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# The Prediction of Freeway Traffic Conditions for Logistics Systems

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**ABSTRACT** With a steady increase in the number of vehicles predicted, traffic congestion has become a significant logistical challenge. The increase in traffic not only results in pollution and traffic congestion, but also leads to increased travel time and productivity loss. Thus, traffic prediction has become an important research topic in the academia. In fact, logistics managers are more concerned about predicting short-term traffic conditions than the accuracy of prediction. Therefore, this study used a discrete-time Markov chain and online traffic monitoring data to predict the probability of traffic congestion and identify the freeway bottlenecks. The findings of the study revealed the high probability of National Freeway 3's northern section being non-congested during the morning and afternoon rush hours. However, several bottlenecks were found in the links to nearby urban areas. The results of this study can not only facilitate logistics managers to optimize vehicle routes but can also support transportation control centers with regulating traffic flow in freeways during peak periods.

**INDEX TERMS** Discrete-time Markov chain, freeway traffic congestion, logistics management, short-term traffic prediction.

## I. INTRODUCTION

With an increase in the number of vehicles predicted, traffic congestion has become a significant challenge worldwide. In Taiwan, for example, there were 341 vehicles per 1,000 persons in 2018 [1]. The deterioration in traffic conditions makes countermeasures to mitigate the effects of increasing fuel consumption, travel time, pollution, traveler dissatisfaction, and productivity loss [2]. However, coping with traffic congestion by building more freeways or expanding the existing freeway network is not a valid solution because of budget and land constraints, as well as the corresponding increase in trips caused by capacity expansion. Hence, many researchers have focused on short-term traffic prediction [3], [4], an important research topic that is also the focus of this study, to determine an efficient approach to utilize the current traffic infrastructure [4]. The majority of recent research applies traffic monitoring data and time series and neural network (NN) approaches to fit the dynamic characteristic of transportation systems and traffic flow over a relatively short time period [5]. However, a previous study [4] indicated that traffic data possess stochastic, trend, and seasonality properties. Seasonality and trend can be obtained from long-term monitoring data, but the short-term data appears rather stochastic. Thus, these studies may be hindered by such data characteristics [4]. Additionally, the results of this research may disregard the systemic problems relevant to the basic need of logistic management, namely faster delivery, higher service level, and reliability [6]. In fact, logistics managers are more concerned about short-term traffic conditions than the accuracy of prediction [7], [8].

The objective of this study was to provide a process for predicting the probability of traffic congestion in the specific segment of freeway containing several consecutive links. The process applied the concept of probabilistic breakdown, which is based on discrete-time Markov chains (DTMC), to freeway segments since the probability of congestion at each link was defined by the concept of probabilistic breakdown. Additionally, the scope of the study comprised congestion caused by heavy traffic regardless of incidents, accidents, roadwork, and weather conditions.

This paper is organized as follows. Section 2 presents information about discrete-time Markov chains and open data

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on traffic congestion prediction. Section 3 summarizes the steps to obtain the data and analyze them. The results and discussion are presented in Section 4. Finally, summary and conclusion are provided at the end of this paper.

## II. BACKGROUND

### A. TRANSPORTATION IN LOGISTICS SYSTEMS

Rapid motorization and urbanization present significant challenges to logistics systems; hence, technologies and managerial strategies are being continuously developed and modified to provide customers with efficient service [7]. The production procedures rely on a logistics system to connect the disparate activities from manufacturing to delivery and returns from the customers [8]. Structured coordination of all the components in the value chain is essential for optimal efficiency. To this end, transportation becomes the key element in logistics systems and directly affects the total logistics costs [8]. In general, transportation is nearly half the total cost of logistics and amounts to 4%-10% of the product selling price [9].

Currently, an increasing number of companies implement the just-in-time (JIT) principles, which is deemed the solution for attaining quality breakthroughs, productivity advancement, and waste reduction [10]. Ideally, the JIT-supply based manufacturing system works on zero inventory. It is inevitable that smaller and more frequent orders, precise scheduling, and shortened lead times requested by customers can be hindered by the increasing traffic congestion in the streets and freeways [11]. Since traffic congestion causes delivery delays, it becomes very costly for logistics service providers and distribution firms to formulate diverse countermeasures, such as shifting warehouse location, redesigning shipment size, and shipping cargoes at night [12].

