2017

A Hybrid Approach of Traffic Flow Prediction Using Wavelet Transform and Fuzzy Logic

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By

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A Thesis
Submitted to the Faculty of Graduate Studies
through the School of Computer Science
in Partial Fulfillment of the Requirements for
the Degree of **Master of Science**
at the University of Windsor

Windsor, Ontario, Canada

2017

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ABSTRACT

The rapid development of urban areas and the increasing size of vehicle fleets are causing severe traffic congestions. According to traffic index data (Tom Tom Traffic Index 2016), most of the larger cities in Canada placed between 30th and 100th most traffic congested cities in the world. A recent research study by CAA (Canadian Automotive Association) concludes traffic congestions cost drivers 11.5 million hours and 22 million liters of fuel each year that causes billions of dollars in lost revenues. Although for four decades' active research has been going on to improve transportation management, statistical data shows the demand for new methods to predict traffic flow with improved accuracy.

This research presents a hybrid approach that applies a wavelet transform on a time-frequency (traffic count/hour) signal to determine sharp variation points of traffic flow. Datasets in between sharp variation points reveal segments of data with similar trends. These sets of data, construct fuzzy membership sets by categorizing the processed data together with other recorded information such as time, season, and weather. When real-time data is compared with the historical data using fuzzy IF-THEN rules, a matched dataset represents a reliable source of information for traffic prediction. In addition to the proposed new method, this research work also includes experiment results to demonstrate the improvement of accuracy for long-term traffic flow prediction.

DEDICATION

First of all, I dedicate this research to my creator almighty Allah. I would also like to dedicate my research to my mentor, my advisor, my brother Jahid; without whom I wouldn't achieve whatever I achieved in my life. I dedicate this research to his parenthood towards me, which gives me the independence for being a child until the end. I dedicate this research to my parents. My mother Razia, who always supported me through thick and thin. I dedicate this research to her sacrifices that she made for me. My father has been the source of motivation for me. I dedicate this research to his hard work, which inspired me to concentrate more. I dedicate this research to my elder brother Zakir as well, who has taught me to be able to stay grounded and confident to face any challenges. Last of all, I dedicate this research to my Moon who gave me peace and always looked after me like a true companion. I dedicate this research to her love she gave me.

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my supervisor Dr. Xiaobu Yuan for providing me with an exciting opportunity to work in an interesting and challenging field of research. His vision helped me to get innovative in my thinking and also motivated me to research.

My humble gratitude goes to my internal reader Dr. Mehdi Kargar for his extensive support for my research. He has always helped with any of my queries regarding my research. He suggested me with his valuable insights which helped me to improve my research.

I am thankful to my manager at work Jim Reid. He has trusted on me like no one else. He supported me while I was struggling with my research. Without his continuous support, it would have been so much tougher.

Finally, I would like to appreciate my Graduate Coordinator Karen, who has always helped me with her suggestions and appreciations.

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LIST OF ABBREVIATIONS/SYMBOLS

FFT	Fast Fourier Transform
AADT	Annual Average Daily Traffic
FT	Fourier Transform
WSDOT	Washington State Department of Transportation
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform

CHAPTER 1

INTRODUCTION

1.1 Transport Management System

Urbanization is a process through which population in urban areas increases over a short period of time; becoming more specialized, which brings socio-economic development in an urban area. The main reasons behind urbanization are better jobs, fancy lifestyle, more scope for social interactions and rich cultural diversity etc. According to Statistics Canada, over 80 percent of Canadians tend to live in urban areas, mostly in the three big cities Montreal, Toronto and Vancouver [1]. Compared to 1911, when 45% of the total population used to live in urban cities, 36% more people moved to reside in urban areas making it 81% of the entire population at 2011 [1]. Figure 1 depicts the above information provided.

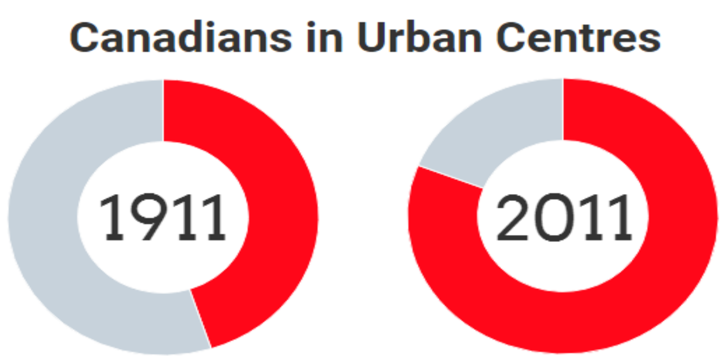

Figure 1: Population Percentage in Urban Centers in Canada [1]

With all the better perspective of life, urbanization also brings some unavoidable difficulties to the inhabitants of urban cities. Govt. as well as private sectors have developed a good amount of city-system to tackle these problems caused by the process of urbanization. City-system includes an economic system, health care system, transportation system and infrastructure planning e.g.

Traffic condition of a city, if not the most; is one of the most important aspects of an excellent socio-economic sustainability of an urban area. As nearly all of the people in any metropolitan area highly dependent on road transportation network for completing their essential daily functions, traffic information system has always played the most vital role. Traffic information system involves collecting, categorizing and processing of current as well as historical traffic data by any govt. or non-govt. organizations to circulate traffic-related information to the people. Traffic information system mainly consists three key elements which are traffic related data collection, data processing, information dissemination [2] which is described in Figure 2.

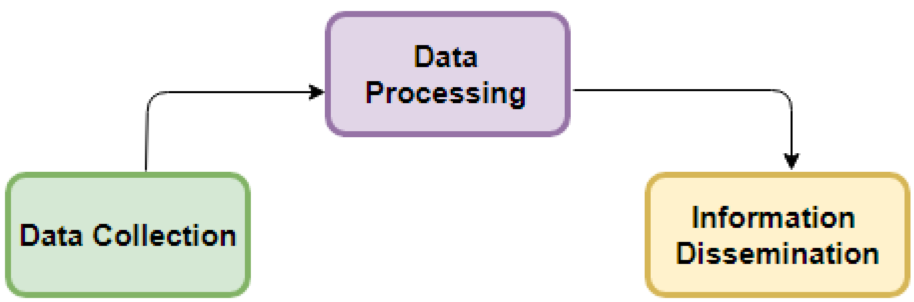

Figure 2: Main components of classic Transportation Information System [2]

Moreover, this type of management system also involves processing collected data for prediction of traffic condition, road infrastructure development, substructure planning of a city, etc. Planned traffic management and control system requires extensive information regarding operational state and characteristics of traffic flow [2]. Parameters which are most relevant to traffic management system might include but not limited to [2]:

- Traffic Flow or Volume – the number vehicles crossing a road intersection per unit of time;

- Road Information – data regarding a particular road such as geographical information of the route, number lanes and connected highways;
- Weather Condition – relevant information of weather against traffic flow in a given time which might include temperature, weather events (snow, rain, wind speed, fog), etc.;
- Traffic Density – vehicle count occupying a road lane per unit of length in a given time;
- Incident – an unexpected event that takes place on a particular road which might impact the flow of traffic in a roadway. Relevant details with this event may include location, date/time, type of impact, weather condition, number of vehicles involved, etc. [2]; and
- Time of measurement – time in which count of vehicles and road information is taken into consideration as inputs to be inputted into the traffic management system.

These parameters can be measured by using different measurement tools such as detectors, sensors or can be measured from any vehicle using some vehicle sensors as well such as speedometer, intelligent heat detector, etc. In spite of having multiple measurement tools, traffic information system provides a better output if the system is provided with accurate and robust input.

The traffic information management system is a broad term which consists of many sub-modules. These sub-modules are developed to achieve different types of objectives. Table 1 discusses different submodules of traffic management system and their objectives.

Sub-Modules	Description	Objectives
Congestion Management	Prediction of traffic flow in a particular time of a day which helps to come up with a plan for mitigation of regular or irregular congestion.	• Monitoring congestion in a particular time at a day • Prediction of congestion • Road characteristics prediction
Incident Management	Early detection of unexpected events and response plan to mitigate the number of occurrence of such incidents.	• Unexpected event detection • Response Assistance • Mitigation plan
Traffic Broadcast	The process of transmitting traffic information to drivers.	• Choosing unclassified traffic information to be broadcasted such as delays, travel time; to a driver • Categorizing road maps with related information
Corridor Management	Distribution of roads among vehicles in the same corridor of road network [2], e.g. using different routes from source to destination.	• Finding alternative routes from source to destination • Pre-trip and en-route advisory [2]
Travel Demand Management	Improving traffic flow by managing travel demand [2]	• Congestion Pricing • Ramp metering

Table 1: Sub-Modules of traffic information system [2]

1.2 Traffic Congestion Management

One of the most determining sub-module of any advanced transportation management information system is congestion control. As described in section 1.1, urbanization provides any metropolitan area with increased number of population which ensures the fleet size of vehicles increasing time to time. This phenomenon causes vehicle overload in the road network of an urban area which eventually causes recurrent congestion. Traffic congestion can be defined as an event in which use of road network increases with increased number of vehicles characterized by decreased mean speed of vehicles and increased time in travel. Each street or intersection in a road network has an individual capability of transporting vehicles. This is defined as the capacity value of the path in a road network. When the demand passes the capacity value of the road, congestion occurs. After this kind of condition arises vehicles stays in a particular junction more than the average time which increases the travel time for any vehicle on that particular road. This scenario is known as the traffic jam. Such condition can be influenced by weather, unscheduled phenomenon like accidents, construction, etc. Traffic congestion can be classified as following,

- Recurring Congestion
- Nonrecurring Congestion

Recurring congestion is known as “peak-hour” traffic. Most of the metropolitan inhabitants and commuters experience recurring traffic congestion on a daily basis [3]. Recurring congestion is often seen as the capacity problem and logically combated with raising roadway capacity [3]. People get out of the home in the morning to reach work, appointments, etc. and at the evening they tend to get back to the house. This circular process turns highways and major roads into gridlocks [3]. Peak-hour or rush-hour can be defined as the span of time when the demand from a road crosses the capacity level of that particular road. Rush hour in a weekday can be entirely different compared to the rush hour on a weekend or holiday. Down *at el.* estimates 66.4 percent people travel between 6:00 to 9:00 am in the morning who generally work outside [4] This study shows the impact of rush hour in the road network. With time the ratio of vehicles on the roads increases and which causes increased traffic congestion. As the rush hour on weekdays doesn't change over time, so the congestion keeps on happening in those times causing recurring congestion. However, peak hour travel is reinforced by other human tendencies as well, including school schedules and sleeping pattern [3]. So, peak hour pattern of a metropolitan city is predictable and keeping this on mind traffic congestion can be determined.

Unlike recurring congestion which is expected on a weekday or a weekend, nonrecurring congestion is usually unexpected [3]. Nonrecurring traffic congestion can be described as traffic delays occurred due to accidental vehicle collision, vehicle breakdown, road construction, extreme weather, special events, etc. This kind of congestion can happen during any time of a day due to any number of unexpected events which slows the traffic. Unlike recurring congestion which is more abstract, nonrecurring congestion has a more straightforward reason. But sometime nonrecurring congestion follows pattern as well such as if it is snowing; particular road might face more congestion as vehicles slow down and create bottlenecks in the main roads of the road network.

While recurring congestion happens to be the main reason behind traffic congestion, nonrecurring congestion also has a severe impact on traffic congestion. Therefore, even if recurring congestion is considered to be the main cause of traffic congestion, nonrecurring congestion needs to analyzed for pointing out the reasons behind traffic congestion and predicting traffic congestion. Below a graph representation is presented which shows traffic congestion is equally caused by recurring congestion as well as nonrecurring congestion.

