1. Introduction

1.1 Introduction about traffic congestion

In today's era of continuous urbanization and population growth, traffic congestion has been on the rise all over the world. Due to the high density of people and vehicles, especially in large cities, traffic congestion takes up a lot of people's time and energy and becomes a major traffic and social problem. Traffic congestion is also a serious problem in the development of autonomous driving, because one of the things that autonomous driving is trying to achieve is to reduce congestion and make it easier for people to get around.

Congestion is a traffic condition characterized by slower speeds, longer travel times and increased vehicle queues. And in dealing with traffic congestion problems, there are several points that people need to think about: the first thing is about the diagnosis of traffic congestion, which means how to define a traffic congestion when it happens; the second thing is about the causes of traffic congestion, which aims to understand the reasons that cause a road congestion; the third thing is about the prognosis of traffic congestion, which means after the causes of traffic congestion are found and accurately defined, how can we predict the traffic congestion and proactively report it before it happens.

Bayesian network is a type of probabilistic graphical model that can be used to represent the joint probability distribution over a set of random variables under uncertainty, and it can provide an efficient way to capture the complex relationships between different factors and their effects on traffic congestion. Using Bayesian networks, traffic managers can diagnose congestion and predict the causes of congestion.

1.2 Related researches of traffic congestion

There are some existing studies and articles which use Bayesian network to solve the traffic problems, after searching and reading these studies, I classify them into studying two aspects of traffic problems:

Incident Prediction: a study in 2017 explores an application of Bayesian network theory based on probability risk analysis to causation analysis of road accidents, taking Adelaide Central Business District (CBD) in South Australia as a case, which includes driver, road, environment, vehicle and road crash as variable class, and divides them in different variables. The results provide theoretical support for urban road management authorities when analyzing induction factors and improving safety performance within their respective systems. The relevant Bayesian network is showed in this picture

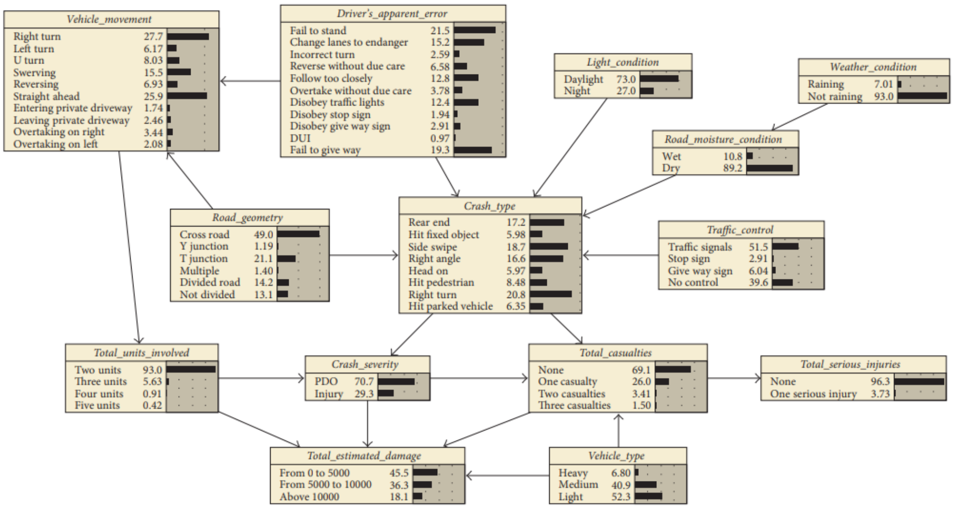


FIGURE 4: The Bayesian network model after parameter learning in Netica 6.02.

Figure 1: BN Model for road incident

Another study in 2011 used references to expert knowledge and data fusion method to explore a topological structure of Bayesian network, which apply a joint tree engine to infer the probability distribution of traffic accident types under the influence of factors such as vehicle type, accident location and traffic participants.