### B. DISCRETE-TIME MARKOV CHAIN

A Markov chain is a mathematical system that is widely used for both short- and long-term analysis of stochastic systems [13]. Theoretically, the statistical model is considered a stochastic characteristic that evolves over time with a definite probability. Additionally, the stochastic process can be considered as possessing the Markov property when it depends only on the previous state. The Markov model argues that the current state of the system evolves from the original state with time, and that the state transition can be displayed by a certain probability. Theorizing that the Markov chain has a countable stationary state, many researchers applied it to studying the evolution of material through a series of countable states [14].

The Markov chain is a discrete-time stochastic process [13] in which the conditional probability of transiting to the future event only depends on the current state and is unrelated to past states [14]. The stochastic process $X = X_t : t \geq 0$ with countable state S can be considered as a Markov chain for any state of $i, j \in S$ and t $\geq 0$ if

$$p_{ij} = P\left(X_{t+1} = j | X_t = i_t\right) \quad \text{for } i, j = 1, 2, \cdots, \text{m}, \quad \text{and } t = 1, 2, 3 \cdots \tag{1}$$

where $p_{ij}$ is the transition rate from state $i$ to state $j$ and m is the total number of possible states. On the other hand, the $p_{ij}$ is defined as the conditional probability of each specific transition and is determined by empirical evidence. At any state, however, the aggregate of all transition probabilities must be one, i.e., $\sum_{j\in S} p_{ij} = 1, i \in S$. Eq. (1) is based on the Markov chain property, which means that the future state $X_{t+1}$ can be established only by the current state $X_t \in S$ and is unrelated to all the other previous states, e.g. $X_0, X_1, \cdots, X_{t-1}$.

As aforementioned, S is a countable and finite state, which can be depicted as S $= \{S_1, S_2, \cdots, S_m\}$. In this context, transition matrix P comprises all transition probabilities and is displayed below.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \tag{2}$$

Here, P is the stochastic matrix and the aggregate of each row must be one [14].

The Markov chain model is established with state and transition matrix. If the initial moment at $t = 0$, the state probability matrix is $\Pi^0 \in S$. After the nth transition, the state probability of future state $\Pi^n$ can be computed using transition matrix P as follows.

$$\Pi^1 = \Pi^0 \times P$$
$$\Pi^2 = \Pi^1 \times P = \Pi^0 P^2$$

In this context, the transition can be derived as follows.

$$\Pi^{\text{n}} = \Pi^0 \times P^n \tag{3}$$

In the countable Markov process, the state matrix can be computed by utilizing the above formula [13]. This concept can be applied to the prediction of traffic conditions in freeways, as smooth traffic flow could be interrupted during rush hour and then recover during off-peak hours.

### C. OPEN DATA

This section is about the concept of open data that is published by the government and should be freely available to every organization, person, and company [15]. Additionally, the open data platform is defined as a repository that is used to manage and release data to users [9]. The purpose of releasing government-owned data is to better empower citizens, reform public service, enhance transparency, and foster innovation [16]. Hence, there are several advantages to open government data [17].

1) Developing new applications – by utilizing open data to deduce, link, cross-reference, and combine with other data from various sources, new applications can be developed and original knowledge can be obtained.

**TABLE 1.** ETC gantry location along national freeway 3.

| Link No. | | Gantry ID | | Distance |
|---|---|---|---|---|
| Southbound | Northbound | From | To | (km) |
| 1 | 5 | 03F0447 | 03F0498 | 4.9 |
| 2 | 4 | 03F0498 | 03F0525 | 3.3 |
| 3 | 3 | 03F0525 | 03F0559 | 3.7 |
| 4 | 2 | 03F0559 | 03F0648 | 8.4 |
| 5 | 1 | 03F0648 | 03F0698 | 5.5 |

2) Enhancing innovation – accessing open data encourages users to exploit, view holistically, and gain deep insight into the potential of the data.

3) Attaining feedback from external sources –users' ideas can be collected by way of a data interchange platform to reinforce internal analyses.

4) Increasing transparency – open data not only provides public control over government actions, but also increases trust in the government, thus contributing to greater satisfaction.

