附件一

行政院國家科學委員會補助專題研究計畫 ☑成果報告 □期中進度報告

應用車輛辨識系統提昇起迄旅次矩陣推估之研究 (III/III)

Application of Automatic Vehicle Identification System to Enhance the Estimation of O-D Matrices (III/III)

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摘　要

本計畫分為三個研究年期進行。其中，第一年期旨在應用車輛辨識系統（automatic vehicle identification, AVI）提昇靜態起迄旅次矩陣之推估。第二年期則在旨在結合格位傳遞理論（cell transmission model, CTM）及卡門濾波理論（extended Kalman filtering, EKF），提出一個整合型動態起迄矩陣反覆推估方法。第三年期除整合前兩年期之研究成果外，亦進一步利用交通型態分群及遺傳規劃模式（genetic programming, GP）進行入口匝道交通量之中長期預測，俾利動態起迄旅次矩陣之推估。此三年研究成果摘述如下：

第一年期旨在應用車輛辨識系統（automatic vehicle identification, AVI）提昇靜態起迄旅次矩陣之推估。車牌辨識系統（license plate recognition system, LPR）是 AVI 的一種技術，其隨著影像辨識技術之成熟。該系統可用於自動辨識車牌號碼，並加以儲存、比對及處理。如在高速公路上部分路段加以設置，即可比對各通過車輛之實際行駛路段，相較於路段偵測器可提供更多起迄流量推估之所需資訊。基此，本研究建構一雙層數學規劃模式。其中，上層以設置成本、起迄旅次推估誤差率及隱私權侵犯等最小化為目標，決策變數為 LPR 之設置區位。下層模式則依據上層設置 LPR 區位所能提供之交通資訊，進行靜態起迄旅次推估。最後，利用遺傳演算法進行模式求解。為驗證本模式之有效性與應用性，分別應用於簡例及實例（中山高）。結果均顯示 LPR 最佳設置區位位於路網兩端及中間流量較高之區段。次佳區位則會選擇設在流量較低區段，以減少隱私權之侵犯。

第二年期旨在結合格位傳遞理論（cell transmission model, CTM）及卡門濾波理論（extended Kalman filtering, EKF），提出一個整合型動態起迄矩陣反覆推估方法。其中，CTM 為一中觀車流模擬方法，可用以精確且迅速地推估上匝道車流至目的地匝道之到達時間與分佈型態，並將其輸入 EKF 進行該時段之起迄矩陣推估。而推估所得之起迄矩陣則進一步再代入 CTM 重新模擬其到達型態，如此反覆以致收斂為止。為驗證本模式之有效性與應用性，分別應用於簡例及實例（中山高北部路段）。結果顯示，在簡例驗證上，本模式可達到相當精確之成果，其 RMSE 可達 0.0414。但在實例應用時，則 RMSE 值則較高，顯示仍存有相當程度之改善空間。基此，本計畫後續將進一步進行本演算法之改良，以作為下一研究年度進一步與車牌辨識系統結合之基礎。

第三年期進一步提出一套高速公路入口匝道交通量之中長期預測兩階段模式。本模式利用 K-means 演算法先進行交通型態分群（traffic pattern clustering），再利用遺傳規劃模式（genetic programming, GP）建構各群之交通量預測模式。最後進一步整合第一年期及第二年期之研究成果，進行動態起迄旅次矩陣之推估。為驗證本模式之可行性，本研究利用中山高頭份至北斗交流道間之路段進行實例驗證，結果證明本研究所提模式可精確預測上匝道交通量，以及動態起迄矩陣。

關鍵字：動態起迄旅次矩陣推估、車牌辨識系統、格位傳遞模式、卡門濾波、遺傳規劃

Abstract

This project covers three research years. The first research year is to apply the technique of automatic vehicle identification (AVI) to enhance the estimation of OD matrices. License plate recognition system (LPR) is one of the most popular and mature AVI techniques, which can efficiently identify, store and match license plate numbers of passing vehicles to provide partial trail information for the estimation of O-D matrices. The second research year of this project aims to propose an integrated algorithm by hybridizing cell transmission model (CTM) and extended Kalman filtering (EKF) to estimate arrival distribution and O-D proportions respectively and iteratively. In the third research year, a novel approach is proposed to estimate medium-to-long term freeway on ramp traffic which is then used to estimate dynamic origin-destination (O-D) matrices by integrating the proposed models in the previous research years. The research results are briefly introduced below:

The first research year is to apply the technique of LPR technology to enhance the estimation of OD matrices. Based on this, this study proposes a bi-level multi-objective programming model to determine the optimal locations of LPR by minimizing three objectives: error rate of estimated O-D matrix, LPR installation cost and privacy invaded. Due to the combinatorial characteristics of this problem, genetic algorithm (GA) is employed to solve the optimal locations of LPR. A pseudoinverse technique is further used to estimate the O-D matrix based on the information provided by loop detectors at roadway segments as well as by LPR installed at some selected locations. These extra traffic equations are derived from a pairwise comparison of the recognized license plate numbers between any two arbitrary LPR. To investigate the applicability and effectiveness of our proposed model and solving algorithms, one exemplified example and one field case study (Taiwan No.1 freeway) are conducted. The results consistently show that the optimal locations of LPR would be at both ends and middle of a series of the segments with heavy link traffic, should a relative small number of LPR be installed. For wider coverage, additional LPR may be installed at the segments with light link traffic to account for the privacy invasion.

The second research year of this project aims to propose an integrated algorithm by hybridizing cell transmission model (CTM) and extended Kalman filtering (EKF) to estimate arrival distribution and O-D proportions respectively and iteratively. An exemplified example of a freeway corridor are used to investigate the capability of CTM in replicating traffic dispersion phenomenon. Results show that CTM can accurately capture the traffic dispersion under various traffic conditions. The degree of traffic dispersion gets large as traffic flow increases. To demonstrate the applicability of the proposed estimation algorithm, a case study of Taiwan No.1 Freeway is conducted. Results show that the proposed algorithm can estimate the O-D proportion with a low average RMSE of 0.0414.

In the third research year, we propose a novel approach to estimate medium-to-long term freeway dynamic origin-destination (O-D) matrices. The proposed approach includes a two-stage prediction model with an integrated algorithm. The two-stage prediction model uses K-means algorithm to extract clusters of traffic patterns and then employs genetic programming to predict the traffic in each cluster. The integrated algorithm combines cell transmission model with extended Kalman filtering to estimate the arrival distributions and the O-D proportions. To demonstrate the applicability of the proposed approach, a field study of on-ramp traffic patterns on a freeway is examined. The results show that the proposed approach can accurately predict the traffic and satisfactorily estimate the O-D proportions along a freeway.

Keywords: Dynamic origin-destination matrices estimation, License plate recognition, Cell transmission model, Kalman filtering model, Genetic programming.

1. INTRODUCTION

Accurate dynamic origin-destination (O-D) information is essential for implementing real-time traffic control applications, such as route guidance and ramp metering. Over the past two decades, some researchers have devoted to develop the estimation algorithms for the dynamic O-D matrices based on observable mainline and ramp flow rates (*e.g.* Chang and Wu, 1994; Chang and Tao, 1996, 1999; Lin and Chang, 2005, 2007); while some others have introduced additional assumptions or exogenous information, such as route choice behaviors, prior O-D matrix information, and sequence of observational periods of traffic counts data, while estimating the dynamic O-D matrices (e.g. Bell, 1983, 1991; Yang *et al.*, 1992, 1995; Lo *et al.*, 1996; Hazelton, 2001). Yet estimation of dynamic O-D matrices still remains challenging in that the number of estimated parameters is far greater than the available information. To tackle this challenge, Chang and Wu (1994) subjectively assumed that the vehicles entering a freeway in a specific time interval are distributed within a small range (i.e., two time intervals). This assumption certainly limits the applicability and accuracy of the algorithms. Some previous studies (e.g. Chang and Wu, 1994; Chang and Tao, 1996; Lin and Chang, 2005, 2007) also made subjective assumptions on traffic arrival distributions, which are not valid for various traffic conditions from free-flow to gridlock.

In view of the importance of arrival distribution prediction in estimating the O-D matrices and the essence of estimation efficiency for real-time applications, more recently, Chiou *et al.* (2010) have proposed an integrated algorithm which combined cell transmission model (CTM) with extended Kalman filtering (EKF) to respectively and iteratively estimate the arrival distributions and O-D proportions. Firstly introduced by Daganzo (1994), the CTM can efficiently simulate traffic hydrodynamics under various traffic conditions. However, the arrival distribution estimations using CTM are based on an unrealistic assumption that the on-ramp traffic along a freeway remains unchanged over time. To rectify this unrealistic assumption, a medium-to-long term (e.g. next two to four hours) prediction model of on-ramp traffic along a freeway is required.

Most of the existing traffic prediction models use statistical methods or artificial intelligent methods to conduct a short-term prediction (e.g. next 5 minutes). Such short-term prediction models may experience low performance for medium-to-long term traffic prediction since traffic patterns can change dramatically (e.g., from peak hours to off-peak and vice versa). According to field observation, daily traffic patterns do repeat spatially and temporally over and over again. To enhance the prediction performance for a medium-to-long term traffic, this paper proposes a novel approach, which includes a two-stage prediction model with K-means algorithm to extract clusters of traffic patterns and a genetic programming (GP) to predict the traffic for each cluster separately. In the prediction process, 10 hours of historical traffic data are collected and used to identify the similar cluster of traffic patterns. The input values of learned GP model belonging to that cluster are used to predict the subsequent two hours. With the predicted medium-to-long on-ramp traffic, CTM is used to simulate the arrival patterns. EKF is then employed to estimate the O-D proportions. To validate the accuracy and applicability of the proposed approach, an empirical study on a freeway is examined.

