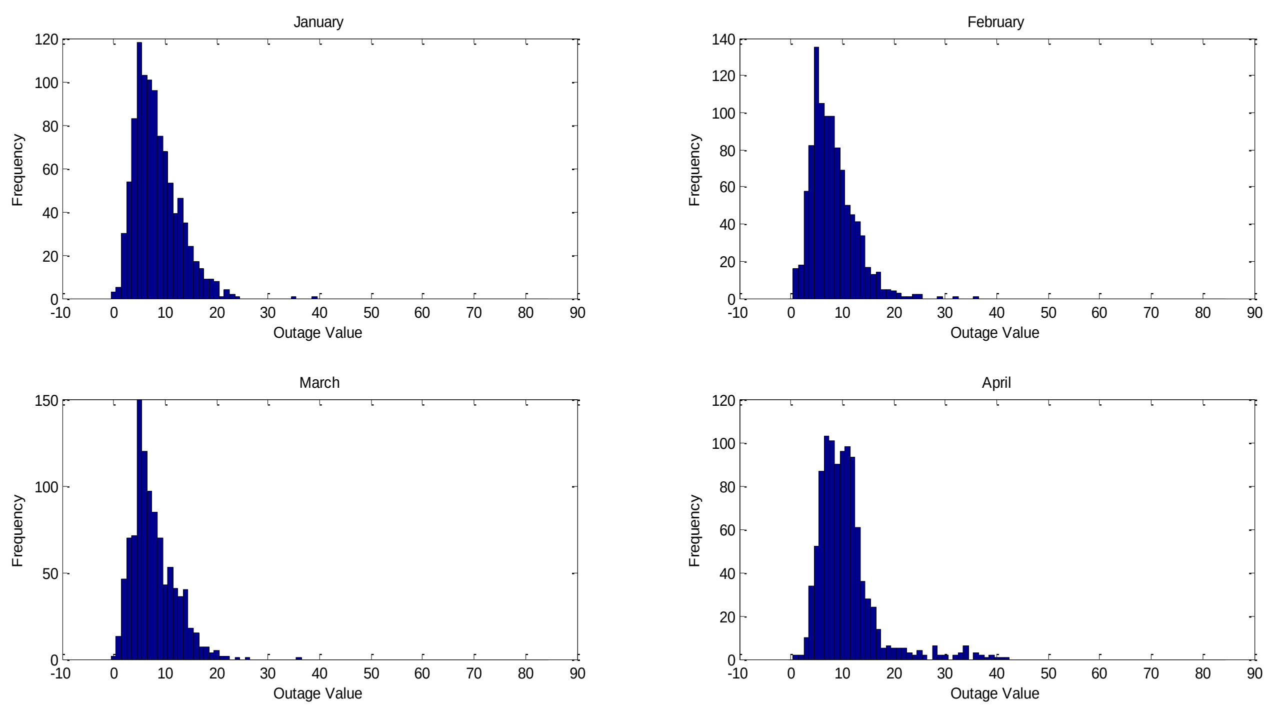
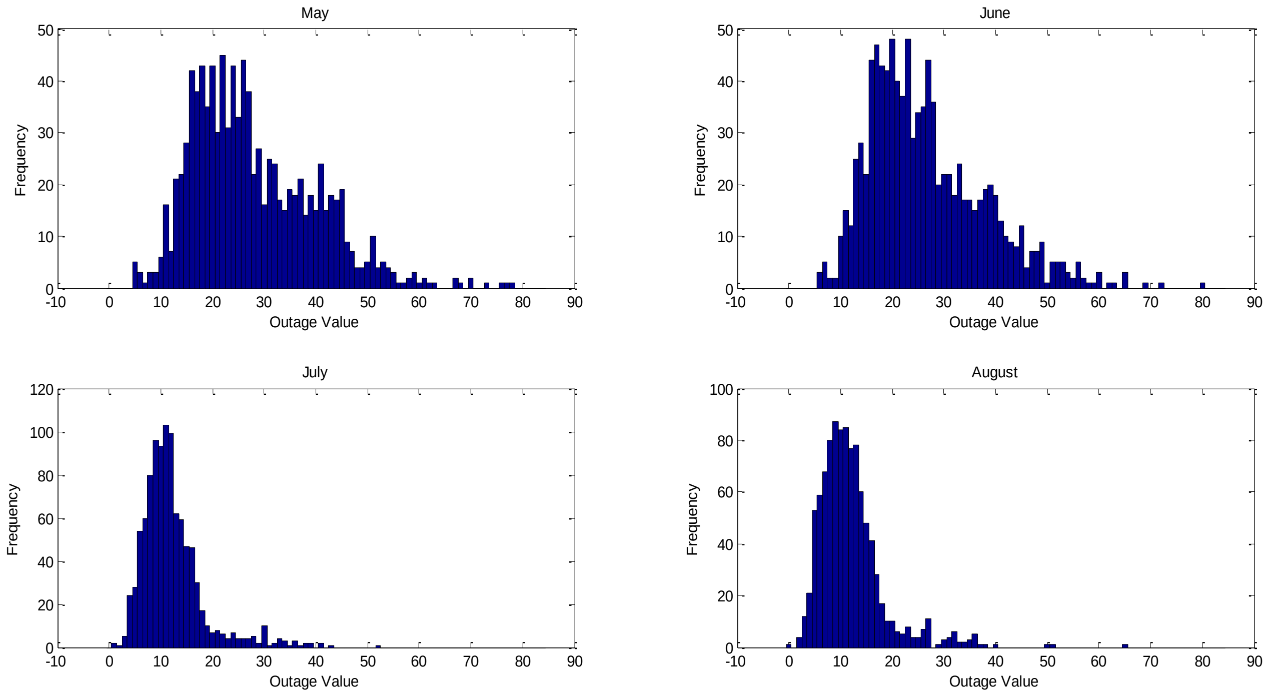



**Figure 6.3 (a)-(c) Lawrence Weekly Predictions by MCS**

**(a)**



**(b)**




**(c)**

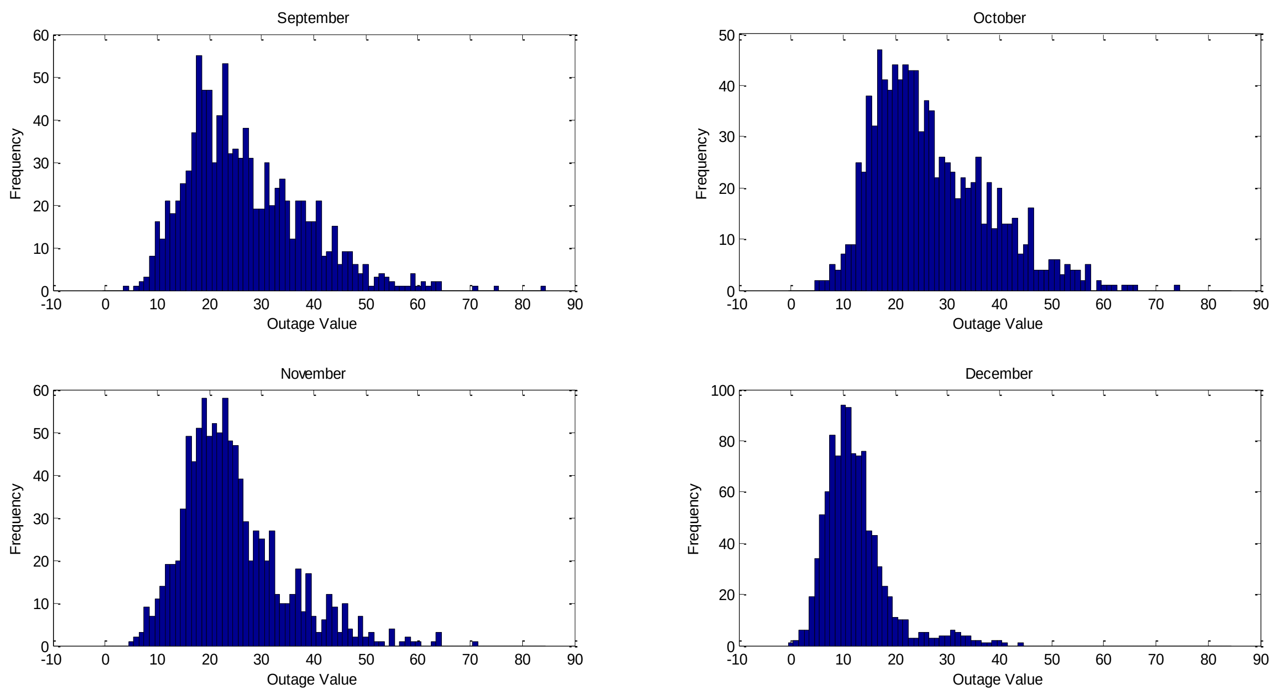
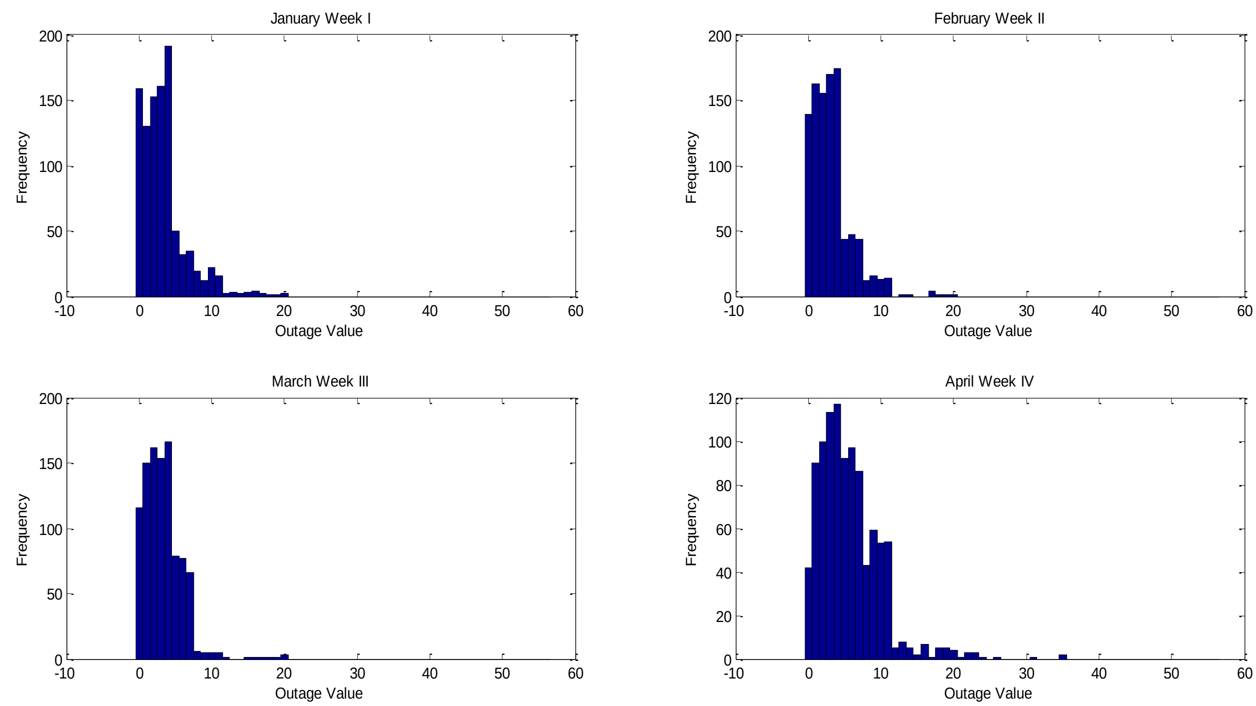
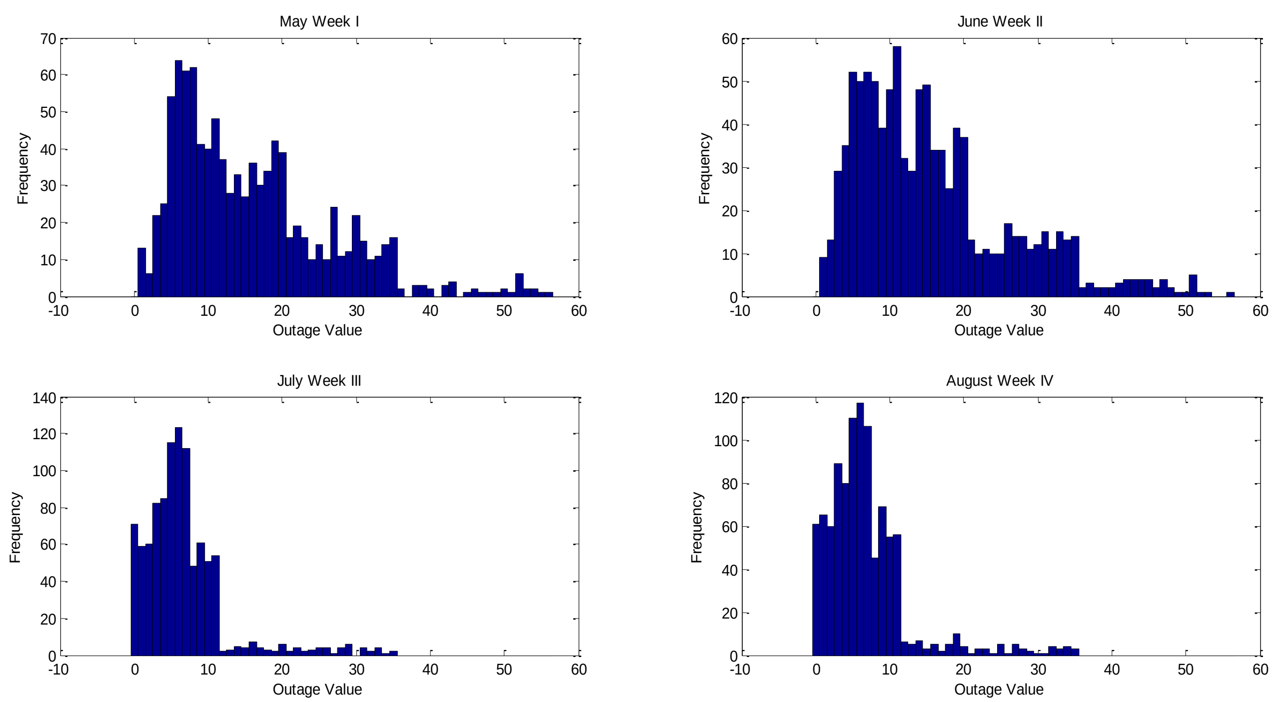