Congestion prediction and diagnosis: There are two different methods when these studies deal with congestion prediction. One method is to use a normal Bayesian network. A study in 2021 proposes a Bayesian network based probabilistic congestion estimation approach for monitoring traffic conditions. The proposed BN-based approach considers both speed (which is called Speed Performance Index) and volume (which is called Level of Services) related measures to provide an estimate of the probable congestion state in terms of probability. The study builds two different Bayesian networks for recurring and non-recurring congestion, and the dataset for non-recurring congestion was selected because a hurricane, a natural disaster, occurred during this time. The comparison of these two Bayesian networks is shown below:

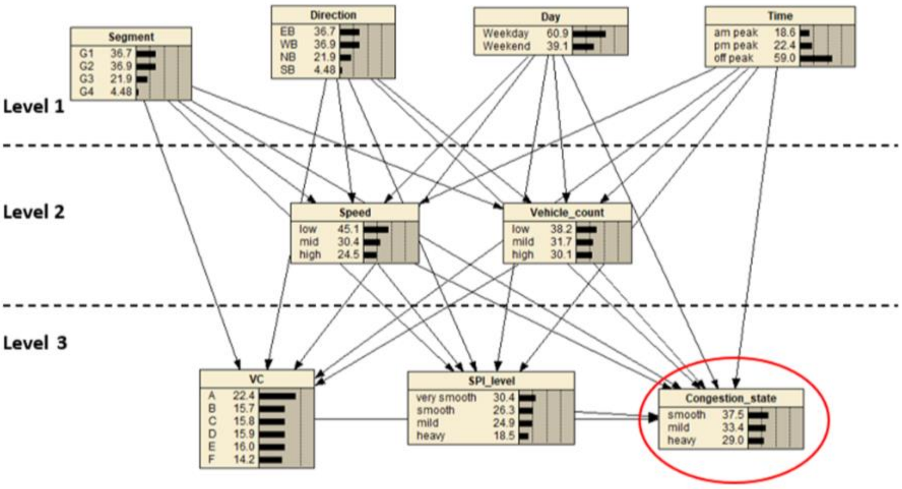


Figure 2: BN Model for recurring situation

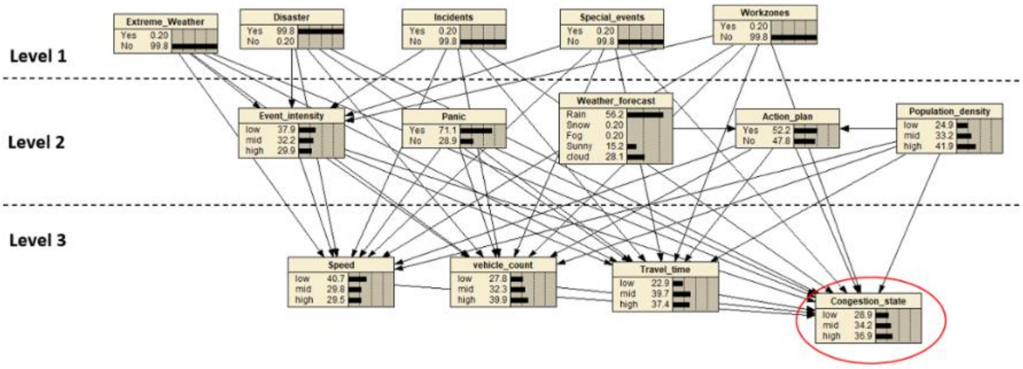


Figure 3: BN Model for nonrecurring situation

Another study in 2020 discusses a method for multi-cause automatic real-time identification of urban road traffic congestion based on the Bayesian network. The proposed model has high flexibility and strong interpretability, which can help better express the correlation between nodes and achieve real-time automation. The results of a study conducted in Quanxiu Street, Quanzhou City, showed that five causes of traffic congestion had higher detection accuracy rates than contrast methods, such as pedestrian influence, peak traffic, parking occupied roads and unreasonable signal timing. A 2016 study proposes a Bayesian Network (BN) analysis approach to model the probabilistic dependency structure of causes leading to traffic congestion on a given road segment. It also analyses the probability of traffic congestion under different road condition scenarios, such as time of day, incident, weather, and conditions on adjacent links. This article serves as my main reference for my research work, and the Bayesian network constructed by this study is shown below:

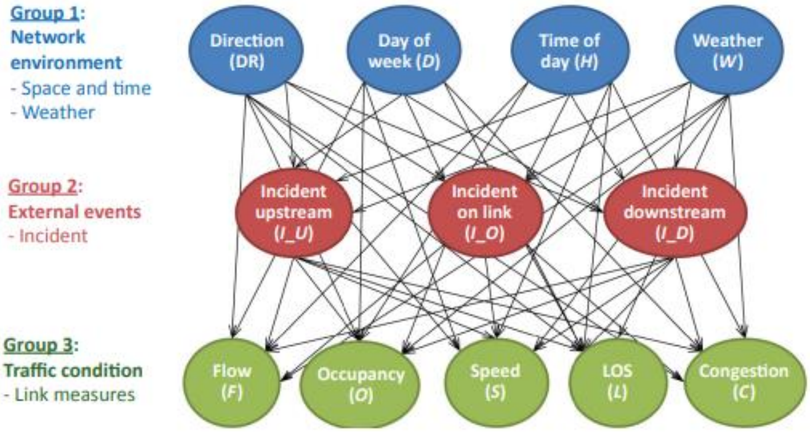


Figure 4: BN Model of the study in 2016

The other method is to use a dynamic Bayesian network. In a study in 2018, a dynamic Bayesian network model is proposed to describe the change and dissipation of road congestion. The prediction results show that this method is feasible in predicting the flow state and dissipation time of vehicles, providing drivers with the shortest routes to less congested roads. Another study in 2021 discusses a new dynamic Bayesian graph convolutional network (DBGCN) that can be used to characterize congestion propagation in road networks, and it is able to simulate congestion propagation processes for customized scenarios by learning latent rules from observed data, and reveal variations in congestion patterns according to road network structure. The overall framework of DBGCN is shown below:

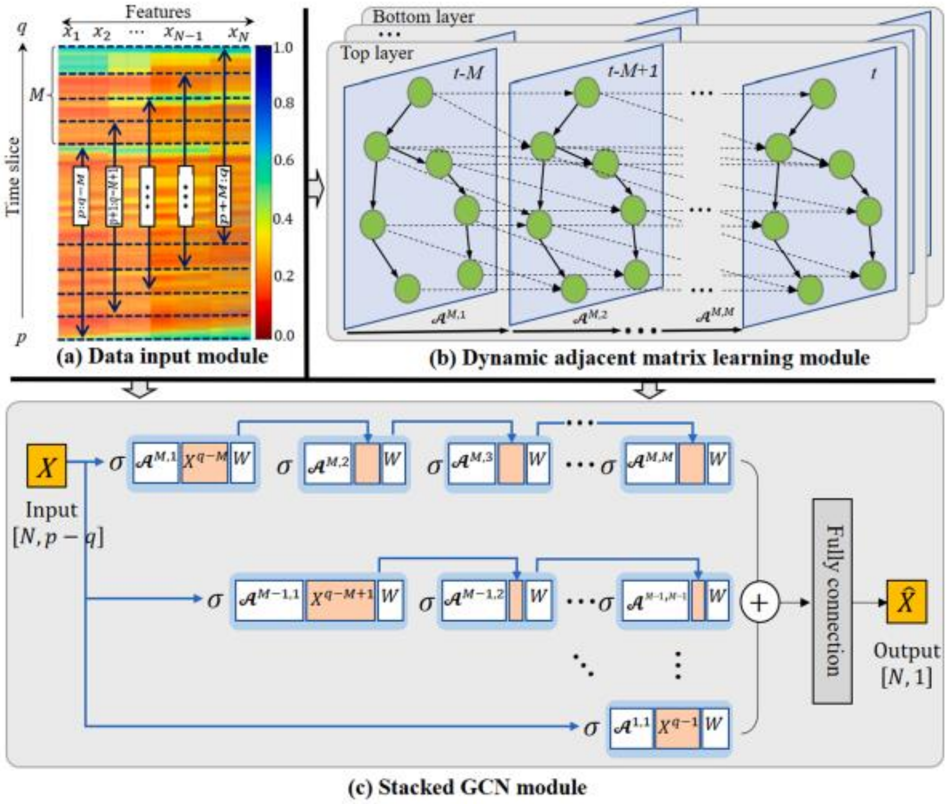


Figure 5: DBGCN Model of study in 2021

Also, a study in 2006 presents a new arterial road incident detection algorithm called TSC_ar. This algorithm uses Bayesian networks to model the causal dependencies between traffic events and parameters, allowing for robust and dynamic knowledge base in order to detect incidents with high accuracy while keeping false alarm rate low. Additionally, incorporating intersection traffic signals into data processing further improves accuracy of results.