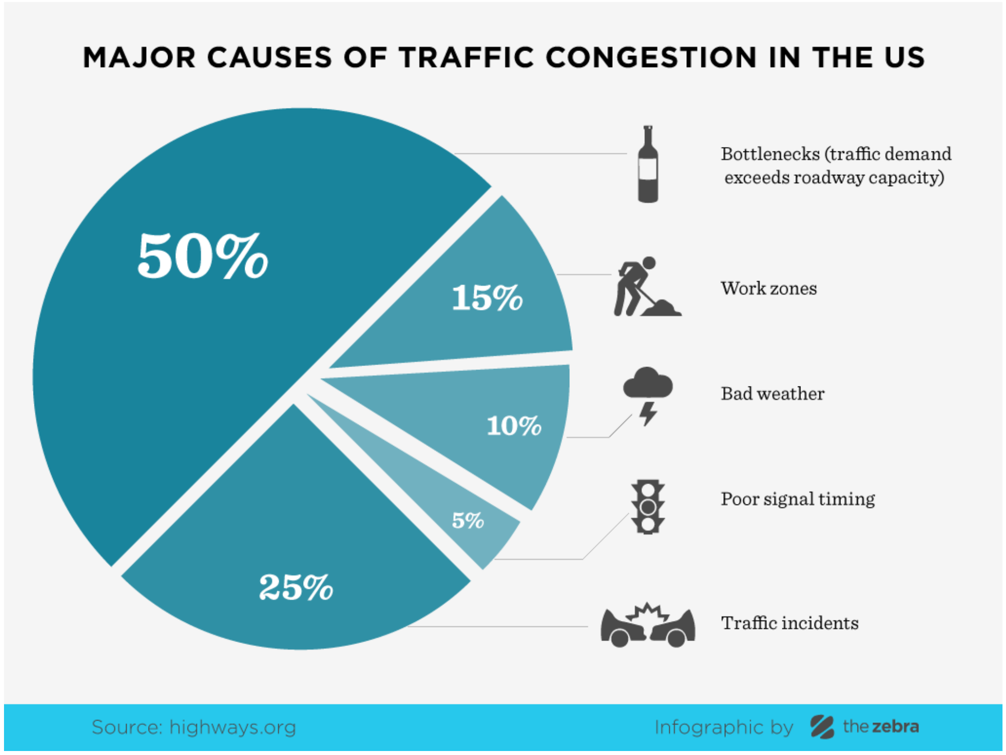

Figure 3: Major Causes of Traffic Congestion in the US [highway.org]

The most important requirements for congestion management are predicting the time of congestion and the volume of vehicles on a particular road. Predicting the time of congestion helps to define the pattern of recurring and nonrecurring congestion and helps for planning to identify objectives for congestion management system. Table 1.1 discussed the goals of congestion management which includes prediction of congestion as well as road characteristics prediction. Prediction of congestion also provides substantial evidence for determining rush-hour traffic time and traffic variation between peak hours and non-peak hours.

1.3 Problem Statement and Motivation

Continuous growth of metropolitan areas in its size of inhabitants and infrastructures are causing significant drawbacks in the urban transportation system. These disadvantages include traffic congestion, lack of corridors, insufficient roads in road networks, etc.

Traffic congestion has a severe impact on not only the quality of life for the inhabitants of an urban area but also on the overall economic stability of that area. Productive work hours, as well as precious personal and family time, are wasted. While shipping merchandises from one place to another, if it takes longer travel time by trucks, it affects consumers economically. Lost productivity of the workforce due to the longer travel time of passenger trips and freight deliveries hinders economic development of the nation. Delays in travel time, increase fuel consumptions; which are considered as the main reason behind environmental pollution. In a recent study conducted by Canadian Automotive Association, it is reported that traffic congestions in the main cities of Canada cost drivers 11.5 million hours and 22 million liters of fuel each year [5]. Table 2 lists 20 worst bottlenecks of some major cities in 2015 described in the analysis report conducted by CAA in January 2016 [5]. The report states that the delay in these bottlenecks costs about $300 million every year [5].

Rank	CMA	Location	Length	Annual Total Delay (hours)	Annual Delay Cost (mill.)	Potential Annual Fuel Savings (liters)
1	Toronto	Hwy 401 between Hwy 427 & Yonge St	15.3	3218	82.28	5721
2	Toronto	DVP/404 between Don Mills Rd & Finch Ave	10.5	2174	55.51	3478
3	Montreal	Hwy 40 between Blvd Pie-IX and Hwy 520	10.6	1956	45.60	4197
4	Toronto	Gardiner Expy between S Kingsway & Bay St	7.4	1076	27.51	1671
5	Montreal	Hwy 15 between Hwy 40 & Chemin de la CôteSaint-Luc	3.9	812	18.93	1653
6	Toronto	Hwy 401 between Bayview Ave & Don Mills Rd	3.3	485	12.40	934
7	Toronto	Hwy 409 between Hwy 401 and Kipling Ave	1.6	274	6.99	553

8	Montreal	Hwy 25 between Ave Souligny & Rue Beaubien E	2.1	259	6.04	591
9	Vancouver	Granville St at SW Marine Dr.	1.6	245	6.08	679
10	Vancouver	W Georgia St between Seymour St & W Pender St	1.2	149	3.70	603
11	Toronto	Hwy 401 between DVP & Victoria Park Ave	1.3	143	3.66	395
12	Toronto	Black Creek Dr. between Weston Rd & Tretheway Dr.	0.8	114	2.91	391
13	Toronto	Hwy 401 between Mavis Rd & McLaughlin Rd	0.8	103	2.63	164
14	Montreal	Hwy 40 between Hwy 520 & Blvd Cavendish	0.9	96	2.23	207
15	Vancouver	Granville St between W Broadway St & W 16th Ave	0.6	88	2.19	276
16	Montreal	Hwy 20 near 1re Avenue	0.8	84	1.97	174
17	Qc. City	Hwy 73	0.7	78	1.81	127
18	Toronto	Hwy 401 interchange at Hwy 427	0.6	73	1.87	194
19	Toronto	Hwy 400 at Hwy 401	0.6	62	1.60	216
20	Vancouver	George Massey Tunnel on Hwy 99	0.6	60	1.50	97
Total			65.2	11546	287	22322

Table 2: Canada's Worst Bottlenecks, 2015 [5]

The road network which exists in these major cities clearly is not coping with the increasing demand leading to severe traffic congestion. Nevertheless, construction of new roads to be added to the road network is time consuming whether now the smartest solution is using the roads which are already there in the road network. Figure 1.4 presents traffic index data of the larger most cities in Canada (Tom Tom Traffic Index 2016). Most of the cities are between 30^{th} and 100^{th} most traffic-congested cities, and it has been the scenario of the last couple of years.

FULL RANKING

All Continents ▾ | Canada ▾ | Large (Population > 800 thousand) ▾

WORLD RANK	FILTER RANK	CITY	COUNTRY	CONGESTION LEVEL (Extra travel time)		MORNING PEAK	EVENING PEAK
36	1	Vancouver	Canada	34%	↓1%	50%	65%
64	2	Toronto	Canada	28%	↓3%	48%	60%
81	3	Montreal	Canada	26%	↓1%	47%	57%
86	4	Ottawa	Canada	26%	↓2%	43%	58%
115	5	Edmonton	Canada	21%	↓2%	30%	40%
122	6	Calgary	Canada	19%	↓3%	28%	39%

Figure 4: Best and Worst Largest Cities for Traffic in Canada (Tom Tom Traffic Index, 2016)

Since current estimates reveal congestion rate is above normal and might even grow further, there is always room for new researches regarding management of transportation. Prediction of congestion being one of the most vital components of such systems can help to predict future demand which contributes to prevent traffic congestion using different corridor. Traffic forecast accuracy improves the performance of various components of transportation systems e.g. corridor management, transit signal priority control, traveler information system [21]. Prediction process relies on data both historical and real. Using only real data or only historical data might lead to erroneous prediction as the traffic tends to exhibit chaotic behavior especially in the metropolitan area [6]. There are a lot of factors which might influence traffic flow in a particular time e.g. vehicle collisions, weather conditions, holidays, the day of the week, season, etc. The uncertainty of data causes uncertainty in the prediction of traffic. Over the years' scientists have developed lot of methods to predict traffic congestion such as, time series models [7,8], Kalman filter theory [9,10], Markov Chain Model [11], fuzzy-neural approach [12], sequential learning [13], local regression models [14,15], Bayesian network [16,17], neural networks [18, 19] and deep learning approach [20] etc. Some of the works combine different methods to come up with a new approach to predict traffic prediction. However, there is no technique that clearly outperforms any other techniques with the same sets of inputs in the same experiment environment [6]. More and more research is being conducted combining two or more methods to predict traffic flow.

This thesis implements a new hybrid approach, combining wavelet transform and fuzzy logic to predict traffic flow and volume of vehicles using real historical and actual current data. From a long time, scientists have been using mathematical transformation on signal to analyze data frequency with respect to time. As traffic data is chaotic, to cope with the uncertainty of data, fuzzy logic is implemented to turn chaotic characteristic of data into stochastic behavior. Sharp variation point or zero crossing point has been used to reveal the similar trend of traffic flow from traffic count per hour. Zero crossing points refer to the beginning and ending of a trend. So, the window size for taking traffic count is one hour. For predicting traffic flow in real- time by keeping the integrity of variation trend, the length of two sharp variation points is reasonable [22].

In the remaining of the thesis, Chapter 2 provides insights of the related works for prediction of traffic and discusses the data type used to predict traffic. Detail discussion of the mathematical transformation of time series signal by wavelet transform is presented in Chapter 3. This remainder of this chapter discusses using Morlet transformation as continuous wavelet transform and sharp variation points of traffic data to subdivide similar trend of traffic flow. This chapter also describes the use of scaling functions for wavelet transformation. Chapter 3 also provides information of some current researches regarding wavelet transformation which is being used for traffic flow prediction. Chapter 4 mainly describes fuzzy logic systems and the concepts of fuzzy membership sets for classifying traffic data. Chapter 5 covers data categorization and forming fuzzy membership sets. The design and implementation of the new algorithm are presented in this chapter as well. Chapter 6 describes experiment environment, simulation and accuracy analysis. Experiment results are presented using tables figures and graphs.

Results are compared with other related works to demonstrate the proficiency of this new hybrid approach. Chapter 7 talks about future work and concludes the thesis.

CHAPTER 2

LITERATURE REVIEW AND BACKGROUND MATERIAL

2.1 Input Data in Previous Methods

Different approaches use traffic data differently with the dissimilar time span. Some of the approaches use current data for categorizing and processing those data to predict traffic volume or traffic speed in the future. For example, Random Walk Forest [7] uses current traffic conditions to predict traffic flow. On the other hand, methods like Arima Process [23] reveals short-time traffic conditions of a particular location in the road network based on previous traffic flow of that particular area. Moreover, there are other methods presented by R. Chrobok *at el.* and J. Rice *at el.* which integrates historical data with current data for classification purposes for forecasting.

Li *at el.* in his method compares using historical data with both historical and real-time data to predict traffic congestion [21]. In his paper, Li *at el.* used 24 data sets with each dataset covering a single day. Each data set contains traffic flow from 5:00 am to 10:00 am and 2:00 pm to 8:00 pm. This method considers two cases for fuzzy rule construction. In the first case, historical information is being used for constructing fuzzy rules, while historical and real-time data are used in rule construction in the second case [21]. The performance of this model is determined by comparing against three commonly used performance measures for prediction models. They are as followings [2]:

- Mean Absolute Error (MAE) = $\frac{\sum_{n=1}^{N} \sum_{i=1}^{I} |\hat{x}_i^n - x_i^n|}{NI}$

- Mean Relative Error (MRE) = $\frac{\sum_{n=1}^{N} \sum_{i=1}^{I} \frac{|\hat{x}_i^n - x_i^n|}{x_i^n}}{NI}$

- Mean Square Error (MSE) = $\frac{\sum_{n=1}^{N} \sum_{i=1}^{I} (\hat{x}_i^n - x_i^n)^2}{NI}$

Here, $\hat{x}_i^n$ represents traffic forecasts at i-1 time for any occupancy level i in n number of run [2]. While N denotes the total number of runs and I indicate the total number of data points for prediction [2]. Here occupancy means the characteristics of a road being occupied with vehicles. After the prediction process is completed using fuzzy logic for both flow (time) and occupancies for all the cases, it is determined that the level of error is less if the experiment is conducted using both historical and real-time data compared to using only historical data [2]. Table 3 and Table 4 proves the claim giving conducted experiment results.

Method	Historical Data Only	Historical Data combined with Real Time Data
MRE (%)	12.48	11.97
MAE	1.67	1.54
MSE	8.05	6.71

Table 3: Performance Measure for Forecasting Occupancy [21]

Method	Historical Data Only	Historical Data combined with Real Time Data
MRE (%)	5.84	5.61
MAE	5.97	5.75
MSE	65.75	58.49

Table 4: Performance Measure for Forecasting flow (time) [21]

From above method presented by Li *at el.* [2], it can be suggested that using a combination of historical data with real-time information for prediction traffic situation is a better approach with marginally improved accuracy. There are also methods developed on the basis of time series data. For instance, Volterra Neural Network [26] and ARIMA [7] process attempts to predict the value of a predictable variable based on the previous values of that variable at a regular interval [6]. Nicholson *at el.* provided information about the length of dataset [27]. Based on spectral analysis it is an optimal approach to choose at least 17 days of historical data to predict the future flow of traffic volume [27]. Some research concentrates only using weekdays data as researchers provided necessary prove that weekday flow is quite different compared to weekends flow of traffic [27]. Different factors are considered during prediction of traffic such as,

- different weekdays [24]
- different time periods during the day [27],
- holidays [28]
- special events [24]
- seasonal differences [24] etc.

