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A Weather Related Causal Analysis on Consolidated Delay At Newark Liberty International Airport

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TABLE OF CONTENTS

Acknowledgements 8
Abstract 9
1. CHAPTER 1 Introduction 10
1.1 Background 10
1.2 Motivation 10
1.3 Objectives 14
1.4 Dissertation Outline 14
2. CHAPTER 2 Literature Review 16
2.1 Graphical Models 16
2.2 Bayesian Networks 16
2.3 Characteristics of Bayesian Networks 17
2.4 Learning in Bayesian Networks 17
2.4.1 Structure Learning 18
2.4.2 Parameter Learning 18
2.4.3 Unobserved Nodes 18
2.5 Advantages and Disadvantages of Bayesian Networks 19
2.5.1 Advantages 19
2.5.2 Disadvantages 20
2.6 Belief Updating 20
2.7 Temporal Frames 21
2.8 Dynamic Bayesian Network 22
2.9 Bayes Inference 22
2.10 Exact Algorithms 22
2.11 Approximate Algorithms (Stochastic Sampling) 23
2.12 DBN Tools 25
2.12.1 Netica 25
2.12.2 GeNIe 25
3 . CHAPTER 3 System Proposal 26
3.1 Proposal of Hypothesis 26
3.2 Research Sources and Tools 26
3.2.1 Newark Liberty International Airport 26
3.2.2 Web Data Sources 27
3.2.3 FlightAware 27
3.2.4 Wunderground 27
3.2.5 GeNIe 27
3.2.6 Web Scraping Tool 28
3.3 Scope and Limitations of Study 29
3.3.1 Scope of Study 30
3.3.2 Limitations of Study 30
3.4 Model Parameterisation 31
3.5 Weather Concepts and Delay Definition 32
3.5.1 Precipitation 33
3.5.2 Wind 34
3.5.3 Visibility 35
3.5.4 Delay Definition 36
4. CHAPTER 4 Data Collection and Integration 37
4.1 Data Input 37
4.1.1 Flight Information (FlightAware) 37
4.1.2 Weather Information (wunderground) 41

University of Cape Town

4.2 Weather Related Delay Analysis 44
5 . CHAPTER 5 Design Analysis and System Evaluation 47
5.1 Network Experimentation Analysis 47
5.2 Weather Analysis Considerations 48
5.2.1 Visibility Analysis (Heuristic) 48
5.2.2 Precipitation Analysis (Heuristic) 50
5.2.3 Wind Analysis (Heuristic) 52
5.3 Weather Information 56
5.4 Consolidated Information (Weather & Aviation) 58
5.5 Experimental Results 60
5.5.1 Precipitation Analysis 61
5.5.1.1 Temporal Network Topology for Precipitation 61
5.5.2 Visibility Analysis 66
5.5.2.1 Temporal Network Topology for Visibility 66
5.5.3 Wind Analysis 71
5.5.3.1 Temporal Network Topology for Wind 71
5.5.4 Validation Results in GeNIe 75
6 . CHAPTER 6 Conclusion 77
6.1 Precipitation 77
6.2 Visibility 78
6.3 Wind 78
6.4 Summary 79
Bibliography 81
Glossary of Terms 85
Appendix 87
1.1 Temporal Order 88
1.2 Node Property 88
1.3 Delay Node 90
1.4 Validation (Delay by Precipitation) 92
1.4.1 Import Data File 92
1.4.2 Learn Network 92
1.4.3 Learn Parameters 94
1.4.4 Validation Results 95
1.5 Validation (Delay by Visibility) 97
1.5.1 Import Data File 97
1.5.2 Learn Network 98
1.5.3 Learn Parameters 100
1.5.4 Validation Results 100
1.6 Validation (Delay by Wind & Direction) 101
1.6.1 Import Data File 101
1.6.2 Learn Network 101
1.6.3 Learn Parameters 103
1.6.4 Validation Results 104

University of Cape Town

TABLE OF FIGURES

Figure 1: Integration of System Process 37
Figure 2: Flight Details Page in flightaware.com 39
Figure 3: Graph Structure for Airport Delays 44
Figure 4: Temperature & Dew Point Graph (March-June 2010) 48
Figure 5: Barometric Pressure Graph (March-June 2010) 49
Figure 6: Daily Traffic Movements at KEWR (Source: Drotleff et al. 2010) 49
Figure 7: Hourly Weather Observations at KEWR (30 March 2010) 51
Figure 8: Wind and Gust Graph (March-June 2010) 51
Figure 9: Newark Liberty International Airport Approach Chart (Source: flightaware.com) 53
Figure 10: KEWR Maximum Allowable Winds Chart (Source: Allan et al. 2001) 54
Figure 11: Combinations of Wind Directions Chart at KEWR (Source: Minnesota Climatology Working Group) 55
Figure 12: Wind Rose Data for KEWR (Source: Iowa Environmental Mesonet 1948 – 2012) 56
Figure 13: Barometric Pressure at KEWR (March 2010) 57
Figure 14: Temperature and Dew Point at KEWR (March 2010) 57
Figure 15: Temporal DBN Nodes for Precipitation 61
Figure 16: Temporal Node Graph for Precipitation in GeNIe 62
Figure 17: Detailed Chart for Precipitation in GeNIe 63
Figure 18: Detailed Delay Graph for Precipitation in GeNIe 63
Figure 19: Temporal Network for Precipitation (Nodes 1-3) 64
Figure 20: Temporal Network for Precipitation (Nodes 4-5) 64
Figure 21: Temporal DBN Nodes for Visibility 66
Figure 22: Temporal Node Graph for Visibility in GeNIe 67
Figure 23: Detailed Chart for Visibility in GeNIe 67
Figure 24: Detailed Delay Chart for Visibility in GeNIe 68
Figure 25: Temporal Network for Visibility (Nodes 1-3) 69
Figure 26: Temporal Network for Visibility (Nodes 4-5) 69
Figure 27: Temporal Network for Wind and Direction (Nodes 1-3) 71
Figure 28: Temporal Network for Wind and Direction (Nodes 4-5) 72
Figure 29: Detailed Delay Chart for Wind in GeNIe 73
Figure 30: Detailed Chart for Wind in GeNIe 74
Figure 31: Detailed Chart for Wind Direction in GeNIe 74
Figure 32: GeNIe – Enabling Temporal Plate 87
Figure 33: Time Step Count Dialogue Box 87
Figure 34: Temporal Order Dialogue Box (Delay Node) 88
Figure 35: Properties Dialogue Box (Delay Node) 89
Figure 36: Discretised Values Normalised in the CPT in GeNIe 90
Figure 37: Delay Node Discretisation in Excel Pivot Table 90
Figure 38: Delay Node Discretisation in GeNIe 90
Figure 39: Data Import for Precipitation (CSV format) 92
Figure 40: Learn New Network for Precipitation in GeNIe 93
Figure 41: Automatic Data Training for Precipitation by GeNIe 93
Figure 42: Learnt Network for Precipitation by GeNIe 94
Figure 43: GeNIe Automatic Results for Precipitation and Delay 94
Figure 44: Learning Parameters for Precipitation in GeNIe 95
Figure 45: Learning Parameters for Precipitation with EM in GeNIe 95
Figure 46: Validation Dialogue Box for Precipitation in GeNIe 96

University of Cape Town

Figure 47: Validation Results for Delay in GeNIe (Precipitation) 97
Figure 48: Data Import for Visibility (CSV format) 98
Figure 49: Learn New Network for Visibility in GeNIe 99
Figure 50: Learnt Data Network for Visibility by GeNIe 99
Figure 51: Learnt Parameter Results for Visibility in GeNIe 99
Figure 52: Learn Parameters for Visibility in GeNIe 100
Figure 53: Validation Results for Delay in GeNIe (Visibility) 100
Figure 54: Data Import for Wind & Direction (CSV format) 101
Figure 55: Learn New Network for Wind & Direction in GeNIe 102
Figure 56: Learnt Network for Wind & Direction in GeNIe 102
Figure 57: Validation Results for Wind & Direction in GeNIe 103
Figure 58: Learnt Parameters for Wind & Direction in GeNIe 103
Figure 59: Validation Delay Results in GeNIe (Wind & Direction) 104

University of Cape Town

LIST OF TABLES

Table 1: Consolidated Weather and Delay Data in Excel (Source: Wundergound and Flightaware) 59
Table 2: Pivot Table Analysis for Consolidated Delay 59
Table 3: GeNIe Validation Results 76
Table 4: Normalized Bins in Excel Pivot Table 89

University of Cape Town

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University of Cape Town

Abstract

The closure of the European airspace due to the eruption of the Icelandic volcano Eyjafjallajokull in 2010 proved a major challenge for airlines and aviation authorities on a global scale. In contrast, more seasonal adverse meteorological conditions afflict many airports in the northern eastern seaboard of the United States. Newark Liberty International Airport (KEWR) is a representative airport that endures severe weather based delays.

This dissertation explores the utilisation of Bayesian Networks (BN) and heuristic analyses to investigate weather based delays at Newark Liberty International airport (KEWR). In particular, it aims to understand which weather variables (namely, precipitation, visibility and wind) have the most impact on weather based delays at KEWR in contrast to past studies that have studied more generic weather phenomena (e.g. thunderstorms) at the same airport.

An analysis using temporal functionality with Bayesian Networks (BN) software and heuristic analyses was conducted. Data extracted from weather and aviation based websites was extracted using software. The quality of the information was cross referenced with official data sources and validated using BN tools.

The results revealed a causal correlation chain between crosswinds above a certain threshold and high delays at KEWR at various points in the experimentation. Though other meteorological elements examined had an impact on delays, airport authorities and airlines can mitigate these factors to a certain scale using Federal Aviation Authority (FAA) approved technology and training.

Consequently, the implications could be significant on existing FAA and regional policy with Ground Delay Program (GDP) and Noise Abatement Procedures (NAP). These policies can be profound and far reaching for airlines, in terms of operating procedures and fuel cost implications. These findings can further alter the balance between efficiency, public safety and airline costing affecting all major stakeholders as this dissertation will investigate.

University of Cape Town

1. CHAPTER 1 Introduction

1.1 Background

Commercial aviation can be categorised into business and personal segments, and is utilised by public institutions and private corporations as an engine for economic growth at a local and global level. Airport delays are considered a major inhibitor to this catalyst of growth, constraining both global airport infrastructure and airline network capacity. Constraining factors are varied in nature, but typically comprise financial, economic, technical, political and meteorological dimensions.

Though the causes of delays are often complicated and involve a multiplicity of factors, it is the lack of adequate advance warning systems that affect passenger ability to predict airport delays and organise alternative transport arrangements.

Adverse meteorological conditions are a contributing factor obliging Air Traffic Control (ATC) to reduce air traffic density both on approach and departure at airports for safety considerations. This has an impact on arrivals and departures at numerous regional airports.

Effective resource allocation has improved airline delays caused by airspace capacity restraints normally handled via Ground Delay Programs (GDP) through Air Traffic Control Management (ATCM) centres. These compulsory ground delays act as a buffer to prevent airborne delays, reducing airborne traffic density by delaying departing aircraft. Airlines are cognizant of the fact that a delicate balance of airborne delays exists and must be balanced sensitively with airline service punctuality. Noise Abatement Procedures (NAP) are also an important consideration for departing aircraft in reducing their noise footprint in the airport vicinity.

In summary, many of the delay factors are beyond the control of both airlines and local airport authorities. Most delays can be measured and managed comfortably through more effective management practices. However, where delays are of a meteorological nature, this is more difficult to predict and manage.

1.2 Motivation

The main motivation for the research in this dissertation centres on gaining an insight into why airlines experience delays at airports. In particular, this dissertation is interested in exploring the temporal causal patterns of delays linked to weather phenomena, with emphasis on precipitation, visibility and wind.

The inability of airlines to effectively manage weather uncertainty has financially

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impacted the aviation industry. The aviation sector has already been suffering from waves of bankruptcies in the 1980s and again from the Global Financial Crisis (GFC) from 2008 until the present day. During this time, the airlines have been forming alliances for competitive advantages with global reach as well as consolidating market segments of geographical reach. The seasonality coupled with weather variability has only added to the industry woes. The US and European aviation authorities seek a smooth transition for their national carriers into key but volatile markets internationally as enablers of vital infrastructure that will promote economic growth and prosperity.

The Federal Aviation Authority (FAA) has issued directives dealing with publicly funded Airport Improvement Programs (AIP) at airports in the United States that deal with pooling of resources in the short and long term. The Airport Cooperative Research Program (ACRP) performs applied research on problems shared by airport operating agencies, with various deterministic models that measure simple-trend analysis in a time series extrapolation (i.e. year on year).

The blanket ban on flights in North American and European airspace in early 2010 due to the volcanic ash from Iceland's Eyjafjallajökull volcano encapsulates a perfect example of unpredictability in the airline industry.

Severe weather conditions with temperatures dropping below zero in double digits were experienced in Europe and on the eastern seaboard in North America in the early 2010s. This resulted in considerable delays in both domestic and transatlantic flights due to the severity of these weather environments. The unprecedented weather conditions undermined public confidence in air travel as a means of reliable transport.

Selecting suitable airport data to validate the hypothesis in this dissertation required a concerted effort to analyse data quantitatively and qualitatively from various sources, which are as follows:

- Accessibility of local aviation data[1] was unavailable to the general public due to commercial sensitivities. Alternative electronic means of gathering local aviation data proved unsatisfactory in validating the hypothesis, due to the low quality and volume of data encountered.
- A range of the busiest US airports was considered in this investigation to measure the appropriateness in exploring the sensitivity, frequency and impact of adverse weather delays at airports, given the comprehensive and high-quality data encountered.

New York City Terminal Area was deemed a suitable location for the investigation, due to the complex interaction of convective weather systems in the US Northeastern Seaboard Corridor and therefore, it became a natural choice. This was also due to the suitability of the relevant airport data. The airports comprising this terminal area are:

- Newark International Liberty International Airport (KEWR)
- John F. Kennedy International Airport (JFK)
- La Guardia International Airport (LGA)
- Teterboro International Airport (TEB)

[1] South African Civil Aviation Authority

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Other US airports that were deemed suitable for extracting weather-related data to test the hypothesis are:

- Atlanta Hartsfield International Airport: A study by Robinson (1989) on weather-related delays concluded that maximum delay per operation was caused initially by heavy fog, followed by thunderstorms and visibility respectively.
- Chicago O'Hare International Airport: Weber et al. (1991) concluded that in the North Eastern US, thunderstorms ranked top in causing weather-related delays, followed by heavy fog and reduced visibility respectively.
- San Francisco International Airport: Clark et al. (1997) concluded that weather-related delays were due to limited visibility from the marine stratus, followed by seldom-occurring thunderstorms.

Furthermore, the majority of weather-related conditions described at the above airports related to Instrument Meteorological Conditions (IMC). However, some weather-related delays such as high-surface winds, afar and in the vicinity of an airport in the NY Terminal Area, occurred under Visual Meteorological Conditions (VMC).

As an example, high winds, related to IMC after a front had passed, were clearly an important cause of delays at KEWR. This non-obvious weather phenomenon was observed by Allen et al. (2001) in KEWR, one of the four major airports in the NY Terminal Control Area. This made KEWR a very suitable candidate for using its data to test the hypothesis in this investigation, since no other airport presented these unique weather conditions. Also, KEWR had been listed as one of the top US airports for weather-based delays, based on recent historical data (Evans 2002).

Furthermore, this weather phenomenon can only be explained by the complex interaction of weather systems (especially in winter) in the north eastern corridor of the United States. This greatly affects the vicinity of all the airports (mainly KEWR), which are already in a highly congested airspace.

To this end, sensitivity, frequency and impact on scheduled airline operations relating to airport capacity and airspace congestion in the NY Terminal Control Area, are all factors affecting delays at KEWR.

According to the FAA Airport Capacity Benchmark Report, the reduction in capacity at KEWR due to adverse weather is 24% of the average VFR capacity. This figure rests in contrast to the higher than average 31 busiest airports in the United States (21.43% of average VFR capacity) (Allan et al. 2001).

The sensitivity of adverse weather to airport delays at KEWR (especially high departure delays), stems from the fact that due to runway and gate limitations (i.e. high gate utilisation), departing flights are pushed back instead of waiting at the gates, in order to make space for arriving traffic.

Other constraining factors that prevent KEWR's parallel runways being used for independent IFR parallel approaches is the limited spacing of only 950 feet between them. Runway 11-29 is too short for many jet operations and is therefore, limited to smaller regional domestic flight sectors.

The impact of weather on an airline's schedule is proportional to the scheduled activities. This is in relation to the normal airport capacity versus adverse weather capacity. Clearly, airports overscheduled in capacity in normal VFR conditions, will be even more so in IFR conditions. Consequently, a decrease in capacity caused by adverse weather early in

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the day severely impacts the chances of recovery improving throughout the day. Most flight control is performed before departure, and naturally, the majority of the inefficiencies, and thus delays, manifest in departure operations. (Allan et al. 2001)

According to the Air Transportation Association (ATA), in 1999 and 2000, KEWR had the highest ATC departure delays in the United States, with an average of 18.5 minutes, suggesting that ATC is a major contributor to delays at KEWR. This could partly be explained by the restrictions placed by ATC, with adverse weather affecting the balance of net traffic flow through KEWR (e.g. GDP). Hence, the most significant observation from Allan et al. (2001) is the close correlation between weather and the restrictions applied. Further observations conclude that downstream airspace capacity limitations were a primary flow constraint and the main cause of surface delays at KEWR.

Wind speed and direction are important safety factors because they determine the runways in use and dictate which arrival and departure procedures will be implemented at each airport in the NY Terminal Control Area. Wind direction is one of the most important factors in determining the routing of air traffic through the terminal space (Donaldson 2010).

High wind does not regularly feature in the highest root causes of weather-related delays, but it is nevertheless a category that is often overlooked when considering what type of weather leads to delays.

It was found that strong surface winds had a very significant negative impact on airport operations at KEWR. Convective weather was found to be the leading contributor to delays at KEWR between September 1998 and August 2000. It was further uncovered from the study conducted by Allen et al. (2001) that 40% of arrival delays occurred in association with delay days characterised by convective weather, both within and at a considerable distance from the New York Terminal Area.

These delay causality results are very important for studies on the effectiveness of changes made to the US aviation system to reduce delays at airports such as KEWR, as well as prioritising FAA research and development expenditure.

Moreover, identifying good long-term solutions for delays would be problematic without an accurate source of information on the cause of the delay. For this purpose, a concerted effort has been made to estimate delays at an airport such as KEWR by relating the delay to any convective weather at, or a long distance away from the airport's location, and to determine if the delays are due to high winds in otherwise fair weather. This is a trait that has generally been ignored in all NY airport delay studies, including those at KEWR.

New benefit categories in departures during convective weather and high surface winds need to be considered in future studies of terminal weather information systems. The findings on the magnitude of delays at KEWR resulting from low ceiling/visibility and high winds suggest future research at NY should include the development of ceiling/visibility and surface wind prediction products that would aid in properly timing GDP's (Allan et al 2001).

Accurately attributing the cause of delay has become increasingly important, both to the aviation community and its users. A key finding of the study conducted by Allan et al. (2001) is that delay is a major problem of convective events, both near and far from KEWR. This suggests new technology and tools for traffic planners, particularly in a highly congested airspace like NY, need to focus not only on arrival problems, but equally, if not more, on departures.

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Hence, it is reasonable to assume that there is a causal relation between weather conditions and flight delays or cancellations. Cancellations are often caused by severe wind, rain, and fog banks. Airports' challenges during such conditions are not as difficult to predict as the delays that less severe weather phenomena may cause. With less severe weather (e.g. haze) it is difficult to estimate the possibility of delays and at which times during the day these are likely to occur is much harder to manage.

Striving to manage unpredictable meteorological environments is commonplace in the airline industry. The absence of reliable data due to commercial sensitivities makes it difficult to construct a model to analyse flight delays at airports, as previously mentioned.

Furthermore, to test the hypothesis, alternative experimental testing of temperature data from KEWR was conducted, but found to be inconclusive and weak and thus, not included in this dissertation. A more representative set of weather variables (namely precipitation, visibility and wind) was selected upon which to test the hypothesis. Hence,

this dissertation examines the use of Dynamic Bayesian Networks (DBN) and Excel heuristic modelling techniques for approximating airport delays based on weather data.

1.3 Objectives

The objective of this dissertation is to explore the application of BN and Excel heuristic modelling techniques to investigate the use of precipitation, visibility and wind forecasts in better approximating delays at an airport. The availability of suitable weather forecast and airport delay data is investigated, and the most appropriate weather and delay variables to study are selected. A DBN is constructed and its ability to estimate departure delays based on precipitation, visibility and wind information is presented.

While other weather variables like humidity and barometric pressure also influence convective weather systems, precipitation, visibility and wind, are deemed the most representative to understanding delays at KEWR (Allan, Gaddy, and Evans 2001). The first step is thus to see if suitable data can be found and then to determine if any other weather variable can likely be linked to airport delays.

In the absence of a free causal model for this dissertation, a Dynamic Bayesian Network and an Excel heuristic model will be constructed for the study.

Newark Liberty International Airport (KEWR) was chosen as the airport for the experimentation due to its high delay weather based history, as previously mentioned. The weather and delay information for this airport would be directly relevant in the causal modelling tool using DBN and Excel heuristic modelling. KEWR is located in the eastern seaboard of North America and is severely affected by weather systems in the winter season. Given its geographical location and delay history it represented an ideal airport for research in this dissertation.

1.4 Dissertation Outline

This dissertation also describes the use of DBN tools to study the link between weather conditions and airport delays.

In chapter 2, a literature review is conducted to review the different types of models

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considered to understand the impact causality can have in a network structure, especially with the updating of its node structure. Several tools are considered during this investigation, to predict which one has more potential for the experimentation conducted. Furthermore, a comprehensive analysis of all relevant algorithms that best befit the objectives will also be discussed.

In chapter 3, a hypothesis will be put forth to support or refute whether precipitation, visibility or wind can better approximate airport delays supported by the experimentation of the dissertation. To this end, the scope and technicalities of the model are discussed at length to understand the parameters utilised on the data within the objectives set in chapter 1.

In chapter 4, the system integration proposed is presented and discussed in detail, alongside the quality data sought and utilised during experimentation. Any data quality issues and their implications will be discussed in detail in this chapter.

In chapter 5, an exploratory design analysis will be presented in addition to the results of the experimentation which will be evaluated for the time period examined. This will initially begin with the network topology and observations for the weather variables investigated (i.e. precipitation, visibility and wind).

Lastly, chapter 6 will examine the conclusions reached from the empirical observations noted during the experimentation, where the hypothesis proposed in chapter 3 could be confirmed or refuted. Further recommendations on future research will also be addressed in this chapter.

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2. CHAPTER 2 Literature Review

In this chapter, a review into the available graphic models will be explored with particular emphasis on BN. A more detailed review will then follow on the particular advantages and disadvantages of using BN, to study the use of precipitation, visibility and wind forecasts as a better way of approximating delays at an airport. A general outline of the BN modelling tools will be given as assessment of the most suitable algorithm to understand how a causal network model can be used for approximating airport delays. The last section relates to articles that explain the relevance in this field of what has already been accomplished.

2.1 Graphical Models

A graphical model is probabilistic, showing conditional independence in a structure made up of random variables. This can be interpreted as a combination of probabilistic and graph theory. To this end it provides the ideal framework in resolving uncertainty and complexity that occurs frequently in applied mathematics and engineering (K. Murphy 2000).

Graphical probabilistic models can be divided into two main categories as follows:

- Acyclical Graphs (Directed): Included in this category are BN with a more sophisticated definition of independence which takes into account the direction of arcs. This network structure (topology) represents a factorisation of the joint probability of all random variables. Model parameters are represented in a Conditional Probability Table (CPT) for each node, where its probabilities depend on every combination of the parent node values.
- Cyclical Graphs (Undirected): These graphs mainly represent a Markov network with no direction in its arcs related to its graph structure. As such, Markov networks have a simple definition of independence, where two sets of nodes A and B are conditionally independent if all paths between A and B are separated by a third set C and are not subjected to any causal directionality (Russell and Norvig 2009).

2.2 Bayesian Networks

The nodes in a BN represent pre-chosen random variables and its arcs represent independence assumptions linking these nodes. This provides a framework representing joint probability distributions conveying a realistic outlook of linking temporal causal patterns to airport delays.

Why use Bayesian networks and not statistical methods to build a realistic predictor of

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airport delays?

The concept of softened logic compared to hardened probabilities refers to the fragile nature of Boolean logic when dealing with exceptions of hard data (Pearl 1988). If an observer were to assume that fog causes delay with a probability of 1, but the evidence amounted to some planes being able to operate at the airport during these conditions without delay, it would not be possible to accommodate that observation in a Boolean probabilistic framework. Hence it is assumed that once the truth is softened in Boolean logic, the truth-values are measured on a grey scale and these inconsistencies disappear (Pearl 1988).

In the research the following approach is used:

- Firstly to present a principle of causality as a way to infer the graph structure from the precipitation, visibility and wind data collected.
- Secondly, to apply the use of precipitation, visibility and wind forecasts as a way of approximating airport delays in a defined period via temporal causal patterns (i.e. time series).

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2.3 Characteristics of Bayesian Networks

BN can also have the following characteristics at the more fundamental levels described below:

a) Representation:

A probabilistic graphical model is a graph whose nodes represent random variables, and the lack of a link between nodes represents conditional independence assumptions. It can therefore be assumed that they provide a compact representation of joint probability distributions.

b) Parameter:

The most common assignment performed with Bayesian networks is probabilistic inference. In fact a graphical model specifies a complete Joint Probability Distribution (JPD) of all variables. Given the JPD, all queries relating to possible inference can be answered by summing out all irrelevant variables (marginalisation) through variable elimination, dynamic programming, approximation algorithms and inference in DBN.

c) Structure:

The two things to specify for a BN are: graph topology (structure) and the parameters of each Conditional Probability Distribution (CPD). It is possible to learn both of these from the data, but learning structure is much harder than learning the parameters (Korb and Nicholson 2004). Hidden nodes are variables whose values are unknown, hence learning becomes much harder when certain nodes are hidden or there is missing data rather than when everything is observed.

2.4 Learning in Bayesian Networks

There are three main types of inference in BN: structure learning, parameter learning and inference of unobserved nodes.

2.4.1 Structure Learning

In its most basic form a BN is defined by an expert and then inference is performed where this knowledge reduces the search space considerably (de Campos and Castellano 2007). In other applications the task of defining the graph structure is not feasible to construct manually and the graph structure and parameters of local distributions must be learned from historical data.

Reinforcement Learning (RL) is an area of machine learning that has been used in correlating factors in airport delays. Consequently, using an approximate dynamic programming algorithm as an approach increases the search space considerably, which has been solved with Bayesian inference using 'Markov Chain' Monte Carlo methods (Balakrishna, Ganesan, and Sherry 2008).

2.4.2 Parameter Learning

For a BN to be complete and be able to specify a complete JPD, it is necessary to specify for each node its probability distribution (conditional upon its parents). Often these conditional distributions include parameters which are unknown and must be estimated for the data. A normal approach would be to use the maximum likelihood, but direct maximisation of the likelihood or posterior probability is often too complex when unobserved variables are present. A good approach to this problem is the EM (Expected-Maximisation) algorithm which alternates computing values of unobserved variables (i.e. conditional on correctly observed data) and maximises the complete likelihood. Under a normal set of conditions this process converges on the maximum likelihood value for the parameters set.

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2.4.3 Unobserved Nodes

A Bayes network relates only to nodes that are related probabilistically through various degrees of causal dependency, resulting in reduced computational demand. Moreover, unobserved nodes not considered in a modelled solution may be excluded due to their high complexity in the solution or their lack of impact in the final estimation of the results.

The essence of Bayes methodology is to provide a mathematical law explaining how to modify the existing network state in the light of new evidence. Naturally, it allows scientists to combine new data with existing knowledge and expertise (Pearl 1985).

Bayes rule follows;

1. $$P(R = r \mid e) = \frac{P(e \mid R = r)P(R = r)}{P(e)}$$

Where P(R=r¦e) denotes the probability that a random variable R has a value r given evidence e. In this case, the denominator is just a normalising constant to ensure it adds up to 1 as per below; i.e. it can be computed such that summing all possible values of R in the enumerators comes to 1.

2. $$P(e) = P(R=0 \mid e) + P(R=1 \mid e) + \ldots = \sum_r P(e \mid R=r)\, P(R=r)$$

The above formula is referred to as marginal likelihood, and gives the prior probability of evidence (Pearl 1985). The importance of these formulas is directly relevant to this dissertation; evidence of weather and flight delay data has been used to calculate updated posterior probabilities, such that precipitation, visibility and wind forecasts can be used for approximating airport delays through temporal causal patterns.

It can be said that, 'The simplest conditional independence relationship encoded in a BN can be stated as follows: a node is independent of its ancestors given its parents, where the ancestor/parent relationship is with respect to some fixed topological ordering of the nodes' (Murphy 1998).

How can a node be independent of its ancestors given its parents if it has a fixed topological order?

In BNs, it is assumed that neither the model's structure nor the parameters change with time; i.e. the model is time invariant. It is possible to add extra hidden nodes that represent the current 'regime', hence creating various models to capture time similar to sequential shots from a camera. In the case where the state space can change over time, the model structure needs to be changed. DBN are appropriate to measure 'time variability' as they are also directed acyclical graph models representing dependencies between variables.

In general terms, hidden Markov models and linear dynamic systems represent the hidden state in terms of state variables and can have complex interdependencies. Hence, the graphical structures provide an easy way to visualise and specify these conditional independencies and allow parameters to be set for the model (Pearl 1988).

The probability values stored in a CPT are used to infer posterior probabilities of each node (i.e. given its parents). Hence, this approach of building a model reveals dependencies and independencies between nodes within a given search space. Using the underlying structure and Markov's property stating that all dependencies are explicitly modelled, a restriction of the problem of statistical inference (i.e. to utilise relevant nodes as evidence) can be used by way of Bayes theorem (Korb and Nicholson 2004).