The remainder of this paper is organized as follows. Section 2 gives the definition of the problem, variables and related parameters. Section 3 introduces the framework, the traffic prediction model, the CTM arrival distribution model, and the EKF O-D matrices estimation. A freeway corridor with 15 interchanges is conducted to demonstrate the applicability and performance of the proposed approach in Section 4. Finally, concluding remarks and suggestions for future research are discussed.

2. PROBLEM DEFINITION

Consider a typical linear freeway corridor with N segments, coding 0 to N-1, as shown in Figure 1. Assume that detectors are installed at all on-ramps, off-ramps, and mainline links. The information that is readily available for estimation of dynamic O-D distribution is the time series of entering flow, $q_i(k)$, exiting flow, $y_j(k)$, and mainline flow, $U_l(k)$. The notations used in this paper are defined in Table 1.

Table 1 Definition of variables and parameters

Variables/ parameters	Definition
$q_0(k)$	The number of vehicles entering the upstream boundary of the freeway section during time interval *k*.
$q_i(k)$	The number of vehicles entering freeway from on-ramp *i* during time interval *k*, $i = 1,2,\ldots, N - 1$.
$y_j(k)$	The number of vehicles leaving freeway from off-ramp *j* during time interval *k*, $j = 1,2,\ldots, N - 1$.
$y_N(k)$	The mainline volume at the downstream end of the freeway section during time interval *k*.
$U_i(k)$	The number of vehicles crossing the upstream boundary of segment *i* during time interval *k*, $i = 1,2,\ldots, N - 1$.
$T_{ij}(k)$	The number of vehicles entering the freeway from on-ramp *i* during time interval *k* that are destined to off-ramp *j*, where $0 \le i < j \le N$.
t_0	The length of one unit time interval.
$b_{ij}(k)$	The proportion of $q_i(k)$ heading toward destination node *j* during time interval *k*.
$\rho_{ij}^{m}(k)$	The fraction of $T_{ij}(k\text{-}m)$ vehicles departing from entry node *i* during time interval *k* that takes *m* time intervals to exiting node *j*.
$\rho_{ilj}^{m}(k)$	The fraction of $T_{ij}(k\text{-}m)$ trips from entry node *i* during time interval *k* that takes *m* time intervals to mainline node.

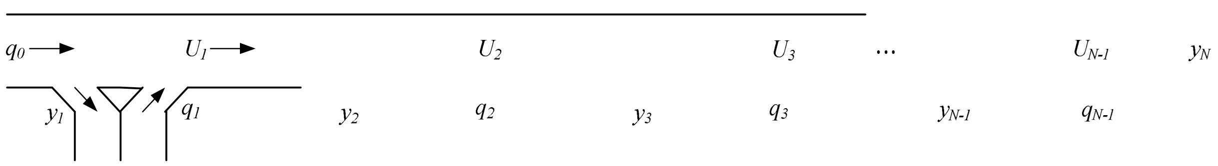


Figure 1 A typical linear freeway corridor

The relation between the dynamic O-D pattern and resulting link flow can be expressed by equations (Lin and Chang, 2007):

$$q_i(k) = \sum_{j=i+1}^{N} T_{ij}(k), \qquad i = 0,1,\ldots, N-1 \tag{1}$$

$$T_{ij}(k) = q_i(k) \cdot b_{ij}(k), \qquad 0 \le i < j \le N \tag{2}$$

The above two equations are subjected to the following natural constraints:

$$0 \le b_{ij}(k) \le 1, \qquad 0 \le i < j \le N \tag{3}$$

$$\sum_{j=i+1}^{N} b_{ij}(k) = 1 \qquad i = 0,1,2,\ldots N-1 \tag{4}$$

Consider the speed variation among drivers, it is reasonable to assume that the travel time of vehicles from node *i* to node *j* during time interval *k* are distributed among time intervals *k*-*M*,…, *k*-1, and *k* where *M* is the maximum number of intervals required for vehicles to traverse the entire freeway section. The traffic volume leaving freeway from off-ramp *j*, $y_j(k)$, can thus be expressed as

$$y_j(k) = \sum_{m=0}^{M}\sum_{i=0}^{j-1} q_i(k-m)\cdot\rho_{ij}^{m}(k)\cdot b_{ij}(k-m) \quad (5)$$

$$U_l(k) - q_l(k) = \sum_{m=0}^{M}\sum_{i=0}^{j-1}\sum_{j=l+1}^{N}\left[q_i(k-m)\rho_{il}^{m}(k)\right]b_{ij}(k-m) \quad (6)$$

where $\rho_{ij}^{m}(k)$ shall satisfy the following relations:

$$0 \le \rho_{ij}^{m}(k) \le 1, \quad 0 \le i \le j \le N, \quad m = 0,1,\ldots,M \quad (7)$$

$$\sum_{m=0}^{M}\rho_{ij}^{m}(k+m) = 1, \ \ 0 \le i < j \le N \quad (8)$$

Obviously, the system formulation has a large number of state parameters, *i.e.*, $b_{ij}(k)$ and $\rho_{ij}^{m}(k)$. The number of these unknown parameters increases with the necessary *M* value. As such, some more information is required to ensure this proposed model to be computationally efficient and tractable.

To deal with the large number of unknown parameters, Chang and Wu (1994) simplified the formulations by assuming that the speeds of vehicles entering the freeway at the same time interval are distributed in a small range. Therefore, Eqs. (5) and (6) can be rewritten as

$$y_j(k) = \sum_{i=0}^{j-1}\left[q_i(k-t_{ij}^{+}(k))\right]\theta_{ij}^{+}(k)b_{ij}(k-t_{ij}^{+}(k))) + \sum_{i=0}^{j-1}\left[q_i(k-t_{ij}^{-}(k))\right]\theta_{ij}^{-}(k)b_{ij}(k-t_{ij}^{-}(k))) \quad (9)$$

$$U_l - q_l(k) = \sum_{i=0}^{l-1}\sum_{j=l+1}^{N}\left[q_i(k-t_{ij}^{+}(k))\right]\theta_{ij}^{+}(k)b_{ij}(k-t_{ij}^{+}(k))) + \sum_{i=0}^{j-1}\left[q_i(k-t_{ij}^{-}(k))\right]\theta_{ij}^{-}(k)b_{ij}(k-t_{ij}^{-}(k))) \quad (10)$$

By simplifying the formulation as Eqs. (9) and (10), the number of unknown parameters reduces from (M + 1)N(N + 1)/2 to 3N(N + 1)/2. However, if the target freeway corridor is sufficiently long and experiences moderate congestion, the speeds of vehicles for the same O-D may vary in a wide range. Then, Eqs. (9) and (10) are not adequate for capturing all complex interrelations between traffic flows and O-D patterns. To deal with these limitations, Lin and Chang (2005) proposed a new set of generalized formulations by employing a distribution to represent the potential variation of travel times among drivers due to the impact of congestion and due to the difference in their desired speeds. They assumed that the travel time of drivers departing from node *i* during time interval *k* to node *j* follow a specific distribution. Since the travel times for the same O-D pair drivers departing during the same time interval follow a distribution, Lin and Chang (2005) replaced $\rho_{ij}^{m}(k)$ with a cumulative density function for one time interval as follows:

$$\rho_{ij}^{m}(k) = \int_{m\cdot t_0}^{(m+1)t_0} f_{ij}^{m}(x)dx \quad (11)$$

By applying the above travel time distribution concept, the relationships between ramp volumes and O-D proportions can be rewritten as:

$$y_j(k) = \sum_{m=0}^{M} \sum_{i=0}^{j-1} q_i(k-m) \cdot \rho_{ij}^{m}(k) \cdot b_{ij}(k-m)$$

$$= \sum_{m=0}^{M} \sum_{i=0}^{j-1} q_i(k-m) \cdot \left[\int_{m \cdot t_0}^{(m+1)t_0} f_{ij}^{m}(x)dx \right] \cdot b_{ij}(k-m) \quad (12)$$

$$U_l(k) - q_l(k) = \sum_{m=0}^{M} \sum_{i=0}^{j-1} \sum_{j=l+1}^{N} \left[q_i(k-m) \rho_{il}^{m}(k) \right] b_{ij}(k-m)$$

$$= \sum_{m=0}^{M} \sum_{i=0}^{j-1} \sum_{j=l+1}^{N} q_i(k-m) \left[\int_{m \cdot t_0}^{(m+1)t_0} f_{ij}^{m}(x)dx \right] b_{ij}(k-m) \quad (13)$$

Compared to Chang and Wu (1994), the number of unknown parameters for Eqs. (12) and (13) has reduced from 3N(N + 1)/2 to 2N(N + 1)/2. On the other hand, Lin and Chang (2005) represented the different speeds of vehicles for the same O-D pair with a distribution of travel time.

Although the relevant studies (e.g. Chang and Wu, 1994; Chang and Tao, 1995; Lin and Chang, 2005, 2007) have shed light on the dynamic OD matrices estimation, most of them made subjectively assumptions regarding arrival distributions, which may not be valid for various conditions from free-flow to gridlock. In addition, most of these models are too complex, causing low efficiency in estimation. In view of the importance of the arrival distribution prediction and the estimation efficiency required for real-time implementation, this study aims to develop a model that can accurate capture the traffic hydrodynamics under various traffic conditions in an efficient manner.