2.2 Sources of Data

As data is the main requirement for predicting traffic, it is most important to collect traffic data from trusted sources. The data used in previous researches are collected from Traffic Management Bureaus, loop detectors, video surveillance camera, GPS-enabled vehicles, mobile devices, crowdsourcing etc. [6]. Shiliang Sun *at el.* in his Bayesian approach to predict traffic volume collected data (volume/hr) which was recorded by Traffic Management Bureau of Beijing [16]. For time series prediction using different neural networks techniques such as Volterra, RBFNN researchers used volume per hour techniques on different windows like 15 min, 1 hour. Loop detectors are one of the most common approaches to collect data for predicting especially short time traffic which is used by many famous approaches such as CATA, CATB, Slip-Road [29]. A lot of methods uses sensors placed in road intersection for collecting traffic count. There are researches conducted using FFT or AADT method to generate synthetic data sets to encounter information scarcity for predicting traffic volumes as well [22]. Crowdsourcing has become one of the best approaches to collect data for predicting traffic. Mobile devices have become really popular. Google Maps uses mobile devices used by people to gather data in a roadway.

2.3 Forecasting Techniques

Researches on the past used a lot of techniques to forecast traffic volume and congestion time. Table 5 describes primary methods in the area of traffic flow analysis and traffic flow prediction with by listing their advantages and disadvantages.

Title	Main Author	Year	Advantages	Disadvantages	Cited By
A Bayesian network approach to traffic flow forecasting	S. Sun	2006	Ability to create Bayesian Network of a traffic flow on a given time by coping with incomplete data	Unexpected conditions such as events, holidays, accidents might affect the accuracy	283
Traffic Forecast Using Simulations of Large Scale Networks	R. Chrobok	2001	Real-time data is incorporated, special events are taken into consideration	Only used to forecast short time flow	62
Dynamic Prediction of Traffic Volume Through Kalman Filtering Theory	I. Okutani	1984	Short term prediction considering stochastic phenomena with higher accuracy	Bad result in chaotic situation	591
Short-term traffic flow forecasting based on Markov chain model	G. Yu	2003	Short term prediction considering most recent state of traffic which gives better prediction	Can't forecast long-term traffic and also fails to produce result during chaotic situation	63

Real Time Road Traffic Prediction with Spatio-temporal Correlations	W. Min	2011	Very high accuracy only in really short term	Less accuracy in long term and only considers real-time data	298
Multi-step Prediction of Volterra Neural Network for Traffic Flow Based on Chaos Algorithm	L. Yin	2012	Considers both historical and real time data for long term prediction	Takes too much time as considers a lot of data.	13
Traffic Flow Forecasting: Comparison of Modelling Approaches	B.L. Smith	1997	Easy to implement and fast	Only considers historical value so less accurate and cannot respond to unanticipated events	436
Traffic Flow Prediction with Big Data: A Deep Learning Approach	Y. Lv	2015	Examines historical and real-time data to be inputted in a greedy approach which provides fantastic performance	Takes a lot of time and the data used are produced synthetically	139
Type-2 Fuzzy Logic Approach for Short-term Traffic Forecasting	L. Li	2006	Produces prediction interval instead of a single prediction value which refers to superior accuracy	The data used has a lot of missing values	70
Real-time Traffic Flow Predicting Using Augmented Reality	M. Zhang	2016	Produces better accuracy	Doesn't consider chaotic situation, data used to predict is generated synthetically	1

Table 5: Advantages and Disadvantages of Previous Popular Methods

CHAPTER 3

WAVELET TRANSFORMATION

3.1 Signal Processing

The world immersed itself with information. Any variable which represents any information can be denoted as a signal. Examples of signals includes human vocals, the sound of aeroplane, temperature in a day, human gestures, etc. Human body being a complex system transmits and receives signals from outside of the body as well as from inside the body and process those signals to work. Mathematically a signal can be defined as a real or complex-valued function of one or more variables [32]. Signal varies from one dimension to multi-dimensions. One dimensional signals represent only a single variable such as daily mean temperature, annual rainfall etc.; whereas two-dimensional signal accounts for a function whose domain consists of a two-dimensional real plane such as time-frequency analysis. Figure 5 and Figure 6 represents a one dimensional and a two-dimensional signal respectively.

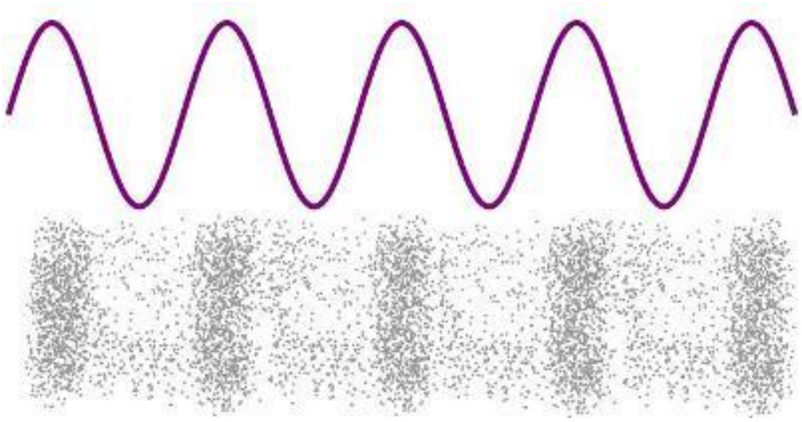

Figure 5: One-Dimensional Signal (Waveform)

Figure 5 represents a waveform signal. This signal can be mathematically represented as,

F(x) = waveform; Here, x is referred as an independent variable.

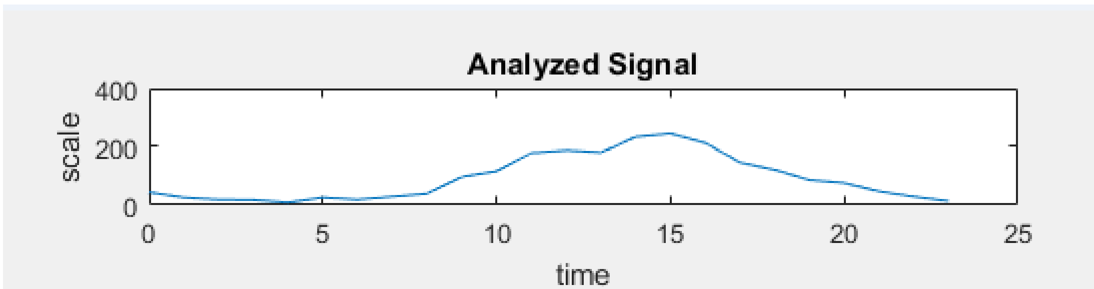

Figure 6: Two-Dimensional Signal Representing Time-Frequency

Figure 6 represents a time-frequency signal, where x-axis represents time t in a discrete space (1:00 to 24:00), and y-axis represents the scale of frequency f over that time. Mathematically this can be expressed as function of both variables,

$F(t, f) = F(t) + F(f)$.

Processing a signal refers to a method by which more useful information can be revealed from a signal. For example, human hears sound waves and through the auditory path the brain receives the sound wave and process it to extract information such as low pitch noise, high pitch noise, etc.

3.2 Mathematical Transformation of Signal

Mathematical transformation is used on signals to obtain further information which is not readily available on that original signal [33]. This is a way to process the raw signal to transform into processed signal which provides more information. Most of the signals used in engineering practices are time-domain signals in their original format. Time-domain signals represent a graph in which x–axis represents independent variable time and y-axis represents dependent variable amplitude/frequency [33]. These kinds of graphs are used to measure frequency on the basis of time. Plotting time-domain signals in a graph, time-amplitude representation of that signal can be obtained. This kind of representation does not always provide the best information for any signal processing related application [33]. In most of the cases, much of the extended information is hidden in the amplitude of that signal [33]. The frequency spectrum of any signal reveals the component of the frequency of that signal. This shows characteristics of frequency components in the signal such as high frequency, low frequency, etc.

Frequency is related to the change of rate of a variable [33]. If a variable change rapidly with respect to time, we define it to be a variable of high frequency. Whereas if it does not change rapidly or change smoothly, it is called a variable with low frequency. For example, if publication frequency of newspaper is considered, daily newspaper has a higher frequency than the weekly and the monthly newspaper.

3.2.1 Fourier Transform

One of the most famous mathematical transformation used to measure the frequency component of a signal is Fourier Transformation (FT). FT transforms a time-domain signal and represents a processed frequency-amplitude signal with one axis being the amplitude and other representing frequency [33]. An amplitude of a wave can be defined as the measure of change over a single wave period. This kind of representation reveals the amount of each frequency existing in the frequency-amplitude signal. For example, if we consider a voice signal represented Figure 7, we get to know the time along x-axis and along y-axis we get to know the amplitude of the voice signal, which can be defined as how loud the voice is.

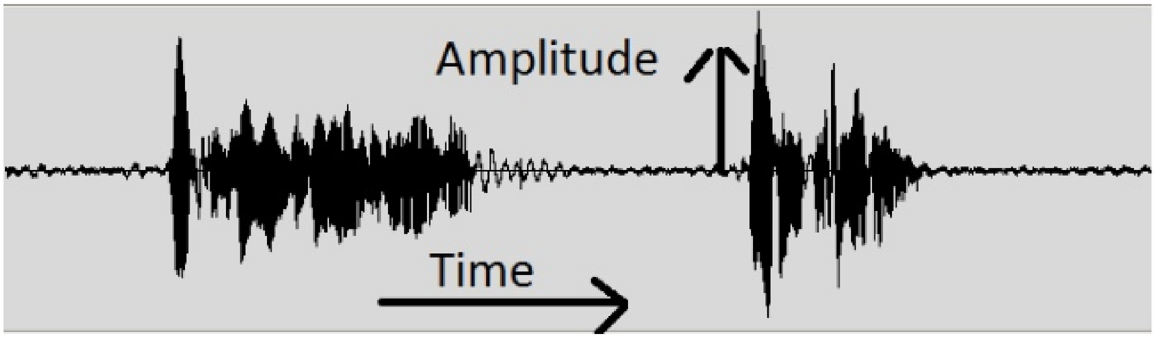

Figure 7: Voice Signal Representing Time and Amplitude [34]

Plotting a signal in the time-domain can be informative, while scientists find it useful to put a signal in the frequency-domain as well [34]. As discussed earlier, in frequency-domain representation of graph frequency is represented along the x-axis, whereas; amplitude is represented along the y –axis. Figure 8 plots a signal in time-domain and frequency-domain graphs.

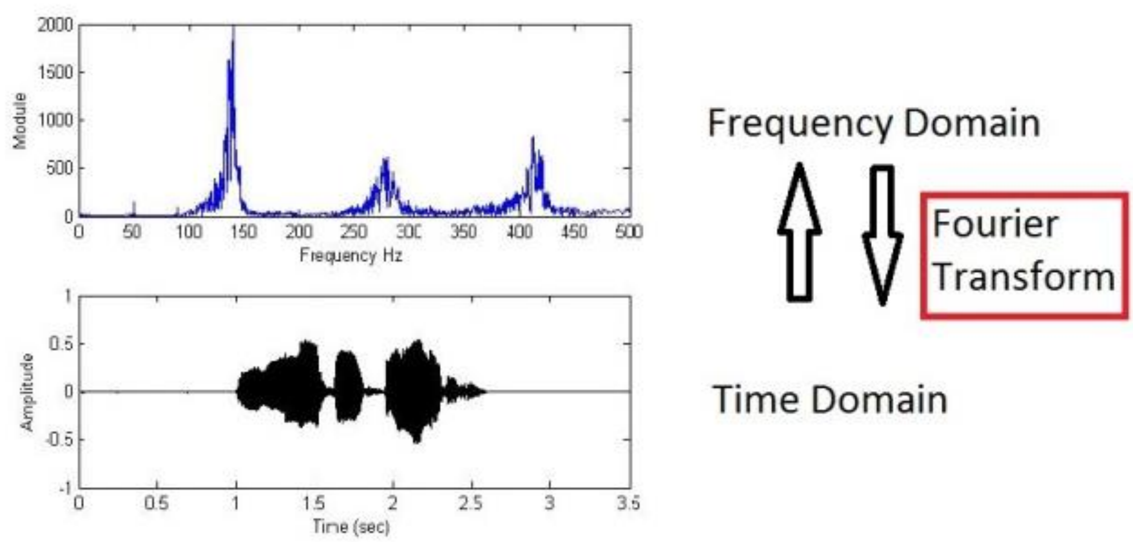

Figure 8: Fourier Transformation [34]

The first graph represents the frequency-domain representations of the signal. The three spikes refer to the high, medium and low pitches/tones of the voice. The process of transforming a signal from time-domain to frequency-domain and from frequency-domain to time-domain can be referred as Fourier Transformation [34]. The amplitude differs from one frequency to another which represents the different amplitudes and their frequency. Having FT on signals helps to reduce noise, compress data, detecting changes in frequencies etc.

