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ENHANCING TRAFFIC SAFETY: A COMPREHENSIVE APPROACH THROUGH REAL-TIME DATA AND INTELLIGENT TRANSPORTATION SYSTEMS

Summary. Today, traffic accidents are still a difficult and urgent problem for many countries around the world. Traffic accidents on highways are often more serious than accidents on urban roads. Therefore, disseminating emergency information and creating immediate connections with road users is key to rescuing passengers and reducing congestion. Thus, this study applies data fusion and data mining techniques to analyze travel time and valuable information about traffic accidents based on the real-time data collected from On-Board Unit installed in vehicles. The results show that this important information is the vital database to analyze traffic conditions and safety factors, thereby developing a smart traffic information platform. This result enables traffic managers to provide real-time traffic information or forecasts of congestion and traffic accidents to road users. This helps limit congestion and serious accidents on the Highway.

Keywords: traffic accident, highway, big data, data mining, intelligent transportation system

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1. INTRODUCTION

The implementation of eTag sensors on the Freeway in Taiwan serves a dual purpose: facilitating toll calculations and generating valuable traffic-related data. This data encompasses essential metrics such as travel times, traffic volumes, speeds, and the tolls necessary to traverse different segments between ramps. The authority and road users can readily access and reference this information, as it is promptly stored on servers [1].

In the event of an accident on the Freeway, the conventional reporting mechanism involves telephonic communication with the traffic control center. The accident's location is determined based on milestones and verified through traffic cameras before dispatching rescue teams. Subsequently, the traffic control center disseminates accident information to road users through broadcasting and online platforms [2]. Despite this established process, this study proposes leveraging smart technologies to streamline the processing and dissemination of traffic information.

One notable limitation of the existing eTag system is its inability to access real-time information about road conditions if the distance between two eTag sensor gantries is too extensive. This limitation often hampers road users' ability to make informed decisions, such as changing routes or adjusting their driving speed. The eTag system may not capture comprehensive traffic information for a particular section between sensor gantries, creating an information gap [3].

To address this gap, the study suggests integrating the capabilities of the On-Board Unit (OBU) with the eTag system. When a vehicle equipped with the OBU passes through an eTag sensor gantry, data transmission occurs for comparative analysis, ensuring data integrity and mitigating the information gap issue. Beyond managing the vehicle fleet, the OBU contributes real-time information about the vehicle and road conditions. This data is relayed in real-time to the traffic information platform specifically developed for this study.

The integration of real-time information from the OBU into both the eTag database and the larger big data repository, which includes data from both the eTag and the OBU, enables comprehensive data mining and visualized analysis. The study envisions employing various models and data analyses to extract valuable traffic information and safety factors. The ultimate goal is to utilize real-time cloud computing to enhance the completeness of the traffic information service, as illustrated in Fig. 1.

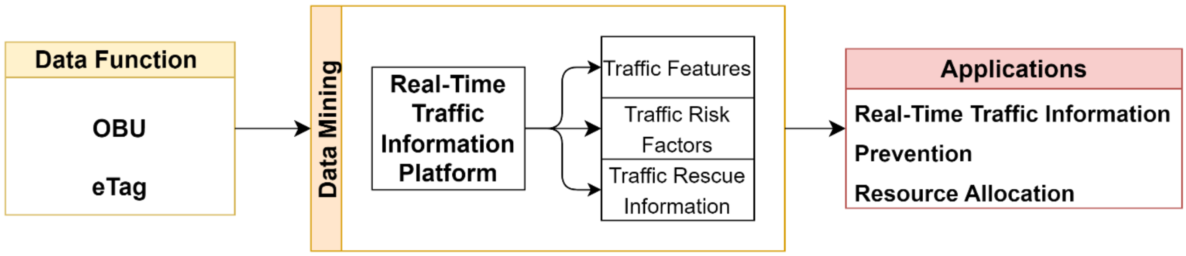

Fig. 1. Establishment of study foundation

By integrating data from eTag and the OBU, this study seeks to optimize the potential for data mining techniques. The collected and analyzed data about the Freeway will be instrumental in establishing relevant models, and the big data analysis model will further uncover useful traffic information. The overarching aim is to advance the capabilities of the traffic information service through a more thorough integration of eTag and OBU data.

The remainders of the paper are arranged as follows. Section 2 shows literature review. Section 3 presents study data and methods. Section 4 illustrates data analysis and discussions. In Section 5, conclusions are displayed.

2. LITERATURE REVIEW

Passive delays in the delivery of emergency or accident information can prevent neighboring road users from obtaining real-time updates. Real-time communication can be achieved by using the OBU and mobile devices such as Vehicle Information and Communication System (VICS) in Japan to send information to neighboring vehicles quickly. Numerous research works suggest that trip time can be predicted using eTag data. In order to enhance data integrity and match forecasts with factual circumstances, several researches integrate vehicle detector or OBU data for thorough examination [4]. Certain researches use the OBU to gather more accurate data for fleet management and monitoring. Predictions and data analysis are rarely integrated into actual applications inside the domestic traffic information infrastructure, nevertheless.

Various factors contribute to traffic safety, including individuals, vehicles, and the surrounding environment [5]. The OBU has the capability to monitor both individuals and their vehicles. Additionally, the author aim to utilize data from road sensors for analyzing and predicting vehicle flow. However, in the event of an accident, most road users typically receive information passively from the police or broadcasting. Predicting and preventing factors that could lead to accidents and understanding road conditions are crucial.

Providing road users with reminders before emergencies can significantly reduce the severity and occurrence of accidents. Beyond understanding accident causes, the knowledge gained can be employed to develop preventive strategies for accident occurrence. The accident forewarning acts as a behavioural indicator between the core indicator and performance indicator, aiming to enhance traffic safety. Utilizing the accident forewarning as an intermediary indicator can improve the accuracy of assessments and help dissect the complex causes of accidents [6, 7]. The following section will delve into the development of the accident forewarning and the associated challenges encountered thus far.

There are a few previous studies that have addressed this issue, specifically as follows: Swiftly and accurately identifying sections on the Freeway prone to accidents [8]-[10]. Quickly and precisely evaluating the impact of strategies aimed at enhancing traffic safety, as demonstrated by [11]. Serving as the foundation for assessing safe driving behaviors [12]. Developing driveway security devices and measures for traffic safety [13]-[15]. Allowing the insurance market to implement price discrimination based on driver safety [16, 17]. Conducting further exploration into driving behaviors, vehicle designs, and their interactions with the road environment.

Currently, the traffic information service platform lacks complete integration of eTag data analysis and application in Taiwan. Also, it does not facilitate the transmission of emergency information. The strength of this study lies in combining eTag data with the OBU data to construct a comprehensive Big Data database. This integrated data undergoes classification using data mining techniques, with relevant models applied to extract valuable traffic information. The study envisions an advanced traffic platform offering a holistic traffic information service, covering general road conditions and accidents. Additionally, the application of accident forewarning is expected to improve and expand with ongoing advancements in computing power and wireless communications technology. The accuracy of information analysis relies on a multitude of data sources, emphasizing the importance of the precision of these relevant sources for accurate information assessments.

In summarizing the literature on traffic information and safety considerations, the focal points in traffic information services are the accuracy of information transmission. Nevertheless, the integrity of data also plays a significant role in influencing analysis and prediction outcomes. Challenges arise when the distance between sensors is extensive, hindering the acquisition of information on a Freeway section and resulting in insufficient data integrity.