3. THE PROPOSED FRAMEWORK

Figure 2 presents the detailed framework of the proposed approach. Throughout the prediction process, K-means algorithm is used to cluster traffic patterns and genetic programming (GP) is used to predict traffic information. Moreover, CTM is used to simulate the arrival patterns and EKF is used to estimate the O-D proportions.

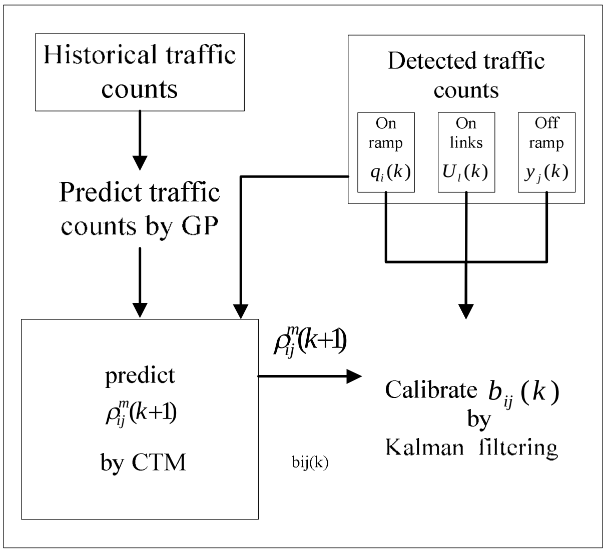


Figure 2. Framework of the proposed approach

To replicate traffic behaviors by CTM, traffic demand of each OD pair has to be given in advance. That is, a set of $b_{ij}(k)$ has to be determined and used to assign the detected on-ramp traffics to different downstream interchanges. Once the arrival distributions of all entering traffic have been successfully simulated, $\rho_{ij}^m(k)$ can be computed and used to calibrate the O-D proportions of entering traffic $q_i(k)$ by EKF, namely $b_{ij}'(k)$. Then, the new O-D proportions $b_{ij}'(k)$ will be used to replicate a revised arrival distribution $\rho_{ij}^{m}{}'(k)$ in an iterative manner. The proposed algorithm for estimating dynamic O-D matrices is depicted in Figure 3.

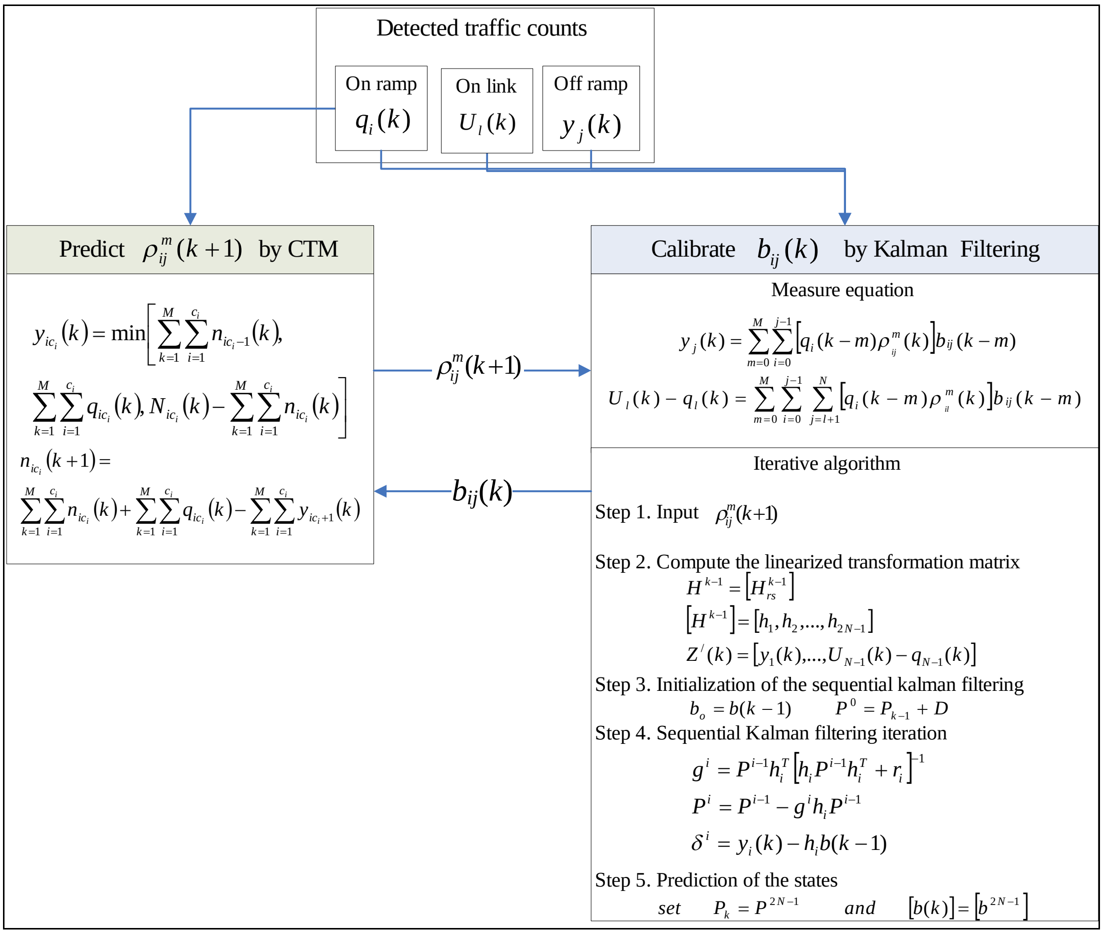


Figure 3 Framework of the proposed algorithm

From Figures 2 and 3, there are three sub-models in the proposed framework: traffic prediction model, cell-based traffic arrival pattern distribution model, and extended Kalman filtering model, each of which are described in the following sections, respectively.

4. TWO-STAGE TRAFFIC PREDICTION MODEL

Although numerous studies have employed various methods to predict traffic flows, such as the statistical time-series or regression model (Chang and Miaou, 1999), Sequential Learning model (Chen, 2001), Artificial Neural network (Dia, 2001), Kalman Filtering model (Okutani, 1984), and Grey Prediction model (Chiou *et al.*, 2007). However, most of these studies mainly focused on short-term traffic prediction under the assumption that the traffic pattern will remain unchanged. In this case, the traffic flow for medium-to-long term traffic periods may significantly differ from previous short-term traffic periods, hence the mentioned prediction models are inapplicable. In Taiwan's case, to stimulate the arrival distribution of traffic flow from Taipei to Kaohsiung, on-ramp freeway traffic for the next four to six hours must be effectively and efficiently predicted. Hence, medium-to-long term traffic prediction becomes necessary.

According to our field observations, traffic pattern did repeat spatially and temporally over and over again. In order to simplify the prediction process, past historical traffic flows (a week or a month) are divided into sufficient long traffic periods which will allow a specific pattern to be recognized (e.g. twelve hours) with a rolling horizon concept. These traffic periods are then classified into several clusters so that the traffic period in each cluster will exhibit a similar pattern. Finally, genetic programming (GP) is employed to develop a traffic prediction model for each cluster separately. Thus, two-stage traffic prediction model is proposed in this study.

With respect to the nature of traffic patterns which may repeat spatially and temporally, the purpose of this study is to classify traffic patterns into a certain number of clusters each of which exhibit similar patterns. The traffic pattern is defined as a sequence constituted by 5-minute traffic data within a twelve hours period. Consequently, each of traffic patterns contains a total of 144 time intervals (5-minute). By using a concept of rolling horizon as depicted in Figure 4, each of traffic patterns is generated in a lag of one-hour. For example, the first traffic pattern of an on-ramp traffic data is Monday 12:00 am ~ 12:00 pm, the second traffic pattern is Monday 1:00 am ~ 1:00 pm, the third is Monday 2:00 am ~ 2:00 pm, etc. Taking the middle part of Taiwan No.1 Freeway between Toufen Interchange to Beidou Interchange (a total of 15 interchanges) during May 25th to May 31st (from a Monday to Sunday).The number of traffic patterns is totally 2,355.