2.5 Advantages and Disadvantages of Bayesian Networks

BN can be very powerful, with distinct advantages over other graph models in inferring posterior probabilities. The main advantages are as follows:

2.5.1 Advantages

- Bodies of knowledge can be easily organised and mapped out using cause-effect relationships amongst key variables (if known).

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- The causality or cause-effect between variables can be measured indicating the strength of the relationship. In this manner, factors, associations and probabilities can be adjusted and validated accordingly.
- BN are very powerful for integrating data and knowledge from a varied array of domains and sources (e.g. weather and aviation data).
- Bayesian Networks are proficient at handling complex uncertainty scenarios in a very intuitive manner.
- If data is missing, average or inferred values can be used to prevent outliers from skewing the data results.
- The graph is easily visualised and communicated to stakeholders (software permitting).
- Expert knowledge can be applied to nodes in the graph space in the form of numerical values.

2.5.2 Disadvantages

As noted above, the advantages of using BN are considerable compared to other statistical or graph models, but there are also shortcomings presented as follows:

- Considerable time can be required, computing and compromising on key numerical values in the CPT
- Watcheye and Pang (2004) have expressed concerns about the computational complexity of Bayesian Network inference. They record time exponential to network size complexity in computational terms, for solving multi-criteria problems involving a large number of nodes in the graph space.
- The value of BN as a stand-alone Decision Support Systems (DSS) is limited, since it requires all the components of the problem domain to be present in the graph space to be modelled in the BN (Castelletti and Soncini-Sessa 2007).

2.6 Belief Updating

Belief Updating is used to update a belief network with a new state of the network, having been changed from its previous state. Moreover, Bayesian updating takes fractions of a second in most practical networks the size of hundreds of nodes as opposed to non-Bayesian networks which incur heavy timing penalties. Belief Updating in BNs is a computationally complex task with algorithms being NP-hard (i.e. worst case scenario) as described by Cooper's work (1990). There are several efficient algorithms that make belief updating in graphs with many variables feasible. Pearl (1988) developed a message-passing scheme that updates the probability distribution for each node in a BN in response to observations of one or several variables. Lauritzen and Spiegelhalter (1988), Jensen, Olesen, and Andersen (1990) and Dawid (1992) proposed an efficient algorithm that first transforms the BN into a tree, where each node in the tree corresponds to a subset of variables in the original graph. The algorithm then exploits several mathematical properties of this tree to perform probabilistic inference, prior to updating.

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Regarding information that is represented in this BN graph, if there is evidence of an event having occurred, an update can be performed of the belief network. Hence with new evidence on nodes, updated values on a CPT can be populated to infer revised CPDs via belief updating to serve as better approximations to airport delays. The structure defined in a DBN represents a variable in time, i.e. a time slice. The complexity of variables and the graph structure can in many cases be reduced to allow for more efficient inference (node absorption). There are two types of reasoning for this as follows:

- Diagnostic Reasoning: Implies evidence for reasoning is available for the child node.
- Predictive Reasoning: Implies evidence is available for the parent nodes to reason regarding the state of its child node.

The construction of a BN consists of two phases which may be inferred from observing data (Korb and Nicholson 2004). The first phase is the structure in the graph topology; the second corresponds to the CPT that represents the strength of the directed arcs between the nodes storing the node probability values for this structure which must be learnt (Pearl 1996).

A typical approach for structured learning falls into two categories:

- Parameter based: The use of statistical techniques attempts to identify the dependencies and independencies between variables that exist in isolation where no expert knowledge is present (Korb and Nicholson 2004). In other cases, expert knowledge may exist and may be used to infer further relationships between variables in the network structure. A Bayesian network can then be used to analyse the pattern in these dependencies.
- Complete Structure: Using scoring metrics to evaluate performance compared to other structures, where the structure is then redefined until one is found that provides an effective solution. This approach is often less used, but has shown more favourable results in the long term for cases based on metric approaches (Korb and Nicholson 2004).

2.7 Temporal Frames

A BN can include a temporal network comprising nodes within a temporal plate. A temporal plate is a time dependent section or slices within the network that holds a measure of time. These temporal nodes are objects or variables that are observed and vary with time in units called ‘time slices’ (K. Murphy 2000). Time slices can be any unit of time - a second, hour, day, month or year relevant to the period of experimentation.

Time slices can then be observed as they change generating a trend or temporal causal pattern during an observed period of time. It is also feasible to model multiple nodes and observe how they vary with respect to each other in time, with initial and end conditions. A temporal arc is used to indicate how relevant past events are to the current conditions

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and once set, the probabilities relating to the time slice can be updated in the node properties made up of past and current conditions (e.g. t=0; t=1).

2.8 Dynamic Bayesian Network

Fairly frequently the value of a node variable is dependent, amongst other factors, upon its preceding time slice e.g. daily precipitation, visibility and wind are dependent on the previous day's values. DBN contains temporal arcs of temporal order P (positive integer), which denotes that the value of the child node in time slice T is dependent of the value of the parent node in time slice (T-P). Temporal arcs are typically used with temporal order P=1 and with the parent and child temporal node being the same in value and property, as with the example when the precipitation, visibility and wind depend on the previous day's values. This is typically applicable to other variables like relative humidity, barometric pressure, etc. Nevertheless, P can be set to an even earlier value if necessary, where the parent and child temporal node can differ in a more elaborate DBN. In general, a DBN can be greatly appreciated as an expanded static BN where supplementary nodes exist to characterise variables in previous time slices.

2.9 Bayes Inference

In this section, a review will be conducted of the most frequently used algorithms to address the challenges of Bayes Inference.

The increasingly complex area of Artificial Intelligence (AI) encompasses an area called Machine Learning (ML). This area of machine learning is engaged in the science of designing and developing algorithms for graphic structure learning. The primary aim of these algorithms is to identify patterns autonomously in the areas of complexity, followed by the manifestation of predictive behaviour of such algorithms from a sensory suite or pre-programmed database. Many applications can be reduced to BN inference, where researchers can use BN algorithms instead of specialised algorithms for every application.

Algorithms for inference in BNs fall into two main categories as follows:

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2.10 Exact Algorithms

Exact algorithms make no compromises on the accuracy of the solution. As such, they tend to be more computationally intensive than approximate algorithms.

In the past, a lot of emphasis was placed on the exact inferencing with two leading categories: variable elimination and recursive conditioning. This algorithm has a complexity that is exponential with graph tree width where its purest form of elimination and conditioning are named structure-based as their complexity is only sensitive to the graph structure. The tree width measure parameter is only concerned with the resemblance of a graph to a tree.

This algorithm complexity is explained, as follows:

- Variable elimination: eliminates (via integration or summation) the non-observed non-query variables on an individual basis by distributing the sum over the product.

- Recursive conditioning: allows space-time trade-off and matching efficiency variable elimination when enough space is used (i.e. divide and conquer principle).

The complexity of inference algorithms is determined by the number of arcs and states which each node may take up (Abramson et al. 1996). Moreover, temporal arcs are added to capture the dependencies between time dependent nodes, where the number of nodes and arcs also defines the size of the CPT.

Other exact algorithms that are relevant to modelling tools in BN (e.g. GeNIe) are as described below:

- Clustering Algorithms: These are the fastest known exact algorithms for belief updating in Bayesian networks, proposed by Lauritzen and Spiegelhalter (1988) and improved by several researchers, including Jensen, Olesen and Andersen (1990) and Dawid (1992).
- The clustering algorithm works in two phases: compilation of a directed graph into a junction tree and probability updating in the junction tree.
- However, relevance reasoning (Lin and Druzdzel 1997) has challenged this practice and has demonstrated that it may be an advantage to pre-process the network before transferring it into a junction tree.
- As a result, the clustering algorithm is the default GeNIe algorithm which is sufficient for most applications. Only when the network becomes too large and complex is it recommended to switch to an approximate algorithm, given that it is faster. An approximate algorithm like a stochastic sampling algorithm would be able to deal with large networks effectively.
- Polytree Algorithm: This is the belief updating algorithm for singly connected networks (polytrees) that was proposed by Pearl (1986) as a message passing algorithm. In fact, it is the only belief updating algorithm that is of polynomial complexity that works in singly connected networks (i.e. networks in which two nodes are connected by a maximum of one undirected path) and also for multiple connected networks.

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2.11 Approximate Algorithms (Stochastic Sampling)

This algorithm category produces a global optimum solution at the expense of accuracy, saving computational resource; consequently it will usually converge rapidly towards the optimum solution within a 5% accuracy margin (Yuan and Druzdzel 2002). Moreover, approximate algorithms tend to reduce their search space in their pursuit to find a global solution close to the optimum.

Approximate algorithms emerged at the time when exact algorithms reached a point of maturity in handling efficiently tree widths that were too large. In this regard, approximate algorithms gained popularity given that they were independent of tree width. Currently, these algorithms are the choice for high tree width graphs, yet they lack sufficient parametric structure.

An influential category of approximate inference algorithms is based on reducing the inference problem to a constrained optimisation problem, employing loopy belief propagation and its generalisations. Stochastic sampling algorithms are especially important for inference in BNs containing continuous variables.

The most common approximate inference algorithms are Importance Sampling, Loopy Belief Propagation and General Belief Propagation amongst others. Other approximate algorithms that are relevant to modelling BNs (especially GeNIe) are described below:

- Probabilistic Logic Sampling: This algorithm described in Henrion (1988) is known for being the first algorithm applying stochastic sampling to belief updating in BNs. In essence, the algorithm is based on forward (i.e. according to the weak ordering implied by the directed graph) generation of instantiations of nodes guided by their probability. If a generated instantiation of an evidence node is different from the observed value, the entire sample is discarded. Consequently, this makes the algorithm very inefficient if the prior probability of evidence is low. The algorithm is very efficient in cases where no evidence has been observed.
- Likelihood Sampling: The likelihood sampling algorithm makes an attempt at improving the efficiency of the probabilistic logic sampling algorithm by instantiating only non-evidence nodes. Each sample is weighted according to the likelihood of evidence given the partial sample generated. Hence, it is a simple algorithm with no overhead that generally performs well and certainly better then probabilistic sampling in cases with observed evidence. This algorithm is described in Fung and Chang (1989) and Shachter and Peot (1989) and the algorithm implementation in GeNIe is based on Fung and Chang (1989).
- Self Importance Sampling: Controls the generation of sample to account for bias due to the disproportionate sampling of cases that represent the most probable hypothesis. This algorithm is described in Shachter and Peot (1989).
- Heuristic Importance Sampling: Controls the simulation to account for bias due to the disproportionate sampling of cases that represent the most probable hypothesis. Also this algorithm is described in Shachter and Peot (1989).
- Backwards Sampling: This algorithm attempts to defy the problems with unlikely evidence by sampling backwards from the evidence nodes. As nodes can be sampled both backwards and forwards, depending on whether they have direct ancestors or descendants sampled, this algorithm is an ingenious extension to forward sampling algorithms (Yuan and Druzdzel 2002). This algorithm is described in Fung and Del Favero (1994).
- AIS Sampling: This is one of the best sampling algorithms available (Jian Cheng and Druzdzel 2000), surpassed by the APIS-BN algorithm of Yuan and Druzdzel (2002). In challenging cases, such as reasoning under very unlikely evidence in large networks, it will produce a significant reduced error rate in posterior probability distributions compared to other sampling algorithms. The Adaptive Importance Sampling for BNs algorithm is described in Cheng and Druzdzel (2000).
- EPIS Sampling: This algorithm produces results that are more precise than the AIS-BN algorithm and in certain network cases produces results that are of a higher precision. The Estimated Posterior Importance Sampling algorithm for BNs (EPIS-BN) is covered in Yuan and Druzdzel (2002).

Moreover, the early algorithms proposed for updating probability were very constrained in terms of scope, being applicable only to trees and singly connected networks.

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Approximate algorithms for updating do exist, but are only utilised when their complexity is high. The general Bayesian problem is the NP-hard approach for algorithm learning (Pearl 1996).

2.12 DBN Tools

There are a number of tools available for Bayesian network modelling. A wide variety of BN software programs are available of which the following were selected to evaluate (Kevin Murphy 1998):

2.12.1 Netica

Netica utilises probabilistic inference amongst its less complex algorithms to solve both simple and complex challenges. Subsequently, expert knowledge is then sought to build relationships through directed nodes in the graph before inferences can take place (Pourret, Naïm and Marcot 2008).

Netica is a software tool that uses the principal of causality to perform probabilistic inference as previously discussed. Once evidence has been entered, probabilistic inference by node absorption can dramatically reduce the complexity of the problem by preserving its original scope of global relationships. However, inference is often carried out by compiling the net and exercising belief updates on time variables. It will then update the CPT with its JPD for each directed node in the graph.

2.12.2 GeNIe

GeNIe (Graphical User Interface) is a software package that is used to create theoretical models intuitively with a graphical click and drop interface. GeNIe is the graphical interface to SMILE that consists of a fully portable Bayesian Inference engine developed by Decision Systems Laboratory at the University of Pittsburgh.

The primary features are as follows:

- Graphical editor to create and modify visual network models
- SMILE engine to develop custom interface models for GeNIe
- Supports chance nodes with General, Noisy Max and Noisy Adder distributions Multiple network support
- Complete Integration with MS Excel
- Cross compatibility with other BN software
- Supports observation cost of nodes
- Supports diagnostic case management

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3. CHAPTER 3 System Proposal

3.1 Proposal of Hypothesis

This study proposed the following hypothesis:

A causal relationship exists between airport delays and the weather variables of precipitation, visibility and wind. These weather variables can be used to predict airport delays in the absence of more severe weather phenomena.

This chapter describes a methodology to capture weather related variables that can be linked to delays at airports irrespective of other contributory delays. In particular this dissertation will confirm or refute whether a temporal causal pattern exists between precipitation, wind and visibility and whether such temporal causal activity linked to delay can be established. Experiments will be conducted to determine whether the aforementioned hypothesis remains valid.

As an established and controlled and realistic environment for experimentation Newark Liberty International Airport (KEWR) was chosen. Both weather and flight data from the same airport but from various data repositories were chosen that would ensure consistency of the experimental results with which to test the hypothesis.

3.2 Research Sources and Tools

3.2.1 Newark Liberty International Airport

A review was made of airports that supplied this kind of information that was both comprehensive and of high quality.

KEWR was first named Metropolitan Airport, and then changed to Newark Liberty International Airport. It is owned by the city of Newark and operated by the Port Authority of New York and New Jersey. KEWR is located 24km south west of midtown Manhattan in New York. It is an airport that has consistently emerged as having undergone extensive research in a range of fields, including airport delays. KEWR is notorious for experiencing surface and airborne delays for both inbound and outbound flights, and was the most delayed airport in the US after La Guardia in the year 2000. A combination of limited airport traffic infrastructure and cold weather fronts from the north arctic weather systems that are the first to hit the eastern coast of the United States is the main factor (Evans and Clarke 2002). For these reasons, Newark Liberty International airport was selected as the basis for this experimentation to investigate whether weather variables can be used as a way of approximating delays.

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3.2.2 Web Data Sources

After extensive research several data sources on the web were identified which conformed to the strict data eligibility criteria supporting the KEWR experimentation. Initially the search lacked accuracy as the sources of information that were found on the web provided data asymmetry, where weather data for a time period was available but flight information was restricted at KEWR. There was a lack of available flight delay information from flight tracking websites. This included both private corporations and official aviation authorities like the FAA.

The following websites were used for data analysis:

3.2.3 FlightAware

FlightAware (www.flightaware.com) is an aviation software and data services company that tracks both private and commercial aircraft on its website with information obtained from reliable and official sources like the FAA. Other commercial entities provide complementary data that is also used in conjunction with FAA data. The website provides airport activity, flight and airport maps with weather overlays, aviation historical data used for experimentation, flight planning and other services. Further information regarding this website is discussed in section 4.1.1.

3.2.4 Wunderground

Wunderground (www.wunderground.com) is a commercial weather service website providing real-time weather data via the Internet. This site provides weather services to all major cities around the world, as well as other personalised weather services. In the United States, most of this weather comes from the National Weather Service (NWS) as public domain information source. It also uses observations from members with automated Personal Weather Stations (PWS) that are distributed via the web from live feeds obtained from National Oceanic and Atmospheric Administration (NOAA) weather radio stations around the world (Guiney 2007). Further information regarding this resource is discussed in section 4.1.2.

In summary, finding a comprehensive website that holds all the information sought is both unlikely and unrealistic. Instead the most comprehensive web sites for each type of information were sought (i.e. weather and aviation data). Both of these websites are used professionally in many different industries.

The following graphical tool was used to model the Bayesian networks for this research.

3.2.5 GeNIe

The Graphical Network Interface (GeNIe) is a software tool developed by the University of Pittsburgh (U.S.) for decision theory analysis and graphical representation of union probabilities or network occurrences. This software is particularly proficient at modelling BN with its potential for modelling noisy data and uncertainty, and predicting the probabilities of related variables in a given system. It arranges the complex network of nodes and inferences in a topology that can be easily visualised (Druzdzel 1999).

DBN modelling tools like GeNIe provide key algorithms such as those used for inference in which there are a variety of options including approximate and exact algorithms as previously discussed. Given that a global optimum solution avoiding local minima is highly desirable, the likely algorithm used will be either a heuristic or an approximation algorithmic approach.

A 'time frame' dimension can be added to BN which allows existing variables in the graph to be analysed as a time series, similar to multiple continuous shots captured by a camera. Hence, the characteristics of BN make them an ideal tool to help with decision making as a way of identifying which weather variable is better at approximating airport delays. Given traditional statistical approaches to this issue require complete and reliable data sets for modelling. However, weather and flight delay information at airports is often scarce and unreliable.

Additionally, SMILE (Structural Modelling, Inference and Learning Engine) forms the main part of GeNIe, providing a full platform of independent functions library that includes BNs. Although SMILE is built on a visual C++ independent platform, an outer shell is provided for developer environment to build graphical decision models such as GeNIe that are Windows platform dependent.

GeNIe's ability to learn causal relationships in an environment of new network variables and learn its parameters afterwards makes it an ideal starting point for processing weather variables and airport delay data. Moreover, the topology and numerical probabilities can be a combination of expert knowledge, measurements and objective data making it an ideal tool for research.

A specific tool was developed to aid data extraction from websites. This tool was fine tuned to elicit the high quality data sought for experimentation.

3.2.6 Web Scraping Tool

This section describes the design a web scripting tool to extract the necessary information from the flightware.com website.

For this purpose, an agile software engineering approach was used for the development of the screen scraping model to extract data from the flight tracking website FlightAware. The powerful, modular and simple language Python was used to scrape data from the FlightAware website automatically via batch scripts.

Initially challenges were encountered with limited data being scraped from the website but were quickly resolved by modifying the script to include a larger batch of processed flight data that included domestic and international flights. Selecting the correct historical data sometimes proved challenging due to the discrepancies in date format between flights. Ultimately, it was decided that all flight detail data was to be selected for extraction to simplify the process limited to four months due to data availability.

The website flightaware.com did not have facilities to download detailed flight information. A scripting program was thus designed to create an output file of all relevant information, in raw format that was needed for post-processing and cleaning.

The post-processed data was subsequently imported into Excel where macros were run to tidy up the data and enable smooth integration with a DBN modelling tool.

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During the execution of the batch file running in the background on a standard desktop (Pentium processor), any status change in the web server at FlightAware would render the process invalid and the batch files would have to be restarted (i.e. possibly due to data corruption), so caution was exercised by choosing the run times carefully where operational down times were unlikely taking into account the time differences in the United States.

Moreover, the run times for extracting complete data sets from FlightAware would take in excess of five hours, due to the large volume of data being generated from the batch files.

Memory issues on the PC did not pose a problem, but were taken into account as running the script generated over 30,000 individually extracted records from the FlightAware website. Once the file was extracted, it was configured into a CSV format ready for post-processing in Excel used for heuristic analyses and modelling in GeNIe.

A process was followed that comprised the following procedures for the web scraping tool:

- Data Cleaning (Non filtered data)
- Data and Website Login Credential Access (password/FTP/Firewall)
- Data Export File and Batch Routines (file size limited by PC cache)
- Excel Data Processing (Advanced Filtering/Pivot Tables)
- Data Export to Notepad2 (ASCII format)
- Initial Learning (Blank and Continuous data)
- Initial Parameters (Discrete Threshold)
- Learning of Algorithm Refinement (records, runtime errors, etc.)
- Graphic Refinement and Network Topology

The merging of the data extracted from the FlightAware and the Wunderground websites required a common field being used as an identifier. The unit of time for linking flight and weather data was chosen as day; flight and weather records matching exactly on a specific date and spanning a four month time period were extracted. This was used to create a data set which was then screened for errors and inconsistencies in preparation for further integration; however outliers were processed in GeNIe.

In summary, collecting, extracting, merging and post-processing data from the FlightAware website was not straightforward and involved considerable human and computing effort. Ensuring that the maximum number of detailed flight records was extracted and processed via a batch file, provided ample opportunities to categorise and classify high quality data. It took considerable time and effort to merge the two data sets in preparation for the next steps for consolidation. However, this was a crucial stage that needed post-processing integration with the DBN model.

3.3 Scope and Limitations of Study

This section will address the topics covered in this dissertation and highlight those topics outside its scope.

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3.3.1 Scope of Study

The scope of this is as follows:

- The study was confined to passenger airlines and not cargo operators in the United States.
- The geographical area covered exclusively the metropolitan area of Newark Liberty International Airport (KEWR).
- All types of aircraft were considered irrespective of size or longevity.
- The study only considered outbound delays at Newark Liberty International Airport, and were calculated as the difference between scheduled and actual departure time.
- No formula was employed to monetize delays at either flight or airport level.
- Flight routes included a mixture of domestic and international delays.
- Several weather variables (namely precipitation, visibility and wind) were observed for approximating delays and gain an understanding of temporal causal patterns.
- No operational delays at airports were considered in this study.

To summarise, the above scope of study served as a benchmark for Proof-of-Concept (PoC) with KEWR airport serving as a main airport with high qualitative and quantitative weather and flight information.

3.3.2 Limitations of Study

Some limitations were introduced in this dissertation to focus on the main aforementioned items comprising the following:

- Information used in this dissertation complemented the data extracted from flightaware.com for flight information and wunderground.com for weather information.
- Historical data relating to weather and flight information was limited to the months of March, April, May, and June 2010 due to data availability.
- Delay data obtained at flight level was aggregated to KEWR on a daily basis.
- Where data was absent from the aforementioned websites, an alternative third party provider was used to supplement existing information, with extrapolated values if necessary.
- Network modelling used Off-The-Shelf (OTS) commercial applications, relating in particular to DBN models.
- Outliers were treated as such and missing data was dealt with in subsequent sections of this study.
- The data obtained from the aforementioned websites was assumed to be bona fide and of high quality. However, margins of error were presented later in this study.

University of Cape Town

3.4 Model Parameterisation

In this subsection, the aim is to analyse how the algorithm should behave through parameterisation when assessing relationships between the variables. Further data analysis will reveal the importance of weighting of variables in the solution.

Missing data was resolved using statistical regression analysis for value estimation, but the use of expected maximisation algorithm (e.g. Converging Average) was not used due to the continuous data available.

The neighbour selection was used as a method of classifying the nearest node because it complies with specific criteria in a search space environment. In the search space in the graph, where each node represents a possible state and each arc a transition between states, the selection of neighbours has a wide reaching effect on the neighbour selection algorithm.

Moreover, performing subtle changes to this process can increase the effectiveness of the algorithm. Ideally, the state graph (node absorption) should be sufficiently small in diameter to allow the selection algorithm to easily move between possible candidates.

The selection algorithm can optimise the graph by minimising node collection of nearby states with local minima. The importance of this is that if a large number of connected nodes have a low energy state, forming a local optimal state can leave the algorithm wandering in a random state for long periods of time (i.e. increasing run times), rather than moving away from the local optimum. Candidates generated should be similar to parents, preventing the selection of very good or bad candidates to obtain a good solution with minimum run times.

It is important to consider that neighbouring nodes differ only by a single arc with an unlikely solution moving from collections of local minima groupings. The diameter of the search space was always large, $O(n_2)$, where the problem of moving from one candidate to another underscores the existence of potential minima.

Calculating BN solutions in a GeNIe application was expensive both in terms of CPU and memory resources. The relationship of this resource with expenditure was exponentially proportional to the number of linked nodes in the graph space. The computational costs are twofold:

- Candidate Generation: Selecting where to add the arc and learning the new CPT for the node under observation
- Scoring New Network: Assessing the performance of the new network in inference terms

The increase in ML times is exponentially proportional to the size of the graph. Additionally, the time employed on candidate generation of any individual node is entirely independent of the size of the network; it is only dependent on the number of parents of the node under observation.

Furthermore, the parameterisation necessary for a multi-objective problem are often conflicting and are too complex to solve effectively (NP Hard). This dissertation sees a single-objective problem being more practical and realistic.

However, during the parameterisation phase allowances in the investigation were made for all data variability during the four months time period series, identifying and

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rectifying where possible violations of data constraints and inconsistencies whilst respecting other important parameters. With regard to the search space size and parameterisation, run times were not foreseen to be problems as no large data sets were run during experimentation.

To this effect, not every weather variable can be modelled in this experimentation. Barometer pressure, air conductivity and other similar variables were not included due to the increasing complexity of the model, as well as the size requirements of the graph space.

Weather patterns on the east coast of the North America cause large delays at airports including KEWR. Since airline traffic can easily be categorised as eastbound (international) or westbound (domestic), the weather pattern in the proximity of an airport can have a dramatic effect on KEWR traffic affecting outbound delays. Westbound moderate weather patterns can be dealt with more straightforwardly due to the possibility for en route diverts of domestic flight destinations.

Eastbound severe weather patterns can have more dramatic consequence on airport delays, as larger aircraft tend to have fewer alternatives to en-route diverts due to the lack of airport and navigation infrastructure. Disruptive convective weather systems from the Northern Pole can restrict en-route airline alternatives during emergencies on the east coast of North America.

3.5 Weather Concepts and Delay Definition

Some background weather details are provided for the variables chosen. The criticality of precipitation, wind and visibility as meteorological phenomena are major factors in airport delays (Allan, Gaddy and Evans 2001).

Convective weather systems or activity (i.e. thunderstorms) represent a major threat to airline safety. Given the broad availability of weather information, airline pilots sometimes find the very abundance of this tends to be part of the problem where it can be challenging for pilots to screen non-essential data, focus on critical data and then correctly calculate the circumstantial risk involved (Chang et al. 2001).

A management framework for preflight weather planning and in-flight decision-making can be summarised in three basic steps though only the former is of concern:

- Perceive: weather hazards which could affect scheduled flight
- Process: information that determines whether these hazards create risks and if they can be mitigated or eliminated at the pre-planning stage
- Perform: action to mitigate or eliminate the associated risk

In aviation the FAA Flight Services Station remains the most widely used source of comprehensive weather information into 'bundles' or packages for pilots. These packages are derived from NWS data and other flight information sources like the NOAA Weather Service Office (Chang et al. 2001).

The weather specific information is packaged into a standard briefing that includes sky conditions, weather synopsis, visibility, and weather conditions relating to departure, en-route and destination point. Other relevant data items included are; adverse conditions, altimeter settings, cloud tops, dew point, icing conditions, surface winds, winds aloft, temperature, thunderstorm activity, precipitation and visibility (Chang et al. 2001).

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The root causes of weather reside in the uneven heating of the earth's surface, which when evaluating weather conditions translates into the following three basic meteorological elements:

- Temperature and dew point
- Wind (speed and direction)
- Moisture (humidity)

Uneven heating (i.e. temperatures) supports the development of low pressure systems, which can affect large areas. Surface low pressure systems usually have 'fronts' associated with them, a front being defined as the boundary between two air masses of different combinations of temperature, pressure and moisture.

A 'classic' northern hemisphere low pressure system with the expected cold and hot fronts aids in visualising overall temperature, wind and humidity patterns in a wide area. It is a well known fact that air circulates counterclockwise around low pressure systems in the northern hemisphere and conversely in the southern hemisphere.

Hence, what role does weather play in aviation? A combination of moisture, wind and temperature can create a range of near infinite conditions that affect airline schedules (Chang et al. 2001). Specifically, this creates three basic weather elements at KEWR as follows:

- Reduce visibility
- Create turbulence
- Reduce aircraft performance

Weather analysis is normally viewed in terms of how current and forecast conditions will affect visibility, turbulence and aircraft performance. In practical terms and for aviation purposes this translates into the meteorological phenomenon below (Chang et al. 2001).

3.5.1 Precipitation

The only precipitation weather phenomenon considered was 'rain' and can be described as the formation of water spheroid droplets formed by the condensation of water vapour in the atmosphere. It is formed when the sun's heat evaporates water turning it into water vapour. The water vapour then rises to a level in the atmosphere where the temperature is low enough to condense the water vapour into large enough droplets (i.e. 100% relative humidity) that fall by gravitational pull back to earth.

In practical terms, convective activity in and around the vicinity of KEWR is the leading cause of thunderstorms that can bring abundant precipitation to affect runway conditions at KEWR. Hence precipitation can drastically reduced visibility at airports which can cause minima separation of aircraft to operate under IFR (Instrument Flight Rules) rules following IMC (Instrument Meteorological Conditions) when departing from or arriving at KEWR. Rain can also affect braking ability of aircraft when landing on shorter runways like 29/11 (crosswind runway) in reduced visibility conditions at KEWR.

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However, thunderstorms affecting the flight path of any departing aircraft will usually require modification of the flight plan for re-routing as they cannot fly straight through them due to the inherent risk associated with them.

Icing and freezing levels (i.e. solid precipitates) should also be taken into consideration as these can affect the runways used at KEWR for departing aircraft, as well as its performance calculations for take-off and impact on airport operations measurable in average aircraft delay. De-icing is the process of removing any form of frozen containment from the surface of an aircraft, and is necessary for an aircraft's moving surfaces. Though most aircraft have installed heating systems for de-icing critical areas of the aircraft, this is normally employed where de-icing cannot reach. Anti-icing agents are used extensively in aircraft to prevent the formation of any frozen containment on their surface. This activity has a major effect on delay at KEWR, as specialised airport vehicles with pressured anti-icing systems are needed to ensure the performance integrity (e.g. aerodynamics) of an aircraft before take-off in a critical time frame.