In this investigation, the objective is for the OBU to gather data on vehicle flow, integrating eTag data. Subsequently, these data will undergo conversion, filtering, compensation, and fusion through various data processing procedures, including data mining techniques. The aim is to predict travel time, extract valuable traffic information, and establish a comprehensive set of analysis procedures, methods, and mechanisms. Subsequently, the traffic information platform can provide real-time updates to road users, enabling them to avoid congested Freeway sections, reduce travel time, and enhance traffic speed. Additionally, this information can be referenced and applied by traffic management authorities.

The main tasks of this study encompass: First, providing real-time travel information and predictions. Second, offering accident prediction information. Third, supplying emergency relief information. Final, integrating information services for safety and rescue within the smart traffic information platform.

3. DATA AND METHOD

3.1. Data Collection

The Traffic Data Collection Support System (TDCS) on the Freeway gathers eTag data, with the original data being publicly accessible. There are six file types, detailed in Tab. 1, with the M06 file type specifying the original data. The data containing the initial path tends to be the most comprehensive, boasting the largest data volume. Daily, an average of 4 million data entries are processed, necessitating a daily file size of about 1GB or potentially more. Given the continuous 24-hour collection of vehicle flow data on the Freeway, the system may accumulate over 1 million data entries per hour, presenting a challenge to existing data processing methods concerning current data analysis techniques, efficiencies, and software and hardware capabilities.

Besides eTag data, this study also uses data from OBU for analysis. The OBU has the capability to gather detailed information about the vehicle, including basic data, operational status, and precise location. The data formats are specified in Tab. 2. When merging data from the OBU and eTag, challenges such as inaccuracies, discrepancies, noises, fragmentation, or irrelevant information may appear. Consequently, there may be a need for data processing and normalization.

The integration and extension of functions of the OBU applied in this study is presented in Fig. 2. This research uses the data to build the big database. During the combination of data from the OBU and eTag, issues such as incorrectness, inconsistency, noises, fragmentation or irrelevance of data may arise. Thus, data processing and normalization may be required.

Tab. 1

The file kinds of eTag data

No	File name	Description
1	TDCS_M03A_YYYYMMDD_hhmmss.csv	Traffic volume
2	TDCS_M04A_YYYYMMDD_hhmmss.csv	Average travel time
3	TDCS_M05A_YYYYMMDD_hhmmss.csv	Average driving speed
4	TDCS_M06A_YYYYMMDD_hhmmss.csv	OD raw data (daily)
5	TDCS_M07A_YYYYMMDD_hhmmss.csv	OD average length (daily)
6	TDCS_M08A_YYYYMMDD_hhmmss.csv	OD average traffic volume (daily)

OD: Origin-Destination.

Tab. 2

Data formats from the OBU

Vehicle route data						
Date: 20160802000000 ~ 20160802164759						
Vehicle No.: CAR2						
Vehicle No.	**OBU**	**Driver**	**GPS time**	**Longitude**	**Latitude**	**Location**
CAR2	6860422853	DR-2	2016/08/02 00:02:33	120.2429	22.8794	Dongfang Rd., Hunei District, Kaohsiung City
CAR2	6860422853	DR-2	2016/08/02 00:03:01	120.2429	22.8794	Dongfang Rd., Hunei District, Kaohsiung City
CAR2	6860422853	DR-2	2016/08/02 00:05:01	120.2429	22.8794	Dongfang Rd., Hunei District, Kaohsiung City
CAR2	6860422853	DR-2	2016/08/02 00:07:01	120.2429	22.8794	Dongfang Rd., Hunei District, Kaohsiung City
CAR2	6860422853	DR-2	2016/08/02 00:07:33	120.2429	22.8794	Dongfang Rd., Hunei District, Kaohsiung City
CAR2	6860422853	DR-2	2016/08/02 00:09:01	120.2429	22.8794	Dongfang Rd., Hunei District, Kaohsiung City

3.2. Method

The Intelligent Transport System (ITS) serves as an application designed for the coordination of people, roadways, and vehicles. Its purpose is to provide instantaneous information, thereby improving the security, efficiency, and convenience of the transport system while mitigating the environmental impact of traffic. Cloud technologies are employed in storing, disseminating, and processing the substantial volume of data derived from traffic information. The positive outcomes can only be achieved through comprehensive data processing and strategic managing, as illustrated in Fig. 3.

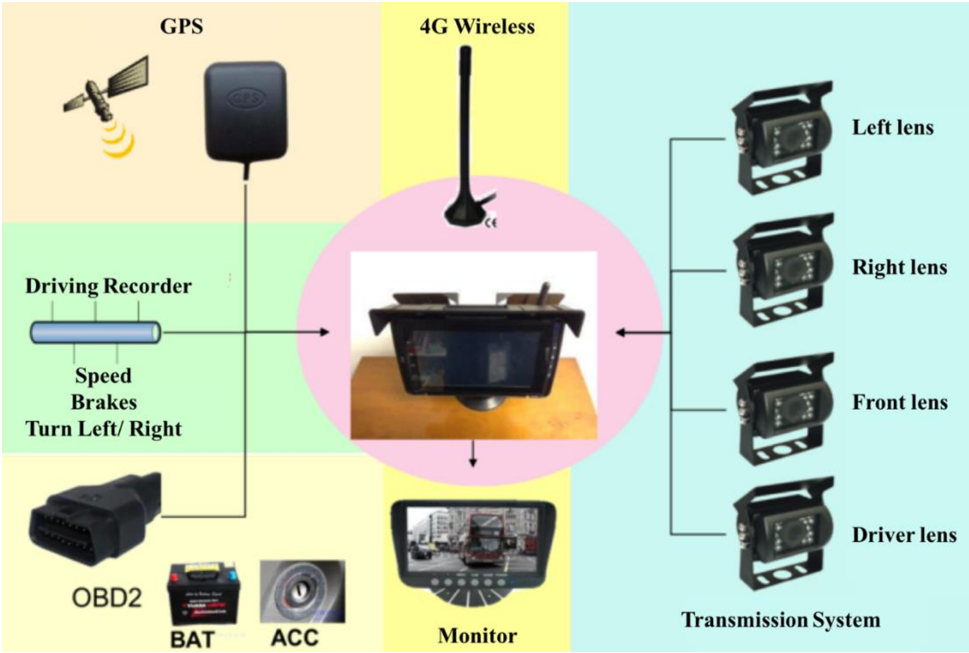

Fig. 2. Functions of the OBU

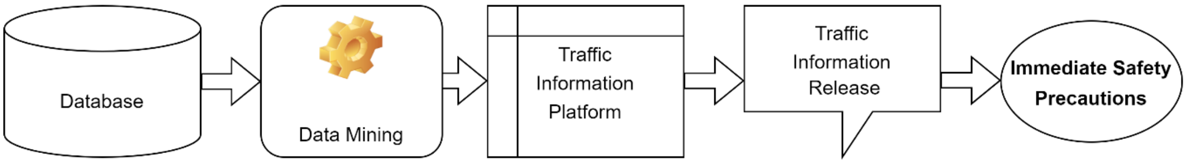

Fig. 3. The traffic information platform diagram

3.2.1. Data Pre-processing

As we delve into the intricate process of thoroughly analyzing information from ITS, it becomes evident that key stages such as data collection, information transmission, integration, and disclosure necessitate the establishment of supporting mechanisms. In this study, the compliance analysis model takes center stage, meticulously screening and analyzing conditional data, gradually shaping them into valuable information. This intricate process is distilled into five essential steps: data filtering, conversion, compensation, fusion, and extension, as shown in Fig. 4.