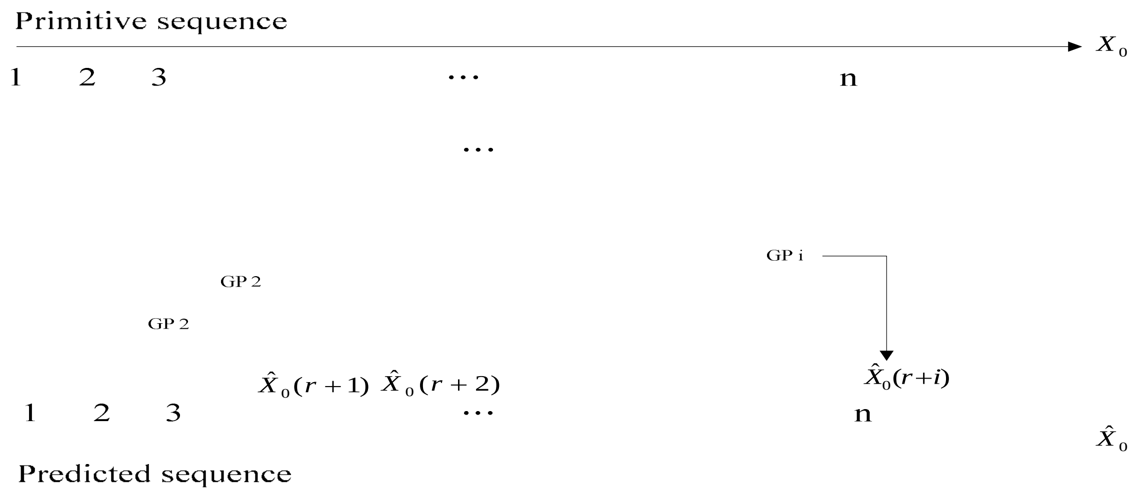


Figure 4. The concept of rolling-horizon

By following the generation of traffic patterns, a K-means method is used to classify them into several exclusive clusters. For each of clusters, the first 120 time intervals of each traffic patterns in the same cluster is used to train the genetic programming (GP) prediction model while the rest of 24 time intervals of these traffic patterns is used to validate the model performance.

The traffic prediction input and output nonlinear system can be expressed as:

$$x(t+1) = f[x(t), x(t-1), ..., x(t-d)] \quad (14)$$

where $x(t)$ denotes the detected traffic data at time t. The maximum number of time lags is denoted as d, the relationship between the traffic data in previous and current time intervals is represented by the a nonlinear function f[]. The nonlinear system is assumed to be modeled by a p^{th} order finite traffic pattern:

$$x(t+1) = b_0 + \sum_{k=1}^{p} b_k(d_1, d_2, ..., d_k) \prod_{j=1}^{k} x(t - d_j) \quad (15)$$

Where $b_k(d_1,d_2,\ldots,d_k)$ is the coefficient of the k^{th} order of traffic data with a lag of $d_1,d_2,\ldots,d_k$, and $d_i \le d_{i+1} \le d$.

4.1 Traffic Patterns Clustering

Clustering is a process in which a group of unlabeled patterns are partitioned into a number of sets so that similar patterns are assigned to the same cluster, and dissimilar patterns are assigned to different clusters. Clustering has become a widely studied problem in a variety of application domain, such as data mining and statistical data analysis. While several algorithms have been proposed in literatures for clustering, the *K*-means method remains an effective and easily implemented algorithm.

The *K*-means algorithm must extract a given number of clusters of patterns from a training set. This research uses a two-step clustering process to find the optimal number of clusters, and then uses K-means to assign these traffic periods into several clusters so that the traffic period in each cluster will exhibit a similar pattern.
This clustering algorithm is composed of the following steps:
Setp 1: Find the optimal number of clusters with two-step clustering.
Step 2: Randomly select the initial candidates D-periods space point for k cluster from the dataset.
Step 3: Assign each pattern to the nearest cluster using distance measurements as indicator variables $\{r_k^{(n)}\}$. In the assignment step, this research set $\{r_k^{(n)}\}$ equals to one, if mean k is the closest mean to data point $\{x^{(n)}\}$; otherwise $\{r_k^{(n)}\}$ is zero.

$$\hat{k}^{(n)} = \arg\min_k \{ d(m^{(k)}, x^{(n)}) \}$$

$$r_k^{(n)} = \begin{cases} 1 & if \quad \hat{k}^{(n)} = k \\ 0 & if \quad \hat{k}^{(n)} \ne k \end{cases} \quad (16)$$

Step 4: Re-compute the centroids of these k clusters to find new cluster centers D-periods space point,

$$m^{(k)} = \frac{\sum_n r_k^{(n)} x^{(n)}}{R^{(k)}} \qquad where \quad R^{(k)} = \sum_n r_k^{(n)} \quad (17)$$

and compute the sum of square error E. The algorithm achieves this result by minimizing a square-error function E of the sum of all distances of points from the mean of their clusters, such that

$$E = \sum_{i=1}^{k} \sum_{x \in c_i} \sum_{d=1}^{D} d(\overline{X}_{id}, x) \quad (18)$$

where $\overline{X}_{id} = \frac{\sum_{x \in c_i} x}{|C_i|}$ is the mean point of cluster C_i.

Step 5: Repeat Steps 3 and 4 until convergence. Typical convergence criteria includes no further reassignment of patterns to new clusters, the change in error function *E* falls below a threshold, or a predetermined number of iterations has been reached.

4.2 Traffic Prediction

The medium-to-long term traffic prediction models are developed in this study and employed to predict a total of *m* $\left(i.e. n+1^{th}, n+2^{th}, ..., n+m^{th}\right)$ periods of sequence based on its historical and primitive *n* time-series data, $X^0 = \{x^0(k), 1 \le k \le n\}$ for each cluster separately, where $x^0(k)$ is a time-series data at time *k* and *m* is the length of prediction period. Since the number of traffic patterns needed to construct the prediction model is unknown a priori, the GP algorithm is especially suitable for the traffic prediction model. Genetic programming is a technique for programming computers by means of natural selection (Koza, 1992). It is a variant of the genetic algorithm developed by Holland *et al.* (1975), based on the concept of adaptive survival in natural organisms.

The GP algorithm is a global optimization scheme based on the mechanism of natural selection and offspring generation. It starts with a population of randomly generated individual trees. Every tree corresponds to the linear combination of traffic flow. Every generated tree is then evaluated for fitness. The fitness value of every tree is utilized as the measurement for selection to generate offspring trees. Brief introductions to these methods are provided below.

Step 0: Define function set and terminal set.

Programs are expressed in genetic programming as syntax trees rather than as lines of code. The tree includes nodes and links. The nodes indicate the instructions to execute. Function sets may consist of the arithmetic functions of addition, subtraction, multiplication, and division as well as a conditional branching operator; the function set, *F*, for this research is *F* = {＋, －, ×}. The links indicate that the arguments for each instruction called terminals set may consist of the program's independent variables and numerical constants. The terminal set, *X*, for this research is *X* = {*x*(*t*),*x*(*t*-1), … ,*x*(*t*-10), *x*(*t*-11)}, and

$$x(t+1) = f(x(t), x(t-1), ..., x(t-11)) \tag{19}$$

Step 1: Initialize random population size.

Randomly generate a population of *N* traffic pattern.

Step 2: Evaluate fitness value of the chromosome.

Randomly select programs from the population, evaluate them from tree structure of GP with training cases, and rank them according to fitness.

Given $\Phi_{gq}(t) = \left[\phi_{gq}^1(t), \phi_{gq}^2(t), ..., \phi_{gq}^r(t)\right]$ is convert from g^{th} generation and q^{th} tree of GP, where $\phi_{gq}^k(t)$ is one of $\prod_{j=1}^{k} x(t-d_j)$ by (2) and r is the number of item j^{th} of the tree. C_{gq} is coefficient of $\Phi_{gq}(t)$

The fitness measure defined as the value of the meaning square error between the value of the individual mathematical expression and the target polynomial, the fitness value is expressed as:

$$E_{gq} = \sqrt{\frac{\sum_{t=1}^{L}(y(t) - \hat{C}_{gq}\hat{\Phi}_{gq}^T(t))^2}{L}} \tag{20}$$

where *L* is the number of data series used for evaluations, the traffic pattern in the g^{th} generation is contained in the terminals of the best tree associated with the least fitness value defined as:

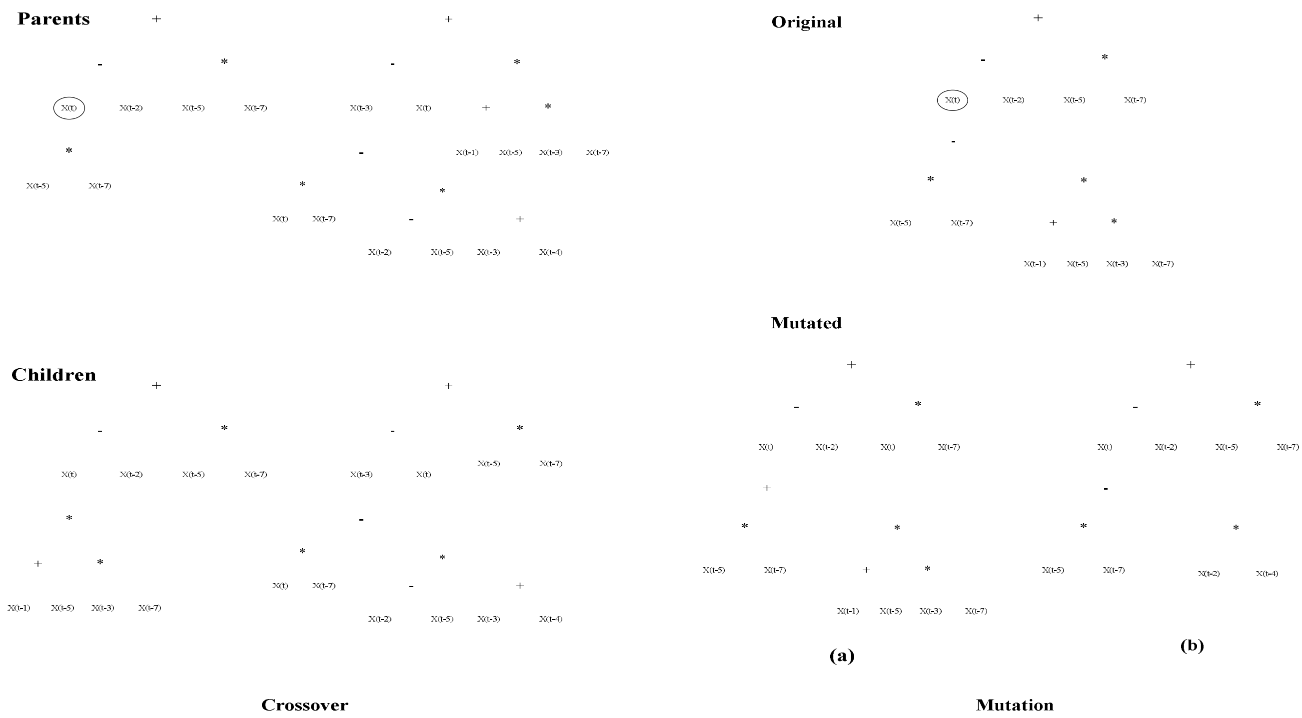
$$E_g^* = \min_{q=1,\dots,Q}(E_{gq}) \tag{21}$$

Step 3: Generate a new individual by applying genetic operations. The genetic operations include reproduction, crossover and mutation:

Step 3-1: **Reproduction.** Replace the least fit two programs by copies of the best fit two.