**Figure 6.4 (a)-(c) Lawrence Monthly Predictions by MCS**

**(a)**


January Week I
February Week II
March Week III
April Week IV
Frequency
Outage Value

**(b)**


May Week I
June Week II
July Week III
August Week IV
Frequency
Outage Value

**(c)**

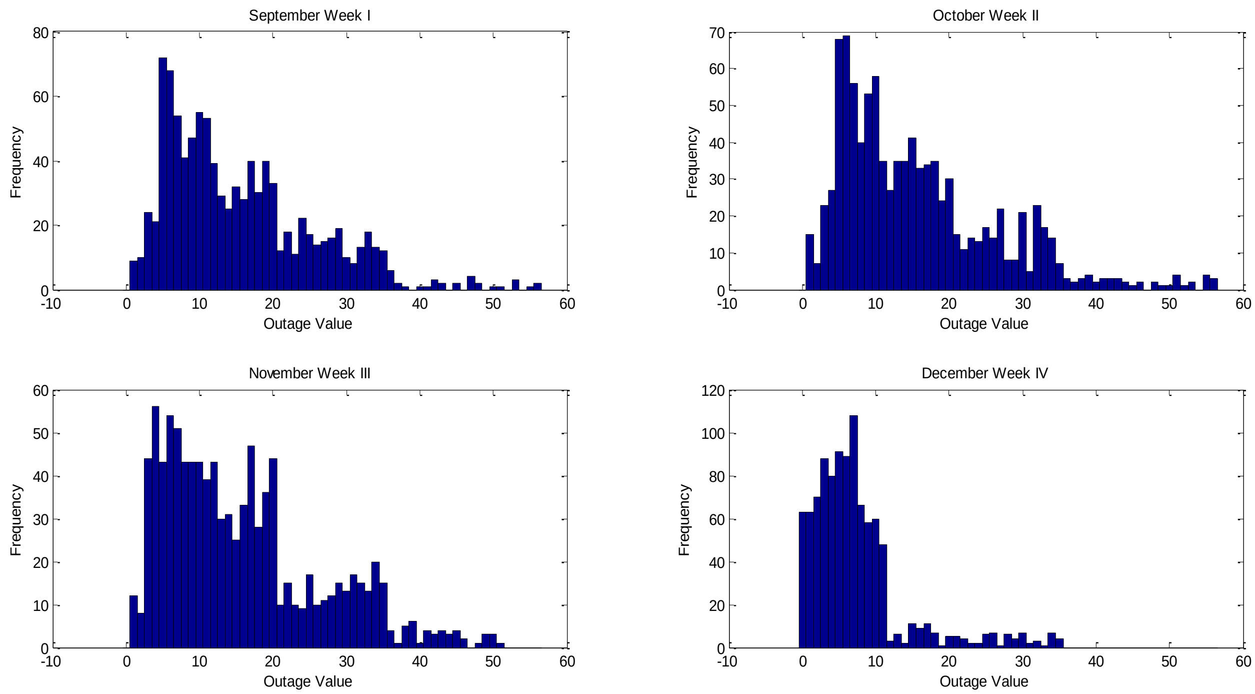
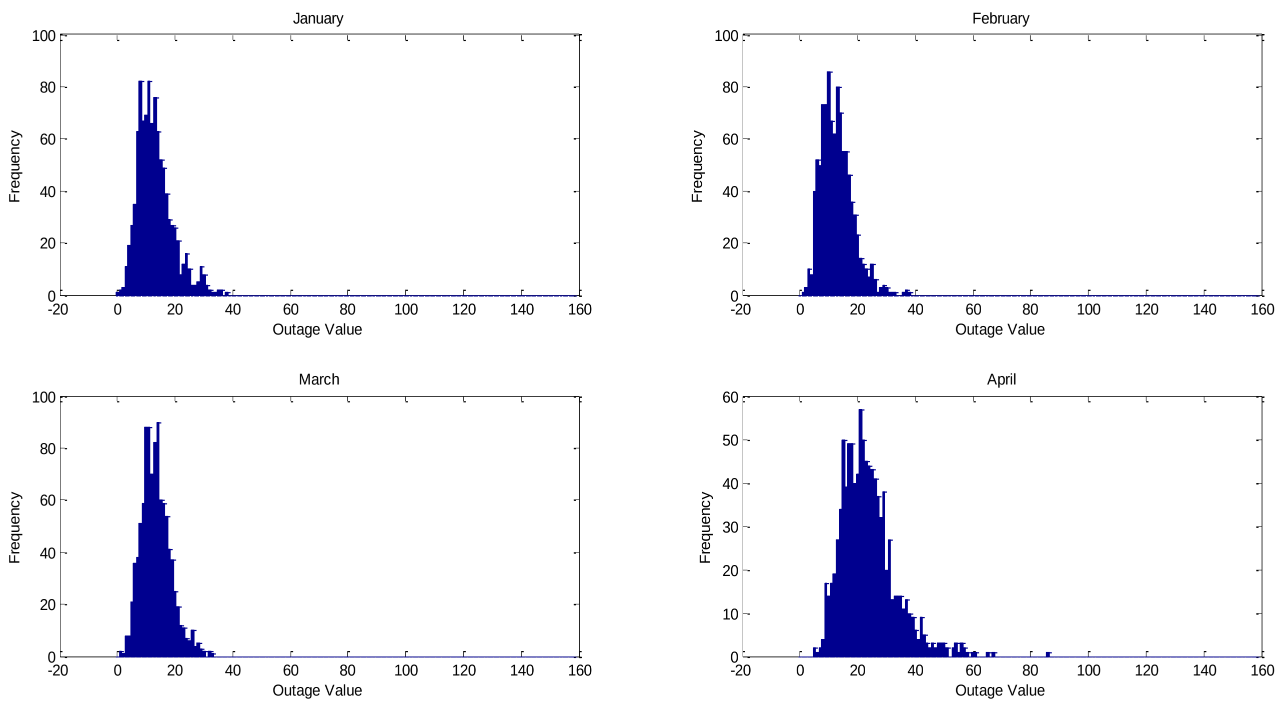
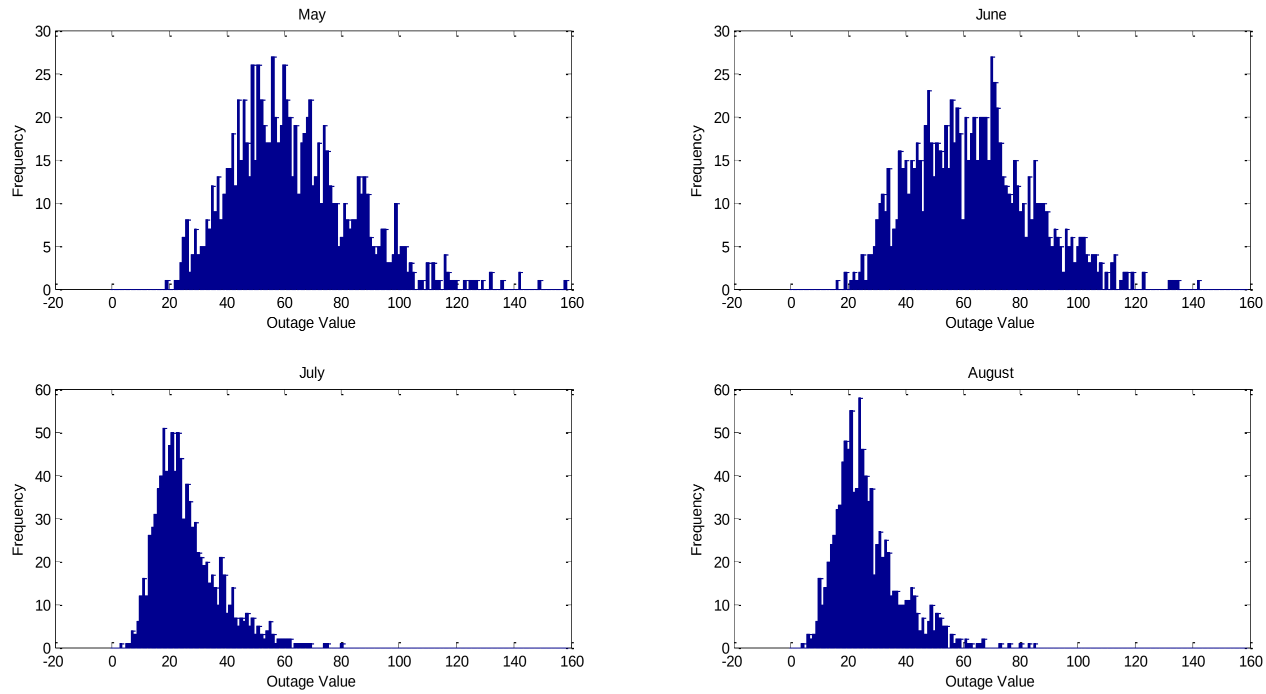