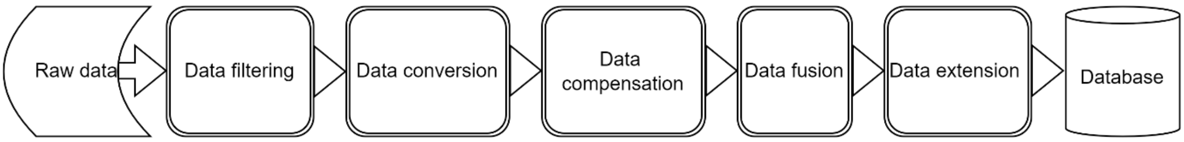

Fig. 4. Data preprocessing process

- ❖ Data filtering: The data may contain abnormal or extreme values, possibly due to equipment abnormalities, specific driving behaviors, or inherent vehicle properties. Excessive presence of such data may impact the accuracy of subsequent algorithms. Therefore, it is essential to filter these data first.
- ❖ Data conversion: Initial frequencies and content of data collected by each device may vary. Consequently, data conversions can be performed to ensure uniform usability in subsequent applications. To identify missing data, data collection over a specific time interval is necessary to confirm any gaps.
- ❖ Data compensation: Data may be missing due to device abnormalities post-collection, or defects may emerge after data filtering. In such cases, the algorithm, prediction model, and historical data can be employed to compensate for any missing data on the device at any given time.
- ❖ Data fusion: When a section of the Freeway lacks data, data extension will be conducted for compensation. When data from the OBU at a specific time becomes representative for the Freeway section, it will be fused with the prediction data. According to the weighted fusion method outlined by the Institute of Transportation under the Ministry of Transportation and Communications (MOTC) [18], the OBU-collected data, along with instantaneous speed and predicted traffic speed, will be fused. Both values are used because the OBU data may be less representative when the number of vehicles is lower. The weighted method helps account for the properties of vehicle detection (VD) data. When there is sufficient data from the OBU, the data will be closer to true values, and their weights may approach 100 percent, indicating that the prediction value can be completely spared. Data fusion will be carried out through model construction, and the general formula is shown as follows:

$$S = w_e s_e + w_g s_g \tag{1}$$

Where:
S = speed after data fusion;
w_e = data extension estimated value weight;
s_e = data extension estimated speed value;
w_g = GPS-based vehicle probe speed weight;
s_g = GPS-based vehicle probe speed.

- ❖ Data extension: Data extension may occur within a section on the Freeway or between sections on the Freeway. Within a Freeway section, data extension may be conducted to expand the data range when it does not align with the section's length. This extension is seamless, and potential errors are accounted for. Additionally, data extension can occur between Freeway sections to extend data from a fully conforming section to one without any data. It is assumed that vehicle flow may exhibit a directional extension, enabling data from the upstream Freeway section to be extended for predicting data in the downstream section of the Freeway.

3.2.2. Traffic Information Platform Development

This research primarily explores the realm of Big Data, focusing on the development of a real-time dynamic information system dedicated to the instantaneous computation of Big Data. As the volume of historical traffic data rises and traffic systems grow in complexity, it becomes crucial for the platform to possess the capacity to manage Big Data effectively. Consequently, the central emphasis of this study lies in devising methods to process, analyze, synthesize, harness, utilize, disseminate, and store large datasets derived from real-time traffic information swiftly and efficiently. The goal is to construct a comprehensive traffic information platform tailored for highways, serving both general and emergency purposes. The architectural layout of the platform is illustrated in Fig. 5.

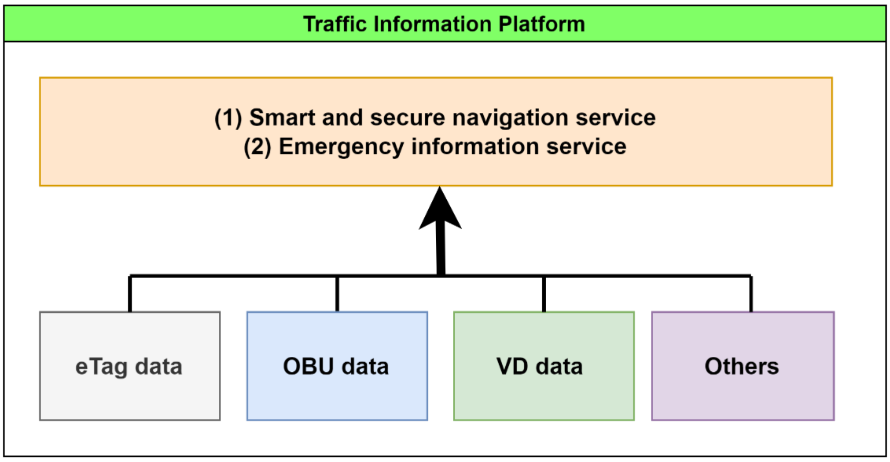

Fig. 5. Traffic information platform

This study aims to create a smart traffic information platform using Information and Communications Technology (ICT) and Data Mining for real-time decision-making. The system analyzes eTag and OBU data to generate Big Data, offering insights like vehicle flow, travel time, trip count, vehicle types, and more. Additionally, it manages traffic information, predicts congestion, and provides visualization of results.

The platform primarily offers two types of traffic information services. The first type is a smart and secure navigation service primarily catering to road users, while the second type is an emergency information service providing advanced warnings to road users. To meet the evolving traffic needs of the Freeway in the future, this research establishes a prediction model and develops the platform with functions including: intelligent and safe navigation service and emergency information service. The platform will be equipped with the following functions:

(1) Smart and secure navigation service:
- a. To inquire about road conditions in real-time.
- b. To identify easily congested sections on the Freeway, issue forewarning about congestion intervals, and predict travel times on those sections.
- c. To provide suggested routes and real-time guidance to road users.
- d. To offer historical data about vehicle flow information to relevant authorities for analysis and applications.

(2) Emergency information service:
- a. To provide rescue services after accidents occur.
- b. To issue emergency alerts and push notifications to road users to control of potential accident risks.
- c. To offer suggested routes and guidance to enhance smooth traffic and reduce accidents. As the Freeway section is a closed road with no alternative routes for vehicle evacuation after an accident, this may lead to a serious blockage and unforeseen impacts on road capacity.

The information platform will be capable of forecasting easily congested sections, planning alternative trips during congestion, and reporting accidents on Freeway sections to help road users make informed decisions. For instance, road users may choose alternative routes based on comparisons of travel time, average speed, and congestion conditions.

4. DATA ANALYSIS AND DISCUSSION

4.1. Occurrence of Accidents

Central Taiwan is served by four Freeways, specifically Freeways No. 1, 3, 4, and 6. According to Tab. 3, there were a total of 3,727 accidents in 2016, with 2,270 occurring on Freeway No. 1. Accidents on Freeway No. 1 constituted 61 percent of all accidents on Central Taiwan's Freeways in 2016, surpassing half (50 percent) of the total accidents on these Freeways. Consequently, Freeway No. 1 is chosen as the focus of this study. While the central section of Freeway No. 1 spans 158 kilometers, accidents are not uniformly distributed; instead, they are concentrated in specific sections. This study targets segments with a relatively higher accident frequency. The research target is set from the Taichung system to the Puyan system (kilometer range 165-207), is shown in Tab. 4, as it encompasses 1,386 accidents, representing more than half (50 percent) of the total accidents on the central section of Freeway No. 1.