Step 3-2: **Crossover.** Create a new offspring for the new population by recombining randomly chosen parts from two selected programs in each parent tree and swapping the sub-tree rooted at crossover points as exemplified in Figure 5(a).

Step 3-3: **Mutation.** Randomly select a mutation point in a tree and substitute the sub-tree rooted there with a randomly generated sub-tree, as illustrated in Figure 5(b).



(a) Crossover (b) Mutation

Figure 5. Genetic operations

Step 4: If fitness tends to zero, stop the procedure. Otherwise proceed to next step.

Step 5: Generate a new population using genetic operations, and return to Step 2.

4.3 Pattern Recognition

The pattern recognition stage first employs the cluster center of every group produced by K means as cluster seed, then calculates the squared Euclidean distance of the input series and cluster center of every clusters. It then assigns the input objects to specific cluster according to the nearest cluster using a distance measure. For each pattern x_i, compute its membership $m(c_j|x_i)$ in each cluster c_j. The membership function $m(c_j|x_i)$ defines the proportion of pattern x_i that belongs to the j^{th} cluster c_j. The k-means algorithm uses a hard membership function, that is the membership $m(c_j|x_i) \in \{0,1\}$, if the pattern x_i closest to the cluster c_j (minimum squared Euclidean distance), then $m(c_j|x_i)$=1; otherwise $m(c_j|x_i)$=0.

The process can be summarized in the following steps:

Step 0: Input a set *S* of D-periods point set.
Step 1: The cluster center of every group produced by K means used as cluster seed.
Step 2: Compute the distance of each input objects such that

$$dist(x, y) = \sum_i (x_i - y_i)^2 \tag{9}$$

Step 3: Assign the input objects to specific cluster according to minimum squared Euclidean distance.
Step 4: Use the input objects and the prediction patterns of the specific cluster to predict traffic flow.

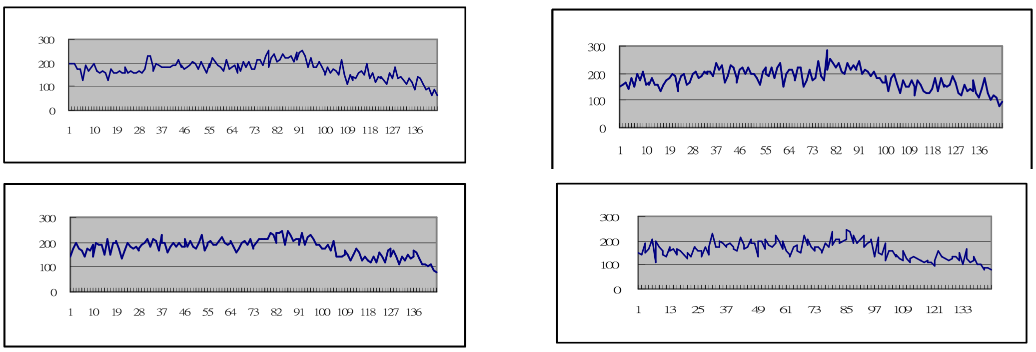
4.4 Results

To examine the feasibility of the proposed prediction model, the traffic data sets were employed and implemented. This research applied traffic counts with five minutes time interval in real-time from loop detectors at the mid-section of Taiwan No.1 Freeway, a three-lane freeway measuring 120 km long, with 15 on ramp interchanges from Toufen Interchange to Beidou Interchange within a week (2009, May 25th to 2009, May 31st). The week of traffic data an hour into the future are then inputted into the proposed prediction algorithm.

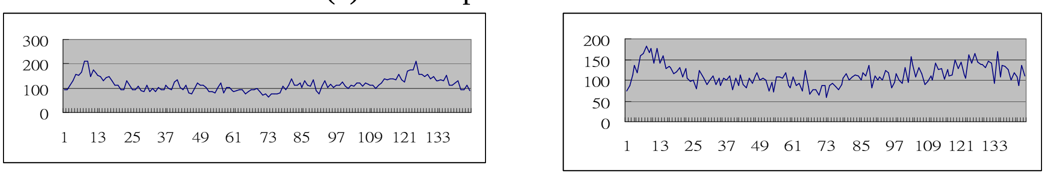
This section introduces *k*-means algorithm to the cluster traffic patterns, and employs genetic programming (GP) to develop a traffic prediction model for each cluster separately. The detailed process and results is as presented.

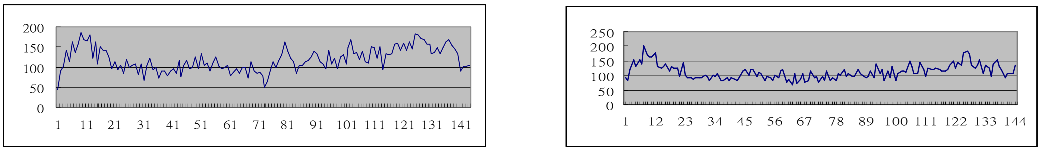
4.4.1 Clustering Traffic Pattern with K-means

Using *k*-means to cluster a week of traffic data with a rolling horizon concept between Toufen Interchange and Beidou Interchange, when traffic pattern reaches 2355, for example, the optimal clustering number is 72 clusters. Within the 3 cluster groups, each cluster consist of 4 traffic pattern. Cluster Group 1 includes Taichang (Mon.12-24), Taichang system (Tue.12-24), Taichang (Wed.12-24) and Taichang (Thu. 12-24) traffic patterns. The Cluster Group 2 includes Taichang system (Mon. 8-20), Taichang system (Tue.8-20), Taichang system (Wed. 8-20) and Taichang system (Thu. 8-20). Fengyuan (Mon.21-Tue.9), Fengyuan (Tue. 21-Wed.9), Fengyuan (Wed. 21-Thu.9) and Fengyuan (Thu. 21-Fri.9) are in Cluster Group 3, with a total of 46 traffic patterns clustered in the same group.

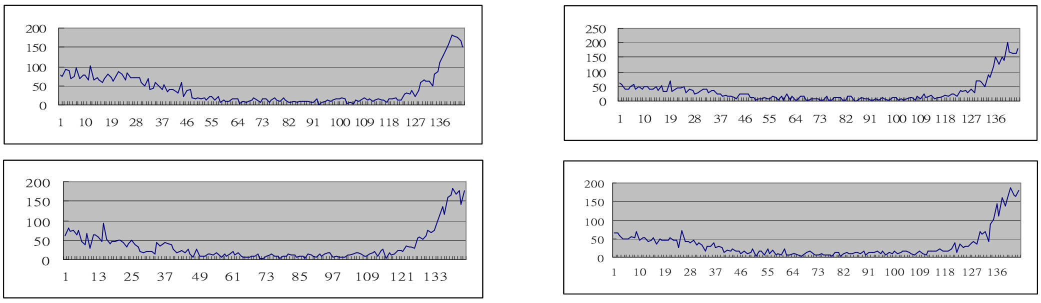


(a) Traffic patterns of Cluster 1





(b) Traffic patterns of Cluster 2



(c) Traffic patterns of Cluster 3

Figure 6. Examples of clustered traffic patterns

4.4.2 Estimated Traffic Predicting Models

Because the system is to find a mathematical function of some independent variable, the terminal set of GP includes the independent variable and numerical constants. The terminal set of this research, T, is $\{x(t), x(t-1),..., x(t-11)\}$, the Function set is $\{+,-,\times\}$, and the population size will be 50. The crossover operation is commonly performed on about 60% of the individuals in the population, the reproduction operation is performed on about 8% of the population, and the mutation operation is performed on about 1% of the population. The fitness is the Mean square error, and the initialization method is the direct method, while the other parameters are as shown in Table 1.

Table 1. Parameter settings of GP

Parameters	Values
Fitness	Mean square error
Terminal set	$x(t)$, $x(t\text{-}1)$,…, $x(t\text{-}11)$,
Function set	+, −, ×
Population size	50
Reproduction probability	0.08
Crossover probability	0.6
Mutation probability	0.01
Initial minimum depth	2
Number of generations	300
Initialization method	Direct method

The medium-to-long term traffic prediction model employs genetic programming (GP) to develop a traffic prediction model for each cluster separately. As mentioned above, for the three Cluster Groups, the prediction model is shown in the Table. Accordingly, Cluster 1 with $x(t)$ and square of $x(t)$ is used to predict next time interval traffic , Cluster 2 with $x(t)$ $x(t\text{-}1)$ $x(t\text{-}2)$ $x(t\text{-}5)$ and $x(t\text{-}10)$ is used to predict next time interval traffic, and Cluster 3 with $x(t)$ $x(t\text{-}2)$ $x(t\text{-}3)$ and $x(t\text{-}5)$ is used to predict next time interval traffic.