3.2.2 Disadvantages of Fourier Transform

Although FT is probably the most used mathematical transformation in this world for engineering applications, there are lot of other transformations as well such as Wavelet Transformations, Featured Transformations, Wigner Distribution, etc. Each and every transformation technique have their advantages and disadvantages with their area of applications. Fourier Transformation has some drawback of itself as well. Fourier Transformation has a reversible characteristic which means this technique allows a signal to go back to its raw signal after being processed and vice verse [33]. But with even if FT has this characteristic, this technique only can represent one representation either frequency-domain or time-domain, at a given time [33]. This means, there will be no frequency information in a time-domain signal and no time information in frequency-domain signals [33]. As FT is mainly used to reveal frequency information in a time-domain signal this technique provides the best performance when the signal is stationary [33]. This technique does not tell in which time that frequency exists. Stationary signal refers to those signals in which frequency contents do not change over time [33]. For example, statistics proves that an average of 50 Hz of electricity is needed in each house of the residents of the USA per day. So, every day the electricity consumed in a house in the USA is 50 Hz which doesn't change over time. FT could produce a frequency-domain representation of this scenario to reveal the frequency of 50 Hz electricity of a house in the USA. On the other hand, if any house uses 50 Hz, 60 Hz and 70 Hz in consecutive days using FT won't provide time-frequency ratio of electricity use for that house which can be a valuable information to have experimented. Therefore, if time localization of frequency component for any signal is needed for further investigation time –frequency representation of that signal is required.

3.3 Wavelet Transform

Waves can be denoted as oscillation function of time and space such as sine wave or sinusoid [35]. A wavelet is nothing but a small wave that represents energy (frequency) with respect to time for providing a tool to analyze non-stationary signals [35]. Wavelet possesses the ability for analyzing simultaneous time and frequency components of a signal with strong mathematical foundation [35]. When it comes to signal processing particular frequency component occurring at any time can provide interesting information [33]. Wavelet transform can process a raw signal by providing time-frequency representation of that signal [33].

Fourier Transformation transforms a signal by deconstructing the signal into waves that are infinitely long [34]. Concentrating on the frequency domain, it becomes tough to isolate the frequency with respect to time as the frequency with a high resolution never stops. Recalling the example of the use of electricity at a house in use, it becomes tough to explain the frequency of using 50 Hz of electricity with respect to time because this frequency exists all time in the signal. So, the time becomes uncertain fi while transforming a signal focus is only on the frequency component. To solve this problem, a signal is deconstructed into small wavelets and then added together to process a newly transformed signal using wavelet transform [34]. For example, if a signal possesses frequencies of 1000 Hz, firstly wavelet transform deconstructs this signal by splitting the signal into half through passing the signal from a high-pass to low-pass filters [33]. This operation generates two versions of the original signals, one consisting of high-pass portion (500 to 1000 Hz) and another consisting of low-pass portions. After that, wavelet transform performs the same task again on those high-pass and low-pass filters until the original signal is decomposed to a certain level. This process decomposes the original signal into n number sub-signals where each signal corresponds to different frequency bands by limiting time [33]. After that wavelet transform adds all the sub-signals and plot them into a graph to represent time-frequency representation of a graph. Wavelet transform generally processes a signal in the wavelet domain rather than frequency domain [34]. The time limiting quality of wavelet transform has proved this technique to be very effective when it comes to time-frequency analysis by providing more resolution in the time-domain resolution. For higher frequencies, wavelet transform squishes the wave together whereas, for lower frequencies it stretches them out. This phenomenon is handled by the scale parameter of the wavelet [34].

3.3.1 Types of Wavelet Transform

There are mainly two types of wavelet transforms,

I. Continuous Wavelet Transform (CWT)
II. Discrete Wavelet Transform (DWT)

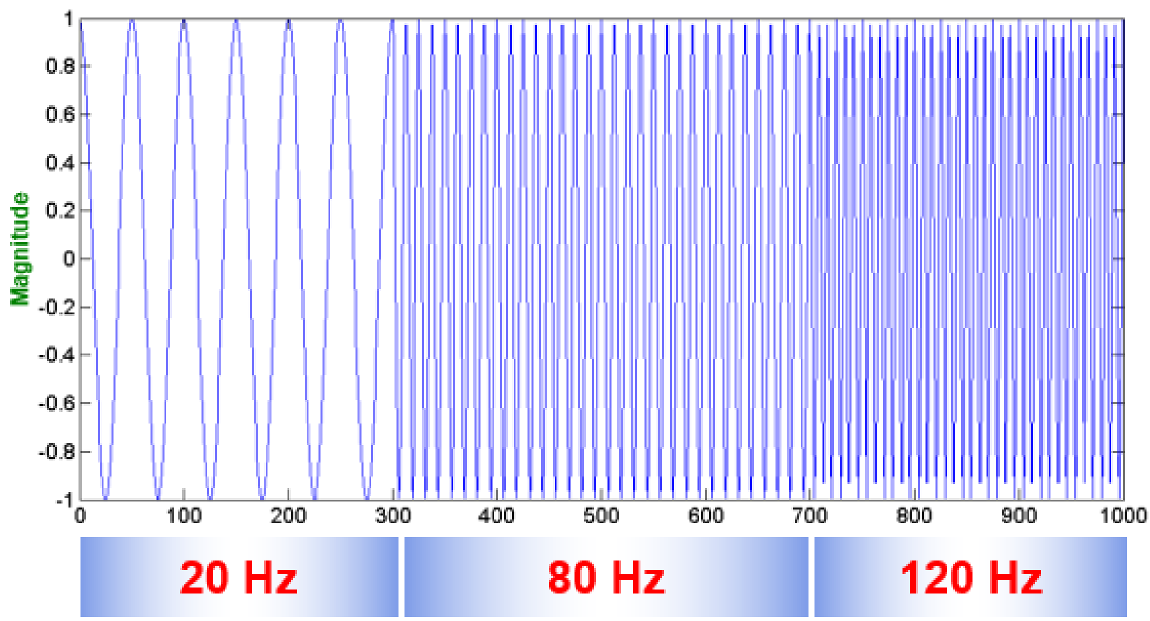

Figure 9: Non-stationary Signal Broken into Stationary Sub-signals

From the concept of wavelet transform it is already being discussed how wavelet transform decomposes a raw signal into time-limited sub-signals with same frequency bands. This process is also known as making a non-stationary signal stationary. So, over a small-time period, the frequency spectrum remains unchanged. Figure 9 shows how wavelet transformation decomposes a signal of 120 Hz into three sub-signals such as 0-20

Hz, 20-80 Hz and 80-120 Hz. Thus, over a period of time, the signal only provides a time-frequency representation at a maximum 20 Hz frequency spectrum and similarly 80 Hz for the second signal and 120 Hz for the third one. So, in the first signal, the frequency spectrum remains 20 Hz at all time making it as a stationary signal. Wavelet transform uses a wavelet function $\boldsymbol{\Psi}(\mathbf{t})$ to perform this task, and the transformation is computed separately for different segments of the time domain signals. Mathematical representation for Continuous Wavelet Transform can be described as below,

$$CWT_x^{\psi}(\tau, s) = \frac{1}{\sqrt{s}} \int x(t)\ \psi^{*}\left(\frac{t-\tau}{s}\right)dt$$

The above equation represents the transformed signal as a function of two variables. The first variable is $\boldsymbol{\tau}$ and the second variable is **s**, where $\boldsymbol{\tau}$ can be defined as the **translation** and **s** can be defined as the **scale** parameter. $\boldsymbol{\Psi}(\mathbf{t})$ is the wavelet function.

The **scale** parameter in the analysis of wavelet is almost identical to scale used in the Google or Bing map [33]. A high scale in a map corresponds to a less detailed view of an area and low scale corresponds to a highly-detailed view of an area. Similarly, in wavelet analysis, low frequency or high scale denotes global information of a processed signal whereas, high frequency or low scale denotes a local information of a transformed signal which more detailed and might reveal the hidden pattern of information [33]. Generally, in practical applications, high frequencies do not last through the entire raw signal whereas, low frequencies last the entire signal. Scaling parameters are mainly used for either stretching or compressing a signal [33]. So, larger scale stretches the signal, and small value of scale parameter shrinks the signal. Figure 10 and Figure 11 represents two transformed signals by wavelet transform (Morlet) with a small scaling and a large scaling value.

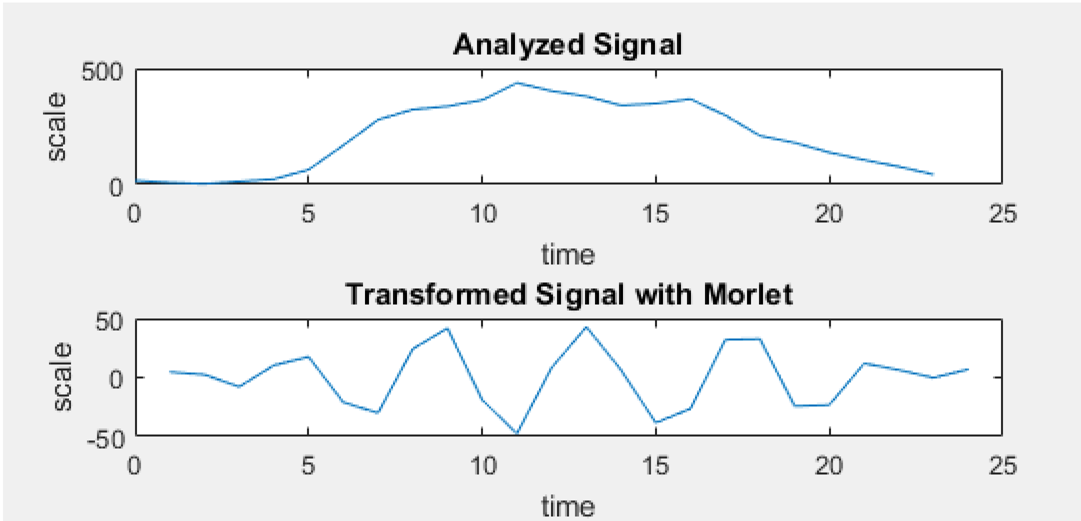

Figure 10: Transformed Signal with Scale Value = 3

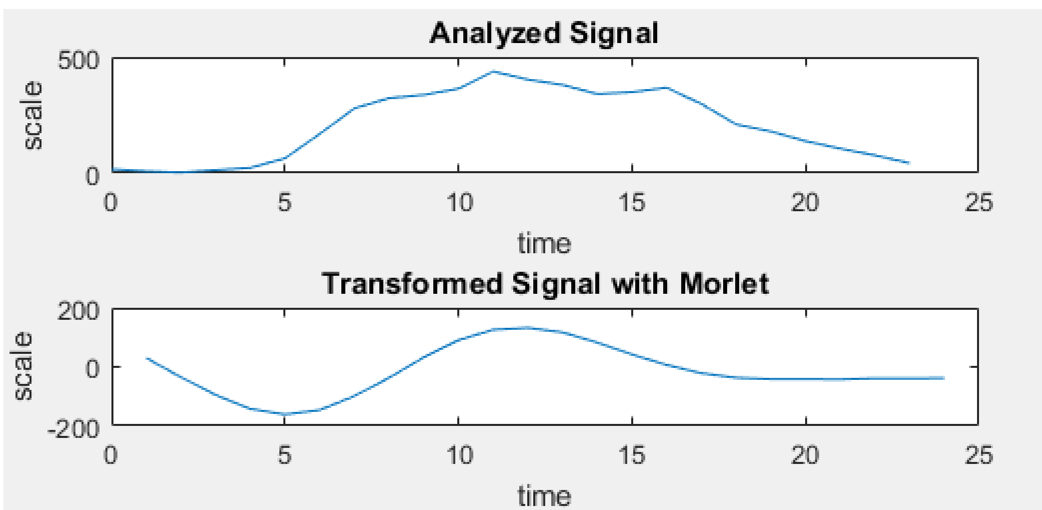

Figure 11: Transformed Signal with Scale Value = 10

As from the definition of a continuous variable we know that a continuous variable can be of any value within defined range. For example, time in a race. This variable can be denoted from minute to nanosecond. The characteristics of this type of pure continuous behavior of the CWT makes the computation for transforming a signal really time-consuming. That's why scientists discretize time for continuous wavelet transform in order to compute transformation of a signal using a computer [33]. But even after that, transformation of a signal does not acquire discrete transformation. DWT on the other hand, transforms a signal revealing sufficient amount of information taking linear computation time [33].

Discrete Wavelet Transform transforms a signal, using a finite (discrete) number of wavelet scale parameters and translation variables concentrating on some defined rules such as a number of coefficients that represents the wavelet. This is the main difference between CWT and DWT. The scale discretization conducted by CWT is finer compared to DWT which makes CWT better when it comes to provide more information. This is the best reason to choose CWT for time-frequency analysis to precisely localize signal transients.

3.4 Sharp Variation Points

Wavelet analysis transforms a signal and represents the processed signal using an approximation as well as detailed coefficients. After transforming the signal, the wavelet detail coefficient provides positive and negative values. A zero-crossing point between the values of detail coefficients represents the sharp variation points in the original signal. Figure 12 shows the sharp variation points alongside the transformed signal curve.