Tab. 3

The number of accidents on Freeways in 2016

Locations	Directions					
	North	West	East	North-South	South	Total
Freeway No. 3	589	0	2	3	562	1156
Freeway No. 4	0	45	29	0	0	74
Freeway No. 6	0	156	71	0	0	227
Freeway No. 1	1043	0	0	0	1227	2270
Total	1632	201	102	3	1789	3727

4.1.1. Variable Screening

The initial screening of variables is conducted through two approaches. Initially, the author refers to literature to examine various accident types, considering the impact of congestion, and utilizes variables such as backup (induced or not induced) and the number of driveways occupied for analysis. Subsequently, the author delves into the original data. Finally, a preliminary screening of variables related to accident occurrence is performed, as depicted in Fig. 6.

Tab. 4

The number of accidents on Freeway No. 1 (from Mileage 99 to 257k)

Interchanges	Mileage	North	South	Total
Hsinchu system-Toufen	99-110k	35	13	48
Toufen-Touwu	110-125k	31	33	64
Touwu-Miaoli	125-132k	22	8	30
Miaoli-Tongluo	132-140k	29	18	47
Tongluo-Sanyi	140-150k	26	39	65
Sanyi-Houli	150-160k	35	48	83
Houli-Taichung system	160-165k	13	53	66
Taichung system-Fongyuan	165-168k	46	98	144
Fongyuan-Daya	168-174k	39	282	321
Daya-Taichung	174-178k	77	106	183
Taichung-Nantun	178-181k	26	58	84
Nantun-Wang Tian	181-189k	54	34	88
Wang Tian-Changhua system	189-192k	13	23	36
Changhua system-Changhua	192-198k	168	80	248
Changhua-Puyan system	198-207k	109	173	282
Puyan system-Yuanlin	207-211k	79	31	110
Yuanlin-Beidou	211-220k	97	39	136
Beidou-Hsilo	220-230k	65	29	94
Hsilo-Huwei	230-235k	33	22	55
Huwei-Dounan	235-240k	16	12	28
Dounan-Yunlin system	240-243k	5	8	13
Yunlin system-Dalin	243-250k	21	18	39
Dalin-Minsyong	250-257k	3	1	4
Total		1043	1227	2270

Data Sources: Central Region Office, National Freeway Bureau, MOTC, Taiwan, 2016 [18]

4.1.2. Data Analysis

The analysis proceeds through the following steps: First, after excluding ineffective data, the total number of accidents is reduced to 1,254. Second, types of accidents: The original data categorizes accidents into rear-end accidents and others. Third, identification of induced backup: The original data indicates whether backup occurred or not. Finally, counting driveways occupied: The original data classifies accidents based on the number of lanes occupied (one lane, two lanes, and three or more lanes).

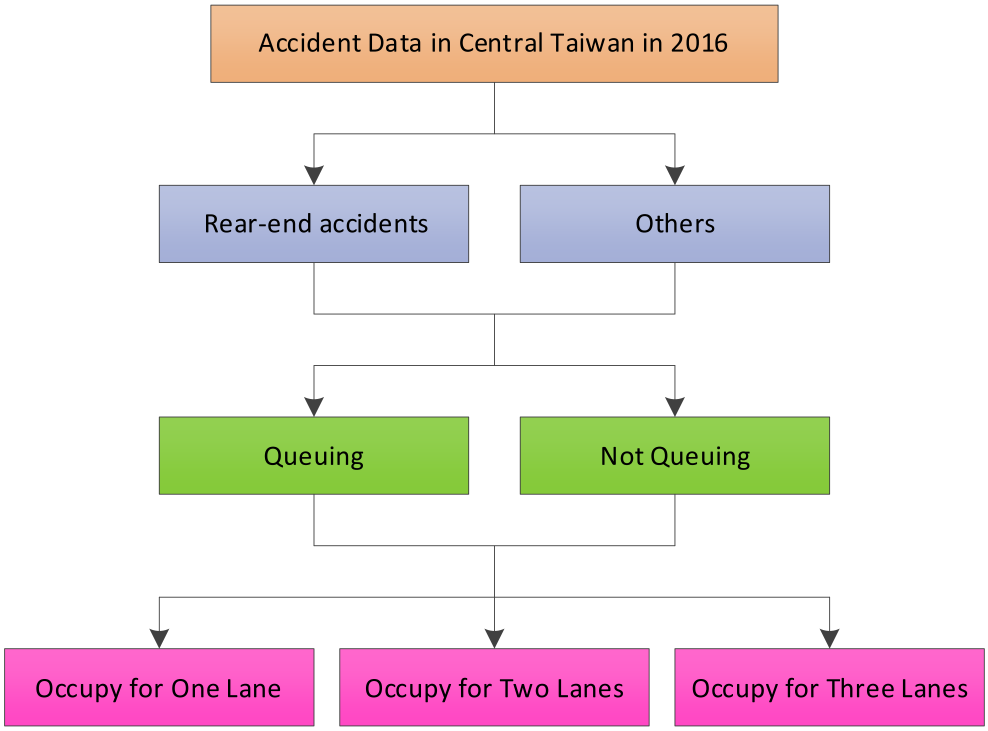

Fig. 6. Flowchart of variable screening

Preliminary analysis results, outlined in Tab. 5, reveal that among the effective accidents, 1,050 are rear-end accidents (approximately 80 percent), and 1,048 accidents induce backup in vehicle flow. Further analysis, as shown in Fig. 7 and Fig. 8, is conducted separately for situations with or without backup in the vehicle flow. It is evident that, regardless of whether backup is induced, the majority of rear-end collisions typically involve the occupation of only one lane. This pattern is attributed to the nature of rear-end accidents, where the following vehicle often fails to pay attention to the leading vehicle, and instances of deviation from the driveway are relatively uncommon.

Tab. 5

Variable analysis for rear-end accidents

Have Queuing Line	**Not Have Queuing Line**
1048	2

Data Sources: Central Region Office, National Freeway Bureau, MOTC, Taiwan, 2016 [18]

As rear-end accidents accounted for nearly 80 percent of the accidents, this study classifies special accident types such as sideswipe collisions against the side rail and rollover as other accidents with the analysis steps remaining the same as aforementioned. As shown by Tab. 6, as in rear-end accidents, after the accident happens, queening line in the vehicle flow may be induced for further analysis. From Fig. 9 and Fig. 10, we can see that most accidents would only occupy one lane, but three or more lanes may be occupied under special circumstances owing to specific types of accidents.