Table 2. Estimated GP traffic prediction models

Clusters	GP models

Cluster 1	$x(t+1)$= -0.003054$x(t)\,x(t)$ +1.451312$x(t)$
Cluster 2	$x(t+1)$=0.000004$x(t$-2$)x(t$-5$)x(t$-10)-0.000249$x(t)x(t$-1)+0.076631$x(t$-2)+0.992306$x(t)$
Cluster 3	$x(t+1)$= 1.0081 $x(t)$+0.000062 $x(t$-2$)x(t$-4$)x(t$-5) -0.000117 $x(t)x(t$-3$)x(t$-5)

4.4.3 Prediction Performance

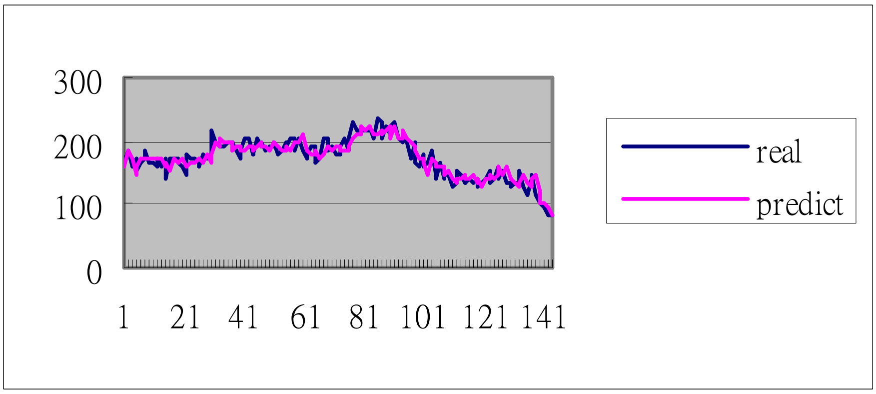
The mean absolute percentage error (MAPE) of the predicted traffic value of each time interval and each real traffic value is used to evaluate the performance of the proposed algorithm, defined as:

$$\text{Training } MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x^0(t)-\hat{x}^0(t)}{x^0(t)}\right| \times 100\% \tag{22}$$

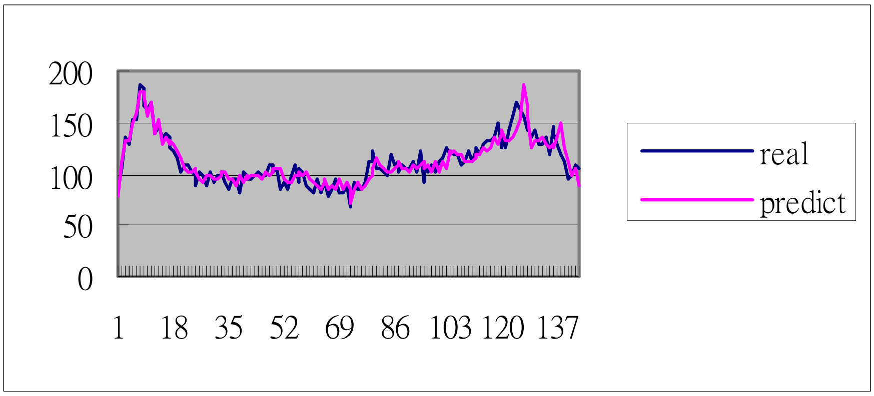
$$\text{Validation } MAPE = \frac{1}{m}\sum_{k=1}^{m}\left|\frac{x^0(t)-\hat{x}^0(t)}{x^0(t)}\right| \times 100\% \tag{23}$$

where $\hat{x}^0(k)$ is the predicted value of traffic entering interchange and $x^0(k)$ is the real value of traffic entering interchange.

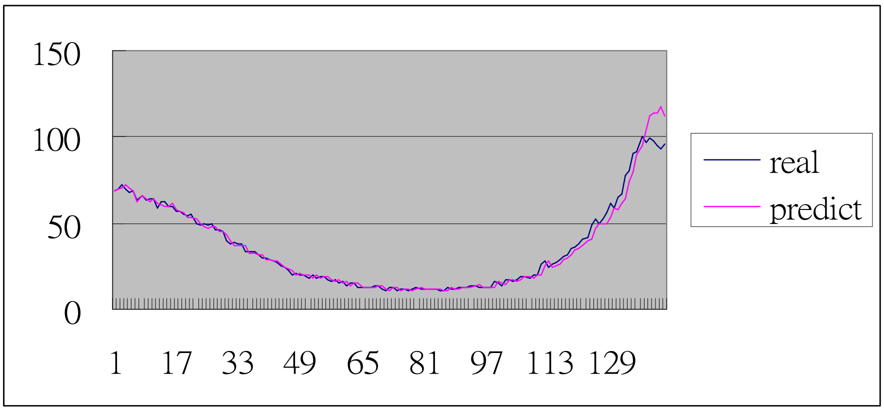
Using the GP traffic prediction model for the data set between Toufen Interchange and Beidou Interchange (traffic data with a rolling horizon), the optimal clustering number is 72. Taking GP with 120 rolling interval, each predicts next 2 hours, using 24 time intervals. Taking the three Cluster Groups, as mentioned above for example, the training MAPE of various cluster are 6.48%, 6.91% and 5.93%, with the Validation MAPE equal to 9.02%, 9.50% and 10.21% respectively. All cluster average training and the Validation MAPE is 6.88% and 10.35%. The comparison between the predicted versus the center traffic pattern of cluster under the three clusters is shown in the figure below.



(a) Cluster 1



(b) Cluster 2



(c) Cluster 3

Figure 7. Predicted and real traffic patterns of three example clusters

5. CELL-BASED ARRIVAL DISTRIBUTION MODELING

This study employs CTM to predict the arrival distribution of an O-D pair traffic, which will then be used to compute $\rho_{ij}^{m}(k)$.

5.1 Cell Transmission Model

As shown in Figure 8, a freeway is equally discretized into homogeneous sections (cells), numbered consecutively from i = 1 to I starting with the upstream end of the road, where the length of each cell is the distance traveled by a vehicle in one clock tick under light traffic.

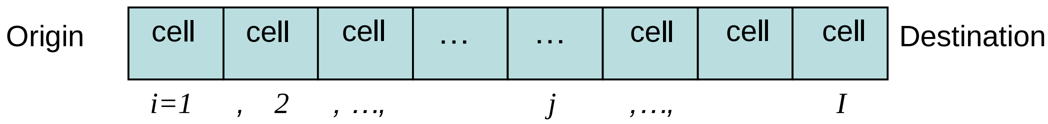


Figure 8. Cell representation of a freeway corridor

In light traffic, all vehicles in a cell can be assumed to advance to the next cell with each click. It is unnecessary to know where within the cell they are located. Therefore, the system's evolution obeys:

$$n_{i+1}(t+1) = n_i(t) \qquad \text{for } t = 0, 1, 2, \dots, T \tag{24}$$

where $n_i(t)$ is the number of vehicles in cell i at time t. It is assumed that this equation holds true for all traffic flows unless queuing occurs. The following two variables are introduced to incorporate queuing in the model: (1) $Q_i(t)$, the maximum flow from cell i – 1 to i during time interval t (when the clock advances from t to t + 1), also known as "capacity," and (2) $N_i(t)$, the maximum number of vehicles that can be present in cell i in time t. Thus, $N_i(t) - n_i(t)$ is the amount of empty space in cell i at time t.

The CTM assumes a simplified version of the fundamental diagram, usually based on a trapezium form, as shown in Figure 9, and provides simple solutions for realistic networks. It is assumed that a free-flow speed v at low densities and a backward shockwave speed w for high densities are constant ($v \geq w$).