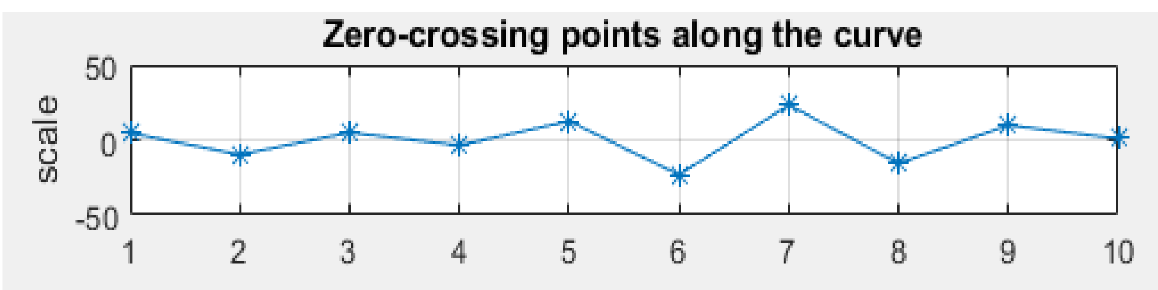

Figure 12: 10 Sharp Variations Points Alongside Transformed Signal Curve

Signals usually contain high and low frequencies. For low frequencies, the fine frequency resolution is needed as components vary s7lowly with time and for high frequencies as they vary quickly over time fine time resolution is necessary [37]. Wavelet transformation uses multiresolution analysis to analyze signal which satisfies the low-frequency and high-frequency characteristics of a raw signal. As for low value of scale parameter, wavelet transform provides finer detailed information, it becomes easier to locate special feature of the signal such as sharp variation points. From section 3.3 we know wavelet transform of a signal can be denoted as,

$$\mathrm{CWT}_x^{\psi}(\tau, s) = \frac{1}{\sqrt{s}} \int x(t)\ \psi^*\left(\frac{t-\tau}{s}\right) dt$$

Here $\boldsymbol{\Psi}(\mathbf{t})$ refers to the wavelet function to transform the signal. If we use Morlet wavelet function to transform the signal, then $\boldsymbol{\Psi}(\mathbf{t})$ can be written as [38],

$$\psi(t) = e^{ist} e^{\frac{-t^2}{2\sigma}}$$

After discretizing scales for transforming a signal, wavelet transform can be represented as,

$$Wq(t, s) = \frac{1}{\sqrt{s}} \sum_{n=1}^{N} q(n)\left(\frac{n-t}{s}\right)$$

Here, q(n) represents the time series, and n ranges from 1 to N for the whole set vector. For a particular factor of scale, sharp variation points must satisfy the following condition.

$$W_q(t, s) W_q(t+1, s) < 0$$

The detail coefficients represent values positive and negative. So, the multiplication between two consecutive coefficients if becomes less than zero then those points will be revealed sharp variation points of the signal.

CHAPTER 4

FUZZY LOGIC

4.1 Definition

The uncertainty of data refers to those data which may contain noise that restricts itself to provide correct and precise value. Here the term “noise”, can be denoted as observation error, missing data point, measurement uncertainty, etc. Requiring precision in predicting systems translates to requiring higher accuracy through collecting noise free data [39].

There are a lot of methods developed to cope with data uncertainty such as probability theory, the Bayesian network, Markov model, etc. Instead of using real correct number, probabilities of the value being correct can be employed. In the real world, there are no certainties among different variables. Thus, it is always a good choice to associate the probability of correctness or certainty with a particular variable. For example, the probability of having a disease with the result of a test. Bayesian methods having advantages like dealing with uncertainty by including prior probabilities have some disadvantages as well. Bayesian networks don’t work well with missing values thus; it cannot cope with the real-world changes simultaneously. Many alternative methods have been suggested to encounter this problem. Fuzzy logic has emerged as one of the most popular methods to deal with this problem.

Lofti Zadeh *at el.* first presented the concept of fuzzy logic as a method of processing data by discussing partial set membership opposite to crisp set membership [40]. Considering all the uncertainties in data, a predictive system does not need to find precise information but can find close to accurate information considering noisy data as input. Fuzzy logic is a method that helps a system to arrive to an accurate conclusion based on imprecise, vague or missing input information [40]. Fuzzy logic implements a rule-based IF A AND B THEN Z approach to design systems in order to solve problems rather than modeling a mathematically descriptive solution [40]. Table 7 describes about some applications developed on the basis of fuzzy logic.

Product	Company	Fuzzy Logic Rule
Air Conditioner	Hitachi, Sharp, Mitsubishi	Prevents too hot and too cold temperature oscillation and consumes less power
Elevator Control	Fujitec, Mitsubishi Electric, Toshiba	Reduces waiting time-based on passenger traffic
Factory Control	Omron	Schedules tasks and assembly line strategies
Golf Diagnostic System	Maruman Golf	Select golf club based on golfer's physique and swing
Health management	Omron	Over 500 fuzzy rules to track and evaluate employee's health and fitness
Refrigerator	Sharp	Sets defrosting and cooling times based on usage [41].
Shower System	Panasonic	Suppress variations in water temperature
Cruise Control in Car	Isuzu, Nissan	Adjusts throttle setting to set speed based on car speed and acceleration [41]
Copy Machine	Canon	Adjusts Drum Voltage based on picture density, temperature and humidity
Auto Transmission	Honda, Nissan, Subaru	Selects gear ratio based on engine load, driving style and road condition [41].

Table 6: Applications of Fuzzy Logic [Kosko at el. [41]]

4.2 Fuzzy Sets and Membership Function

While using fuzzy logic for prediction or decision making, set membership is the key to a system which faces uncertainty. Mathematically a set is defined as the collection of variables with some definition or domain information. Any randomly selected variable from a range of values either belongs to the set or does not belong to the set [42]. For example, let us consider a set of people with a height of 6 feet, who are considered as tall. Now, the task is to determine whether a person is tall or not considering 6 feet height as the base height. Therefore, if a person is 6 feet or above he/she is considered as tall and not tall otherwise. Figure 13 describes this scenario,

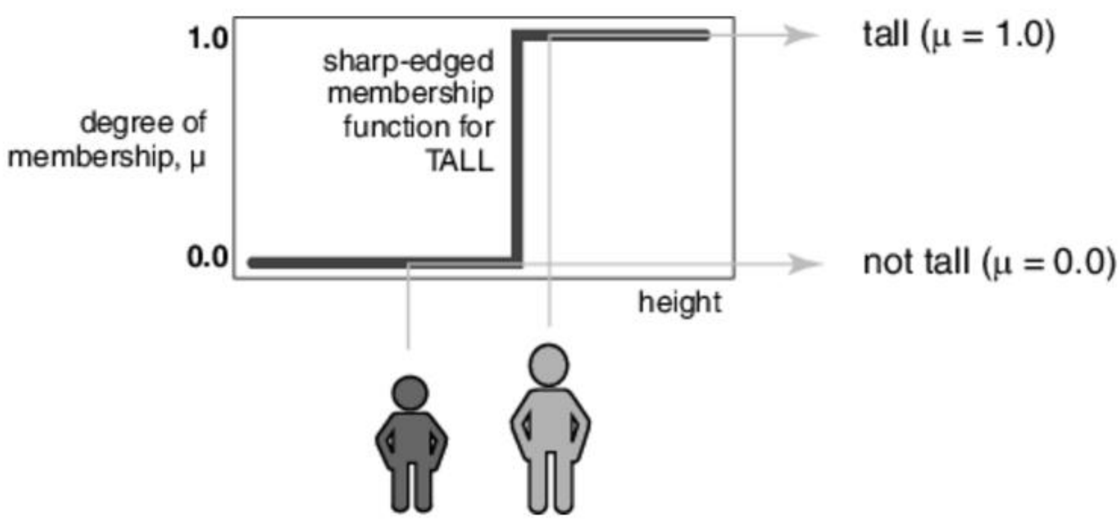

Figure 13: Graph Representation of Crisp Set and Inputs (Retrieved from www.mathworks.com)

The membership function μ represents the domain of the set which is 1.0, either a person's height is 6 feet so he/she is inside the crisp set or he/she is not. Real world scenario has been described by sharp-edged membership function for binary operation [42]. But having a situation like this, the binary system cannot distinguish between two persons having heights 6′11′′ and 7′11′′. In the real world, both of these persons are tall. On the other hand, the binary system also cannot distinguish between two individuals with heights 5′11′′ and 6′. The person, having a height of 5′11′′; is tagged as not tall even after he/she has one-inch difference to be tall. The result is clearly missing ambiguity in this type of binary system.

The fuzzy set theory solves this ambiguity of the binary system by introducing the degree of membership to the solution to find the tallness of a person [42]. Figure 14 shows fuzzy set approach by denoting the degree of membership with a continuous membership function.

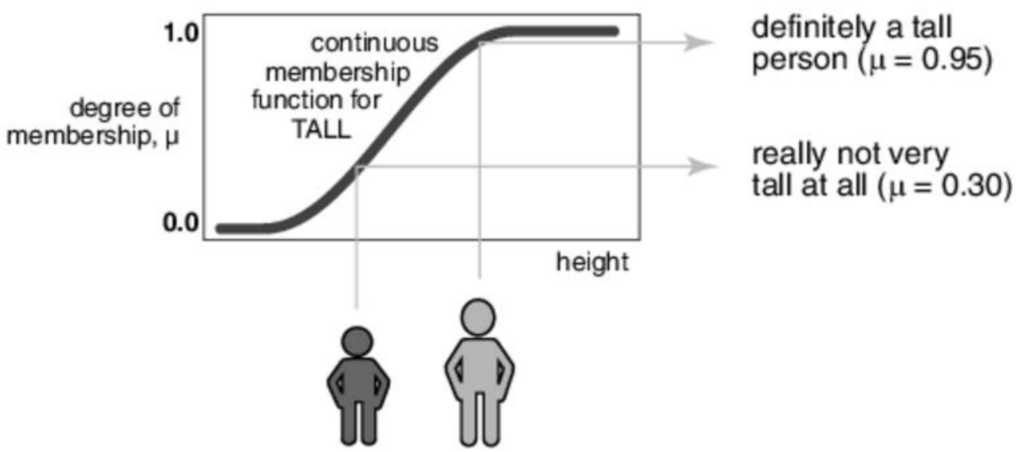

Figure 14: Graph Representation of Fuzzy Sets and Inputs (Retrieved from www.mathworks.com)

The membership function defines the criteria of a person to be tall or not tall. The vertical axis denotes the value of the height of a person. According to the inclining membership function, the person having a membership value 0.3 is not tall. But the person having membership value 0.95 is very tall.

If X is a space of points and a generic element of that space X is denoted by x. So,

$$X = \{x\}.$$

A membership function can denote a fuzzy set A in space X,

$$fA(x).$$

For any value y, the degree of membership is higher if y is close to fA(x) and lower if y is far from the fuzzy set [42]. Membership functions for fuzzy sets can be defined in any way as long as membership functions follow the fuzzy IF-THEN rules.

4.3 Fuzzy Logic System

According to Boolean logic any variable x in the space X, is a member of F(y) = t if the value of x is equivalent t. So, either x is a member of F(y) or not. Fuzzy logic is a superset of traditonal Boolean logic [43]. Fuzzy logic promotes partial membership to encounter data uncertainty for prediction, thus providing membership values between complete membership and complete non-membership criteria [43]. Fuzzy Logic System has three main components which are,

- Fuzzifier
- Inference Engine
- Defuzzifier

Inference engine stores all the fuzzy IF-THEN the rules to check for the degree Membership of any variable in the same space as of the fuzzy logic set. For example, “If A is B Then X is Y”. Here the portion “A is B” is known as the antecedent and “X is Y” is known as the consequence. Fuzzifier inputs crisp sets into fuzzy sets to activate rules [43]. Finally, the Defuzzifier generates output from the input data set. Figure 15 represents a system design of Fuzzy Logic System (FLS).