**Figure 6.5 (a)-(c) Topeka Weekly Predictions by MCS**

**(a)**



**(b)**




**(c)**

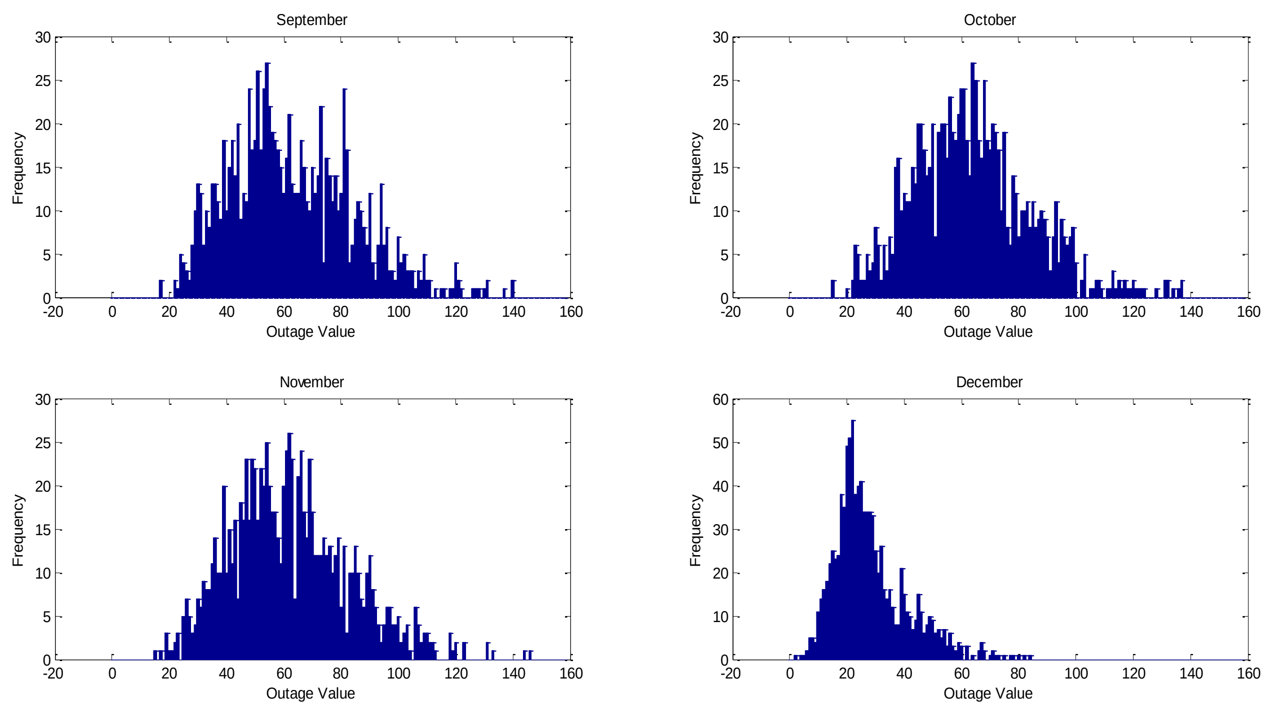



**Figure 6.6 (a)-(c) Topeka Monthly Predictions by MCS**

# Appendix B - CPT of Wichita for Other Cases of Outage Reduction

**Table 6.1 Conditional Probability Table of Wichita for 20% outage reduction case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.426 | 0.226 | 0.151 | 0.121 | 0.060 | 0.000 | 0.000 | 0.015 | 0.000 |
| Input State 2 | 0.314 | 0.102 | 0.178 | 0.127 | 0.140 | 0.089 | 0.025 | 0.025 | 0.000 |
| Input State 3 | 0.200 | 0.055 | 0.000 | 0.110 | 0.138 | 0.166 | 0.110 | 0.110 | 0.110 |
| Input State 4 | 0.446 | 0.092 | 0.215 | 0.123 | 0.092 | 0.031 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.253 | 0.133 | 0.080 | 0.187 | 0.187 | 0.080 | 0.053 | 0.027 | 0.000 |
| Input State 6 | 0.216 | 0.047 | 0.063 | 0.016 | 0.094 | 0.188 | 0.204 | 0.094 | 0.078 |
| Input State 7 | 0.200 | 0.000 | 0.480 | 0.160 | 0.000 | 0.160 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.242 | 0.000 | 0.126 | 0.168 | 0.253 | 0.168 | 0.042 | 0.000 | 0.000 |
| Input State 9 | 0.200 | 0.000 | 0.027 | 0.080 | 0.120 | 0.093 | 0.080 | 0.173 | 0.227 |

**Table 6.2 Conditional Probability Table of Wichita for 30% outage reduction case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.498 | 0.198 | 0.132 | 0.106 | 0.053 | 0.000 | 0.000 | 0.013 | 0.000 |
| Input State 2 | 0.400 | 0.089 | 0.156 | 0.111 | 0.122 | 0.078 | 0.022 | 0.022 | 0.000 |
| Input State 3 | 0.300 | 0.048 | 0.000 | 0.097 | 0.121 | 0.145 | 0.097 | 0.097 | 0.097 |
| Input State 4 | 0.515 | 0.081 | 0.188 | 0.108 | 0.081 | 0.027 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.347 | 0.117 | 0.070 | 0.163 | 0.163 | 0.070 | 0.047 | 0.023 | 0.000 |
| Input State 6 | 0.314 | 0.041 | 0.055 | 0.014 | 0.082 | 0.165 | 0.178 | 0.082 | 0.069 |
| Input State 7 | 0.300 | 0.000 | 0.420 | 0.140 | 0.000 | 0.140 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.337 | 0.000 | 0.111 | 0.147 | 0.221 | 0.147 | 0.037 | 0.000 | 0.000 |
| Input State 9 | 0.300 | 0.000 | 0.023 | 0.070 | 0.105 | 0.082 | 0.070 | 0.152 | 0.198 |

**Table 6.3 Conditional Probability Table of Wichita for 40% outage reduction case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.570 | 0.170 | 0.113 | 0.091 | 0.045 | 0.000 | 0.000 | 0.011 | 0.000 |
| Input State 2 | 0.486 | 0.076 | 0.133 | 0.095 | 0.105 | 0.067 | 0.019 | 0.019 | 0.000 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Input State 3 | 0.400 | 0.041 | 0.000 | 0.083 | 0.103 | 0.124 | 0.083 | 0.083 | 0.083 |
| Input State 4 | 0.585 | 0.069 | 0.162 | 0.092 | 0.069 | 0.023 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.440 | 0.100 | 0.060 | 0.140 | 0.140 | 0.060 | 0.040 | 0.020 | 0.000 |
| Input State 6 | 0.412 | 0.035 | 0.047 | 0.012 | 0.071 | 0.141 | 0.153 | 0.071 | 0.059 |
| Input State 7 | 0.400 | 0.000 | 0.360 | 0.120 | 0.000 | 0.120 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.432 | 0.000 | 0.095 | 0.126 | 0.189 | 0.126 | 0.032 | 0.000 | 0.000 |
| Input State 9 | 0.400 | 0.000 | 0.020 | 0.060 | 0.090 | 0.070 | 0.060 | 0.130 | 0.170 |

**Table 6.4 Conditional Probability Table of Wichita for 50% outage reduction case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.642 | 0.142 | 0.094 | 0.075 | 0.038 | 0.000 | 0.000 | 0.009 | 0.000 |
| Input State 2 | 0.571 | 0.063 | 0.111 | 0.079 | 0.087 | 0.056 | 0.016 | 0.016 | 0.000 |
| Input State 3 | 0.500 | 0.034 | 0.000 | 0.069 | 0.086 | 0.103 | 0.069 | 0.069 | 0.069 |
| Input State 4 | 0.654 | 0.058 | 0.135 | 0.077 | 0.058 | 0.019 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.533 | 0.083 | 0.050 | 0.117 | 0.117 | 0.050 | 0.033 | 0.017 | 0.000 |
| Input State 6 | 0.510 | 0.029 | 0.039 | 0.010 | 0.059 | 0.118 | 0.127 | 0.059 | 0.049 |
| Input State 7 | 0.500 | 0.000 | 0.300 | 0.100 | 0.000 | 0.100 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.526 | 0.000 | 0.079 | 0.105 | 0.158 | 0.105 | 0.026 | 0.000 | 0.000 |
| Input State 9 | 0.500 | 0.000 | 0.017 | 0.050 | 0.075 | 0.058 | 0.050 | 0.108 | 0.142 |