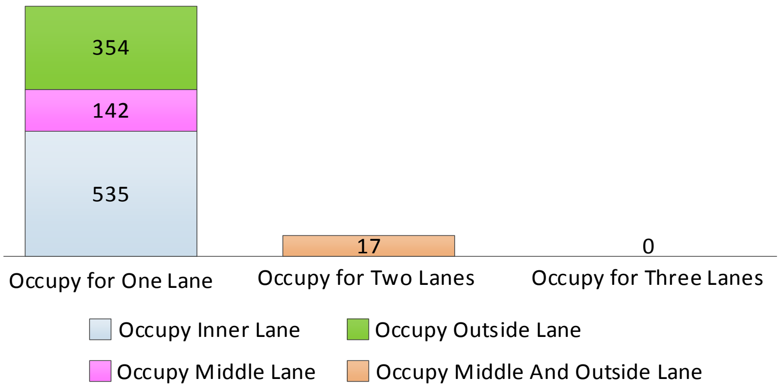

Fig. 7. Statistics of rear-end accidents where queuing is induced

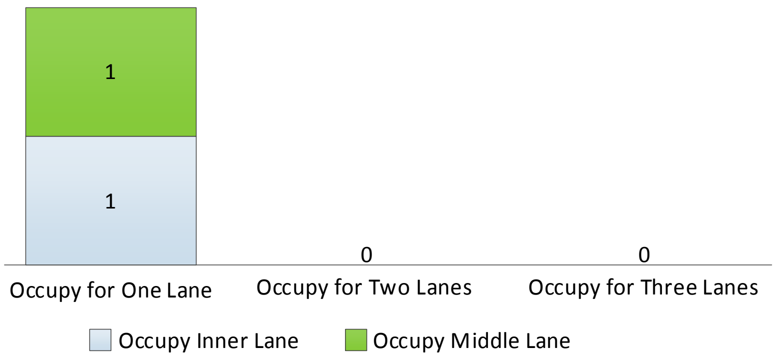

Fig. 8. Statistics of rear-end accidents where queuing is not induced

Tab. 6

Variable analysis for other accidents

Have Queuing Line	Not Have Queuing Line
201	3

Data Sources: Central Region Office, National Freeway Bureau, MOTC, Taiwan, 2016 [18]

4.2. Accident Prediction

The objective of the intelligent traffic information platform on the Freeway is to enhance the efficiency and safety of the Freeway, as depicted in Fig. 11. In this segment, the author aims to develop a predictive model for accidents on the Freeway by integrating traffic information such as accident records, current vehicle flows, and dynamic data on future vehicle fleet composition. Apart from providing real-time alerts for potential accidents, the platform has the potential to mitigate the risk of accidents for drivers. Furthermore, the information platform can be customized for emergency rescue efforts, thereby minimizing the time required to address accidents and subsequently diminishing the impact of accidents on the Freeway's overall efficiency.

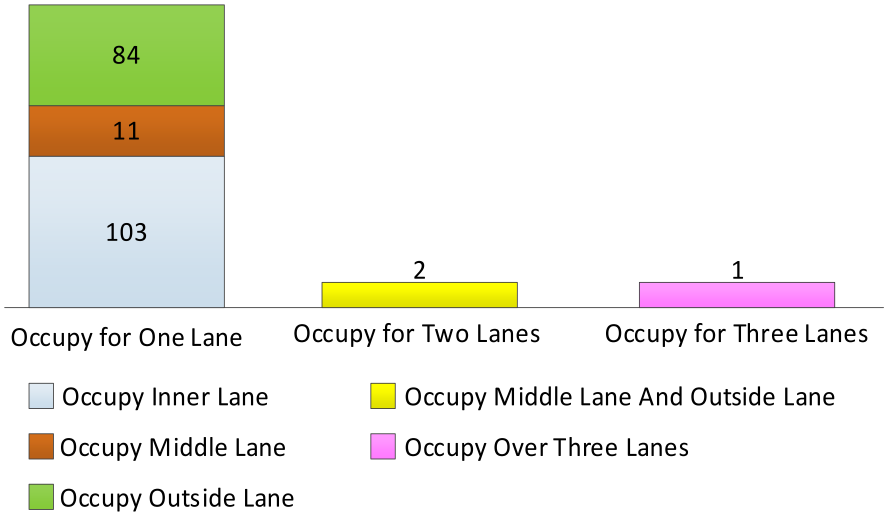

Fig. 9. Statistics of other accidents where queening is induced

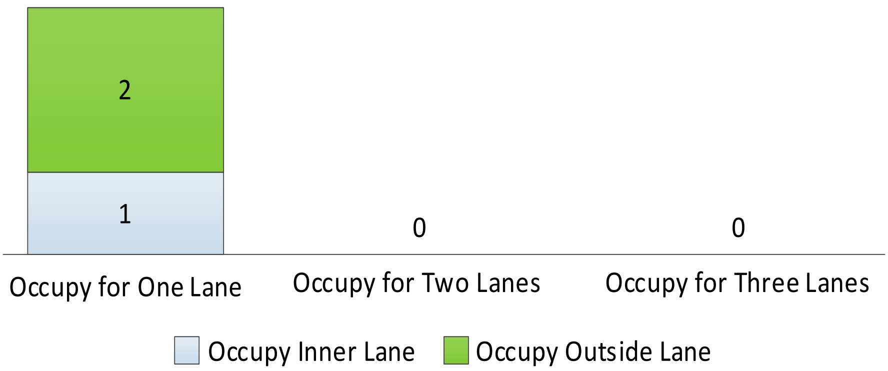

Fig. 10. Statistics of other accidents where queening is not induced

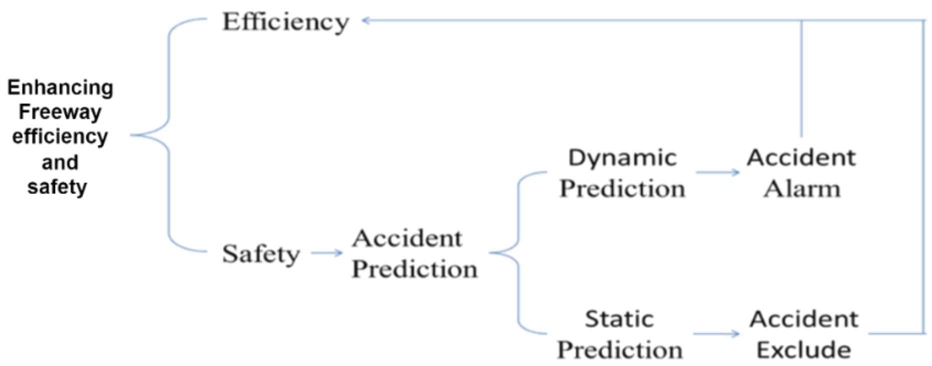

Fig. 11. Enhancing Freeway efficiency and safety with intelligent traffic information platform

This research focuses on the section of the Freeway between two interchange roads, using Empirical Bayes Estimation to calculate the total numbers and expected values of all accidents (Fig. 12), rear-end accidents (Fig. 13) and sideswipe accidents (Fig. 14) on individual sections of Freeway No.1. These findings will serve as a reference for allocating emergency vehicles.