It is also important to note that expert knowledge (Henrion 1988) indicates that the formation of ice, snow and fog resulting from a high relative humidity will have different critical temperatures from precipitation but are not included in the experimentation as they are not present in the study period of March to June 2010.

3.5.2 Wind

Wind can be described as a vector in terms of intensity and direction or bearing. Typically, prevalent winds will have a sustained value (knots or kph) and the direction the wind is coming from, in this case concerning runways 4/22 LR and 11/29 (i.e. bearing 110˚ and 290˚ from north magnetic) at KEWR.

Gusts can be defined as sporadic bursts of wind of a measurable maximum intensity and direction or bearing on the runway that may affect airport operations depending on the type of aircraft. Commercial airlines have operation specifications that need to be FAA approved that limit the crosswind that each aircraft can land in (i.e. quite often these values change if the runway is wet or icy).

Though wind is a primary cause affecting airport runway use at KEWR, noise abatement regulations and terminal airspace constraints (TAC) associated with surrounding airports play a prominent role. La Guardia airport (LGA) and J. F. Kennedy airport (JFK), KEWR's third runway 11-29 intersects 22LR and is largely used in the afternoon in the westerly direction and occasionally in the morning due to wind conditions. Usage in the afternoon will handle approximately 50% of all arrivals in conjunction with runways 22L and 22R of arrivals (Drotleff et al. 2013).

Given the identification of high wind days, GDPs are more likely to be implemented in the New York area (incl. KEWR). In particular, this occurs with the advent of west/north west winds that make it challenging for ATC to maintain aircraft spacing and limiting capacity by forcing traffic into suboptimal runway configurations at KEWR (Allan, Gaddy and Evans 2001).

The primary runways 4/22 at KEWR allow for maximum winds from 20 – 28 kts (including gusts) for wind directions ranging from a magnetic bearing of 260˚ - 340˚, but typical northwest or southeast winds above this threshold complicate traffic arrangements resulting in departure and arrival delays. The strong northwest winds are usually more problematic at KEWR resulting in the use of runway 11-29 to relieve traffic,

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although with reduced capacity, but these are usually associated with low pressure weather systems during the winter (Allan, Gaddy and Evans 2001).

The overall traffic pattern at KEWR is highly asymmetrical concerning movements of aircraft from 06:00 to 12:00 and 13:00 to 22:00. In the morning peak between 6:00 and 12:00, there is a short but pronounced peak at 08:00 followed by a steady rise in traffic from 10:00 peaking at 16:00 (Figure 6). Traffic at KEWR subsequently declines from 21:00 onwards. Understanding weather related delay propagation is important depending on the time of the day and its cumulative delay effect on the daily flight patterns at KEWR. Traffic will also vary by day of the week, whether it's week day or weekend, though variability across weekdays is negligible. Variability in passengers at KEWR in the summer-winter is noticeable though outside the scope of this dissertation as only the months of March, April, May and June 2010 were considered. These months were not considered peak seasonal periods in terms of airport movements (Drotleff et al. 2013).

The number of movements of 'heavy' aircraft and their distribution throughout the day, greatly impacts the aggregate delays experienced at KEWR. It is hence known that KEWR is highly sensitive to weather conditions. KEWR's performance when experiencing delays from which it does not recover, seems to be a consequence of over-scheduling during the afternoon hours i.e. demand for aircraft movements exceeds the capacity of the airport infrastructure to handle it (Drotleff et al. 2013).

KEWR shows a daily mean Actual Taxi-Time Out (ATTO) of 30 minutes. In reality, values as high as 35-40 minutes occur from 08:00 to 09:00 and from 17:00 to 20:00. There is a significant higher level of ATTO associated with large departures at KEWR. In January to September 2010, the number of movements at KEWR was 8% lower than the corresponding period in 2007. While the average departure delay was 35% lower pointing to the well known fact that the relationship between demand and delay at high utilised queuing systems like at KEWR is very non-linear. (Odoni et al. 2011).

3.5.3 Visibility

This weather phenomenon also known as 'Ceiling & Visibility' is a major contributor to delays at major airports. Similar to delays due to wind, low visibility at KEWR is likely to see the implementation of GDP under IMC rules to reduce capacity to acceptable safety levels. However, there are multiplicities of factors that can cause low visibility conditions at KEWR. East coast storms caused by low pressure systems can bring heavy rain, freezing (previously discussed) and snow that can bring many challenges to airports resulting in airport delays (Allan, Gaddy and Evans 2001).

Low visibility conditions start to form when the difference in ambient temperature and the dew point temperature is less than 2.5°C, with the effects becoming clearly visible at equal temperatures, though normally in aviation a spread of 4°C is allowed as a safety margin. Fog begins to form when water vapour condenses into tiny water droplets in the air or by a process of sublimation when a solid changes states by evaporation like dry ice (frozen carbon dioxide). The opposite is also true, where water vapour is formed from the evaporation of water and later condenses to show water suspended in the air as fog. Hence this cooling effect can be due to radiation or advection processes of warm air over cold surfaces. The relative humidity has to be near 100%, which can be achieved by adding moisture to the air or dropping the ambient temperature, but the most important element, 'condensation nuclei', has to be in place for the water to condense.

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The type of fog that afflicts an airport depends on its proximity to a water mass. In general, the further an airport installation is from a body of water, the greater the probabilities of experiencing radiation fog as opposed to advection fog. However, since KEWR is in close proximity to Newark Bay the likelihood of this weather phenomenon occurring is highly likely in the spring season.

3.5.4 Delay Definition

According to the Aviation System Performance Metrics (ASPM) there are different categories of delays as governed by the FAA. Passenger delays are monitored by Airline Service Quality Performance Systems (ASQP). This dissertation shall attempt to define a metric for delay suitable to this study.

Various delay definitions include the following:

- Carrier Delay: Includes aircraft cleaning, damage, cargo loading, computer, crew legality, engineering inspection, maintenance, weight and balance and other similar activities.
- Late Arrival Delay: Arrival delay at airport due to late incoming aircraft, normally apparent on short-haul routes with low turn-around times. This can give rise to an effect called 'Delay Propagation' if it occurs early in the day.
- NAS Delay: Caused within the control of the National Airspace System (NAS) which may include; weather, airport operations, heavy traffic and ATC.
- Security Delay: Caused by the evacuation of a terminal/concourse, inoperative screening equipment and other similar events.
- Weather Delay: Caused by extreme weather phenomena either at the departure point, en-route, or point of arrival.
- OPSNET Delay: Delays to IFR aircraft of 15 minutes or more for individual flights controlled by ATC including weather, taxiing, holding air/ground, equipment malfunction, airport volume and reduced capacity.

The many types of delays that can affect an airline can be summarised by classifying them as inbound or outbound delays. Within that category they can be further subdivided into airborne and land borne. Given that this study deals with aircraft departures, the definition of delay shall be defined as the difference between estimated and scheduled departures and actual departures as prescribed by ATC. The FlightAware website uses a proprietary algorithm to estimate the planned arrival time of flights, but since there is only a concern with flight departures this was considered outside the scope of this dissertation.

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4. CHAPTER 4 Data Collection and Integration

This section describes how the process was designed for experimentation. Figure 1 describes the three basic elements needed for the system design, namely 'Data Input', 'System Model' and 'Data Output':

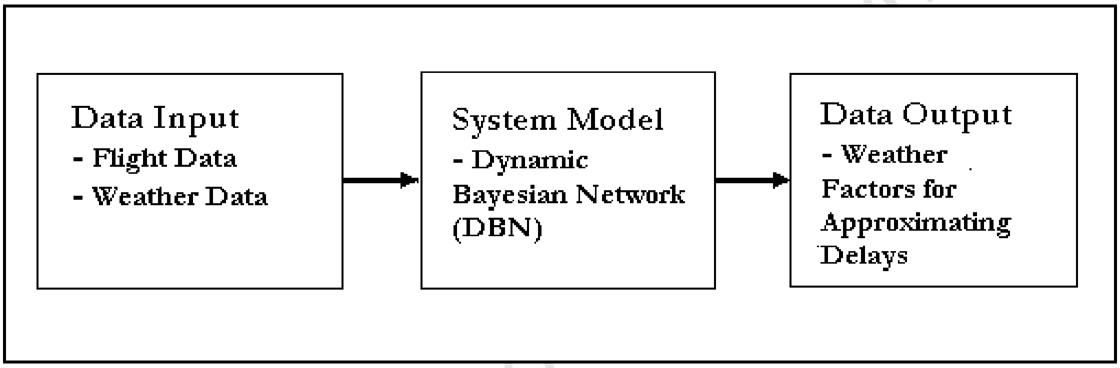

Figure 1: Integration of System Process

The following section described the data source and input needed for the investigation. The analysis was conducted using a BN tool called GeNIe, which will produce outputs based on aggregated delays at KEWR.

4.1 Data Input

4.1.1 Flight Information (FlightAware)

The FlightAware website displays scheduled/actual departure times, and is deferred by five minutes due to networking transmission delays and security considerations. However, a commercial option for real-time tracking is available but was not deemed necessary for this dissertation as not enough value added could be justified.

The website compiles, aggregates, and processes data from a variety of government sources, airlines and commercial data providers, as well as using FlightAware's proprietary flight tracking algorithm. The consistency, high quality and position reporting of US domestic flights proved a major asset when analysing data provided on the website compared to other flight tracking websites. Flights cancelled due to heavy weather conditions were not present in the historic data tables, and consequently were not considered for the purpose of this dissertation.

Certain anomalies appeared in the raw data extracted from the website, in particular pertaining to arrival times, with 'result unknown' fields. This was an infrequent indication that an important message status has not been sent or received, which could indicate a clogged telecommunications infrastructure or that the aircraft had left FlightAware's coverage area or that ATC had not updated their status, which was considered a rare occurrence.

The interpretation of departure and arrival times proved a major challenge in the flightaware website. It was important to use a standard benchmark for all flight time comparisons for consistency purposes, and hence the arrival and departure times on the individual flights page was used. The departure and arrival times indicated 'wheels up' and 'wheels down' times that were used and not the gate-to-gate positions which are commonly employed for flight times. Delays are very often possible due to the complexity of airport taxiing infrastructure and congestion at certain times, if gate-to-gate times are used, skewing the results.

Recent features added to the website included more specific information like a gate number, indicating the aircraft has taxied and docked at a specific gate. This was useful for estimating passenger delays on the ground but not specifically for other flight operations. Hence, the website mostly tracked en route flights delays without any addition of padded time.

For the purpose of this experimentation, flight levels and altitudes will be treated as identical given that there is a negligible difference between them. The aircrafts' altitudes are displayed as Mean Sea Level (MSL) via an altimeter, to avoid constant adjustments and inaccuracies during flight tracking. Occasionally flight data relating to the position, speed and altitude was not broadcast due to airlines operating the same flight number on two separate flights with different Origin-Destination (OD) pairs.

Local times are displayed at US airports for the purpose of simplification, as opposed to the universally accepted aviation 'Zulu' time and the duration of flight times relates exclusively to the amount of time between 'wheels up' and 'wheels down'.

An aircraft showing the status of 'scheduled', signifies that its flight plan has been approved, 30 minutes to 24 hours before the departure time. Hence flight plans that are not approved or have been cancelled are not displayed in the website.

Figure 2 is a sample of an individual flight display web page from FlightAware with all the aforementioned information.

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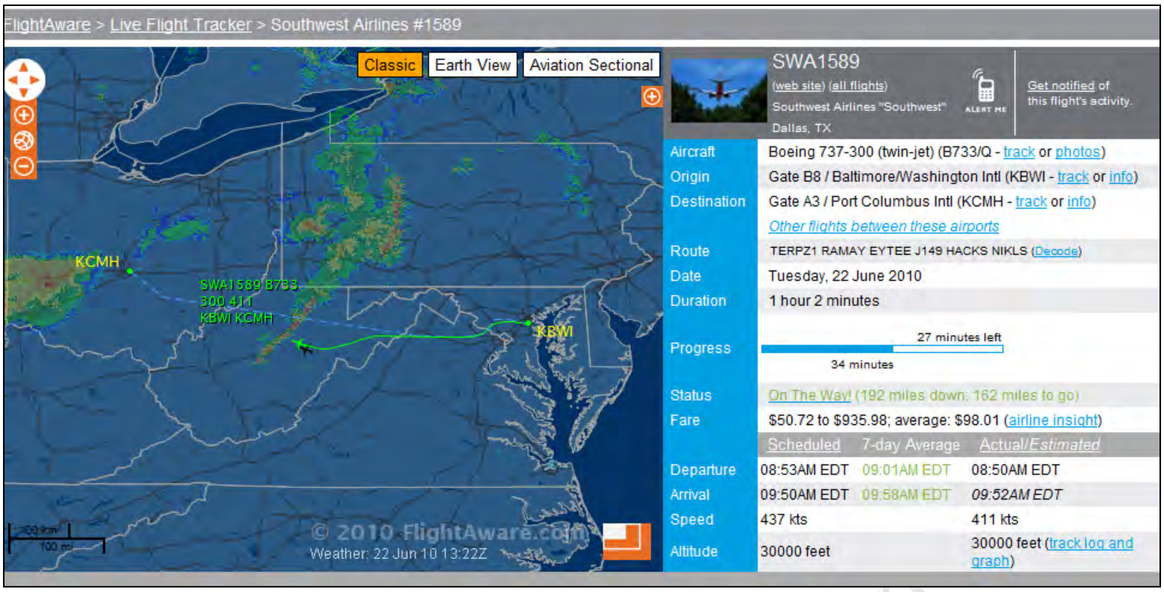

Figure 2: Flight Details Page in flightaware.com

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The flight information section illustrates the following:

- Flight Number: SWA1589 (i.e. Southwest Airlines "Southwest" call-sign)
- Aircraft: Boeing 737-300 – Description of aircraft in flight (single-aisle jet)
- Origin: Gate B8 / Baltimore – Indicating the departure gate at departure airport
- Destination: Gate A3 / Port Columbus International – Indicating the arrival gate at destination airport
- Route: Indicates the reporting points, way points and navigational aid co-ordinates that the flight is scheduled to follow upon departure (abbreviated)
- Date: Indicating local day and date of flight
- Duration: How long the scheduled flight is considered to take (weather permitting)
- Progress: Actual flight progress on existing flight path (weather permitting)
- Status: Indicates the actual status of the flight and navigational distances covered and remaining to destination
- Fare: Range of fares paid by passengers for the actual flight
- Departure: Indicates the scheduled, seven-day average and actual/estimated departure time from the local airport (EDT: Eastern Daylight Time)
- Arrival: Indicates the scheduled, seven-day average and actual/estimated arrival time at the destination airport (EDT: Eastern Daylight Time)
- Speed: Indicates the scheduled versus actual/estimated aircraft speed on the flight path (weather permitting)
- Altitude: Measures the scheduled altitude on the flight plan versus the actual/estimated altitude on the flight path (weather and ATC permitting)

In Figure 2, a snapshot of basic information details the flight, the route parameters and en-route progress with a clean section below of actual versus historical data for comparison purposes. Further information in the track log and graph link depicts two-dimensional data (altitude/speed versus time) of the actual values recorded by Flightaware compared to details from the flight plan.

The map section depicts a solid line for the tracking of an en route flight, indicated by reporting points received from that aircraft every 30-90 seconds on US domestic flights. The dashed line represents the planned flight route as planned by ATC. Often a planned flight might deviate from the planned route due to weather, traffic or other operational factors that influence an alternative Flight Plan (FP). The data block is necessary as a visual means to uncluttered map space whilst displaying basic flight detail information. Hence, flights can take one or two minutes to appear on the screen due to tracking position and orientation inefficiencies close to the ground. The map section displays standard FAA airline symbology very similar to that used by air traffic control.

In summary, information interpreted from FlightAware without due consideration to term definitions used would be seriously misguided given the rigorous description used in the flight details page. A baseline to work from with clarification on all term definitions would give more credibility to the data used during experimentation. The following flight information was selected:

- Date (dd-mm-yy)
- Flight number
- Aircraft model
- Origin and destination airports (OD)
- Flight duration (hh:mm)
- Actual departure (hh:mm)
- Delay (calculated)
- Speed (knots)
- Altitude (feet)

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Using complex filtering functionality in Excel, it was possible to select relevant OD city pairs from the joint-extracted data and perform a heuristic analysis via pivot tables on the most frequent OD pairs for inspection. This functionality was particularly useful when building consolidated day delay information per airline from KEWR to other destinations as city pairs. The merged data from Excel could then be saved in a space delimited file ASCII format ready for further integration into GeNIe.

Historical flight data from the FlightAware website was extracted using a previous batch file routine programmed in Python with dates ranging from March to June 2010. This also included comprehensive information relating to individual flights, both domestic and international.

A sample of extracted raw data contained the following items:

- Flight number

- Aircraft type
- Origin and destination
- Flight route
- Date of flight (dd-mm-yy)
- Flight duration (hh:mm)
- Flight progress (hh:mm)
- Flight status
- Scheduled and actual departure times (UTC)
- Scheduled and actual arrival times (UTC)
- Average departure and arrival time (UTC)
- Scheduled and actual flight speeds (knots)
- Scheduled and actual flight altitude (feet)

For the purpose of this dissertation, the estimated and actual departure flight times also had to be extracted from the FlightAware website using Python scripting code. This information was then used as a template to scrape other important data items for processing.

4.1.2 Weather Information (wunderground)

The Wunderground website has historical data that can be extracted in a Comma Separated Values (CSV) file format. Column header information was also extracted for descriptive purposes, given the large volume of data. Excel was used as a tool to link, process and review the data more easily from these sources.

There were specific variables of particular interest to be used with the DBN model relating to variables involving precipitation, visibility and wind. All available data was downloaded in a CSV file format from the website in case it was needed for further a posteriori analysis. The extract contained the following items:

- Weather date (dd-mm-yy)
- Ambient temperature (degrees F)
- Dew point temperature (degrees F)
- Relative humidity (%)
- Sea level pressure (mbar)
- Visibility (km)
- Wind speed and direction (kph)
- Gust speed (kph)
- Precipitation (mm)
- Event (interpreted by Wunderground)

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The previously mentioned variables were carefully observed in preparation for merging with flight detail information, to be processed under a single ASCII file for DBN integration.

Though the maximum, minimum and averages were captured for that day, the data was correlated with hourly data that was obtained from the website weather.gladstonefamily.net and was cross referenced for accuracy.

The Citizens Weather Observation Program (CWOP) monitors thousands of manual and automatic weather stations around the globe for weather monitoring and prediction. The information captured in Wunderground is the result of consolidated raw data from multiple stations around a target location.

The margins of error for the location are ±1.84% degrees latitude and ±0.1% degrees longitude (source: KEWR). This raw data format can be downloaded from the website in an Excel Web query based file format 'IQY' for the last 56 days, as historic data.

The raw data downloaded contains the following items:

- Time (UTC)
- Barometric pressure (hPa)
- Temperature (°C)
- Dew point (°C)
- Relative humidity (%)
- Wind speed (kph)
- Wind direction
- Analysis barometric pressure (hPa)
- Analysis temperature (°C)
- Analysis dew point (°C)
- Analysis relative humidity (%)
- Analysis wind speed (mph)
- Analysis wind direction (magnetic bearing)

It is important to note that, when data was not available or was believed to be erroneous, it was left blank for clarification purposes in the source data. Only later during the experimentation were blank values estimated.

All the readings have a 'MADIS rating' of 100% QC (Quality Control) check (i.e. all observations approved); with all 'KEWR Analysis versus KEWR' data results within acceptable range and hence with acceptable calibration of instruments confirmed.

However, the following tolerances or errors are permitted as follows[2]:

[2] Note: If error rate is positive, then the analysis variable value is higher than the reported variable meaning the sensor is reading more conservatively than necessary.

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- Barometer: Average error (-0.4mbar; STD Dev. 0.4mbar)
- Temperature: Average error (24hr; -0.7°F, day; -1.4°F, night; 0.4°F)
  Standard dev. (24hr; 2.0°F, day, 2.0°F, night; 1.3°F)
- Dewpoint: Average error (24hr; 1.8°F, day; 1.7°F, night; 2.1°F)
  Standard dev. (24hr; 1.5°F, day, 1.7°F, night; 1.1°F)
- Wind: Wind vector, the average wind over a specified period

Different vector lengths, the anemometer reads high or low, or that you are in open or shielded space.

Having extracted historical data from both websites, a common data header in 'Date' was found as a possible common link between files. As previously mentioned, during heuristic analyses using Excel functionality like 'Vlookup' a third import file was created to import into GeNIe.

The following weather related data headers were identified as being the drivers for pattern identification in GeNIe:

- Weather date (dd-mm-yy)
- Wind speed (incl. gusts) (kph)
- Visibility (km)
- Precipitation (mm)
- Dew point maximum (°C)
- Average dew point (°C)
- Minimum dew point (°C)
- Humidity maximum (%)
- Average humidity (%)
- Minimum humidity (%)
- Pressure maximum (hPa)
- Average pressure (hPa)
- Minimum pressure (hPa)
- Visibility maximum (km)
- Average visibility (km)
- Minimum visibility (km)
- Maximum wind (kph)
- Average wind (kph)

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- ➢ Gust speed (kph)
- ➢ Precipitation (mm)
- ➢ Event (interpreted by wunderground)

4.2 Weather Related Delay Analysis

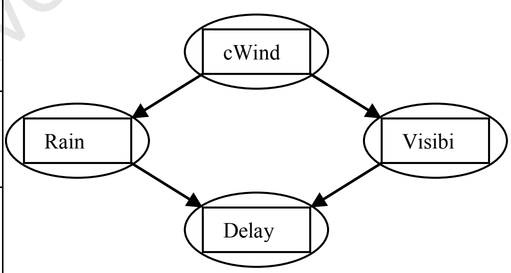
The importance of using a DBN utility for this experiment is fundamental since this would aid our understanding of the objectives of this dissertation. Moreover, the time variability of DBN makes it particularly useful in measuring how weather data variables change over a specific time interval in a fixed topology network.

The information flow of tools within a modelling environment allows for data to be processed more efficiently. As a result, more scenarios can then be run during experimentation increasing the quality and reliability of the results with a validation analysis for each weather variable to confirm the accuracy of the data. An example of a tool within this can be the web scraping tool that was used in this area. Not only did the script play an important part in extracting the flight detail information, but also in making sure it is in a format that can be combined with weather data and further integrated into a DBN utility like GeNIe.

Consider the example below that will demonstrate the use of BN applied to the field of aviation. The model is used for approximating delays at airports based on a certain ranges of variables relating to wind, visibility and precipitation that will create rainy (R) or low visibility (V) conditions for the runway. Based on certain forecasted weather variables (i.e. precipitation, visibility and wind), a delay can be estimated per unit (aircraft) as per the framework in figure 3.

P(cW=F)	P(cW=T)
0.8	0.2

cW	P(R=F)	P(R=T)
F	0.8	0.2
T	0.2	0.8



cW	P(V=F)	P(V=T)
F	0.9	0.1
T	0.8	0.2

R	V	P(D=F)	P(D=T)
F	F	1.0	0.0
T	F	0.2	0.8
F	T	0.01	0.99
T	T	0.02	0.98

Figure 3: Graph Structure for Airport Delays

The nodes are all binary, which will be denoted by T (True) and F (False). It can be appreciated that the event 'Delay' (D=true) has two possible causes for simplicity: either it is rain (R=true) or there is visibility (V=true).

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Furthermore, it can be appreciated that Pr(D=true | R=true, V=false) = 0.8, and hence, Pr(D=false | R=true, V=false) = 1.0 - 0.8 = 0.2, since the sum must be one. Also, since cW node has no parents, its CPT specifies its prior probability that the critical wind speed has been reached (0.2), and hence there will be a 20% chance of delays. However, it must be stated that this model has certain limitations, as it does not consider any other variability or factor causing delay given that there are only two known variables: 'Rain' and 'Visibility'.

For the purpose of clarity, the simplest conditional independence relationship embedded in a BN can be summarised as follows:

A node is independent of its ancestors given its parents, where the ancestor/parent relationship is with respect to some fixed topological ordering of the nodes (Kevin Murphy 1998).

The joint probability distribution of all the nodes in the graph above is as follows:

P(cW, R, V, D) = P (cW) * P(R | cW) * P(V | cW, R) * P(D | cW, R, V)

But by using the conditional independence relationships, it can be rewritten as

P(cW, R, V, D) = P (cW) * P(R | cW) * P(V| cW) * P(D | R, V)

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In the third term, V is independent of R given its parent cW, and also D is independent of cW given R and V.

This conditional independence relationship allows us to compact the joint probability distribution. If there were n binary nodes, the full joint would require O(2n) space to represent, but the factored form would only require O(n2k) space to represent, where k is the maximum fan-in of a node, and fewer parameters improves learning.

The formulas to work out the probability chain for rain or ice given delays is as follows:

$$\Pr(R=1 \mid D=1) = \frac{\Pr(R=1 \mid D=1)}{\Pr(D=1)} = \frac{\sum_{cW,V} \Pr(cW = cW_1, R=1, V=i, D=1)}{\Pr(D=1)}$$

$$\Pr(V=1 \mid D=1) = \frac{\Pr(V=1 \mid D=1)}{\Pr(D=1)} = \frac{\sum_{cW,R} \Pr(cW = cW_1, R=r, V=1, D=1)}{\Pr(D=1)}$$

Where

$$\Pr(D=1) = \sum_{cW,R,V,D} \Pr(cW = cW_1, R=r, V=i, D=1)$$

Most BN software, model relationships between variables at a particular point in time or during a specific time interval. The creation of causal relationships between variables in itself projects a temporal dimension. Hence, it is clear that BN do not explicitly model temporal relationships between variables. The only approach to modelling the past, a present and future relationship between variables is with the addition of auxiliary variables like date or time, i.e. variables with a temporal dimension.

Moreover, it is important to denote changes over time explicitly when performing tasks involved in monitoring. In this particular case, there is not only the need to model if there is a dependency between weather variables and delay, but also to model how that relationship changes over time to be able to establish a delay correlation in the future to manage or minimise delays.

When constructing a DBN, a domain will consist of a set of preselected variables as follows:

$$Y = \{Y1,\ldots,Yn\}$$

Each variable is represented by a node in the BN. In constructing a DBN for modelling changes over time, a node will be included for every variable Yi for a particular time step. Hence, the current time step is represented by t, with the previous being t - 1 and the forward one being t + 1 as follows:

$$Y = \{Y_1^{t+1}, Y_2^{t+1}, \ldots, Y_n^{t+1}\}$$

Therefore, each time step is a time slice and the relationship between variables in a time slice is called an intra slice arc. Moreover, a temporal BN could use specific approximated weather conditions as inputs from another BN that in turn can establish the causal factors in analysing delays.

In summary, the necessary checks and balances (data governance) were carried out to validate that the data sources were set to a high standard for their use during the experimentation.

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5 . CHAPTER 5 Design Analysis and System Evaluation

In this chapter, an exploratory design analysis will be presented, followed by the system evaluation results, starting with the observations of weather variables: wind, visibility and precipitation. For the system evaluation, a quantitative and qualitative approach was taken, initially based on the heuristics of observing data trends and continuous data (Excel), discretised experimentally for GeNIe. As a result, the findings are presented and the results of each weather variable are discussed.

5.1 Network Experimentation Analysis

Given the abundant data observed, it was not only critical to analyse the trends between weather variables and delay, but it was also essential to establish causality and whether this causality was time dependent. It was also important to establish specifically how the findings related to the research question in the objectives section of the introductory chapter.

Accordingly, two software tools, Netica and GeNIe, were considered for the experiment. Both software tools were straightforward to use in a network environment and demonstrated basic functionality for BN. However, GeNIe displayed a greater versatility and richness of features, including analysis of temporal variables in a network, which Netica did not offer. Subsequently, GeNIe was chosen as a more capable tool to analyse which weather variables correlated better to delay. It also offered improved graphics, showing how the findings related to the objectives of this dissertation. Bayesian Networks' non-deterministic approach in these types of forecasts made it feasible to include knowledge-based assumptions (e.g. bad weather causes delays) as input into the model for any relevant field.

Previous research into weather-related delays at KEWR supported this approach (Allan, Gaddy and Evans 2001). For the purpose of this investigation, the experiment was structured in three sections:

- Investigation of the causal relationship between wind, visibility and precipitation with respect to weather-related delays, and consequently, which variable is the most effective at estimating delays at KEWR.
- Refinement of the parameters within the model CPT for all node weather variables (i.e. wind, visibility and precipitation) in graphical form, and how the experimental results translate into significant findings of the causal relationship between weather and delays at KEWR.
- Consolidation of all delayed flights at Newark Liberty International Airport and the use of this information with specific weather variables (namely wind, visibility and

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precipitation) from the temporal template in GeNIe, for analysis and interpretation.

For the purpose of the experiment and with respect to delay nodes, negative delays are normalised to zero and calculated as the difference between the scheduled and the actual departure time, resulting in a negative number. Normalising this number will prevent any bias towards the consolidated airport delay at a later stage in the experiment. A mixture of flight destinations was used in the data sample, which consisted of short- and long-haul flights, in order to minimise any bias during experimentation towards any specific flight sector.

Consolidation of all flight delays at KEWR was then modelled, including long-haul and short-haul flights. The common 'Date' field was used to consolidate all individual flights for each day of the experiment, linking the two merged data sets containing flight and weather information.

5.2 Weather Analysis Considerations

The following considerations were taken into account from a graph analysis carried out during the experimental period.

5.2.1 Visibility Analysis (Heuristic)

In aviation, visibility refers to weather associated with low visibility conditions and is a measure of the distance an object or light can be clearly determined.