**Table 6.5 Conditional Probability Table of Wichita for 60% outage reduction case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.713 | 0.113 | 0.075 | 0.060 | 0.030 | 0.000 | 0.000 | 0.008 | 0.000 |
| Input State 2 | 0.657 | 0.051 | 0.089 | 0.063 | 0.070 | 0.044 | 0.013 | 0.013 | 0.000 |
| Input State 3 | 0.600 | 0.028 | 0.000 | 0.055 | 0.069 | 0.083 | 0.055 | 0.055 | 0.055 |
| Input State 4 | 0.723 | 0.046 | 0.108 | 0.062 | 0.046 | 0.015 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.627 | 0.067 | 0.040 | 0.093 | 0.093 | 0.040 | 0.027 | 0.013 | 0.000 |
| Input State 6 | 0.608 | 0.024 | 0.031 | 0.008 | 0.047 | 0.094 | 0.102 | 0.047 | 0.039 |
| Input State 7 | 0.600 | 0.000 | 0.240 | 0.080 | 0.000 | 0.080 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.621 | 0.000 | 0.063 | 0.084 | 0.126 | 0.084 | 0.021 | 0.000 | 0.000 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Input State 9 | 0.600 | 0.000 | 0.013 | 0.040 | 0.060 | 0.047 | 0.040 | 0.087 | 0.113 |

**Table 6.6 Conditional Probability Table of Wichita for 70% outage reduction case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.785 | 0.085 | 0.057 | 0.045 | 0.023 | 0.000 | 0.000 | 0.006 | 0.000 |
| Input State 2 | 0.743 | 0.038 | 0.067 | 0.048 | 0.052 | 0.033 | 0.010 | 0.010 | 0.000 |
| Input State 3 | 0.700 | 0.021 | 0.000 | 0.041 | 0.052 | 0.062 | 0.041 | 0.041 | 0.041 |
| Input State 4 | 0.792 | 0.035 | 0.081 | 0.046 | 0.035 | 0.012 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.720 | 0.050 | 0.030 | 0.070 | 0.070 | 0.030 | 0.020 | 0.010 | 0.000 |
| Input State 6 | 0.706 | 0.018 | 0.024 | 0.006 | 0.035 | 0.071 | 0.076 | 0.035 | 0.029 |
| Input State 7 | 0.700 | 0.000 | 0.180 | 0.060 | 0.000 | 0.060 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.716 | 0.000 | 0.047 | 0.063 | 0.095 | 0.063 | 0.016 | 0.000 | 0.000 |
| Input State 9 | 0.700 | 0.000 | 0.010 | 0.030 | 0.045 | 0.035 | 0.030 | 0.065 | 0.085 |

**Table 6.7 Conditional Probability Table of Wichita for 80% outage reduction case**

| Outage Level | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Input State 1 | 0.857 | 0.057 | 0.038 | 0.030 | 0.015 | 0.000 | 0.000 | 0.004 | 0.000 |
| Input State 2 | 0.829 | 0.025 | 0.044 | 0.032 | 0.035 | 0.022 | 0.006 | 0.006 | 0.000 |
| Input State 3 | 0.800 | 0.014 | 0.000 | 0.028 | 0.034 | 0.041 | 0.028 | 0.028 | 0.028 |
| Input State 4 | 0.862 | 0.023 | 0.054 | 0.031 | 0.023 | 0.008 | 0.000 | 0.000 | 0.000 |
| Input State 5 | 0.813 | 0.033 | 0.020 | 0.047 | 0.047 | 0.020 | 0.013 | 0.007 | 0.000 |
| Input State 6 | 0.804 | 0.012 | 0.016 | 0.004 | 0.024 | 0.047 | 0.051 | 0.024 | 0.020 |
| Input State 7 | 0.800 | 0.000 | 0.120 | 0.040 | 0.000 | 0.040 | 0.000 | 0.000 | 0.000 |
| Input State 8 | 0.811 | 0.000 | 0.032 | 0.042 | 0.063 | 0.042 | 0.011 | 0.000 | 0.000 |
| Input State 9 | 0.800 | 0.000 | 0.007 | 0.020 | 0.030 | 0.023 | 0.020 | 0.043 | 0.057 |