## III. METHOD

### A. DATA COLLECTION AND PRETREATMENT

In this study, data retrieved from the Ministry of Transportation and Communications ROC (http://tisvcloud.freeway.gov.tw/) were applied to develop a discrete-time Markov model (DTMM). The raw data were collected from numerous RFID based electronic toll collection (ETC) devices, which are placed in gantries and remotely read the electronic tags embedded in vehicles when they cross the gantry. Additionally, the identification information is preloaded into electronic tags; this mainly includes time interval, vehicle type, gantry number, traffic flow, and travel time. Then, the data are aggregated into five-minute intervals for each detector and are provided for route guide reference and Internet research. This study focused on the northern section of National Freeway 3. Therefore, the research data were collected from a 25.8 km segment between the Tucheng and Daxi junctions. Table 1 shows the gantry number and distance of the study area. The data for this study were collected over six months, from January 1 to June 30, 2019. This study extracted traffic flow ($flow_{sedan}$ *and* $flow_{van}$) and travel times of sedans ($TT_{sedan}$) and vans ($TT_{van}$) on weekdays, then calculated the total travel time ($S_{TT}$) and *Speed* using equations (4) and (5).

$$S_{TT}(min.) = \frac{\left(TT_{sedan} \times flow_{sedan} + TT_{van} \times flow_{van}\right)}{\left(\left(flow_{sedan} + flow_{van}\right) \times 60\right)} \tag{4}$$

$$Speed(\text{km/hr}) = Distanceofroute \times 60 \big/ S_{TT} \tag{5}$$

### B. DEFINITIONS OF TRAFFIC STATE AND VARIABLE

Naturally, traffic monitoring data are nonlinear and the daytime and nighttime traffic speed patterns vary (see Figure 1).