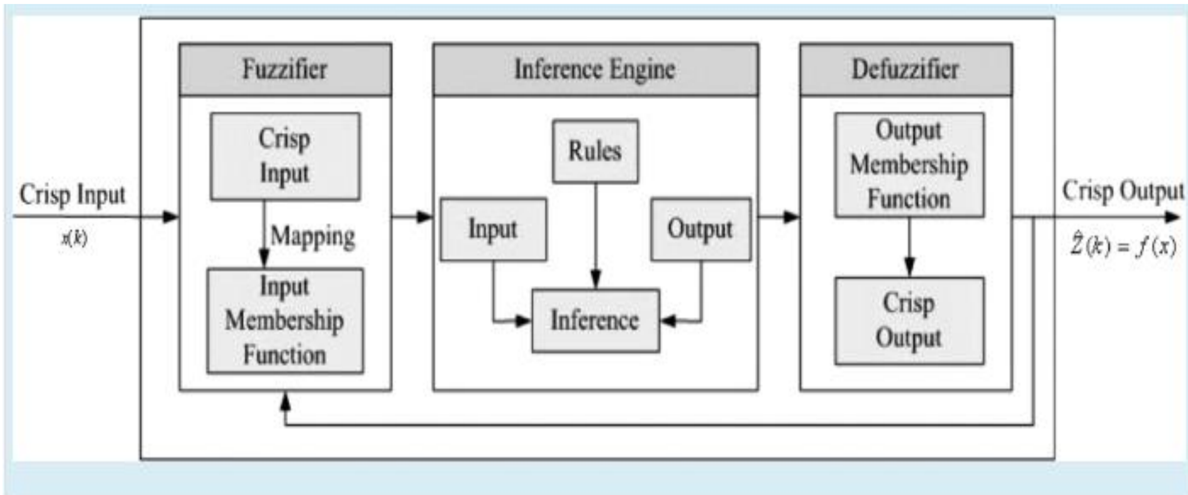

Figure 15: Fuzzy Logic System Structure [43]

CHAPTER 5

DATA CATEGORIZATION AND DESIGN of ALGORITHM

5.1 Data Categorization

As it has been discussed in section 2.1 that using historical and real-time data provides marginally better accuracy when it comes to traffic prediction, this thesis also uses historical data and real-time data to predict traffic volume. Nicholson *at el.* [27], proposed that 17 days of data are optimal for prediction. So, the test dataset should at least consist of 17 days of historical data which can be used training data sets. For short-term prediction, well-known method such as CATA, CATB, Slip Road uses 13 hours of data to predict traffic volume and traffic speed. CATA uses data which is being acquired using loop detectors with a 5-min span. This process does not encounter stochastic behavior of traffic data. On the other hand, Volterra Neural network, New Volterra NN and RBF Neural Network predicts traffic flow by using time series data (24 days from 10 AM to 2 PM and 4 PM to 8 PM). The prediction window size differs from method to method. For example, CATA, CATB, Slip road can predict traffic volume up to 15 minutes with a 5-min short span. On the other hand, processes which use time series information tries to predict traffic for long term such neural network approaches generally predict up to a couple of hours or more.

This thesis used real recorded traffic data provided by Washington State Department of Transportation (WSDOT), USA. WSDOT determines traffic count data from most of the roads in the city road network. This research uses traffic count for the road at Rhododendron, Coupeville on milepost 20:02 point, Eastbound. Figure 16 shows the location of the road in the Google Map.

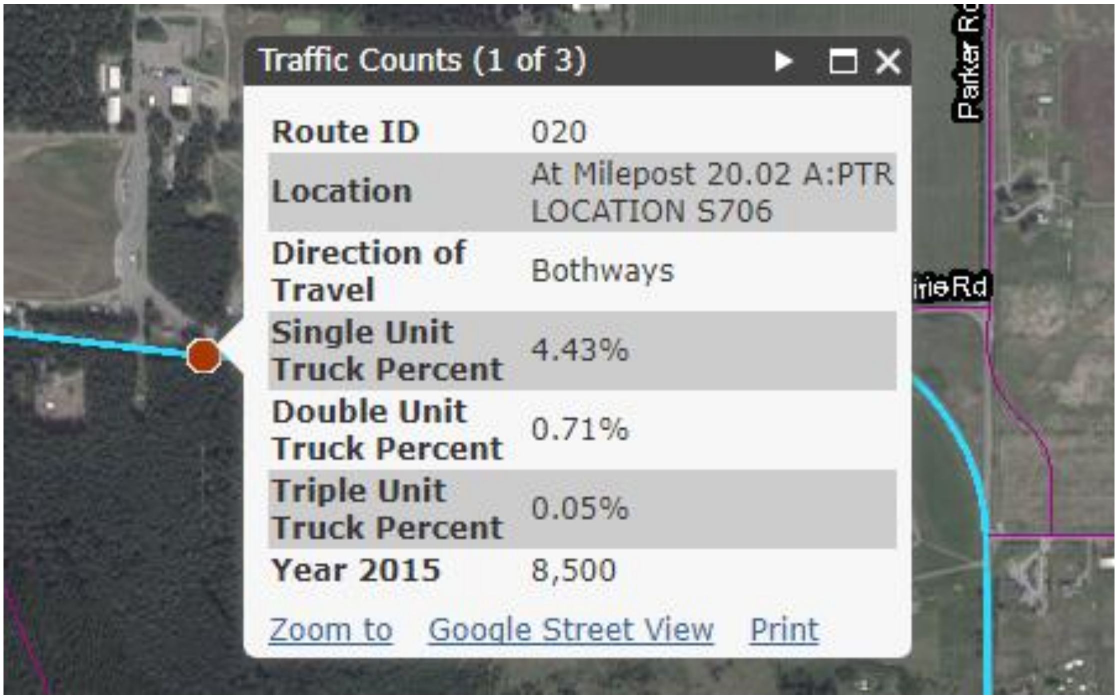

Figure 16: Location of The Road on Which The Experiments are Conducted (Retrieved from http://www.wsdot.wa.gov/)

26 datasets have been collected from WSDOT which represents traffic count/hr for 26 days from the year 2014. 25 datasets have been used as training data and two days of data have been used for experimental purposes. As the data recorded for volume count per hour, so this research uses one hour for the prediction window. Therefore, this study predicts traffic volume per hour in the future at any given time. Prediction for traffic in a weekday and weekend can be performed in a lot of methods; given the circumstances as traffic flow differs between weekends and weekdays.

The data collected from WSDOT are classified by adding more chaotic data to form fuzzy traffic data set. Chaotic information such as, season, the average temperature in a day, weekday/weekend, weather events, Holidays, Holiday after one day, etc. This information is chaotic in a way that the information keeps on changing with time. There are seven data components added to the existing dataset (volume/hour) to make it more robust. Three seasons are considered which are Winter, Summer, and Spring. Weather data depends on the season. Average temperature drops in winter, whereas; it rises in summer also in Spring. The flow of traffic in weekdays is entirely different compared to the flow of traffic in weekends. Holidays changes the flow of traffic and coming holiday might change the traffic condition as well. So, the data is categorized taking into consideration all the chaotic behavior which makes the frequency of traffic non-stationary which means flow changes over time. Weather information for the year 2014 is retrieved from Weather Underground website. Table 7 shows data classification (Chaotic Information) for prediction of traffic which is being used in this research.

As there are seven extra data components used to make the dataset more robust, a fuzzy classifier is used to compare real data with stored data with the degree of membership. From the definition of the degree of membership denoted by μ discussed in chapter 4.2, first the level of preciseness is defined. Three categories of preciseness are defined which depends on the value obtained from the degree of membership. These values range from 0 to 1, so the degree of membership can be defined as μ [0,1]. This means, the degree of membership of any historical traffic dataset will be determined on the basis of similarities between real-time dataset and historical datasets. This degree of membership can be of any value from 0 to 1. This topic is elaborately described in section 5.2.1.

Date	Month	Day	Season	Avg. Temp	Events	Holiday	HoidayAfter
1/1/2014	January	Wednesday	Winter	6		1	0
1/21/2014	January	Tuesday	Winter	3	Fog	0	0
2/4/2014	February	Tuesday	Winter	0		0	0
1/16/2014	January	Thursday	Winter	6		0	0
1/5/2014	January	Sunday	Winter	3		0	0
1/12/2014	January	Sunday	Winter	9	Rain	0	0
1/19/2014	January	Sunday	Winter	7		0	1
1/26/2014	January	Sunday	Winter	5	Fog	0	0
2/22/2014	February	Sunday	Winter	2	Rain, Snow	0	0
2/2/2014	February	Sunday	Winter	3		0	0
2/9/2014	February	Sunday	Winter	3	Rain, Snow	0	0
2/23/2014	February	Sunday	Winter	3	Rain, Snow	0	0
5/4/2014	May	Sunday	Spring	13	Rain	0	0
9/7/2014	September	Sunday	Summer	14		0	0
1/25/2014	January	Saturday	Winter	6	Fog	0	0
1/6/2014	January	Monday	Winter	6		0	0
1/13/2014	January	Monday	Winter	9	Rain	0	0
1/20/2014	January	Monday	Winter	4	Fog	1	0
1/27/2014	January	Monday	Winter	3	Fog	0	0
2/3/2014	February	Monday	Winter	2		0	0
2/10/2014	February	Monday	Winter	7	Fog, Rain	0	0
2/24/2014	February	Monday	Winter	3	Rain, Snow	0	0
5/5/2014	May	Monday	Spring	13	Rain	0	0
9/15/2014	September	Monday	Summer	14		0	0
7/11/2014	July	Friday	Summer	16	Foggy	0	0
1/28/2014	January	Tuesday	Winter	7	Fog, Rain	0	0
Total :26 d							

Table 7: Chaotic Information Added with Traffic volume/hour.

5.2 Design of Algorithm

5.2.1 Overview

Hybrid Approach is applied in this research to predict traffic volume/hour. This hybrid approach consists of two smaller algorithms, and they are named as, SVPFinder and FuzzyClassifierPredictor.

SVPFinder- algorithm finds sharp variation points of a time-frequency signal by using discrete time continuous wavelet transform. This research has utilized Matlab to use wavelet library for processing a signal using continuous wavelet transform. Morlet and Mexican Hat wavelet have been used as the wavelet function to transform the signal. Only Morlet wavelet have been used to find out the sharp variation points which represents the beginning and ending of a traffic trend as Morlet wavelet provides detail information of a signal, so the system finds out more sharp variation points which provides better accuracy while predicting traffic. Mexican hat provides better localization of patch events or gap events. This method uses both of the techniques to transform a signal [44].

Algorithm 1: SVPFinder

```
1. INPUT: SIGNAL VECTOR (traffic volume/hr), time, Scale (3)      // Scale, s = 3; always
2. OUTPUT: SVP                                                      // Sharp variation points
3. IF cwt -> 1                                                      // cwt =1 (Morlet)
        4. Plot (Analyzed Signal)                                   // plot the raw signal
        5. cwt (SIGNAL VECTOR, Scale, 'Morlet')
        6. Plot (cwt)
        7. Define Zero-Crossing function or SVP                     // see section 3.4
        8. zx = SVP (cwt)                                           // zx -> Zero crossing function
        9. Plot (wt(zx))                                            // plot zero crossing with stars
        10. return zero crossing or SVP points
11. ELSE cwt ->2                                                    // cwt =2 (Mexican Hat)
        12. Repeat (4 – 10)
```

This above algorithm reveals zero crossing points using Morlet and Mexican Hat. Figure 17 and Figure 18 draws graph representations of an original signal, transformed signal and zero crossing points alongside transformation curve using Morlet and Mexican Hat wavelet.