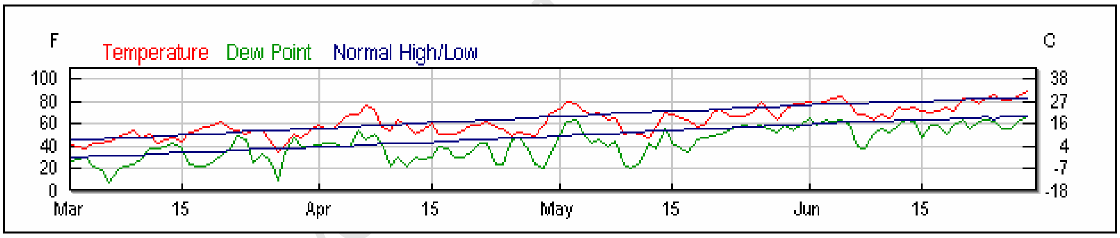

Figure 4: Temperature & Dew Point Graph (March-June 2010)

During the entire experiment, low visibility had a close correlation with ambient temperature and dew point temperature at KEWR. This observation was supported by the work from Villiers, Nieman and Niemann (2007). Low visibility conditions (e.g. fog, haze) are known to have an effect on the 'Normal' and 'Low Delay' categories. In Figure 4, a close correlation was observed between low visibility and both ambient temperature and dew point temperature (typically less than 4°C).

From the wunderground data, days reporting fog in 2010 can be seen on the graph in Figure 4 as 14 March, 30 March and 21 April. The implications are that airline pilots will have a keen interest between the spread of these weather variables at their departure time and airport, as well as at their destination airport upon arrival, in order to minimise the risk of adverse weather and diversions. However, whether reduced visibility remains a viable option to predict weather-related delays remains to be explored in the experiment. Low visibility conditions, as interpreted in Figure 4, were usually observed in the early morning or late evening, thereby, minimising the impact on airport operations at KEWR.

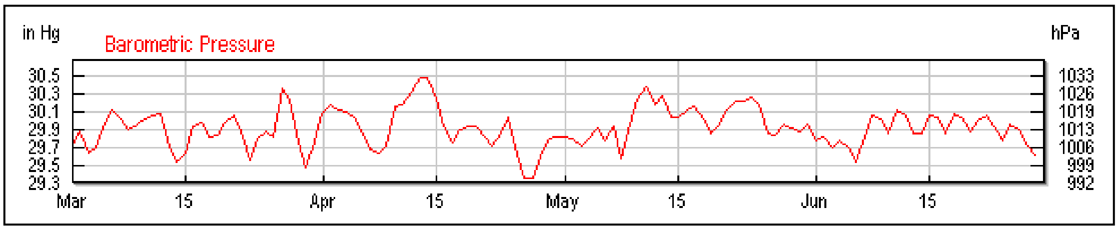

Figure 5: Barometric Pressure Graph (March-June 2010)

It was also observed that for the visibility analysis during the experiment, low barometric pressure, as seen in Figure 5, accompanied low visibility on 30 March, with values as low as 993 hPa[¤] (minimum). This was also the case on 26 April, with values of 991 hPa (minimum), corresponding with low visibility conditions of 2 km (minimum) on both days at KEWR. The implications for airlines are that sudden low-pressure fronts are a clear indication of adverse weather systems bringing thermal advection in the form of precipitation with reduced visibility. While it remains unlikely that low visibility is a good candidate to predict weather-based delays at KEWR, thermal advection shows potential as a variable to approximate delays given the lack of technologies to mitigate its effects.

In Figure 5, no discernable precipitation pattern was found to have an impact on delays, with minimal impact on delay categories 'Normal', 'Low Delay' and 'High Delay'. This was also closely associated with high relative humidity (83%). Low barometric pressure (993hPa) was found on 30 March with precipitation levels totalling 452 mm. Intense precipitation throughout the day affected visibility but generally, with minor impact on aggregate delays.

Figure 6: Daily Traffic Movements at KEWR (Source: Drotleff et al. 2010)

Figure 6 demonstrates that daily traffic patterns have been relatively constant at KEWR during the last decade, as supported by research accomplished by Drotleff (2007).

It was important to establish why daily traffic movements are constant at KEWR, because it illustrates the operational patterns and constraints at the airport independent of weather throughout the day. This will aid in the understanding of how airport delays propagate at different times throughout the day, based on such operation constraints. Airlines are careful to schedule around weather patterns where possible to give them the

[¤] 1 mmBar = 0.75006 mmHg was noted as the different pressure units in the raw data file and graph axis. Also the equivalent pressure of 1 mmHg = 133.3223 Pa was noted in the graph in Figure 5 best chance of minimising delays, should these occur for specific traffic patterns at KEWR.

Additionally, in Figure 6, an example to illustrate these delays can be seen in the morning peak-departure traffic between 07:00 and 09:00, where any adverse weather fronts in the vicinity of KEWR would have an immediate cause-effect impact on restrictions and consequently, cause delays for departing traffic. The net effect would be that airlines would be struggling to reduce delays for the remainder of the day, including considering cancellations (e.g. Pawn strategy[‡]). Conversely, supposing local adverse weather fronts affect KEWR at 21:00, some delays would ensue with limited impact, given the reduced number of travelers flying out of KEWR at that time of the day.

The following heuristic analyses serve to better understand time-dependent intricacies of weather variables and prevent experimental bias in GeNIe's results.

5.2.2 Precipitation Analysis (Heuristic)

Precipitation refers to weather conditions associated with any product of condensation that is the consequence of atmospheric water vapour falling to earth by gravitation. However, for the purpose of the experiment, only liquid precipitates were considered because these were the only ones included in the weather data set.

- In essence, why are hourly observations required and how do they relate to the dissertation objectives?

Regular and timely observations of weather variables can be an invaluable asset to pilots in forecasting weather conditions at an airport before departure. As previously mentioned and of particular relevance, are the ambient and dew point temperatures, because they provide forewarning of weather conditions in the near term. A close range of the weather variables in question (typically less than 4°) indicates likely reduced visibility conditions (especially haze, fog, etc.), but this depends on the time of day. If these conditions arise in a morning flight with stable weather predicted, then the value range of these weather variables is expected to increase, with a lower risk of reduced visibility, and consequently, fewer delays at the destination airport. If however, those same conditions exist at the destination airport in the late afternoon or evening, then it indicates that at sunset the ambient temperature will drop closer to the critical range, thus increasing the chances of reduced visibility (e.g. fog) at the destination airport. Reduced visibility conditions (e.g. fog), can also be separated into several main categories at the destination airport.[†]

Figure 7 shows the hourly effect of precipitation levels on visibility and potentially on delay as well. Precipitation was found to be the main cause of a low cloud base, with visibility improving when no precipitation was present. This occurred in 51% of all observations during the entire experiment at KEWR.

‡ Pawn strategy – refers to the cancellation of specific airline flights (normally short haul) for the benefit of the remaining flights (usually long haul), which are normally more profitable.

† Radiation Fog is likely to occur when the land mass near an airport cools off due to thermal radiation in calm weather with clear skies. However, advection fog occurs when moist air passes over a cool surface.

Hourly Observations

Time (EDT)	Temp.	Windchill	Dew Point	Humidity	Pressure	Visibility	Wind Dir	Wind Speed	Gust Speed	Precip	Events	Conditions
12:16 AM	11.0 °C	-	9.0 °C	88%	1004.6 hPa	12.9 km	NNE	33.3 km/h / 9.3 m/s	-	0.3 mm	Rain	Light Rain
12:51 AM	10.6 °C	-	7.8 °C	83%	1005.7 hPa	12.9 km	NNE	40.7 km/h / 11.3 m/s	50.0 km/h / 13.9 m/s	0.3 mm	Rain	Light Rain
1:51 AM	9.4 °C	-	6.1 °C	80%	1005.6 hPa	12.9 km	NNE	37.0 km/h / 10.3 m/s	51.9 km/h / 14.4 m/s	0.0 mm		Overcast
2:51 AM	8.9 °C	-	5.6 °C	80%	1004.5 hPa	12.9 km	North	31.5 km/h / 8.7 m/s	-	0.0 mm	Rain	Light Rain
3:51 AM	8.3 °C	-	4.4 °C	77%	1002.8 hPa	16.1 km	North	38.9 km/h / 10.8 m/s	48.2 km/h / 13.4 m/s	0.0 mm		Overcast
4:36 AM	8.0 °C	3.2 °C	4.0 °C	76%	1002.6 hPa	16.1 km	North	42.6 km/h / 11.8 m/s	55.6 km/h / 15.4 m/s	0.0 mm	Rain	Light Rain
4:51 AM	7.8 °C	2.7 °C	3.3 °C	73%	1002.2 hPa	16.1 km	North	46.3 km/h / 12.9 m/s	59.3 km/h / 16.5 m/s	0.0 mm	Rain	Light Rain
5:10 AM	7.0 °C	1.4 °C	3.0 °C	76%	1001.2 hPa	16.1 km	North	50.0 km/h / 13.9 m/s	59.3 km/h / 16.5 m/s	0.0 mm	Rain	Light Rain
5:51 AM	7.0 °C	1.5 °C	3.0 °C	76%	1001.6 hPa	12.9 km	North	48.2 km/h / 13.4 m/s	66.7 km/h / 18.5 m/s	N/A	Rain	Light Rain
6:27 AM	6.0 °C	1.0 °C	3.0 °C	81%	1000.9 hPa	6.4 km	NNE	35.2 km/h / 9.8 m/s	63.0 km/h / 17.5 m/s	1.5 mm	Rain	Rain
6:51 AM	6.1 °C	0.5 °C	2.8 °C	80%	1001.3 hPa	6.4 km	NNE	44.4 km/h / 12.3 m/s	63.0 km/h / 17.5 m/s	3.6 mm	Rain	Rain
7:01 AM	6.0 °C	0.4 °C	3.0 °C	81%	1001.6 hPa	4.8 km	NNE	44.4 km/h / 12.3 m/s	57.4 km/h / 15.9 m/s	0.3 mm	Rain	Rain
7:18 AM	6.0 °C	0.2 °C	3.0 °C	81%	1000.9 hPa	3.2 km	NNE	48.2 km/h / 13.4 m/s	68.5 km/h / 19.0 m/s	1.8 mm	Rain	Heavy Rain
7:45 AM	6.0 °C	0.2 °C	3.0 °C	81%	1000.2 hPa	3.2 km	North	48.2 km/h / 13.4 m/s	57.4 km/h / 15.9 m/s	5.3 mm	Rain	Rain
7:51 AM	5.6 °C	-0.6 °C	2.8 °C	82%	1000.3 hPa	3.2 km	North	51.9 km/h / 14.4 m/s	63.0 km/h / 17.5 m/s	5.3 mm	Rain	Rain

Figure 7: Hourly Weather Observations at KEWR (30 March 2010)

Another important consideration is the relative humidity at the destination airport. As the ambient temperature decreases, the likelihood of precipitation increases because the reduced volume of air can hold less and less water, until it reaches its saturation point. When this point is reached, precipitation starts gravitating towards the earth with reduced visibility and hence, a greater chance of increased delays at KEWR.

Atmospheric pressure in the form of high-pressure fronts create anti-cyclones[§] and can dictate the direction (i.e. clockwise) and strength of surface winds at the destination airport. With a known position of such weather fronts, the speed and direction of winds aloft can also be calculated and the effect on aircraft delays determined. Conversely, cyclones bring low-pressure fronts with air circulating counter-clockwise (Northern Hemisphere) around the centre of the low-pressure vortex. The impact on delay is considerable because again, strong surface winds can turn into wind shear, crosswinds and dangerous down drafts in the vicinity of an airport runway.

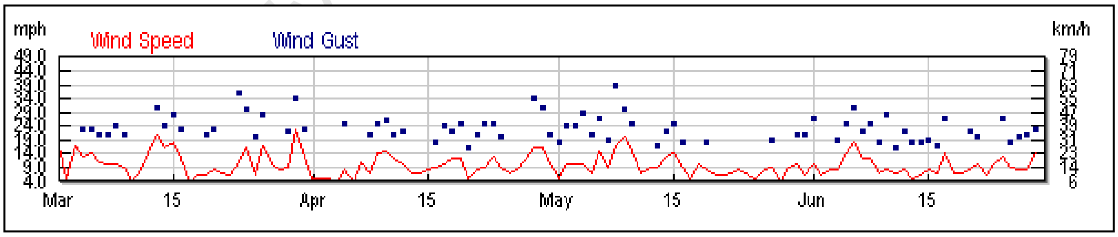

Figure 8: Wind and Gust Graph (March-June 2010)

KEWR ATC has an obligation to direct arriving and departing traffic into the direction of the wind, over and above the additional information pilots receive on weather (e.g. Weather briefings, TAF's[‡], NOTAMS, etc.) in the airport vicinity. Any change in wind direction necessitates a decision by ATC on whether there will be changes to the airport approach and hence, runway use, for safety considerations. This will override any other consideration, notwithstanding potential delays, as depicted in Figure 8.

[§] Large scale circulation of winds around a region of high atmospheric pressure rotating in a clockwise manner (Northern Hemisphere)

[‡] Terminal Aerodrome Forecast

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In thunderstorms, intense precipitation can occur, as well as other weather factors such as wind, thunder and lightning. The main features of thunderstorms are cells that are formed due to ascending moist air cooling quickly at given altitudes, thus forming increasingly bigger solid precipitates (e.g. hail) in a vertical cycle of air, reaching altitudes of 60 000 ft.

New York Terminal Radar Approach Control (TRACON) is a single airborne location in New York (NY) that provides flight arrival and departure services for several large airports in the vicinity. Given that arriving and departing traffic in the NY TRACON area have to remain at traffic pattern altitudes, ATC issues advisories for flight path deviations around thunderstorms, or implements GDP to flights whose flight path intersects storm cells. However, thunderstorms are not covered in the scope of this dissertation due to a lack of quantitative historical data compared to other weather variables.

The historical dataset analysed during the experiment revealed that thunderstorms were not always observed with precipitation in the 'Event' column, and hence, it was inferred that precipitation was not always explained by thunderstorms.

5.2.3 Wind Analysis (Heuristic)

Wind refers to weather conditions associated with large or small local movements of steady air mass. However, wind gusts comprise sporadic wind bursts, often in unpredictable directions, with short time intervals. Typically, gusts are more problematic than steady winds in aviation, because they are normally caused by other meteorological phenomena e.g. thunderstorms.

Several patterns emerged during the analysis that demonstrated a high correlation between wind and 'Low Delay' and 'High Delay' categories. Though initial analysis indicated the wind speed (average) to be the single factor correlating with the delays seen in Figure 8, it was in fact, wind direction that played a major part in correlating between the 'Low Delay' and 'High Delay' categories.

Several patterns emerged during the analysis that demonstrated a high correlation between wind and 'Low Delay' and 'High Delay' categories. Though initial analysis, indicated wind speed (average) as the single factor correlating to delays seen in Figure 10, it was in fact, wind direction that played a major part in correlating to the 'Low Delay' and 'High Delay' categories.

Upon closer investigation, certain wind directions as can be observed in Figure 12 had a greater effect on the 'Low Delay' and 'High Delay' category with particular emphasis on NW/SE winds above a certain speed threshold for the entire experimental period at KEWR.

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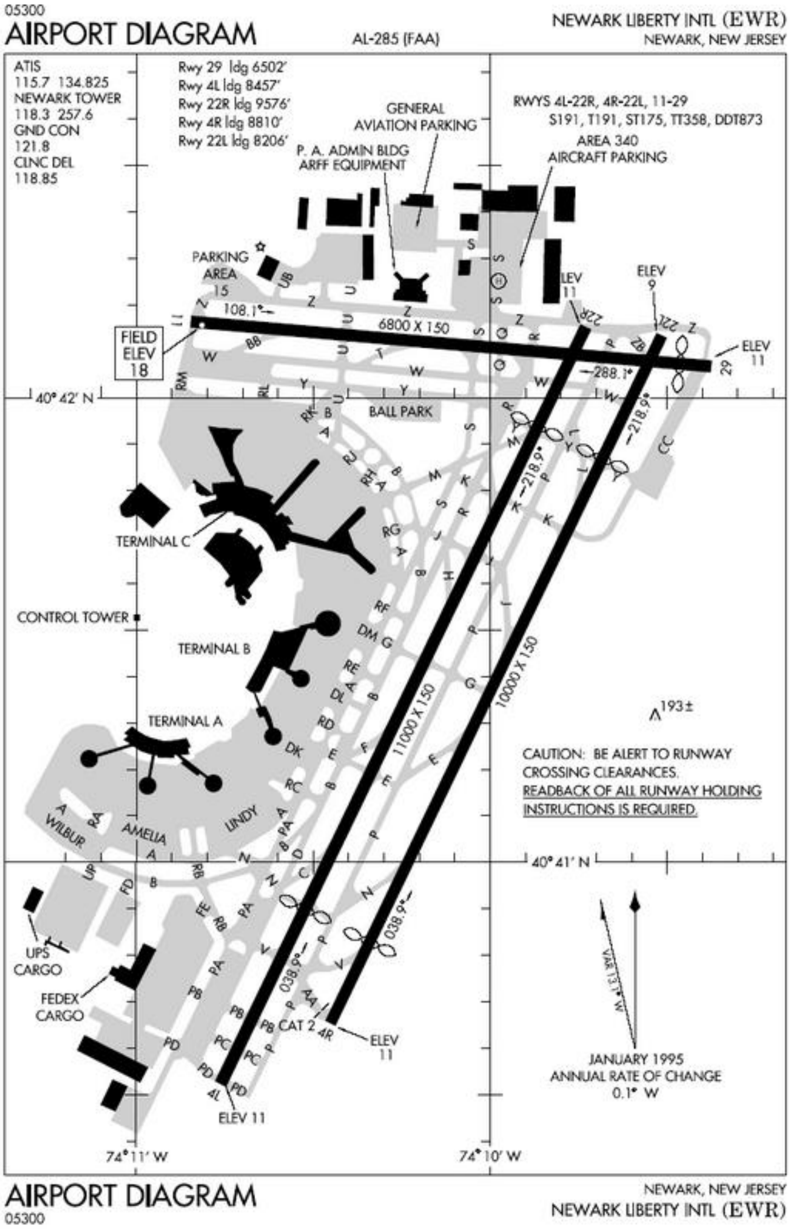

Figure 9: Newark Liberty International Airport Approach Chart (Source: flightaware.com)

The graph in Figure 9 demonstrates the three runway layouts at KEWR, with the potential effect wind direction can have on runway use and hence, airport delays. More specifically, the graph in Figure 9 demonstrates the orientation of the two main runways: 4LR/22LR (Magnetic bearing; 040°/220°) Right and Left (R&L) with a shorter overflow runway of orientation 11/29 (Magnetic bearing; 110°/290°). A NW (north-west) or SW (south-west) wind above a certain threshold would close the main runways 4LR/22LR due to crosswinds, with the subsequent activation of runway 11/29.

Departing and arriving aircraft can take off into the wind (head wind) and with the wind (tail wind) below a certain threshold speed, but not if the crosswind threshold is surpassed.

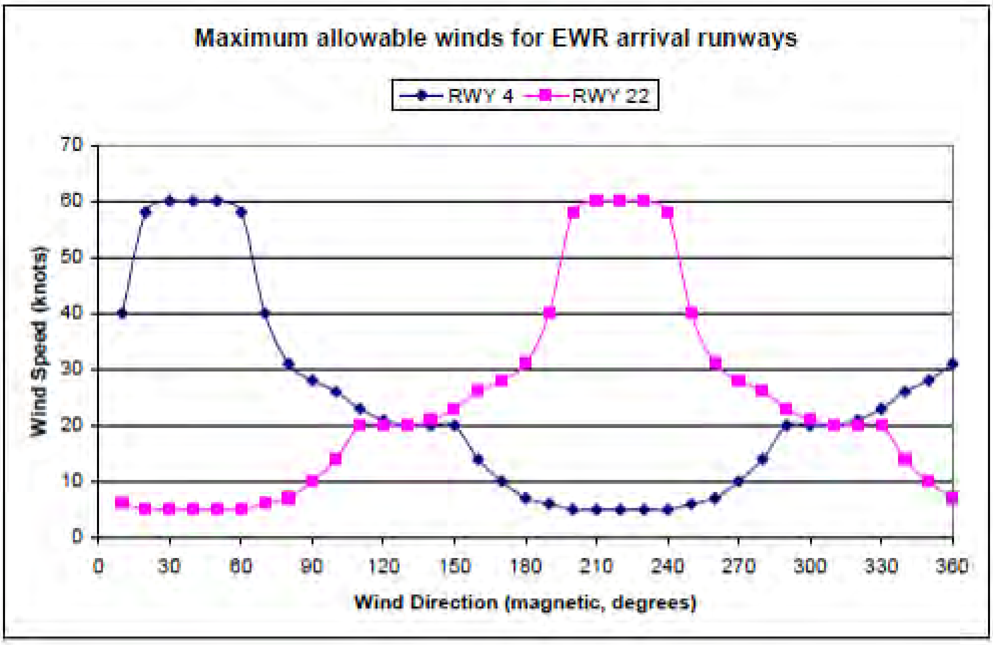

Figure 10: KEWR Maximum Allowable Winds Chart (Source: Allan et al. 2001)

Upon closer investigation, certain wind directions, as observed in Figure 10, had a greater effect on the 'Low Delay' and 'High Delay' categories. Particular emphasis was given to NW/SE winds above a certain speed threshold, for the entire experiment at KEWR.

➢ Having explored wind speed in the vicinity of an airport, what are the implications of wind direction on airport delays?

In Figure 10, the wind direction (magnetic degrees) in itself will not be sufficient to have a considerable impact on delays. However, when it is combined with wind speed and gusting, then the implications are major, depending on the aircraft size and runways in use.

Furthermore, in Figure 10, the wind chart depicts a maximum wind speed for landing operations from a magnetic bearing on runways 04/22. It also indicates that from a bearing range of 10°– 60°, flights landing on runway 22 can land with a maximum tail wind of 5 knots and similarly, land on runway 03 with a maximum headwind of 60 knots. This is applicable for any sized jet. The same threshold applies to runway 04. However, a clear 20 knot threshold was set for crosswinds in the bearing ranges of 100°–150° and 285°– 330°, where flights would be considerably delayed or diverted to other airports in the vicinity.

The implications and impact on delays if these thresholds are exceeded, stems from the fact that ATC will most likely transfer arrivals to runway 11/29, with a subsequent reduction in airport capacity, and restrict the type of aircraft (e.g. Boeing 737 or similar) able to land at KEWR. As previously explained, the effect of this is that larger aircraft are likely to be diverted to the nearest airport, causing considerable delays.

Hence, this weather variable could be a good indicator of weather impact (i.e. high surface winds) on delays at KEWR because there is an immediate go/no go threshold on

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this type of weather event. Furthermore, no technological aid can mitigate its effects, which makes the case stronger for wind as a suitable indicator of delays at airports.

In summary, the chart in Figure 10 displays the maximum wind speed for every wind direction at KEWR. This is critical to understand when crosswinds are deemed too strong to use the main runways, 4LR/22LR. A range of NW/SW winds that are deemed as crosswinds at KEWR can be seen quite clearly from the graph.

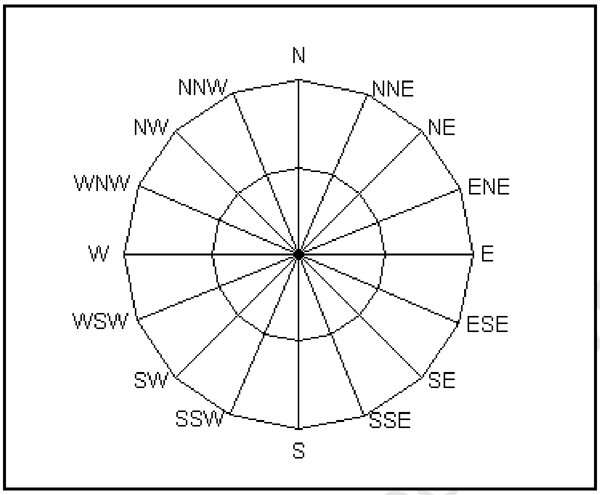

Figure 11: Combinations of Wind Directions Chart at KEWR (Source: Minnesota Climatology Working Group)

For the purposes of the experiment, a range of wind directions was considered (Figure 11). The crosswinds previously analysed showed a high correlation between westerly wind direction and the 'High Delay' category[3,4], with the other wind directions that caused delays in the 'Low Delay' category being less frequent at KEWR. This was later confirmed during further testing in GeNIe.

In addition, historical observations by meteorologists using a 'Wind Rose' at KEWR (Figure 12), display wind intensity and direction simultaneously in a northwesterly direction, posing multiple challenges for arriving and departing traffic.

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[3] 'EWR issued a Ground Delay Program affecting flights arriving between 2010-07-16 17:01 and 2010-07-16 21:59 due to WEATHER / WIND. Flights were being delayed an average of 35.0 minutes. There were 141 flights that were affected by this delay.' [Source: FAA Advisory 2010]

[4] 'EWR issued a Ground Delay Program affecting flights arriving between 2010-07-18 12:59 and 2010-07-18 19:59 due to WEATHER / WIND. Flights were being delayed an average of 23.0 minutes. There were 162 flights that were affected by this delay.' [Source: FAA Advisory 2010]

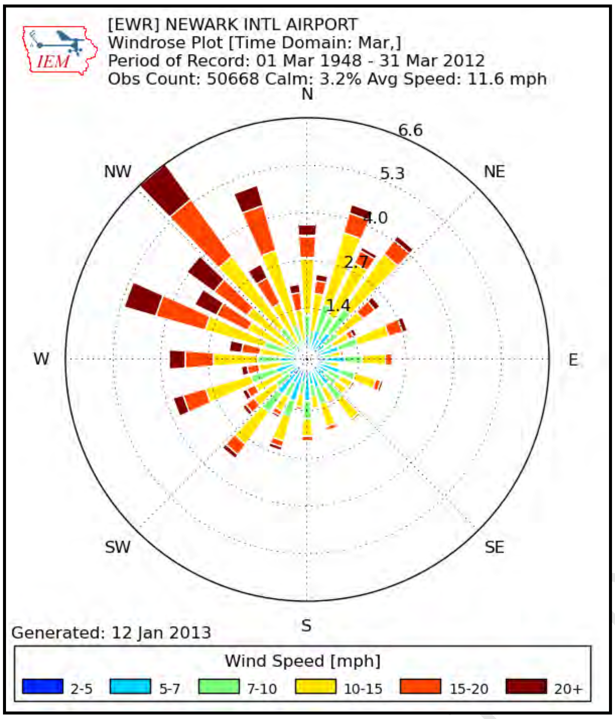

Figure 12: Wind Rose Data for KEWR (Source: Iowa Environmental Mesonet 1948 – 2012)

Essentially, the interaction and complexity of weather variables in a short time frame can have a dramatic effect on meteorological and operational conditions at KEWR without forewarning (e.g. fog), producing delays. The variability and sensitivity to delays were important factors when considering which weather nodes to take into account for predicting delays at KEWR, in line with the dissertation objectives.

5.3 Weather Information

Historical weather data was available from the wunderground website and was downloaded for subsequent analysis. For more detailed information, refer to Section 4.1.2.

As part of the heuristic analysis, the following section aims to offer quantitative examples of meteorological phenomena for the month of March 2010.

The graph in Figure 13 represents the barometric pressure at KEWR for the calendar month of March 2010, which upon observation, revealed data trends relating to other weather variables in the experiment. In particular, a sudden drop in barometric pressure usually associated with a weather front of unstable weather, normally indicates a possible causal impact on other weather variables, such as ambient and dew point temperature. The interaction of the latter weather variable could have a causal effect on precipitation, visibility and wind, with ensuing delays at KEWR.

At a more granular level, a decrease in barometric pressure normally indicates a drop in atmospheric temperature, thus reducing the volume the air occupies, given that the air molecules have less energy at any given time. Simultaneously, as the air volume reduces, relative humidity increases in relation to its volume, and upon reaching its saturation point (i.e. 100%) or dew point temperature, precipitates are formed. Hence, moisture is released in the form of liquid droplets because the air cannot possibly hold any more moisture.

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Conversely, a sudden climb in barometric pressure decreases relative humidity for a given volume and indicates stable weather, normally in the form of a warm weather front, minimising the chances of precipitation, low visibility and often, high surface winds‡.

- What consequences and effects do the above weather events have on the weather variables under scrutiny in this investigation and more specifically on airport delays at KEWR?

To further our understanding, we can deduce that low barometric pressure fronts (e.g. thunderstorms) convey unstable weather systems, prompting pre-emptive action by ATC in preparation for possible airspace restrictions. These can include fix cancellations or if deemed appropriate, the downgrading of flight conditions from Visual Meteorological Conditions (VMC) to Instrument Meteorological Conditions (IMC). If these considerations by ATC are carried out, then safety measures for arriving and departing traffic are executed. This increases the separation between flights (i.e. Miles in Trail), which are flying in unpredictable and unstable weather conditions with likely reduced visibility, causing an impact on delays at KEWR and other airports in the vicinity.

However, given the dissertation objectives, this does not necessarily mean that visibility is an appropriate metric to be used in approximating airport delays at KEWR, since aircrew and aircraft can mitigate these adverse weather effects.

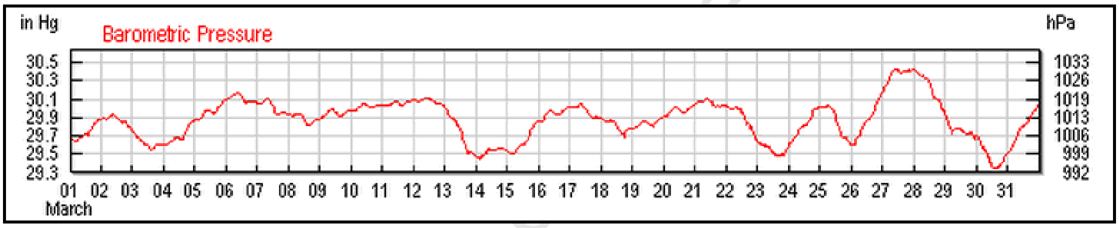

Figure 13: Barometric Pressure at KEWR (March 2010)

As several examples revealed, a closer inspection of Figures 13 and 14 depicted data trends on certain dates in March that better explained how weather variables interact, causing delays at KEWR.