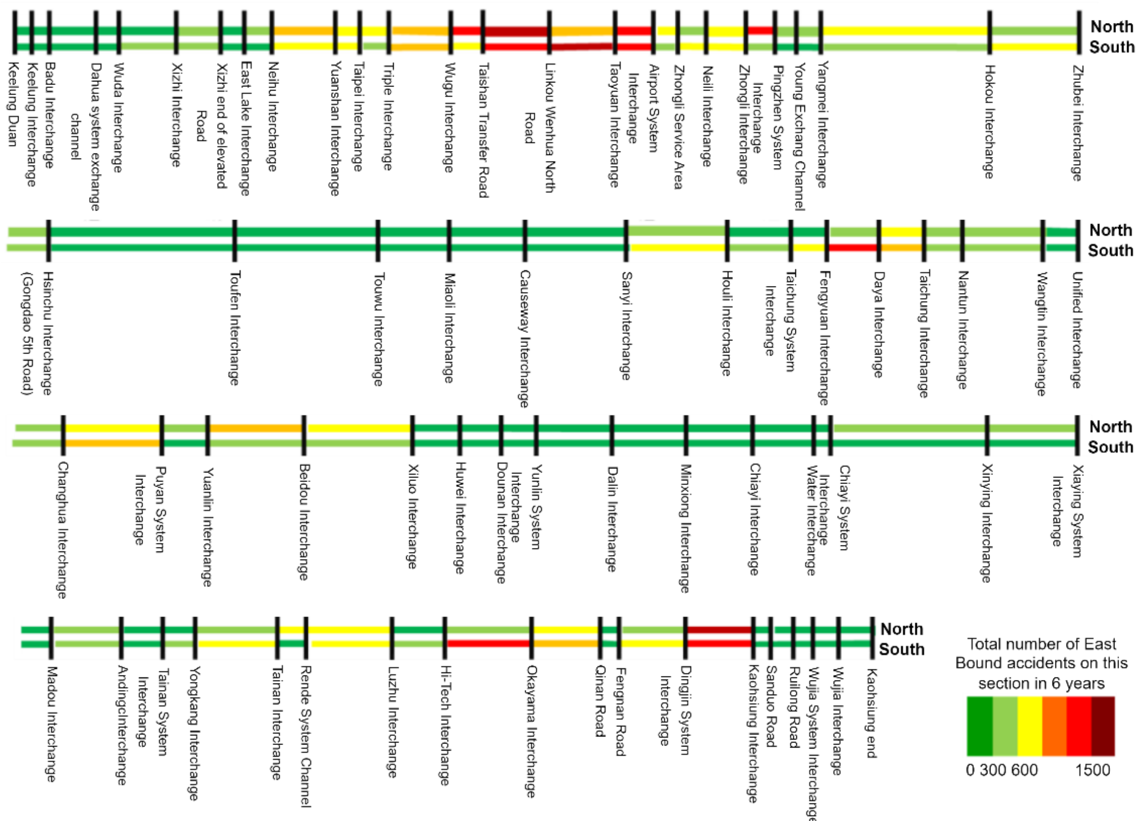

Fig. 12. Total number and expected value of all accidents on each section of Freeway No.1

To deliver immediate accident alerts to highway drivers, this research presents an accident prediction model developed from the accident warning system. While conventional studies commonly depend on dynamic traffic data, the distinct data essential for accident warnings cannot be substituted with OBU information. Consequently, this investigation is compelled to employ expressway vehicle flow data to initially evaluate the probability of accidents under various traffic conditions on each expressway segment. Subsequently, utilizing OBU data, the study identifies distinct causes of accidents within varied traffic flows, validating accident alerts tailored for different accident types.

Given the variation in accident warnings for different accident types, this section will initially focus on seeking warnings for rear-end accidents, as outlined in Tab. 7. The data necessary for analyzing rear-end accident warnings involve the speeds, longitudinal accelerations, and decelerations of both the leading and following vehicles. However, this data might not be obtainable through the existing OBU. While the OBU can gather information about the driver's position, vehicle speed, and even lateral and longitudinal accelerations and decelerations, it lacks the capability to collect data about the leading and following vehicles' positions, speeds, and related accelerations and decelerations. To confirm the accident warning, data from the driver's OBU alone is insufficient; information from surrounding vehicles is also essential. This necessity prompts the use of alternative methods to refine the accident warning system on the Freeway.

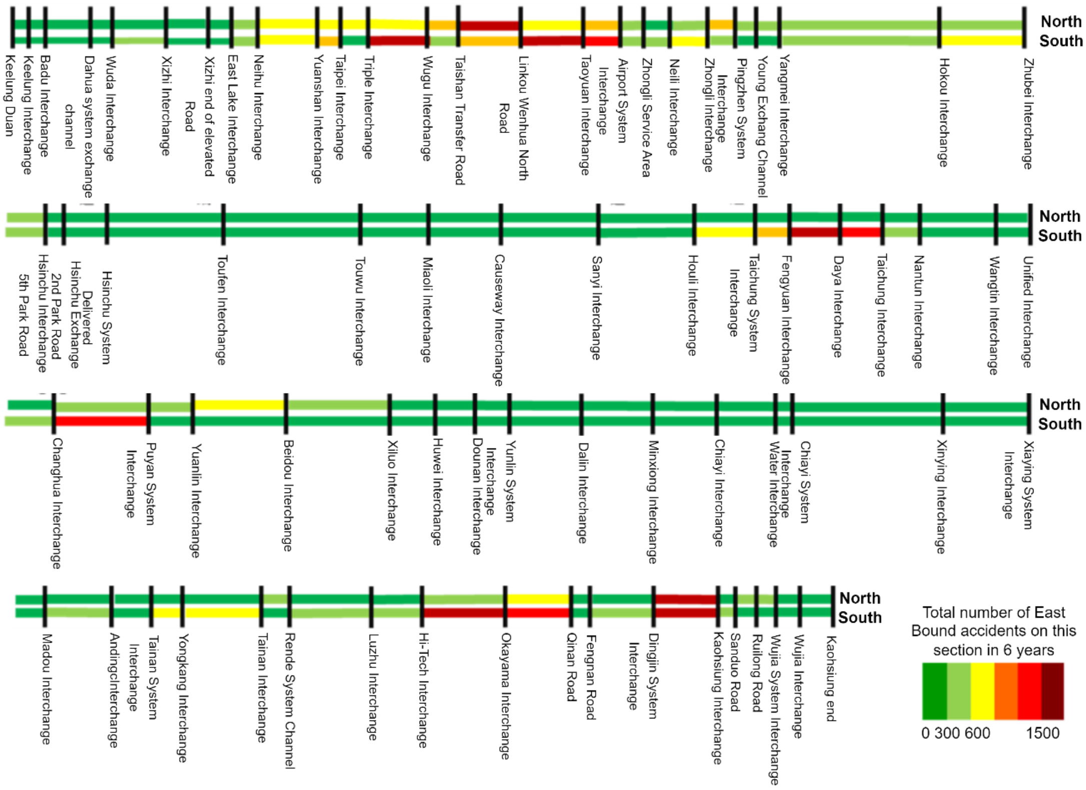

Fig. 13. Total number and expected value of rear-end accidents on each section of Freeway No.1

Tab. 7

The rear-end accident warnings

a	$V_f > V_l$			$V_f \leq V_l$		
	$a_l < 0$	$a_l = 0$	$a_l > 0$	$a_l < 0$	$a_l = 0$	$a_l > 0$
$a_f < 0$	P	C	C	P	C	P
$a_f = 0$	P	P	P	I	P	I
$a_f > 0$	P	C	C	I	C	I

Where:
V_f = the following vehicle speed;
a_f = the following vehicle longitudinal acceleration and deceleration;
V_l = the leading vehicle speed;
a_l = the leading vehicle longitudinal acceleration and deceleration;
P = Conflicts are likely to happen (Possible);
C = Conflicts happen (Conflict occur);
I = Conflicts are unlikely to happen (Impossible).