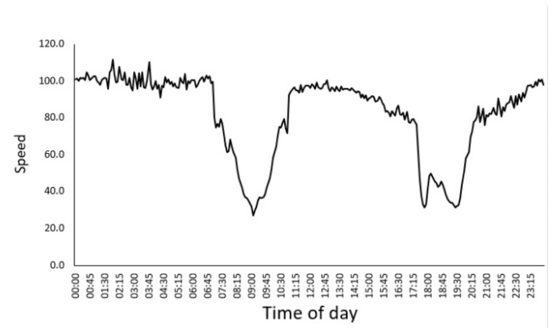



**FIGURE 1.** Traffic speed in link 1 on January 24, 2019.

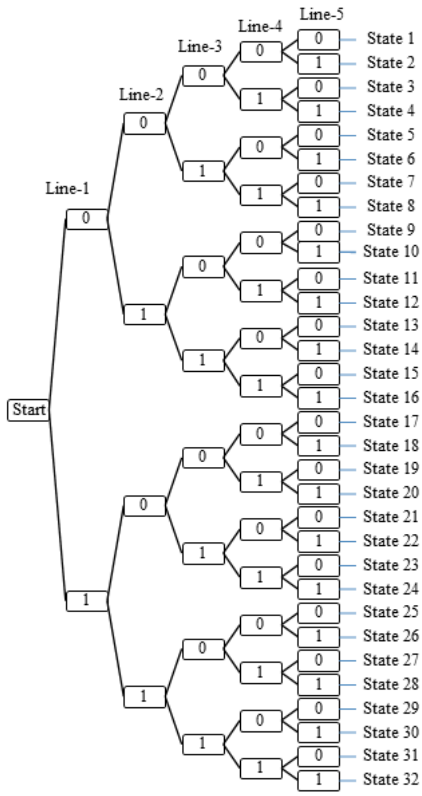


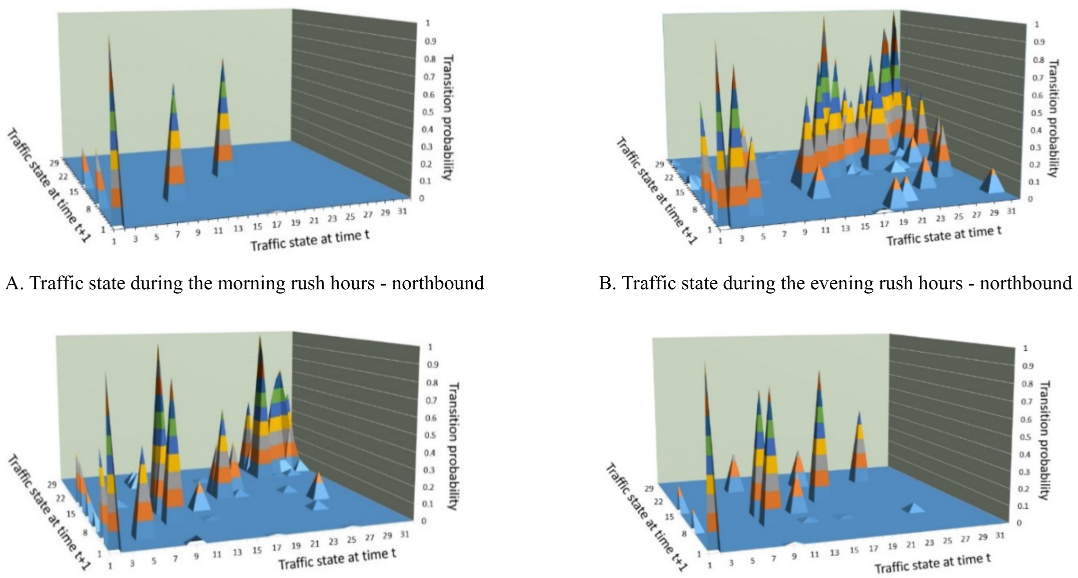

**FIGURE 2.** Illustration of traffic state.

Therefore, this study used the aforementioned dataset to examine the data from the morning (7:00 - 10:00) and evening (16:30 - 19:30) rush hours from link 1 to link 5, which are near the urban area of North Taiwan. This study intends to identify the bottlenecks and provide probability of traffic congestion to facilitate optimal vehicle route planning. Therefore, this study referenced a previous study [18] and set the traffic speed of 80 km/h (50 mph) as the threshold. The traffic was considered congested when speed dropped below 80 km/h for ten minutes, and the congestion was considered ended when the vehicle was in motion at a speed up to 80 km/h.

Additionally, a binary variable was utilized to define the traffic state: if a specific link of the freeway during an interval was congested, the traffic state was denoted as 1, otherwise it was 0. This study evaluated the traffic conditions in these

**TABLE 2. One-step transition matrix of southbound rush hour during A.M. rush-hour for line 1-5.**

| $X(t)$ | 1 | 5 | 9 | 13 | 17 | 19 | 25 | 26 | 27 | 28 | 29 | 30 | 31 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.92 | 0.5 | 0.11 | 0.17 | 0.3 | 0.330 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0.5 | 0 | 0 | 0.04 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0.05 | 0 | 0.83 | 0.5 | 0 | 0 | 0.09 | 0 | 0.08 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0.01 | 0.17 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 |
| 17 | 0.01 | 0 | 0 | 0 | 0.57 | 0.33 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0.04 | 0.33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0.01 | 0 | 0.05 | 0 | 0.04 | 0 | 0.84 | 1 | 0.15 | 0 | 0.2 | 0.5 | 0.08 |
| 26 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 27 | 0 | 0 | 0 | 0.17 | 0 | 0 | 0.01 | 0 | 0.54 | 0 | 0 | 0 | 0.15 |
| 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.08 | 0.67 | 0 | 0 | 0 |
| 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0.04 | 0 | 0.08 | 0 | 0.73 | 0 | 0.23 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.33 | 0 | 0.5 | 0 |
| 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.08 | 0 | 0.06 | 0 | 0.54 |
| Π | 0.47 | 0 | 0.26 | 0 | 0.02 | 0 | 0.19 | 0 | 0.01 | 0 | 0.04 | 0 | 0.01 |




A. Traffic state during the morning rush hours - northbound

B. Traffic state during the evening rush hours - northbound

C. Traffic state during the morning rush hours - southbound

D. Traffic state during the evening rush hours - southbound

**FIGURE 3. Three-dimensional view of the transition probability matrix.**

five links. Thus, 32 traffic states are derived and presented in Figure 2.

### *C. ASSESSMENT OF THE TRANSITION PROBABILITY MATRIX*

Using the defined traffic states, the congestion occurrences in these five southbound and northbound links during the morning and evening rush hours can be counted and the associated one-step transition matrices can be computed. For brevity, only portions of the southbound links in the morning peak period are shown in Table 2. In this study, the transition probability matrix displays the likelihood that a future state will follow the current state in the next five minutes. There is a diagonal probability trend in the matrix. The diagonal trend (inclination) indicates that the traffic state is likely to remain in the same or adjoining state. A higher probability indicates