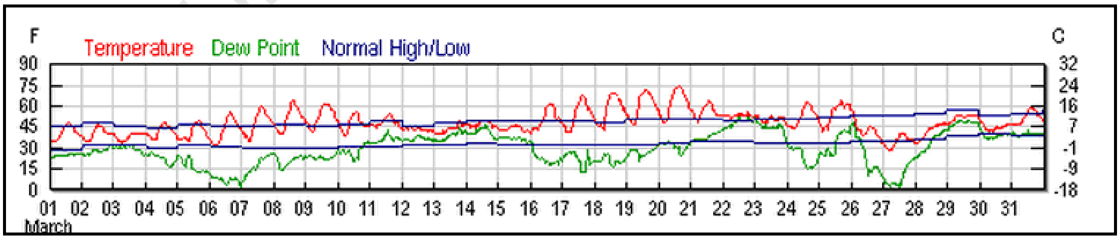

Figure 14: Temperature and Dew Point at KEWR (March 2010)

- On 3 March and 4 March 2010 in Figure 13, a clear and sudden drop in barometric pressure from 29.9 Hg to 29.6 Hg was noticeable, with an impact on low visibility in Figure 14 for the same graph point. As previously explained, given the narrow range between the ambient temperature and dew point temperature, this seemed a clear

‡ High surface winds have been identified at KEWR even after stable weather fronts, which are not likely at any other airports in the US.

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case for low-visibility conditions, and instrument flying conditions would have been necessary. Thus, visibility for the above dates was reduced from 16 km to 6 km at KEWR.

- During 13 March and 14 March (Figure 13), a clear drop in pressure again, from 30.1 Hg to 29.4 Hg, resulted in maximum wind speeds of 52 kph, gusting at 72 kph, for the same time interval at KEWR.

  Moreover, historical data showed a strong precipitation of over 100 mm, indicating a high correlation with pressure reduction. Visibility was also adversely affected, decreasing to 1–2 km, bordering aviation minima and hence, impacting on delays at KEWR.

- 22 March and 24 March 2010 showed a drop in pressure from 30.1 Hg to 29.5 Hg (Figure 13), further reducing visibility to 2 km, with increased wind speeds of 48 kph, gusting at 63 kph, at the same graph point. Precipitation accumulated on 22 March 2010 was 300 mm at KEWR.

- Lastly, on 28 March and 29 March 2010, a similar barometric pressure drop from 30.4 Hg to 29.3 Hg occurred, with a reduced visibility of 2 km and maximum wind speeds reaching 58 kph and gusting at 69 kph, at KEWR. This phenomenon can be a particular problem for landing traffic because the crosswind threshold is superseded, thus greatly affecting delays.

5.4 Consolidated Information (Weather & Aviation)

All flight delay information at KEWR was consolidated, using the sum function in Excel, on a per day basis.

To consolidate the weather and aviation information, a sort function in Excel was used to find the common dates between the weather and aviation data files. This combined file, with the consolidated delay calculated in minutes, is described in Table 2. Each column heading is represented by a variable, and the data within each column was evaluated to find any correlations between variables, using Excel pivot tables.

Both the heuristic approach of using Excel pivot tables and the use of GeNIe to calculate the approximation of delays yielded a robust, complementary and comprehensive approach to maintain the quality of the experiment with greater chances of alignment with the dissertation objectives.

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	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	W
1	Date	Temp Max	Temp Ave	Temp Min	DP Max	DP Ave	DP Min	Humid Max	Humidity Ave	Humidity Min	Press Max	Press Ave	Press Min	Visib Max	Visib Ave	Visib Min	Wind Max	Wind Ave	Gust Sp	Delay (min)
2	31/05/2010	31	25	18	18	15	12	78	57	36	1016	1014	1013	16	15	8	32	9	42	166
3	31/03/2010	16	12	8	6	4	3	76	64	51	1016	1007	999	16	16	11	35	21	42	391
4	30/05/2010	30	25	20	16	12	8	78	53	27	1013	1011	1010	16	16	13	32	15	52	159
5	30/03/2010	10	8	5	8	3	2	83	80	76	1006	998	993	16	7	3	58	37	69	0
6	30/04/2010	27	20	13	7	0	-3	42	31	19	1013	1010	1007	16	16	16	32	16	39	777
7	29/05/2010	26	22	17	16	14	11	84	68	52	1015	1013	1010	16	16	13	26	15	35	187
8	29/03/2010	12	10	8	10	8	6	93	88	83	1014	1008	1005	16	9	2	45	14	52	115
9	29/04/2010	22	15	6	-5	-6	-10	41	27	13	1011	1009	1006	16	16	16	52	25	77	802
10	28/05/2010	20	17	13	12	11	9	80	66	52	1015	1014	1013	16	16	16	14	7	23	630
11	28/03/2010	8	5	0	6	1	-5	86	72	58	1030	1024	1015	16	15	6	39	13	56	120
12	28/06/2010	18	15	12	8	6	3	64	51	42	1022	1021	1020	16	16	16	13	8	0	61
13	28/02/2010	5	2	0	-1	-3	-4	82	68	54	1005	1003	1002	16	14	6	34	9	42	436
14	28/04/2010	15	9	3	-2	-5	-9	55	39	22	1007	1002	1000	16	16	16	48	26	64	281
15	27/05/2010	28	21	13	17	12	8	73	59	45	1013	1010	1006	16	14	2	26	14	37	48
16	27/03/2010	5	1	-2	-5	-12	-16	61	40	18	1030	1028	1022	16	16	16	32	15	42	279
17	27/06/2010	18	15	12	8	6	3	64	51	42	1022	1021	1020	16	16	16	13	8	0	1040
18	27/02/2010	3	1	-2	-2	-4	-6	75	67	59	1003	999	996	16	16	14	26	16	32	225
19	27/04/2010	16	10	4	7	2	-6	86	55	24	1001	994	991	16	14	4	48	19	61	1766
20	26/05/2010	35	26	17	17	15	12	78	54	30	1017	1011	1006	16	16	16	27	12	37	3149
21	26/03/2010	14	7	0	8	-2	-12	82	54	25	1021	1009	1002	16	16	13	48	28	60	2661
22	26/06/2010	18	15	12	8	6	3	64	51	42	1022	1021	1020	16	16	16	13	8	0	2071
23	26/02/2010	2	0	-3	0	-4	-6	89	77	64	997	988	980	16	6	0	47	22	60	291
24	26/04/2010	12	11	10	8	8	7	89	85	80	997	994	991	16	10	2	24	12	29	1854
25	25/05/2010	27	21	14	16	13	12	87	66	45	1025	1022	1017	16	15	10	21	9	27	2706
26	25/03/2010	17	11	5	6	0	-4	62	44	26	1017	1011	1003	16	16	13	27	9	39	1667

Consolidate_Import / Consolidation / GeNIe_Import1 / Precip_Events

Table 1: Consolidated Weather and Delay Data in Excel (Source: Wundergound and Flightaware)

Temporal observations and the count of evidence from the weather variables were important considerations when deciding how they could best be represented in GeNIe as per Table 2. Excel was used to collate all observations per month for discretised weather variable bins (e.g. Visibility: 12-16 km) and applied to GeNIe's temporal plates.

	Wind, Visibility & Precipitation													
	March - 2010													
Date	Wind Ave (kph)					Wind Dir.	Visibility Min (km)			Precipitation (mm)				Event
	Range: 6-37						Range: 0-16			Range: 0-1013				
	6-11	12-18	19-25	26-32	33-37		0-5	6-11	12-16	1-250	251-500	501-750	>750	
01/03/2010	0	0	0	1	0	NW	0	0	1	0	0	0	0	No Rain
02/03/2010	1	0	0	0	0	NE	0	0	1	0	0	0	1	T:Rain
03/03/2010	0	0	0	1	0	NNE	0	1	0	1	0	0	0	13:Rain-Sr
04/03/2010	0	0	1	0	0	NNW	0	0	1	0	0	0	0	No Rain
05/03/2010	0	0	1	0	0	N	0	1	0	0	0	0	1	T:Snow
06/03/2010	0	1	0	0	0	NW	0	0	1	0	0	0	0	No Rain
07/03/2010	0	1	0	0	0	WNW	0	0	1	0	0	0	0	No Rain
08/03/2010	0	1	0	0	0	WNW	0	0	1	0	0	0	0	No Rain
09/03/2010	0	1	0	0	0	WNW	0	0	1	0	0	0	0	No Rain
10/03/2010	1	0	0	0	0	E	0	0	1	0	0	0	0	No Rain
11/03/2010	0	1	0	0	0	NE	0	1	0	0	0	0	0	No Rain
12/03/2010	0	0	1	0	0	NE	1	0	0	1	0	0	0	91:Rain
13/03/2010	0	0	0	0	1	NE	1	0	0	0	0	0	0	1013:Rain

Table 2: Pivot Table Analysis for Consolidated Delay

During March, April, May and June 2010, a single temporal node was used to represent a calendar month. This temporal node contained a CPT that represented the total number of observations for a discretised range (e.g. Visibility: 12-16) in a given calendar month. This was expressed as a percentage of the total number of observations during the entire experiment. Hence, this method intended to avoid representing individual nodes for each delay value, which would make analysis of the model a challenge for the entire experiment. The remaining temporal delay node (i.e. time slice) would represent the final results, which would be measured against the evidence for the precipitation, wind or visibility nodes, and would yield the most accurate results for delay causality.

5.5 Experimental Results

The experiment with time intervals March, April, May and June 2010 represented a stochastic process of random weather and delay variables (i.e. historical data), characterised by the use of a dynamic system (i.e. time variant).

Furthermore, the experiment in GeNIe was divided into three main sections representing weather variables used for approximating delay at KEWR:

- Precipitation
- Visibility
- Wind

The analysis revealed which variable was the most effective in approximating delays at KEWR, using the observed historical data as a CPD for each node in GeNIe. This was aligned with the objectives set out in the introductory chapter.

In each experiment, two types of graphic structure were displayed in GeNIe. These were displayed in a typical GeNIe network topology for the experiment and were divided into 'Rolled' and 'Un-Rolled' structures in DBN mode.

By unrolling the network topology structure, Bayes inference was performed on the last time slice for every weather variable, in order to better approximate delays in July at KEWR. The CPD for the July node would give an indication as to how effective a weather variable was, in estimating delays at KEWR.

Bayes inference was performed using historical data from wunderground.com. This data was entered as virtual evidence in a CPT representing 31 days in July. Entering hard data as evidence would have been unrealistic and would have biased the posterior marginal probability of delay for July.

The above methodology for inference was performed for the precipitation and visibility variables but not for the wind variable. Inference on the wind variable for the last time slice was performed on the two components of wind intensity (i.e. speed) and wind directionality (i.e. magnetic bearing). Separate data sets were entered as virtual evidence for each wind variable, as this ensured the best accuracy.

The expected results for all three weather variables showed a CPD for the Delay node in each weather category. The marginal posterior probability of the Delay node revealed which weather variable was better, thus approximating delays better at KEWR. In addition, the heuristic analyses conducted, provided confirmation and complemented the findings for the best suited variable in estimating delays. These delays were discretised as shown:

- Normal: 0 – 1499 (minutes)
- Low Delay: 1500 – 2999 (minutes)
- High Delay: > 2999 (minutes)

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5.5.1 **Precipitation Analysis**

5.5.1.1Temporal Network Topology for Precipitation

This experiment determined if the precipitation variable was the most effective in approximating delays at KEWR.

In Figure 15, a rolled network for the Precipitation and Delay node was displayed in the temporal plate with five time steps as a time parameter. The 'Event' node was time invariant and for that reason, remains outside the temporal plate for the entire experiment.

The values in the CPT for the 'Event' node had an accurate spread of probabilities for the experimental period March, April, May and June 2010, and hence, it was not necessary to model them in the temporal plate.

The 'Event' node contained the following weather variables:

- Rain
- Rain_Thunderstorm
- Fog
- Fog_Snow
- Fog_Rain_Thunderstorm
- Snow
- None (no event reported)

Where more than one weather variable was recorded, its values represented all the meteorological conditions for a given day. This was expressed as a percentage of the total number of weather variables' value for the entire experiment.

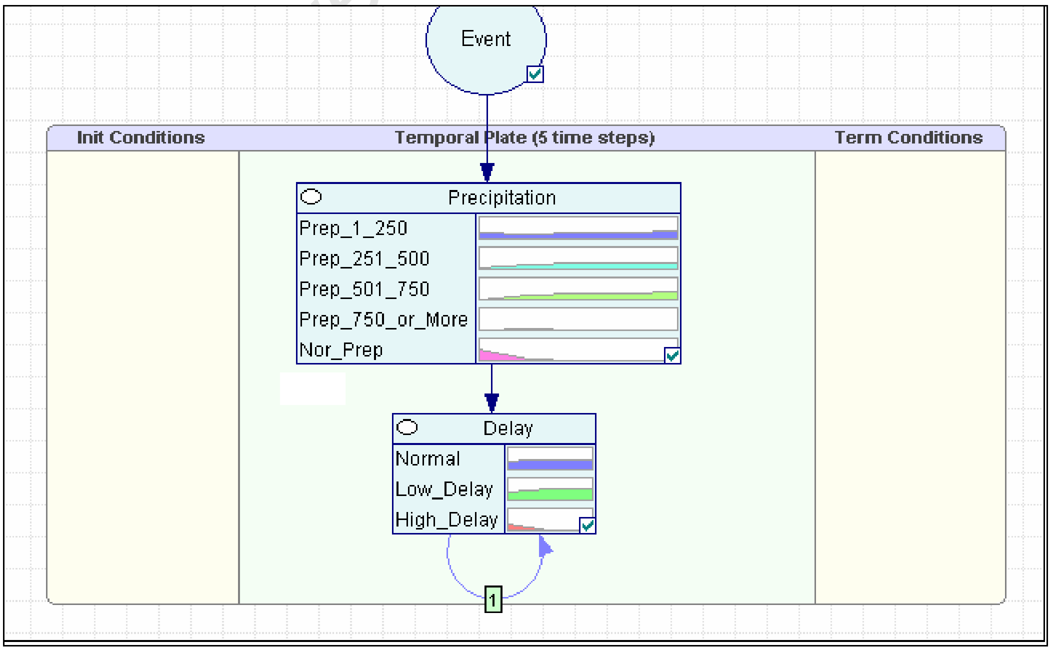

Figure 15: Temporal DBN Nodes for Precipitation

The graph space in Figure 15 displays two temporal nodes discretised for Precipitation (five bins) and Delay (three bins), with both of temporal order one. No initial conditions were specified (i.e. anchor nodes[5]) outside the temporal plate linking child nodes to the temporal plate, and conversely, no terminal nodes were linked with one or more parent node[6] to the temporal plate.

An anchor node was only connected to the first time slice in an unrolled network (temporal plate), and conversely, a terminal node was only connected to the last node in an unrolled network.

In the precipitation analysis, all observed values in the precipitation data set were discretised as follows:

- Prep_1_250: All observed daily values from 1 mm to 250 mm of liquid precipitation
- Prep_251_500: All observed daily values from 251 mm to 500 mm of liquid precipitation
- Prep_501_750: All observed daily values from 501 mm to 750 mm of liquid precipitation
- Prep_750_or_More: All observed daily values in excess of 750 mm of liquid precipitation
- No_Prep: Included all daily observed values of 0 mm or precipitation traces which accounted for over 50% of all observed values during the entire experiment

All values in each discretised bin are displayed as a percentage of all observations for the entire number of days in any given month, throughout the experimental period.

A temporal order of 1 indicates a temporal order of influence, where the current temporal node (t) has an effect on the previous temporal node (t-1). This was deemed to be a reasonable assumption during the experiment, indicating a clear time variant dependency of delay (t) with delay (t-1). Moreover, a temporal order of 2 in an unrolled network was where a child node was '2 Order' slices ahead of the parent node.

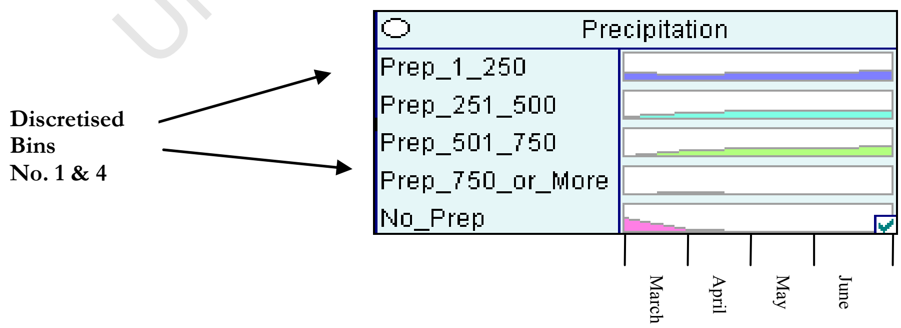

Figure 16: Temporal Node Graph for Precipitation in GeNIe

[5] Anchor nodes are nodes with starting conditions before the temporal plate

[6] Parent nodes have other dependent nodes called 'Child Nodes' which are direct descendants

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In Figure 16, the frequency count for precipitation stands for the number of observations in each bin for the experimental period (i.e. March, April, May and June 2010). Therefore, this Precipitation node symbolises five time slices rolled into an original node in the temporal plate. An obvious observation in Figure 16 was the lack of precipitation at the beginning of March (i.e. 52% of all observations), with a steady decline in the number of observations towards the end of March. This indicates that the low levels of precipitation detected early on, may prove this an unsuitable candidate to approximate delays at KEWR.

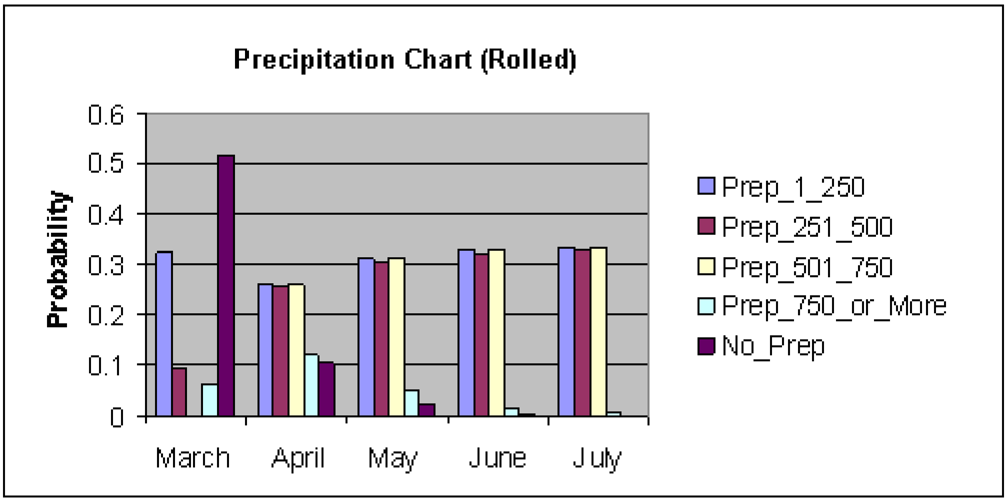

Figure 17: Detailed Chart for Precipitation in GeNIe

In Figure 17, the bins represent discretised experimental data before inference was performed. The temporal probability distribution of precipitation clearly indicates the lack of any observations in the 'Prep_501_750' bin for March and a high number of observations with no precipitation in the bin 'No_Prep', accounting for 51% of all occurrences in the same month.

The experimental data showed that March was generally a dry month with small quantities of precipitation. The months of April, May and June showed a steady increase in the number of observations in the bins 'Prep_251_500' and 'Prep_501_750', as seen in Figure 17. The highest observation in the former category was in April, with 16% of all observations; typically a wet month in the Northern Hemisphere.

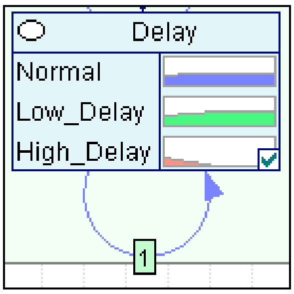

Figure 18: Detailed Delay Graph for Precipitation in GeNIe

Figure 18 shows a rolled Delay node consisting of three discretised bins for 'Normal', 'Low Delay' and 'High Delay', respectively. A value of 18% was observed for the 'High Delay' category in the month of March, with a low number of observations in all precipitation categories, except 'Prep_1_250', as seen in Figure 17. From this, it can be inferred that 'High Delays' can occur even with precipitation. However, the effect of high precipitation on delay was not observed in the results, and its subsequent use as a candidate variable to approximate delays at KEWR, was not particularly strong.

A more detailed analysis was carried out in GeNIe using the option to unroll the precipitation network from the temporal plate. This option presented five time slices in the graph space where each node was populated with historical data from a CPT. Moreover; a CPD for the Precipitation node was considered for every discretised bin in the 'Event' node because this ensured accuracy in the experimental output.

In addition to this, a discrepancy was observed in the Precipitation node before and after inferencing, with updated posterior probabilities showing a large deviation in all bins except 'Prep_1_250'. This can be seen between Figures 16 and 20.

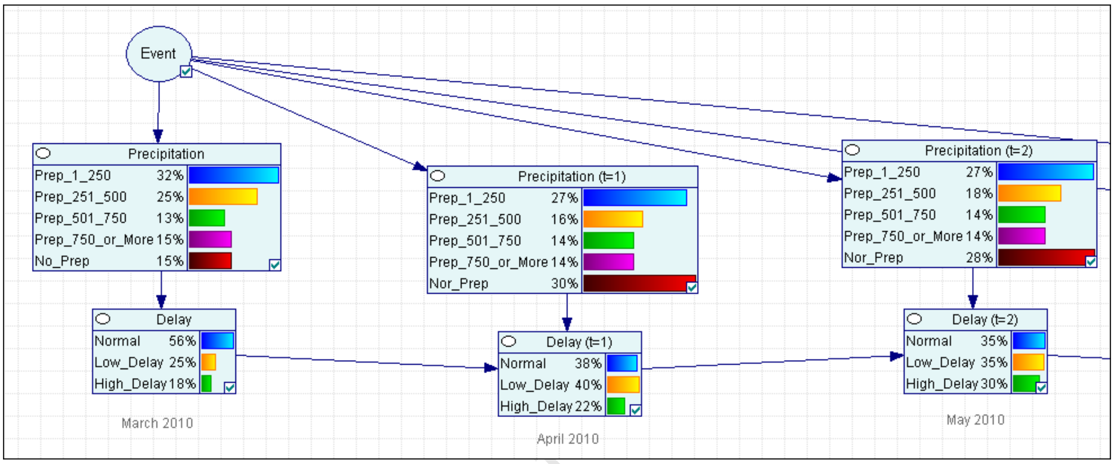

Figure 19: Temporal Network for Precipitation (Nodes 1-3)

Lastly, in Figure 20, inference was performed on the Precipitation node for July, employing soft evidence input data from wunderground.com. This showed the same posterior probabilities for the Delay node in July, with 37% of all occurrences in the 'Normal' and 'Low Delay' bin, compared to only 27% in the 'High Delay' bin. It is worth noting that the month of July 2010 was a particularly precipitation free month.

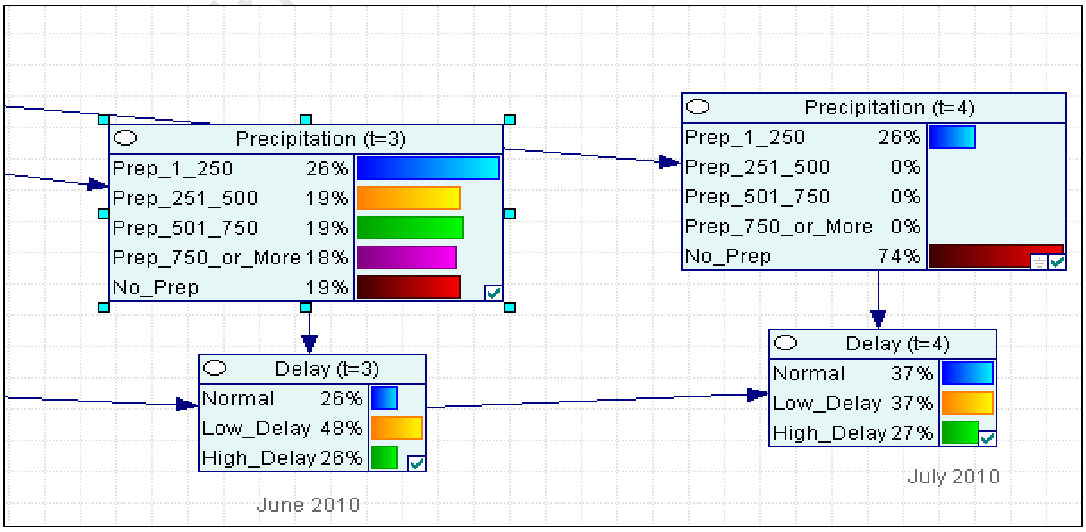

Figure 20: Temporal Network for Precipitation (Nodes 4-5)

In summary, applying inference on the Precipitation node in July updated the marginal probability of delay with new values in the CPT. These values would form the basis of a comparison at the end of the experimental results, as to which weather variable was best suited at approximating delays. Once more, the variable precipitation did not disclose itself as a strong candidate for approximating delays at KEWR, due to the low number of observations in the 'High Delay' category and low correlation/impact with the remaining delay categories.

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5.5.2 **Visibility Analysis**

5.5.2.1Temporal Network Topology for Visibility

This experiment was created to examine the effects of the visibility variable in GeNIe and its usefulness in delay approximation.

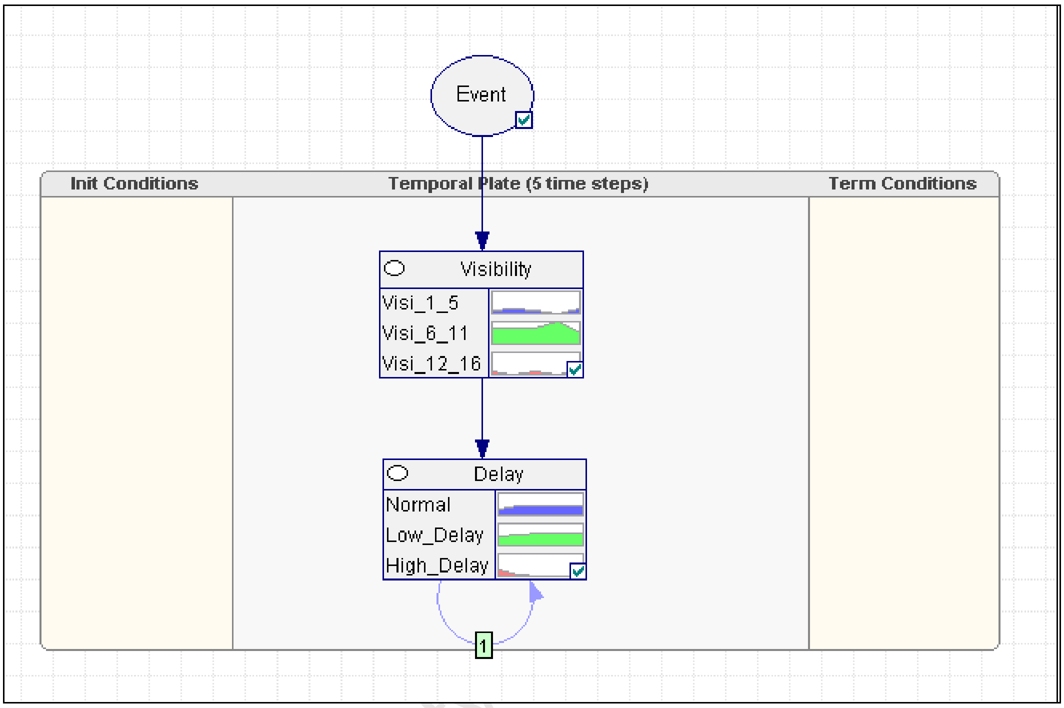

Figure 21: Temporal DBN Nodes for Visibility

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For the visibility experiment, two temporal nodes were created containing three discretised bins for the Visibility node, as illustrated in Figure 21. The discretisation of the Delay node was not altered in relation to the other experiments, and all other parameters relating to the temporal order were unaffected.

In the visibility experiment, the observed historical values were discretised into the following bins:

- Visi_1_5: These values consisted of an observed daily minimum distance of 1 km to 5 km (above aviation minima)
- Visi_6_11: Values consisted of an observed daily minimum distances of 6 km to 11 km
- Visi_12_16: All observed daily minimum distances from 11 km to a maximum visibility of 16 km

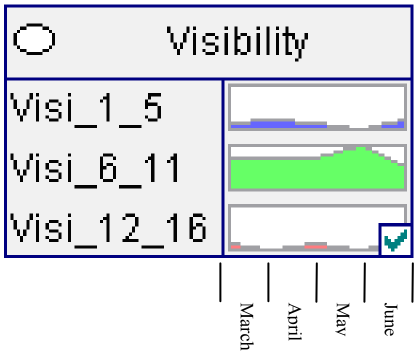

Figure 22: Temporal Node Graph for Visibility in GeNIe

Figures 22 and 23 demonstrate a notable marginal probability profile for the Visibility node in the 'Visi_6_11' bin containing 60% of observations for the months of March, April and May. June exemplifies an unusually high number of observations examined in the same bin category, with 93% of all observed values. This high number of occurrences was most likely due to the numerous summer thunderstorms, which affected the North Eastern Seaboard Corridor, where KEWR is located.

Given the range of graph values illustrated, 60% of occurrences (e.g. in March 2010) occur above minima (i.e. 2 km) in the visibility range of 6–11 km in Figure 23, thus questioning its suitability as a variable to predict delays,. Most of the restrictions on visibility are seasonal, and this is further complicated by the close presence of KEWR to large bodies of water, which can have an impact on delays due to phenomena such as advection fog. Delays are also due, in part, to the fix restrictions imposed by ATC at KEWR.