2. Data analysis

2.1 Introduction about open datasets

Since most of the papers do not explicitly state the source of their data, the reason may be that they do not use public datasets, but rather datasets obtained in cooperation with relevant authorities. I found several relevant datasets online, a small number of which were obtained from the papers, and I briefly describe them below.

1) Florida Department of Transportation’s Traffic Information (FDOT)
   Traffic Information (fdot.gov)
   This dataset provides statistical traffic information for Florida’s State Highway System, which provides not only historical information about the traffic situation, but also a website to watch the traffic data in real-time.

2) South Australian Government Data Directory
Road Crash Data - Dataset - data.sa.gov.au
This department for Infrastructure and Transport provides a dataset for road crash data, which includes time, location, type of crash, weather when crash happened etc.

3) Open Data Portal of Queensland Government
Transport and Main Roads - Organisations - Open Data Portal | Queensland Government
This dataset provides also many datasets for transport, which include traffic data and also crash data of different roads in Queensland.

4) Chicago traffic tracker on data.gov
Chicago Traffic Tracker - Historical Congestion Estimates by Segment - 2018-Current - Catalog (data.gov)
This dataset is from a official dataset of the United States government, which contains the historical data of traffic such as speed, street name etc., which can be used to estimate congestion.

5) Caltrans Performance Measurement System (PeMS)
Caltrans PeMS
This dataset provides over ten years of data for historical analysis in the California-area from different detectors and sensors, which contains almost all kinds of traffic data, and there is also a real-time website which shows the real-time traffic situation in California.

6) National Center for Environmental Information
National Centers for Environmental Information (NCEI) (noaa.gov)
This dataset manages one of the largest archives of atmospheric, coastal, geophysical and oceanic research in the world, and the weather condition part is useful for our study, because it provides data which is collected by different sensors all over the world hourly, such as hourly precipitation, visibility and windspeed etc.

2.2 Introduce about my dataset and variables

After searching and learning about these relative datasets, I chose PeMS and NCEI as the sources of my dataset. A vehicle detection sensor (VDS) on the I-105-E freeway in Los Angeles was chosen as the source of my data because this part of the freeway is one of the busiest areas in the United States, connecting two freeways I-105 and I-710, so it's also one of the most congested areas. The design of this part of the freeway and the location see below:

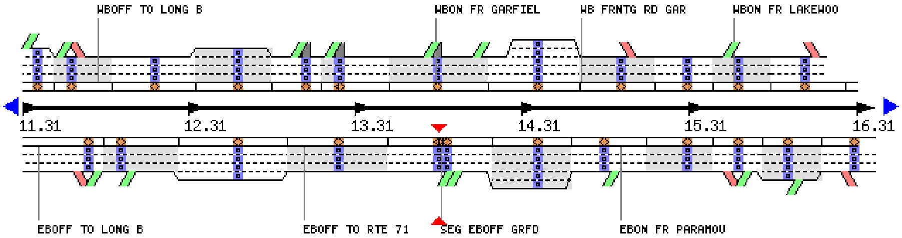


Figure 6: draft of selected area

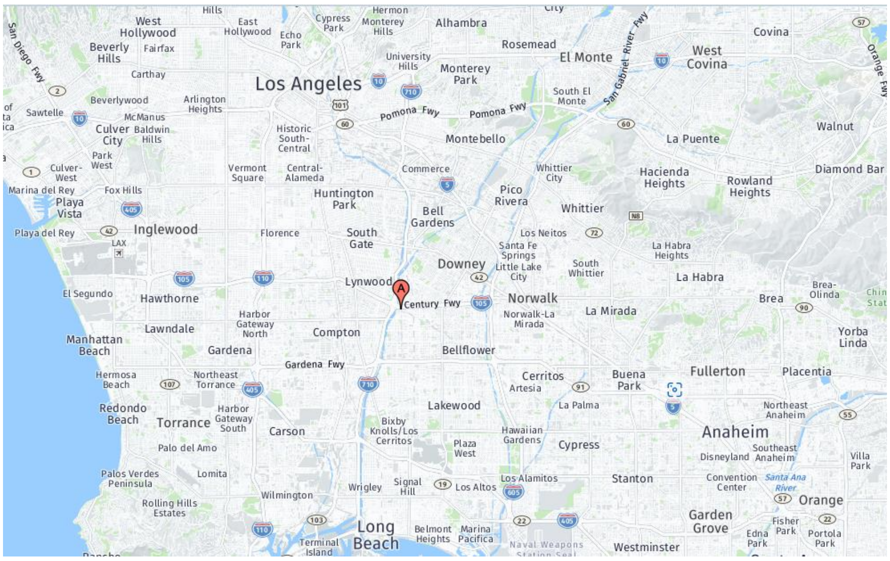


Figure 7: location of selected area

And then I choose a Station which records weather data near this vehicle detection sensor, which named Los Angeles downtown USC, and the location shows below:

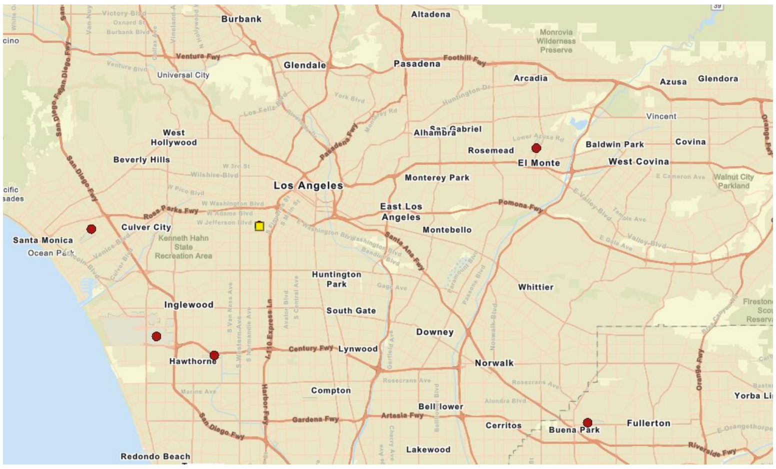


Figure 8: location of selected weather station

The traffic and weather data are collected from 2022.12.1-2023.2.28 and is recorded hourly, which obtained as a 2161-by-8 matrix. the traffic data is collected from the Vehicle Detection Sensor, which contains Speed (mph), Flow (Vehicle/hour) and Occupancy (%), and the weather data is collected from the weather station, which contains Hourly precipitation (inch) and Hourly visibility (mile). And the variables used in the Bayesian network model are presented in the table. A total of 8 variables were selected, and only discrete variables will be considered, that is, nodes that take discrete values. And the variables are categorized into 2 groups: Network Environment and Traffic condition as follows:

Network environment variables represent the environmental factors, Time of day, Day of week, Hourly precipitation and Hourly visibility are considered as environmental factors which have the possibility to influence the traffic congestion. Time of day takes 3 states {AM peak; PM peak; Off peak}, Day of week takes 2 states {Weekday; Weekend}, Hourly precipitation takes 4 states {No rain; Light rain; Moderate rain; Heavy rain}, and Hourly visibility takes 2 states {Clear; Haze}. The detailed descriptions for these state definitions are presents in Table 1, and these 4 variables can be recognized as background variables, which has a causal influence on problem variable.

Traffic condition variables represent link performance measures describing traffic states on the target area. This study includes 4 variables consisting 3 basic traffic steam parameters, Speed, Flow and Occupancy. These three variables take 4 same discrete states {very low, low, high, very high}, and these states are defined according to the value range of each variable, which is also called as normalization. In this study, each variable will be normalized, and corresponding to the range between 0 and 1. And then it will be divided into 4 states as above. The Congestion is a binary variable that indicates whether this area is congested. As the study in 2016, occupancy and flow values are used to determine the value of congestion. It takes two states {congest; uncongest}, “uncongest” if occupancy<Occcrit and “congest” if occupancy>Occcrit, where Occcrit represents the critical occupancy at which flow becomes maximum, as shown in the figure below.