**TABLE 3. Steady-state probability.**

| State | Southbound AM | Southbound PM | Northbound AM | Northbound PM |
|---|---|---|---|---|
| 1 | 0.47 | 0.86 | 0.96 | 0.43 |
| 2 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0.01 |
| 4 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0.01 |
| 6 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0.02 |
| 8 | 0 | 0 | 0 | 0 |
| 9 | 0.26 | 0.10 | 0.01 | 0 |
| 10 | 0 | 0 | 0 | 0 |
| 11 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0.01 |
| 14 | 0 | 0 | 0 | 0 |
| 15 | 0 | 0 | 0 | 0.01 |
| 16 | 0 | 0 | 0 | 0 |
| 17 | 0.02 | 0.03 | 0.03 | 0.05 |
| 18 | 0 | 0 | 0 | 0.04 |
| 19 | 0 | 0 | 0 | 0 |
| 20 | 0 | 0 | 0 | 0.01 |
| 21 | 0 | 0 | 0 | 0.01 |
| 22 | 0 | 0 | 0 | 0.01 |
| 23 | 0 | 0 | 0 | 0.03 |
| 24 | 0 | 0 | 0 | 0 |
| 25 | 0.19 | 0.01 | 0 | 0.06 |
| 26 | 0 | 0 | 0 | 0.01 |
| 27 | 0.01 | 0 | 0 | 0 |
| 28 | 0 | 0 | 0 | 0.03 |
| 29 | 0.04 | 0 | 0 | 0.10 |
| 30 | 0 | 0 | 0 | 0 |
| 31 | 0.01 | 0 | 0 | 0.15 |
| 32 | 0 | 0 | 0 | 0.01 |

that traffic is more likely to transition to that state if uncertain disruptions occur. Additionally, steady-state probabilities can be computed using Eq. (3), $\Pi^n = \Pi^0 \cdot P^n$. The steady-state probabilities are calculated by using library of Python, and whole results are shown in Table 3.

## IV. RESULTS AND DISCUSSION

### A. ONE-STEP TRANSITION PROBABILITY

In total, 7,640 data items, retrieved from the Ministry of Transportation and Communications website, were analyzed using the discrete-time Markov model. As shown in Table 2 and Figure 3, the one-step transition probability revealed the likelihood of a future state following the current state. Referring to Table 3, state 1 has the highest probability (0.92) to transit to the same state, which means southbound traffic is in motion at speeds over 80 km/h in links 1-5 when the initial traffic condition is non-congested during the morning rush hour.

To highlight the traffic conditions during various time periods and in the different travel directions, this study utilized a three-dimensional view to display the transition probability matrix (see Figure 3). Figure 3 C indicates the number of state evolution in the southbound route during the morning rush hours. It revealed that its traffic condition is more complex than the northbound route during the same period. Furthermore, the traffic states of the northbound route during the afternoon peak hours and the southbound route during the morning peak hours are more complex than the opposite directions' traffic states during the same periods.

### B. STEADY-STATE PROBABILITY

For insight into the traffic conditions in specific links, this study used the transition probability matrix to calculate steady-state probability. As shown in Table 3, state 1 during the various time periods and different travel directions all have the highest steady-state probability (0.47, 0.86, 0.96, and 0.43 respectively). The results imply that these traffic conditions in links 1-5 are non-congested. Conversely, state 17 in the southbound and northbound travel directions has a lower steady-state probability (0.02, 0.03, 0.03, and 0.05 respectively), which means that link 1 experiences traffic congestion rarely.

In the southbound direction, the steady-state probability of state 9 is 0.26 and 0.10 during the morning and evening rush hours respectively, while state 25 is 0.19 and 0.01 during the morning and evening rush hours respectively. The results indicate that southbound traffic breaks down easily in link 2 regardless of the rush hours. In the northbound travel direction, 16 transition states were found in the afternoon rush hours, which indicates that the traffic condition is most complex during the evening rush hours. However, traffic congestion rarely occurs in links 1-5 in both travel directions, because the steady-state probability of state 32 is very low (0 and 0.01 respectively).

### C. SUMMARY AND CONCLUSION

The purpose of this study was to provide logistics managers a set of probabilities of freeway traffic conditions using discrete-time Markov chains (DTMC), in which the traffic state evolved in five-minute intervals. The study found that the traffic condition of the freeway was contingent upon the time period and travel direction. However, obtaining and understanding reliable prediction of traffic conditions is crucial for optimal transportation routes and vehicle capacity utilization.

As shown by the results of this study, congestion often appears in the same freeway segments that are considered traffic bottlenecks. To improve logistics performance, logistics managers can adopt these results to formulate an appropriate travel scheme. However, there are existing strategies to avoid traffic congestion, for example, selecting alternative routes among various customers during rush hours, shipping cargoes at night, and rearranging the visit sequence of vehicles. Thus, these results combined with congestion avoidance strategies can be the foundation of a sound and customized travel plan.

The process of predicting probability of traffic conditions can be extended to logistics and supply chain management. For empirical application, this process can be a dynamic decision support system requiring access to data from government websites. The prediction process will provide decision-makers with real-time information. However, the results and findings of this paper are limited in scope as they use partial traffic data from a segment of National Freeway 3. Hence, our future research will utilize this prediction process to investigate other freeway segments, and the discrepancy in the probability of traffic congestion can be a basis to determine the traffic bottlenecks.

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