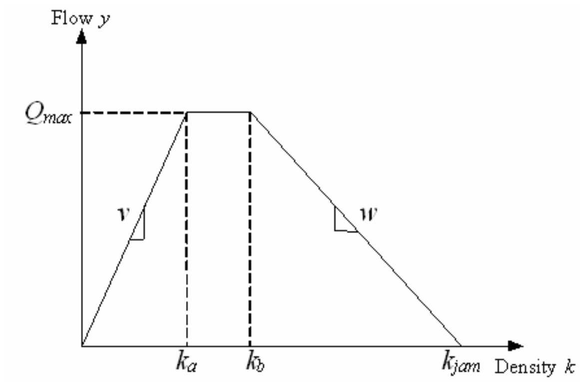


Figure 9. Fundamental diagram of CTM

With these, we define $y_i(t)$ as the number of vehicles that can flow into i for time interval t as:

$$y_i(t) = \min\{n_{i-1}(t)\, ,\, Q_i(t)\, ,\, \frac{w}{v}[N_i(t) - n_i(t)]\} \tag{25}$$

The CTM is based on a recursion where the cell occupancy at time t + 1 equals its occupancy at time *t*, plus its inflow and minus the outflow:

$$n_i(t + 1) = n_i(t) + y_i(t) - y_{i+1}(t) \tag{26}$$

If the remaining storage capacity and flow capacity of next cell is sufficient, all vehicles will move forward to the next cell; otherwise, only part of them can move proportionally, the logic is as:

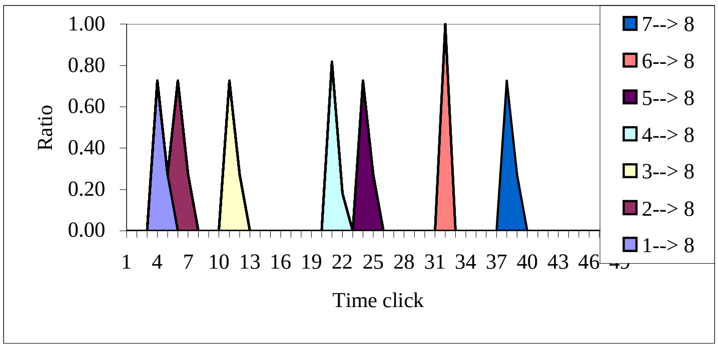
$$\begin{aligned} &\textit{if} \quad y_i(t+1) + r_i(t+1) \le \min[Q_i(t+1), N - n_i(t+1)] \\ &\textit{then} \quad Q_{i+1}(t+1) = y_i(t+1) + r_i(t+1) \end{aligned} \tag{27}$$

$$\begin{aligned} &\textit{if} \quad y_i(t+1) + r_i(t+1) > \min[Q_i(t+1), N - n_i(t+1)] \\ &\textit{then} \quad Q_{i+1}(t+1) = 1 - \left[\min[Q_i(t+1), N - n_i(t+1)] \big/ y_i(t+1) + r_i(t+1) \right] \end{aligned} \tag{28}$$

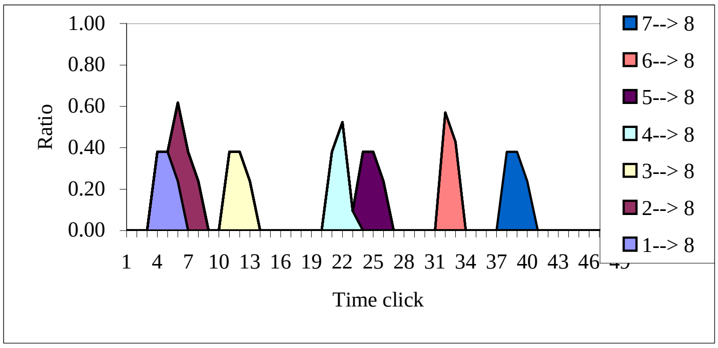
5.2 Replicating Traffic Dispersion Phenomenon

To demonstrate the capability of CTM in replicating the traffic hydrodynamics and to investigate the degree of traffic dispersion under various traffic conditions, a simulation on a three-lane freeway section with eight interchanges has been conducted. Parameters are set as follows: free flow speed=120 km/hr, jam density=125 vehicles per kilometre per lane, capacity=7,200 vehicles per hour, cell storage capability=375 vehicles, time click=30 seconds, and cell length=1 km.

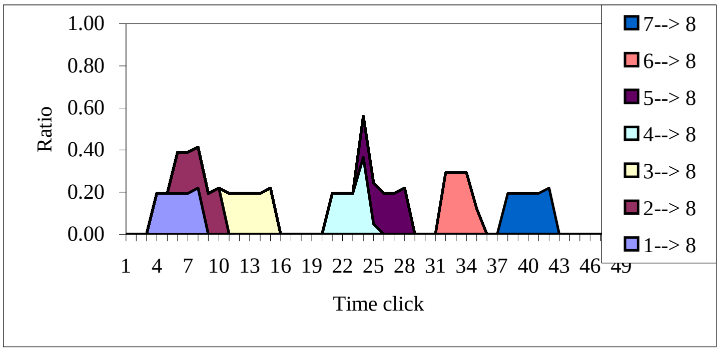
Four scenarios with various traffic conditions are simulated, including free-flow, light synchronized flow, heavy synchronized flow and congested flow. Taking the traffics entering at seven interchanges (No.1 to No.7) and heading to No.8 interchange in time interval *t*=1 for example, their arrival distributions under various traffic conditions are graphically depicted in Figure 10. As shown in Figure 10(a), almost all traffics arrive at No.8 interchange within one or two time intervals under free-flow condition. Once the traffic flow increases, the degree of traffic dispersion will significantly appear. As shown in Figures 10(b)-(d), the same entering traffic will arrive at No.8 interchange among a wider range of time intervals ranging from two to three time intervals under light synchronized flow, four to five time intervals under heavy synchronized flow, and six to eight time intervals under congested flow, suggesting the capability of the CTM model in replicating traffic dispersion phenomenon.



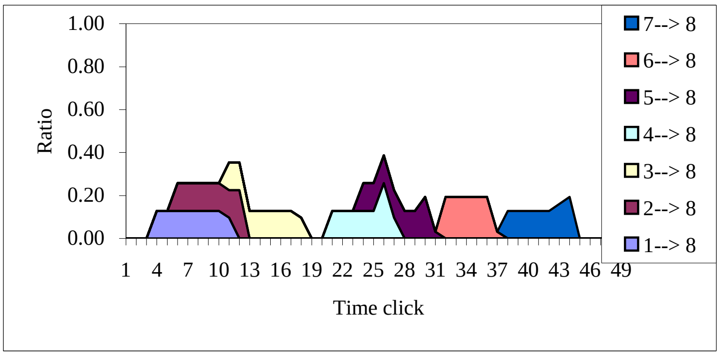
(a) Free-flow



(b) Light synchronized flow



(c) Heavy synchronized flow



(d) Congested flow

Figure 10. Distributions of No.8 interchange arrival traffics from various origins

6. EXTENDED KALMAN FILTERING MODEL

In the above model formulation, the information of each O-D pair can be estimated using the data provided by the surveillance system or historical information, and the unknown set of parameters are O-D proportions, $b_{ij}(k)$.

As used in most existing approaches, the dynamic O-D parameters, $b_{ij}(k)$, are assumed to follow the random walk process between successive time intervals:

$$b_{ij}(k+1) = b_{ij}(k) + w_{ij}(k), \quad 0 \le i < j \le N \tag{29}$$

$$B(k+1) = B(k) + W(k) \tag{30}$$

$$Z(k) = H(k) \cdot B(k) + W(k) \tag{31}$$

$$Z(k) = \left[y_1(k), y_2(k), ..., y_N(k); U_1(k) - q_1(k), ..., U_{N-1}(k) - q_{N-1}(k) \right]^T \tag{32}$$

where, $w_{ij}(k)$, a random term, is an independent Gaussian white noise sequence with zero mean and its covariance, $Z(k)$, is a column vector, $H(k)$ is a matrix with its entries given by the corresponding coefficients in Eqs. (12) and (13), and $e(k)$ is an observation noise vector, which can be defined as a Gaussian white noise with zero mean and its covariance matrix, and R = Var[$e(k)$] = diag[$r_1, \ldots, r_{2N-1}$] is a diagonal positive definite matrix. $B(k)$ is a matrix of the O-D proportions of entering flows $b_{ij}(k)$. $W(k)$ is a matrix of white noise $w_{ij}(k)$.

The proposed estimation algorithm, based on the extended Kalman filtering concept, is presented as follows.

Step 0: Initialization.

Parameters settings include cell length L_i, i = 0,1,. . . , N-1, time interval, t_0. $\text{var}[e(k)] = diag[r_1, r_2 ...]$. $X(0) = E[b(0)]$. $P(0) = Var[b(0)]$. Besides, on-ramp, link and off-ramp flows are given.

Step 1: Determine $\rho_{ij}^m(k)$ by CTM.

Step 2: Compute the linearized transformation matrix based on the determinant $\rho_{ij}^m(k)$.

$$H^{K-1} = \left[H_{rs}^{k-1} \right]$$

$$H^k_{j,Ni+j-i(i+1)} = \sum_{m=0}^{M} q_i(k-m) \cdot \rho_{ij}^m(k) \qquad for \quad 0 \le i < j \le N$$

$$H^k_{N+l,Ni+j-i(i+1)} = \sum_{m=0}^{M} q_i(k-m) \cdot \rho_{ij}^m(k) \qquad for \quad 0 \le i < j \le N$$

$$\left[H^{K-1} \right] = \left[h_1, h_2, ..., h_{2N-1} \right]^T$$

$$Z'(k) = \left[y_1(k), y_2(k), ..., y_N(k); U_1(k) - q_1(k), ..., U_{N-1}(k) - q_{N-1}(k) \right]^T$$

Step 3: Initialization of the sequential Kalman filtering method.

set $b_0 = b(k+1)$

$p_0 = p_{k+1} + D$ where $D = \left[d_b, ..., d_b \right]$ is a covariance matrix of $W(k)$

Step 4: Sequential Kalman filtering iterations.