# Appendix C - Predictions of Yearly Outages for Topeka and Lawrence with Outage Reduction

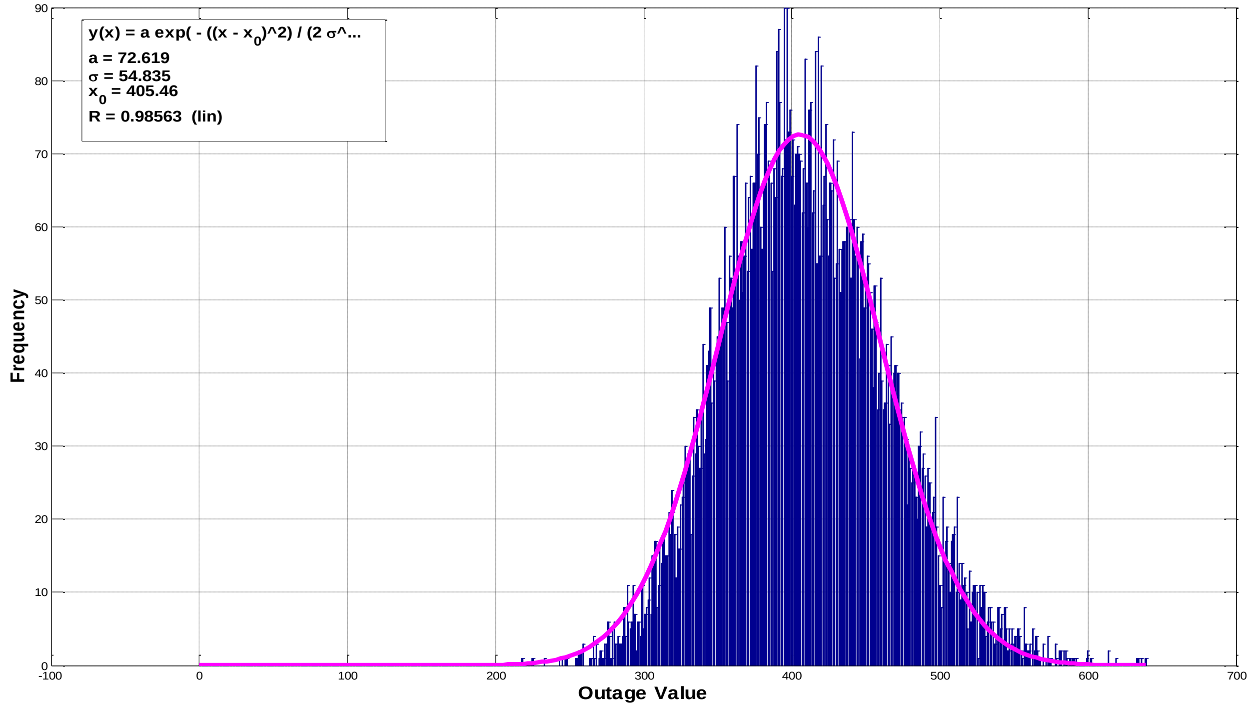



**Figure 6.7 Topeka Yearly Outages with 10% Outage Reduction**

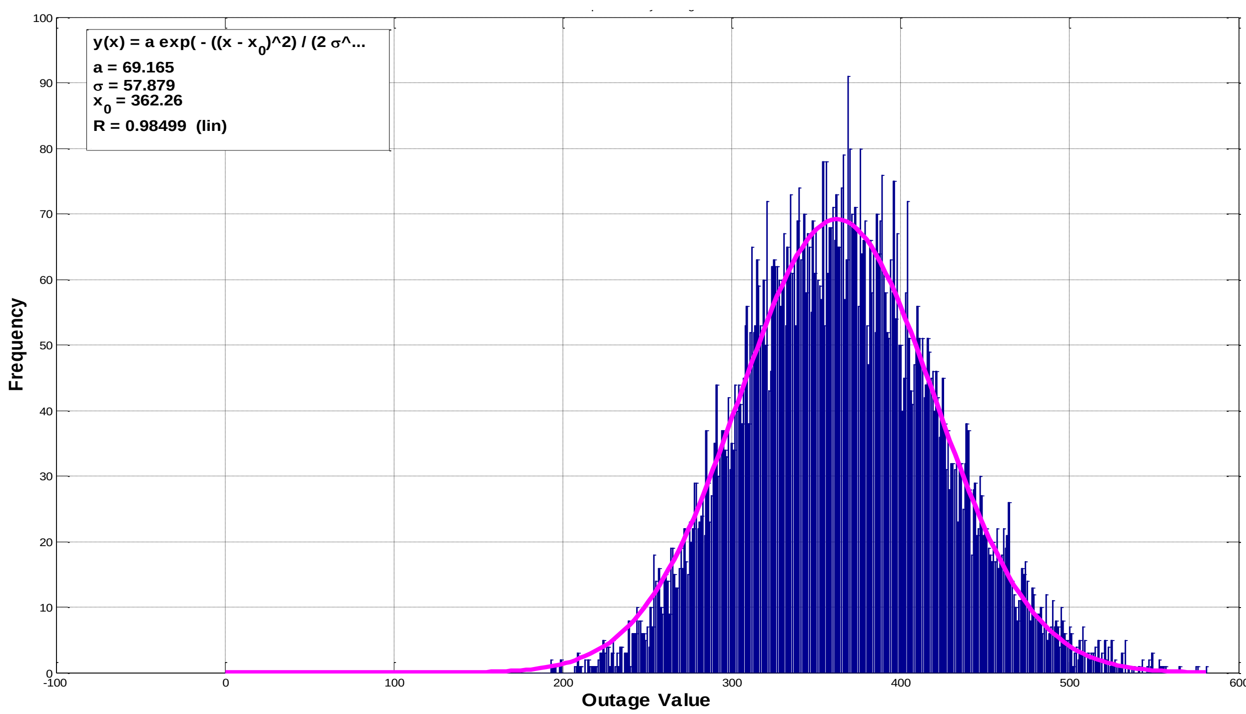



**Figure 6.8 Topeka Yearly Outages with 20% Outage Reduction**

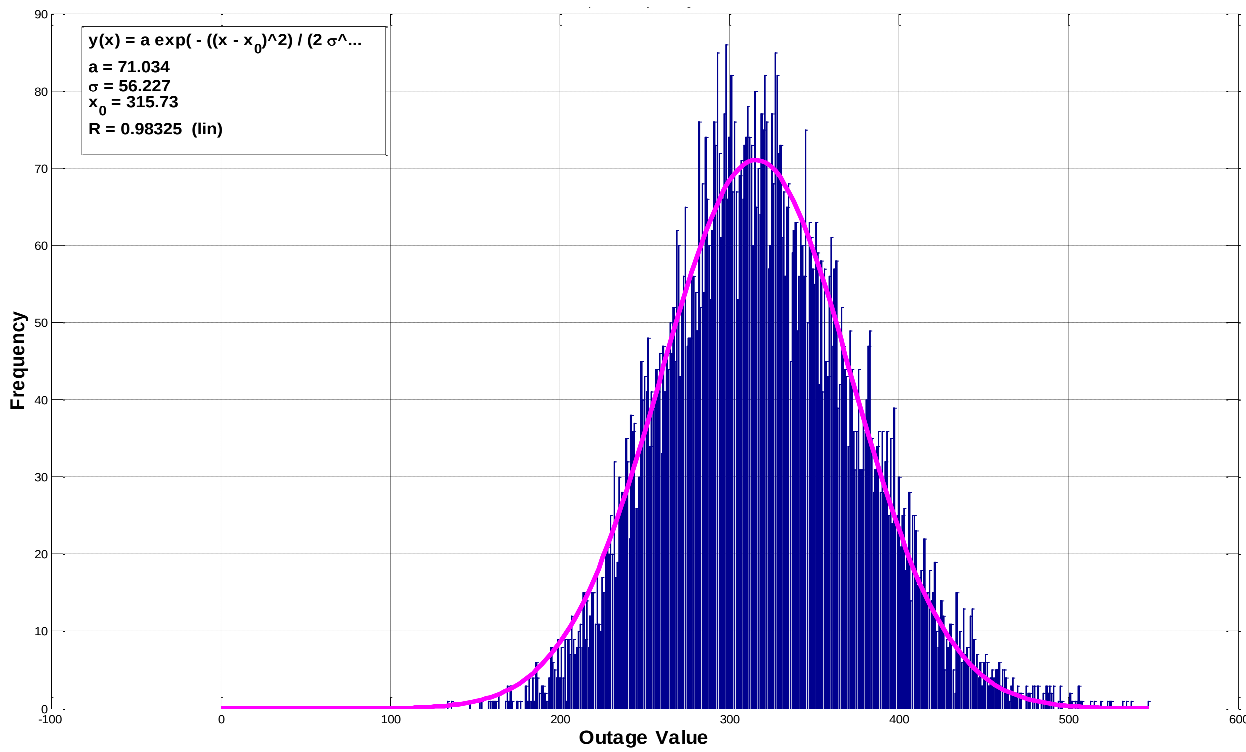



**Figure 6.9 Topeka Yearly Outages with 30% Outage Reduction**

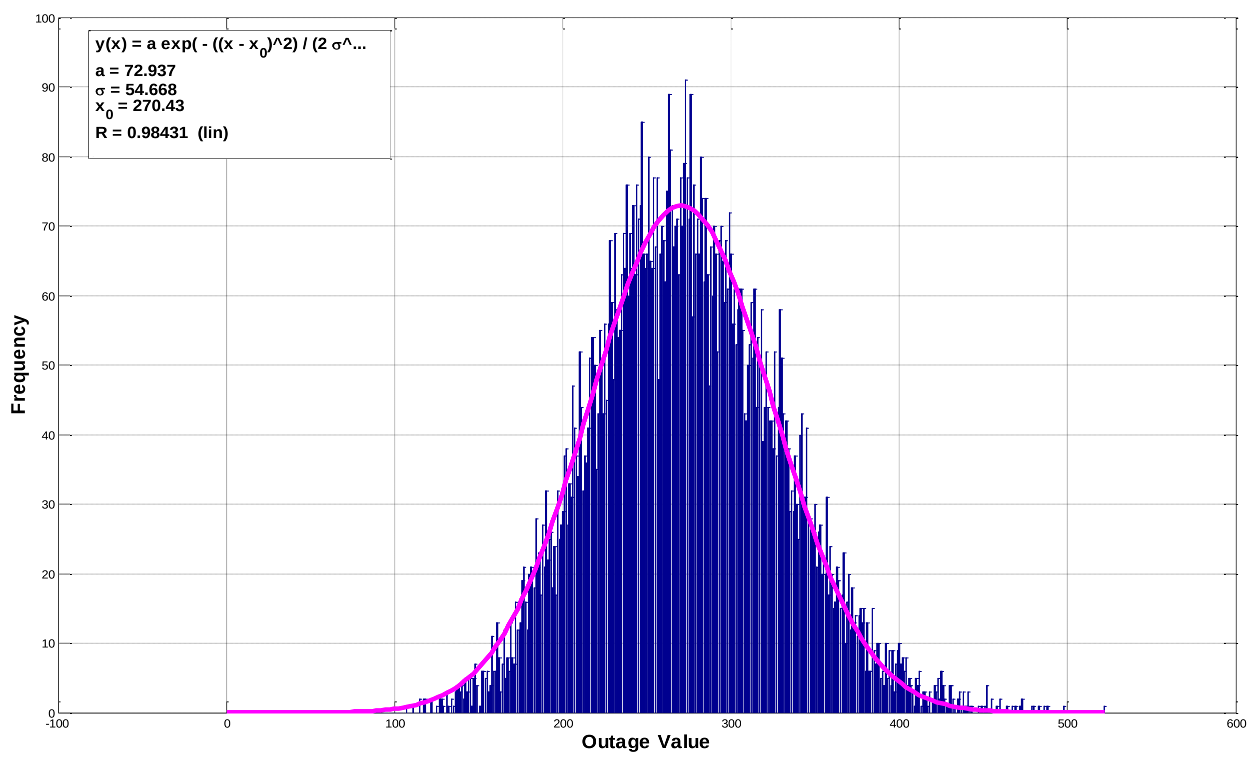