In July, the marginal probability of delay was estimated at 33%, weighted for all bins considered before inference was performed on the Visibility node for the same period. This is illustrated in Figure 23.

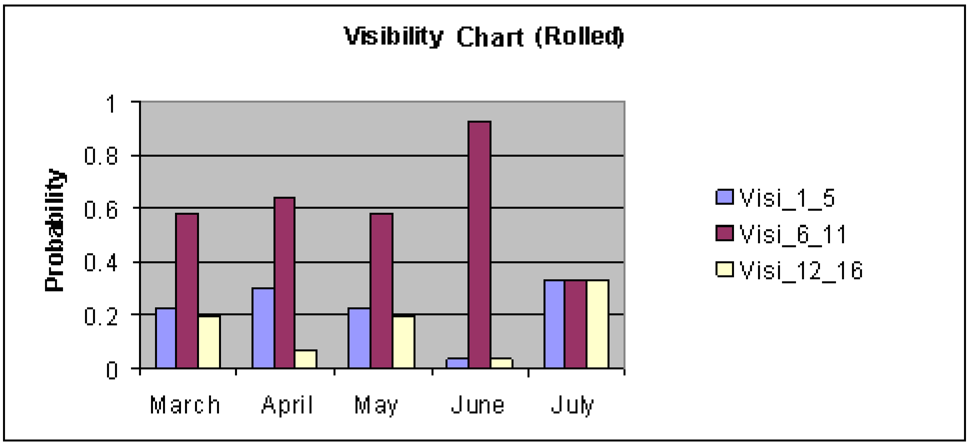

Figure 23: Detailed Chart for Visibility in GeNIe

In Figure 23, the seasonality patterns emerge clearly, showing that the spring and summer months have a higher probability of delays due to reduced visibility. The impact and reach of delays at KEWR are considerable if departure fix restrictions are imposed by

ATC. Hence, for this reason, the visibility category was not likely to be considered a suitable weather variable for approximating delays at KEWR.

The effect of the observations in the 'High Delay' bin for March was not clear from the experimental results and could not adequately be explained by the observations in the Visibility node in the "Visi_6_11" bin category. Hence, the high number of observations for the 'High Delay' bin must be explained away by other factors, including the possibility of a high influence from wind, as analysed in the experiment in Section 5.5.3.

Thus, the high number of observations in the 'Visi_1_5' bin for April, as illustrated in Figure 23, should have had an impact in the 'High Delay' bin, but only had an effect on the 'Normal' and 'Low Delay' bins (i.e. 40% and 58% respectively) This is denoted in Figure 24. This implied that low visibility conditions did not have a significant impact in the 'High Delay' bin during the experimental period. These observations were noted as being mitigated by the extensive use of technology in an airport environment.

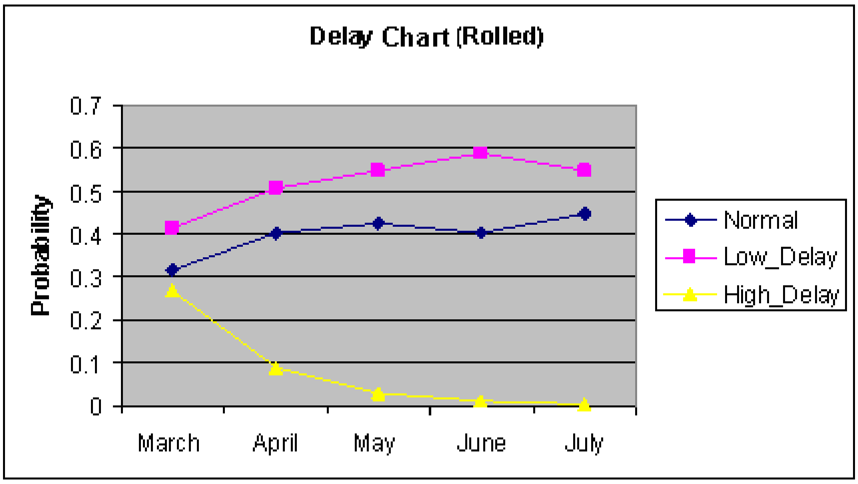

Figure 24: Detailed Delay Chart for Visibility in GeNIe

The effect and impact of visibility on delay categories (as previously mentioned) as a candidate variable is questionable for predicting delays, because its graph gradient, with respect to probability, is low (i.e. impact) when compared to the 'Normal' and 'Low Delay' categories. Hence, given the dissertation objectives this variable would not constitute an ideal candidate for approximating delays at KEWR.

The discretised values for visibility in all bins were verified for March and May, because the number of observations in each bin might be misleading due to their similar marginal probabilities in the experiment. Verification of all the values in each bin was conducted to ascertain that they pertained to their correct bin, and that they were discretised correctly. No errors were found in the discretisation process.

As viewed in Figure 25, a static DBN can be displayed by unrolling the dynamic network into individual time slices, each representing the calendar months of the experimental period.

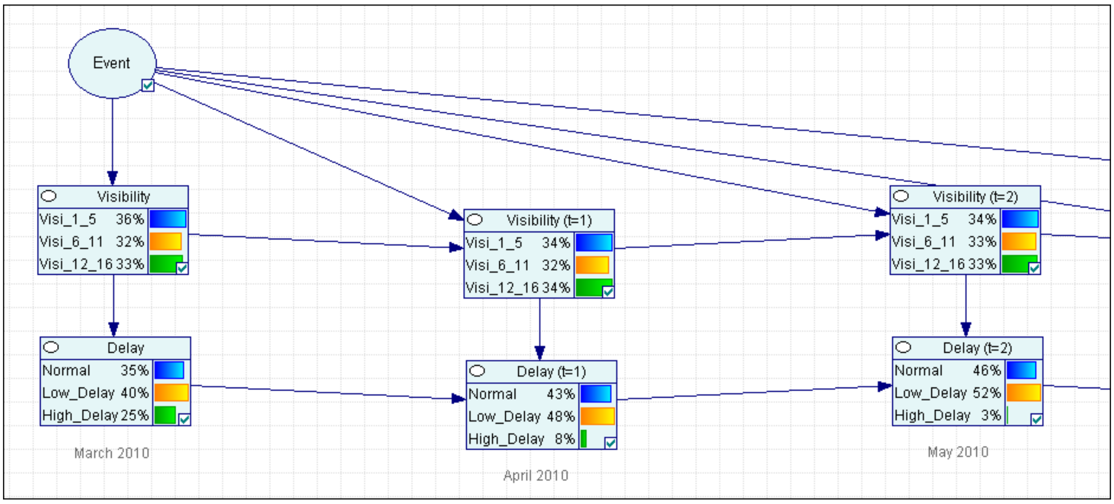

Figure 25: Temporal Network for Visibility (Nodes 1-3)

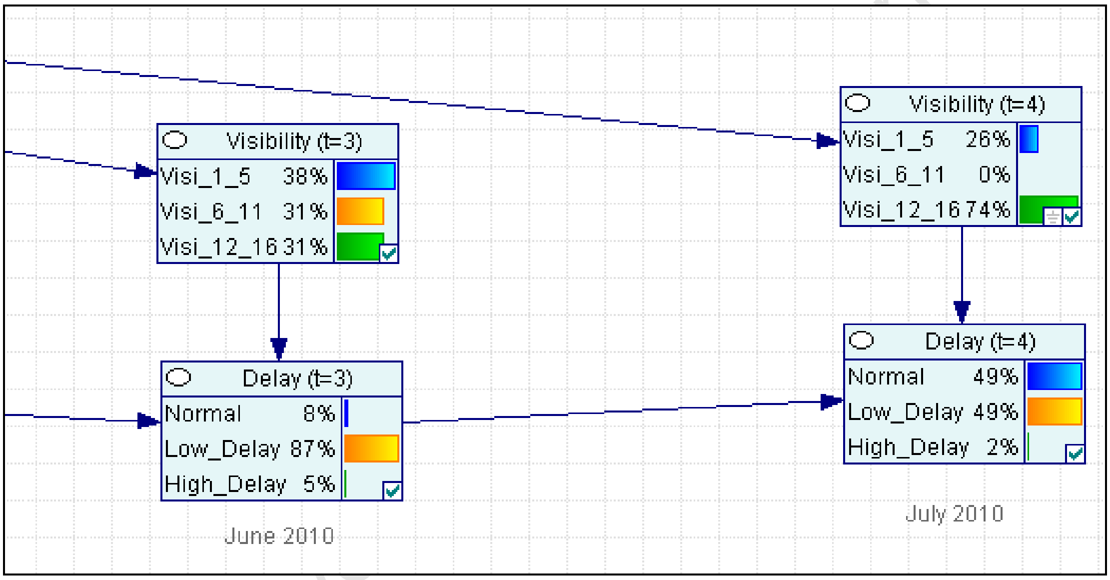

Figure 26: Temporal Network for Visibility (Nodes 4-5)

As shown in Figures 25 and 26, the unrolling of the temporal visibility network unveiled five time slices containing chronological data that populated the CPTs pertaining to each Visibility node. All the nodes showing solid dark arcs confirmed the conditional dependence of each connecting node in the graph space. Hence, the node values of each CPT contained within filtered through its adjacent node in the direction of its arcs (temporal order of 1). Examining Figure 25, the Delay nodes for all bins in March show a significant difference in observations from April, May and June in the 'Low Delay' bin category, with 40% of observations in March, as opposed to 87% observations in June. The Delay values observed after inference on the Visibility node in July, updated its values in the CPT, using the 'Event' node's conditional dependence to other nodes.

A verification process showed that the observed values in the source data for each bin (i.e. per calendar month) were correct and that they were discretised without errors in preparation for the experiment. This apparent discrepancy was mainly due to the close proximity of weather variables in each bin category and might have shown differently if further discretisation was carried out. Hence, a narrower band of observed values per bin for the Visibility node would have given different category observations in the experiment.

In addition, Bayes inferencing was performed on the last Visibility node in July, using soft evidence from wunderground.com. This reported 74% of the observations in the 'Visi_12_16' bin, with further reporting of low visibility conditions in the 'Visi_1_5' bin, containing 26% of all occurrences (e.g. thunderstorms).

The effect of Bayes inference on the Visibility node in July reported 49% of observations for both the 'Normal' and 'Low Delay' bin and only 2% in the 'High Delay' bin category. These results did not reveal any unforeseen surprises, due to the mitigating factors of the technology used, as previously discussed.

In summary, having performed Bayes inference on the Visibility node for July 2010 on the unrolled visibility network, no significant delays were observed for the spring and summer months, revealing a positive correlation during the experimental period. Hence, in conclusion, it was unlikely that the visibility variable was a strong candidate in approximating delays at KEWR.

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5.5.3 Wind Analysis

5.5.3.1 Temporal Network Topology for Wind

This experiment was conducted to examine the effects of wind intensity and directionality and its efficiency in delay estimation.

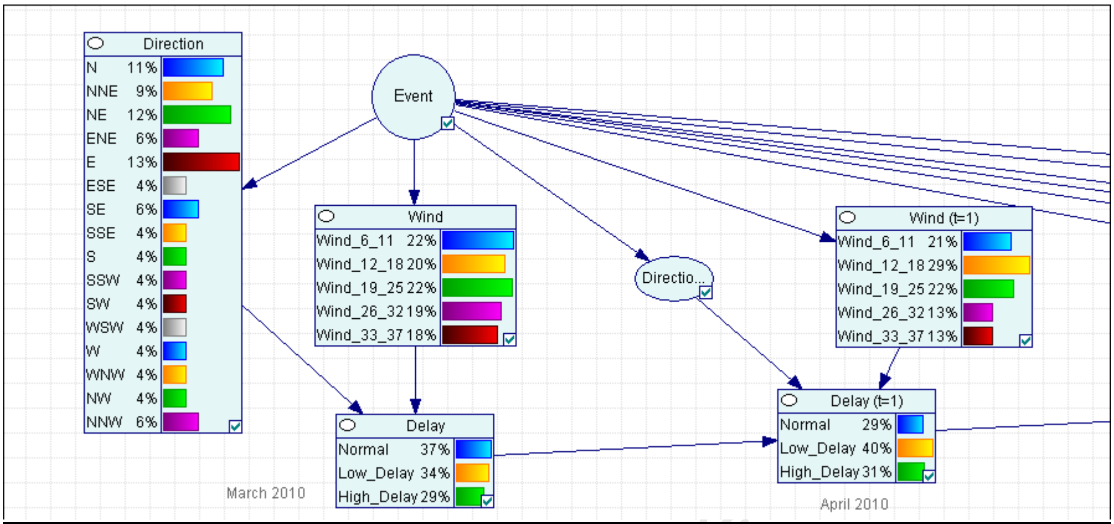

Figure 27: Temporal Network for Wind and Direction (Nodes 1-3)

Wind intensity was discretised into five bins for all the ranges of observed values in the experimental data.

GeNIe was unrolled into individual time slices or temporal nodes to input the individual CPT for each temporal node (i.e. calendar month).

The direction component added complexity to the wind variable and was modelled as a separate node and included in the temporal plate, as per Figure 27. Therefore, both components needed to be modelled into separate wind and direction nodes, adding their respective marginal probabilities' of delay to the Delay node through conditional dependence for the entire experiment. Wind directionality was subdivided into 16 separate magnetic courses, as described in Figure 11, but rarely did a predominant wind persist for a period of 24 hours or more.

Additionally, the number of time slices was set to five, the same as with the other weather variables modelled in the experiment. This provided the needed accuracy when inferencing approximate delays in the last time slice, with the 'Event' node including the same static values in the CPT as the other weather variables in the experiment.

In March (Figure 27), the wind node showed a marginal probability of 22% of all observations for the 'Wind_6_11' and 'Wind_19_25' bins, with others reporting similar probabilities. The lowest number of observations was recorded for the 'Wind_33_37' bin with 18% of all observations.

Moreover, for the same month, the values in the Direction node showed notoriety for occurrences in the following directional headings: N, NNE, NE and E by means of 11%, 9%, 12% and 13% of all observations respectively. The NNE and NE wind directions provided favourable wind conditions for departing and arriving traffic on the two main runways 04/22 at KEWR. The highest number of observations recorded was 13% for the Easterly direction in the same period which, when combined with wind speeds under 20 kph, did not pose a challenge for departing and arriving traffic, given it was under the crosswind threshold.

In March, the impact of the marginal probability on the Delay node (i.e. given conditional dependence) favoured the 'Normal Delay' bin with 37% of all observations. Conversely, the lowest number of observations for the Delay node was recorded in the 'High Delay' bin with 29% of all occurrences for the same period.

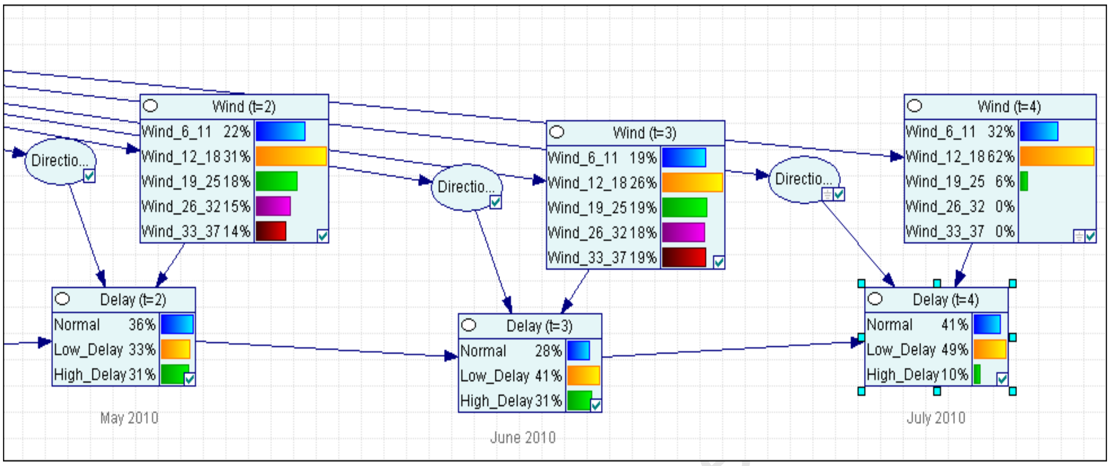

Figure 28: Temporal Network for Wind and Direction (Nodes 4-5)

During April, May and June a noticeable number of observations were recorded in the Wind node for the 'Wind_12_18' bin, with values of 29%, 31% and 26% respectively. This indicated a steady and leading pattern of observations for higher wind values, with respect to other bins for the same period. Conversely, the lowest number of observations reported was in the highest wind category namely, the 'Wind_33_37' bin, which also demonstrated a progressive increase of 13%, 14% and 19% of all occurrences during the same time period. This was partly explained by the high convective activity at the time with multiple occurrences of thunderstorms in the vicinity of KEWR. However, in the last time slice, this value fell to zero when inferencing was performed, denoting stable weather in the region.

In June (Figure 28), the observations for all wind bins except 'Wind_12_18' varied from 18% to 19% of all occurrences. This was considered to be from convective weather systems in the area at the time.

In April, the wind directionality favoured the 'WNW' bin with 13% of all observations, thus explaining away the number of high occurrences in the 'High Delay' bin for the same time period. Alternative, wind directionality also showed a preference for the 'E' and 'ENE' and 'NW' bins with 8%, 8.5% and 7.5% of all observations respectively, as per Figure 28. The 'NW' and 'WNW' bins were investigated for their marginal probability in the high observations in the 'High Delay' bin, with no other explanations found other than possible crosswinds at KEWR.

Figure 28 shows a strong preference for the 'WSW' bin patterns in May and June, emerging with 10.5% and 13% of all occurrences respectively, in contrast to the 'ENE' bin for May, which showed only 12% of all observations. The Delay node during the entire experiment showed a steady increase in the 'Low Delay' bin, reaching a maximum of 49% of all observations in July. In May, an evident drop in this bin was observed, but this was considered acceptable given the favourable wind directionality (i.e. WSW and

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ENE) for the same time period, which reported more incidences in the 'Normal' Delay bin with 36% of all observations.

In July, Bayes inference was completed for the Directionality node in conjunction with the Wind node. For the same time period, the impact of the marginal probability on the Delay node was noticeable and a sudden increase in the 'Wind_12_18' bin with 62% of all occurrences was reported (Figure 28). A spike was also observed in the directionality 'NW' bin (i.e. crosswind direction) with 42% of all occurrences, as per Figure 31. For the time period June to July, this was considered a direct effect of causal delay, given the increase in the observation numbers in the 'Low Delay' bin from 41% to 49% of all occurrences. Consequently, the high number of observations in the 'Wind_12_18' bin was not considered problematic even with unfavourable wind directionality (i.e. crosswinds), which explained why there were so few observations in the 'High Delay' bin with only 10% of all occurrences.

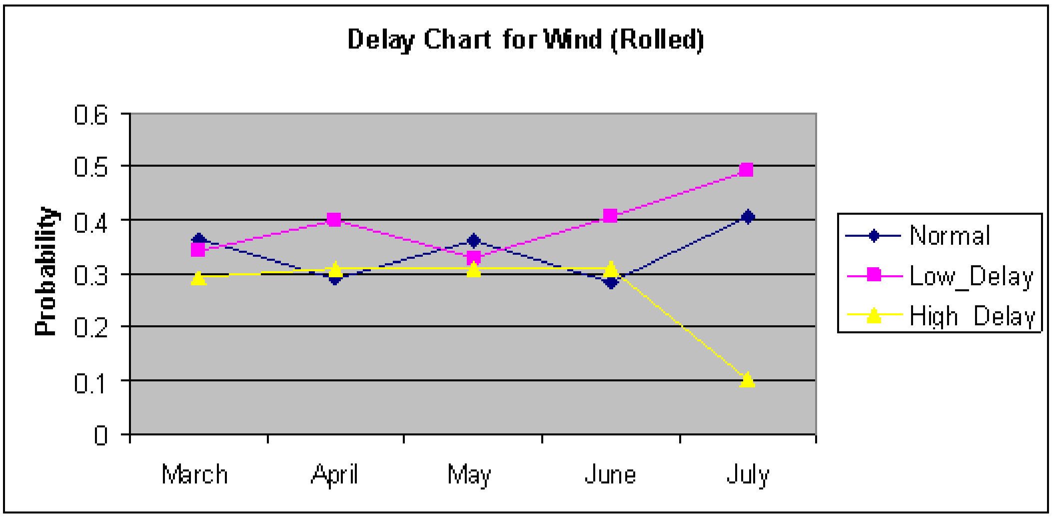

Figure 29: Detailed Delay Chart for Wind in GeNIe

From May to July, the trend patterns for low delays (Figure 29) indicate a sharp gradient response to wind sensitivity, clearly impacting numbers in the 'Low Delay' bin category. This evidently supports a cause-effect chain for the weather variable in question, as per the dissertation objectives, by having an immediate impact on airport delays at KEWR and thus, is considered a suitable candidate to predict airport delays.

Additionally, in July, the low number of observations for the 'Wind_26_32' and 'Wind_33_37' bins explained the sudden decrease in the marginal condition probabilities for Delay in the 'High Delay' bin from 31% to 10%, as per Figures 28 and 30. This causal event was a direct result of performing inference in the wind node for the same time period.

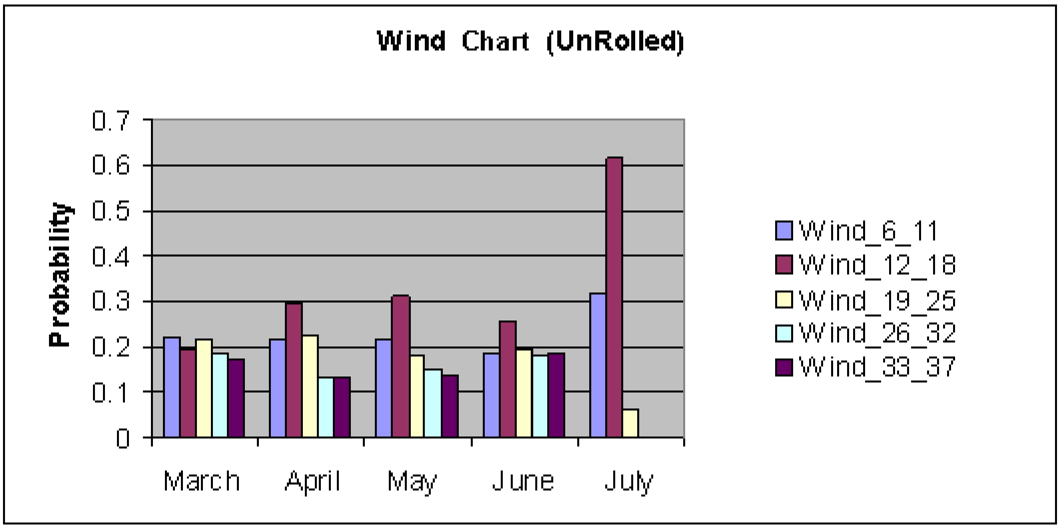

Figure 30: Detailed Chart for Wind in GeNIe

The leading wind category can be illustrated in the 'Wind_12_18' bin, closely followed by the 'Wind_19_25' bin, which when combined with directionality can bring operations on runway 04/22 to a halt if crosswinds exceed the threshold, causing unintended delays at KEWR. It was also important to consider that gusting speeds can add double digits to wind speeds.

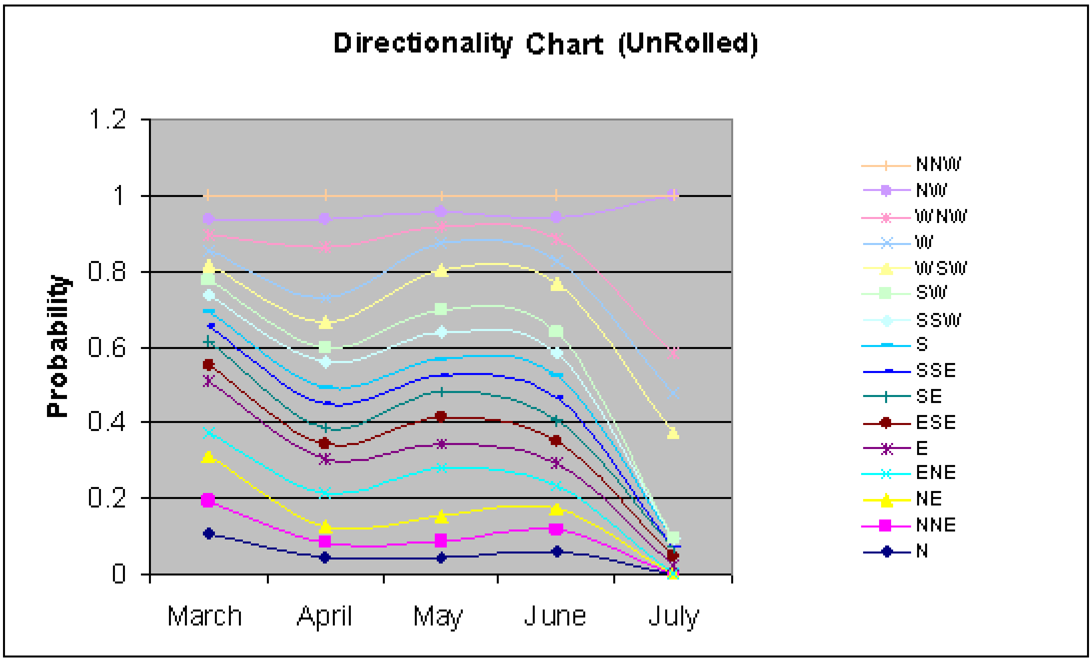

Figure 31: Detailed Chart for Wind Direction in GeNIe

In Figure 31, the directionality of winds clearly retains a crosswind component (in dependently of threshold values) with a high chance of them occurring, which coupled with wind speed, demonstrates an apparent propensity to succumb to cause-effect chain delays at KEWR. As such, it was apparent from the empirical evidence that this weather variable was the most effective in alerting weather related delays at KEWR.

Moreover, previous experiments were performed with the wind as a single variable with delay. However, the results did not register added value when inferencing approximate delays and were hence, discarded for this experiment. As a result, a more comprehensive unrolled network structure was considered for July, with wind directionality as an added temporal node, yielding a more accurate marginal probability of delay at KEWR.

5.5.4 Validation Results in GeNIe

The experimental results of the three weather variables were measured to verify which variables gained the highest accuracy in approximating delays at KEWR in GeNIe.

The validation process required a step by step approach to be taken for each of the weather variables, to ensure a successful outcome when reporting true accuracy of delay. See Appendix Section 1.4 for further information.

These steps were as follows:

- Importing data file
- Learning network
- Learning parameters
- Validation results

Furthermore, the validation process was conducted on different data sets from which the model was learnt, to ensure a realistic framework when reporting delays at KEWR.

To this end, the verification process was set up in two parts as described below:

- Training data set (90% bivariate)[7]
- Test data set (10% bivariate)

The values for the test data were chosen at random to ensure an unbiased approach to the test results, using naïve Bayes networks In addition to this, the training data set was used for each variable to learn the model, using accuracy as a scoring function in the test results, in order to better understand how to approximate delays at KEWR. This scoring function allowed an understanding into how accurate each weather variable (precipitation, visibility and wind) was, when quantitatively approximating delays at KEWR. Table 3 shows the variable "Wind & Direction" with the highest scoring function in the 'Low' and 'High Delay' categories. On the contrary, the variable "Precipitation" showed the highest value for the overall and 'Normal Delay' categories. For more detailed information, refer to Section 1.5.4 in the Appendix.

The results in Table 3 demonstrate the attained validation values in the training data set and their accuracy with respect to delay. See Appendix 1.1 for a detailed step by step review of the functionality that was used in GeNIe for the experiment.

Table 3 illustrates the GeNIe results in approximating delays at KEWR, with clear scoring categories for each delay variable.

[7] Weather and delay variable node

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In summary, the numbers in Table 3 represent the classification category. The delay category shows overall performance, and the other rows specific accuracy for each class (i.e. the higher the value, the higher the classification accuracy). It can be concluded that even though the "Precipitation" weather variable scored highest in the 'Normal Delay' category as a scoring function, this value does not reflect the objectives of this dissertation, because any value in this delay category is considered normal in aviation. Hence, the next weather variable that scores highly in the 'Low' or 'High Delay' category as a scoring function is the "Wind & Direction" weather variable. A more detailed analysis of the results of each variable was conducted, and reported in the concluding section of the next chapter of this dissertation.

	WEATHER VARIABLE		
	Precipitation	Visibility	Wind & Direction
Delay Category	0.388	0.296	0.296
High Delay	0.03	0	0.16
Low Delay	0.35	0.414	0.441
Normal Delay	0.692	0.428	0.235

Table 3: GeNIe Validation Results

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6 . CHAPTER 6 Conclusion

This dissertation investigated weather related delays at Newark Liberty International Airport (KEWR) for the time period March 2010 to June 2010. The purpose of the current study was to determine:

- Which weather variable: precipitation, visibility or wind is better suited at approximating severe delays at KEWR?

The above mentioned objective has been achieved in this investigation. Hence, the proposed hypothesis in Chapter 3 has been confirmed.

The experimental results show that inferencing on the weather variable wind and direction in July had an immediate effect on marginal probability of delay in the same month. The wind and direction variable had a result in the 'Low Delay' category of an 8% increase on the posterior marginal probability of delay from 41% in June to 49% in July of all monthly observations. Figure 28 refers.

However, the validation results indicated that precipitation had the highest accuracy rating as a scoring function of 0.388 in overall delay calculations, 0.03 in the high delay, 0.35 in the low delay and 0.692 in the normal delay category within GeNIe. This overall highest accuracy score was surprising and partly explained by the exceedingly high score for precipitation in the normal delay category.