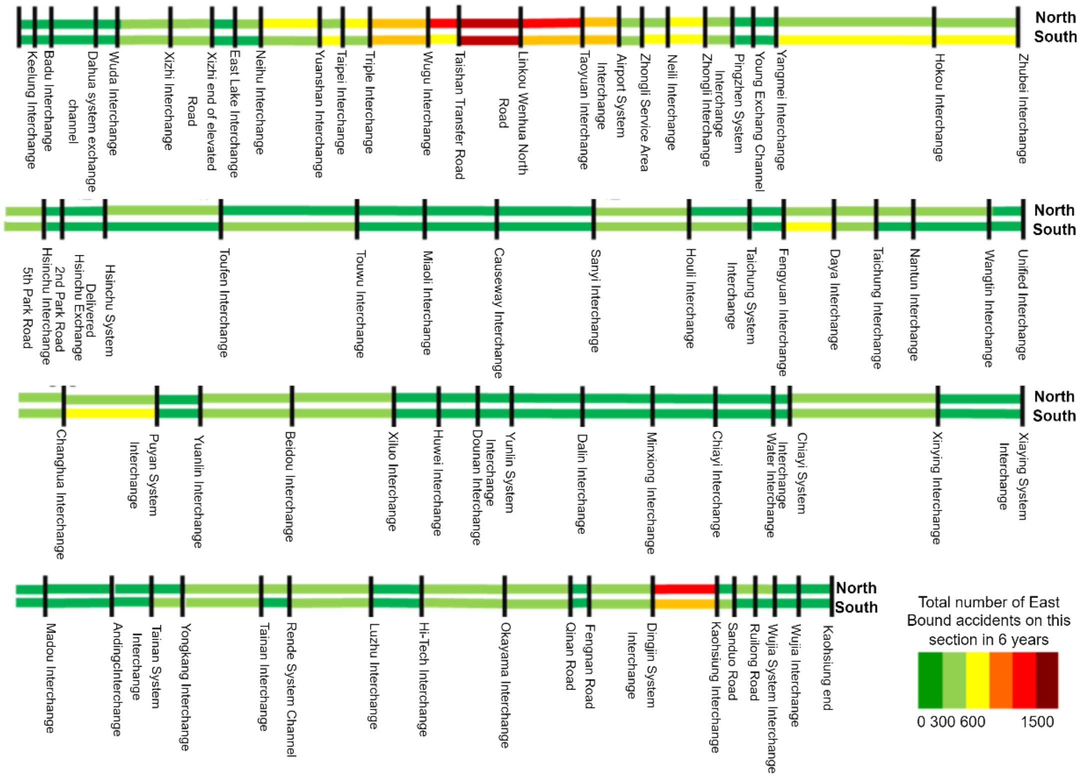

Fig. 14. Total number and expected value of sideswipe accidents on each section of Freeway No.1

4.3. Dispatch of the Rescue Vehicle

Dispatching a vehicle should be planned for system optimization after acquiring prediction data. The relationship between the required input data and the available output data is illustrated in Fig. 15. Input data encompasses existing data and prediction data. Existing data may consist of four items: (1) The location of each fleet branch; (2) The number of available vehicles in each fleet branch; (3) The relative distance between each fleet branch and the standby location. Notably, as prediction data cannot precisely determine the exact accident location, it can only predict the probability of accident occurrence in each section of the Freeway. In practical accident handling, vehicles may stand by at the entrance of interchange roads in the upstream section of the Freeway or passing bays within the Freeway section. Therefore, this study only estimates the relative distance based on the standby location. Additionally, (4) the relative time required can be calculated based on the relative distance and the vehicle speed.

Through the prediction results, this study can organize data into three items for further use by Planning Support Tools: (1) Estimating the time when an accident may occur; (2) Deriving available standby locations within the section of the Freeway; (3) Estimating or dispatching the number of vehicles required for accident handling based on the probability of accident occurrence.

The output data may include the four items: (1) The expected time of arrival indicates the time required for each fleet branch to arrive at the standby location; (2) The number of attending vehicles indicates the actual number of vehicles from each fleet branch attending the accident. The number of attending vehicles shall at least satisfy the need for vehicle evacuation from the accident; (3) The locations of departure indicate the locations of fleet branches where the attending vehicles come from; (4) Service routes shall indicate the routes from the fleet branches to the standby locations; (5) The support conditions indicate the conditions and numbers of available vehicles between the fleet branches.

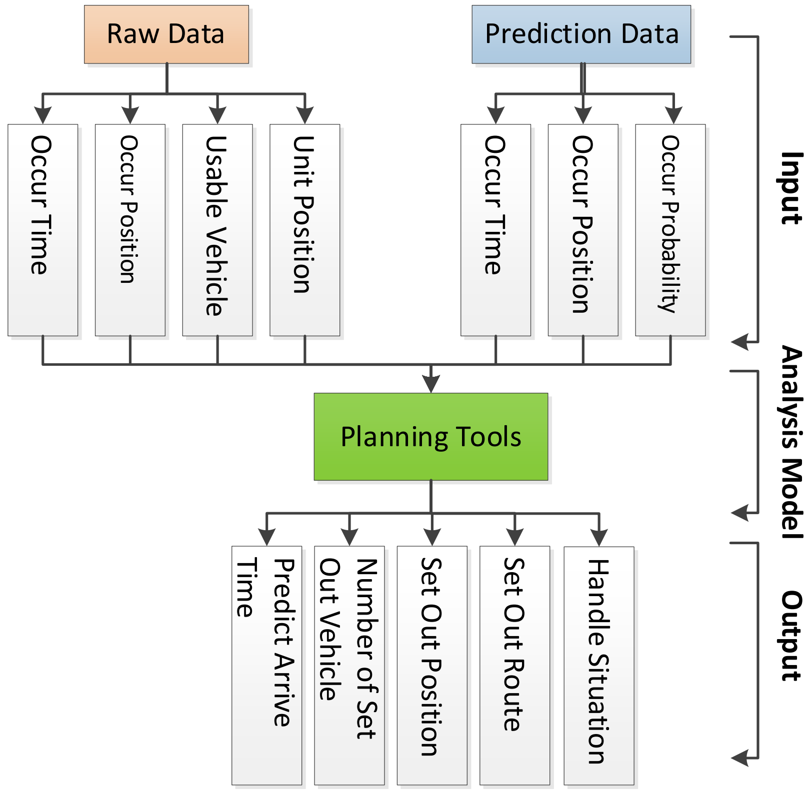

Fig. 15. The relationship between the input data and the output data

Freeway No. 1, from 165k to 207k (Taichung system-Puyan system), is the focus of analysis in this study. Along this stretch, there are eight interchange roads and two fleet branches associated with the National Freeway Police Stations. These are the Tainan fleet branch, responsible for National Freeway No. 1 from Sanyi interchange road to Nantun interchange road, and the Yuanlin fleet branch, overseeing National Freeway No. 1 from Nantun interchange road to Hsilo interchange road. Consequently, the author will provide further details on the background of the data.

Using mathematical planning models and network flows, this study will construct an optimized model for the deployment and dispatching of vehicles. The model will take into account various constraints, including the number of available vehicles from each fleet branch and the distance between the fleet branch and each section of the Freeway. The study will employ network effectively flows to identify vehicle movements in the spatial-temporal network, aiding in model development.