**Figure 6.10 Topeka Yearly Outages with 40% Outage Reduction**

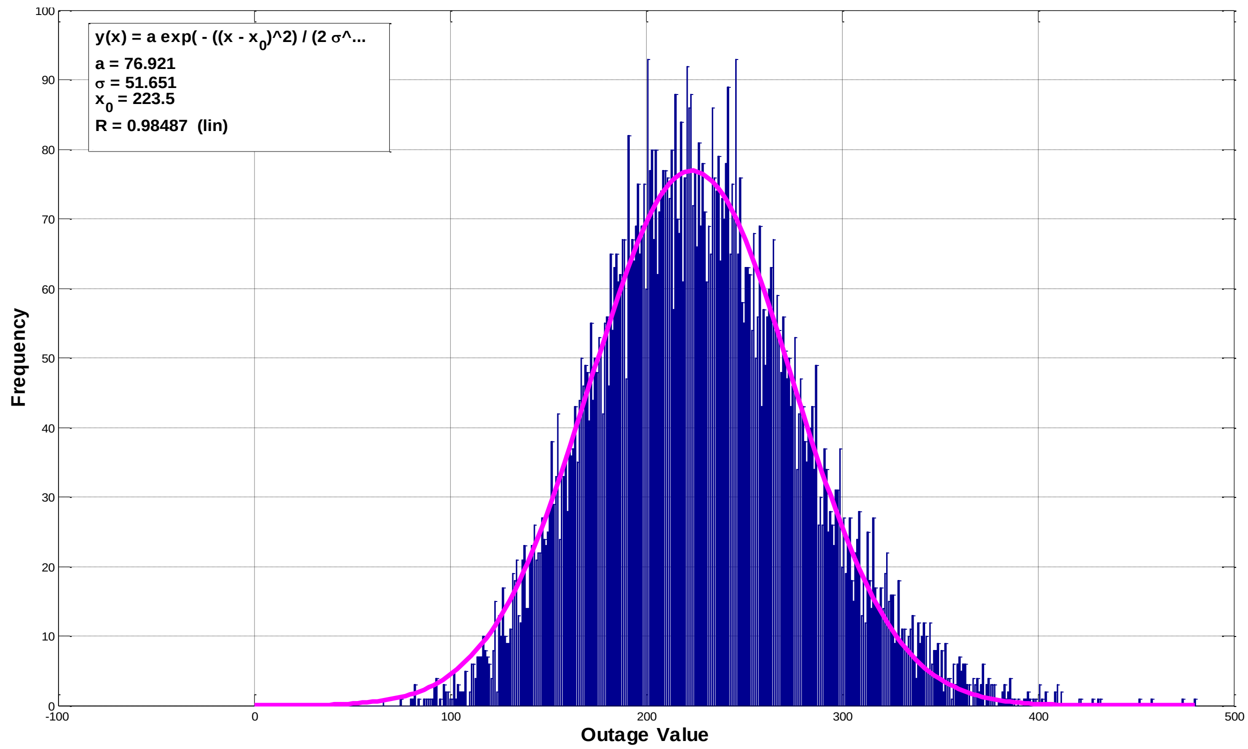



**Figure 6.11 Topeka Yearly Outages with 50% Outage Reduction**

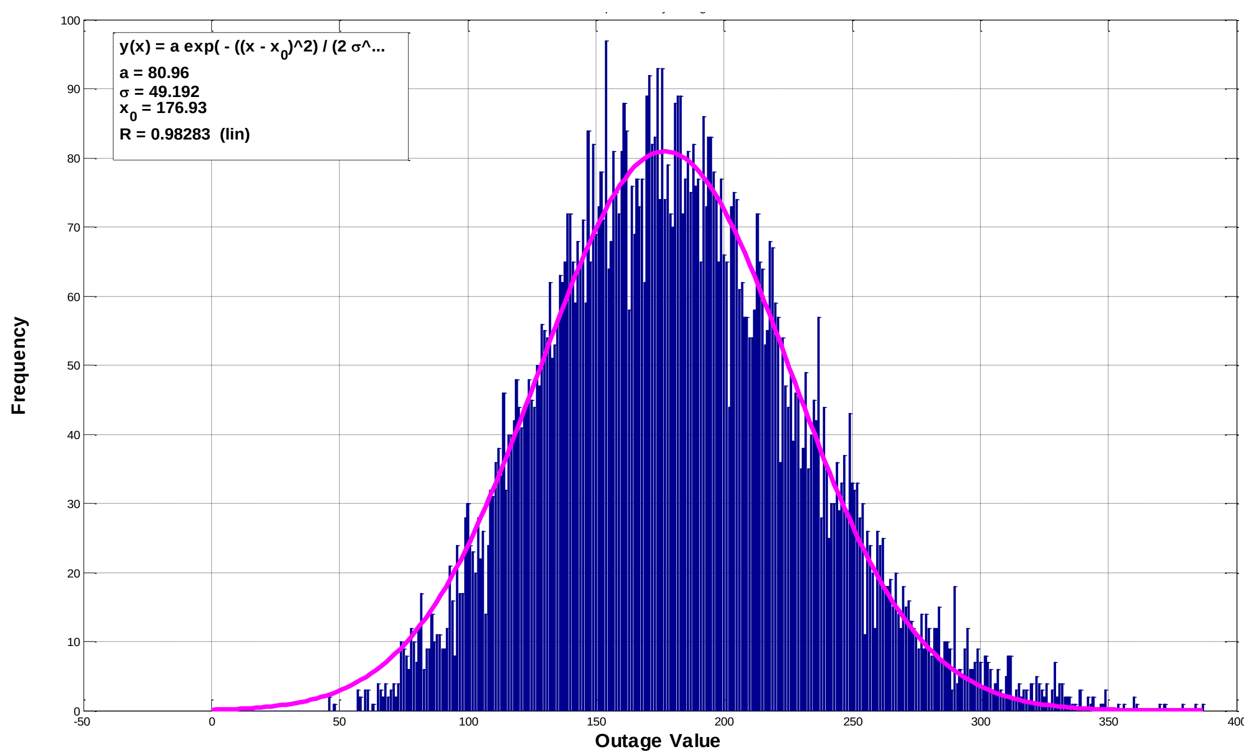



**Figure 6.12 Topeka Yearly Outages with 60% Outage Reduction**

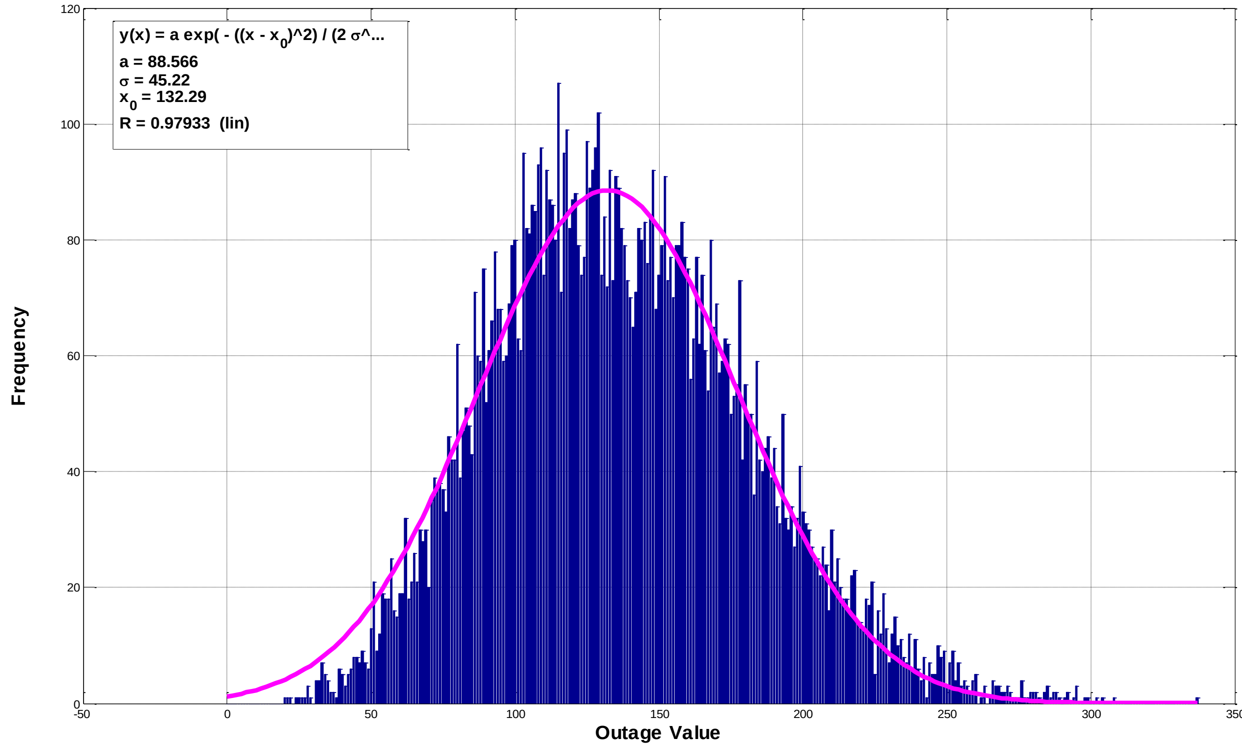



**Figure 6.13 Topeka Yearly Outages with 70% Outage Reduction**

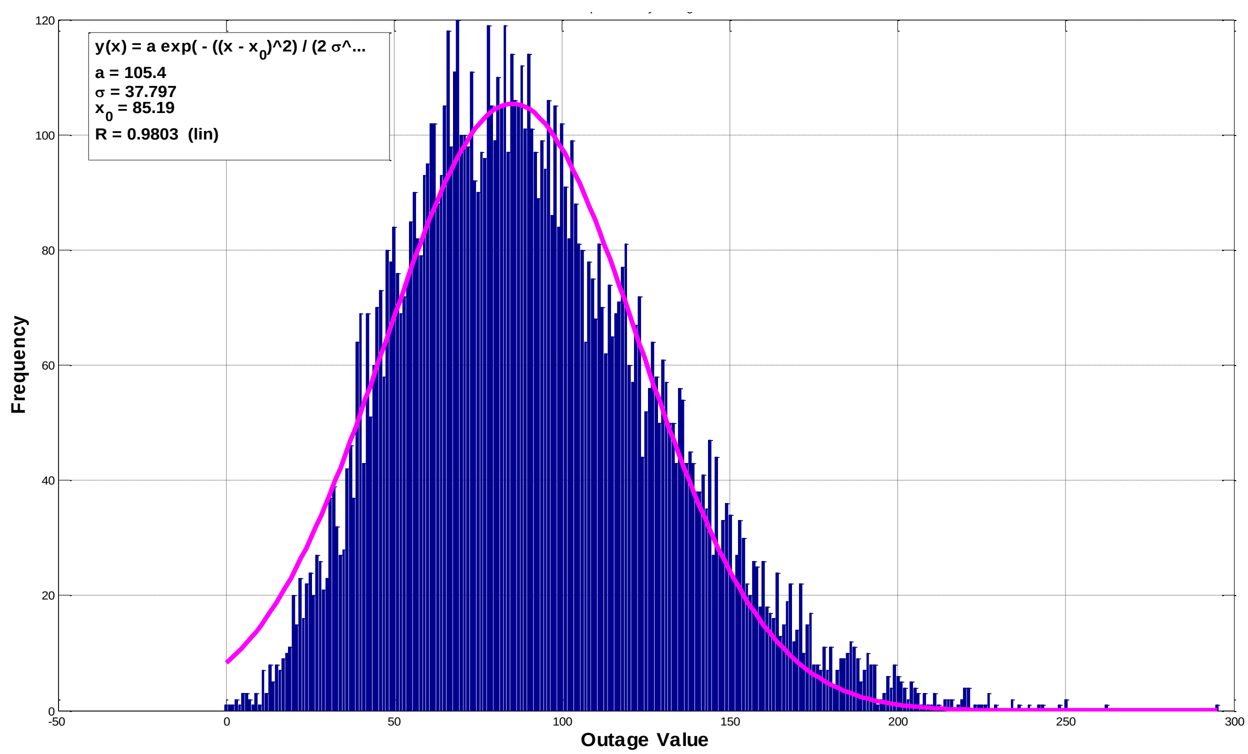