One of the most significant findings to emerge from this investigation is that weather variables per se do not have the most significant direct impact on departure delays at KEWR. It is the effect of certain weather conditions experienced at KEWR that influences the decisions of Air Traffic Control (ATC) to implement Ground Delay Program (GDP) which has a causal effect on departure delays.

A summary of the findings for each weather variable was investigated that caused departure delays at KEWR. Moreover, given the inherent complex interrelation of weather variables which often created adverse meteorological conditions, it was not always possible to analyse variables in isolation (e.g. wind & direction). The following variables were summarised for the conclusion:

6.1 Precipitation

Concerning this weather variable, the experimentation did reveal a high correlation between precipitation and delay but only in the low and normal delay categories.

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Heuristic analyses in Excel revealed that only under intense precipitation would there be a high number of observations in the 'Low Delay' category (with impact on visibility) at KEWR. The only noticeable effect on delay was during intense precipitation which affected visibility at KEWR, but not enough to compromise minimum aviation visibility (4.6km), and hence causing severe delays.

Further observations in GeNIe revealed that the absence of precipitation still reported significant delays suggesting that other weather factors also played a major role. In general, GeNIe demonstrated that observations in the 'High Delay' category were progressively reduced during the experimental period, but precipitation had a more prominent effect than visibility in this category. However, precipitation had a lesser impact than visibility in the 'Low Delay' category.

Moreover, during the verification process, precipitation only attained a value representing classification accuracy of 0.388 in the overall delay category with 0.03. 0.35 and 0.692 in the high, low and normal delay categories respectively.

6.2 Visibility

This variable was challenging, as 'Low Visibility' was referenced often by FAA advisories in the experimental data and on multiple occasions as the main cause of delays at KEWR. Heuristics analysis with Excel demonstrated a clear correlation[8] between ambient temperature and dew point with dew, frost or fog emerging upon convergence to small margins between these two variables. It was found during the investigation that visibility was not greatly impacted by precipitation. Low ceilings impacted visibility even if precipitation was absent; however, visibility was significantly reduced during severe precipitation with a clear effect on minimums (i.e. minimum visibility for pilots).

'Low Visibility' is another definition for 'Low Ceilings' (FAA) for which commercial pilots are trained, utilising FAA approved equipment, undergoing strict pilot training with the support of airport infrastructure (e.g. ILS – Instrument Landing System). This was further supported by the results in GeNIe which predicted increasing delays in the 'Low Delay' and 'Normal' categories with 49% in July, but a reduced number of observations in the 'High Delay' of just 2% in July for this category, as observed in Figure 26.

Furthermore, during the verification stage the visibility variable scored better than expected, with an overall classification accuracy delay value of 0.296 along with 0.414 and 0.428 for the low delay and normal categories respectively. However, this variable was not considered a likely candidate for approximating delays as it did not score in the 'High Delay' category.

6.3 Wind

The analysis of wind was a complex factor compared to other variables; wind intensity and directionality coupled with frequent variability made it a complex variable to consider and analyse. Having analysed closely the heuristic analysis of wind intensity and directionality, it was observed that the smaller runway 11/29 at KEWR was being utilised heavily via GDPs only when wind intensity exceeded 20kph in a North-Westerly or South-Easterly direction.

The experimental results in GeNIe seemed contrived for the wind variable in the 'High Delay' category for July with only 10% of observations. The remaining 'Normal' and

[8] (Source: FAA Advisory 2010)

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'Low Delay' categories supported and were aligned with the heuristic analysis in Excel with 41% and 49% respectively of observations for July in Figure 32, implying that delays caused due to wind through GDP at KEWR were more accurate (FAA advisories). Hence, the fact that GeNIe results for the 'High Delay' category challenged the heuristics in Excel suggesting that strong crosswinds in a North-Western or South-Eastern direction did cause significant delays at KEWR as per the heuristic analysis.

Throughout the experimentation, the quality and accuracy of the data was paramount in obtaining solid investigational results as proven during validation. However, inconsistencies in the source data did appear which had to be mitigated through manual extrapolation, validation and regression analysis in GeNIe (BN tool). This weather variable did not achieve the highest score in the overall delay category. Nevertheless, the wind variables obtained the highest delay score in high delay as well as in low delay categories of all experimental values as a scoring function, which made it a more suitable variable to approximating delays at KEWR.

To this end, the wind and direction variable obtained during the verification process a general score representing classification accuracy of 0.296 with a 'High Delay' value of 0.16 and a 'Low Delay' predictability of 0.441. Hence, this variable was deemed as the most suitable to approximating delays at KEWR even though it wasn't the highest scoring function value in general Delay. This is further corroborated by the results in GeNIe and further heuristic analysis.

6.4 Summary

The results of the heuristic investigation are aligned with the outcome of the experimental findings in GeNIe. A direct causal effect of a weather variable resulting in delay was anticipated. However, what emerged from observations was a complex causal chain of events initiated by a weather variable (i.e. wind) directly causing a non-weather event (i.e. implementation of Ground Delay Program at KEWR) resulting in severe delays at KEWR. The severity of the delays was particularly noted when the correct meteorological conditions convened with NW/SW crosswinds in excess of 20kph.

The significance of these results has gone some way towards improving our understanding of how individual meteorological factors, can play a vital role in clarifying the causes of weather based delays at KEWR. Moreover, the complexity in analysing the interaction of weather factors independently of delays further complicates what elements comprise non-weather based factors (e.g. GDP) in the causal chain of events resulting in differing degrees of delays.

In practical terms, the implementation of a GDP based on wind conditions imposes a restrictive operational environment with a reduced throughput in arrival traffic that can safely use KEWR. This operational restriction has a direct causal effect on departing traffic conditions while a GDP is in operation.

The limitations of this study centre mainly on the lack of data availability to contend with the effects of seasonality in the Northern Western seaboard year round for modeling in GeNIe. Furthermore, non-commercial traffic (i.e. General Aviation) and air cargo traffic was not considered for analysis in this research. Other categories of delays comprising aircraft surface movements and airborne delays were also not included as part of this investigation.

It is recommended that further research be undertaken using more data to understand the effects of seasonality at KEWR using similar modelling BN tools (e.g. GeNIe).

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Further analyses from this modeling tool could be conducted to explore and model the impact of complex causality chains of Federal and regional policy level of GDP and Noise Abatement Procedures (NAP) at KEWR.

The implications of Federal Aviation Authority (FAA) policy on airlines are far reaching and diverse. Notwithstanding, GDP and NAP restrictions on departing traffic, this needs to be a balanced carefully with a policy for public safety, cost implications for airlines and the aviation industry as a whole. A careful balance must be chosen between efficiency, public safety and airline economics to safeguard the interests of all stakeholders.

In summary, weather factors alone are not the single element in identifying temporal delay patterns at airports. The complex chain of causal factors needs to consider the human inputs as well to understand delays at KEWR. The use of inference tools like GeNIe serves to better understand how to both utilise expert knowledge and how data can be integrated into a probabilistic model for inferencing and approximating delays at airports.

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Glossary of Terms

ACRP	Airport Cooperative Research Program
ASQP	Airline Service Quality Performance Systems
AI	Artificial Intelligence
AIP	Aeronautical Information Publication
ASCII	American Standard Code for Information Interchange
ASPM	Aviation System Performance Metrics
ATA	Air Transport Association
ATC	Air Traffic Control
ATCM	Air Traffic Control Management
ATCS	Air Traffic Control Services
ATTO	Actual Taxi-Time Out
CPD	Conditional Probability Distribution
CPT	Conditional Probability Table
CWOP	Citizens Weather Observation Program
DBN	Dynamic Bayesian Network
DSS	Decision Support System
E	East
EDT	Eastern Daylight Time
ENE	East North East
ESE	East South East
FAA	Federal Aviation Authority
FP	Flight Plan
GDP	Ground Delay Programs
GFC	Global Financial Crisis
GUI	Graphic User Interface
IFR	Instrument Flight Rules
IMC	Instrument Meteorological Conditions
JFK	J.F. Kennedy Airport Code
JPD	Joint Probability Distribution
KEWR	Newark International Liberty Airport (ICAO)
LGA	La Guardia International Airport
MADIS	Meteorological Assimilation Data Ingest System
ML	Machine Learning
MSL	Mean Sea Level
N	North
NAP	Noise Abatement Procedure

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NAS	National Airspace System
NE	North East
NNE	North North East
NNW	North North West
NOAA	National Oceanic and Atmospheric Administration
NOTAM	Notices To Airmen
NW	North West
NWS	National Weather Service
OD	Origin Destination
OPSNET	Operations Network
OTS	Off the Shelf
PoC	Proof of Concept
PWS	Personal Weather Station
RL	Reinforcement Learning
S	South
SE	South East
SMILE	Structural Modelling, Inference and Learning Engine
SSE	South South East
SSW	South South West
SW	South West
TAC	Terminal Airspace Constraints
TAF	Terminal Area Forecast
TEB	Teterboro International Airport
TRACON	Terminal Radar Approach Control Facilities
VMC	Visual Meteorological Conditions
W	West
WNW	West North West
WSW	West South West

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Appendix

This Appendix describes the step by step functionality that was used in GeNIe for the experimentation.

The temporal plate was enabled by selecting 'Dynamic Models' then 'Enable Temporal Plate' from the 'Network' menu, as displayed in Figure 32.

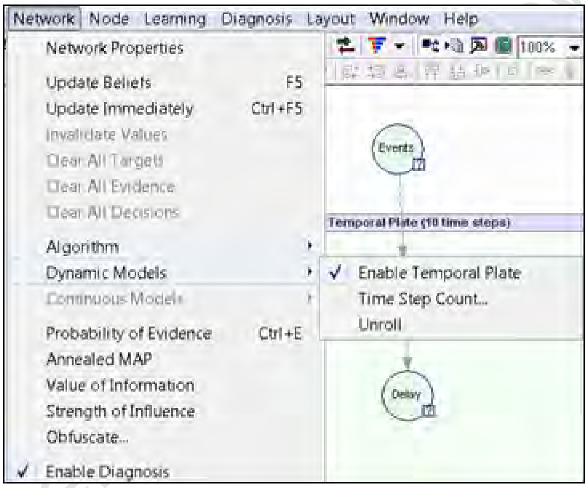

Figure 32: GeNIe – Enabling Temporal Plate

Once the 'Enabled Temporal Plate' option had been selected, the 'Chance' nodes (discussed later in this section) were created by selecting the 'Chance' icon from the menu bar. To specify the number of slices in the temporal plate, the 'Time Step Count' option was selected from the 'Dynamic Models' option under the 'Network' menu. The diagram in Figure 33 illustrates the dialogue box to specify the number of time slices in the temporal plate.

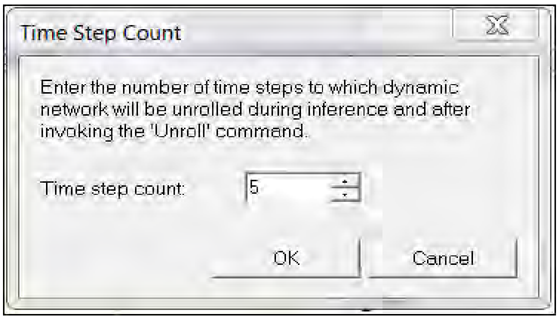

Figure 33: Time Step Count Dialogue Box

The number of time slices was set to five, given that the first four slices would represent each calendar month in the experimental data set. The last delay time slice corresponded to the predicted delay nodes for July 2010 in GeNIe after inferencing. Each weather variable was then analysed in detail against the delay, to observe which variable was better at approximating delays.

- Rolled Network: This was set up as a DBN with all the time variant weather and delay nodes rolled up into the temporal plate as two nodes. Any time invariant node like 'Event' was presented outside the temporal plate.
- Unrolled Network: This represented a de facto BN which characterised a DBN. Each populated node depicted the number of observed values per discretised bin as a percentage of the total number of observations for a particular calendar month.

1.1 Temporal Order

This determines in what order the chance nodes and their predecessors are prearranged accordingly to the semantic nature of the node topology within the GeNIe graph space.

During the experimentation, a temporal order of one was deemed suitable for all weather and delays node variables. This indicated that the temporal order of influence on the current node (t) was being influenced directly by the CPT of the previous temporal node (t-1). Diagram in Figure 34 refers:

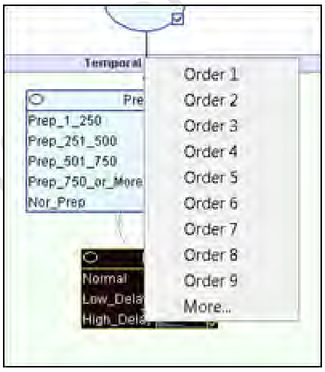

Figure 34: Temporal Order Dialogue Box (Delay Node)

The above dialogue box in Figure 34 appears when selecting an arc from and to the Delay node.

1.2 Node Property

The diagram in Figure 35 demonstrates the general characteristics of node properties in the temporal plate[9], as follows:

[9] Node properties are not specific to temporal plates

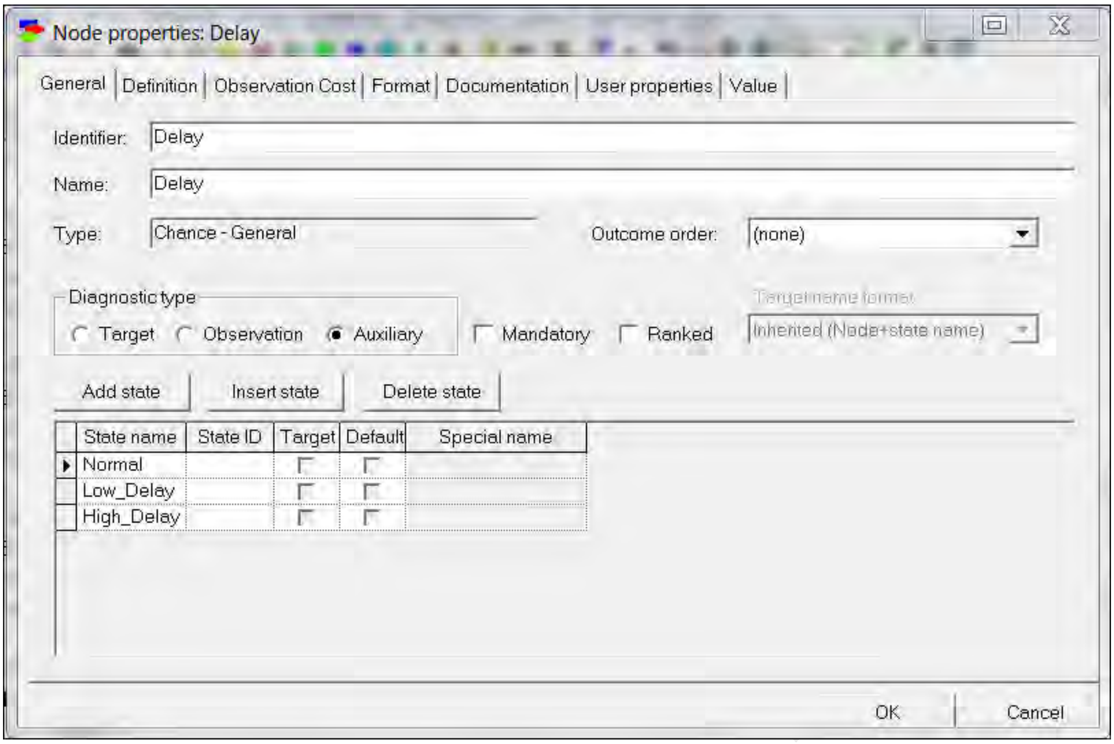

Figure 35: Properties Dialogue Box (Delay Node)

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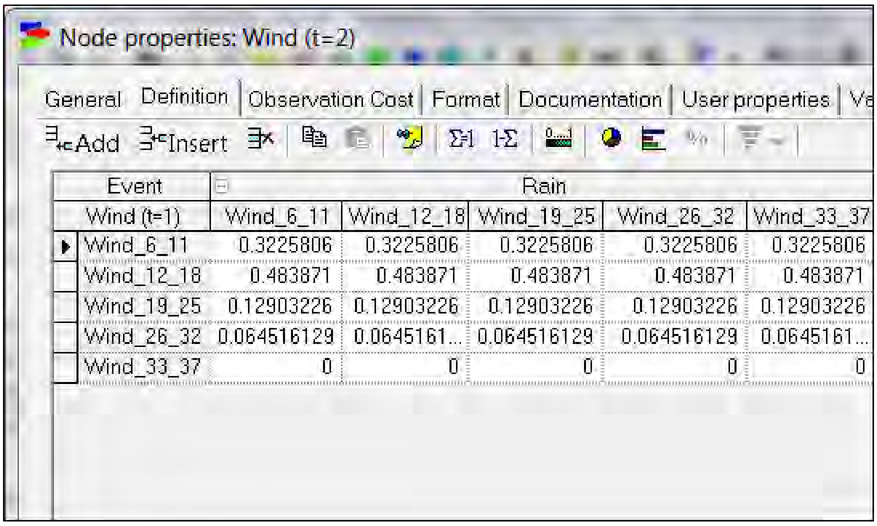
The monthly observed values in the CPD table correspond proportionately to the values in the Excel pivot table analysis used for the wind variable (all values normalised to one), as denoted in blue in Table 4.

	Wind, Visibility & Precipitation					
	Wind Ave (kph)					Wind Dir.
	Range: 6-37					
	6-11	12-18	19-25	26-32	33-37	
01/05/2010	1	0	0	0	0	SSE
02/05/2010	0	1	0	0	0	SW
03/05/2010	0	1	0	0	0	WSW
04/05/2010	0	1	0	0	0	W
05/05/2010	0	1	0	0	0	SSW
27/05/2010	0	1	0	0	0	E
28/05/2010	1	0	0	0	0	SSE
29/05/2010	0	1	0	0	0	SSW
30/05/2010	0	1	0	0	0	WNW
31/05/2010	1	0	0	0	0	SE
	10	15	4	2	0	
	0.3225806	0.483871	0.129032258	0.064516129	0	
					1	1

Table 4: Normalized Bins in Excel Pivot Table

The values in light blue in Table 4 correspond with those in Figure 36 entered as a CPT for the wind variable in GeNIe.



Node properties: Wind (t=2)

General | Definition | Observation Cost | Format | Documentation | User properties

Event	Rain				
Wind (t=1)	Wind_6_11	Wind_12_18	Wind_19_25	Wind_26_32	Wind_33_37
Wind_6_11	0.3225806	0.3225806	0.3225806	0.3225806	0.3225806
Wind_12_18	0.483871	0.483871	0.483871	0.483871	0.483871
Wind_19_25	0.12903226	0.12903226	0.12903226	0.12903226	0.12903226
Wind_26_32	0.064516129	0.0645161...	0.064516129	0.064516129	0.0645161...
Wind_33_37	0	0	0	0	0

Figure 36: Discretised Values Normalised in the CPT in GeNIe

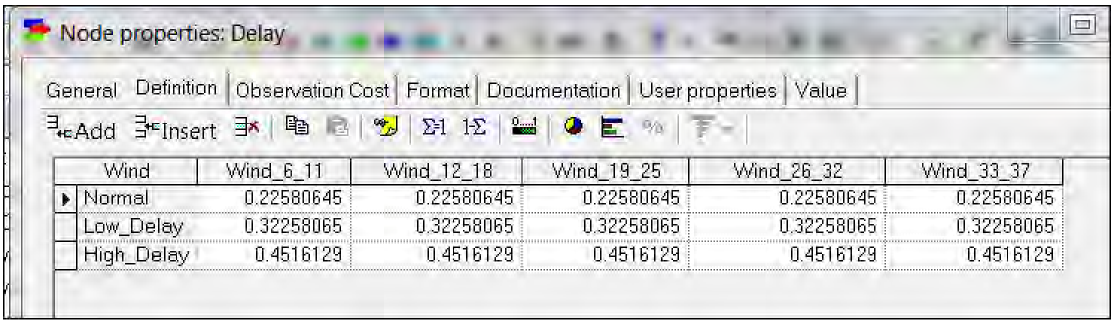
1.3 Delay Node

The same methodology as was used for the wind weather variable was employed for calculating CPT in the Delay node. The discretised delay variable values were obtained again from an Excel pivot table for every calendar month in the experimentation. As seen in Figure 37.

March Delay Cat		
Delay Cat.	Total	
High Delay	7	0.233333
Low Delay	10	0.333333
Normal	13	0.433333
Grand Total	30	1

Figure 37: Delay Node Discretisation in Excel Pivot Table

The corresponding values can be seen in Figure 38 entered in the Delay node in GeNIe.



Node properties: Delay

General | Definition | Observation Cost | Format | Documentation | User properties | Value

Wind	Wind_6_11	Wind_12_18	Wind_19_25	Wind_26_32	Wind_33_37
Normal	0.22580645	0.22580645	0.22580645	0.22580645	0.22580645
Low_Delay	0.32258065	0.32258065	0.32258065	0.32258065	0.32258065
High_Delay	0.4516129	0.4516129	0.4516129	0.4516129	0.4516129

Figure 38: Delay Node Discretisation in GeNIe

The observed delay node values entered in the CPT in GeNIe closely, but not exactly, match those of the Excel pivot table discretised values. The normalisation button Σ=1 in

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the menu bar could be used to normalise to one, if each bin value was not rounded to the correct decimal place.

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1.4 Validation (Delay by Precipitation)

GeNIe functionality was used to verify the data accuracy for the experimentation. A file was generated for historical data comprising precipitation and delay information in a CSV format.

1.4.1 Import Data File

Once the import file was generated and discretised into appropriate ranges or bins, it was imported into GeNIe by selecting the 'Open Data File' facility under the 'File' menu. The data in GeNIe can be seen in Figure 39.

Precipitation	Delay_Cat
750	Normal
1-250	Low Delay
0	High Delay
750	High Delay
0	Low Delay
0	Low Delay
0	Low Delay
0	High Delay
0	High Delay
0	Normal
1-250	High Delay
0	Normal
1-250	Normal
1-250	Low Delay
0	Normal
0	Low Delay
0	Normal
0	Normal
0	Low Delay
251-500	Low Delay
1-250	Normal
0	Normal
1-250	Low Delay

Row 1 of 108

Figure 39: Data Import for Precipitation (CSV format)

1.4.2 Learn Network

For GeNIe to verify the accuracy of the results and relate it to a graph structure with nodes, all the columns were selected. Figure 40 illustrates this.

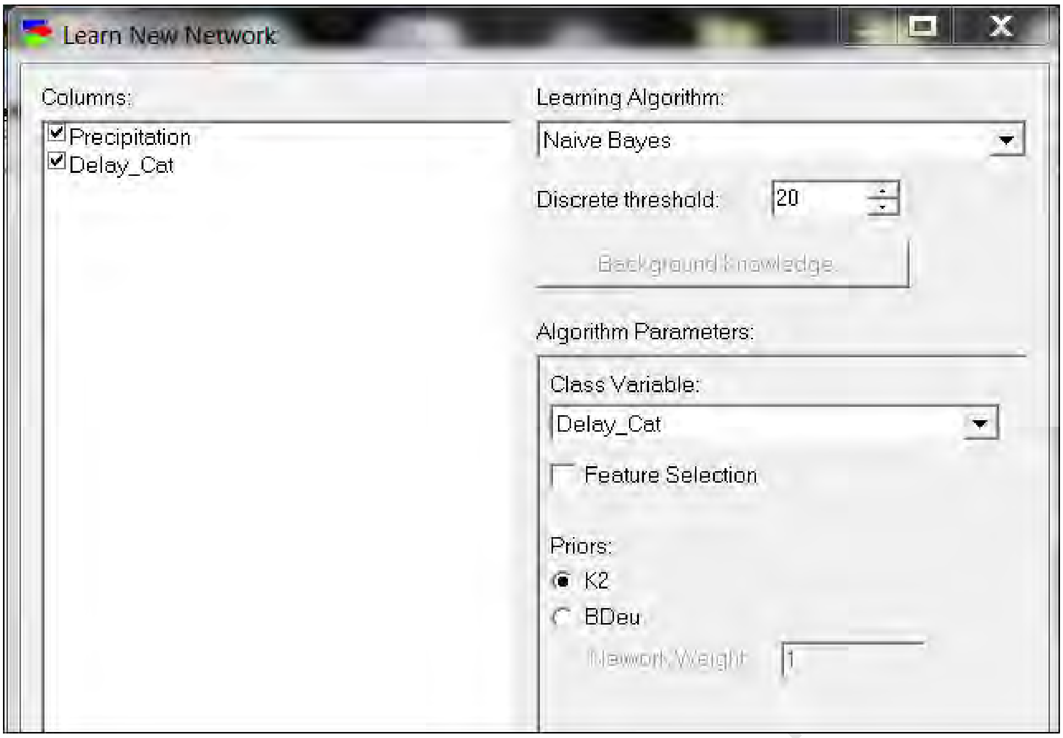


Figure 40: Learn New Network for Precipitation in GeNIe

The most appropriate Learning Algorithm was as follows:

Naive Bayes: this algorithm requires fixed structure with a continuous data set to be discretised before it can be run as a learning method. The advantage is that with a small quantity of training data it can perform parameters learning quite proficiently.

The algorithm parameter section would be set to default values. The option of the class variable used was aimed at assessing the accuracy of the data used for the 'Delay' class variable. Once all the algorithm parameters were verified, GeNIe would apply these to the historic data imported and network for validation before commencing self-training on the data. Figure 41 refers.

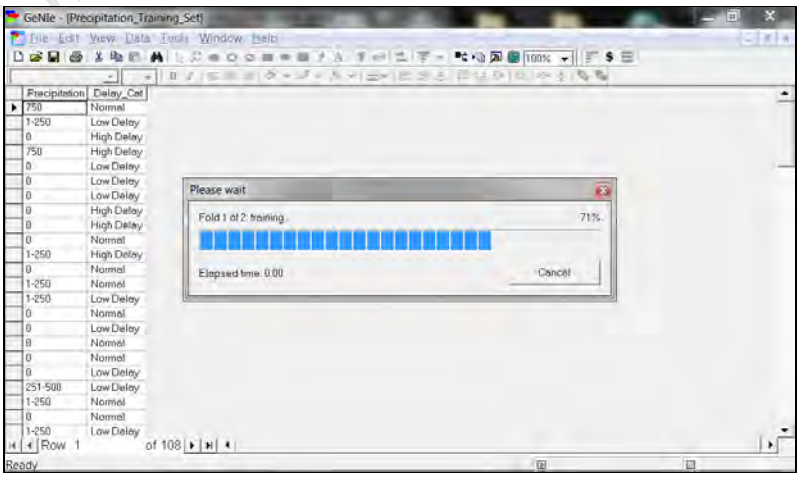


Figure 41: Automatic Data Training for Precipitation by GeNIe

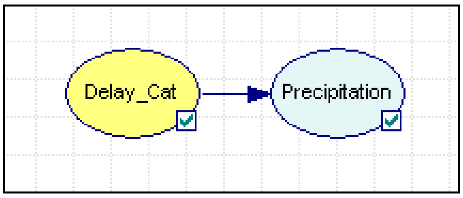
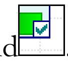


Figure 42: Learnt Network for Precipitation by GeNIe

The learnt network was found to indicate that the Precipitation node was causally linked to the Delay node, wholly inferred by GeNIe[10], but was shown with the arrow pointing in the opposite direction as it was easier to resolve the classification problem for GeNIe. Further analysis by updating the network via the 'Thunderbolt' icon  updates the statuses of the nodes from invalid to valid.

Displaying the Precipitation and Delay node as a bar chart, reveals a surprising similarity with the results obtained for the Delay node in July 2010 as in Figure 20. Figure 43 refers.

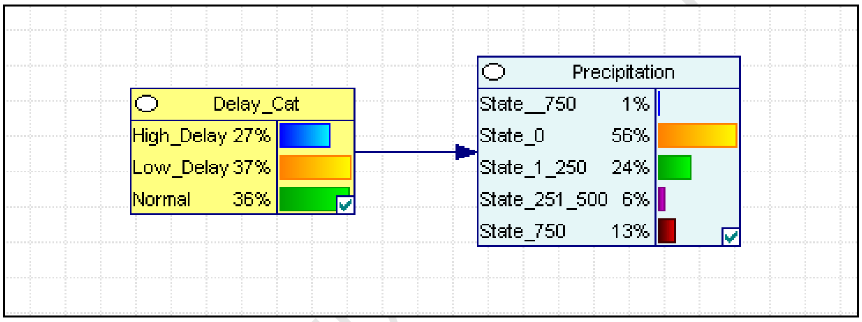


Figure 43: GeNIe Automatic Results for Precipitation and Delay

The result of the learnt network structure was causal in nature and created a precipitation node and a delay node without specifying any background knowledge, as GeNIe infers the correlation between nodes. Upon updating the network and displaying the results in the Bar Chart (Figure 43), it can be clearly observed that the results approximate closely to those in the Delay node in Figure 20.

1.4.3 Learn Parameters

Once the network structure in GeNIe was finalised, the 'Learning Parameter' option was selected from the 'Learning' menu option, as seen in Figure 44.

[10] In general, it is more natural to have the arcs pointing into the class variable 'Delay', but this is not a workable solution for GeNIe. In effect, this would create a multitude of feature variables and the class variable would need a vast amount of parameters, meaning that a large amount of data would be needed to learn the model. Hence, by orienting the arcs as in Figure 43 a convenient property can be used where every feature is conditionally independent of all others given class variable 'Delay', necessitating very few parameters to learn the model. Though this example may be unrealistic, it performs exceedingly well at classification tasks.