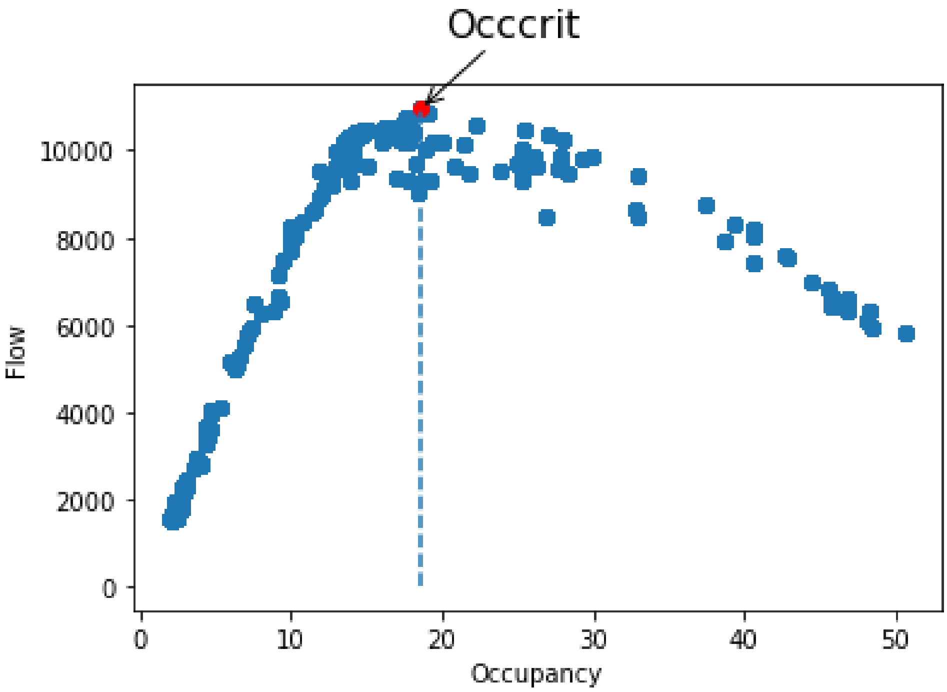


Figure 9: Occupancy-by-speed scatter

In this dataset, Occcrit = 18.6%, maximum flow = 10956. This binary congestion indicator will be used as the problem variable, which the Bayesian network model want to compute the posterior probability given observations of values for information variables (which contain symptom variables and background variables), and this variable will be used in performing the congestion diagnosis and prediction. And the data discretization for occupancy by speed and flow by speed show below:

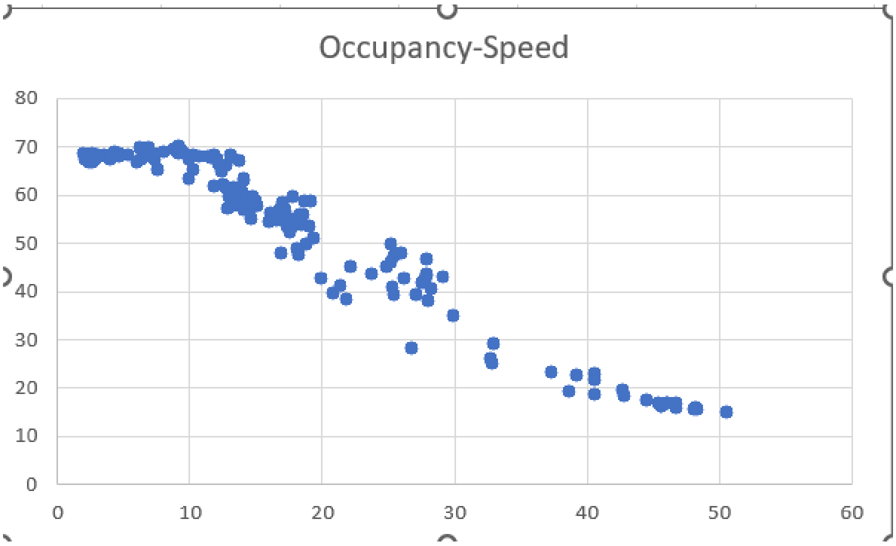


Figure 10: Occupancy-by-speed scatter

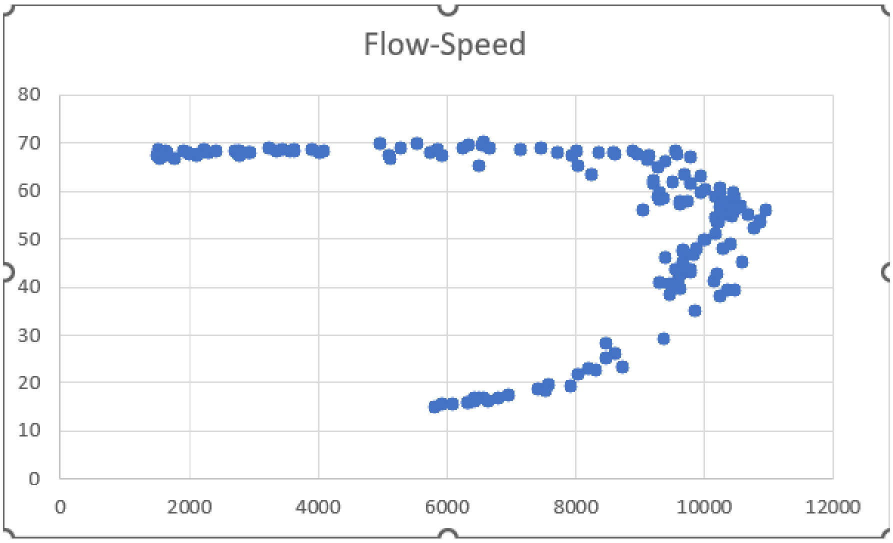
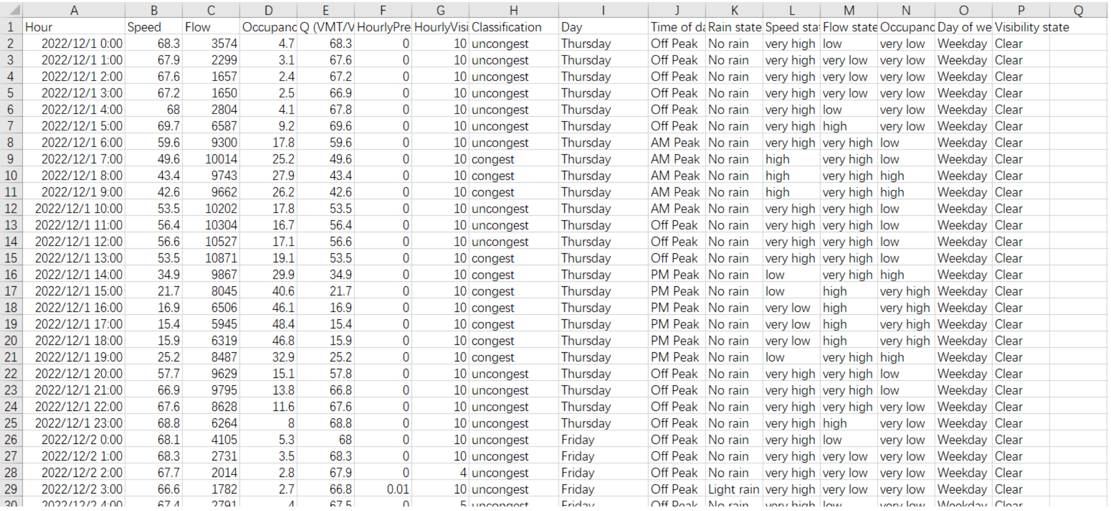


Figure 11: Flow-by-Speed scatter

An example of the dataset is shown in the picture below:



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	Hour	Speed	Flow	Occupanc	Q (VMT/V	HourlyPre	HourlyVisi	Classification	Day	Time of da	Rain state	Speed stat	Flow state	Occupanc	Day of we	Visibility state	
2	2022/12/1 0:00	68.3	3574	4.7	68.3	0	10	uncongest	Thursday	Off Peak	No rain	very high	low	very low	Weekday	Clear	
3	2022/12/1 1:00	67.9	2299	3.1	67.6	0	10	uncongest	Thursday	Off Peak	No rain	very high	very low	very low	Weekday	Clear	
4	2022/12/1 2:00	67.6	1657	2.4	67.2	0	10	uncongest	Thursday	Off Peak	No rain	very high	very low	very low	Weekday	Clear	
5	2022/12/1 3:00	67.2	1650	2.5	66.9	0	10	uncongest	Thursday	Off Peak	No rain	very high	very low	very low	Weekday	Clear	
6	2022/12/1 4:00	68	2804	4.1	67.8	0	10	uncongest	Thursday	Off Peak	No rain	very high	low	very low	Weekday	Clear	
7	2022/12/1 5:00	69.7	6587	9.2	69.6	0	10	uncongest	Thursday	Off Peak	No rain	very high	high	very low	Weekday	Clear	
8	2022/12/1 6:00	59.6	9300	17.8	59.6	0	10	uncongest	Thursday	AM Peak	No rain	very high	very high	low	Weekday	Clear	
9	2022/12/1 7:00	49.6	10014	25.2	49.6	0	10	congest	Thursday	AM Peak	No rain	high	very high	low	Weekday	Clear	
10	2022/12/1 8:00	43.4	9743	27.9	43.4	0	10	congest	Thursday	AM Peak	No rain	high	very high	high	Weekday	Clear	
11	2022/12/1 9:00	42.6	9662	26.2	42.6	0	10	congest	Thursday	AM Peak	No rain	high	very high	high	Weekday	Clear	
12	2022/12/1 10:00	53.5	10202	17.8	53.5	0	10	uncongest	Thursday	AM Peak	No rain	very high	very high	low	Weekday	Clear	
13	2022/12/1 11:00	56.4	10304	16.7	56.4	0	10	uncongest	Thursday	Off Peak	No rain	very high	very high	low	Weekday	Clear	
14	2022/12/1 12:00	56.6	10527	17.1	56.6	0	10	uncongest	Thursday	Off Peak	No rain	very high	very high	low	Weekday	Clear	
15	2022/12/1 13:00	53.5	10871	19.1	53.5	0	10	congest	Thursday	Off Peak	No rain	very high	very high	low	Weekday	Clear	
16	2022/12/1 14:00	34.9	9867	29.9	34.9	0	10	congest	Thursday	PM Peak	No rain	low	very high	high	Weekday	Clear	
17	2022/12/1 15:00	21.7	8045	40.6	21.7	0	10	congest	Thursday	PM Peak	No rain	low	high	very high	Weekday	Clear	
18	2022/12/1 16:00	16.9	6506	46.1	16.9	0	10	congest	Thursday	PM Peak	No rain	very low	high	very high	Weekday	Clear	
19	2022/12/1 17:00	15.4	5945	48.4	15.4	0	10	congest	Thursday	PM Peak	No rain	very low	high	very high	Weekday	Clear	
20	2022/12/1 18:00	15.9	6319	46.8	15.9	0	10	congest	Thursday	PM Peak	No rain	very low	high	very high	Weekday	Clear	
21	2022/12/1 19:00	25.2	8487	32.9	25.2	0	10	congest	Thursday	PM Peak	No rain	low	very high	high	Weekday	Clear	
22	2022/12/1 20:00	57.7	9629	15.1	57.8	0	10	uncongest	Thursday	Off Peak	No rain	very high	very high	low	Weekday	Clear	
23	2022/12/1 21:00	66.9	9795	13.8	66.8	0	10	uncongest	Thursday	Off Peak	No rain	very high	very high	low	Weekday	Clear	
24	2022/12/1 22:00	67.6	8628	11.6	67.6	0	10	uncongest	Thursday	Off Peak	No rain	very high	very high	very low	Weekday	Clear	
25	2022/12/1 23:00	68.8	6264	8	68.8	0	10	uncongest	Thursday	Off Peak	No rain	very high	high	very low	Weekday	Clear	
26	2022/12/2 0:00	68.1	4105	5.3	68	0	10	uncongest	Friday	Off Peak	No rain	very high	low	very low	Weekday	Clear	
27	2022/12/2 1:00	68.3	2731	3.5	68.3	0	10	uncongest	Friday	Off Peak	No rain	very high	very low	very low	Weekday	Clear	
28	2022/12/2 2:00	67.7	2014	2.8	67.9	0	4	uncongest	Friday	Off Peak	No rain	very high	very low	very low	Weekday	Clear	
29	2022/12/2 3:00	66.6	1782	2.7	66.8	0.01	10	uncongest	Friday	Off Peak	Light rain	very high	very low	very low	Weekday	Clear	
30	2022/12/2 4:00	67.4	2791	4	67.5	0	5	uncongest	Friday	Off Peak	No rain	very high	low	very low	Weekday	Clear	

Figure 12: example of dataset