**Figure 6.14 Topeka Yearly Outages with 80% Outage Reduction**

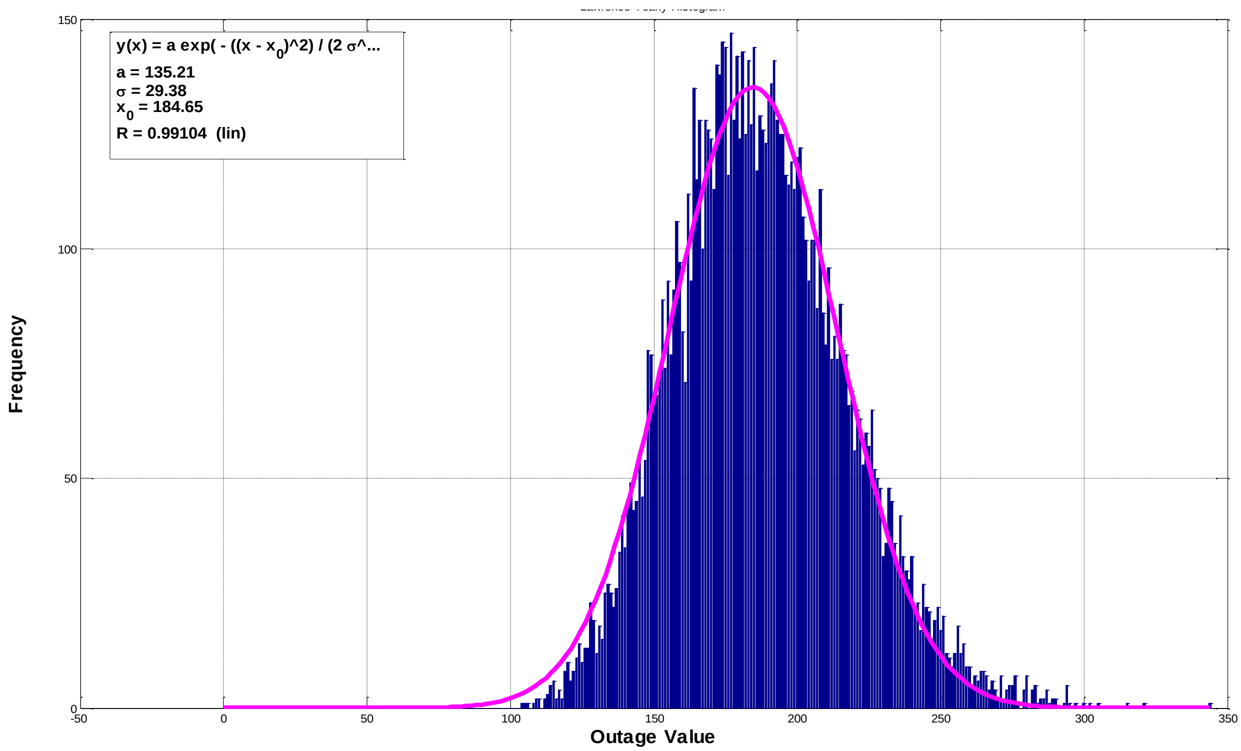



**Figure 6.15 Lawrence Yearly Outages with 10% Outage Reduction**

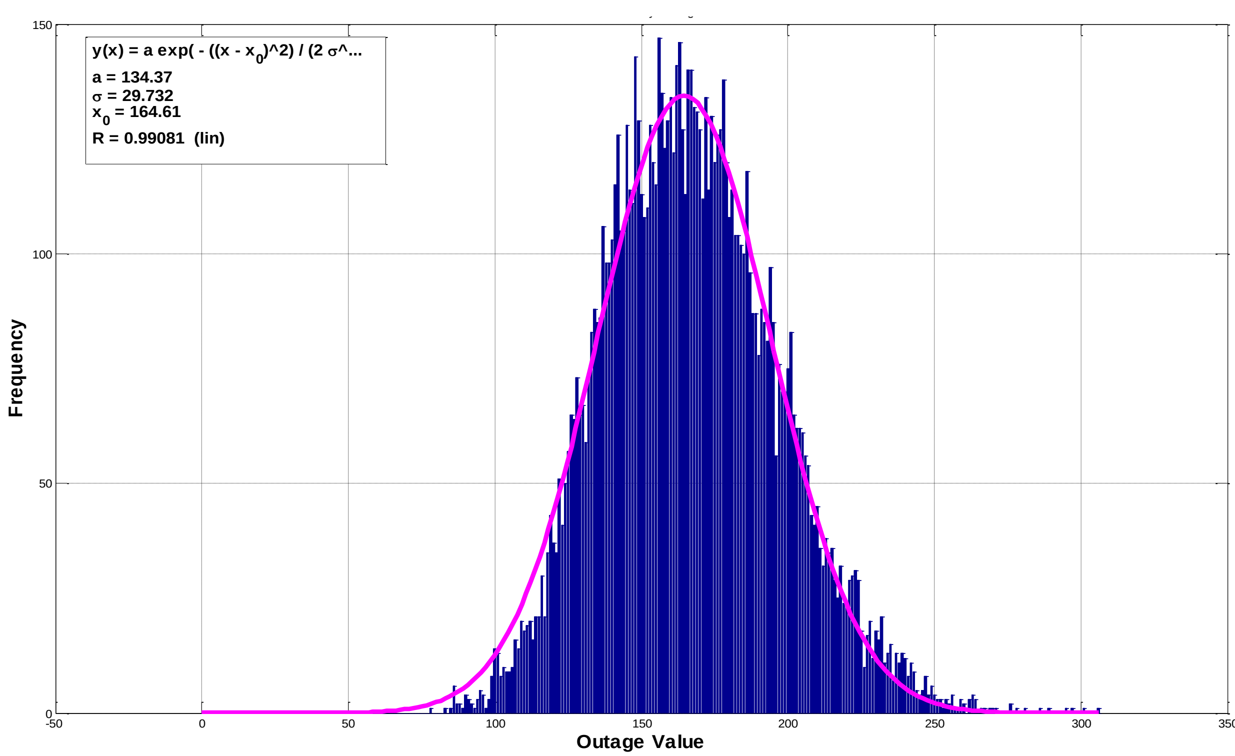



**Figure 6.16 Lawrence Yearly Outages with 20% Outage Reduction**

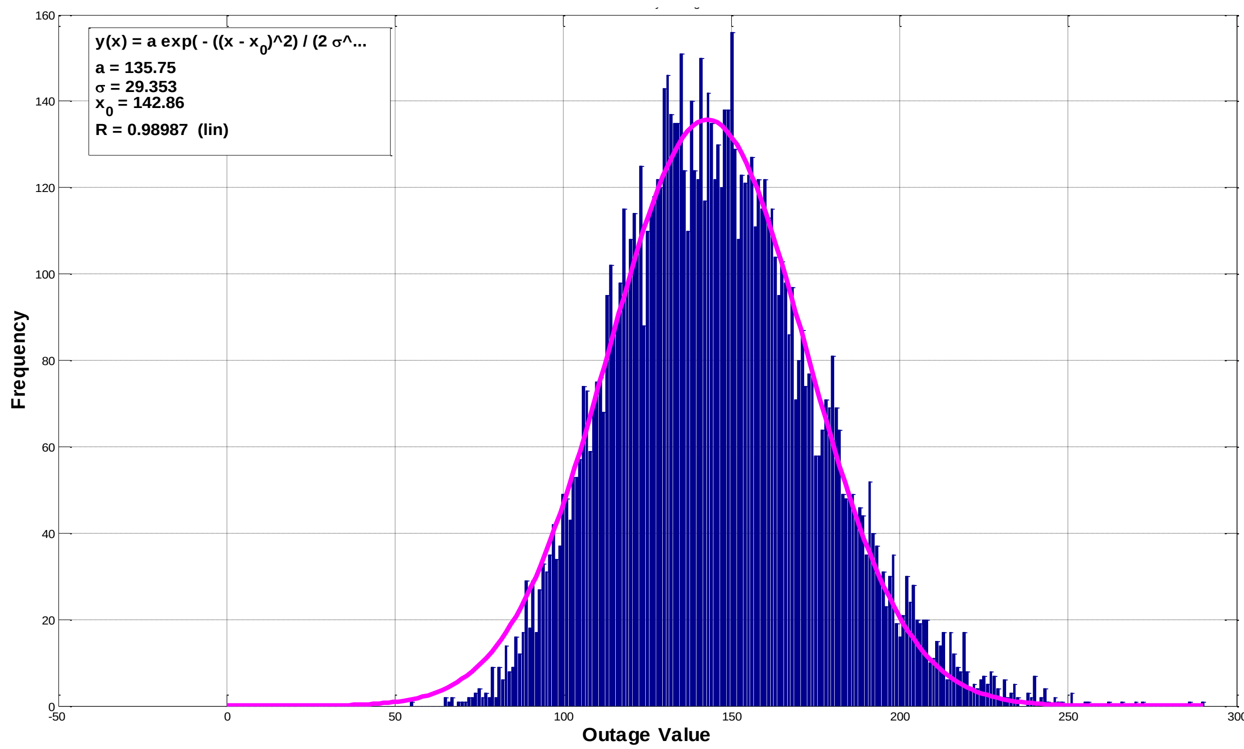



**Figure 6.17 Lawrence Yearly Outages with 30% Outage Reduction**

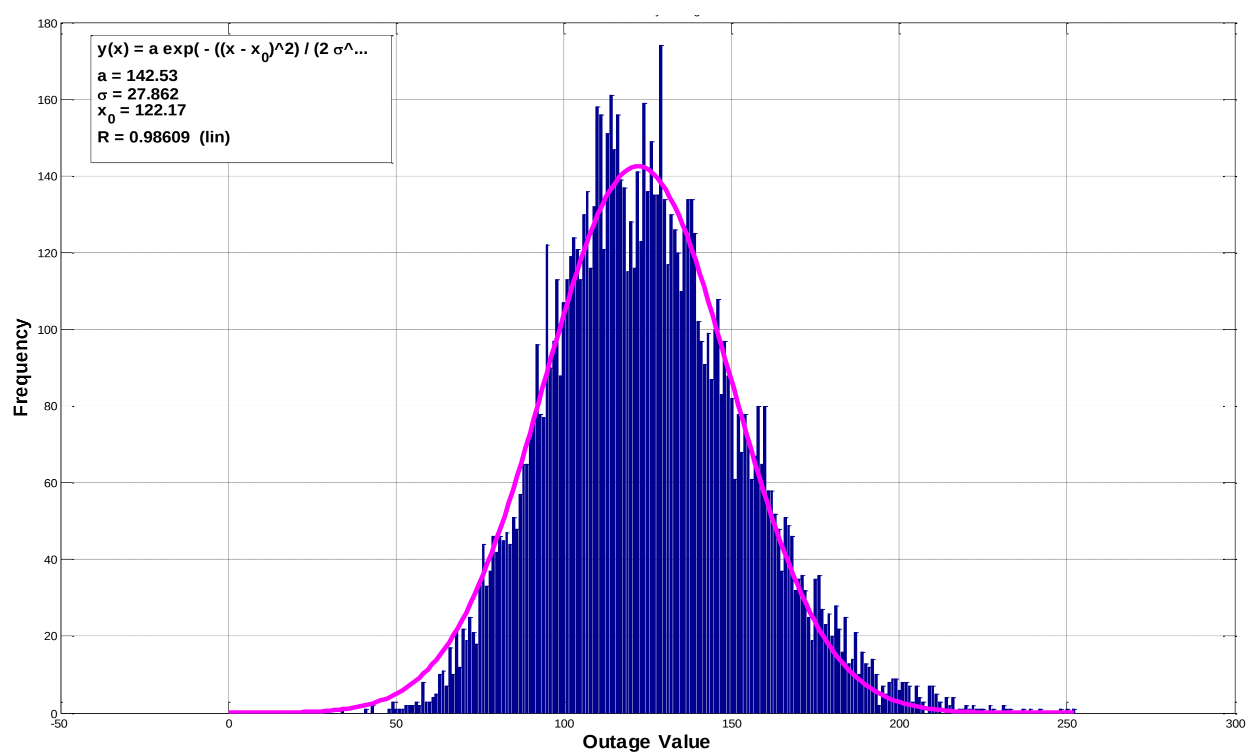