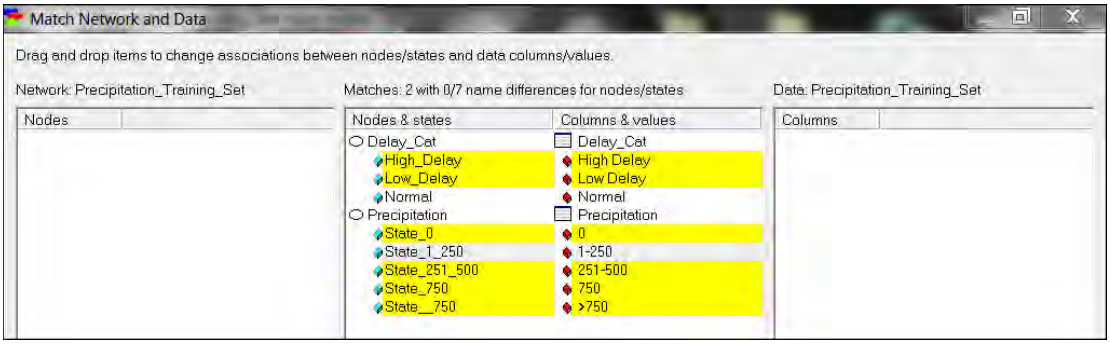


Figure 44: Learning Parameters for Precipitation in GeNIe

The middle column comprised, the appropriate 'Nodes & states' and had to match exactly the 'Columns & values' in the data file imported into GeNIe. Once this was completed the 'Learn Parameters with EM' dialogue box appeared as in Figure 45. All default data values were observed.

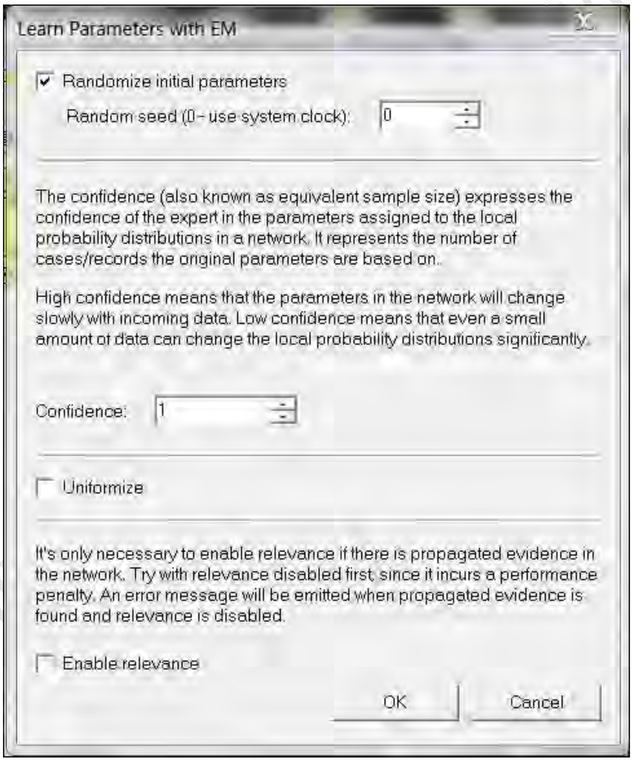


Figure 45: Learning Parameters for Precipitation with EM in GeNIe

1.4.4 Validation Results

The option to validate the data accuracy was executed, selecting the 'Validate' option under the 'Learning' menu option opening a dialogue box as shown in Figure 46. Again, the appropriate 'Nodes & states' were matched to the 'Columns & values' in the historic data file imported.

Once this was competed, a validation dialogue box appeared. Figure 46 refers.

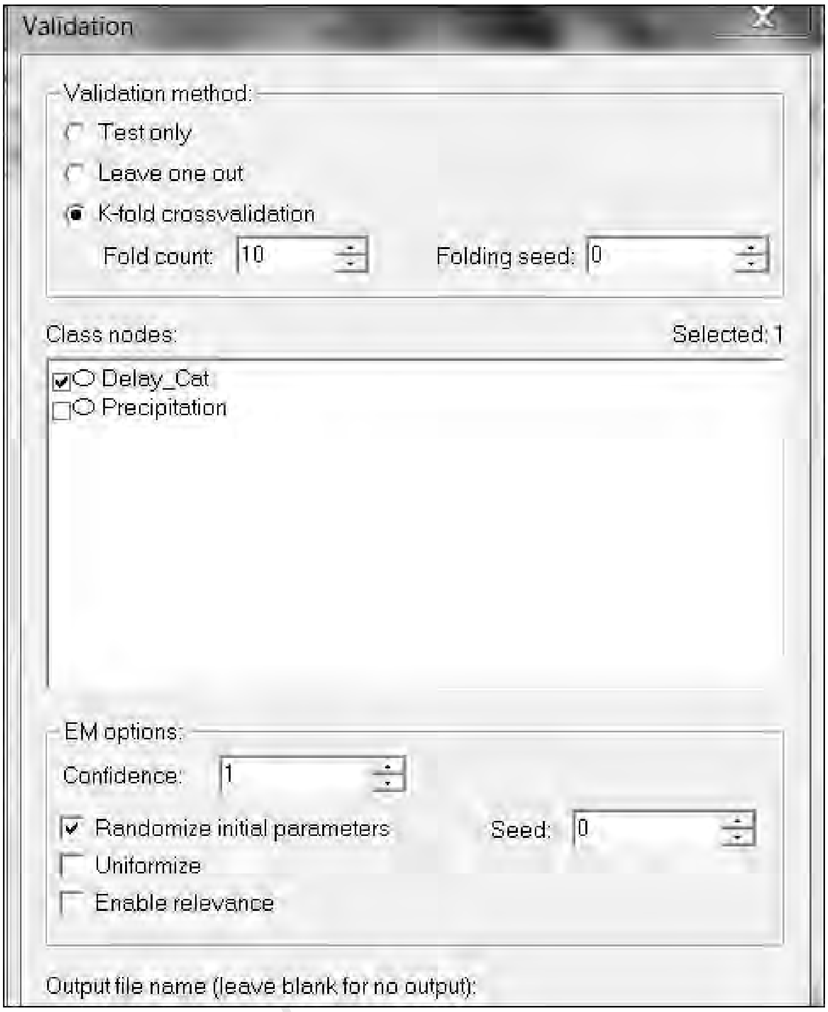


Figure 46: Validation Dialogue Box for Precipitation in GeNIe

The validation method chosen was ‘K-fold crossvalidation’ mode with a ‘Fold count’ of ten, as its purpose was for the data set to be verified to reduce variability (i.e. 90% training data and 10% test data). This was a technique used to assess how the results were generalised to an independent data set. The Class mode ‘Delay’ was selected as the only relevant option, as observed in Figure 46. The results were later the generated.

The validation results generated accuracy for delay as seen in Figure 47.

University

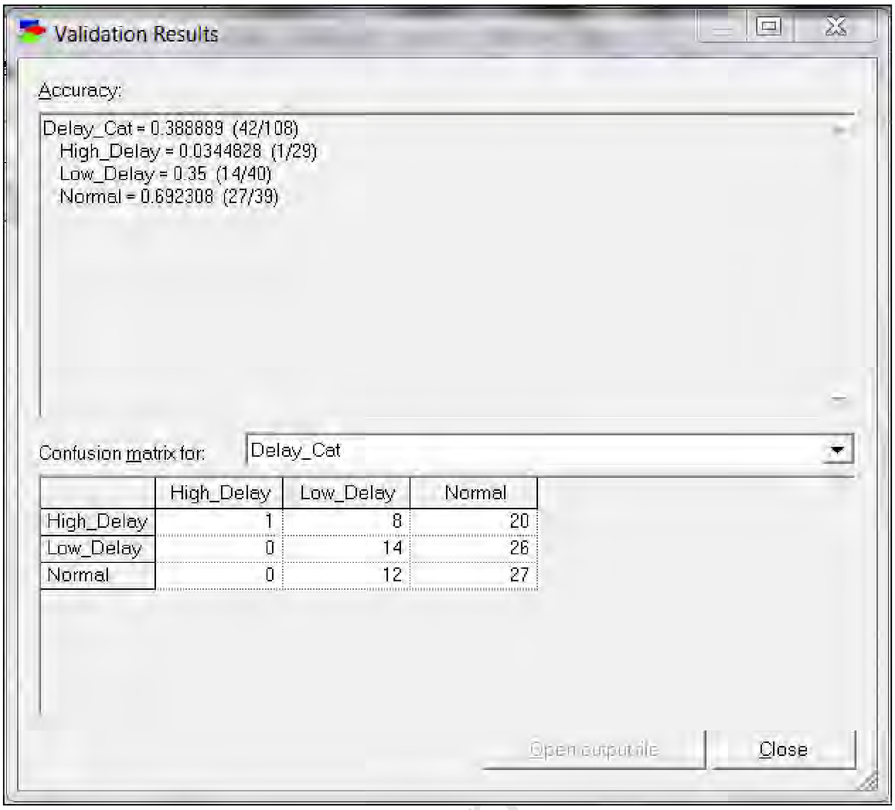


Figure 47: Validation Results for Delay in GeNIe (Precipitation)

1.5 Validation (Delay by Visibility)

The delay and visibility variables were used in GeNIe to confirm the correctness and integrity of the historical data used during experimentation and to investigate its efficacy in calculating delay effectively at KEWR.

1.5.1 Import Data File

The first step in the validation process was to generate a data file with visibility (min) and delay values for the experimental period. Once this was completed a CSV file could be imported into GeNIe.

	Vis_Min	Delay_Cat
▶	12_16	High Delay
	12_16	Normal
	6_11	Low Delay
	6_11	High Delay
	12_16	Low Delay
	12_16	Low Delay
	12_16	Low Delay
	12_16	High Delay
	12_16	High Delay
	6_11	Normal
	1_5	High Delay
	1_5	Normal
	6_11	High Delay
	12_16	Low Delay
	12_16	High Delay
	12_16	Low Delay
	12_16	Normal
	12_16	Normal
	12_16	Low Delay
	1_5	Low Delay
	1_5	Normal
	12_16	Normal
	12_16	Low Delay

Row 1 of 108

Figure 48: Data Import for Visibility (CSV format)

The imported CSV file can be seen in Figure 48 with the weather variable 'Vis_Min' (i.e. minimum visibility). This weather variable was chosen given its span of possible values present during the experimental period.

1.5.2 Learn Network

The 'Learn New Network' functionality was used under the 'Data' menu option, for GeNIe to learn the network. It was decided that the default Bayesian Search algorithm would not be suitable for this experimentation as it was not the most accurate and instead the Naives Bayes algorithm was used. The sample size was selected as '50' (i.e. same as precipitation) and the 'Link Probability' and 'Prior Link Probability' were set to a default value. The Class variable used for the learning algorithm was 'Delay' (minimum visibility) Figure 49 illustrates this as follows:

University of Cape Town

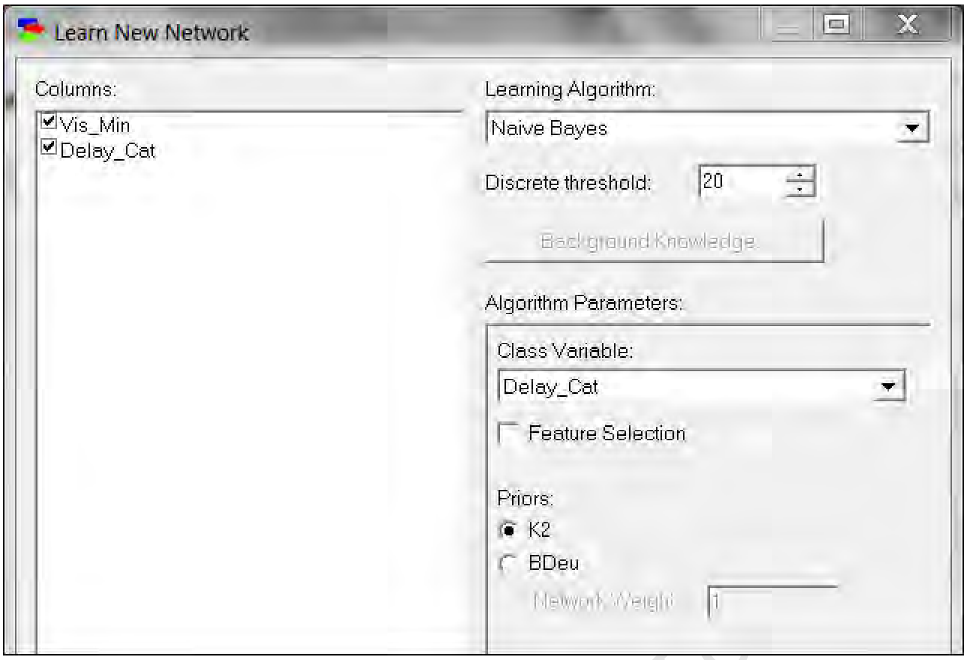


Figure 49: Learn New Network for Visibility in GeNIe

The resulting network topology was created between visibility and Delay nodes in less than one minute as the learning algorithm ran the test data file. Figure 50 refers:

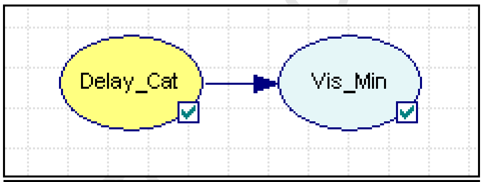


Figure 50: Learnt Data Network for Visibility by GeNIe

The GeNIe validation results diverge in the 'High Delay' category quite significantly, where there was a more even spread of observations in the Delay category in comparison to April 2010 from figs. 25 and 26. These results were unexpected with no apparent explanation but most likely due to an algorithm parameter variation; however analysis of algorithm parameter validation was outside the scope of this dissertation. Figure 53 depicts the validation results:

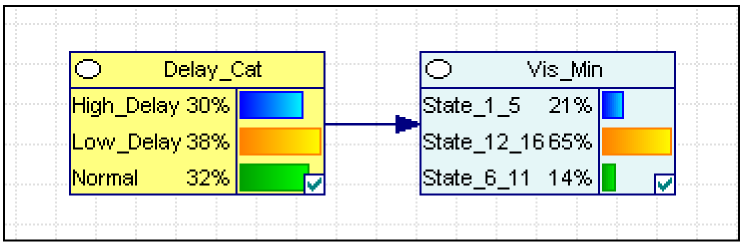


Figure 51: Learnt Parameter Results for Visibility in GeNIe

1.5.3 Learn Parameters

GeNIe had again correctly matched the 'Columns & values' to the 'Nodes & states' fields for the visibility variable, as shown in Figure 52. The fact that GeNIe referred to the nodes nomenclature differently was inconsequential to the results.

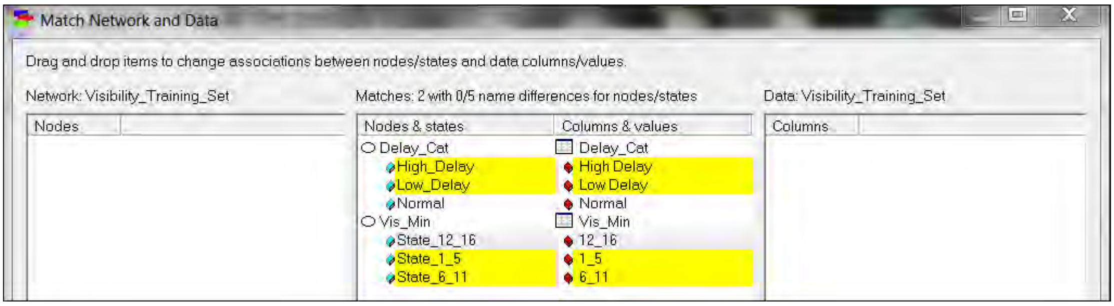


Figure 52: Learn Parameters for Visibility in GeNIe

The new learnt network coupled with the learnt parameters EM functionality was run in GeNIe with no unexpected results. This test confirms the integrity of the historical data used for experimentation.

1.5.4 Validation Results

The validation process in GeNIe indicated expected data results in the category in 'Normal' in over 42% (15/35) of all occurrences. This was in line with heuristic analyses performed with Excel pivot tables. Figure 53 refers:

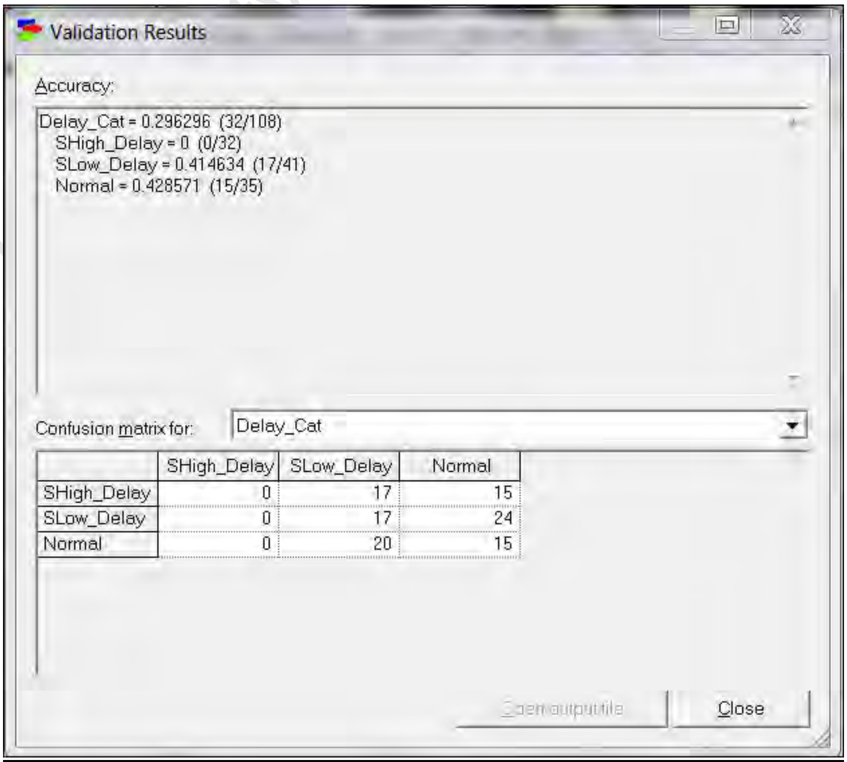


Figure 53: Validation Results for Delay in GeNIe (Visibility)

Cape Town

1.6 Validation (Delay by Wind & Direction)

The accuracy and integrity of the data could be validated for the wind experiment in the GeNIe validation process. The necessary steps are as follows:

1.6.1 Import Data File

As previously stated, the initial step is to prepare a discretised file containing wind, wind direction and delay variables in a CSV format. Once this necessary step is carried out, it can be imported into GeNIe's file import facility for posterior analysis. The imported file with discretised values in GeNIe appears in Figure 54.

Wind_Cat	Wind_Dir.	Delay
26-32	NW	High Delay
6-11	NE	Normal
19-25	NNW	High Delay
19-25	N	High Delay
12-18	NW	Low Delay
12-18	WNW	Low Delay
12-18	WNW	Low Delay
12-18	WNW	High Delay
6-11	E	High Delay
12-18	NE	Normal
19-25	NE	High Delay
26-32	NE	Normal
26-32	NNE	High Delay
19-25	NNE	Low Delay
6-11	W	High Delay
6-11	WSW	Low Delay
6-11	WSW	Normal
6-11	E	Low Delay
6-11	E	Low Delay
12-18	ENE	Normal
19-25	NW	Normal
6-11	SSE	Low Delay
26-32	N	Low Delay

Row 1 of 108

Figure 54: Data Import for Wind & Direction (CSV format)

The imported file can be examined to include the wind variables (i.e. wind intensity and direction). Average wind was chosen as a representative variable from the historical data set given the wide margin of values available. Moreover, if maximum wind was chosen it would not necessarily capture calm wind conditions at KEWR.

1.6.2 Learn Network

The new network structure was learnt with GeNIe as with previous experiments. The same learning algorithm and its parameters were chosen in the wind experiment. The class variable used was 'Delay' Figure 55 refers.

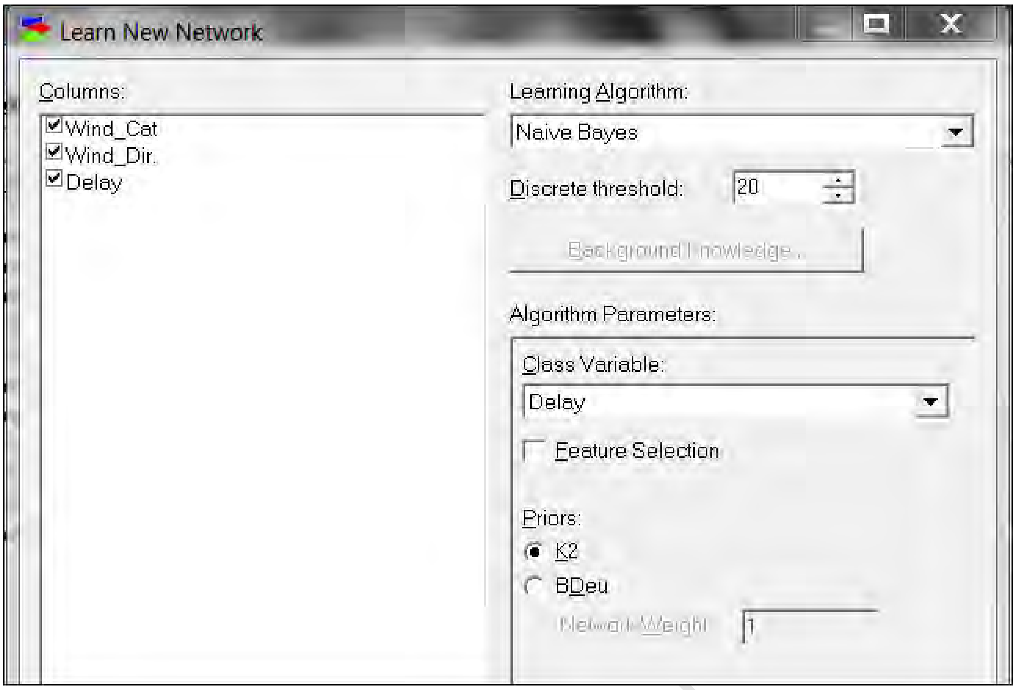


Figure 55: Learn New Network for Wind & Direction in GeNIe

Again a resulting network topology was created from the learning algorithm in GeNIe between the wind, wind direction and Delay node variables. Figure 56 refers.

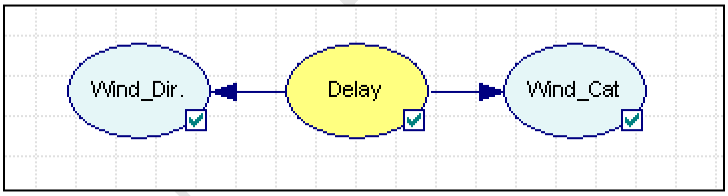


Figure 56: Learnt Network for Wind & Direction in GeNIe

The validation results in GeNIe were in line with expected values as calculated in GeNIe manually and via heuristics (namely Excel), showing 'Low Delay' category as being the marginal probability of delay relating directly to delay proportionality in the data when modelled as a wind variable. In the node delay, 40% of observations are in the 'Low Delay' category which is expected throughout the experimentation. Figure 57 refers.

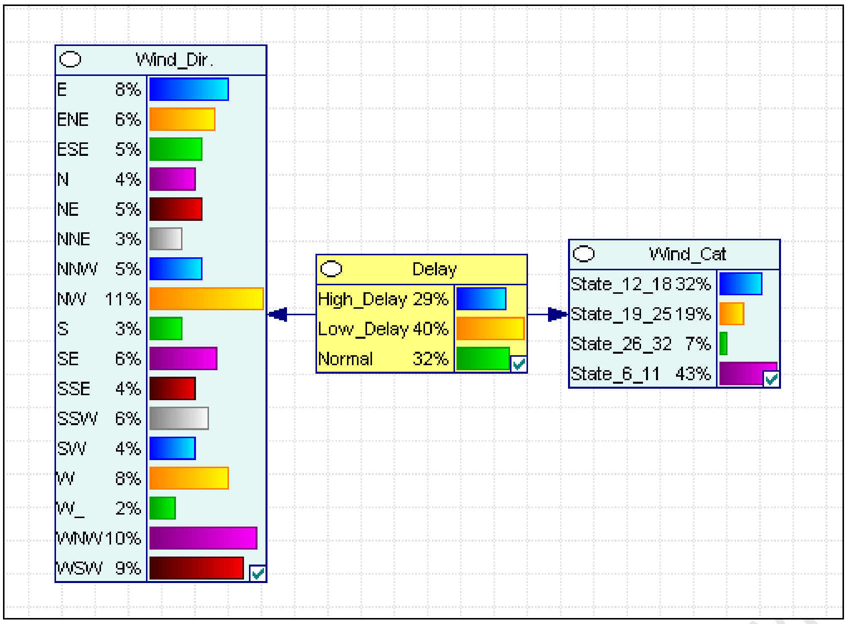


Figure 57: Validation Results for Wind & Direction in GeNIe

1.6.3 Learn Parameters

Again, GeNIe correctly matched up the 'Nodes & states' with the 'Columns & values' for the wind and Delay nodes as shown in Figure 58. This demonstrated GeNIe's capability to learn graph structures and algorithm parameters with minima data input or manual intervention.

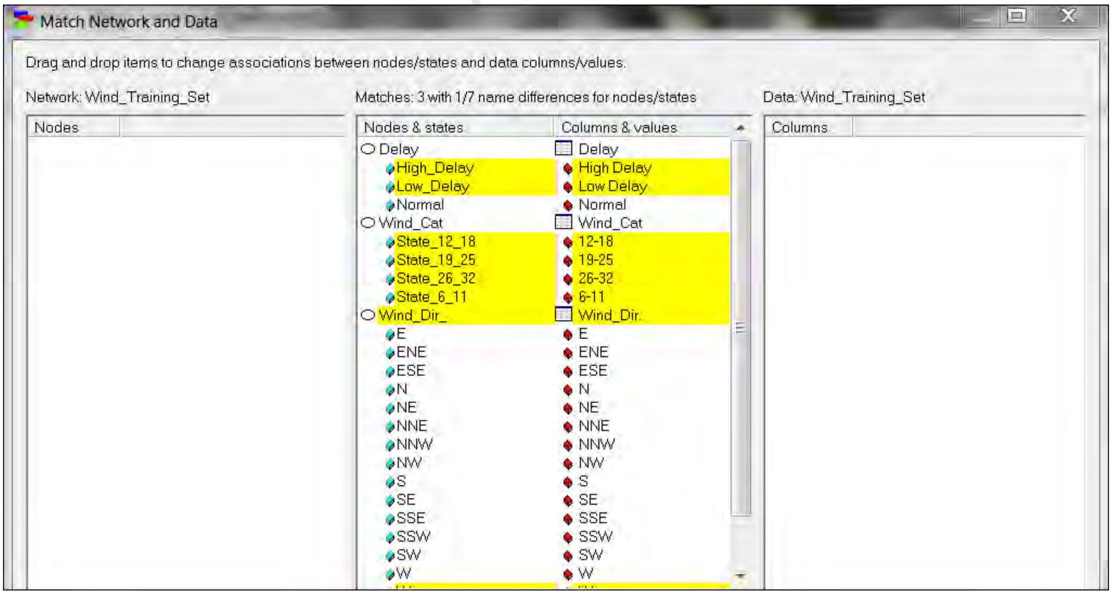


Figure 58: Learnt Parameters for Wind & Direction in GeNIe

The new network with set parameters was again run in GeNIe with no unexpected results and in line with previous heuristics.

1.6.4 Validation Results

The GeNIe validation results reported best data accuracy for 'High Delay' category of 16% (5/31) and 'Low Delay' category with a percentage of occurrences in excess of 44% (19/43). This again was in line with the expectations of historical data analysed, except for the overall accuracy for Delay. Figure 59 shows the results:

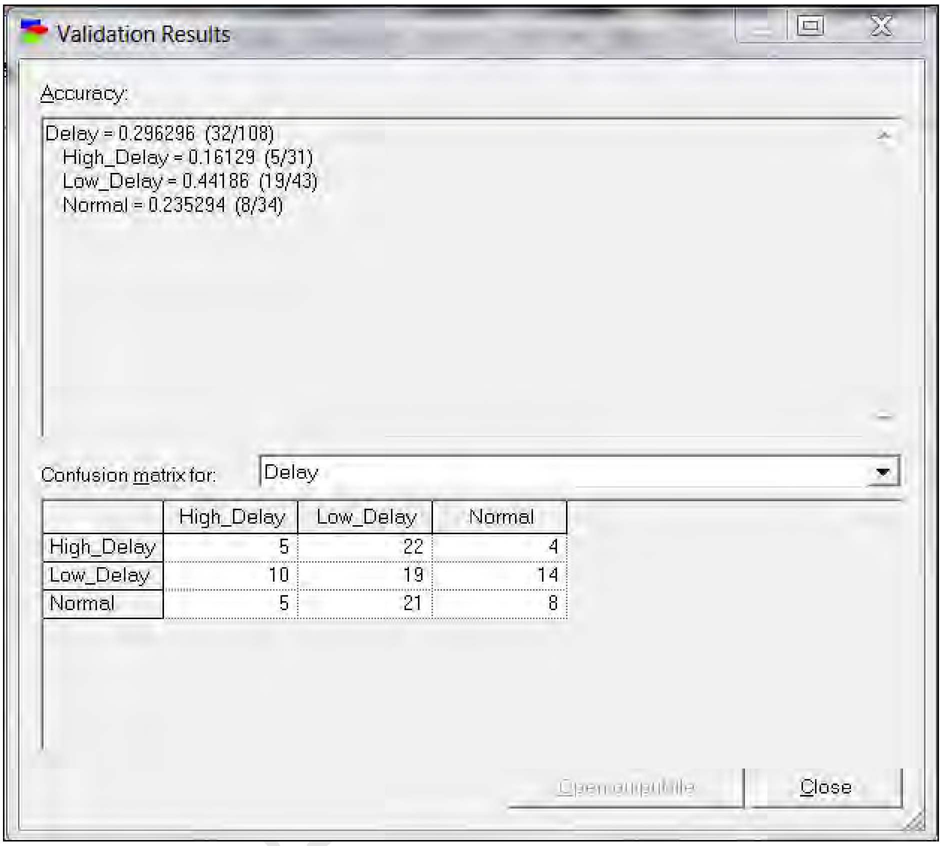


Figure 59: Validation Delay Results in GeNIe (Wind & Direction)