The flows of vehicles in the spatial-temporal network primarily serve to identify vehicle movements at a specific time and location, as illustrated in Fig. 16. A network layer represents the service route of a vehicle. If the numbers of available vehicles from two fleet branches are m and n, respectively, there will be a total of m+n network layers. The lateral axis denotes the distribution of spaces where vehicles might stop, including each fleet branch and each section of the Freeway, while the longitudinal axis represents a continuous time schedule.

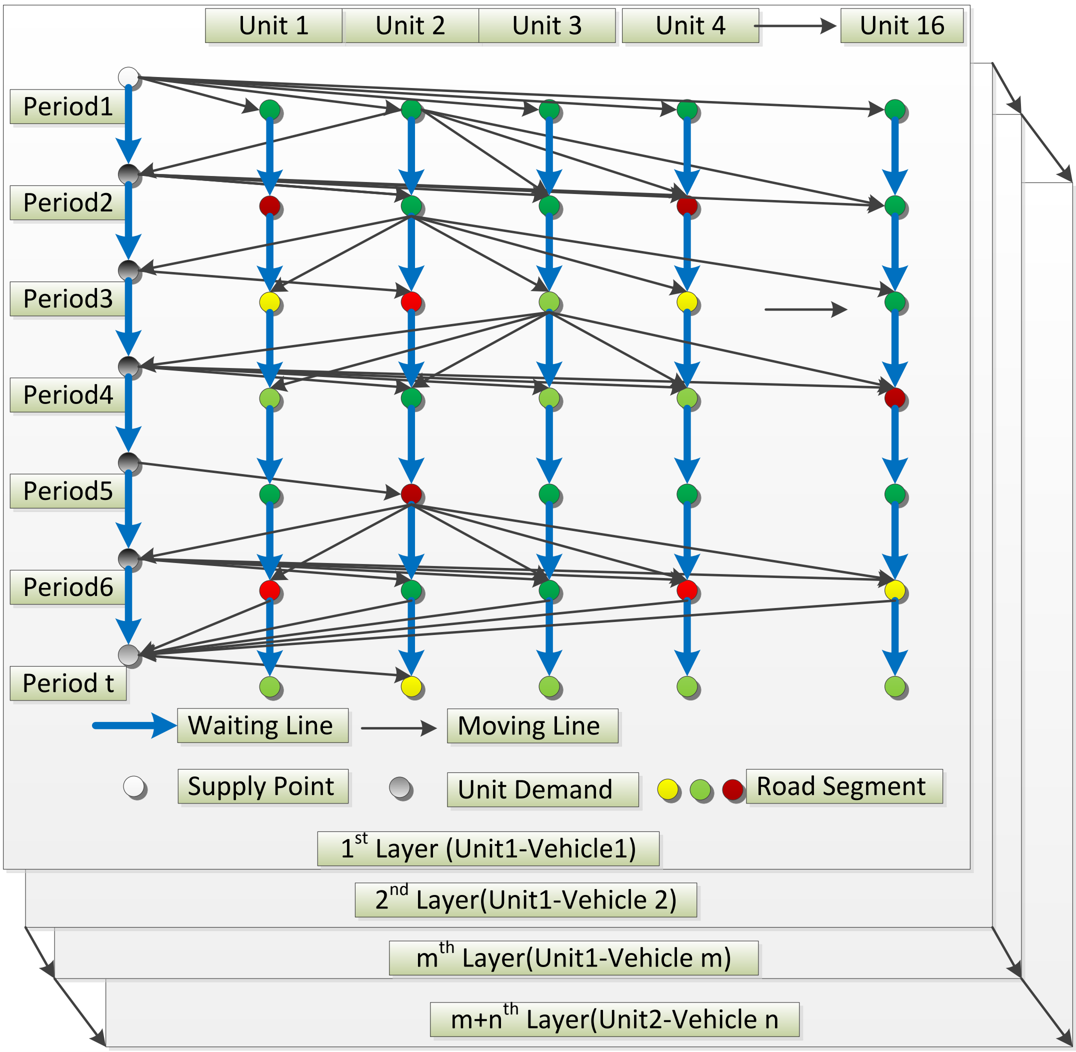

Fig. 16. The network diagram of vehicle evacuation due to an accident

The spaces between the nodes along the longitudinal axis indicate time intervals, such as 1 hour, 4 hours, 6 hours, or 12 hours. This study will use a 1-hour time interval for further planning. Planners can design an appropriate time interval to achieve accurate prediction results based on their future needs when using the model. The length of the network indicates the planning period's duration, the nodes in the network represent the spatial/temporal nodes of a vehicle at a specific time, and the nodal line indicates the vehicle's activities between two spatial/temporal nodes. The vehicle flow along the nodal line illustrates the vehicle's movement in its activities. The nodal line can be further divided into the vehicle stagnant nodal line and the vehicle moving nodal line, while the nodes can be further divided into the supply node, the demand node of the fleet branch, and the demand node of a section of the Freeway. Details of the two types of nodal lines and the three types of nodes are outlined as follows:

(1) The stagnant nodal line: The stagnant nodal line is the line extended downward from each spatial/temporal node, indicating that a vehicle remains stationary at a specific space point during a particular period. The cost of the stagnant nodal line is intentionally set to 0. It's worth mentioning that if the vehicle flow starts from the supply node, representing the

fleet branch, and ends at the demand node of the same fleet branch along the stagnant nodal line, it means the vehicle from the fleet branch is never put to use.

(2) The moving nodal line: The moving nodal line connects different spatial nodes, indicating the spatial-temporal flow of the vehicle. The cost of the moving nodal line is the cost of flow, typically set as the driving distance. Notably, the nodal line representing vehicle flow from the fleet branch into a section of the Freeway network moves at the same point in time, as the time interval required to travel from the fleet branch to the section of the Freeway is greater than the driving time. However, when a vehicle moves between sections on the Freeway or returns from a section to the fleet branch, it is considered as providing services at the next point in time. Therefore, the nodal line will be connected to the next point.

(3) Supply node: The first spatial/temporal node at each fleet branch position serves as the supply node of the network, with the supply amount set at 1.

(4) Nodes on the section of the Freeway: Different colors indicate different probabilities of accident occurrence.

(5) Demand node of the fleet branch: The final spatial/temporal node at each fleet branch position represents the demand node of the network, with the supply amount set at 1.

5. CONCLUSIONS

Regarding accident occurrence, Data Mining and preliminary statistical analysis have been completed. There are currently 6000 vehicles equipped with the OBU, with roughly 70 percent of them having been on the Freeway. Subsequently, approximately 100 vehicles that have traveled on National Freeway No. 1 (from Taichung system to Puyan system) were used for data analysis, incorporating information from their OBU, eTag data, and VD data, to understand changes in vehicle flow after an accident occurs.

This study primarily utilizes the expected number of accidents on Freeway No. 1 as a reference for emergency vehicle allocation. Initially, vehicle flow data (from VD) and accident data are combined to analyze the accident risk (such as rear-end accidents) associated with different states of vehicle flows. Subsequently, data from the OBU is employed to understand the driving behaviors exhibited by drivers in different states of vehicle flows and identify forewarnings for rear-end accidents. The ultimate goal is to establish a real-time Freeway accident risk prediction model, with warnings issued through a smart traffic information platform.

Concerning the dispatch of rescue vehicles, the preliminary construction of the spatial-temporal network based on vehicle flows has been completed. The next step involves establishing an optimized mathematical model for vehicle evacuation from accidents based on the spatial-temporal network of vehicle flows.

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