**Figure 6.18 Lawrence Yearly Outages with 40% Outage Reduction**

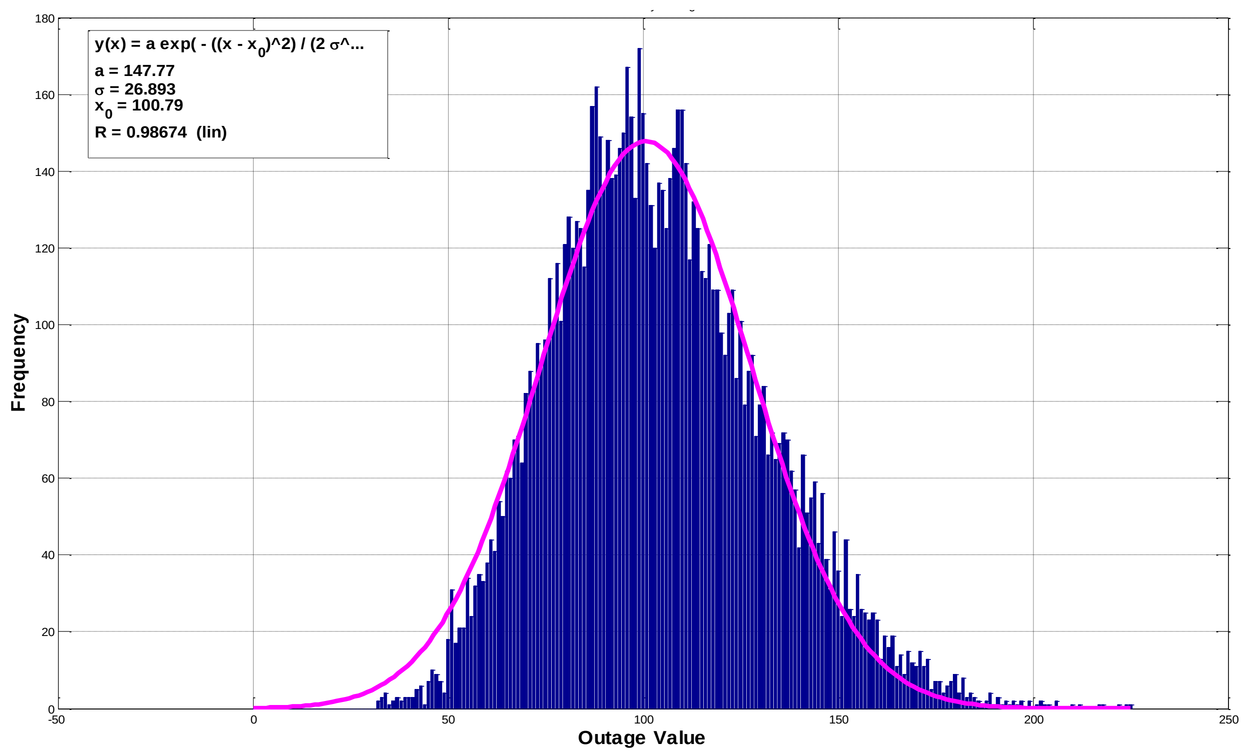



**Figure 6.19 Lawrence Yearly Outages with 50% Outage Reduction**

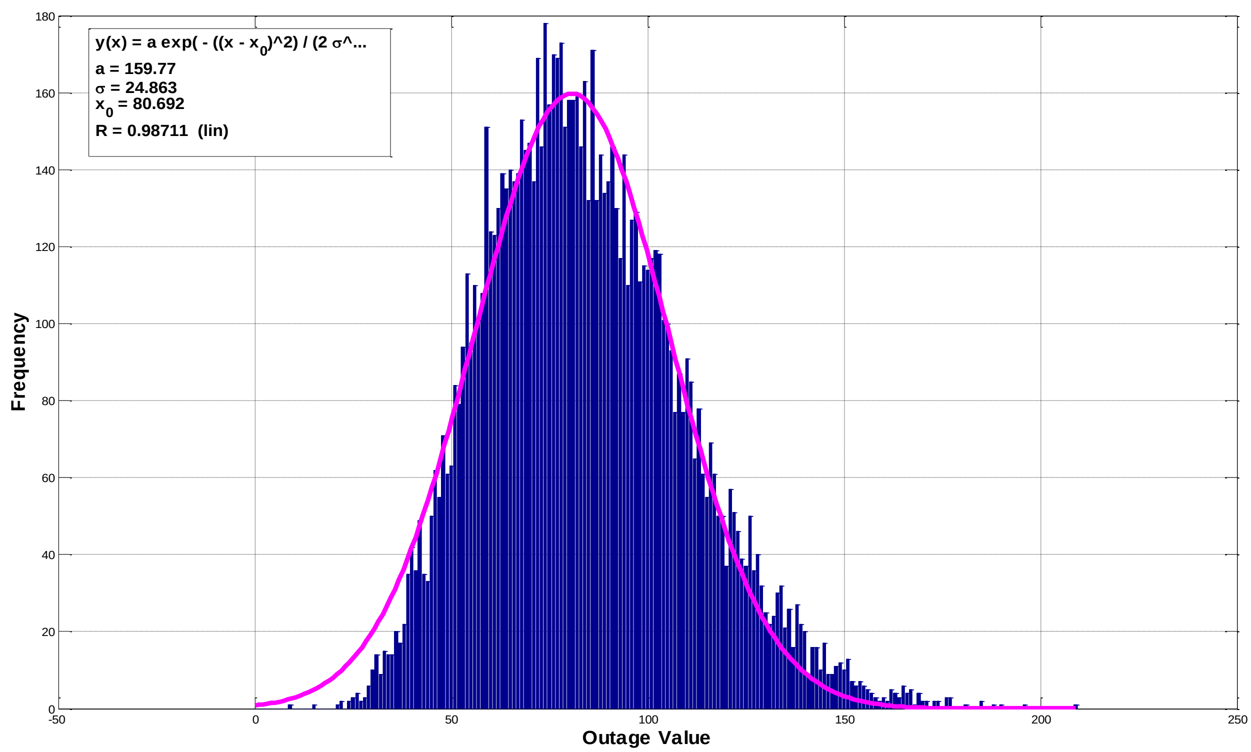



**Figure 6.20 Lawrence Yearly Outages with 60% Outage Reduction**

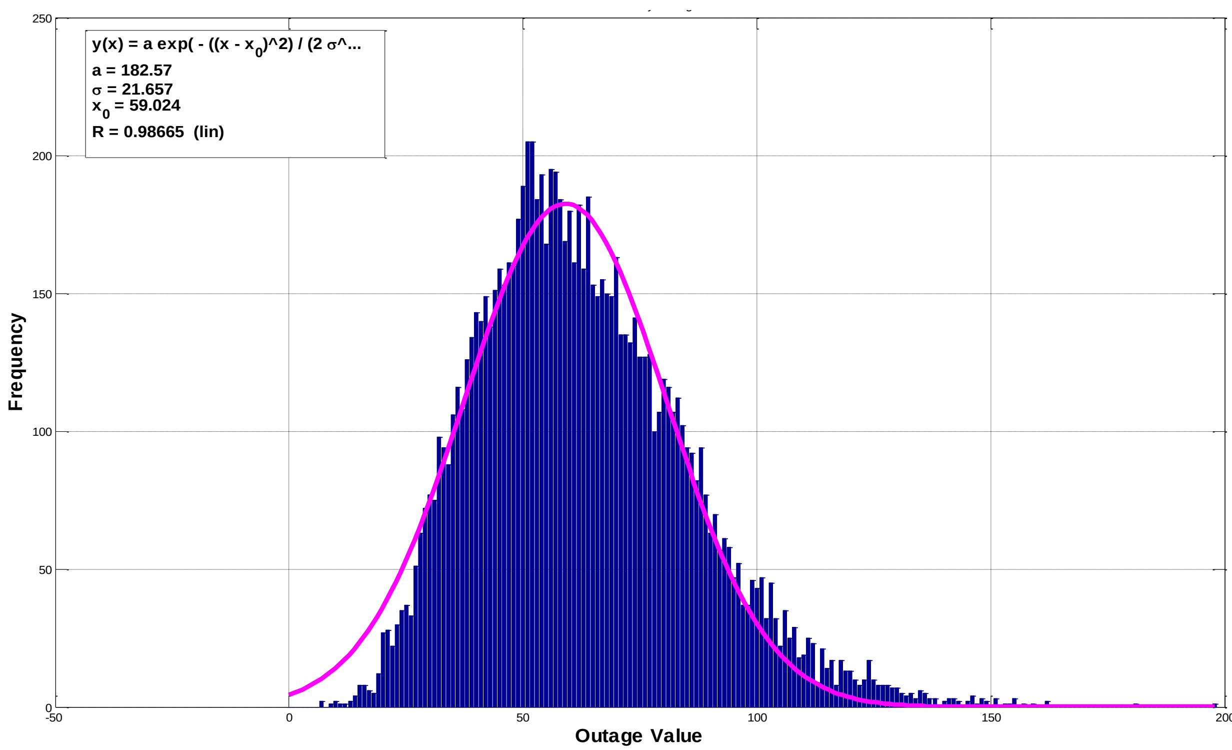



**Figure 6.21 Lawrence Yearly Outages with 70% Outage Reduction**

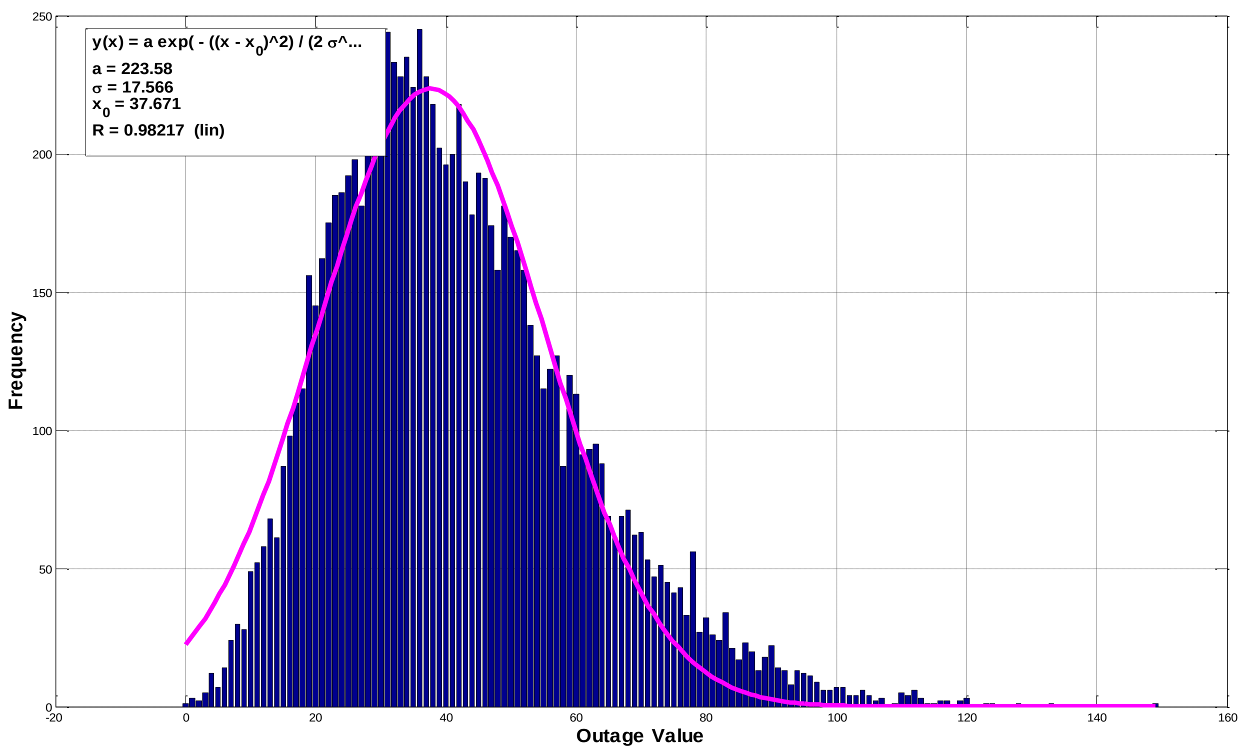



**Figure 6.22 Lawrence Yearly Outages with 80% Outage Reduction**