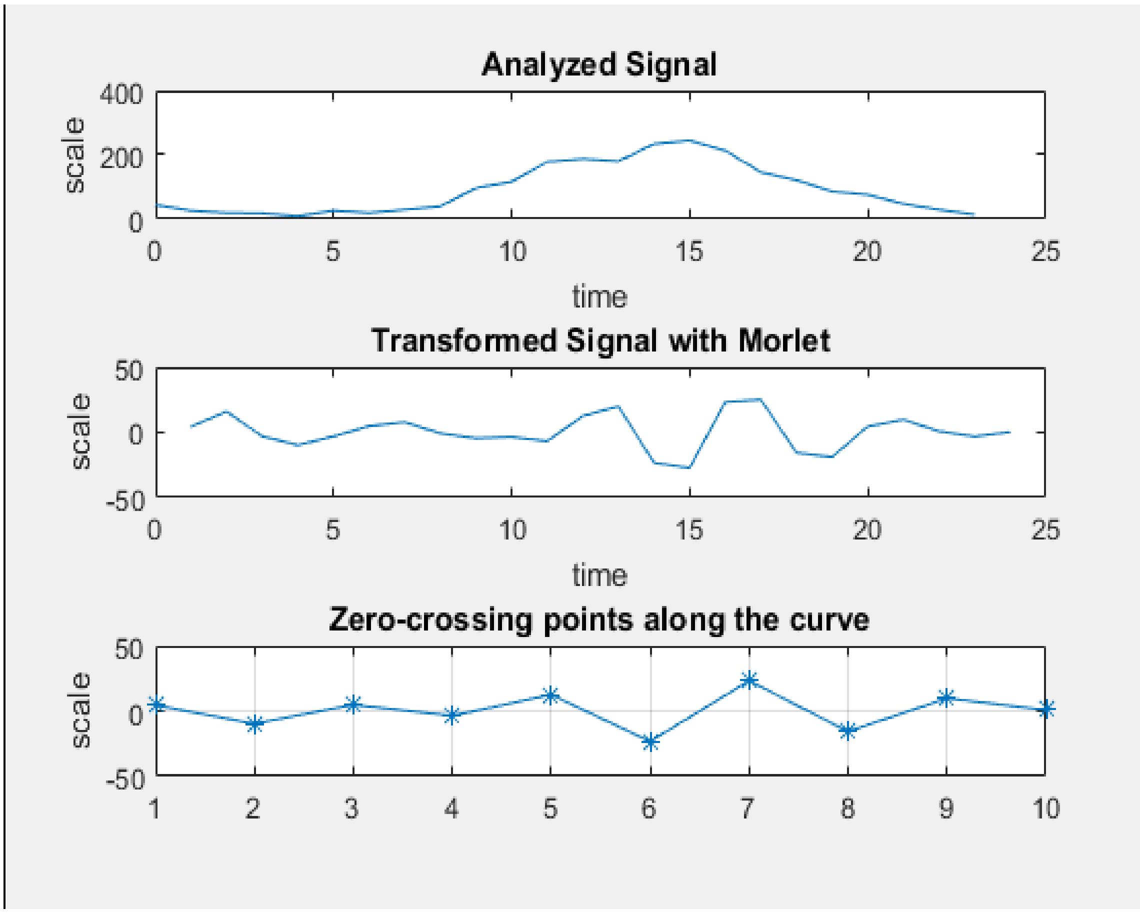

Figure 17: Wavelet Transformation using Morlet Wavelet Function

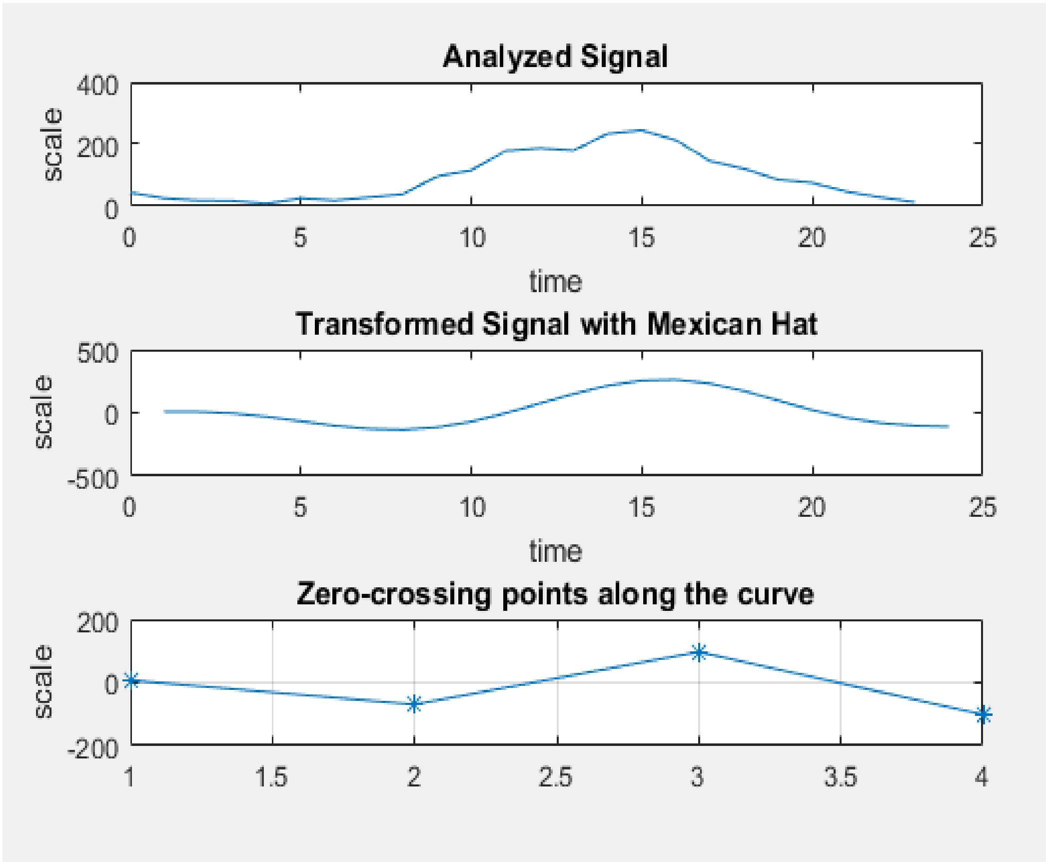

Figure 18: Wavelet Transformation using Mexican Hat Wavelet Function

After this SVPFinder reveals sharp variation points of a signal, this method saves sharp variation points of each dataset (day) in the database. FuzzyClassifierPredictor algorithm classifies dataset adding chaotic information and then runs IF-THEN rules for the new real data to match with the historical data. In the first step of this algorithm, this method uses the following function to find the average distance of the real-time traffic flow data with historical traffic data.

$$\mu ph = \sqrt{\sum_{k=1}^{Ky} (Yphk - Xphk)^{\wedge}2 / Ky}$$

Here, Yphk represents real-time traffic data; whereas, Xphk represents historical traffic data and Ky represents the number of records. After identifying the best match, two consecutive closest sharp variation points of the matched historical data are used to predict traffic flows and then again Yphk and Xphk is determined to find the best match until the last hour of prediction.

From the discussion in section 5.1 about the degree of membership, since this method uses 7 extra data components to build fuzzy membership sets, to encounter Boolean logic; degree of membership is characterized into three categories. They can be denoted as,

- Highly Similar Dataset (HSD), with degree of membership >= .86, [6/7]
- Medium Similar Dataset (MSD), with degree of membership >= .714 <.86, [5/7]
- Less Similar, with degree of membership (LSD) >= 0 < .5714, [4/7]

As, Nc (number of data components) = 7. Hence this method classifies dataset, as HSD for having at least 6 similar data out of 7, as MSD for having at least 5 similar data and LSD for having at least 4 similar data out of 7.

After finding the SVP's of a signal this method first finds average distance between real-time and historical data to choose a dataset with minimal discrete distance. If that dataset is a member of HSD having at least 5 similarities with real-time data, the system takes 2 SVP's of that dataset and predicts future volume until the end of traffic trend within those two SVPs'. If the selected dataset is not an HSD, the system looks for a matched MSD with minimal discrete distance. And lastly, the system looks for an LSD dataset if there is no MSD with minimal discrete distance. The system keeps on doing this constant process until the last hour of prediction is not completed.

ALGORTIHM 2: FuzzyClassifierPredictor

INPUT: REAL-TME SIGNAL VECTOR (Rv) // Rv = scalar vector of traffic volume

OUTPUT: PREDICTION FOR TRAFFIC

1. Make HSD, MSD, LSD sets
2. While (prediction < 16 hours) // 0-8 hr for minimal distance similarity
3. Process Info of Rv and save it in a LIST // Rv has 7 data components
4. Compare (Rv with HSD, MSD, LSD) // Discrete Distance
5. Find Match // Similarity
6. Prediction of traffic volume for next two SVP's
7. If (Prediction Duration == 16 hrs)
   Break;
8. Determine traffic volume

End;

5.2.2 Time Complexity

Time complexity of different modules are given below,

- Wavelet Transform – O(n^2)
- Sharp Variation Point Detection – O(n)
- Data Reduction Using Fuzzy Logic – O(logn)

CHAPTER 6

EXPERIMENT AND RESULTS

6.1 Overview

This chapter discusses the experiments and the results obtained by conducting experiments proposed by this hybrid method. In this chapter, a real example is being demonstrated which describes the workflow of the proposed algorithms. After that, this chapter compares the results of this research with other traditional methods. This episode also proves the superiority of this approach for predicting traffic volume.

6.2 Experiment Analysis

The experiment is conducted using 26 datasets representing 26 days of traffic flow, which has 624 data points as each dataset provides 24 data points. These data points refer to traffic volume count for 24 hours in a day. Training data consists of data for 25 days. The hybrid approach is then tested using the dataset for one day.

As described in section 5.1, datasets are collected from WSDOT. Each dataset represents data from a day in 2014. The datasets are selected randomly. Traffic signal for January 27, 2014 and January 26, 2014 are predicted using this hybrid approach.

SVPFinder as described in section 5.2.1 reveals sharp variation points alongside transformed curve from the original signal presented in Figure 17. SVPFinder algorithm saves sharp variation points in the database. Table 8 depicts the SVP of different dates revealed by SVPFinder algorithm.

Date	SVP1	SVP2	SVP3	SVP4	SVP5	SVP6	SVP7	SVP8	SVP9
1/27/2014	2	3	5	7	9	11	14	16	18
1/26/2014	2	4	5	6	8	10	13	16	18
1/06/2014	1	3	5	7	9	11	13	16	18
1/13/2014	2	3	5	7	9	11	14	16	18
1/12/2014	2	3	4	6	8	10	12	13	15
1/05/2014	1	3	4	8	12	14	16	19	21

Table 8: SVP of different dataset until 9:00 PM

After finding the sharp variation points, this hybrid approach uses FuzzyClassifierPredictor algorithm to classify and match real-time data with historical data. First this algorithm categorizes each dataset by adding seven chaotic information which was also discussed in section 5.2.1. Zhang *at el.* described the process of calculating discrete difference between real data and historical data using the following function, as described in section 5.2.1 [22].

$$\mu ph = \sqrt{\sum_{k=1}^{Ky} (Yphk \ - Xphk)\text{^}2 \ / Ky}$$

This method then calculates Yphk, which represents real-time data. For example, if at 1:00 AM the real-time traffic count is 8; then, Yphk =8. Now this research compares this value with historical data. For any historical data which is denoted as Xphk, if at 1:00 AM the count is 9. Then, using the equation presented above discrete difference is calculated.

$$\mu = \sqrt{(8-9)^{2}/_{1}} = 1$$

This function is used to find the discrete distance between real-time data and historical data. Table 9 shows an example of this phenomenon, where discrete distance is measured between real-time traffic, which is January 27, 2014; and other historical data.

Date	**1-8**	**1-9**	**1-10**	**1-11**	**1-12**	**1-13**
1/06/2014	17.505	26.838	28.103	34.435	44.538	59.515
1/13/2014	17.799	18.133	20.979	25.200	30.685	37.064
1/12/2014	182.380	254.380	283.473	284.076	304.284	315.100

Table 9: Discrete Difference of Traffic Count Between January 27, 2014 and Other Historical Data

A fixed number of hours is selected first to calculate the distance between the real-time data and historical data [22]. Zhang *at el.* proposed to measure distance from 1:00 AM to 8:00 AM at the first place before starting to compare previous data with real time data. In this research, the minimum distance between the real-time data and historical data from 1:00 AM to 8:00 AM is,

$$\mu_8 = 17.50521112.$$

This is the difference between January 27 and January 06. So, the system will check for the next two consecutive sharp variation points in the traffic flow of January 6 after 8. Table 8 shows the next two sharp variation points recorded for January 6 which are at 9 AM and 11 AM. The segment of data which represents traffic count in between these two sharp variation points, is used to predict traffic flow. After that, the system find out the discrete distance from of real-time data with historical data form 1 AM until 11 AM. Table 9 shows, this time the lowest difference is between January 27 and January 13 which is,

$$\mu_{11} = 25.20034993.$$

Now, the system will check for next 2 sharp variation points in the traffic flow of January 13 and use the traffic count for that trend to predict traffic flow for January 27. Table 10 shows the predicted values and their dates compared to the original values from January 27.

Prediction Span (Hours)	Original Traffic Count (January 27, 2014)	Predicted Traffic Count	Predicted Traffic Date
1 Hour (8 - 9)	339	311	January 06, 2014
2 Hour (9-10)	269	265	January 06, 2014
3 Hour (10-11)	257	278	January 06, 2014
4 Hour (11-12)	286	267	January 13, 2014
5 Hour (12-13)	256	279	January 13, 2014
6 Hour (13-14)	302	299	January 13, 2014
7 Hour (14-15)	277	293	January 13, 2014
8 Hour (15-16)	301	301	January 13, 2014
9 Hour (16-17)	299	308	January 13, 2014
10 Hour (17-18)	204	193	January 13, 2014
11 Hour (18-19)	115	120	January 13, 2014
12 Hour (19-20)	65	83	January 13, 2014
13 Hour (20-21)	63	61	January 13, 2014
14 Hour (21-22)	32	24	January 13, 2014
15 Hour (22-23)	20	23	January 13, 2014
16 Hour (23 -24)	7	21	January 13, 2014

Table 10: Original and Predicted Traffic Count with the Predicted Date

While predicting traffic flow, the system also determines the degree of membership for the fuzzy membership set which refers to the date that provided the minimum distance μ_8. As the complete set and the fuzzy set has seven components, if the fuzzy set has at least six of it's seven components similar to the complete set, then the degree of membership is .86 for the fuzzy membership set. From the value of the degree of membership, a fuzzy membership set is labeled as HSD, MSD or LSD which is described in section 5.2.1. From this we can find the similarity between the predicted data set with original data set. More similarity between historical data and real-time data provides better accuracy measure while it comes to predicting traffic flow. Section 6.2 describes this claim.