For i = 1, 2, …, 2N-1

$$g^i = p^{i-1} h_i^T \left[h_i p^{i-1} h_i^T + r_i \right]^{-1}$$

$$p^i = p^{i-1} - g^i h_i p^{i-1}$$

$$\delta^i = y_i(k) - h_i b(k-1)$$

Truncation:

$$\alpha' = \underset{0\le\alpha\le1}{MAX}\left[\alpha \middle| 0 \le \left[b^{i-1}\right] + \alpha\delta^i g^i \le 1\right]$$

Set $\left[b^i\right] = \left[b^{i-1}\right] + \alpha\delta^i g^i$

Normalization:

For m=1, 2, …, N-2

$$\beta_m = \sum_{j=m+1}^{N} b^i_{mj}$$

$$b^i_{mj} = b^i_{mj} / \beta_m \qquad j=m+1,\ldots,N.$$

Step 5: Stop condition test.

Check the convergence of estimated O-D proportions. If preset stop conditions (convergence level or number of iterations) has not been met, then go to Step 1. Otherwise, go to Step 6.

Step 6: Prediction of the states.

Set $p_k = p^{2N-1}$ and $\left[b(k)\right] = \left[b^{2N-1}\right]$, $k = k + 1$, go to Step 1.

7. CASE STUDY

In this empirical case study, an entire week (from May 25 to May 31, 2009) of 5-minute traffic counts are extracted from the loop detectors over the 120-km stretch of Taiwan Freeway No. 1 between Toufen Interchange and Beidou Interchange, within which 15 on-ramp interchanges exist. The mainline of this stretch has three lanes.

To investigate the effects of initial value settings of O-D proportions on the performance of the proposed approach, two initial value settings are attempted: one by randomly generated (RG) technique and the other by equal share (ES) technique. Taking origin interchange No. 12 as an example, the associated O-D proportions are denoted as $b_{12,13}(k)$, $b_{12,14}(k)$, and $b_{12,15}(k)$. With RG technique, three random numbers 0.2, 0.9, and 0.5 are generated and then normalized such that the sum of three proportions equals 1; namely, $b_{12,13}$ (k)=0.125, $b_{12,14}$ (k)=0.563, and $b_{12,15}$ (k)=0.312. In contrast, with ES technique, the three proportions are simply set as $b_{12,13}$ (k)=0.333, $b_{12,14}$ (k)=0.333, and $b_{12,15}$ (k)=0.333.

The distributions of real $b_{12,15}$ proportions (from Zhanghua Interchange to Yuanlin Interchange) along with the estimated O-D proportions by both RG and ES techniques are demonstrated in Figure 11. Note that the proposed approach can predict real O-D proportions quite accurately for these two initial value setting techniques. However, RG technique is slightly superior to the ES technique in terms of the prediction accuracy. Thus, the RG technique is adopted for predicting the remained O-D proportions.

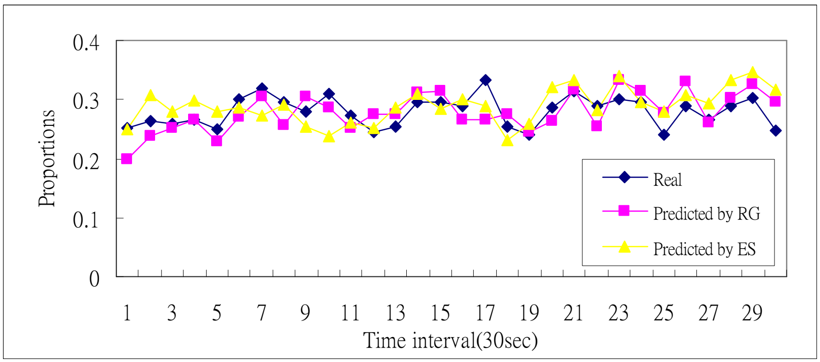


Figure 11. Comparison of real $b_{12,15}$ proportions with predicted values by RG and ES techniques

Figure 12 displays the process of convergence for the time interval k=986, $b_{1,15}$, Toufen Interchange to Beidou Interchange. The results show that the overall *RMSE* is 0.1043, indicating a rather good fitness of the proposed approach.

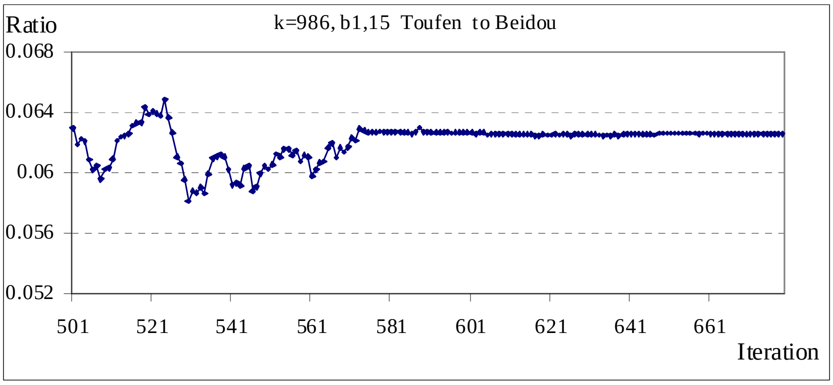


Figure 12. The process of convergence

8. CONCLUDING REMARKS

This paper has developed an integrated estimation algorithm by combining cell transmission model (CTM) and extended Kalman filtering (EKF) to respectively and iteratively estimate the arrival distribution and the O-D proportions. Our results from an exemplified example of a freeway corridor have shown that CTM can surely capture the traffic dispersion under various traffic conditions. The degree of traffic dispersion will get enlarged as traffic flow increases. The results from a case study on Taiwan No.1 Freeway have also shown that the proposed algorithm can accurately estimate the O-D proportions with a low RMSE of 0.0414. The applicability of the proposed integrated algorithm has been proven.

Several directions for future research can be identified. First, the applicability and efficiency of the proposed algorithm on a large scale network should be further examined. Second, due to data availability in the case study, the O-D matrices are arbitrarily given and then used to generate "real time" detected traffic flows by traffic simulation software, DynaTaiwan. However, with advanced traffic surveillance technologies, it is feasible to collect real time traffic information in the future study to further examine the applicability of the proposed algorithm. Third, the proposed algorithm is only valid for the case of linear freeway corridor. In the future study, route choice behaviors should be incorporated to the proposed algorithm to suit for more complicated networks. Fourth, the estimation accuracy of the proposed algorithm under various traffic conditions also deserves further investigation and comparison. Last but not least, comparisons with other algorithms should also be conducted to demonstrate the superiority of the proposed algorithm.

9. 計畫成果自評

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估 ☑達成目標 □ 未達成目標（請說明，以 100 字為限） □ 實驗失敗 □ 因故實驗中斷 □ 其他原因 說明：
2. 研究成果在學術期刊發表或申請專利等情形： 論文：☑已發表 □未發表之文稿 □撰寫中 □無 專利：□已獲得 □申請中 □無 技轉：□已技轉 □洽談中 □無 其他：（以 100 字為限） 本計畫各年期發表文章與指導論文寫作分別臚列如下： **第一年期：** 國內研討會論文 1 篇：[17] 國際研討會論文 1 篇：[18] 碩士論文寫作 1 名（完成）：[25] 碩士論文寫作 1 名（進行中）：[26] 博士論文寫作 1 名（進行中）：[27] **第二年期：** 投稿國內研討會論文 1 篇：[20] 投稿國際研討會論文 1 篇：[19] 碩士論文寫作 1 名（完成）：[26] 博士論文寫作 1 名（進行中）：[27] **第三年期：** 國內研討會論文 1 篇：[20] 國際研討會論文 2 篇：[19] 國內期刊(TSSCI)論文 1 篇：[22] 國際期刊論文 1 篇：[21] 投稿期刊論文 2 篇：[23, 24] 博士論文寫作 1 名（進行中）：[27]

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

本計畫為三年期計畫，具體完成之研究成果如下：

1.建立車牌辨識系統（LPR）預測模式

在進行動態起迄旅次矩陣預測時，由於 LPR 所辨識車輛之部份行徑資料必須加以進一步推估及判斷，方能據以建立有效之流量方程式。基此，本研究利用中觀車流模式（cell transmission model，CTM）及短及中長期交通量預測模式進行短期車輛推移之模擬，俾作為起迄矩陣推估之用。

2.中長期交通量預測模式－兩階段預測模式

基於交通型態會重複發生的特性，本研究先利用 K-means 以滾動時間軸特性，進行上匝道交通型態之分群，再利用遺傳規劃法（genetic programming model）進行各分群交通量預測模式之建構，俾進行中長期交通量之預測（2 至 4 小時），以作為動態起迄矩陣推估之輸入資料。

3.建立中觀車流模式

為能有效進行進入匝道交通量在研究路網上時空推移之模擬，本研究利用格位傳遞模式（CTM）中觀車流模式模化在時間 t 進入高速公路之交通量，到達其目的地交流道之到達型態分佈情形，俾反應不同交通狀態下，到達分佈擴散情形(dispersion)，以更精準推估動態起迄矩陣。

4.建立動態起迄旅次矩陣之推估模型

本研究整合兩階段交通量預測模式、CTM 推估交通量到達擴散分佈型態預測模式，以及 LPR 增列之交通觀測方程式，利用卡門濾波理論進行動態起迄矩陣之推估。

以往有關動態起迄矩陣推估之相關研究，大多必須假設車輛到達目的地交流道之分佈型態（平均分佈於少數區間內或假設為常態分配），其僅能適用於某一種交通型態（例如，自由流、同步流或擁塞流）下之推估。本研究所提出之整合動態起迄矩陣推估模式，不僅可適用於不同交通型態下之動態起迄矩陣推估，亦能進行中長期交通量預測，方能真正達到動態起迄矩陣推估之目的。

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