6.2 Results and Analysis

This hybrid approach is modeled and tested by using more time-frequency data than most of the methods from the past. This method uses 26 real-valued datasets which represent 728 data points that depicts time-frequency signal of traffic flow. More data are aggregated with the existing data which made the used data more robust for predicting accurate traffic flow.

$$Accuracy = 1 - 1/\mathrm{T}\sum_{i=1}^{T}[forecastvol(i) - vol(i)]/vol(i)$$

The above equation is used by a lot of method which are mainly used for short-term traffic prediction to calculate the accuracy of prediction [22, 29]. This method accurately predicted traffic volume for both weekday and weekend. As, the data points provided traffic count per hour; so, the minimum window for traffic prediction is 1 hour. Prediction accuracy is calculated using above equation and compared with short-term prediction method [29] in Table 11.

Method Name	60 Min
CATA	.87
CATB	.886
CATC	.881
CATD	.84
CATE	.833
SLIP-ROAD	.847
Hybrid Approach	.92

Table 11: Forecasting Accuracy for One Hour and Comparison with Traditional Approaches

Proposed approach in this research is also capable of predicting long-term traffic flow up to 16 hours. The following equation is used by lot of neural network methods developed for long-term traffic prediction such as Volterra, New Volterra, RBFNN; to find the prediction percentage error [45].

$$\text{MAPE} = \left(\frac{1}{n}\sum\frac{|Act|-Fore}{|Act|}\right) * 100$$

The percentage error than substituted from 100 to get the accuracy of the prediction. Table 12 outlines the predicted accuracy using above equation and compares it with traditional neural network approaches for long-term prediction accuracy.

Method Name	Prediction 2h	Prediction 4h	Prediction 8h	Prediction 16 h
New Volterra	96.02%	92.80%	Can't predict	Can't predict
Volterra	92.18%	92.07%	Can't predict	Can't predict
RBFNN	94.79%	89.96%	Can't predict	Can't predict
Zhang [22]	95.13%	89.25%	84.62%	79.07%
Hybrid Day 1	95.13%	93.86%	94.96%	80.69%
Hybrid Day 2	96.51%	94.21%	93.67%	81.54%

Table 12: Prediction Results for Hybrid Approach on Real Data

Table 12 compares accuracy measurement determined by the presented hybrid approach with other modern approaches. As it seems clear that, with other modern approaches the accuracy falls down with time. But the hybrid approach presented in this thesis solves this resolution problem. As we can see, the prediction accuracy of the 8^{th} hour is more compared to the accuracy measured in the 4^{th} hour.

Now one of the most interesting prospect that this research revealed is as this is a hybrid approach, using both wavelet and fuzzy logic system the result and the preciseness of the result have been perfected in the domain of data percentage used. Table 13 represents the best accuracy of prediction denoted by members of HSD, MSD, LSD datasets in weekdays. Here only MAPE equation is used to find the error measure and then substituted from 100. Minimum distance is not considered for finding this accuracy.

Accuracy of data in HSD datasets (1 hr)	Accuracy of data in MSD datasets (1 hr)	Accuracy of data in LSD datasets (1 hr)
99.71%	98.53%	97.05%

Table 13: Accuracy Prediction Using Different Fuzzy Membership Sets

The dataset used in this method has 56% of data representing HSD dataset while MSD represents around 28% and other 16% are LSD. All the highest accuracies over time while predicting traffic, were attained by datasets representing Higher Similarity Dataset; which is represented in Table 10. So, this can be proved that taking into consideration other variables such as whether, weekdays, season higher prediction accuracy can be obtained while predicting traffic.

Taking into consideration only the 56% dataset, which refers to high similarity between original real-time data and historical data this research reduces about 44% data using fuzzy logic. Data reduction causes less space and time complexity. For the input size n, which represent the number of data points; a prediction algorithm will have to perform steps proportional to n. This process makes the algorithm to have a time liner time time-complexity O(n). This thesis uses fuzzy logic and reduces traffic data by 44%, which improves the time-complexity. This hybrid approach performs log(n) steps to predict traffic flow. So, the time-complexity becomes sub-linear and can be denoted as O(log(n)).

The real signal and the predicted signal for the weekday is compared on the similarity of Sharp variation point based on wavelet analysis. Figure 19 denotes the original signal and its representation and Figure 20 denotes the predicted signal and its representation.

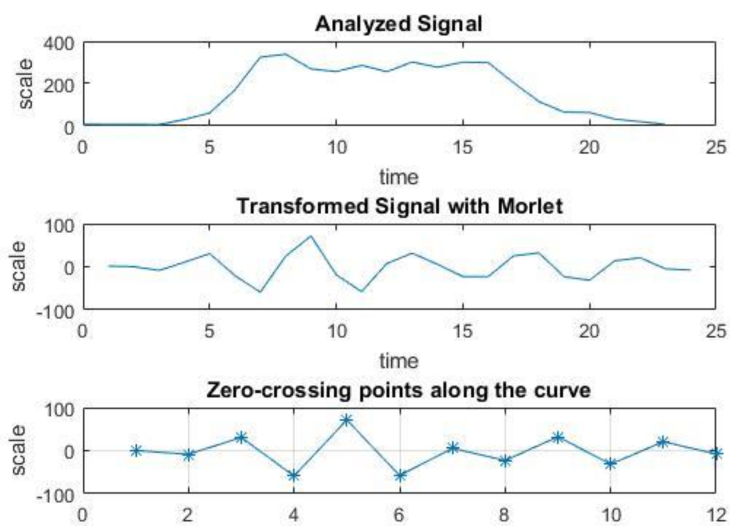

Figure 19: Original Signal for Testing Application Accuracy

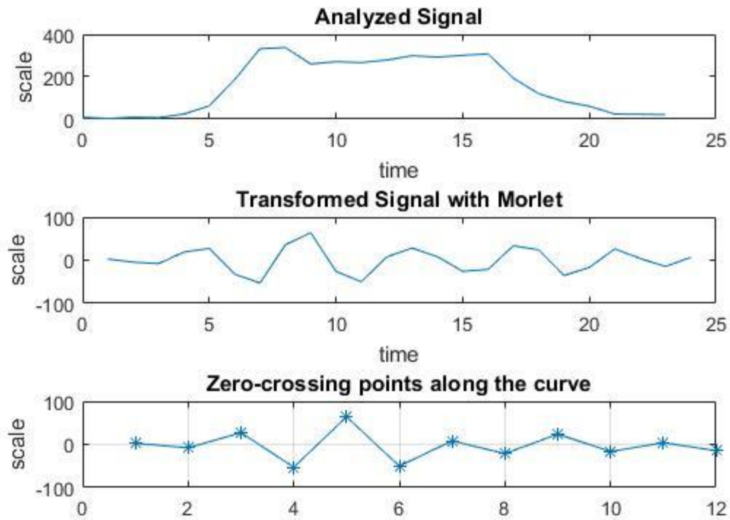

Figure 20: Predicted Signal by Hybrid Approach

Figure 21 represents the SVP comparison between original and predicted signal and they reveal higher similarity.

Predicted	1	3	5	7	9	11	14	16	18	20	22	23
Original	2	3	5	7	9	11	14	16	18	20	22	24

Figure 21: Sharp Variations Points of Original and Predicted Signal with 83.33% Accuracy

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Concluding Remarks

Presented data and analysis in this thesis provides extensive proof that, especially in urban environment traffic congestion still imposes a huge threat. Congestion management being one of the most important aspect of traffic information system provides necessary solutions for predicting and managing traffic congestion.

Traffic congestion as stated before can be recurrent or certain and it can also be non-recurrent or uncertain. To cope with the uncertainty of traffic flow, wavelet transform provides better solutions compared to most of the traditional approaches. Also, using fuzzy logic makes the prediction easier; as, it is being proved in this research that less data can be used to predict traffic flow and better accuracy can be determined by classifying data into categories. Similar categories provide better chance to have more accurate prediction of traffic flow.

7.2 Future Improvement and Direction

The prediction acquired using wavelet transform and fuzzy logic system provides better accuracy with higher accuracy and for longer period of time. As in longer period of time, the accuracy tends to lower down a bit, couple of other methods can be implemented to find better solutions.

- An accuracy threshold value can be set to find better accuracy by fine tuning the transformation curve by using less value in scale function while transforming a signal through wavelet.
- Data mining approach can be obtained to find the main reasons that fluctuate the traffic flow. As, it is clear that weekday flow is completely different than weekend

flow; sometimes, traffic flow in a same day can fluctuate due to different reasons. Weather events sometimes have more effect on traffic flow than season.

- A modern data mining tool can be developed by using this research as the basis. Data mining framework will be able to use other methods such as fourier analysis, deep learning approach, Bayesian network to predict traffic flow which might make it easier to compare and choose the best method.
- This thesis predicts the traffic flow using wavelet transform and fuzzy logic. This research can be enhanced by predicting travel time between a source and a destination at a particular time in a day as well.

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APPENDICES

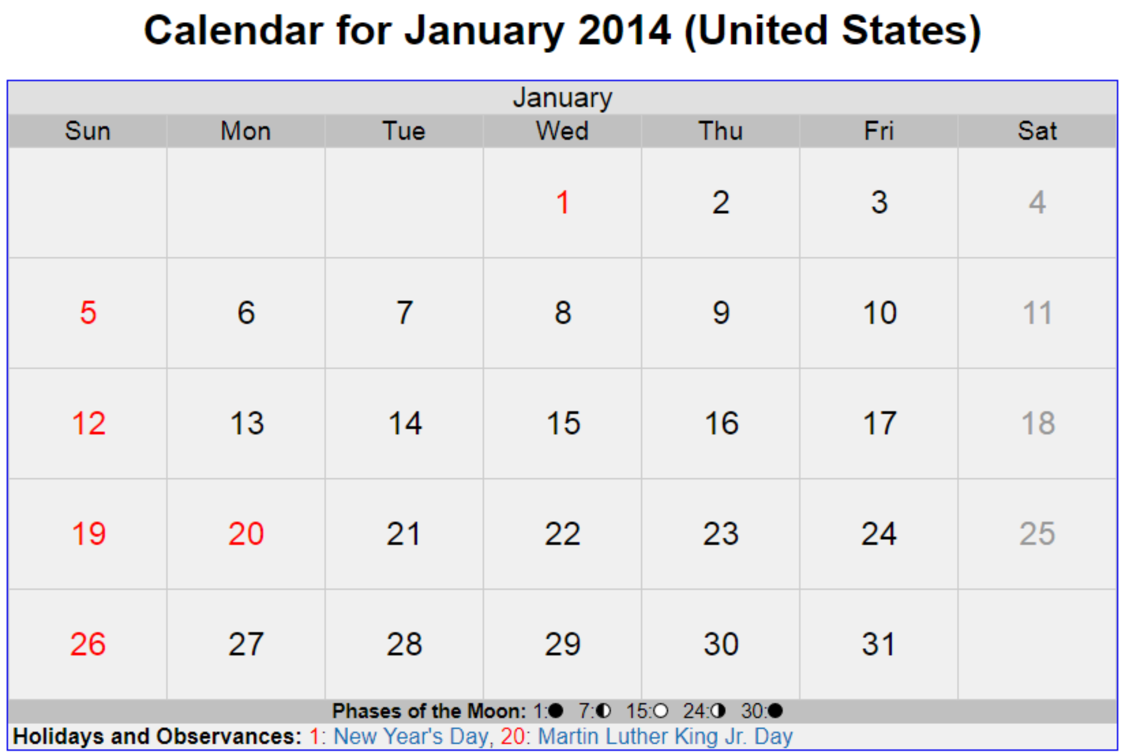
Appendix A

The following table shows the fuzzy membership sets and their degree of membership compared to the complete set discussed in section 6.2.

Date	Set Information	Degree of Membership
January 27, 2014	Complete Set	1
January 01, 2014	MSD	.714
January 21, 2014	HSD	1
February 04, 2014	HSD	.857
January 16, 2014	HSD	.857
January 05, 2014	MSD	.714
January 12, 2014	MSD	.714
January 19, 2014	LSD	.571
January 26, 2014	HSD	.857
February 22. 2014	HSD	.857
February 02, 2014	MSD	.714
February 09, 2014	HSD	.857
February 23, 2014	HSD	.857
May 04, 2014	LSD	.428
September 07, 2014	LSD	.428
January 25, 2014	HSD	.857
January 06, 2014	HSD	.857
January 13, 2014	HSD	.857
January 20, 2014	HSD	.857
February 03, 2014	HSD	.857
February 10, 2014	HSD	1
February 24, 2015	HSD	1
May 05, 2014	MSD	.714
September 15, 2014	LSD	.571
July 11, 2014	MSD	.714
January 28, 2014	HSD	1

Appendix B

Following Figure shows the vacation calendar of the month of January 2014, retrieved from www.timeanddate.com website.



Calendar for January 2014 (United States)

January						
Sun	Mon	Tue	Wed	Thu	Fri	Sat
			1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	

Phases of the Moon: 1:● 7:◐ 15:○ 24:◑ 30:●

Holidays and Observances: 1: New Year's Day, 20: Martin Luther King Jr. Day

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